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Using geographic information science and remote sensing to analyze drivers of tropical forest dynamics across spatial levels and deforestation contexts

Ruben Weber

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Prüfer*innen der Dissertation:

1. Priv.-Doz. Dr. Sven Günter
2. Prof. Dr. Thomas Knoke

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“It's the questions we can't answer that teach us the most. They teach us how to think. If you give a man an answer, all he gains is a little fact. But give him a question and he'll look for his own answers.”

Patrick Rothfuss, The Wise Man's Fear.

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Abstract

In recent decades, tropical forest dynamics have been characterized by widespread deforestation accompanying forest degradation and fragmentation. This trend continues to threaten the multiple ecosystem services and functions provided by tropical forested landscapes, which play indispensable roles for planet Earth and our life on it. To design and implement efficient forest protection policies, the availability of reliable data on forest dynamics and the related drivers at different spatial levels is a prerequisite. Despite recent advances in this regard, there is still a lack of cross-scale pantropical studies, which facilitate general conclusions from a global perspective. In this thesis, I address this gap by including information from different geographical scopes, i.e., international to local, and different tropical countries, i.e., Zambia, Ecuador and the Philippines. More specifically, I analyze the influence of (i) the spatial scale, in accordance with the panarchy framework, and (ii) different deforestation contexts, derived from the forest transition theory, on: (a) the role of relevant drivers of forest cover change, (b) the capacity to monitor forest dynamics accurately and (c) stakeholder perceptions about future threats to tropical forest and preferred policy instruments. This thesis is based on my work as an active author on peer-reviewed scientific articles. Overall, it provides a comprehensive overview of up-to-date methods to collect, process and analyze data on tropical forests from primary and secondary sources. This includes, for instance, the use of geographical information science, spatial statistics, remote sensing techniques, global and national official statistics, ground verification, surveys or questionnaires, participatory mapping activities, spatial econometrics, multivariate regression models, quality analysis of land cover maps, principal component analyses or analyses of variance.

The findings of this thesis prove that tropical forest dynamics and the related drivers are sensitive to the deforestation context or the forest transition stage of a studied area, suggesting that there is no one-size-fits-all solution to tropical deforestation. For instance, in the case of Zambia, spatial econometric modelling and map accuracy assessments revealed underdeveloped monitoring capabilities when compared to Ecuador and the Philippines. At the same time, the analyses of stakeholder perceptions and community focus group discussions disclosed weaker governance structures, lower confidence in policy instruments and lower alertness about possible threats to forest. These results combined point to potentially adequate measures to tackle the challenges in Zambia and in similar contexts of early forest transition: i.e., improving mapping capabilities for the detection of early deforestation and forest degradation, awareness-raising initiatives and enhancing governance frameworks. On the contrary, stakeholders in late/post-transition areas exhibited higher alertness about commercial drivers of deforestation and an increased confidence in policy instruments, despite the higher heterogeneity of drivers and the worse accuracy of state-of-the art forest datasets in these contexts. Considering the global agenda for reforestation and forest restoration initiatives, these findings underpin the need for developing robust and comprehensive monitoring capabilities, able to distinguish multiple drivers and detecting regrowth forests, to counter potential biases of stakeholders' perceptions in late/post-transition contexts.

Furthermore, the results of this thesis confirm the existence of scale-related effects as outlined by the panarchy framework, based on an increased likelihood of human-environment interactions and more direct land and resource demands at local levels, which can propagate over time as cascading effects to larger socio-ecological systems. This is demonstrated, for instance, by the increased complexity of drivers identified by spatial econometric models, stakeholder perceptions and supporting studies at local levels. Thus, these results indicate how addressing anthropogenic causes of deforestation locally can improve the resilience of more conservative structures (e.g., regional, global). Similarly, the local spatial levels showed stronger indirect impacts of neighboring administrative units, suggesting an increased need for applying flexible approaches beyond jurisdictional boundaries (e.g., socio-ecological systems). Moreover, the lower alertness about deforestation drivers and the lower confidence in policy instruments shown by local stakeholders, suggests the need of harmonizing international and national protection aims with a variety of local interests (e.g., direct dependence on agricultural and forest resources, governance structures). Finally, through rigorous quality analysis conducted on global and national datasets, in direct comparison with my own produced maps, it becomes evident that the inclusion of locally obtained data is crucial in enhancing the reliability and accuracy of available information pertaining to forest extent and condition.

In any case, the findings of my publications also confirm that anthropogenic pressure and socio-economic factors (i.e., demography, agriculture, wood extraction and infrastructure) are dominant drivers of tropical deforestation, independently of the deforestation context or spatial scale. These findings imply the universal necessity of ensuring policy coherence when addressing the underlying socio-economic drivers of deforestation. However, the surprisingly strong effects of population density on forest cover, as shown by the econometric modelling, challenge the current understanding of deforestation drivers and suggest clear limitations of sectoral policy far beyond agriculture, forestry or bioeconomy. Furthermore, the cross-scale and cross-country consensus observed among tropical stakeholders concerning the important role of agriculture and the suitability of reforestation and forest restoration measures in the coming decade, evidences the existence of common entry points for collaboration between institutions. At the same time, this result points to a paradigm shift from protected areas to a stronger focus on integrative approaches.

Overall, this thesis has successfully demonstrated the effectiveness of applying the forest transition theory to characterize countries or regions and to identify deforestation patterns. This validation of the theory has significant implications for scientific research, policy development, and practical interventions, as stated above. By incorporating the spatial scale and the panarchy concept into the analytical framework of the forest transition theory, this study has filled a gap in scientific knowledge and enhanced the overall understanding of tropical forest dynamics.

Keywords: tropical forestry, drivers of deforestation, forest transition, spatial econometrics, spatial analysis, geographic information science, remote sensing, Zambia, Ecuador, Philippines

Zusammenfassung

In den letzten Jahrzehnten war die Dynamik der Tropenwälder durch eine weit verbreitete Entwaldung gekennzeichnet, die mit Walddegradierung und -fragmentierung einherging. Dieser Trend bedroht weiterhin die vielfältigen Ökosystemleistungen und -funktionen tropischer Waldlandschaften, die für den Planeten Erde und unser Leben auf ihm unverzichtbar sind. Voraussetzung für die Konzeption und Umsetzung effizienter Waldschutzmaßnahmen ist die Verfügbarkeit zuverlässiger Daten über die Walddynamik und die damit verbundenen Treibkräfte auf verschiedenen räumlichen Ebenen. Trotz der jüngsten Fortschritte in dieser Hinsicht mangelt es immer noch an skalenübergreifenden pantropischen Studien, die allgemeine Schlussfolgerungen aus einer globalen Perspektive ermöglichen. In dieser Dissertation, schließe ich diese Lücke, indem ich Informationen aus verschiedenen geografischen Ebenen, d.h. von international bis lokal, und aus verschiedenen tropischen Ländern, d.h. Sambia, Ecuador und den Philippinen, einbeziehe. Genauer gesagt, analysiere ich den Einfluss (i) der räumlichen Skala, in Übereinstimmung mit dem Panarchierahmen, und (ii) verschiedener Entwaldungskontexte, abgeleitet aus der Waldübergangstheorie (*Forest transition*), auf: (a) die Rolle relevanter Triebkräfte für die Veränderung der Waldbedeckung, (b) die Fähigkeit zur genauen Überwachung der Walddynamik und (c) die Wahrnehmungen der Interessengruppen über künftige Bedrohungen der Tropenwälder und bevorzugte politische Instrumente. Diese Dissertation basiert auf meiner Arbeit als aktiver Autor von wissenschaftlichen Artikeln mit Peer-Review. Insgesamt bietet sie einen umfassenden Überblick über aktuelle Methoden zur Erhebung, Verarbeitung und Analyse von Daten über tropische Wälder aus Primär- und Sekundärquellen. Dazu gehören der Einsatz von geographischer Informationswissenschaft, räumlicher Statistik, Fernerkundungstechniken, globalen und nationalen amtlichen Statistiken, Bodenverifizierung, Fragebögen, partizipative Kartierungsaktivitäten, räumliche Ökonometrie, multivariate Regressionsmodelle, Qualitätsanalysen von Landbedeckungskarten, Hauptkomponentenanalysen oder Varianzanalysen.

Die Ergebnisse dieser Dissertation zeigen, dass die Dynamik der Tropenwälder und deren Triebkräfte vom Entwaldungskontext bzw. von der Waldübergangsphase eines untersuchten Gebiets abhängen. Das deutet daraufhin, dass es keine Einheitslösung für die Entwaldung der Tropen gibt. Im Fall von Sambia beispielsweise zeigten die räumliche ökonometrische Modellierung und die Bewertung der Kartengenauigkeit, dass die Überwachungsmöglichkeiten im Vergleich zu Ecuador und den Philippinen unterentwickelt sind. Gleichzeitig ergaben die

Analysen der Wahrnehmungen der Interessengruppen und die Diskussionen in den Fokusgruppen schwächere *Governance*-Strukturen, ein geringeres Vertrauen in politische Instrumente und eine geringere Wachsamkeit gegenüber möglichen Bedrohungen für den Wald. Diese Ergebnisse deuten auf potenziell geeignete Maßnahmen zur Bewältigung der Herausforderungen in Sambia und in ähnlichen Kontexten einer frühen Waldumwandlung hin: bzw. die Verbesserung der Kartierungskapazitäten zur Erkennung von früher Entwaldung und Walddegradierung, Sensibilisierungsinitiativen und die Verbesserung der *Governance*-Rahmenbedingungen. Im Gegensatz dazu zeigten sich die Akteure in Gebieten, die sich in der späten Übergangsphase befinden, aufmerksamer gegenüber den kommerziellen Triebkräften der Entwaldung und hatten ein größeres Vertrauen in politische Instrumente. In diesen Gebieten waren die Triebkräfte jedoch heterogener und die Genauigkeit der aktuellen Walddaten schlechter. In Anbetracht der globalen Agenda für Wiederaufforstungs- und Waldrestaurierungsinitiativen unterstreichen diese Ergebnisse die Notwendigkeit der Entwicklung robuster und umfassender Überwachungskapazitäten. Das heißt, die Entwicklung von Methoden die in der Lage sind, mehrere Treiber zu unterscheiden und wiederaufwachsende Wälder in solchen Kontexten zu erkennen, um potenzielle Verzerrungen in der Wahrnehmung der Interessengruppen zu vermeiden.

Darüber hinaus bestätigen die Ergebnisse dieser Dissertation das Vorhandensein von skalenbezogenen Effekten, wie sie im Panarchierahmen skizziert werden. Diese Effekte basieren auf einer erhöhten Wahrscheinlichkeit von Mensch-Umwelt-Interaktionen und einer direkteren Land- und Ressourcennachfrage auf lokaler Ebene, die sich im Laufe der Zeit als Kaskadeneffekte auf größere sozio-ökologische Systeme ausbreiten können. Dies zeigt sich beispielsweise an der zunehmenden Komplexität der Triebkräfte, die durch räumliche ökonometrische Modelle, Wahrnehmungen von Interessengruppen und unterstützende Studien auf lokaler Ebene ermittelt wurden. Diese Ergebnisse zeigen, wie die Bekämpfung der anthropogenen Ursachen der Entwaldung auf lokaler Ebene die Widerstandsfähigkeit konservativerer Strukturen (z. B. regionaler und globaler) verbessern kann. Ebenso gab es auf lokaler Ebene stärkere indirekte Auswirkungen benachbarter Verwaltungseinheiten. Das deutet darauf hin, dass flexible Ansätze über die Zuständigkeitsgrenzen hinweg angewendet werden müssen (z. B. sozioökologische Systeme). Die geringere Wachsamkeit in Bezug auf die Ursachen der Entwaldung und das geringere Vertrauen der lokalen Interessengruppen in die politischen Instrumente deutet zudem darauf hin, dass internationale und nationale Schutzziele mit einer Vielzahl lokaler Interessen (z. B. direkte Abhängigkeit von land- und forstwirtschaftlichen Ressourcen, *Governance*-Strukturen) in Einklang gebracht werden müssen. Schließlich ist die Einbeziehung lokal gewonnener Daten entscheidend, um die Zuverlässigkeit und Genauigkeit der verfügbaren Informationen über die Ausdehnung und den Zustand der Wälder zu verbessern. Dies wird deutlich durch eine strenge Qualitätsanalyse globaler und nationaler Datensätze im direkten Vergleich mit den von mir erstellten Karten.

In jedem Fall bestätigen die Ergebnisse meiner Veröffentlichungen auch, dass anthropogener Druck und sozioökonomische Faktoren (d. h. Demografie, Landwirtschaft, Holzgewinnung und Infrastruktur) die Hauptursachen für die Entwaldung in den Tropen sind, unabhängig vom Entwaldungskontext oder der räumlichen Ebene. Aus diesen Ergebnissen ergibt sich die allgemeine Notwendigkeit, bei der Bekämpfung der zugrunde liegenden sozioökonomischen Faktoren der Entwaldung, für politische Kohärenz zu sorgen. Die überraschend starken Auswirkungen der Bevölkerungsdichte auf die Waldbedeckung, die durch die ökonometrische Modellierung aufgezeigt wurden, stellen jedoch das derzeitige Verständnis der Entwaldungsfaktoren in Frage und deuten auf klare Grenzen der sektoralen Politik hin, die weit über die Land-, Forst- und Bioökonomie hinausgehen. Außerdem gibt es einen skalen- und länderübergreifenden Konsens zwischen den Akteuren in den Tropen, dass die Landwirtschaft eine wichtige Rolle spielt und Maßnahmen zur Wiederaufforstung und Wiederherstellung der Wälder im kommenden Jahrzehnt geeignet sind. Dies zeigt einen gemeinsamen Ansatzpunkt für eine Zusammenarbeit zwischen den Institutionen. Gleichzeitig deutet dieses Ergebnis auf einen Paradigmenwechsel von Schutzgebieten zu einem stärkeren Fokus auf integrative Ansätze hin.

In dieser Dissertation wurde erfolgreich die Wirksamkeit der Waldübergangstheorie für die Charakterisierung von Ländern und Regionen sowie die Erfassung von Entwaldungsmustern nachgewiesen. Diese Validierung der Theorie hat, wie oben beschrieben, große Auswirkungen auf die wissenschaftliche Forschung, politische Maßnahmen und praktische Interventionen. Durch die Einbeziehung des räumlichen Maßstabs und des Panarchiekonzepts in den analytischen Rahmen der Waldübergangstheorie hat diese Studie eine Wissenslücke geschlossen und das Verständnis der Dynamik tropischer Wälder verbessert.

Schlüsselwörter: tropische Forstwirtschaft, Treiber der Entwaldung, *forest transition*, räumliche Ökonometrie, räumliche Analyse, geographische Informationswissenschaft, Fernerkundung, Sambia, Ecuador, Philippinen

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AFC	Average annual net forest area change (%/yr)
AIC	Akaike information criterion
ANOVA	Analysis of variance
AVHRR	Advanced Very High-Resolution Radiometer
BIC	Bayesian information criterion
CIA	Central Intelligence Agency (US Government)
CGLS-LC100	Copernicus Global Land Service Land Cover Maps 100m Resolution
CSI	Crop Suitability Index
CSO	Central Statistical Office (Zambia)
DEM	Digital Elevation Model
DRC	Democratic Republic of the Congo
ESA	European Space Agency
ESA-CCI LC	European Space Agency Climate Change Initiative Land Cover
et al.	*et alia* (and others)
FA	Forest Area
FAO	UN's Food and Agriculture Organization
FC	Forest Cover
FGD	Focus Group Discussion(s)
FGGD	FAO's Food Insecurity, Poverty and Environment Global GIS Database
FLR	Forest Landscape Restoration
FNF	Forest/Non-forest (Binary map)
FRA	Forest Resources Assessment (FAO)
FRA-RSS	FAO Global FRA Remote Sensing Survey
FROM-GLC	Finer Resolution Observation and Monitoring of Global Land Cover
FT	Forest Transition
GADM	Database of Global Administrative Areas
GCP	Ground Control Point
GCPhoto	Ground Control Photo
GDP	Gross Domestic Product
GFC	Global Forest Change
GFL	Gross Forest Loss (million ha/yr)
GHG	Greenhouse Gas Emissions
GLC	Global Land Cover
GLCC	Global Land Cover Characterization
GLCNMO	Global Land Cover by National Mapping Organizations
GIS	Geographic Information System(s)
gROADSv1	Global Roads Open Access Data Set, Version 1
ha	Hectare(s)
HDI	Human Development Index
HJ 1A, 1B	Huan Jing (Environment)
IF	Impact Factor
ILUA	Integrated Land Use Assessment (Zambia)
ISLSCP II	International Satellite Land-Surface Climatology Project, Initiative II
IUFRO	International Union of Forest Research Organizations
JAXA-FNF	Japan Aerospace Exploration Agency Global Forest/Non-forest Map
JERS	Japanese Earth Resources Satellite
km	Kilometer(s)
LaForeT	Landscape Forestry in the Tropics (project)
Landsat	Land Remote-Sensing Satellite (System)

LCLU	Land Cover and Land Use
m	Meter(s)
MERIS	MEdium Resolution Imaging Spectrometer
MLR	Multiple Linear Regressions
MODIS	Moderate Resolution Imaging Spectroradiometer
NAMRIA	National Mapping and Resource Information Authority
NFI	National Forest Inventory
NFL	Net Forest Loss (million ha/yr)
NFM	National Forest Monitoring
NGO	Non-Governmental Organisation(s)
NTFP	Non-Timber Forest Product(s)
NWFP	Non-wood forest products
MAE	Ministerio del Ambiente de Ecuador
MAATE	Ministerio del Ambiente, Agua y Transición Ecológica (Ecuador)
MLR	Multiple Linear Regression
OBIA	Object-Based Image Analysis
PALSAR	Phased Array Type L-Band Synthetic Aperture Radar
PC	Principal Component
PCA	Principal Component Analysis
PES	Payments for Ecosystem Services
PROBA-V	Project for On-Board Autonomy -Vegetation
PSA	Philippine Statistics Authority
PVA	Share of Potential Vegetation Area
REDD+	Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries
SAR	Synthetic Aperture Radar
SD	Standard Deviation
SDEM	Spatial Durbin Error Model
SDG	Sustainable Development Goal(s)
SEM	Spatial Error Model
SINAGAP	Sistema de Información Nacional de Agricultura, Ganadería, Acuacultura y Pesca (Ecuador)
SLX	Spatially lagged X model
SPOT	Satellite pour l'Observation de la Terre (Airbus)
SRTM	Shuttle Radar Topography Mission
TC	Tree cover
TanDEM-X	TerraSAR-X add-on for Digital Elevation Measurement
TerraSAR-X	Terra (Earth) SAR-X (X-band frequency), cooperation German Aerospace Center and Airbus
TUM	Technical University of Munich
T2B	Top 2 Box scores (Likert scores)
UN	United Nations
UNCBD	UN Convention on Biological Diversity
UNCCD	UN Convention to Combat Desertification
UNDESA	UN Department of Economic and Social Affairs
UNDP	UN Development Programme
UNFCCC	UN Framework Convention on Climate Change
UMD	University of Maryland Department of Geography
USD	United States Dollar ($)
VHR	Very High Resolution
VIF	Variance Inflation Factors
yr	Year(s)

1. Introduction

Despite the abundant literature studying the dynamics of tropical forests and their drivers across time and space, it is still unclear if such patterns are constant across deforestation contexts, and across spatial levels or interrelated geographical jurisdictions, from international to local. In my thesis, I address this gap by exploring how scale-related dependencies influence forest dynamics and their causes across tropical locations with different deforestation contexts or forest transition stages. To answer this overarching research question, I use the inestimable support of geographic information systems (GIS) and spatial data (e.g., remotely sensed and derived maps). With this, my work provides a comprehensive set of innovative approaches and up-to-date spatial methods to monitor and analyze forest dynamics and related drivers at different spatial levels. The results of this thesis are based on original peer reviewed publications in which I participated as an active author. Overall, my results reveal strong dependencies of forest dynamics and their causes, related to the spatial scale and to the deforestation context. My findings can contribute to a better understanding of the drivers of de-/reforestation and forest degradation/restoration in the tropics, while facilitating a more efficient design and implementation of policies that foster the sustainable use of forest resources.

1.1 Terminology

First of all, I would like to clarify some important terminology that will be used throughout this thesis. Forests can be seen from very different perspectives, e.g. putting emphasis on them as a source of multiple ecosystem services, repository for carbon storage, home of biological diversity or indigenous peoples, or as social-ecological systems (Chazdon et al., 2016; Putz and Redford, 2010). However, the major international environmental and forestry organizations, such as those belonging to the United Nations (UN) (e.g., the UN Framework Convention on Climate Change [UNFCCC], the UN Convention on Biological Diversity [UNCBD], the UN Convention to Combat Desertification [UNCCD]), or the International Union of Forest Research Organizations [IUFRO], define *forest* similarly to Food and Agriculture Organization (FAO), based on specific physical thresholds of canopy cover, tree height and area (FAO, 2018). These thresholds are applied with flexibility to be adapted to the different regional or national contexts (Harris et al., 2018) and such classifications typically include other ecological and land-use aspects, such as the age of forest, legal designations of landholdings or distinctions between naturally grown or planted trees. In general, the term *forest area* refers to the total extent of forest (usually in ha or km^2) within some specific boundaries. Otherwise, *forest cover* describes the amount of land area that is covered by forest (normally as a percentage) within some defined limits like the boundaries of a country. Understanding these distinctions is critical, because forest concepts and definitions reflect management objectives and determine how we assess forest dynamics within a particular area (Romijn et al., 2013).

With *forest dynamics* (Figure 1) I refer to the continuous processes that forests experience and change their ecosystems, driven by a range of physical and biological forces (McDowell et al., 2020). Overall, these dynamics are the result of a balance between *forest disturbances* and *forest succession*. On the one hand, forest disturbances can be anthropogenic, such as logging or land clearing, or natural, such as fire, landslides or insect outbreaks. Depending on their nature, intensity and frequency, disturbances can result on *deforestation* (reduction of net forest area) or in *forest degradation* (implying a reduction in forest condition and functions) (Putz and Redford, 2010). This is a clear example on how forest definitions are important. For instance, according to FAO's classification an area temporarily empty of trees can still be designated as forest, while it would be considered deforested if following definitions based on a land cover perspective (Chazdon et al., 2016). On the other hand, forest succession comprises the processes of forest *recovery*, *regeneration* and *regrowth* after a disturbance. Again, this can happen naturally, for instance in abandoned forests (spontaneously or assisted), or actively induced by humans, like in the case of forest plantations, agroforestry or active reforestation/restoration activities (Chazdon, 2013). An increase of the net area of forest by converting other LCLUs is known as *reforestation*. A particular case of reforestation is *afforestation*, which happens in areas, which have been deforested for a longer time. Finally, *forest restoration* or *rehabilitation* comprises the processes which increase forest condition and its functions, but not necessarily its area (Stanturf et al., 2019).

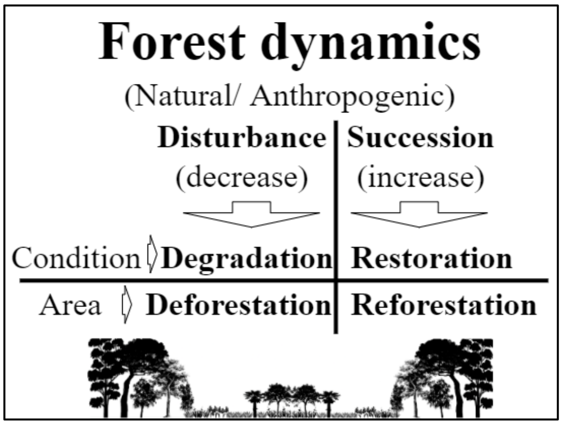


Figure 1. Forest dynamics as the continuous balance between disturbances and succession, driven by natural and anthropogenic forces and ultimately affecting forest condition (degradation and restoration) and forest area (deforestation and reforestation).

Although most of the existing studies typically refer to the “drivers of deforestation and/or forest degradation”, I will often use a more generalized terminology, which captures the bi-directional effects of such drivers on forests. Thus, when referring to *forest dynamics and its drivers,* I include the whole spectrum of interrelated processes, which result not only in negative changes of forest cover and condition (deforestation and forest degradation), but also in increases and improvements (reforestation and forest restoration). With this, my terminology considers the fact that most of the drivers of forest dynamics can affect forest area and condition positively, even if this was not the general trend in the tropics during the last decades. This is not only the case for social fundamental processes such as policy, economic or technological aspects, but also for biophysical and environmental factors.

Other recurrent terms used in this thesis are *scale* and *levels*. Here I use de definition of Cash et al. (2006): *scale* as the “spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon” (i.e., forest dynamics), and *levels* as the “units of analysis that are located at different positions on a scale”. Generally, with *scale* I will refer to the *spatial scale*, thus to the continuous range of levels across the geographical space where environmental, geophysical and ecological phenomena occur, from international to local. This will often refer to *jurisdictional scales,* “defined as clearly bounded and organized political units, e.g., towns, counties, states and nations, with linkages created by constitutional and statutory means”.

1.2 Background & State of the art

1.2.1 Historical and regional patterns of tropical forest dynamics

The history of agriculture or the domestication of plants and animals began only after the last glacial period and the beginning of the Holocene (c. 10,000 BC). This revolution allowed the spatial expansion of humanity and its rapid population increase, which are relatively recent events within the history of Earth (Gupta, 2004). Since then, our species has accelerated forest dynamics by clearing forests and extracting their resources at an unprecedented pace. According to some estimations, global forest extent accounted for almost 50% of the planet’s land area 8,000 years ago (Ball, 2001; Lambin et al., 2003). Nowadays, forest cover has been reduced to almost the half, representing under 30% of the Earth’s land (around 4,000 million ha). From the remaining forests, only a third corresponds to undisturbed primary forests. Nevertheless, the reliability of these estimates is a cause for concern (as they rely on proxies such as conservation parks) and thus, the real numbers are probably lower (FAO, 2020). A few scholars have quantified the historical changes in land cover and land use (LCLU) between the

18th and the 20th century (Klein Goldewijk and Ramankutty, 2004; Ramankutty and Foley, 1999). These studies estimated an approximate 15% reduction of the global forest and woodland areas (from 5,000-6,200 to 4,300-5,300 million ha) between the years 1,700 and 1,990. For the same period, the area of croplands and pastures increased globally from 700-900 to 4,600-5,100 million ha. The authors identified that rapid agricultural expansion (associated with deforestation) happened first in Europe, the North Indian River Plain and East China, followed by North America and the former Soviet Union in the nineteenth century (Lambin et al., 2003; Ramankutty et al., 2002). Other regions (and most of the tropics) started experiencing dramatic increases in agricultural area after 1,850 and especially during the second half of the twentieth century, i.e., Africa, Southeast Asia and Latin America.

Despite the limitations to acquire consistent data across countries and regions (Grainger, 2008), the Forest Resources Assessment (FRA) by the FAO of the UN is still the most comprehensive evaluation of forest resources worldwide. This assessment involves the collaboration of hundreds of experts and organizations across the globe. According to the last report (FAO, 2020), forest areas in tropical countries shrank around 10% (200 million hectares) between 1990 and 2020. This corresponds almost exactly to the total net loss of forest area worldwide for the same period. Thus, tropical forests alone account for nearly all the global deforestation in the last decades. This is remarkable, especially when bearing in mind that tropical forests “only” represent 45% of the world’s forest area. Since 1990, tropical forests have been showing both the highest gross deforestation rates and the largest net changes in forest area, when taking reforested areas in to account. Although these rates have slowed down in the last 10 years, they can still be regarded as dramatic if compared to the trends in other biomes, e.g., temperate or boreal forests. For instance, an average 0.40% of the forest area disappeared annually between 2010 and 2020 in tropical countries, while countries in other regions such as Europe, North America, East Asia or Oceania reported average positive to neutral rates of +0.03%, -0.01%, +0.73% and +0.23% for the same period, respectively. Other recent studies based on remote sensing surveys provide lower estimations regarding the total extent of forests in the tropics and deforestation rates until 2010 (Achard et al., 2014; Hansen et al., 2013). These inconsistencies are related to a more conservative definition of forest based on land cover or specific tree cover thresholds, in contrast to FAO’s definition of forest based on land use. In any case, these other sources reaffirm the general deforestation trend observed in the tropics during the last decades (Table 1).

Table 1. Forest area (FA), cover (FC) and loss (gross [GFL] and net [GNL], the latter considering reforested areas) in tropical regions for the period 1990-2020, based on FAO (2020), Hansen et al. (2013) and Achard et al. (2014).

Time		FAO (2020) [a]			Global Forest Change [b] (Hansen et al., 2013)		Achard et al. (2014)		
Year	Period	FA [million ha] (FC %)	GFL [million ha/yr]	NFL [million ha/yr]	FA [million ha] (FC %)	GFL [million ha/yr]	FA [million ha] (FC %)	GFL [million ha/yr]	NFL [million ha/yr]
Total (Tropics)									
1990	-	2,036.0 (43%)	-	-	-	-	1,635 (34%)	-	-
2000	**1990-2000**	1,934.3 (41%)	-13.8 (-0.68%)	-10.2 (-0.50%)	1,637 (34%)	-	1,574 (33%)	-	-6.1 (-0.37%)
2010	**2000-2010**	1,845.0 (39%)	-13.2 (-0.68%)	-8.9 (-0.46%)	1,551 (33%)	-7.2 (-0.44%)	1,514 (32%)	-7.6 (-0.48%)	-5.9 (-0.37%)
2020	**2010-2020**	1,834.1 (38%)	-9.8 (-0.53%)	-7.4 (-0.40%)	-	-	-	-	-
Africa									
1990	-	702.9 (35%)	-	-	-	-	515.7 (21%)	-	-
2000	**1990-2000**	672.0 (33%)	-3.64 (-0.53%)	-3.09 (-0.45%)	394.3 (16%)	-	501.2 (21%)	-	-1.42 (-0.28%)
2010	**2000-2010**	639.2 (31%)	-3.87 (-0.59%)	-3.28 (-0.49%)	380.4 (16%)	-1.16 (-0.29%)	484.8 (20%)	-1.84 (-0.37%)	-1.65 (-0.33%)
2020	**2010-2020**	601.5 (30%)	-4.11 (-0.65%)	-3.78 (-0.60%)	-	-	-	-	-
Central and South America									
1990	-	1,007.6 (55%)	-	-	-	-	800.2 (54%)	-	-
2000	**1990-2000**	955.3 (53%)	-6.07 (-0.61%)	-5.23 (-0.53%)	855.0 (58%)	-	771.7 (52%)	-	-2.85 (-0.36%)
2010	**2000-2010**	901.4 (50%)	-6.89 (-0.73%)	-5.39 (-0.57%)	810.4 (55%)	-3.72 (-0.44%)	743.3 (50%)	-3.91 (-0.51%)	-2.84 (-0.37%)
2020	**2010-2020**	874.5 (48%)	-3.32 (-0.38%)	-2.69 (-0.30%)	-	-	-	-	-
South and Southeast Asia									
1990	-	326.5 (38%)	-	-	-	-	319.1 (37%)	-	-
2000	**1990-2000**	308.1 (36%)	-3.69 (-1.14%)	-1.84 (-0.58%)	388.0 (45%)	-	301.3 (35%)	-	-1.78 (-0.56%)
2010	**2000-2010**	305.5 (36%)	-2.23 (-0.72%)	-0.26 (-0.09%)	359.9 (42%)	-2.34 (-0.60%)	286.2 33%)	-1.88 (-0.62%)	-1.44 (-0.48%)
2020	**2010-2020**	296.1 (35%)	-2.21 (-0.73%)	-0.94 (-0.31%)	-	-	-	-	-

[a]: Africa includes all the countries in regions: Western, Central Eastern and Southern Africa. For America, the regions South America, Caribbean and Central America were considered. Asia includes countries in South and Southeast Asia.
[b]: Data as calculated and presented by Achard et al. (2014). Forest are all pixels with tree cover above 50%.

If we analyze these estimates across continents, we can see that the deforestation rates in Africa have accelerated and gone from the lowest values among tropical regions in the 1990-2000 period, to show the highest net forest loss estimates during the last ten years, both in absolute and relative terms. The top three African countries regarding their average annual net loss of forest area between 2010 and 2020 were the Democratic Republic of the Congo (DRC), Angola and Tanzania, with 1.1, 0.55 and 0.42 million ha/yr respectively. Africa is an exception to the general slowing down of deforestation rates, which has been observed in the tropics after 2010. This trend is particularly noticeable in Central and South America, where forest loss rates are almost the half when compared to the previous years. Nevertheless, in absolute terms, the numbers of this region are still relevant when considering both forested and deforested areas, due to the contribution of the Amazon basin. During the 2010-2020 period, the largest net forest losses in this continent were observed in Brazil, Paraguay and Bolivia, with 1.5, 0.35 and 0.23 million ha/yr respectively. The countries in South and Southeast Asia have shown the highest gross forest loss values for each period since 1990. Nevertheless, the average annual net forest loss estimates decreased from the highest across regions between 1990 and 2000 (-0.58%) to almost neutral (-0.09%) between 2000 and 2010. This trend has been reversed again in the last ten years and Asian countries have shown higher average annual net deforestation values (-0.31%). In absolute terms, the top three countries contributing to this net loss of forest area in Asia were Indonesia, Myanmar and Cambodia, with 0.75, 0.29 and 0.25 million ha/yr respectively.

The recent deforestation trend in the tropics is linked to processes of forest degradation and landscape fragmentation. Vancutsem et al. (2021) quantify forest dynamics (degradation, deforestation, recovery) at pantropical scale and highlight the importance of the degradation process in moist forests as a precursor of deforestation, while identifying a recent increase in anthropogenic disturbances. Some studies affirm that almost the half the global forest area (2,000 million ha) is degraded, with an important share in the tropics (Stanturf et al., 2014; Vásquez-Grandón et al., 2018). Similarly, other authors have observed that the number of smaller forest fragments has increased, together with their likelihood to suffer further disturbances (Hansen et al., 2020; Taubert et al., 2018). These models predict further forest loss and fragmentation in the near future. Nowadays, the largest remaining forest fragments in the tropics are still found in the Amazon and Congo Basins and in islands of Southeast Asia.

As described above, tropical forest dynamics during the last decades have been characterized by processes of deforestation, forest degradation and fragmentation. This trend poses a threat to the multiple ecosystem services and functions provided by tropical forests (Foley et al., 2005; Edwards et al., 2014), directly affecting soil and water quality, biodiversity and carbon stocks, together with agricultural productivity and local livelihoods (Baccini et al., 2017; Reed et al., 2017; Veldkamp et al., 2020). Erb et al. (2018) estimated that the cumulative carbon emissions from tropical deforestation and LCLU changes over the past centuries are comparable to the contemporary aboveground vegetation carbon stocks (Li et al., 2022). Nevertheless, more precise estimations about LCLU changes and emissions are still needed (Ganzenmüller et al., 2022; Winkler et al., 2021). When compared to the influence of any other terrestrial biome, such changes can have a more profound impact both in the tropics and in distant regions, affecting weather patterns, water cycle, natural catastrophes, food and human health (Brandon, 2014). For instance, a recent study has shown how the Amazon rainforest (the largest forest ecosystem on Earth) is risking dieback as it has been losing resilience to climate and land use change, at least since the early 2000s (Boulton et al., 2022). Some authors have estimated that current tropical deforestation rates, if unabated, would lead to global biodiversity losses equaling mass extinction event (Alroy, 2017; Giam, 2017). Finally, as a last example of the potential negative consequences of recent tropical forest dynamics: extreme warming has been associated with large deforested patches, implying challenges to the long-term public health and occupational/financial security of tropical populations (Zeppetello et al., 2020).

1.2.2 Drivers of forest dynamics and forest transition

Although the causes of forest dynamics in the tropics are complex, often corelated, and vary between regions (Seymour and Harris, 2019), they have been well studied for a few decades. Already in the early nineties, the basis for a classification of these drivers had been introduced in the context of anthropogenic global environmental change (Indarto and Mutaqin, 2016; Turner et al., 1990). A decade later, forest scholars and practitioners observed pantropical patterns of deforestation and distinguished between proximate and underlying causes (Angelsen and Kaimowitz, 1999; Contreras-Hermosilla, 2000; Geist and Lambin, 2002).

Geist and Lambin (2002) defined the proximate causes of tropical deforestation as those forces directly impacting forest cover (Figure 2). The authors observed that these proximate drivers were mostly associated to land use and immediate anthropogenic pressure, and they classified them into three main categories: i.e., infrastructure extension, agricultural expansion and wood extraction. Additionally, they identified other less common proximate causes, such as pre-disposing environmental factors, biophysical drivers (e.g., fires, floods) and social trigger events. In contrast, they defined underlying drivers as rather fundamental social processes that underpin the proximate causes, operating at a broader range of spatial levels, from local to global. They included five major groups of factors: i.e., demographic, economic, technological, policy and institutional, and cultural. Since then, this classification has been widely accepted and recurrently used by researchers to categorize and analyze the drivers of, not only tropical deforestation, but also other processes of forest dynamics, such as reforestation or forest degradation: e.g., Miyamoto et al. (2014), Carodenuto et al. (2015) or Lim et al. (2017).

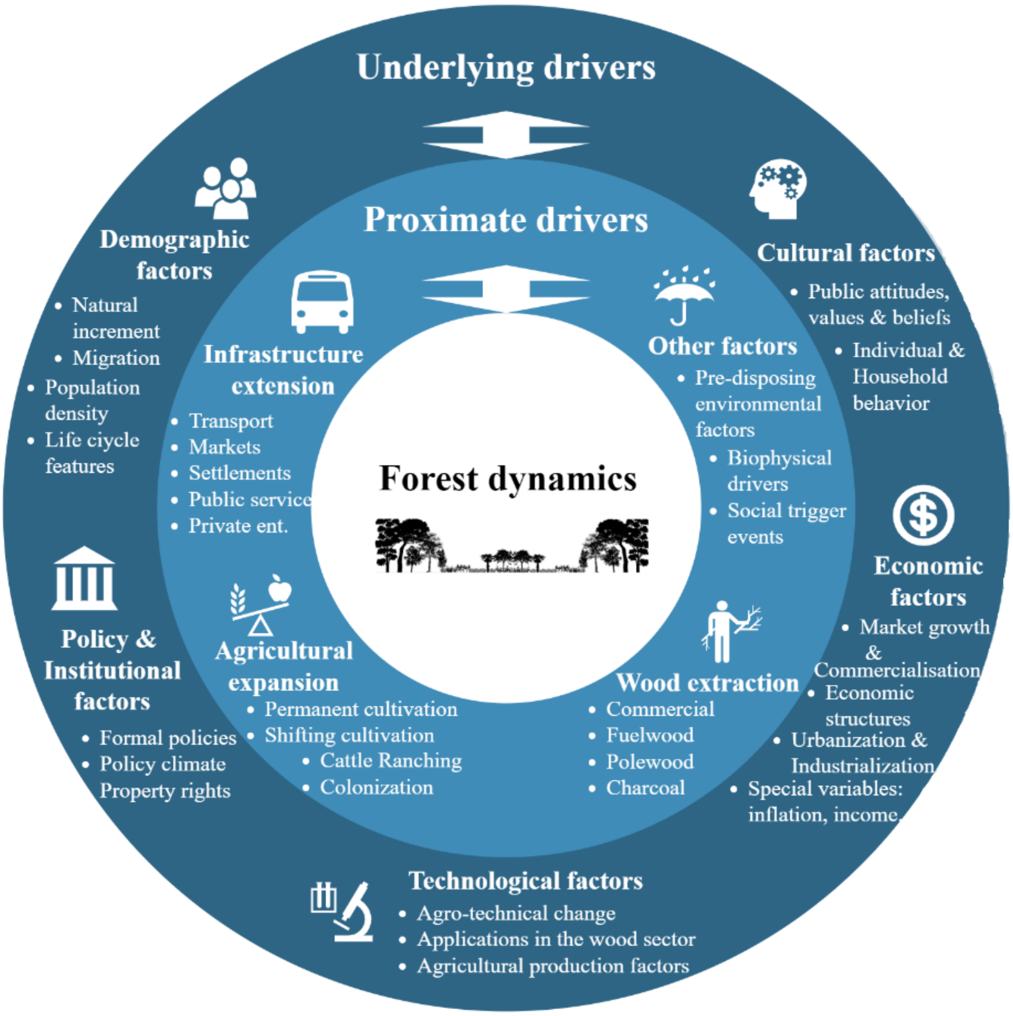


Figure 2. Main proximate and underlying drivers of tropical deforestation as a the principal component of tropical forest dynamics during the second half of the 20th century, identified by Geist and Lambin (2002).

More recent investigations quantifying and characterizing the causes of tropical forest dynamics point to a similar general picture. For instance, research based on econometric analyses identified recurrent determinants of tropical forest cover loss, related to population pressure, higher agriculture economic returns, road accessibility and favorable biophysical conditions (Busch and Ferretti-Gallon, 2017; Köthke et al., 2013). Other studies have focused on analyzing the regional differences with survey or remote sensing data (Curtis et al., 2018;

Hosonuma et al., 2012; Laso Bayas et al., 2022). According to these sources, commodity-driven forest loss is preeminent in the tropics. In particular, commercial agriculture and cattle grazing play a major role in deforestation in Central and South America, similarly to agricultural expansion and oil palm plantations in Southeast Asia. In contrast, shifting agriculture is the dominant driver of deforestation in sub-Saharan Africa, with a stronger contribution of local and subsistence demands. Further proximate causes, such as forestry operations, urbanization, mining, wildfires and other natural disasters, have a smaller contribution to the overall tropical forest loss, when compared to agriculture (Armenteras et al., 2017; Curtis et al., 2018; Ramankutty et al., 2018). Similarly, timber extraction and logging operations (both legal and illegal) contribute to most of forest degradation overall in the tropics and particularly in America and Asia, whereas in Africa fuelwood and charcoal production are still the dominant driving forces (Hosonuma et al., 2012). Apart from studying regional patterns, Hosonuma et al. (2012) explored the driver dependencies across the phases of the forest transition (FT). In a nutshell, the authors classified one hundred (sub)tropical developing countries based on existing data on forest area and historical deforestation rates, in order to use the FT as a conceptual framework for matching bundles of drivers of deforestation and forest degradation with forest cover conditions. With this innovative analytical approach, the research article became a very influential reference for both policy/practice and science.

The FT theory describes the inevitable historical pathway of a country or a region, involving forest cover decline and re-expansion (Grainger, 1995; Mather, 1992) (Figure 3). The phases along this pathway are determined by the speed of socio-economic development and have been characterized and named by different scholars (Angelsen and Rudel, 2013; da Fonseca et al., 2007; Hosonuma et al., 2012). In the beginning, in the so-called “pre-transition”, forest cover is still high and deforestation rates are low in “core forests (beyond the frontier)”. At some point, deforestation rates accelerate entering the so-called “early transition” in “frontier areas”, where the share of disturbed and degraded forests increases accordingly. Once forest cover has reached middle to low levels, deforestation rates decelerate and a “late transition” is entered, characterized by the appearance of “forest-agricultural mosaics” and larger shares of deforested vegetation. Ultimately, when low forest cover and low deforestation rates are reached, the transition from net deforestation to net reforestation occurs, entering the so-called “post-transition” phase. This increases the proportion of regrowth forests, either plantations or natural succession.

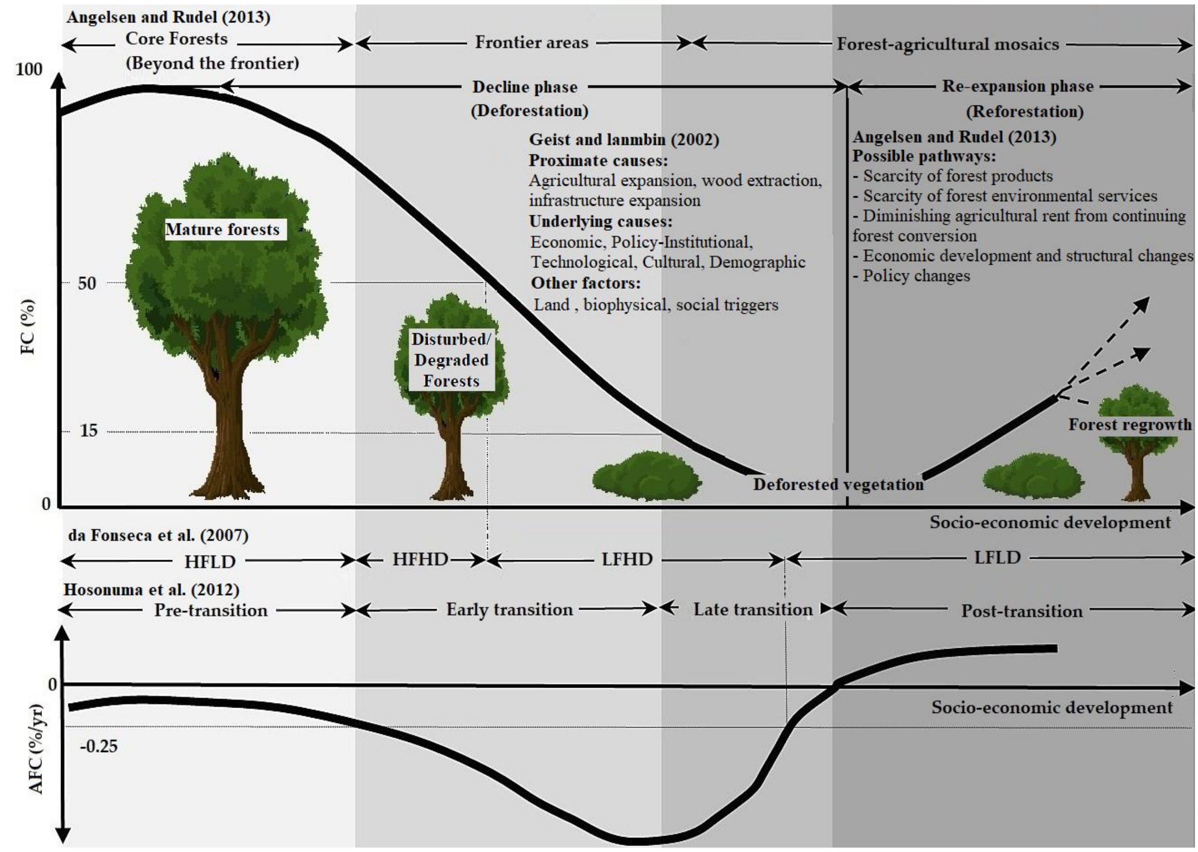


Figure 3. Forest transition (FT) as the evolution of forest cover (FC) and average annual net forest area change (AFC) along with socio-economic development. Phases according to different classifications and characteristic forest types (condition) are shown, together with main causes of the decline phase (Geist and Lambin, 2002) and possible pathways of the re-expansion phase (Angelsen and Rudel, 2013).
Angelsen and Rudel (2013). Quote: “The FT framework suggests that over time a country (or region) moves through three stages: (1) high forest cover and low deforestation (“core forests”), (2) accelerated deforestation and shrinking forest cover (“frontier forests”), and (3) stabilization and eventual reversal of the deforestation process (“forest-agricultural mosaics”)”.
da Fonseca et al. (2007). HFLD: High FC (>50%), Low Deforestation rate (AFC > -0.22%/yr) – HFHD: High FC (>50%), High Deforestation rate (AFC < -0.22%/yr) – LFHD: Low FC (<50%), High Deforestation rate (AFC < -0.22%/yr) – LFHD: Low FC (<50%), Low Deforestation rate (AFC > -0.22%/yr).
Hosonuma et al. (2012). Pre-transition: FC>50% and AFC > -0,25% - Late transition: FC < 15% or AFC = 0% or decreasing AFC - Post-transition: FC < 50% - Early transition: Remaining cases.

The FT concept has been used by several empirical studies (generally analyzing the progression of FC over time) to explain observed patterns in economically developed countries after industrialization (Rudel et al., 2005): e.g., France (Mather et al., 1999; Walker, 1993), Denmark (Mather et al., 1998), Switzerland (Loran et al., 2016; Mather and Fairbairn, 2000), Scotland (Mather, 2004), the United States of America (USA) (Evans and Kelley, 2008; Loehle et al., 1996; Walker, 1993), Germany (Plieninger et al., 2012), Austria (Krausmann, 2006), Portugal (Moreira et al., 2001; Walker, 1993), Spain (Marey-Pérez and Rodríguez-Vicente, 2009; Walker, 1993) or Japan (Mather, 2007; Walker, 1993). However, some studies have also observed the FT in developing countries, such as Puerto Rico (Grau et al., 2003; Rudel et al., 2000; Yackulic et al., 2011), Vietnam (Mather, 2007; Meyfroidt and Lambin, 2009), Brazil

(Baptista and Rudel, 2006; Perz and Skole, 2003), El Salvador (Hecht et al., 2006) or Panama (Sloan, 2016).

Despite some critique to the use of the FT as a framework for operationalizing adequate forest policies (Perz, 2007; Walker, 2008), some scholars have used the FT to study the causes behind the transition from forest cover decline to re-expansion. Such investigations can help us to better understand the drivers of "positive" forest dynamics, i.e., the causes increasing forest area (reforestation) or improving forest condition (restoration). For instance, Angelsen and Rudel (2013) grouped the possible FT pathways into five main schemes: (1) scarcity of forest products, (2) scarcity of forest environmental services, (3) diminishing agricultural rent from continuing forest conversion, (4) economic development and structural changes and (5) policy changes. These schemes derive from the two main pathways (the "economic development" and the "forest scarcity" pathways) presented by Rudel et al. (2005). The "economic development pathway" is characterised by industrialization and economic growth and the migration of labour force to the cities. Agricultural intensification and market networks are causing forest regrowth on marginal land. The "forest scarcity pathway" is characterised by increasing scarcity of forest products and ecosystem services, which leads to raising prices and lower opportunity costs for the conversion of forestland to other land uses. Therefore, investments in forests (plantations and forest management, intensification) are becoming important, policies for protection, sustainable forest management and reforestation are implemented, which shall release pressure from natural forests (Mather et al., 1998; Meyfroidt and Lambin, 2011).

As a response to the general deforestation trend of the last decades and sustained by international environmental agreements (e.g., Paris Agreement or Agenda 2030), the number of measures and programs for the protection and restoration of tropical forests has increased substantially (e.g., Forest Landscape Restoration [FLR], Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries [REDD+]). These programs include a variety of policy instruments, which are conventionally classified into regulatory (command and control), economic and informational (sermons), while comprising positive (carrots) or negative (sticks) incentives and regulations (Bemelmans-Videc et al., 1998). There is no effective silver-bullet solution and generally well-designed mixes of these policies, adapted to the specifics of each context, are recommended (Börner et al., 2020; Fischer et al., 2022; Lambin et al., 2014). In the last years, demand-led and market-based policy instruments in which both public and private actors participate, such as payments for ecosystem services (PES), supply-chain initiatives or certification of forest products, have shown their potential and limitations in halting deforestation, depending on the institutional and governance contexts (Lambin et al., 2014, 2018; Wolff and Schweinle, 2022).

1.3 Justification & Research gap

The design and implementation of effective forest protection measures requires accurate monitoring of forest dynamics and reliable information about the specific forces that drive such dynamics in a particular context (Seymour and Harris, 2019). Ten years after the publication of Hosonuma et al. (2012), the quality and quantity of available information on forest dynamics and their causes in the tropics has improved drastically. This achievement is not only related to the rapid advances on the associated monitoring technologies and capabilities (e.g., remote sensing, national inventories), but it has also been catalyzed by the information and results generated within the frame of forest protection programs and international reporting agreements (e.g., through REDD+ implementation). Nevertheless, despite these advances in the last decades, there is still a lack of pantropical studies, which combine information on forest dynamics, the drivers behind these dynamics, and the suitability or effectiveness of different policy instruments. Even less common are approaches that study such relationships cross-scale: i.e., across spatial levels related to interconnected geographical jurisdictions, from global to local.

Like Hosonuma et al. (2012), most of the supranational studies identifying, categorizing or quantifying the drivers of forest cover change in the tropics still focus on national and regional aggregations (Curtis et al., 2018; Hoang and Kanemoto, 2021; Pendrill et al., 2019a). One main reason behind is that in most cases, certain relevant statistics (e.g., commodity exports, cereal yields or other economic data), are collected at provincial or national levels, if existing at all. This is also the reason why the few pantropical studies compiling information from smaller spatial entities (e.g. project sites or landscapes), tend to use locally reported perceptions or disaggregated estimations (Jayathilake et al., 2021). Thus, deriving meaningful empirical results from local information on drivers of forest dynamics is a challenging task, which implies overcoming a number of mismatches between data of varying nature, quality and very different acquisition methods (Bos et al., 2020). Some authors have attempted to model the effects of pantropical deforestation on climate and agriculture at different spatial scales (Lawrence and Vandecar, 2015; Zeppetello et al., 2020). But so far, most of the studies that analyze the causes of forest dynamics with subnational or even multilevel approaches (considering different interrelated administrative hierarchies), put their focus on single countries (López-Carr et al., 2012; Loran et al., 2016; Moonen et al., 2016; Yackulic et al., 2011).

Similarly, the accurate monitoring of tropical forest dynamics is still facing operational challenges, linked to scale-related limitations of the existing technologies. For instance, most of the existing LCLU maps are produced with a national or global focus (Table 2) (Galiatsatos et al., 2020; Grekousis et al., 2015). This is important as it grants methodological comparability between regions and contexts by considering a larger spatial scope. However, this also implies that these datasets have to be applied carefully at local levels, as their accuracies decrease due to a number of reasons (GFOI, 2020; Harris et al., 2018). Some of the main reasons affecting the local accuracy of global or national maps in the tropics are the lack of reference data collected in situ and the existence of areas with permanent cloud cover (Fritz et al., 2011; Hilker et al., 2012). These issues result in low quality or non-existing observations to train and validate land cover maps locally. Furthermore, the scopes of local analyses do not always perfectly match the temporal and spatial coverage of the used maps. Similarly, the LCLU patches or the structural traits of forest stands targeted on the ground, can be inconsistent with the pixel size of large-extent maps, typically of medium to low resolution (Table 2). This is particularly relevant in tropical landscapes, characterized by mixes of fast-growing forests and non-forest tree-based systems (Caughlin et al., 2021). Another challenge is creating consistent methods of forest classification and definition, which are equally accurate and reliable across regions. This implies overcoming the ecological, biophysical and biochemical differences of the vegetation between biomes and geographical areas (Hansen et al., 2013; Potapov et al., 2021; Rozendaal et al., 2022; Spawn et al., 2020). These dissimilarities result in distinct forest definitions (based on biophysical traits such as forest extent, canopy cover or tree height) depending on the characteristics and reporting purposes of each country or jurisdiction (Harris et al., 2018). Even more challenging is distinguishing forest types based on land use, disturbance levels or forest functions (Putz and Redford, 2010; Vancutsem et al., 2021). This is related to the limitations to identify forest stands and certain selectively-logged tree species for the effective monitoring of forest degradation (Fassnacht et al., 2016). Some promising applications in remote sensing to overcome these scale-related limitations are: (a) the higher resolution of new sensors, (b) the improved performance of computers and classification algorithms (e.g., artificial intelligence), (c) time series analysis, which can provide valuable insights on LCLU history and on ecological characteristics of the forest; and (d), Synthetic Aperture Radar (SAR), which is not affected by sunlight or cloud presence and it can be related to tree volume and/or biomass.

Table 2. Overview of the most relevant global forest and land cover maps published since 2000, adapted from Galiatsatos et al. (2020) and Grekousis et al. (2015).

Product[1]	First release	Year[2]	Overall accuracy (%)[3]	Map Type	Spatial resolution	Sensor[1]	Ref.
UMD	2000	1981-1994	65.0	Land Cover	1km	AVHRR	(Hansen et al., 2000)
GLCC 2.0	2000	1992-1993	66.9	Land Cover	1km	AVHRR	(Loveland et al., 2000)
GLC2000	2005	2000	68.6	Land Cover	1km	SPOT	(Bartholomé and Belward, 2005)
Intact Forest Landscapes	2008	2000, 2013	NA	Forest Cover	30m	Landsat	(Potapov et al., 2008, 2017; Tyukavina et al., 2016)
ISLSCP II	2009	1992-1993	66.9	Land Cover	0.25°	AVHRR	(DeFries and Hansen, 2010; Loveland et al., 2009)
GlobCover	2011	2005, 2009	73.1, 67.5	Land Cover	300m	MERIS	(Bontemps et al., 2011)
GLCNMO	2011	2003, 2008, 2013	76.5, 77.9, 74.8	Tree & Land Cover	1km, 500m	MODIS	(Kobayashi et al., 2017; Tateishi et al., 2011, 2014)
FRA-RSS	2012	1990, 2000, 2005	77.0-81.0	Land Cover	5ha	Landsat	(Lindquist and D'Annunzio, 2016; Lindquist et al., 2012)
Continuous fields of tree cover	2013	2000, 2005	93.0	Tree Cover	30m	Landsat, MODIS	(Sexton et al., 2013)
FROM-GLC	2013	2006-2011	65.0	Land Cover	30m	Landsat	(Gong et al., 2013)
Global Forest Change	2013	2000, 2010	99.6	Tree Cover	30m	Landsat	(Hansen et al., 2013)
Global Land Survey	2014	1990-2000	88.0	Forest Cover	30m	Landsat	(Kim et al., 2014)
GLC Share	2014	1990-2012	82.0	Land Cover	1km	Regional Data + Various	(Latham et al., 2014)
JAXA FNF Map	2014	2007-2018*	85.0-95.0	Forest Mask	25m	PALSAR-2, PALSAR, JERS-1	(Shimada et al., 2014)
ESA-CCI LC	2015	1992-2015*	71.5, 75.4	Land Cover	300m	MERIS, SPOT, PROBA-V, AVHRR	(ESA, 2017a)
Global hybrid forest mask	2015	2000	93.0	Forest Mask	1km	Hybrid (various)	(Schepaschenko et al., 2015)
GeoWiki	2015	2005	87.9, 82.8	Land Cover	300m	MODIS, SPOT, MERIS	(See et al., 2015)
Globeland 30	2015	2000, 2010	78.6, 80.3	Land Cover	30m	Landsat, HJ-1A/b	(Chen et al., 2015)
GLC250-m	2015	2001, 2010	74.9, 75.2	Land Cover	250m	MODIS	(Wang et al., 2015)
MODIS LC Type	2015	2000-2020*	71.6	Land Cover	500m	MODIS	(M. Friedl, 2015)
TanDEM-X FNF	2018	2011-2016	85.0-93.0	Forest Mask	50m	TanDEM-X, TerraSAR-X	(Martone et al., 2018)
CGLS-LC100	2020	2015-2019*	80.6	Land Cover	100m	PROBA-V	(Buchhorn et al., 2020)

[1] For clarification about the abbreviations check the sources or the list of abbreviations included in this thesis.
[2] Hyphen-separated (without asterisk) represents one only map for this acquisition period. Hyphen-separated (with asterisk) or comma-separated represents one map for each year.
[3] As reported by the respective authors.

The interconnectedness of ecosystems at different scale levels is a fundamental concept in theoretical frameworks (e.g., panarchy) that describe complex socio-ecological systems (Gunderson and Holling, 2002). By including the spatial scale dimension to previous analytical frameworks of tropical forest dynamics (i.e., forest transition), I put emphasis on a critical aspect, which has to be regarded when choosing the data and analytical tools, needed to design and implement measures that protect forests effectively. My thesis addresses this research gap and hence contributes to a better understanding of the general causes of forest dynamics in the tropics. For instance, a successful conservation program within a municipality should not only consider the national and regional threats to forest, but also specific factors such as such governance elements (e.g. tenure, access, participation), the livelihood strategies or the dependency on forest resources of the local population (Duguma et al., 2019; Wright et al., 2016). The same applies the other way around, which is undeniable in an "Age of Globalization" with our world becoming increasingly interrelated and interdependent. If issues such as international trade negotiations or the national strategies regarding infrastructure development are ignored during the design of environmental policies, such measures are probably going to fail in achieving their goals (Hoang and Kanemoto, 2021; Pendrill et al., 2019b; Perz et al., 2013). Similarly, countries with net-deforestation at the national level can exhibit strata with increasing forest cover at subnational levels or vice versa. Thus, integrated analyses that consider the circumstances of each jurisdiction across the spatial scale can support more comprehensive deliberations over the appropriate mix of policy tools and strategies needed (Seymour and Harris, 2019). This is for instance the new focus of the so-called "jurisdictional approaches" to manage programs such as REDD+ (Wunder et al., 2020). Although evidence of their effectiveness remains limited, the implementation of such "integrated landscape approaches" is widespread and the evaluation methods continue to improve (Reed et al., 2020).

In addition, my work introduces some innovative approaches to the analysis of forest dynamics in the tropics. These methods include, for instance, the use of complex spatial econometric models, which can contribute to a better understanding of spatial phenomena. Such models can estimate spillovers and the indirect impacts of neighboring units, or provide hints on omitted variables or on how spatial clusters look like. I also present a standardized methodology to classify LCLU in different tropical regions using information from active and passive remote sensors. With this approach, I demonstrate the current challenges in obtaining accurate regional LCLU maps in the tropics, which are reliable at landscape or local levels, even if reference data is available. I further analyze information about both future drivers of deforestation and preferred policy instruments, as perceived by relevant stakeholders. My work also shows some potentials of combining primary data (obtained from key informant interviews, participatory mapping techniques or household surveys) with secondary sources of information on forest cover, such as the Global Forest Change (GFC) dataset or national LCLU maps. As a last example, my work introduces some practical applications on how to perform proximity analyses to understand better the effects of different drivers of forest dynamics at landscape level.

1.4 Research question & Objectives

In this PhD thesis, I address the following overarching research question, which is based on the analytical framework of Hosonuma et al. (2012) and considers the abovementioned background and stated research gaps:

- How do forest dynamics and their drivers in the tropics vary…
    - across deforestation contexts (or across countries/regions in different phases according to the FT theory) …
    - and across spatial levels (or across interconnected administrative jurisdictions, from global to local)?

The core of this thesis is constituted by three research articles which address three general objectives, related to the abovementioned overarching question. Namely, my thesis aims to study the differences across deforestation contexts and spatial levels in the tropics, regarding:

1. … the main drivers of forest cover change, using spatial econometrics.
2. … forest dynamics (LCLU and forest condition), assessing the quality of global and national LCLU maps compared to locally obtained data.
3. … the main drivers of deforestation and forest degradation and the most effective policy instruments, analyzing the perceptions of relevant stakeholders.

Further specific aims of my research include:

4. … exploring how particular spatial dependencies (e.g., impact of neighbors, scale or distance related effects) and the different deforestation contexts alter not only forest dynamics and their drivers, but also the ability to monitor them accurately.

5. … using spatial levels and deforestation contexts to combine information on forest dynamics and drivers of their change, as well as the effectiveness of policy instruments.

6. … providing a wide-ranging overview of methods and examples on how to use spatial data to monitor forest dynamics and drivers at different spatial resolutions and jurisdictional levels.

7. … interpreting the generated results to find implications for science and policy/practice, providing recommendations, which may be relevant for the design and implementation of effective forest protection measures.

1.5 Approach & Main findings

I will target the aims of this thesis by analyzing information from three tropical countries in Africa (Zambia), South America (Ecuador) and Southeast Asia (Philippines). I will work with both secondary sources of information and data collected in situ between 2016 and 2019 as part of the research project "Landscape Forestry in the Tropics" (LaForeT: www.la-foret.org), coordinated by Germany's federal research organization Thünen Institute of Forestry. This extensive field campaign took place through thirty-six landscapes of approximately 100km^2 each, distributed across various regions of the selected countries. This study design intends to facilitate the discussion from a pantropical perspective. Both landscapes, regions and countries constitute gradients of historical deforestation contexts, based on the FT model. The primary data was collected through different means, including ground verification, scoping visits, key informant interviews, community workshops, participatory mapping exercises, household surveys and forest inventories. My investigations will analyze this information using a range of statistical methods, including multivariate econometric models, supervised LCLU classification of remote sensing data, thematic accuracy assessments and different spatial statistics including proximity and density analyses.

Overall, my findings confirm that the direct drivers of tropical deforestation are the same when observed globally and that they are based on human pressure, especially in the form of agricultural or infrastructure expansion and wood extraction. However, the number and variety of single factors behind these direct drivers and other underlying forces (e.g., economic, institutional) increase drastically at smaller spatial levels independently of the analyzed region or deforestation context. My results also reveal a gradual increase of complex spatial interactions at local levels (e.g., leakage effects), embedding patterns which are often independent from the official administrative boundaries. Additionally, my work depicts the recurrent challenges in obtaining accurate and reliable information on forest cover change and its drivers in the tropics, together with up-to-date solutions on how to overcome such limitations. These uncertainties appear to be more relevant not only at local levels with a lack of reference data, but also in areas with advanced stages of deforestation or early stages of reforestation, characterized by complex land cover mosaics (i.e., young regrowth forests, agroforestry and other non-forest tree-based systems). Finally, my results indicate that the overall alertness of stakeholders about commercial drivers and their confidence in policy instruments are significantly lower at subnational levels and also in Zambia (and potentially in other African countries in a similar initial deforestation context). However, despite regional trends (e.g., woodfuel in Zambia), stakeholders agree on the main drivers affecting forest dynamics negatively (i.e., agriculture and logging) and on the most effective policy instruments (i.e., reforestation and forest restoration), independently of the spatial scale of their institution. This suggests common entry points for collaboration to achieve effective policy design and cross-scale implementation, together with a paradigm shift from protected areas to a stronger focus on integrative approaches including reforestation and forest restoration initiatives.

1.6 Publications & Theoretical framework

This thesis is based on the results of original published peer-reviewed articles in which I participated as an active author (Table 3). The core of the thesis is constituted by the main investigations: three research articles with me as a first author, in which the main objectives of the thesis are addressed (Page 16). In Publication 1 (Ferrer Velasco et al., 2020), I will focus on the first objective and I will analyze the scale and context dependency of the main drivers of forest cover change using spatial econometrics. In Publication 2 (Ferrer Velasco et al., 2022), I will cover the second aim and I will study the context and scale dependency of forest dynamics, by assessing the quality of global and national LCLU maps compared to locally obtained data on forest condition. In Publication 3 (Ferrer Velasco et al., 2023), I will address the third objective by studying the context and scale dependency of stakeholder perceptions on the most important future drivers of deforestation and forest degradation and on the effectiveness of policy instruments. Additionally, my work includes five supporting studies with me as a coauthor (Publications 4 to 8), which will be used as auxiliary information to address the main objectives and the further aims of the thesis (Fischer et al., 2021; Gordillo et al., 2021; Kazungu et al., 2021; Nansikombi et al., 2020a; Wiebe et al., 2022). The details on my contributions to these supporting studies are specified in the Results section (Page 59).

Table 3. Publications of the author (**bold**) included in this thesis (main investigations & supporting studies), with details on authors, status, title and journal.

	Publication, authors	Status (Year)	Title	Journal (IF 2021)[a]
A) Main investigations: Peer-reviewed research articles as a first author with a pantropical scope and covering different spatial levels.				
1	**Ferrer Velasco R.**, Köthke M., Lippe M., Günter S.	Published (2020)	Scale and context dependency of deforestation drivers: Insights from spatial econometrics in the tropics.	PLOS ONE (3.752)
2	**Ferrer Velasco R.**, Lippe M., Tamayo F., Mfuni T., Sales-Come R., Mangabat C., Schneider T., Günter S.	Published (2022)	Towards accurate mappi ng of forest in tropical landscapes: a comparison of datasets on how forest transition matters.	Remote Sensing of Environment (13.850)
3	**Ferrer Velasco R.**, Lippe M., Fischer R., Torres, B., Tamayo F., Kalaba F.K., Kaoma H., Bugayong L., Günter S.	Published (2023)	Reconciling policy instruments with drivers of deforestation and forest degradation: cross-scale analysis of stakeholder perceptions in tropical countries	Scientific reports (4.996)
B) Supporting studies: Published peer-reviewed research articles as a coauthor, with focus in one country/region or on a specific spatial level.				
4	Nansikombi H., Fischer R., **Ferrer Velasco R.**, Lippe M., Kalaba K.F., Kabwe G., Günter S.	Published (2020)	Can de facto governance influence deforestation drivers in the Zambian Miombo?	Forest Policy and Economics (4.259)
5	Kazungu M., **Ferrer Velasco R.**, Zhunusova E., Lippe M., Kabwe G., Gumbo D., Günter S.	Published (2021)	Effects of household-level attributes and agricultural land-use on deforestation patterns along a forest transition gradient in the Miombo landscapes, Zambia	Ecological Economics (6.536)
6	Fischer R., Tamayo F., Ojeda Luna T., **Ferrer Velasco R.**, DeDecker M., Torres B., Giessen L. Günter S.	Published (2021)	Interplay of governance elements and their effects on deforestation in tropical landscapes: Quantitative insights from Ecuador	World Development (6.678)
7	Gordillo F., Eguiguren, P., Köthke M., **Ferrer Velasco R.**, Elsasser, P.	Published (2021)	Additionality and Leakage Resulting from PES Implementation? Evidence from the Ecuadorian Amazonia	MDPI Forests (3.282)
8	Wiebe P.C., Zhunusova E., Lippe M., **Ferrer Velasco R.**, Günter S.	Published (2022)	What is the contribution of forest-related income to rural livelihood strategies in the Philippines' remaining forested landscapes?	Forest Policy and Economics (4.259)

[a] Impact Factor in year 2021 according to Clarivate.

All my main investigations include information from the three studied countries, in order to cover as much pantropical variability as possible and to facilitate general conclusions for the tropics (Figure 4a). In contrast, the supporting studies focus in one of the three countries: Zambia (Publications 4 and 5), Ecuador (Publications 6 and 7) and the Philippines (Publication 8). These three countries represent a gradient of deforestation contexts, using the FT theory as a theoretical framework and considering their current forest cover and historical deforestation rates (Page 10). Therefore, Zambia is representing an initial deforestation context, while Ecuador is in a middle phase and the Philippines are representative for an advance deforestation or early reforestation context. The thirty-six landscapes of the LaForeT project, where most of the primary information used in this thesis was collected, are distributed in a total of nine regions (four landscapes per region and three regions per country). These regions represent gradients of deforestation contexts as well, within the national context in each country. Further details about the country and region selection will be explained later in the Methods section when describing the study design (Page 25).

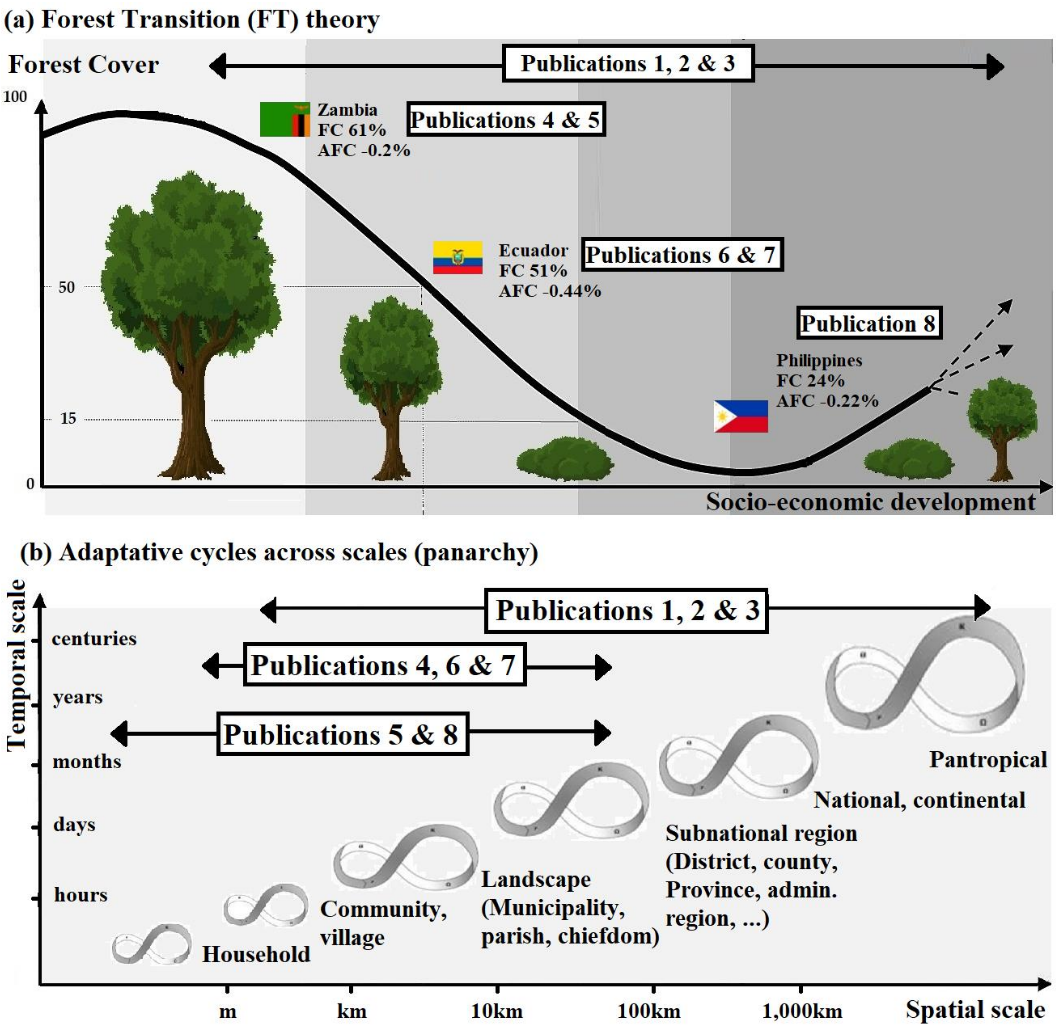


Figure 4. (a) Spatial coverage of the publications of this thesis and situation of the selected countries within the forest transition (FT) curve, as a function of forest cover (FC) against socio-economic development. FC and Average annual net forest area change (AFC) for each country refer to 2016 and the 2000-2016 period, respectively, as reported by FAO (2020). (b) Interrelated adaptative cycles of complex socioecological systems as a function of the temporal and spatial scales, adapted from Allen et al. (2014), including the different spatial levels of tropical forest dynamics covered by the publications of this thesis.

Furthermore, all my three main investigations consider a gradient of spatial levels, from international (pantropical) to local (Figure 4b). In Publication 1 I define three levels of analysis (macro-, meso- and micro-) within each country, associated with official administrative jurisdictions, from provinces and administrative regions at the macro-level, to municipalities and parishes at the micro-level. In Publication 2, I compare the quality of global and national land cover maps, with forest maps produced by myself for subnational regions, using training and validation data obtained locally in the project landscapes of the three countries. In Publication 3, I study the perceptions of stakeholders of relevant forest-related institutions that operate at different spatial levels, i.e., international (e.g., FAO), national (e.g., ministry), subnational region (e.g., regional office) and local (e.g., traditional leaders of communities). Regarding the supplementary studies, the information analyzed was collected at local levels, distributed across different regions of each country. In Publications 4, 6 and 7 I combine data about forest governance at community or landscape level with historical deforestation statistics and other relevant drivers. In the case of Publications 5 and 8, household answers to a questionnaire were analyzed together with further contextual data on forest dynamics at landscape or regional (subnational) level.

Additionally, each of the publications included in this thesis covers a different set of forest-related variables (e.g., forest area change, forest cover, tree cover) and specific drivers of forest dynamics, affecting forest cover and forest condition negatively or positively. The drivers of forest dynamics addressed by my publications are varied and comprise the whole spectrum of driver categories, both proximate and underlying, as defined by Geist and Lambin (2002) (Table 4). The inclusion of country-specific and locally focused studies in this thesis (Publications 4 to 8) provides a complementary perspective to the main focus, which aims to derive conclusions relevant for tropical regions as a whole. By exploring the specific drivers of tropical deforestation at contextual and local levels (e.g., households, particular protected areas), these studies offer valuable insights into the unique political, socioeconomic, and environmental factors contributing to deforestation in individual countries. This approach facilitates a nuanced analysis of policy frameworks, governance structures, and cultural dynamics that influence deforestation rates. Furthermore, examining local studies allows for a detailed examination of region-specific variables, including land-use practices, agricultural systems, infrastructure development, and resource extraction activities. The incorporation of these country-specific and local perspectives enriches this thesis the overall understanding of tropical deforestation, while still providing relevant conclusions that can inform strategies and interventions for tropical regions in general.

Figure 4b also shows the relationship between scales and the nested adaptative cycles of socio-ecological systems comprising a panarchy for tropical forest dynamics, based on Allen et al. (2014) and Gunderson and Holling (2002). In such models, cross-scale linkages are dependent on the position within the adaptative cycle, and conservative structures at larger scales (slower, national or international) provide a sort of memory that encourages

Table 4. Publications and the assessed indicators for forest dynamics and their causes (*secondary data in italics*), within the conceptual framework of Geist and Lambin (2002).

<table>
<tr><th rowspan="2">Publication</th><th rowspan="2">Forest-related variables[1]</th><th colspan="4">Proximate causes</th><th colspan="5">Underlying causes</th></tr>
<tr><th>Infrastructure extension</th><th>Agricultural expansion</th><th>Wood extraction</th><th>Other factors</th><th>Demo-graphic</th><th>Economic</th><th>Techno-logical</th><th>Policy & Institutional</th><th>Cultural</th></tr>
<tr><td colspan="11">A) Main investigations: Peer-reviewed research articles as a first author with a pantropical scope and covering different spatial levels.</td></tr>
<tr><td>1. Ferrer Velasco et al. (2020)</td><td>FA, PVA, FC</td><td>Road density</td><td>Crop Suitability Index</td><td>-</td><td>Total area, PVA, Slope</td><td>Population</td><td>-</td><td>Cereal area yield</td><td>-</td><td>-</td></tr>
<tr><td>2. Ferrer Velasco et al. (2022)</td><td>FC + Forest condition (degraded, regrowth)</td><td>Share of built-up area</td><td>Share of agroforestry, croplands, pastures area</td><td colspan="2">Forest condition (degraded, regrowth)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td></tr>
<tr><td>3. Ferrer Velasco et al. (2023)</td><td>-</td><td>Oil & Mining. Infrastructure and urbanization</td><td>Agricultural expansion. Timber plantations</td><td>Logging, timber extraction. Firewood, woodfuel</td><td>Natural disasters</td><td>-</td><td>-</td><td>-</td><td>6 Policy instruments (Reforestation/restoration, protected areas, …)</td><td>Alertness/ Confidence</td></tr>
<tr><td colspan="11">B) Supporting studies: Published peer-reviewed research articles as a coauthor, with focus in one country/region or on a specific spatial level.</td></tr>
<tr><td rowspan="2">4. Nansikombi et al. (2020)</td><td rowspan="3">FC + Deforestation (TC loss)</td><td rowspan="2">Distance to road, Share of built-up area</td><td rowspan="2">Share of agricultural area, Grazing</td><td rowspan="2">Timber, Poles, Charcoal, Firewood</td><td rowspan="2">Total area, Mean slope</td><td>-</td><td>-</td><td>-</td><td>19 Governance attributes</td><td>-</td></tr>
<tr><td colspan="5">Region/Province dummy</td></tr>
<tr><td>5. Kazungu et al. (2021)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>Household size, age, time</td><td>Income sources, road/market access, land patch</td><td>Crop productivity</td><td>Presence of forest reserve</td><td>Household (education ethnicity)</td></tr>
<tr><td>6. Fischer et al. (2021)</td><td>Deforestation (AFC in native FC) + Forest condition</td><td>Road density</td><td>Share of agroforestry, crops, pastures area</td><td>Share of harvested forest</td><td>Share of primary, succession forests</td><td>-</td><td>Electricity & Market access, Wage, Income source, Literacy</td><td>-</td><td>10 Governance attributes</td><td>-</td></tr>
<tr><td>7. Gordillo et al., (2021)</td><td>Deforestation (AFC in FA)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>Conservation areas (PES)</td><td>-</td></tr>
<tr><td>8. Wiebe et al. (2022)</td><td>FC, AFC</td><td>-</td><td>Share of cropland</td><td>Fuelwood, timber, NWFP</td><td>Total area, Remoteness</td><td>Household size, age</td><td>Paved access, Income sources</td><td>-</td><td>-</td><td>-</td></tr>
</table>

[1] AFC: Average annual net forest area change; FA: Forest Area; FC: Forest Cover; FT: Forest Transition; NWFP: Non-wood forest products; PES: Payments for Ecosystem Services; PVA: Share of Potential Vegetation Area (excludes water bodies, arid areas, built-up…); TC: Tree Cover. [2] Measured as distance from evaluated household to forest edge.

reorganization around the same structures and processes at smaller scales (faster, subnational and local). Similarly, “destructive” processes (i.e., “revolts”) at local (or faster) levels can affect larger spatial (or slower) levels and generate new regimes. With this, panarchy represents an integrative conceptual framework to account for the complex interactions between socio-ecological systems across spatial and temporal scales, that can be used to better understand tropical forest dynamics.

1.7 Thesis outline

The following sections of this thesis, structured as a cumulative dissertation, are outlined in this manner.

In Chapter 2 (Page 25), I will detail the study design, describing how the FT theory was used to build a gradient of deforestation contexts, in order to select the studied landscapes, regions and countries. Then, I will further describe the data and analytical methods used in the included publications. I will present an overview of the available secondary datasets which describe forest dynamics in the tropics, together with the main sources used to derive information about proximate and underlying drivers. I will also detail how both secondary and primary data (e.g., ground verification, participatory mapping, and household interviews) was acquired and treated. Additionally, I will summarize the main statistical methods used to analyze the data in the studies of this thesis, such as multivariate statistical models or thematic accuracy assessments of maps produced with supervised classification methods.

In Chapter 3 (Page 54), I will compile the abstracts and my contributions to the publications included in this thesis (Table 3). The first part of the results includes three peer-reviewed research papers with me as a first author (main investigations). In these studies, a cross-scale pantropical view is taken, with focus on the main objectives of this thesis. The full versions of these publications (three published research articles) are attached in the appendix of this document. In the second part of the results, I present further supporting studies, peer-reviewed articles in which I collaborated as a coauthor. These studies cover a broader spectrum of underlying causes of deforestation (e.g., governance, economic) and a more specific regional focus.

In Chapter 4 (Page 66), I will include a synthesis of my publications, where the interpretations and implications of the main findings will be critically discussed in relation to the abovementioned objectives. This will be done in four subsections. The first two subsections will address the two components of the overarching research question of this thesis (Page 16), based on the results of the three main publications, while using literature and the findings of my auxiliary studies as a support. First, I will analyze tropical forest dynamics and drivers across deforestation contexts or forest transitions. In the same manner, the second subsection of the discussion will analyze the effects of the spatial scale on the drivers of tropical forest dynamics. The third subsection in the discussion section synthesizes the main results and implications of all publications, encompassing aspects related to both forest transition and spatial scale. The fourth sand last subsection of the discussion will cover some methodological aspects and limitations of my investigations, together with further steps or suggestions for upcoming research.

Finally, I will highlight some final remarks or conclusions of my work in Chapter 5 (Page 99).

2. Methods

2.1 Study design: Country, region and landscape selection

My research focuses on three tropical countries in different continents: Zambia, Ecuador and the Philippines. These countries were selected within the LaForeT project (www.la-foret.org) to cover as much pantropical variability as possible, thus comprising a diversity of socioeconomic, biophysical, geographical and demographic features (Table 5). They also represent typical settings of tropical forest dynamics during the last decades; hence, they have been affected by similar drivers of deforestation and forest degradation (Table 6).

Table 5. Compilation of features of interest for the three studied countries.

Features of interest	Zambia	Ecuador	Philippines
Socio-economic information			
Population density[2] 2015 [person/km^2]	21.5	56.7	335.7
Population growth rate 2016 [%]	2.94	1.31	1.59
Life expectancy at birth[1] 2016 [yr]	52.5	76.8	69.2
Share of urban population[1] 2015 [%]	40.9	63.7	44.4
Paved road density[1] 2005-2014 [km/km^2]	0.01	0.02	0.20
GDP per capita[1] 2016 [USD]	3,900	11,000	7,700
Human Development Index[3] 2014	0.586	0.732	0.668
Agricultural share labor force[1] 2015 [%]	9.2	27.8	29.0
Land information			
Total area[1] [Mha]	75.3	28.4	30.0
Mean altitude[1] [m]	1,138	1,117	442
Altitude range[1] [m]	329 - 2,339	0 - 6,263	0 – 2,956
Terrain slope (mean – SD)[4] [%]	2.8 – 5.2	16.7 – 19.1	16.2 – 16.9
Forest cover[5] 2016 [%]	61	51	24
Annual change rate[5] 2000-2016 [%/yr]	-0.2	-0.44	-0.22
Forest share in protected areas[5] 2020 [%]	42.8	25.5	28.2
Agricultural land[6] 2018 [%]	32.1	21.9	41.7

[1] CIA (2016) [2] UNDESA (2015) [3] UNDP (2015) [4] Calculated from Jarvis et al. (2008).
[5] FAO (2020) [6] FAO, electronic files and web site (2022)

First, Zambia is a land-locked plateau in Southern Africa with relatively low population density, life expectancy at birth, Gross Domestic Product (GDP) per capita and Human Development Index (HDI) (CIA, 2016; UNDESA, 2015; UNDP, 2015). Zambia's remaining forest areas are still large (FAO, 2020), but most of them have been partly degraded or affected by shifting agriculture, charcoal production, selective logging, mining, infrastructure development and wild fires (Day et al., 2014; Phiri et al., 2019a, 2019b; Wathum et al., 2016). Almost the half of Zambian forests are under protection, including different forms of national, local and private forest reserves (Nansikombi et al., 2020b). Other examples of policy instruments in place are logging bans for specific tree species or scattered initiatives in REDD+ strategy or NGO-led programs for assisted natural regeneration (Cerutti et al., 2018; Matakala et al., 2015; WeForest, 2017).

Table 6. Main drivers of deforestation and forest degradation found in relevant literature for Zambia (Day et al., 2014; Mabeta et al., 2018; Phiri et al., 2019b; Vinya et al., 2011; Wathum et al., 2016), Ecuador (Mejía et al., 2015; Piotrowski, 2019; Sierra et al., 2021) and the Philippines (Bugayong et al., 2016; Carandang et al., 2013), within the classification of Geist and Lambin (2002).

		Main drivers of deforestation and forest degradation		
		Zambia	**Ecuador**	**Philippines**
Proximate causes	***Agricultural expansion***	Agricultural expansion. Livestock grazing.	Cattle ranching. Conversion of forests to pasture (65% of total). Conversion of forests to crops (25%), mostly small-scale, e.g., cocoa, coffee, corn, sugarcane.	Kaingin, shifting cultivation / traditional swidden (2nd). Forestlands as settlement / resettlement areas (7th). Conversion of forestlands (plantations –e.g., oil palm, rubber-, agroforestry, fishpond) (7th). Highland vegetable farming.
	Wood extraction	Charcoal production. Fuelwood collection. Wood harvesting. Illegal abstraction of forest, fisheries and wildlife resources. Consumption of Non-Timber Forest Products (NTFPs).	Commercial timber extraction. Firewood collection.	Timber harvesting - legal and illegal logging / Timber poaching (1st). Fuelwood gathering and charcoal making (6th&5th). NTFP extraction (8th)
	Infrastructure extension	Settlements. Urban expansion. Mining operations.	Oil operations. Conversion of land for mining, oil and other infrastructure (10% of total).	Transport: Road Construction (10th). Markets: Sawmills, Furniture and Processing Plants. Mining (4th). Hydropower dam construction (11th). Tourism Facilities Development (12th).
Underlying causes	***Economic factors***	Urbanization. Industrialization. High poverty levels and lack of jobs. Mining.	Weak integration of agricultural producers into markets and value chains. Oil/Mining.	Poverty. High demand for wood. Limited livelihood options. Financing of illegal activities.
	Policy and institutional factors	Insecure tenure rights. Low institutional capacity. Inadequate funding. Low staffing levels. Lack of reliable transport. Lack of synergy among policies and legislation. Weak law enforcement. High maintenance costs. Under-pricing of biodiversity resources. Degazettion of forests. Leadership conflicts.	Lack of clear tenure systems and formal land demarcation. Lack of updated zoning in areas of permanent forest production within the state's forest patrimony. Insufficient government control over forests. Policies that drive the expansion of mining, oil, agriculture. Lack of capacity. Misalignment and absence of incentives. Lack of resources for restoration.	Weak institutional capacities. Weak law enforcement. Corruption / collusion. Political interference. Political interference. No political will. Conflicting DENR & LGU interests.
	Technological factors	Invasive species. Brick-making. Tobacco curing. Inefficient technology.	Low agricultural productivity. Poor forest management practices.	Poor forest management
	Cultural factors	Encroachment. Inequitable benefit sharing. Fuelwood dependency, charcoal and firewood consumption.	Lack of equitable access to factors of production.	Irresponsible attitude towards forest. Lack of education. Lack of knowledge. Lack of awareness. Greed.
	Demographic factors	Fast population growth. Population expansion.		Migration. Increasing population.
Other causes	***Land characteristics***		Soil depletion.	
	Biophysical drivers	Fires. Effects of climate change.		Climate change, typhoons, floods, landslides (3th). Forest / brush fire (9th).
	Social trigger events			Peace and order problems.

Second, Ecuador is a mega-diversity hotspot in South America, comprising parts of the Pacific Coast, the Andes and the Amazon basin. Ecuador has twice as population density as Zambia and it is 50% smaller, with a relatively high share of urban population, GDP and HDI (CIA, 2016; UNDESA, 2015; UNDP, 2015). Ecuador is shelter of large primary forests and diverse indigenous groups, especially in the Amazon basin. However, Ecuador has lost an important share of its native forests since the sixties, mostly due to agriculture expansion and pastures, enabled by agrarian reforms and laws incentivizing land-use conversion, but also by road construction for the oil industry (Sierra et al., 2021). Ecuador has a long-established national system of protected areas and since 2008 the Socio Bosque PES program compensates private and communal forest owners for forest conservation (De Koning et al., 2011; Jones et al., 2017). The Ecuadorian Government also has ambitious reforestation plans in the Amazon, aiming to convert 300,000 hectares of pastureland to agroforestry systems (MAGAP, 2014).

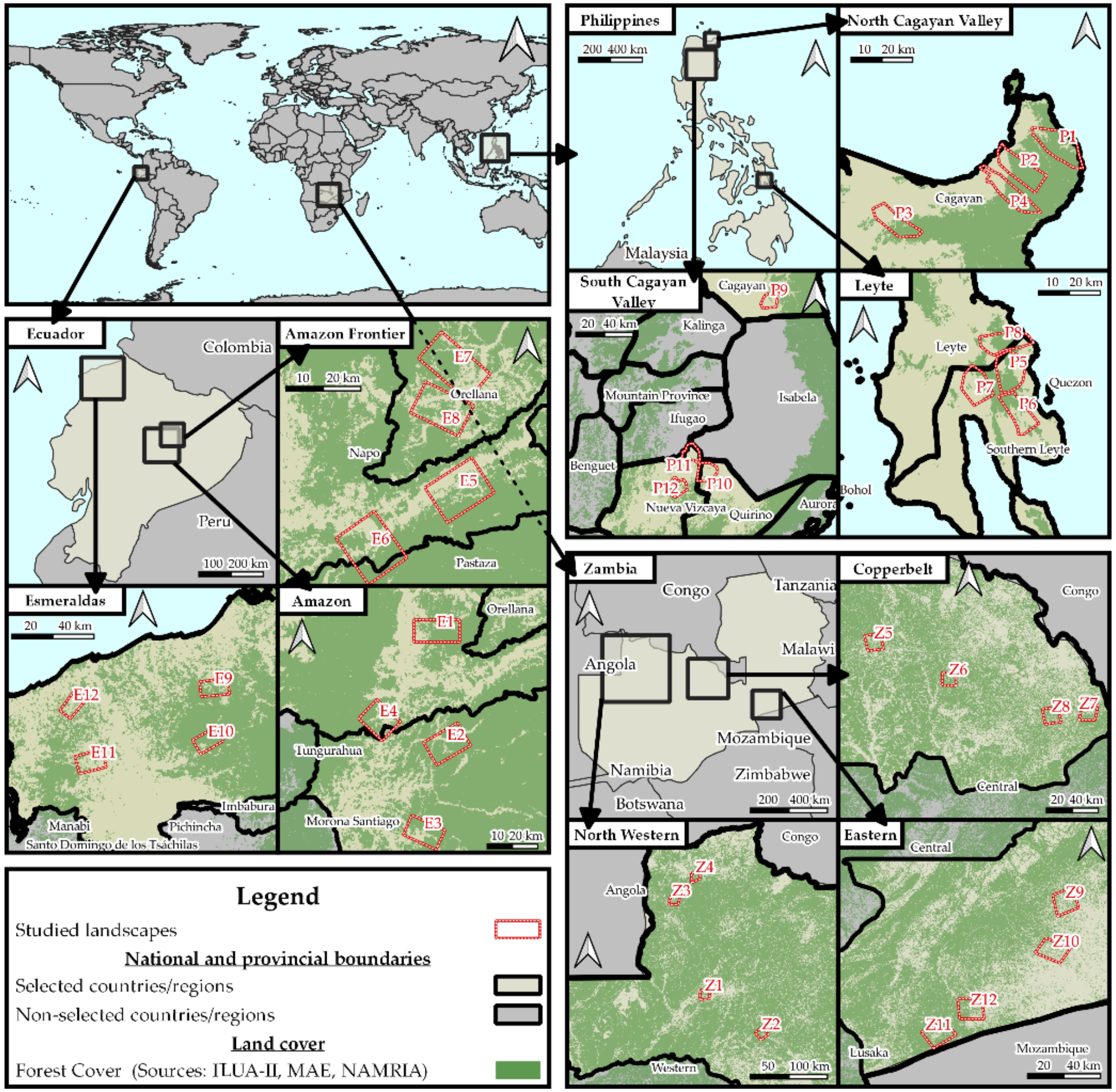
Finally, the Philippines are an archipelago of more than 7,000 islands in Southeast Asia. The Philippines are very densely populated nowadays and a higher share of their land is used for non-forest purposes, such as agriculture and infrastructure (CIA, 2016; UNDESA, 2015; UNDP, 2015). During the twentieth century, the forest cover of the Philippines has drastically decreased from roughly 70% to less than 25%, mostly due to massive commercial timber harvesting, but also because of commodity-driven agricultural expansion, fuelwood gathering and different natural disasters such as typhoons (Bugayong et al., 2016; Carandang et al., 2013). This trend has led to a nationwide logging moratorium since 2011, current net wood imports and numerous management and reforestation programs in place (e.g., Community based forest management [CBFM], National Greening Program [NGP]) (Le et al., 2014).

The countries were selected to represent different phases of the FT, based on their forest cover and historical deforestation rates (Figure 4 and Table 7). Similarly, three regions were selected in each country, building a gradient of deforestation contexts from a national perspective. Within each of these nine regions, four landscapes of roughly 10,000 ha each were selected as the study sites of the project (Figure 5). This constituted a total of thirty-six landscapes, where most of the data for the project and this thesis was obtained (2016-2019). These landscapes were positioned within the limits of independent jurisdictional units (i.e., chiefdom, parish or municipality in Zambia, Ecuador and Philippines, respectively) to ensure consistent formal administration in each of them. They were all multifunctional landscapes, capturing a variety of LCLUs and typical change dynamics of the region representatively.

Table 7. Selected landscapes, regions and countries and their respective deforestation context, forest cover (FC) in 2016 and average annual forest area change (AFC) for the 2000-2016 period. Source: Ferrer Velasco et al. (2022).

Deforestation context (national level, global perspective)				Deforestation context (regional level, national perspective)								
				Initial			Middle			Advanced		
	Country	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]
Initial	Zambia	61	-0.2	North Western	67	-0.17	Copperbelt	70	-0.41	Eastern	55	-0.54
				Chizera	73	-0.61	*Shibuchinga*	62	-0.35	*Nyampande*	42	-2.60
				Mushima	81	-0.16	*Lumpuma*	77	-0.80	*Mumbi*	37	-2.69
				Chibwika	77	-0.15	*Nkambo*	59	-0.51	*Nyalugwe*	73	-0.13
				Sailunga	76	-0.14	*Mushili*	68	-0.59	*Ndake*	56	-0.63
Middle	Ecuador	51	-0.44	Amazon	86	-0.13	Amazon frontier	74	-0.60	Esmeraldas	53	-0.97
				Rukullakta	72	0.46	*Chontapunta*	50	-0.63	*San Francisco*	62	-0.54
				Arajuno	82	-0.50	*Ahuano*	65	-0.49	*Santo Domingo*	88	-0.46
				Canelos	73	-0.67	*Avila Huirino*	62	-0.84	*Cube*	31	-0.14
				Carlos Julio AT	58	-0.56	*San Jose Dahuano*	49	-1.39	*Tabiazo*	24	-1.83
Advanced	Philippines	24	-0.22	North Cagayan Valley	59	-1.19	Leyte	18	0.25	South Cagayan Valley	46	0.54
				Santa Ana	80	-0.35	*Silago*	57	1.89	*Penablanca*	11	-6.23
				Gonzaga I	77	-0.18	*Hinunangan*	42	5.83	*Diffun*	4	8.70
				Lal-lo	53	-0.35	*Sogod*	28	1.63	*Diadi*	4	100
				Gonzaga II	63	-1.32	*Abuyog*	49	-0.11	*Quezon*	36	-3.06

[1] FC: Forest cover or percentage of total land area covered by forests. AFC: Average annual net forest area change. National results for 2016 and 2000-2016 period, respectively, as reported by FAO (2020). Regional and landscape results obtained from LCLU maps used for international reporting: Zambia 2000-2014 (ILUA-II, 2016), Ecuador 2000-2016 (MAE, 2017), and Philippines 2003-2015 (NAMRIA, 2017).
[2] Landscape boundaries cover areas within chiefdoms, parishes and municipalities where field data was collected. Region boundaries: North Western (Mufumbwe and Mwinilunga district), Copperbelt (Lufwanyama and Masaiti district), Eastern (Petauke and Nyimba district), Amazon (Pastaza and Napo provinces, excluding Ahuano and Chontapunta parishes), Amazon frontier (Ahuano and Chontapunta parish plus Loreto in Orellana province), Esmeraldas (Esmeraldas province), North Cagayan Valley (Selected municipalities in Cagayan province), Leyte (Southern Leyte province plus Abuyog municipality), South Cagayan Valley (Quirino and Nueva Vizcaya province).



Landscapes	Name (Parishes, Ecuador)
E1	Rukullakta
E2	Arajuno
E3	Canelos
E4	Carlos Julio Arosemena Tola
E5	Chontapunta
E6	Ahuano
E7	Avila Huirino
E8	San Jose de Dahuano
E9	San Francisco Onzole
E10	Santo Domingo Onzole
E11	Cube
E12	Tabiazo

Landscapes	Name (Municipalities, Philippines)
P1	Santa Ana
P2	Gonzaga I
P3	Lal-lo
P4	Gonzaga II
P5	Silago
P6	Hinunangan
P7	Sogod
P8	Abuyog
P9	Penablanca
P10	Diffun
P11	Diadi
P12	Quezon

Landscapes	Name (Chiefdoms, Zambia)
Z1	Chizera
Z2	Mushima
Z3	Chibwika
Z4	Sailunga
Z5	Shibuchinga
Z6	Lumpuma
Z7	Nkambo
Z8	Mushili
Z9	Nyampande
Z10	Mumbi
Z11	Nyalugwe
Z12	Ndake

Figure 5. Location of the landscapes, regions and countries of the LaForeT project, where some of the data of this thesis was collected. Source: Ferrer Velasco et al. (2022).

Considering this study design (Table 7 and Figure 5), Zambia represents an initial deforestation context at national level. The African country is still in the pre-/early stage of the forest transition with a high forest cover in 2016 (estimated 61%) and moderate deforestation rates (-0.20% of forest area per year between 2000 and 2016) (FAO, 2020). Within the project, the districts of Mufumbwe and Mwinilunga in the North Western Province capture Zambia's relatively intact dense forests, representing an initial deforestation context with high forest cover (67% in 2014) and low deforestation rates (-0.17% annual between 2000 and 2014) (ILUA-II, 2016). The next studied region in Zambia is the Copperbelt Province, where the work was conducted in the districts of Lufwanyama and Masaiti. This Province (middle deforestation context) is characterized by higher ongoing deforestation rates (-0.41% annual between 2000 and 2014), mostly related to human activities such as charcoal production, mining or infrastructure expansion. Finally, the districts of Nyimba and Petauke in the Eastern Province cover a drier ecosystem, which is strongly affected by shifting cultivation and agriculture expansion. Thus, these landscapes embody a region in an advanced deforestation context (-0.54% annual deforestation between 2000 and 2014) within the Zambian context.

Next, Ecuador represents a middle deforestation context at national level. The South American country has reduced forest cover to about 50%, but deforestation is still ongoing at relatively high rates (-0.44% per year between 2000 and 2016) (FAO, 2020). Within Ecuador, four landscapes in the provinces of Pastaza and Napo represent areas of the Amazon region with higher levels of forest cover and primary old-growth forest, thus an initial deforestation context. The middle deforestation context in Ecuador, what we call Amazon frontier region, is represented by landscapes in the county of Loreto (Province Orellana) and in the parishes of Chontapunta and Ahuano (Province Napo). This region had a high forest cover of around 74% in 2016, but it is experiencing accelerated deforestation rates (-0.60% annual average since 2000) (MAE, 2017). Lastly, the province of Esmeraldas (advanced deforestation context) is located in the Pacific Coast of Ecuador and is characterized by historical land conversion (from forest to pastures and agricultural systems) and timber logging activities, associated with still one of the highest deforestation rates in Ecuador (-0.97% annual average from 2000 to 2016 in the studied areas).

Finally, the Philippines were selected as an example of a tropical country in an advanced deforestation phase or early reforestation stage. The Southeast Asian archipelago has reached low levels of forest cover (24% in 2016) and has reported low negative and even positive net forest cover change rates for different periods since the nineties (FAO, 2020). We selected four landscapes in the North of Luzon to represent the early deforestation context within the Philippines. This region (North Cagayan Valley) still includes vast areas of inaccessible primary forest (59% forest cover in 2016), mostly along the Sierra Madre (NAMRIA, 2017). As a middle deforestation context, we selected four municipalities in the South of Leyte Island. This region is characterized by a mix of remaining degraded forest and mosaics of coconut palms and other vegetation types. Finally, as an example of a region in an advanced deforestation context, we selected three landscapes in the provinces of Nueva Vizcaya and Quirino and one (Penablanca) in the province of Cagayan. These landscapes were all characterized by lower forest cover and the existence of difference reforestation initiatives.

2.2 Data

2.2.1 Data on forest dynamics: LCLU information and forest maps

The data about forest dynamics (forest cover/condition) used in my publications (Table 4), will be presented in two subsections. First (Page 31), I will describe the main secondary sources for LCLU and forest maps, both at global and national level. Second (Page 36), I will summarize the methods used to produce our own data on forest dynamics, which include the supervised classification of remote sensing data and participatory mapping activities.

a) Secondary data sources for LCLU and forest maps

a1) Global LCLU maps

The use of remote sensing on a global scale (either for research, civil or military applications) was first possible during the second half of the twentieth century and was tied to the end of the Cold War. This period coincided with the development of the first artificial satellites (Whipple, 1956) and significant improvements in the field of image processing, e.g. Fourier-transform spectroscopy (Anuta, 1970). Already in the early eighties, these advances had led to initial efforts to produce global forest/vegetation cover maps and databases validated with satellite information (Matthews, 1983; Wilson and Henderson-Sellers, 1985). These products, however, still had very coarse resolution (an order of 1°) and were mostly based on local surveys and secondary maps.

Since then, the availability, quantity and quality of the sensors and their related data has improved drastically, allowing for the creation of global forest/land cover products with enhanced spatial and temporal resolution (Table 2). Some examples are a number of maps derived from optical sensors of low (250m to 1km, e.g., AVHRR [DeFries and Hansen, 2010;

Hansen et al., 2000; Loveland et al., 2000, 2009], MODIS [Kobayashi et al., 2017; M. Friedl, 2015; Tateishi et al., 2011, 2014; Wang et al., 2015] or MERIS [Bontemps et al., 2011]) to medium (10 to 30m, e.g. SPOT [Bartholomé and Belward, 2005] or Landsat (Potapov et al., 2008; Lindquist et al., 2012; Hansen et al., 2013; Gong et al., 2013; Kim et al., 2014; Chen et al., 2015; Lindquist and D'Annunzio, 2016; Tyukavina et al., 2016; Potapov et al., 2017, 2022)) resolution. Other attempts to map global forests such as Latham et al. (2014), Schepaschenko et al. (2015), See et al. (2015) or Sexton et al. (2013) have used multi-sensor approaches, thus combining information obtained from different satellites.

The fruitful production of large-scale maps was especially stimulated by the free and open Landsat data policy introduced in 2008, from which teams of researchers and users have benefitted worldwide (Zhu et al., 2019). The same approach is being applied by the European Space Agency (ESA) to the more recent data generated from the Copernicus Programme. PROVA-V-based global land cover maps are available (Buchhorn et al., 2020) and a methodology for "producing a new high resolution global land cover map based on Sentinel-2 imagery" has been developed and implemented in Europe already (Malinowski et al., 2020). At the same time, the first global forest products resulting from Synthetic Aperture Radar (SAR) data, promising as they are not affected by sunlight or cloud presence, have been published in the last years (e.g., TanDEM-X [Martone et al., 2018] or JAXA [Shimada et al., 2014] Forest/Non-forest (FNF) maps). Moreover, in the last years the first pantropical attempts to map forest cover changes and degradation have taken place (Vancutsem et al., 2021). These advances in the last decades have also been catalyzed by the increased processing capacity of computers, the introduction of machine learning and data mining (Lary et al., 2016), together with more complex time-series analyses (Hansen et al., 2013) and innovative image processing methods, such as object-based image analysis (OBIA) (Lindquist and D'Annunzio, 2016).

Of all the presented products, the online-available Global Forest Change (GFC) datasets are probably one of the most widely used and discussed within the scientific community (Hansen et al., 2013). Hansen's dataset presents a global continuous field of tree cover (TC) percentage at a resolution of 30m and with high accuracy for the years 2000 and 2010, together with information on yearly TC loss and gain. However, TC does not necessarily correspond to forest cover and can be also related to plantations or trees outside forest. Similarly, TC loss is not necessarily deforestation and it can be related to sustainable forestry operations, storms or fire, for instance. Additionally, different TC thresholds might apply for each region, depending on the ecological characteristics of the forest. Figure 6, for example, shows how the selection of a certain threshold (x-axis) for the TC layer of 2010, results in very different forest cover (y-axis) in the different regions of the LaForeT project. In Publication 2, I used this graph to find adequate thresholds for each region in order to generate forest cover maps from the GFC 2010 TC layers (Table 8). I also used the GCF datasets to estimate deforestation (average annual TC loss) in the two Zambian-specific articles (Publications 4 and 5). In both cases, 30% was used as a TC threshold to estimate forest cover, after visual validation in the studied landscapes. Nevertheless, Figure 6 suggests that a lower threshold might have been more suitable in the Eastern Province. In Publication 4, I calculated deforestation as the loss of TC (above 30% threshold) for a five-year period previous to field work (2013–2017), within patches of different governance arrangements in 24 communities or villages of Zambia. In Publication 5, I did the same for three 6-year periods between 2000 and 2018, in different buffer areas or distance rings around households of the 12 Zambian LaForeT landscapes.

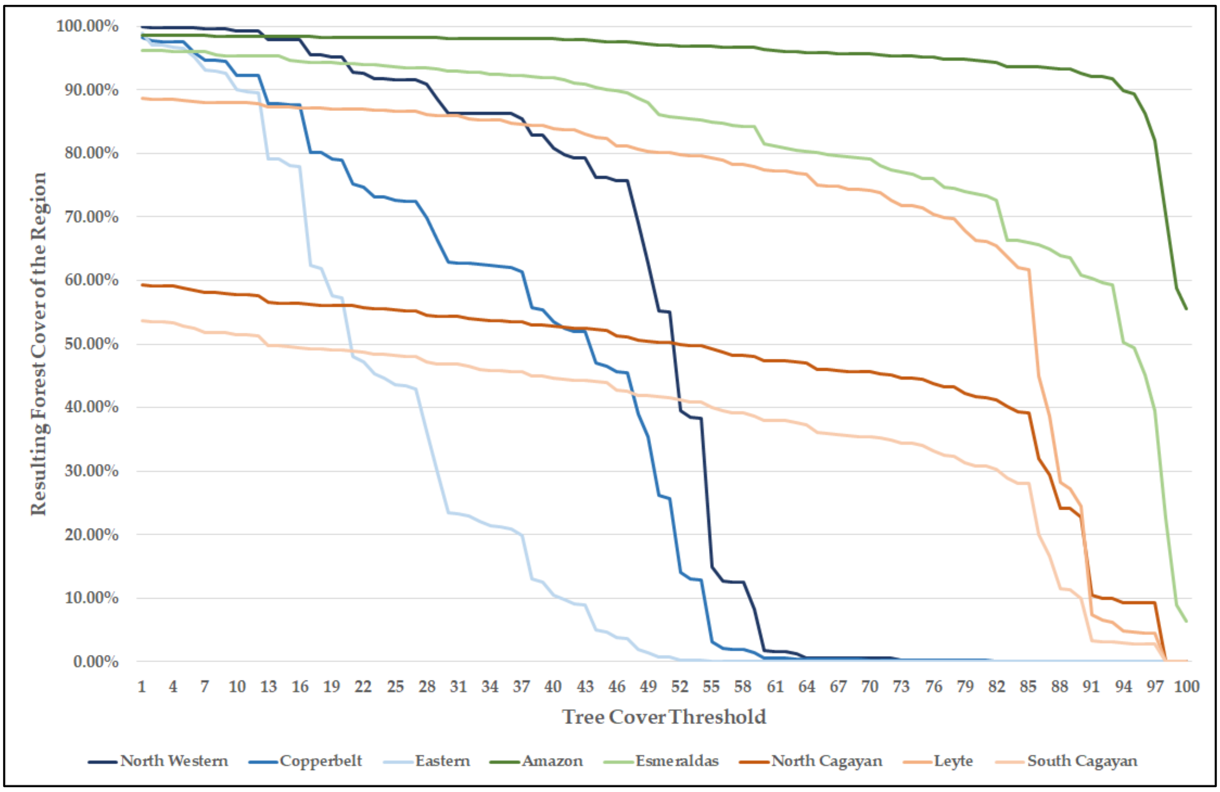


Figure 6. Resulting forest cover of the different regions in relation to the applied tree cover threshold from the Global Forest Change dataset 2010. Adapted from: Ferrer Velasco et al. (2022).

In Publication 2, I used further global LCLU maps to derive forest masks for all the studied regions, comprising an area of roughly 15Mha (Table 8). This included the aforementioned GFC dataset (Hansen et al., 2013), but also other maps introduced above: one more derived from optical sensors (i.e., the CGLS-LC100 [Buchhorn et al., 2020a]) and two derived from

SAR sensors (i.e., TanDEM-X and JAXA FNF [Martone et al., 2018; Shimada et al., 2014]). The layers and years were chosen to be the closest to the date of data collection.

a2) National LCLU maps

National LCLU maps are also very relevant because they are used for national forest monitoring (NFM) purposes and for international reporting of reference levels (e.g., FAO's FRA or for the Intergovernmental Panel on Climate Change [IPCC]). However, the technical and logistical capacities of national mapping agencies in tropical countries are still being improved (Ochieng et al., 2016; Romijn et al., 2015). The three countries included in my study are examples of different stages of development, regarding these NFM capabilities.

Table 8. Summary of the secondary data sources used in my publications to obtain information on forest dynamics (global and national LCLU maps) and the related spatial scopes and units of analysis.

Publication		Spatial scope	Variable studied[1]	Global LCLU maps	National LCLU maps	Unit of analysis
A) Main investigations: Peer-reviewed research articles as a first author with a pantropical scope and covering different spatial levels.						
1	Ferrer Velasco et al. (2020)	Pantropical	FA, FC (ZMB: 2016, ECU: 2014, PHL: 2015)	ESA (2017b)	MAE (2015) NAMRIA (2013)	Official administrative jurisdictions
2	Ferrer Velasco et al. (2022)	Pantropical	FA, FC (~2010-2016)	Buchhorn et al. (2020), Hansen et al. (2013), Martone et al. (2018), Shimada et al. (2014)	ILUA-II (2016), MAE (2017), NAMRIA (2017)	Study regions (~15Mha)
3	Ferrer Velasco et al. (2023)	Pantropical	-	-	-	-
B) Supporting studies: Published peer-reviewed research articles as a coauthor, with focus in one country/region or on a specific spatial level.						
4	Nansikombi et al. (2020)	Zambia	AFC (TC >30%) 2013-2017	Hansen et al. (2013)	-	Governance arrangements
5	Kazungu et al. (2021)	Zambia	AFC (TC >30%) 2000-2006, 2007-20012, 2013-2018	Hansen et al. (2013)	-	Buffer rings around households
6	Fischer et al. (2021)	Ecuador	AFC 2008-2016	-	MAE (2022)	Governance arrangements
7	Gordillo et al., (2021)	Ecuador	AFC 1990-2018 (two periods)	-	MAE (2022)	Buffer rings around PES
8	Wiebe et al. (2022)	Philippines	FC 2015, distance to forest edge	-	NAMRIA (2017)	LaForeT Landscapes

[1] FA: Forest Area; FC: Forest cover or percentage of total land area; ZMB: Zambia; ECU: Ecuador; PHL: Philippines; AFC: Average annual net forest area change; TC: Tree Cover.

Zambia's Forestry Department has recently released the first national LCLU maps for the years 2000, 2010 and 2014, based on Landsat images (ILUA-II, 2016). These maps are the result of the multi-phase Integrated Land Use Assessment (ILUA), and related to the development of Zambia's NFM guided by the UN-REDD+ requirements. Zambian agencies are still working to improve the capacity to monitor changes, update the data or harmonize it with the National Forest Inventory (NFI) (Mutasha and Matanda, 2020). This recent release of the ILUA maps is the reason why in my first publications I worked with global or regional forest maps to estimate forest dynamics in Zambia (Table 8). In the case of Publication 1, I used ESA's 2016-prototype land cover map for Africa based on Sentinel-2, which distinguishes TC (not necessarily forest) from other land cover types (ESA, 2017b). Similarly and as described above, in Publications 4 and 5 I estimated forest cover and deforestation based on the global GFC dataset (Hansen et al., 2013). However, in my latest Publication 2, I worked with the 2014 ILUA map to estimate forest cover in the studied regions.

In the case of Ecuador, the inventory and mapping capabilities of the Ministry of Environment (previously MAE, now MAATE) are relatively long-established. The Ecuadorian mapping agencies produce regularly updated LCLU and deforestation maps, using a combination of Landsat time-series and very high-resolution imagery (i.e., aerial photographs and RapidEye) for training and validation (MAE, 2022; MAE-MAGAP, 2015). These maps distinguish native forests from other LCLU types and are available for the years 1990, 2000, 2008, 2014, 2016 and 2018. In Publication 1 (Table 8), I used MAE's map for 2014 (latest map available at the time of writing the manuscript), to estimate forest cover within the boundaries of different administrative jurisdictions (province, county and parish). In Publication 2, I generated forest masks for the study regions, based on MAE's 2016 LCLU map (MAE, 2017). In Publications 6 and 7, I used national LCLU maps to derive information about deforestation (MAE, 2022). In Publication 6, I estimated the average annual net loss of native forest between the years 2008 and 2016 for 139 governance arrangements in different landscapes. In Publication 7, I calculated the same variable for eight landscapes and for buffer areas or distance rings around four communal forests belonging to the PES-scheme Socio Bosque. I did this for two time periods: from 1990 to the establishment of each Socio Bosque concession and afterwards until 2018.

Philippines' National Mapping and Resource Information Authority (NAMRIA) has very recently published the 2020 national LCLU map, based on Sentinel-2 images, using OBIA classification and in situ verification (NAMRIA, 2022). NAMRIA had used information from other sensors to produce its previous LCLU maps: i.e., 2003 (Landsat), 2010 (combination of ALOS AVNIR-2, SPOT-5 and Landsat) and 2015 (Landsat) (NAMRIA, 2003, 2017, 2013). Thus, NAMRIA has been adapting its methodology and progressively improving the quality of its national LCLU maps, e.g., by including ground validation and accuracy assessment after

2010 (Estoque et al., 2018; Santos, 2018). In my publications, I used both the 2010 and the 2015 LCLU maps, which were the best available sources at the time of writing the manuscripts (Table 8). Thus, in Publication 1, I used NAMRIA's 2010 LCLU map, to estimate forest cover within the boundaries of 17 administrative regions. 81 provinces and 1,652 municipalities. In Publication 2, I generated forest masks for the study regions, based on NAMRIA's 2015 LCLU map. I used this same source in Publication 8, to estimate forest and cropland cover at landscape level, but also the distance of the studied households to the forest edge.

b) Primary data sources for LCLU and forest maps

In my publications I also used information on forest dynamics and LCLU derived from data obtained by myself or by the project team. Basically, this information can be divided into two categories: (a) binary forest maps generated by supervised classification of remote sensing images, using training data on forest condition and disturbance history obtained in situ (Publication 2); and manually digitized LCLU maps including information on forest condition, obtained through participatory mapping exercises with members of local communities (Publications 4 and 6). The details and specifics about these methodologies can be found in the extended versions of these research articles.

b1) Supervised classification of remote sensing data

In Publication 2, we collected ground verification data across the thirty-six landscapes of the LaForeT project between September 2016 and October 2019 (Figure 7). Field teams spent roughly one month and a half in each landscape, collecting a total of 16,676 georeferenced ground control points (GCPs) and more than 14,000 photographs (GCPhotos) with LCLU information. The teams (two to five local experts and researchers) followed a cross-country field protocol, which implied a stratified sampling approach to capture the main forest and LCLUs in each landscape (GFOI, 2020). These strata were identified in situ and delineated by visual interpretation of Google Earth imagery during the design of the field sampling campaign. We used a cross-country classification scheme based on a modification of FAO forest definitions and on IPCC categories, adapted to include typical LCLUs of the studied regions (Di Gregorio, 2005; FAO, 2018; Huxley, 1999). Further details about the sampling campaign (e.g., field protocol and LCLU list) can be found in Publication 2.

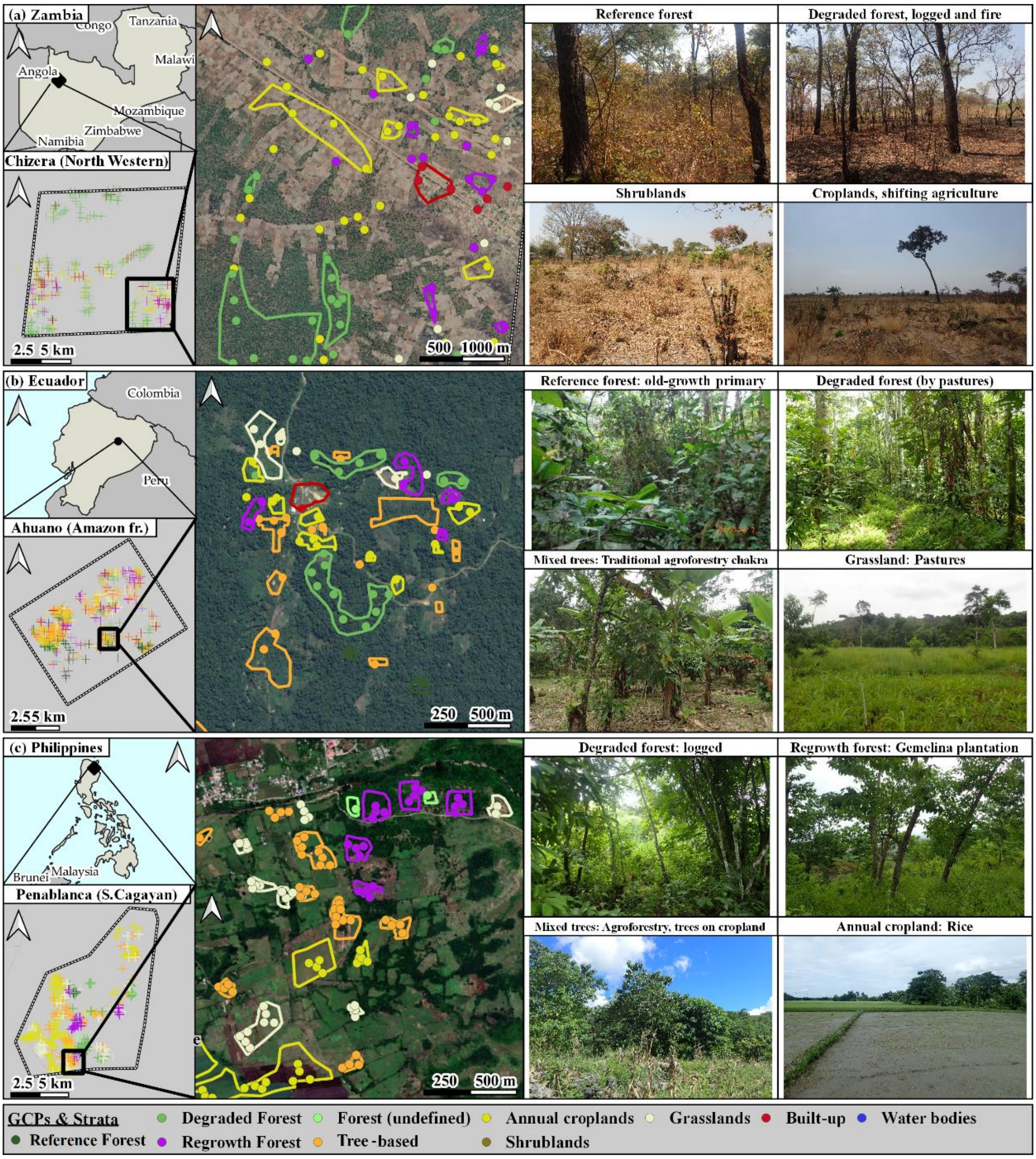


Figure 7. Spatial distribution of ground control points (GCPs), delineation of strata and ground control photos (GCPhotos) in three example landscapes: (a) Chizera, North Western, Zambia; (b) Ahuano, Amazon frontier, Ecuador; (c): Penablanca, South Cagayan Valley, Philippines. Source: Ferrer Velasco et al. (2022).

The researchers, with the help of local inhabitants, included details on forest disturbance and regeneration history: i.e., type (human/natural) and age (up to 20 years) of the last disturbance and type of regeneration (human/ natural). Each class was covered with a representative number of GCPs, which were spatially distributed in each landscape and included a homogeneous LCLU within a radius of 10 m and a minimum distance of 100 m between GCPs (Olofsson et al., 2014). These GCPs were then digitized into 7,123 polygons of homogeneous LCLU (covering a total of 44,408 ha), using Quantum GIS v.3.10 and with the help of current Google

Earth imagery and the GCPhotos. These polygons covered a total of ten LCLU classes: four for forest (reference, degraded, regrowth and undefined), four for deforested vegetation (tree-based systems, annual cropland, shrubland and grassland) and two for non-vegetation classes (built-up and water bodies). Finally, the polygons were split randomly into two independent datasets, conserving the share of the LCLU classes per region: one dataset for training (including 70% of the polygons) and one for the validation (including the remaining 30%).

The following processing steps to create forest maps were performed with Quantum GIS v3.10, SNAP v8.0, ENVI v5.6 and PyCharm v2019.3. First, seven 30-m multi-sensor composites (stacked raster layers) covering the studied regions (a total of approximately 15 million hectares) were created with thirty-nine variables per pixel each: (a) seven mosaicked Landsat-8 bands (optical) and seven related vegetation indices (seasonal selection of bands through three years); (b) twenty-four Sentinel-1-derived bands (SAR), consisting on one sigma nought and three texture values for two points in time and three different polarizations; and (c) one elevation band from the Shuttle Radar Topography Mission (SRTM)-1Sec digital elevation model (DEM). This implied the pre-processing of 269 Landsat-8 Level-2 Surface Reflectance images (Collection 1 OLI/TIRS Combined) and thirty-two Sentinel-1 scenes of Level-1 high-resolution Ground Range Detected (GRD) Interferometric Wide (IW) swath data with Dual VV/VH Polarization. Further details on the selected scenes, variables or indices and the processing methods are included in the full version of Publication 2. We performed supervised classification for each composite, using the regional subsets of the training polygons (70%) and a random forest classifier (Breiman, 2001). Final eight FNF maps were then created for the study regions, after cleaning isolated pixels and applying ocean and regional masks. For each of the regional outputs, confidence maps were generated and further analyzed. Besides, we ranked the importance of the bands based on how much the accuracy decreased when each variable was excluded. Further analysis implied exploring the number of pixels with no optical information (Landsat-8) in each regional mosaic, due to the presence of cloud cover.

b2) Participatory mapping

In Publications 4 and 6, we obtained LCLU information through participatory mapping exercises in focus group discussions (FGD) (O.Nyumba et al., 2018). This FGD were conducted within workshops in the studied communities of both publications: 24 in Zambia (Publication 4), 12 in Ecuador (Publication 6). The workshops included between 15 and 25 community and stakeholder representatives, including different decision makers (e.g., sub-village and customary leaders, forest committee) and social groups (e.g., men/women, young/elder).

Following participatory exercises (Emmel, 2008), two maps were produced on printouts of Google Earth images of roughly 2.5 m^2. The first map defined main governance arrangements, which were later used as units of analysis. The second map included LCLU classes, using the same cross-country classification scheme as in the GCP collection of Publication 2. All mapped information was digitized using Quantum GIS v3.10 (Figure 8).

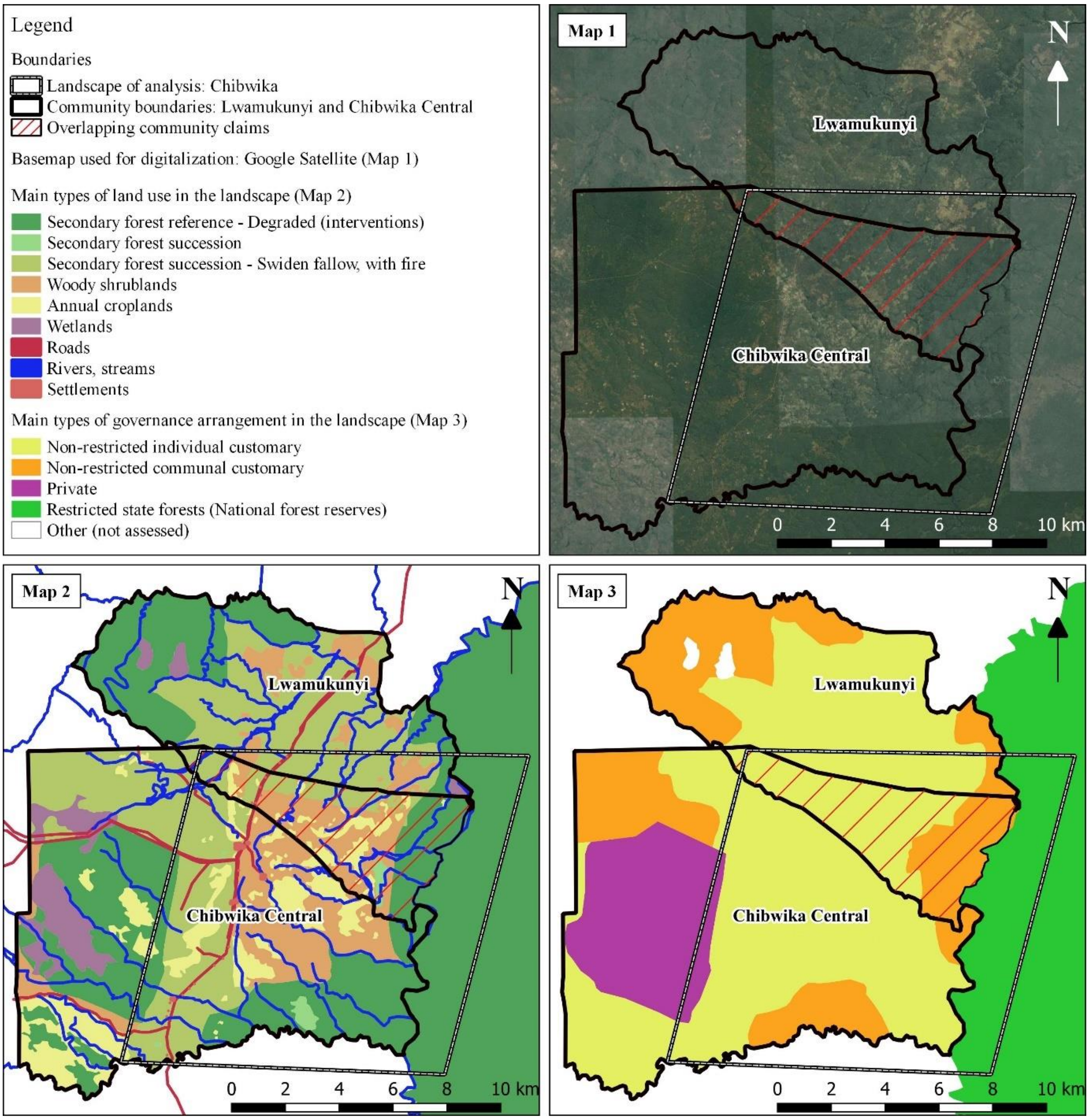


Figure 8. Result of the participatory mapping exercise for the two communities (Lwamukunyi and Chibwika Central) of the landscape in chiefdom Chibwika (Mwinilunga District, North Western Province); showing: basemap based on Google Imagery used for digitalization (Map 1), digitized LCLU (Map 2) and digitized governance arrangements (Map 3). Source: Nansikombi et al. (2020a).

2.2.2 Data on drivers of forest dynamics

In this subsection I will describe the data sources on drivers of forests dynamics, which I used in my publications. First, I will depict the most important secondary sources, ordered by driver categories following the structure of Geist and Lambin (2002) (Table 4). Second, I will present some of the methods used to collect primary data and I will describe the main characteristics of this information. This includes methods such as key informant interviews with representatives of forest-related institutions, household questionnaires and the abovementioned FGD in forest villages, or the production of LCLU maps.

a) Secondary data sources for drivers of forest dynamics

One of the most commonly discussed drivers of deforestation is infrastructure extension. The expansion of cities (i.e., urbanization), roads or industrial facilities (e.g., mining, oil) can be used as a proxy of anthropogenic pressure and of accessibility or proximity of human activities to forest (Hawbaker et al., 2005; Heilman et al., 2002). These drivers imply clear spatially explicit features, which can be easily measured and quantified: e.g., the length or density of roads, the area expansion of built-up or distance of forest to different infrastructure elements. In Publication 1, I measured the total road length in each assessed jurisdictional unit (including highways, roads, paths and railways) from OpenStreetMap (2016) with Quantum GIS v3.10. The total road length was divided by the total area of each respective administrative unit, to calculate road density. OpenStreetMap, despite being a collaborative project with limitations especially in remote tropical areas, has a worldwide coverage and allows for easy comparison between countries. It also showed relatively consistent and acceptable results for the studied countries in general and for the assessed landscapes in particular, when compared to other similar sources of global road networks (e.g. gROADSv1) or even national databases, which were often lacking updated information on non-paved roads. Thus, OpenStreetMap data was also used in Publications 4 and 6. In Publication 4, the distance of different governance patches (e.g., communal forest) to the nearest road was calculated, with patches intersecting with roads having a value of zero. This was adequate in this context due to the relatively low road density and the small size of the patches, derived from participatory mapping. In Publication 6, I calculated road length and density for specific governance arrangement patches at local level, contrasting visually with national databases (IGM, 2018).

Regarding agricultural expansion, commonly seen as the main threat to tropical forests, I included the following variables from secondary sources. In Publication 1, I used FAO’s Food

Insecurity, Poverty and Environment Global GIS Database (FGGD) to estimate the crop suitability index (CSI), as a proxy of potential for agriculture expansion in the studied jurisdictions (FFGD-FAO, 2012; Van Velthuizen, 2007). In Publication 6, I calculated the share of area in each studied landscape covered by croplands, using information from the most recent national LCLU map (NAMRIA, 2017). The use of LCLU maps can provide useful information about LCLU changes and about the extent of specific LCLU types competing with forests, not only croplands, but also, e.g., built-up, plantations, or pastures. In my work, however, I mostly relied in primary information (i.e., in situ validation and participatory mapping) to derive such variables, as they provided more reliable information at local level.

Further indicators for proximate drivers of deforestation in my publications derived from secondary sources include general biophysical and topographic information. For example, the elevation (height above sea level) and slope of terrain can be easily calculated through existing global DEMs of relatively high accuracy and high resolution. These are good indicators of accessibility to humans or of suitable conditions for vegetation growth. For instance, in Publication 1 I used SRTM's DEM (Jarvis et al., 2008) to measure the share of land in each administrative unit with slope below 16% (flatness indicator). Similarly, in Publication 4 I calculated the average slope in each governance arrangement patch from the same DEM source. Similarly, in Publication 1 I calculated the potential vegetation area (PVA) as the share of potentially forested area (including all vegetation types from LCLU maps) in the total land area of the analyzed administrative unit, based on Köthke et al. (2013). Another interesting and easy-to-obtain biophysical indicator is the total area of the analyzed unit. In Publication 1, I relied on information from the Global Administrative Boundaries Database (GADM, 2015). In Publication 6, however, the boundaries of the studied municipalities in the Philippines were provided by local institutions, due to several discrepancies between data sources. As a final indicator in this category, in Publication 6 I also calculated the distance of households to the closest forest edge, based on the information of national LCLU maps (NAMRIA, 2017).

My studies also included data from secondary sources to derive information about the so-called underlying drivers of forest dynamics. First, in Publications 1 and 4 I estimated total population and population density from WorldPop, an spatially-explicit high-resolution dataset of global coverage (Tatem, 2017). Despite being an underlying factor, population pressure is highly correlated with other proximate causes of forest dynamics. Therefore, it can be a good indicator for the expansion of other LCLUs (i.e., agriculture or infrastructure), timber extraction or biophysical aspects (Busch and Ferretti-Gallon, 2017; Mather and Needle, 2000). In

Publication 1 I also included a technological factor for the studied administrative units in the three countries: cereal area yield, as an indicator of agricultural productivity and intensification, releasing pressure from forests (Barbier and Burgess, 2001; Rudel et al., 2009). In this case, I relied on official national statistics about main crop types (i.e., maize and rice) between 1987 and 2015 (CSO, 2017; PSA, 2017; SINAGAP, 2016). In Publication 4, we included a dummy variable about the different Provinces studied, to further account for regional differences which are also associated to these underlying factors or social processes. Finally, in Publication 7, I used the official boundaries of different Socio Bosque sites, in order to analyze deforestation within these conservation areas and around (MAE, 2014). This is an example of how the accurate delineation on forest protection measures, can be useful to monitor and analyze the effect of such “positive” drivers on forest dynamics.

b) Primary data sources for drivers of forest dynamics

In my publications, I also relied on data about drivers of forest dynamics collected by myself or by colleagues and the field teams of the LaForeT project. For instance, in two of my main investigations (Publications 2 and 3), I obtained primary information using very different methods. In Publication 2, I digitized patches or polygons of different LCLU types at landscape level and generated regional maps. This information can serve to estimate LCLU shares or changes related to different proximate drivers such as infrastructure expansion (i.e., built-up), agriculture expansion (i.e., croplands, agroforestry, pastures) or wood extraction (i.e., degraded and regrowth forest). In Publication 3, I collected perceptions of 224 representatives of relevant forest institutions through a cross-country questionnaire. In this questionnaire, we asked about the influence of (a) different proximate drivers on deforestation and forest degradation and (b) policy measures on stopping deforestation/degradation and increasing forest areas, in the future 10 years. These categories were preselected based on relevant literature and they cover the whole spectrum of proximate drivers of deforestation (“Oil & Mining”, “Infrastructure and urbanization”, “Agricultural expansion”, “Timber plantations”, “Logging, timber extraction”, “Firewood, woodfuel”, “Natural disasters” and “Other drivers”), together with the main options of policy instruments to protect forests (“Reforestation, restoration and agroforestry”, “Protected areas”, “Measures against logging”, “Financial instruments”, “Land-use rights” and “Other policy instruments“) (Table 4). The respondents scored each driver and policy based on a Likert scale from 1 (no effect) to 5 (very strong effect). From these answers, I estimated the overall alertness about deforestation drivers (commercial- and subsistence-related) and the overall confidence in policy measures for each respondent. These variables were defined as the share of answers with “strong” (4) or “very strong” (5) influence in each section of the questionnaire, respectively (Top 2 Box scores [T2B] in percentage). Additionally, the respondents listed their top three to five important national drivers and policies, respectively, each with a share of relative relevance adding up to 100. From these responses, I calculated the expected importance of each driver category and the expected effectiveness of each policy instrument category for each stakeholder.

In the supporting studies we also used indicators for drivers of forest dynamics obtained by ourselves. In Publications 4 and 6 we relied on the LCLU areas generated by participatory mapping to estimate driver-related information, as described above for Publication 2 and with the secondary LCLU maps for Publication 6. In Publication 4, we used the share of built-up, agriculture and the total area of the community, obtained during the participatory mapping in FGDs, as input explanatory variables of a multivariate regression analysis with backward elimination. The exact same methodology was followed in Publication 6, in this case including the share of agroforestry, crops, pastures, harvested forest, primary forest and succession forests as input variables. Additionally, we included further variables obtained during the FGD in the regression models of these two publications. These comprised Likert scores for 19 (Publication 4) and 10 (Publication 6) governance elements or underlying factors, based on the forest governance assessment tool of the World Resource Institute (Davis et al., 2013). In Publication 4, further information about charcoal, firewood, timber and poles and livestock grazing was obtained through the same FGDs. The participants of each workshop distributed 100 pebbles representing benefits for the community among the different mapped LCLU classes. Then, the degree of extraction/use was estimated as the ratio of pebbles per governance arrangement patch area. In Publication 6, further key economic variables were derived through key informant interviews with three community leaders per landscape: i.e., (1) percentage households with electricity, (2) percentage of population that can read/write, (3) km from community center to nearest general market, (4) km from community center to nearest agricultural market, (5) hourly rate for wage employment of an unskilled worker in US Dollars, (6) mean percent of household income from forests, (7) mean percent of household income from agriculture.

Publications 5 and 8 also include primary data on drivers, this time collected through household questionnaires in the landscapes of the LaForeT project (1,123 and 993 households, respectively). A structured cross-country questionnaire was used to interview a member of randomly selected and spatially homogeneously-distributed households. In Publication 5 we used the answers to derive variables related to socio-demographics (household size, number of adults, age and gender of the head, duration of residence, ethnicity), land-use (size of patches for land use, total income, livestock units) and location (distance to village center and to main road, distance categories related to land use patches, access to paved road, presence of forest reserve and presence wet miombo). These attributes were included as explanatory variables of a generalized ordered logistic regression model to explain deforestation levels in different distance rings within the studied landscapes. In Publication 8, the same socio-demographic information was used to describe the sample, together with education level and access to paved roads. Additionally, details on the different sources of income were used as input to estimate main livelihood strategies by PCA and to analyze their distribution by cluster analysis. The sources of income distinguished shares of cash and subsistence cropping and livestock, fishing, off-farm, business, remittances, forest-related and other income. Forest-related income further distinguished between timber, fuelwood and non-wooded forest products (NWFP).

2.3 Statistical analysis

The following subsection describes the main statistical methods used in my publications to analyze the abovementioned data. I will present these methods into the following (sub-) subsections: (1) multivariate regression models and spatial econometrics, (2) quality analysis of forest maps, (3) dimensionality reduction, and (4) comparative analysis. These analyses were conducted with a variety of software options in each of the publications: i.e., QGIS, R, JMP and STATA. The specific details on software versions and packages can be found in the respective referenced publications.

2.3.1 Multivariate regression models & Spatial econometrics

Four of my publications included multivariate regression models with forest-related information as a dependent variable and different driver indicators as explanatory variables. In Publications 1, 4 and 6, we conducted multiple linear regressions (MLR), considering spatial models in the case of Publication 1, whereas in Publication 5, we conducted ordered logistic regression (Manly and Alberto, 2016; Williams, 2006). In Publication 1, the outcome was forest cover (as the share of forest in the potential vegetation area) derived from secondary LCLU maps. In contrast, in Publications 4, 5 and 6, the dependent variables were deforestation rates derived from Hansen et al. (2013) and MAE (2017), as specified in the previous subsection. In the case of Publication 5, deforestation rates were converted into three categories (low-medium-high), which explains the use of an ordered logistic regression. The different predictors used in the models of each publication, obtained from both primary and secondary sources, have been specified in the previous subsection (Table 4).

In Publication 1, a total of twelve regressions were conducted for different samples of administrative jurisdictions, as the combination of three spatial levels (macro-, meso-, micro-) and the three countries individually and altogether. The pantropical samples included a total of 3,035 observations at the microlevel (e.g., municipalities), 361 at the meso-level (e.g., counties) and 49 at the macro-level (e.g., provinces). In Publication 4, we conducted two regressions for 80 different patches of governance arrangements in Zambia: one model including both proximate drivers and governance indicators as underlying drivers, and one including only the proximate drivers. In Publication 6, one regression model for 84 patches of governance arrangements in Ecuador was conducted. The ordered logistic model of Publication 5 was applied for a sample of thirty-six distance rings or buffers, three in each of the Zambian studied landscapes.

The input data for the models was examined and pre-treated accordingly to accomplish the necessary assumptions (Dytham, 2011). This involved, for instance, the linear transformations of variables: i.e., logarithmic transformations for both outcome and predictors in Publication 1, square root transformation of explanatory variables in Publication 4, and ordinal transformation of deforestation rates in Publication 5 (Motulsky and Christopoulos, 2004). Also, the predictors were standardized in the models of all publications (e.g., by z-score method), while outliers or missing values had to be removed when appropriate (e.g., Publications 1 and 6, by three-times standard deviation rule). Furthermore, we checked multi-collinearity and removed strongly correlated predictors when necessary, using thresholds for bivariate correlations (Publications 1 and 5) or for variance inflation factors (VIF) (Publications 4 and 6) (Craney and Surles, 2002). Additionally, the linearity of the variables and the residuals was confirmed with Shapiro-Wilk tests when applicablev(Shapiro and Wilk, 1965), while homoscedasticity was assured applying Breusch-Pagan or Bartlett tests (Bartlett and Fowler, 1937; Breusch and Pagan, 1979).

In the case of the MLR models, we used automated stepwise backward elimination to determine the set of optimal predictors. Different stop-rules were used to determine the optimal models, based on Bayesian information criterion (BIC) in Publication 1, Akaike information criterion (AIC) in Publication 4 and r^2 in Publication 6 (Hocking, 1976).

In Publication 1, I also used spatial econometrics, which is a discipline with increasing interest in urban and regional studies, but which has been not widely used in previous studies of tropical deforestation (Arbia, 2016; LeSage, 2014). Nevertheless, such models can contribute to understand spatial phenomena: e.g., spillovers, indirect impacts of neighboring units, or by providing information about omitted variables, or on how spatial clusters look like (Anselin, 2013; Golgher and Voss, 2016; LeSage and Pace, 2009). I first built a spatial weights matrix (W) for each of the twelve samples or models, following the sphere of influence method (Dwyer, 1995). This neighbor matrix reflects how spatial units interact with each other and their connectivity (Figure 9). In order to justify the use of spatial econometrics, we examined the spatial dependency of the model residuals in the twelve non-spatial models, by performing Moran test (Moran, 1950) and the Lagrange Multiplier diagnostic for lag and error models (Anselin, 1988).

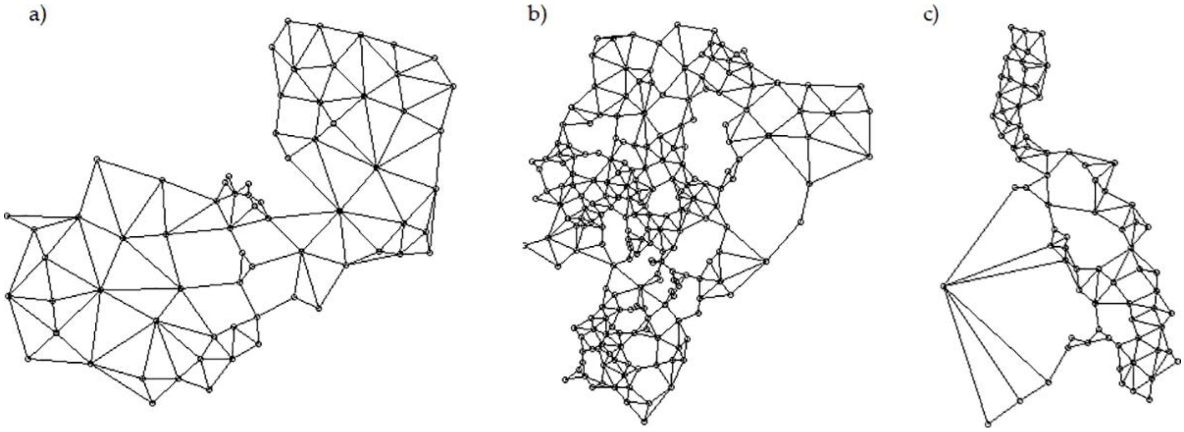


Figure 9. Spatial weights matrices based on sphere-of-influence method, representing the interactions between the meso-level jurisdictional units in (a) Zambia, (b) Ecuador, (c) Philippines. Source: Ferrer Velasco et al. (2020).

We selected the most suitable regression model for each of the twelve samples, applying the LeSage and Pace method for local model specification (LeSage and Pace, 2009; LeSage, 2014). This method uses likelihood ratio tests to demonstrate if a Spatial Durbin Error Model (SDEM, Equation 1) can be restricted to a simpler nested model, such as the spatial error model (SEM, Equation 2), a spatially lagged X model (SLX, Equation 3), or reduced to the non-spatial MLR (Equation 4):

$$Y = B_0 + [B_1X_1 + W_n\theta_1X_{1,n}] + \cdots + [B_kX_k + W_n\theta_kX_{k,n}] + \lambda W_n u + \varepsilon \quad \text{Equation 1: SDEM}$$

if $\theta = 0$:

$$Y = B_0 + B_1X_1 + B_2X_2 + \cdots + B_kX_k + \lambda W_n u + \varepsilon \quad \text{Equation 2: SEM}$$

if $\lambda = 0$:

$$Y = B_0 + [B_1X_1 + W_n\theta_1X_{1,n}] + \cdots + [B_kX_k + W_n\theta_kX_{k,n}] + \varepsilon \quad \text{Equation 3: SLX}$$

if both $\theta = 0$ and $\lambda = 0$:

$$Y = B_0 + B_1X_1 + B_2X_2 + \cdots + B_kX_k + \varepsilon \qquad \text{Equation 4: Non-spatial MLR}$$

Here, Y is the respective forest-related outcome; Xs are the different k predictors or drivers; Bs are the regression coefficients; ε, the error term; W_n represents the row-standardized weight of the neighbor n; θs are the neighbors' impacts; $X_{k,n}$ is the neighbors' value for a certain predictor k; and $\lambda W_n u$ represents the weighted spatial residual error.

Thus, the SLX model accounts for neighbor impacts, the SEM model for spatially correlated errors and the SDEM for both spatial effects. All the specified models were compared to its non-spatial version, by evaluating AIC, BIC, unbiased maximum likelihood estimators of the error variance, standards errors of regression, adjusted coefficients of determination and log-likelihood estimators for the regression coefficients (Kosfeld, 2019).

2.3.2 Quality analysis of forest maps

In Publication 2, we assessed the quality of our map outputs (produced by supervised classification) and the quality of the selected secondary sources (four global and three national LCLU maps, as explained above). To do this, we followed three different approaches or methods: (1) accuracy assessments or error matrices, (2) comparisons of forest cover estimations at regional and landscape level, and (3) analysis of spatial agreements per-pixel.

We created error matrices for all eight map sources in each of the study regions, by measuring the number of correctly classified pixels within the 30% randomly-selected polygons as validation dataset (Table 9). This was possible with the zonal histogram tool of QGIS, which provides a count of each unique value from a raster layer (i.e., LCLU class) for each zone (i.e., validation polygon).

Table 9. Error matrix of the LaForeT maps (own creation), for the total sample (all regions in three countries). Source: Ferrer Velasco et al. (2022).

		Reference dataset[1]			
		Forest	**No Forest**	**Row Total**	**User Accuracy**
LaForeT Forest Map	**Forest**	174,772	14,382	189,154	**92%**
	No Forest	6,701	82,605	89,398	**93%**
	Column Total	181,473	96,987	278,552	
	Producer Accuracy	**96%**	**85%**		
				Overall accuracy	**92%**

[1] Count is the number of pixels (30-m resolution) within the validation polygons.

The quality of a map can be assessed by evaluating its thematic accuracy metrics derived from the error matrices (Olofsson et al., 2014). First, the overall accuracy indicates which proportion of the reference sites (in our case, pixels in validation polygons) were mapped correctly, as a percentage. The inverse of the overall accuracy of a map is the overall error. Also important is the user accuracy or precision, which is the accuracy from the point of view of the user. It represents the reliability of the map or how often a class in the map will be found on the ground. The inverse or opposite metric of the user accuracy is called commission error. Similarly, the producer accuracy (i.e., sensitivity) indicates how often the features or classes on the ground are shown on the map. This is the accuracy from the point of view of the map maker, and its inverse is called omission error. In our work in Publication 2, we calculated these metrics for all the map sources in each region and analyzed the results by country, region and deforestation context. Thanks to our detailed forest condition classification in the validation datasets, we could analyze the sensitivities or producer accuracies of various LCLU types and forest disturbance levels.

We further calculated forest cover according to the selected map sources at landscape level. This was done with QGIS, using the zonal histogram in the case of raster files, and a combination of ‘union’ and ‘dissolve’ functions in the case of polygon shapefiles. The regional aggregations permitted broader comparisons between deforestation contexts and territories. Furthermore, these estimations helped us to examine the quality of the compared map sources visually (Figure 10).

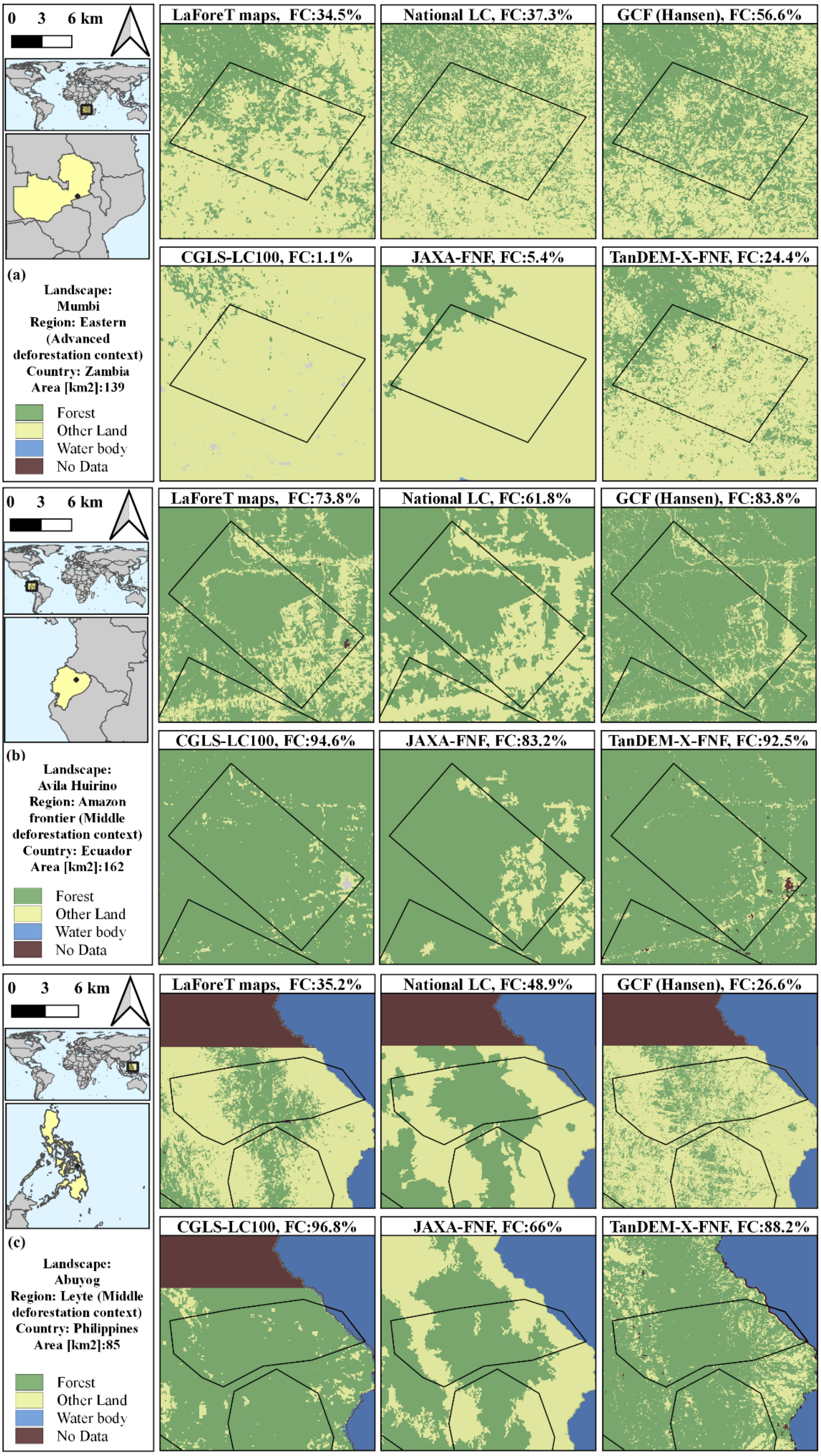


Figure 10. Examples of three landscapes with strong discrepancies in forest cover estimations between the selected datasets (a): Mumbi, Eastern, Zambia; (b): Avila, Amazon, Ecuador; (c): Abuyog, Leyte, Philippines. Source: Ferrer Velasco et al. (2022).

A last step to analyze the quality of the selected forest maps involved comparing pairs of maps per-pixel (Yang et al., 2017). We calculated the overall and the individual-class (forest and non-forest) spatial agreements for every combination of datasets and region. To do this, we needed to resample all maps to the lowest resolution of each compared pair, which we did following nearest neighbor interpolation.

2.3.3 Dimensionality reduction

Principal component analysis (PCA) is a dimensionality reduction method that can be used to simplify the complexity of high-dimensional datasets with multiple variables, while retaining trends and patterns (Dunteman, 2008). As a result, this test produces linear combinations (i.e., principal components or PCs), which can be related to the original variables (Figure 11). This method was used in three of my studies (Publications 3, 6 and 8).

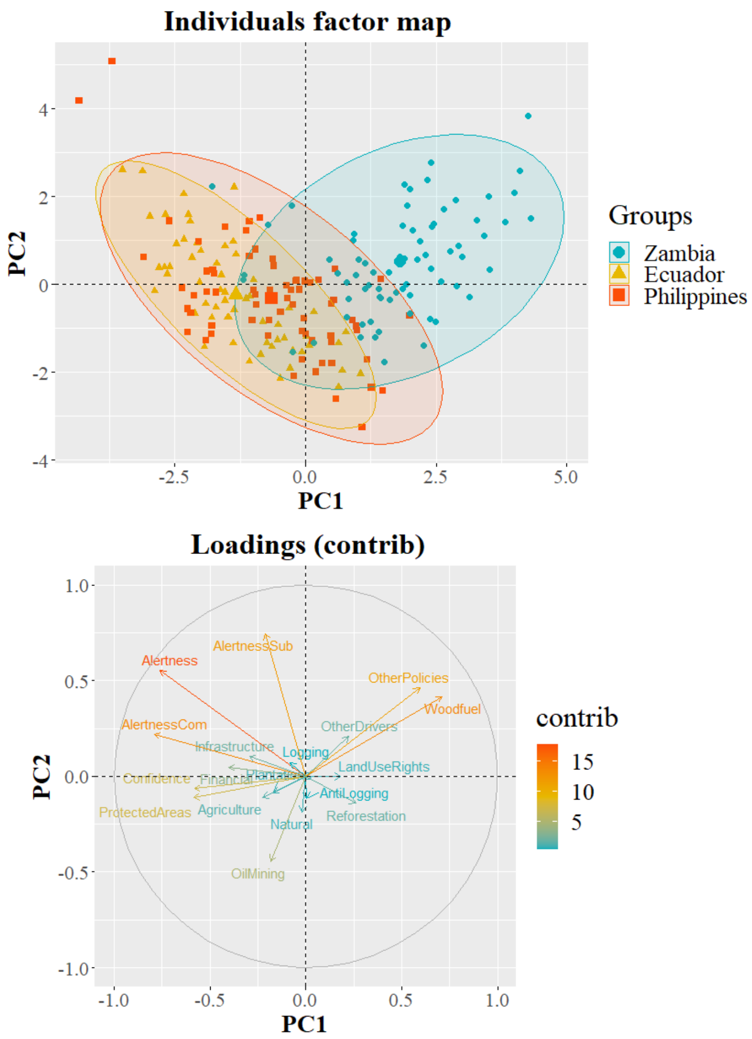


Figure 11. Results of PCA with eighteen variables (perceptions about drivers and policies) from 224 questionnaires: biplots of the individuals grouped by country (ellipse of 95% confidence) and loadings of the variables for the two first components. Source: (Ferrer Velasco et al., 2023).

In Publication 3, PCA was applied to the eighteen studied variables (perceptions of stakeholders), standardized and including a total of 224 questionnaires. In this case, the first intention was to find patterns or relationships between the selected categories of drivers and policy instruments, in order to support further analyses. A second objective was to explore if the number of pre-selected categories could be reduced and still capture most of the variation of the answers. The PCA ratified the importance of certain indicators that contributed strongly to the first PCs (e.g., overall alertness of commercial drivers). However, as most of the PCs explained a similar share of variance, had eigenvalues close to or higher to 1 and were loaded with one or few variables, this suggested that the dimensions could not be reduced easily and that most of the PCs were relevant and related to the included variables. We interpreted that the chosen driver and policy categories based on literature were independent enough and appropriate to describe distinct deforestation processes. Thus, in further analyses we worked with all the originally selected variables and we did not include the PCs.

In Publication 6, PCA was calculated for 25 governance arrangement patches in Ecuador with field governance assessments, in order to identify trends within the governance data and explore how the original governance variables were correlated. In Publication 8, PCA was used as a first step to identify main livelihood strategies (Scoones, 1998) within the 993 studied households in the Philippines, defined as: “the activities, the assets and the access that jointly determine the living gained by an individual or household” (Ellis, 2000). Therefore, we used the shares of the ten selected income sources defined in the Data subsection as input variables of the PCA. Following this first step, PCs with an eigenvalue higher than 1 (Kaiser rule) were selected and used as input a Hierarchical Cluster Analysis, based on the Ward method (Ward, 1963). Such an analysis can create groups of objects (clusters), which are similar to each other with respect to the patterns or values of the analyzed variables (or PCs in this case). Using the first PCs as input for cluster analysis was conducted based on the approach of Lax and Köthke (2017), with the aim of obtaining more stable and pronounced groups representing clearly differentiated livelihood strategies.

2.3.4 Comparative analysis

A further type of statistical methodology, which was employed in my studies, are different types of comparative analyses. For instance, in Publication 3 (Figure 12) we used both parametric and non-parametric one-way analyses of variance (ANOVAs). The parametric ANOVA compares the means of two or more independent groups to detect significant differences among them, regarding a specific variable (Kirk, 1995). Similarly, its non-parametric version, the Kruskal-Wallis one-way ANOVA, aims to detect statistically relevant differences in the distributions of different groups or samples regarding a variable (Kruskal and Wallis, 1952). Usually, the parametric version of ANOVA is seen as a stronger statistical foundation for conclusions, whereas Kruskal-Wallis is easier to use in most of the samples, as it can omit the assumption of normality.

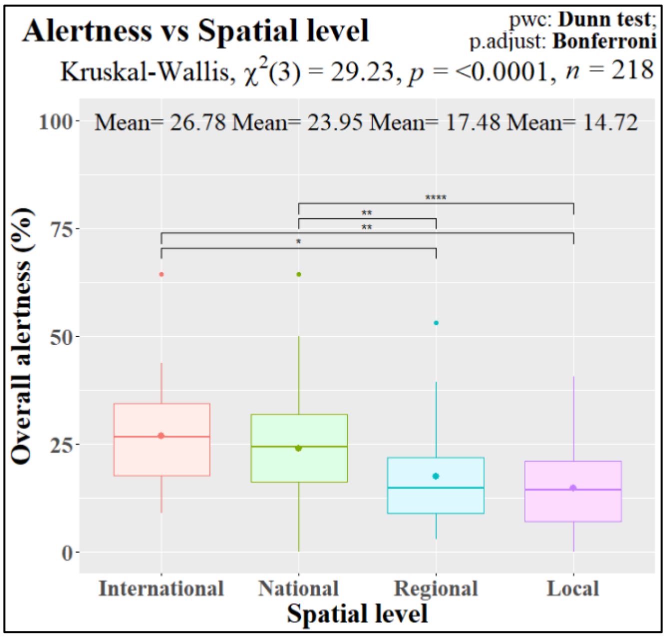


Figure 12. Results of the non-parametric Kruskal-Wallis and Dunn tests for the "overall alertness about deforestation drivers" of interviewed stakeholders across spatial levels. Boxplots including mean values (Mean), chi square statistic ($\chi 2$), p-values (p) and number of observations (n) of the Kruskal-Wallis tests and p-adjustment (p.adjust) and p-scores (sign, ****: <0.0001, ***: <0.001, **: <0.01, *: <0.05, ns: not significant [>0.05]) for the Dunn pairwise comparisons (pwc). Source: (Ferrer Velasco et al., 2023).

In Publication 3, we tested normality for all eighteen variables studied: i.e., overall alertness about drivers (plus distinction commercial/subsistence), overall confidence in policy measures, expected importance of eight driver categories and expected effectiveness of six policy instrument categories. We first checked the distribution of each variable visually in histograms and boxplots and selected a transformation (log, inverse or square-root), which brought the skewness the closest to zero. We further performed Shapiro-Wilk and Mardia tests of univariate and multivariate normality, respectively (Mardia, 1970; Shapiro and Wilk, 1965). As we could not demonstrate normal distribution for most of the studied variables, we relied on the results of the non-parametric Kruskal-Wallis one-way ANOVA; but we conducted parametric tests to compare and support the validity of our results. We tested the differences of all variables across the three studied countries and across the four spatial levels of the respondents' institutions: i.e., international, national, regional (sub-national) and local. We also compared the samples pairwise, to interpret the results for each studied country or spatial level: i.e., for each parametric ANOVA we conducted Tukey tests (Tukey, 1949) and in the case of the Kruskal-Wallis analyses we performed Dunn’s tests (Dunn, 1964) and pairwise Wilcoxon-Mann-Whitney *U* tests (Mann and Whitney, 1947; Wilcoxon, 1945) with Bonferroni correction of the alpha error (Conover and Iman, 1981).

The supporting studies also employed these statistical methods to compare groups. In Publication 5, for instance, a one-way ANOVA comparing deforestation levels across distance categories was conducted as a preliminary step to justify the use ordered logistic regression model. In Publication 7, t-test (Student, 1908), effect size analyses (Fritz et al., 2012; Lakens, 2013) and ANOVAs were employed to compare deforestation rates in different sites and on adjacent areas, before and after the implementation of the PES program Socio Bosque. In Publication 8, we conducted the non-parametric ANOVA (Kruskal-Wallis) to check the statistical significance of the differences between clusters of households, regarding five characteristics: (1) total income, (2) total forest-related income), (3) amount of cropland managed, (4) age of head, and (5) number of members.

In Publications 4 and 6 we also used the Wilcoxon rank test (Wilcoxon, 1945), a non-parametric test to compare two dependent samples or populations. In Publication 4, this test was used to compare the results of all selected variables (i.e., deforestation rates, governance and other driver indicators) across the different types of studied governance arrangements (i.e., restricted state forests, traditionally restricted communal customary forests, non-restricted communal customary forests, non-restricted individual customary forests and forests with overlapping community claims). In Publication 6, the same procedure was followed, but in this case only to compare governance scores across different types of governance arrangements.

3. Results

3.1 Main investigations: pantropical studies as a first author

3.1.1 Publication 1: Scale and context dependency of deforestation drivers

Ferrer Velasco, R., Köthke, M., Lippe, M., Günter, S., 2020. Scale and context dependency of deforestation drivers: Insights from spatial econometrics in the tropics. PloS one 15, e0226830.

Abstract (Publication 1)

A better understanding of deforestation drivers across countries and spatial scales is a precondition for designing efficient international policies and coherent land use planning strategies such as REDD+. However, it is so far unclear if the well-studied drivers of tropical deforestation behave similarly across nested subnational jurisdictions, which is crucial for efficient policy implementation. We selected three countries in Africa, America and Asia, which present very different tropical contexts. Making use of spatial econometrics and a multi-level approach, we conducted a set of regressions comprising 3,035 administrative units from the three countries at micro-level, plus 361 and 49 at meso- and macro-level, respectively. We included forest cover as dependent variable and seven physio-geographic and socioeconomic indicators of well-known drivers of deforestation as explanatory variables. With this, we could provide a first set of highly significant econometric models of pantropical deforestation that consider subnational units. We identified recurrent drivers across countries and scales, namely population pressure and the natural condition of land suitability for crop production. The impacts of demography on forest cover were strikingly strong across contexts, suggesting clear limitations of sectoral policy. Our findings also revealed scale and context dependencies, such as an increased heterogeneity at local scopes, with a higher and more diverse number of significant determinants of forest cover. Additionally, we detected stronger spatial interactions at smaller levels, providing empirical evidence that certain deforestation forces occur independently of the existing de jure governance boundaries. We demonstrated that neglecting spatial dependencies in this type of studies can lead to several misinterpretations. We therefore advocate, that the design and enforcement of policy instruments—such as REDD+—should start from common international entry points that ensure for coherent agricultural and demographic policies. In order to achieve a long-term impact on the ground, these policies need to have enough flexibility to be modified and adapted to specific national, regional or local conditions.

Contributions (Publication 1)

The study was conceptualized and designed by M. Köthke and S. Günter first, but soon adjusted with the participation of all the authors. I obtained and treated the data to build the regression model with the help of M. Köthke. The use of spatial econometrics and the related analysis was done by myself, as well as the writing of the first draft. The three coauthors assisted in the interpretation of the results and in the writing of the final version. I handled the submissions and revisions as well.

Author roles, as detailed in the online article:

- Rubén Ferrer Velasco: Conceptualization, Formal analysis, Investigation, Methodology, Resources, Software, Writing – original draft, Writing – review & editing.
- Margret Köthke: Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.
- Melvin Lippe: Conceptualization, Investigation, Supervision, Writing – review & editing.
- Sven Günter: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation, Writing – review & editing.

3.1.2 Publication 2: Forest mapping across pantropical deforestation contexts

Ferrer Velasco, R., Lippe, M., Tamayo, F., Mfuni, T., Sales-Come, R., Mangabat, C., Schneider, T., Günter, S., 2022. Towards accurate mapping of forest in tropical landscapes: A comparison of datasets on how forest transition matters. Remote Sensing of Environment 274, 112997. https://doi.org/10.1016/j.rse.2022.112997

Abstract (Publication 2)

Tropical forests represent half of the Earth's remaining forest area, but they are shrinking at high rates, which poses a threat to their multiple ecosystem services. As a response, international environmental agreements and related programs require information about tropical forested landscapes. Despite the increasing quantity and quality of remote sensing-based data, the effective monitoring of forests in the tropics still faces operational challenges: (a) applicability at local levels, with lack of reference or cloud-free information; (b) overcoming geographical, ecological, or biophysical variability; (c): stratification, distinguishing forest categories related to functionality and disturbance history.

We conducted an extensive ground verification campaign through 36 landscapes in 9 regions of Zambia, Ecuador and Philippines, which constitute a gradient of pantropical deforestation contexts or forest transitions. We collected over 16,000 ground control points and digitized over 18,000 ha with details on land use and forest disturbance history. We trained a random forest algorithm and generated high-resolution (30 m) binary forest maps covering ~15 Mha, building on 39 optical (Landsat-8), radar (Sentinel-1) and elevation bands, indices and textures. We validated the quality of the outputs across the studied deforestation gradient and compared them to (a): 3 national land cover maps used for international reporting, (b): 4 global forest datasets (Global Forest Change, Copernicus Land Cover, JAXA and TanDEM-X Forest/Non-Forest).

Our method generated highly accurate (92%) forest maps for the studied regions when compared to the global datasets, which generally overestimated forest cover. We achieved accuracies similar to the national maps, following a standardized method for all countries. The difficulties in delineating forest increased in more advanced stages of deforestation, with recurring struggles to distinguish non-forest tree-based systems (e.g. perennials, palms, or agroforestry), shrublands and grasslands. Regrowth forests were repeatedly misclassified across contexts, countries and datasets, in contrast to reference or degraded forests. Our results highlight the importance of in situ verification as accompanying method to establish efficient forest monitoring systems, especially in areas with higher rates of forest cover change and in

tropical regions of advanced deforestation or early reforestation stages. These are precisely the areas where current REDD+ or Forest Landscape Restoration initiatives take place.

Contributions (Publication 2)

CRediT authorship contribution statement, as detailed in the online article:

- Rubén Ferrer Velasco: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Supervision, Writing – original draft, Writing – review & editing.
- Melvin Lippe: Conceptualization, Methodology, Resources, Data curation, Supervision, Writing – original draft, Writing – review & editing, Project administration.
- Fabián Tamayo: Resources, Data curation, Supervision, Project administration.
- Tiza Mfuni: Resources, Data curation, Supervision, Project administration.
- Renezita Sales-Come: Resources, Supervision, Project administration.
- Cecilia Mangabat: Resources, Supervision, Writing – review & editing, Project administration.
- Thomas Schneider: Validation, Writing – review & editing.
- Sven Günter: Conceptualization, Supervision, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

3.1.3 Publication 3: Cross-scale analysis of stakeholder perceptions on drivers and policies

Ferrer Velasco, R., Lippe, M., Fischer, R., Torres, B., Tamayo, F., Kalaba, F.K., Kaoma, H., Bugayong, L., Günter, S., 2023. Reconciling policy instruments with drivers of deforestation and forest degradation: cross-scale analysis of stakeholder perceptions in tropical countries. Sci Rep 13, 2180 (2023). https://doi.org/10.1038/s41598-023-29417-y

Abstract (Publication 3)

Cross-scale studies combining information on policy instruments and on drivers of deforestation and forest degradation are key to design and implement effective forest protection measures. We investigated the scale and country dependency of stakeholder perceptions about future threats to tropical forests (e.g., agriculture, logging, woodfuel) and preferred policy instruments (e.g., reforestation, protected areas, combat illegal logging), by interviewing 224 representatives of forest-related institutions. We conducted analysis of variance and principal component analysis for eighteen variables across three countries (Zambia, Ecuador and the Philippines) and four spatial levels (from international to local). We found that the overall alertness about commercial drivers and the confidence in policy instruments are significantly lower at subnational levels and also in Zambia. Stakeholder expectations about the most important drivers and the most effective policies in the coming decade follow regional narratives, suggesting that there are no one-size-fits-all solutions in international forest policy. However, we found an unexpected consensus across scales, indicating potential for collaboration between institutions operating at different geographical levels. Overall, agriculture remains the driver with the highest expected influence (43%), while a strong favoritism for reforestation and forest restoration (38%) suggests a paradigm shift from protected areas to a stronger focus on integrative approaches.

Contributions (Publication 3)

R.F.V. prepared the data, conducted the statistical analysis and wrote the manuscript draft. M.L. and R.F. designed the different sections of the questionnaire and supervised the collection of data and its digitalization. B.T., F.T. F.K.K., H.K. and L.B. supervised the collection of data and reviewed the final version of the manuscript. S.G. administered the project, supervised the study and acquired funding. R.F.V., M.L., R.F. and S.G. participated in the conceptualization of the study and reviewed different versions of the manuscript.

3.2 Supporting studies:

3.2.1 Publication 4: 'De facto' governance and deforestation drivers in Zambia

Nansikombi, H., Fischer, R., Ferrer Velasco, R., Lippe, M., Kalaba, F.K., Kabwe, G., Günter, S., 2020a. Can de facto governance influence deforestation drivers in the Zambian Miombo? Forest Policy and Economics 120, 102309. https://doi.org/10.1016/j.forpol.2020.102309

Abstract (Publication 4)

Weak forest governance is posited as a key underlying driver of deforestation and forest degradation, but empirical evidence of this linkage is scarce. Many related studies capture the de jure (legal) conditions and miss out the de facto (implementation practices on the ground), particularly when considering the proximate drivers and other factors of deforestation. However, this is central for identifying the specifics of governance for curbing deforestation and forest degradation. We analyze the influence of de facto governance quality on deforestation, accounting for proximate drivers and other factors using stepwise regression. We further compare deforestation rates and drivers across different governance arrangements with differing institutions, tenure and forest access restrictions using Wilcoxon tests to derive conclusions for promising policy instruments that address deforestation. Data for the analysis were obtained through participatory mapping, focus group discussions and geographical information systems. To generate empirical evidence, 238,296 ha of land were mapped within 24 communities spanning three provinces, Copperbelt, North Western and Eastern, in the Zambian Miombo. Regression results revealed that de facto governance quality has some effect but proximate drivers particularly charcoal production, crop agriculture and proximity to roads explain most of the deforestation patterns in the Zambian Miombo. Those drivers seem hardly affected by the weak governance processes. Since scores of governance quality were in general low and hardly varying, we conclude that in our case they were too weak to show effects on the proximate drivers. Only the governance indicator 'local government capacity and effectiveness' although still weak, was significantly linked to low deforestation rates. Comparative results further showed that restricted arrangements (state and traditionally restricted) exhibit lower deforestation than non-restricted arrangements (communal, forests with overlapping community claims, private and individual customary forests). But while crop agriculture was negligible, forest resource extraction was still substantial in restricted state forests, indicating a higher possibility for forest degradation instead. Although private and individual customary forests had higher tenure security, they showed higher deforestation rates than communal and

state arrangements. This challenges the notion that tenure security alone guarantees successful forest conservation. Our results suggest that governance can only affect deforestation drivers positively above certain thresholds. This needs to be further complemented by specific measures such as sustainable production systems, incentives and alternative livelihoods to regulate the proximate and other underlying drivers of deforestation.

Contributions (Publication 4)

In this study, I assisted the field teams during site selection providing the base maps and background spatial data. I also assisted and supervised the digitization of the maps and the management of spatial data. Thus, I calculated all spatially related variables (i.e., road density, shares of area for LCLU classes, deforestation rates, …). I further helped the main author to design the econometric models and to produce main figures (maps) for the manuscript. I participated in the conceptualization phase and I further contributed to write some sections of the draft and to revise the different versions of the complete manuscript.

3.2.2 Publication 5: Household attributes and deforestation patterns in Zambia

Kazungu, M., Ferrer Velasco, R., Zhunusova, E., Lippe, M., Kabwe, G., Gumbo, D.J., Günter, S., 2021. Effects of household-level attributes and agricultural land-use on deforestation patterns along a forest transition gradient in the Miombo landscapes, Zambia. Ecological Economics 186, 107070. https://doi.org/10.1016/j.ecolecon.2021.107070

Abstract (Publication 5)

Dry forests in tropical and subtropical areas continue to experience high deforestation rates that affect households' dependence on forest resources. Little remains understood about the relationship between household factors and deforestation patterns in Zambia. We integrate remotely sensed data with surveys of 1123 households collected in the Miombo areas between 2017 and 2019 to better understand the effects of household attributes on regional deforestation patterns along a forest transition gradient.

We found, in early-to-mid-transition, deforestation patterns systematically decreased further from settlements (homesteads), but this was reversed in regions with advanced forest transition. The socio-demographic attributes, land and non-land-based attributes, and location factors differently affected deforestation across provinces. Although agricultural land-use was significantly associated with deforestation, no distinct patterns emerged across distance categories or along the forest transition. Furthermore, increases in non-farm income reduced the likelihood of high deforestation, but the impact was not always significant across provinces.

Our results indicate that economic effects of distance in Miombo areas complement the forest transition, but are not exclusively related to crop productivity. We assume that different aspects of livelihoods can explain the deforestation patterns in the Miombo areas. Thus, forest management should be regional-specific, such as improving access to financial incentives in North-Western, and reforestation and agroforestry in Copperbelt and the Eastern Province.

Contributions (Publication 5)

In this study, I assisted the field teams during site selection providing background spatial information. I also generated the distance rings related to household information and I calculated the deforestation rates. I produced some of the main figures (maps) for the manuscript. I participated in the conceptualization phase and I further contributed to write some sections of the draft and to revise the different versions of the complete manuscript.

3.2.3 Publication 6: Governance elements and drivers of deforestation in Ecuador

Fischer, R., Tamayo Cordero, F., Ojeda Luna, T., Ferrer Velasco, R., DeDecker, M., Torres, B., Giessen, L., Günter, S., 2021. Interplay of governance elements and their effects on deforestation in tropical landscapes: Quantitative insights from Ecuador. World Development 148, 105665. https://doi.org/10.1016/j.worlddev.2021.105665

Abstract (Publication 6)

After state-centered and market-centered approaches have driven international development cooperation activities in previous decades, improved governance has now come into the focus as a means to help reversing global trends of tropical deforestation. Yet, "good governance" remains a normative, broad and often underspecified concept consisting of a wide range of elements and implicit value judgements. Specific knowledge is missing on the relative importance of single elements, on their interdependencies and their specific effects. Following an analytical approach, we aimed to investigate if single governance elements affect each other and whether they relate to decreasing deforestation. We conducted a quantitative field study in twelve selected landscapes across 160,000 ha of tropical lowland forest in Ecuador. We mapped governance arrangements and land use in participatory exercises. The performance of single governance elements including tenure, forest management practices, law enforcement, institutions, and participation was quantified based on the governance assessment framework of the World Resource Institute. We assessed context information and used satellite-based deforestation data. Principal component analysis showed that all governance elements loaded positively on the first axis. This shows that specific governance elements acted conjointly. They are in general not antagonistic, but interact positively and might reinforce each other. Policy and development work may therefore focus on a smaller number of well-selected governance elements. High performance of specific governance elements, in particular tenure and participation was linked to reduced deforestation. This supports the notion of a number of governance elements as being indeed "good" for low deforestation. This functional understanding draws a more differentiated picture for single governance elements and supports outcome-oriented decisions instead of value-oriented principles that underlie "good governance". Direct deforestation drivers such as agriculture and infrastructure explained larger shares of deforestation as compared to governance. A number of conclusions and recommendations for the specific governance situation in tropical lowland forests of Ecuador are given.

Contributions (Publication 6)

CRediT authorship contribution statement, as detailed in the online article:

Richard Fischer: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Writing - original draft. Fabian Tamayo Cordero: Data curation, Project administration. Tatiana Ojeda Luna: Data curation, Investigation, Writing - review & editing. Rubén Ferrer Velasco: Data curation, Software, Visualization, Writing - review & editing. Maria DeDecker: Data curation. Bolier Torres: Funding acquisition, Project administration, Resources, Writing - review & editing. Lukas Giessen: Supervision. Sven Günter: Funding acquisition, Methodology, Supervision, Writing - review & editing.

3.2.4 Publication 7: Payments for Environmental Services and deforestation in Ecuador

Gordillo, F., Eguiguren, P., Köthke, M., Ferrer Velasco, R., Elsasser, P., 2021. Additionality and Leakage Resulting from PES Implementation? Evidence from the Ecuadorian Amazonia. Forests 12, 906. https://doi.org/10.3390/f12070906

Abstract (Publication 7)

Payments for Environmental Services (PES) are instruments which seem well suited for forest conservation. However, their impact on reducing deforestation might be weakened by negligible additionality and leakage effects; the first refers to the low variation in net deforestation rates even in the absence of PES, and the second refers to the displaced deforestation behavior to other areas not covered by PES. For the case of Ecuador, we examine both issues by assessing the historical deforestation trend of selected PES-enrolled areas and that of their adjacent areas to identify deforestation patterns before and after PES implementation. We analyze the additional effect of PES on reducing deforestation by comparison to a baseline as well as to comparable reference sites at two different spatial scales. We also analyze potential leakage effects of PES by comparing deforestation development in adjacent areas. We show that PES has achieved marginally low conservation impacts in enrolled areas with an average difference in net deforestation rates of 0.02 percent points over a period of 28 years. Overall, PES-enrolled areas depict lower annual net deforestation rates than unenrolled areas, albeit at a negligible rate, and there is also some evidence that deforestation decreased in adjacent areas after PES implementation. Additionally, there exists a statistically significant linear increasing deforestation trend in adjacent areas as distance increases from the PES-enrolled area. Our empirical results, however, raise the suspicion that the choice of PES-enrolled areas might have been influenced by self-selection.

Contributions (Publication 7)

Author contributions, as detailed in the online article:

Conceptualization, F.G. and P.E. (Peter Elsasser); methodology, F.G., M.K., and P.E. (Peter Elsasser); validation, F.G., M.K., and P.E. (Peter Elsasser); formal analysis, F.G.; investigation, F.G.; resources, P.E. (Peter Elsasser); data curation, R.F.V. and P.E. (Paul Eguiguren); writing—original draft preparation, F.G.; writing—review and editing, F.G., P.E. (Paul Eguiguren), M.K., R.F.V., and P.E. (Peter Elsasser); visualization, F.G.; supervision, P.E. (Peter Elsasser); project administration, P.E. (Peter Elsasser); funding acquisition, P.E. (Peter Elsasser). All authors have read and agreed to the published version of the manuscript.

3.2.5 Publication 8: Forest income of rural households in Philippines

Wiebe, P.C., Zhunusova, E., Lippe, M., Ferrer Velasco, R., Günter, S., 2022. What is the contribution of forest-related income to rural livelihood strategies in the Philippines' remaining forested landscapes? Forest Policy and Economics 135, 102658. https://doi.org/10.1016/j.forpol.2021.102658

Abstract (Publication 8)

Forest products have become scarce for local communities in the Philippines. After decades of severe deforestation, a net gain in forest area has only been observed in recent years for the first time. This paper seeks to broaden the understanding of forest livelihood relationships at the turning point of a forest transition trajectory. Based on 993 household surveys from 10 distinct research sites, we use Hierarchical Cluster Analysis to identify six distinct livelihood strategies (LS): remittances-based, livestock-based, crop farming-based, business-oriented, natural resource-based, and wage-based strategies. The highest number of households belongs to the wage-based cluster, which also shows the highest total income. Forest-related incomes only account for small shares of total income for the vast majority of households, although most households collect limited quantities of forest products for domestic use. Nevertheless, one cluster, which includes 12.4% of the sample, generates the largest shares of their income from extractive activities like harvesting forest products and fishing. The households relying most strongly on natural resources in our study sites are also the ones with the lowest total income. Our finding implies that future reforestation policies have to put a special focus on incorporating livelihood benefits for local communities. This should go beyond short-term payments for activities such as tree planting and enable the rural households to derive long-term impacts for human well-being and poverty alleviation. Because most of the forest products reported by our surveyed households were collected for domestic use, they did not contribute much to total household income. This indicates a potential for improving rural income, if forest-product value chains at the smallholder level are improved by future policy interventions.

Contributions (Publication 8)

In this study, I assisted the field teams during site selection providing background spatial data. I also calculated all spatially related variables (i.e., distances to forest edge, shares of area for LCLU classes, deforestation rates, …). I also produced main figures (maps) for the manuscript. I participated in the conceptualization phase and I further contributed to write some sections of the draft and to revise the different versions of the complete manuscript.

4. Discussion

In this section, I will be interpreting the main findings of my thesis and discussing the implications for science, policy and practice. This will be done based on the overarching research question (Page 16) and its two main components (Figure 4), which will be addressed in the two first subsections of the discussion. First (Page 66), I will analyze the results of my main investigations (Page 54) across deforestation contexts or forest transitions, while using my supporting studies (Page 59) and other relevant literature as references. Second (Page 76), I will do the same across different spatial levels, from international to local. In a third subsection (Page 85), I synthesize the primary findings and consequential implications from all publications, encompassing elements pertaining to both forest transition and spatial scale. Finally, in a fourth subsection (Page 92), I will address methodological aspects of my main investigations, including their innovation, limitations and suggestions for further research. For more detailed explanations and complete figures about the results of my main investigations discussed below, please check the Appendix (Page 123).

4.1 Analysis across deforestation contexts or forest transtions

4.1.1 Drivers across deforestation contexts, using spatial econometrics (Publication 1)

Our work in Publication 1 (Ferrer Velasco et al., 2020) confirmed the importance of the national context and the existence of strong regional differences (linked to different forest transition stages) regarding the main drivers of forest cover change. However, we also found recurrent determinants of deforestation in all studied countries, independently of their deforestation contexts (i.e., population pressure, which was astonishingly strong, and the natural condition of land suitability for crop production). As described in the introduction (Page 7), these findings were mostly expected and go in line with the existing knowledge about tropical deforestation patterns (Busch and Ferretti-Gallon, 2017; Hosonuma et al., 2012; Köthke et al., 2013). In this context, our research provides added value by utilizing innovative methods such as spatial econometrics, and by drawing on a large sub-national sample from a diverse range of countries and deforestation contexts (see also subsection 4.4.1 Innovation), allowing for a more comprehensive and nuanced understanding of the influence of the forest transition stage and the national context on drivers of deforestation.

From this investigation, I highlight the strong contextual differences that we observed between the three studied countries or deforestation contexts. This is underpinned by the larger error coefficients of the pantropical models when compared to the national-specific models. This result indicates the relevance of omitted contextual variables, which could be related to expected and known dissimilarities of the three countries, e.g., geographic or ecologic factors. We also found country-specific patterns (i.e., stronger/weaker impacts and positive/negative effects) for some of the studied drivers.

For instance, in the case of Zambia, the potential vegetation area had a positive influence on forest cover, in contrast to the other countries. We interpret this result as a manifestation of the importance of non-forest vegetation types (e.g., woodlands or shrublands) and their compensation effect when being classified and used as forests (Day et al., 2014; Phiri et al., 2019b). This is especially relevant in Zambia, a country that still has a relatively high forest cover (Figure 4), when compared to Ecuador and Philippines (Ferrer Velasco et al., 2022). The Zambian forest ecosystems (vast but degraded to a large extent) are particularly varied and complex, comprising from evergreen closed forests in the North-Western to open miombo or mopane woodlands/bushlands in the South-East (Chidumayo, 2010; Day et al., 2014). The used datasets did not cover this variety in detail and they had a larger scope for the whole African continent (ESA, 2017b). However, these were the best available sources of forest cover information at the time of publishing our article, as the land cover maps resulting from the first national monitoring program in Zambia were still under development and had not been released yet (ILUA-II, 2016). This relatively low quality (confirmed by the findings of Publication 2) was also the reason to later work with a global dataset (GFC) in Publications 4 and 5, by contrasting the GCF information with locally obtained data and defining tree cover thresholds that applied to the studied landscapes (Kazungu et al., 2021; Nansikombi et al., 2020b). The inaccuracies of the land cover maps could also explain the lower explanatory power of our models for Zambia in Publication 1, when compared to the models of the other countries. However, the lower quality of the Zambian models could also indicate the existence of further determinants not included in our analysis, but known to be relevant in the Zambian context and later mentioned in Publication 3, such as wood extraction for charcoal/woodfuel production (Kazungu et al., 2020, 2021), governance aspects (Nansikombi et al., 2020a, 2020b) or fire incidences (Gumbo et al., 2013; Vinya et al., 2011). Some of these characteristics related to the Zambian context have been further explored in Publications 4 and 5. Finally, the influence of population pressure on deforestation in Zambia was also the lowest from the studied countries, probably due to its lower population density, which is characteristic of countries in forest pre-transition stages (van Noordwijk and Villamor, 2014).

In the case of Ecuador, we observed the highest heterogeneity regarding significant predictors (drivers) of forest cover change. This may be related to the socio-economic and ecological contrasts of this diverse country. For instance, flatness proved to be a key biophysical indicator only in Ecuador, as it was positively related to deforestation in all spatial levels. This could be related to the fact that lowland Amazon areas constitute the current deforestation frontier, in contrast to the less-accessible steep slopes typically closer to the Andes (Eguiguren et al., 2020; Sierra et al., 2021). Also, cereal yield was significant at the provincial level in Ecuador, as coastal and central areas where commercial cultivation of rice and maize is extended, show very little to none forest cover. On the contrary, the areas of the Amazon which are characterized by subsistence agriculture or local exports, present rather lower agricultural yields (Ojeda Luna et al., 2019). This heterogeneity within the country confirms the need for establishing strong governance mechanisms that enable effective territorial organization (Fischer et al., 2021; Torres et al., 2014), as already advocated by the recent national strategies (Bolay et al., 2004). In Publication 6 (Fischer et al., 2021), we found empirical evidence that tenure and participation were the governance elements with the strongest capacity to influence deforestation at landscape/community level.

Finally, the models of the Philippines were the “simplest” ones, with the least significant predictors or drivers. Population pressure explained forest cover almost alone, which was expected in this highly populated archipelago. The Philippines have suffered massive deforestation during the last decades, which have resulted in the current national late/post-transition context, with low but stable or even increasing forest cover levels (Le et al., 2014). This rapid depletion of forests has been related mainly to timber harvesting for exports abroad, but also to the accelerated population growth rates, which have increased the local demand on forests resources, e.g., fuelwood for households (Carandang et al., 2013; Wiebe et al., 2022). Thus, a larger part of forests in the Philippines have already been converted to agriculture, when compared to the other two countries, which are still suffering from higher deforestation rates. This could explain why drivers such as crop suitability index were not significant in the Southeast Asian country. This goes in line with our findings in Publication 8 (Wiebe et al., 2022), where we demonstrate that Philippine rural households rely mostly on remittances and wage-based livelihood strategies. However, in this publication we also showed that especially the poorest households in Philippines’ forested landscapes continue to collect forest products, mainly fuelwood, despite being on an advance stage of deforestation. Also interesting is the fact that flatness did not explain forest cover in any of the models of Publication 1 for the

Philippines. This country legally defines forestland precisely based on a slope threshold, which has implications for land use and logging bans (PD, 1975). Thus, all zones above 18% slope are forestland for the Philippine institutions regardless of the presence of trees, as mountain ranges and hardly accessible areas are the usual shelter for forests (Hammond, 1997).

Despite ratifying the importance of the national differences, our work found recurrent drivers of relevance in all the studied countries or deforestation contexts, i.e., population pressure and the natural condition of land suitability for crop production. Population pressure had an extraordinarily strong negative influence on forest cover in all the studied samples. Although demography is well known for being related to the demand for agricultural land and infrastructure, thus putting pressure on forests and other natural resources (Busch and Ferretti-Gallon, 2017; Köthke et al., 2013), we found that its effect was relevant everywhere and up to ten times higher than other significant drivers. With this, our work confirms the importance of population pressure across regions (and scales) in the tropics, together with the possibility of using it as a stand-alone indicator of forest cover decline effectively (Angelsen and Kaimowitz, 1999; Carr et al., 2005; DeFries et al., 2010). Additionally, Publication 1 ratified the key role of the natural condition of the land and its suitability for agricultural production, in triggering the conversion of forests to crops or pastures (Barbier et al., 2010; Naidoo and Adamowicz, 2006). This confirms the relevance of competition for land use and their respective opportunity costs, as a ubiquitous concern in forest-agriculture frontiers.

To summarize, by using spatial econometrics with an unprecedently large subnational sample, we could confirm that the main drivers of tropical deforestation are dependent on the national context and on the different forest transition phases. However, we also confirmed that this process is dominated by socio-economic factors, which are relevant in all studied contexts. Ultimately, our findings present a challenge to the conventional understanding of the impact of demographic factors on tropical deforestation, as classified by Geist and Lambin (2002). Specifically, they suggest that population dynamics are not solely an underlying factor on par with e.g., technological and socio-political factors, but instead play a more prominent role that could be depicted in an outer ring in the representation showed in Figure 2. In contrast to conventional descriptions posited by scholars of the forest transition theory, it is proposed that population pressure may provide a more cogent explanation for the circumstances faced by a nation or region in the course of the forest transition, rather than temporal or other socio-economic factors. Accordingly, population pressure may be regarded as the independent variable along the x-axis in Figure 3.

4.1.2 Forest dynamics and map accuracy across deforestation contexts (Publication 2)

In our work in Publication 2 (Ferrer Velasco et al., 2022), we were able to produce high-resolution (30 m) forest maps for a total of ~15 Mha spread across nine tropical regions (Table 7 and Figure 5). We obtained better accuracies than the compared global and national datasets, which mostly overestimated forest cover. With this, we found empirical evidence that the quality of regional forest maps in the tropics is very region-dependent, and totally related to the existing deforestation context and the associated forest disturbance regimes. Specifically, we detected recurrent lower accuracies and worse results in advanced deforestation contexts and for regrowth forest. In these regions, the spatial disagreements between the compared sources represented between 21% and 41% of the analyzed area. These errors were lower when also considering other regions, ranging from 17% to 24% in the total 15 million ha assessed.

The classification outputs of our forest maps outperformed the results of the compared secondary datasets regarding their overall accuracy (92%). We achieved better accuracies than the global maps and similar to the national ones, but following the same classification method for all countries. This was possible thanks to our innovative classification approach (see 'Methodological discussion', Page 85 and subsection 4.4.1 Innovation), but mostly due to our intensive field campaign to collect training and validation data in situ. The good results of our map products confirm the importance of using up-to-date reference data from the ground when creating tropical forest maps (Fritz et al., 2011). This can also explain the better results of some datasets in specific regions. For instance, JAXA-FNF showed relatively high accuracies in the Philippines, probably because this country was used as a region to train this map's classifier (Shimada et al., 2014).

The best classification results for a forest category across regions and datasets were obtained for 'undefined forests', which were forests identified visually in the satellite images without validation from the ground. Nevertheless, the quality of all the compared maps was clearly region-dependent, due to the worse accuracies of specific forest types, which were distributed unevenly across regions or deforestation contexts. For instance, all the compared maps reported worse results for the Eastern Province in Zambia. This region is characterized by dry ecosystems, typically consisting of woodlands, shrubs and sparse forests. The difficulties to accurately map forest in similar areas are known and related to the characteristics of the local vegetation, with lower canopy densities, less greenness or water content and slower growth rates (Feng et al., 2016; Hill, 2021). Similarly, other regions with a noteworthy presence of non-forest tree-based systems, such as Esmeraldas in Ecuador (i.e., oil palm plantations) or Leyte in the Philippines (i.e., historical expansion of coconut palms within degraded forests), have also been affected by misclassifications of forest (Castellanos-Navarrete et al., 2021; Estomata, 2014). The GFC analysis (Figure 6) clearly demonstrates the regional dependency of ecological features, such as tree cover, and the high sensitivity of maps to such biological aspects. Overall, these results underpin the convenience of including detailed and standardized information about forest disturbance levels in training and classification datasets, in order to avoid the omission of relevant forest types and wrong estimations of forest area and condition (Wang et al., 2019). To reduce the logistic and economic costs of such demanding field campaigns, we emphasize the need for collaborative development of joint and consistent global forest reference databases, together with the coherent integration of NFM and NFI structures in tropical countries.

In general, we found more difficulties to distinguish forests from other LCLU types in regions in more advanced stages of deforestation or early reforestation stages. These complications refer to the confidences of our maps, the overall accuracies and the spatial-agreements among all the compared sources, which were progressively worse in middle and advanced deforestation contexts. Similarly, all forest types showed worse producer accuracies for regions in more advanced deforestation stages, independently of the studied dataset. This resulted in larger variances, uncertainties and errors for the forest cover estimations of these regions. We interpret that these difficulties to map forest precisely can be associated to the accelerated LU dynamics characteristic of advanced deforestation contexts, which result in complex, smaller and more diverse LCLU patches (Smith et al., 2003). Non-forest vegetation classes showed the worse specific class accuracies in our study, while representing a larger share of the landscapes in deforested regions. This refers, for instance, to tree-based systems (i.e., agroforestry, palms, perennials), shrublands and grasslands. Similarly, the same regions with accelerated LU dynamics present sparser and more fragmented forest stands and larger proportions of degraded forests, which again complicates the accuracy of forest cover measurements and disturbance detections (Feng et al., 2016; Vancutsem et al., 2021; Wang et al., 2019).

From all the studied forest types, regrowth forests showed the worse producer accuracies across countries, datasets and deforestation contexts. In our work, this class included mostly young (up to 20 years old) plantation and succession forests grown-up in previously clearfelled areas. Again, this particular forest class is typically found in landscapes, regions or countries of late deforestation or early reforestation contexts. With this result, our work ratifies the challenges to accurately map or identify relatively young regrowth forests in the tropics

(Caughlin et al., 2021; Li et al., 2017; Vancutsem et al., 2021). This finding is especially relevant given the international context, in which the number of reforestation and forest restoration initiatives are blooming in tropical landscapes. This includes a number projects and initiatives (e.g., FLR, Bonn Challenge, Clean Development Mechanism, Great Green Wall of Africa) implemented under the umbrella of Goal 15 of the Sustainable Development Goals (SDGs) for 2030. The objectives of these reforestation projects, sometimes compatible with other conservation programs such as REDD+, include increasing tree cover, and restoring biodiversity or other ecological processes (Holl, 2017; Verchot et al., 2018).

To summarize, our study shows that, along with the blooming of reforestation and forest restoration initiatives, there is a growing demand and need for rigorous methods of forest cover monitoring, implementation and reporting (Murcia et al., 2016; Stanturf et al., 2019). Our study reveals that contemporary techniques employed for evaluating and analyzing fluctuations in forest coverage, such as the Food and Agriculture Organization's reporting system or the Global Forest Change program, are prone to significant inaccuracies and uncertainties in tropical areas. Specifically, we found that the regions where the evaluated maps exhibited discrepancies increased from approximately 17% to 24% of the total 15 million hectares evaluated to between 21% and 41% in areas undergoing either early reforestation or advanced deforestation (Weber et al., 2022).

4.1.3 Perceptions about future drivers and preferred policy instruments across deforestation contexts (Publication 3)

Our findings in Publication 3 (Ferrer Velasco et al., 2023) revealed that the stakeholders in Zambia (and potentially in similar countries in a pre-/early forest transition phase) tend to be less alert about the number of possible commercial threats to forests. At the same time, Zambian stakeholders were skeptical about the effectiveness of a larger number of policy instruments, when compared to the respondents in Ecuador and the Philippines. In line with Publication 1 and literature (Busch and Ferretti-Gallon, 2017; Hosonuma et al., 2012; Köthke et al., 2013), our findings in this study also showed regional differences regarding the perceptions about the most important drivers in each country, as well as about the most effective policy instruments. Nevertheless, certain consensus exists across countries regarding, for instance, the important role of competition of land for agriculture and reforestation measures in the future.

The results of the PCA point to the relevance of *Alertness* (overall alertness about deforestation drivers) and *Confidence* (overall confidence in policy measures) of the interviewed stakeholders in our analysis. At the same time, the ANOVAs, revealed that these two important indicators differed between countries. Namely, Zambia presented significantly lower values for both *Confidence* and *Alertness*.

Lower *Alertness* in Zambia was mostly influenced by the responses about drivers related to the demands of commercial economy. This perception goes in line with the evolution of forest dynamics in the different tropical regions, as South East Asia and South America count with a longer history of deforestation, mostly linked to commercial operators (e.g., logging, agricultural products), when compared to Africa (Hosonuma et al., 2012; Seymour and Harris, 2019). In this sense, the selected countries represent this regional trend quite accurately. We interpreted this result could point to the fact that alertness about drivers might arrive (too) late, once certain deforestation levels have been reached, as in the case of Philippines or Ecuador. Forest cover in Zambia has been decreasing rather slowly in the last decades (suffering mostly forest degradation since the seventies), but this process accelerated in the last years (Phiri et al., 2019a). On the contrary, massive commercial timber harvesting and land use conversion during the twentieth century have drastically decreased the forest cover of Philippines and Ecuador, respectively (Carandang et al., 2013; Sierra et al., 2021; Wasserstrom and Southgate, 2013).

Actually, the same reasoning could make us expect a lower confidence in policy instruments in these countries/regions suffering from more aggressive deforestation, if this would be identified as the result of inefficient regulations and strategies. However, our study showed the opposite results. Namely, the respondents of Ecuador and Philippines had a stronger confidence in a larger number of policy instruments, when compared to the Zambian stakeholders. As mentioned by many respondents and further explored in Publication 4 and related studies, this lower *Confidence* in Zambia was often related to a lack of trust in governance mechanisms (Nansikombi et al., 2020a, 2020b). This, combined with the lower alertness about possible threats to forest, might be seen as problematic, particularly in countries in pre-/early forest transition contexts such as Zambia or other African countries in a similar situation (e.g., Democratic Republic of the Congo, Angola, Gabon, Tanzania, …) (FAO, 2020). From our findings it remains unclear if opposite perceptions, in which the relevance of drivers and possible solutions are more strongly considered by all actors, are possible before assuming uncontrolled deforestation and later forest transition stages. In any case, these results suggest the appropriateness of precautionary measures, such as environmental education, the improvement of governance structures or the enhancement of forest monitoring capabilities, as already underpinned by our findings in Publication 2.

In Publication 3, we also explored the different stakeholder perceptions among the studied countries, regarding the driver categories expected to be most important in the future ten years. As hypothesized, these results (ANOVA supported by PCA) confirmed the existence of significant regional differences and the importance of the national or forest transition context, in line with our previous findings of Publication 1.

In the case of Zambia, the responses showed significantly higher importance of woodfuel and charcoal. These cheap and reliable fuel sources represent over 70% of national energy consumption in the country and are often sold over the national boundaries (Mulenga and Roos, 2021). At the same time, as explored in related investigations such as Publications 5 and 8, these forest products represent a larger share of the income for rural households in Zambia, when compared to the other studied countries (Kazungu et al., 2020; Ojeda Luna et al., 2019; Wiebe et al., 2022). On the other hand, the answers about the importance of timber extraction in Zambia, which is mostly selective and rather contributing to forest degradation than to deforestation itself (Phiri et al., 2019b), were significantly the lowest among the studied countries. Finally and as investigated in Publication 4, the Zambian stakeholders also mentioned a larger number of governance problems which pose the national forests under threat (Nansikombi et al., 2020a, 2020b).

The Ecuadorian representatives expected a significantly higher importance of agriculture, together with drivers related to oil and mining. These results confirm the role of cattle ranching and agricultural expansion in the Amazon basin in general and in Ecuador in particular, where these drivers have been responsible for over 95% of the deforestation between 1990 and 2018 (Hosonuma et al., 2012; Sierra et al., 2021). At the same time, these findings can be explained by the known direct/indirect contribution of the oil industry to deforestation in Ecuador (by creating roads and facilitating access to remote areas) for several decades (Sierra et al., 2021; Wasserstrom and Southgate, 2013). Also more recently, the current concessions for extraction purposes overlap with one fourth of indigenous territories and protected areas in the Amazon-regions of the country (Kleemann et al., 2022).

Finally, the Philippine stakeholders identified a larger variety of driver categories with relatively high importance, when compared to the other studied countries. This result contrasts with our findings in Publication 1, where the models for the Philippines had a lower number of significant determinants. However, it is challenging to compare directly the results of both studies, as most of the categories included in Publication 3 (i.e., woodfuel, logging, infrastructure, oil/mining, natural disasters) were not included in the models of Publication 1, because of correlations with population or lack of spatially explicit quality data. Apart from agriculture, logging and mining, the Philippine respondents highlighted the role of known causes, such as natural disasters (e.g., typhoons, landslides, floods), infrastructure expansion (Boquet, 2017; Carandang et al., 2013; Liu et al., 1993).

Despite these context-related variation, agricultural pressure was still seen as the most dangerous threat to forests in every country. This finding shows that the representatives of forest-related institutions acknowledge the existence of recurrent determinants of deforestation across the tropics, independently of the deforestation context. Namely, they identified forces related to the demand for agricultural land, as already underpinned by the findings Publication 1 (i.e., combination of population pressure and suitability of land for agriculture).

In Publication 3, some of the preferences of the interviewed stakeholders for one or other policy instruments (i.e., expected effectiveness) varied significantly between the three analyzed countries. However, in line with other investigations using the same dataset (Fischer et al., 2022), our findings showed a similar overall picture, with a general preference for reforestation and forest restoration measures, independently of the country or deforestation context studied. The favoritism for reforestation was only significantly lower in Ecuador, due to a stronger preference for protected areas and especially financial instruments, mostly related to positive answers about the national PES program of Socio Bosque (Jones et al., 2017). In any case, in Ecuador reforestation was still the second (and very close to the first) favorite policy instrument. Ecuador, for instance, currently aims to convert over 300,000 hectares of pastureland in the Amazon basin to forest and other agroforestry systems (MAGAP, 2014). These results go in line with the present international agenda and the support for forest restoration and reforestation initiatives across the tropics: e.g., Bonn Challenge, UN Decade on Ecosystem Restoration or the 1 Trillion Trees initiative. Also, reforestation programs such as the National Greening Program, involving nationwide measures of tree plantings or natural regeneration, are commonly regarded as an example of success in reversing the deforestation trend in one of the selected countries (i.e., Philippines) (Le et al., 2014; Wiebe et al., 2022). Protected areas were the second preferred policy instrument overall, but still with almost half the expected effectiveness as reforestation programs. Some mentioned critiques include shifts of deforestation to neighboring regions, or strong dependance on monitoring and law enforcement (Bare et al., 2015; Vuohelainen et al., 2012). The least favoritism for protected areas was observed in Zambia, possibly related to the historic ineffectiveness of such regulatory measures in the region (Lindsey et al., 2014), together with a significantly higher number of answers advocating for other policy solutions, such as enhancing governance or enabling energy and livelihood alternatives. Other explored policy instruments, namely measures against illegal logging and improving land use rights, reported similar results across countries or deforestation contexts, but with medium and low favoritism, respectively. In general, our findings point to a paradigm shift from protected areas to a stronger emphasis on reforestation and integrative approaches. These integrative approaches can include multiple forms of reforestation, natural regrowth, the establishment of agroforestry areas or active/passive forest restoration, as part of protected areas or other effective area-based conservation measures (OECM). It makes sense that in a global context of proliferation of fragmented and degraded forests with related climate and economic consequences, prioritizing reforestation is seen as relevant in all the studied contexts. However, it must be kept in mind that these are just preferences of stakeholders which do not automatically constitute effective policy.

Summarizing, our research indicates that stakeholders in Zambia exhibit a lower level of awareness regarding potential commercial threats to forests compared to stakeholders in Ecuador and the Philippines. Furthermore, Zambian stakeholders express skepticism towards a larger array of policy instruments compared to their counterparts in the other two countries. This finding is particularly concerning if it holds true for countries in an early stage of forest transition, such as Zambia. This has significant implications for policy and practice, highlighting the need to prioritize awareness-raising efforts and build stakeholders' confidence in a diverse range of policy instruments, particularly in countries at the early stages of forest transition. Despite regional disparities in perceptions of the primary drivers and the effectiveness of policy instruments among the countries examined, our study confirms a consensus across these countries, irrespective of their forest transition stage. Notably, this consensus underscores the (perceived) significant role of land competition for agriculture and the importance of reforestation measures for future forest conservation efforts.

4.2 Analysis across spatial levels, from international to local

4.2.1 Drivers across spatial levels, using spatial econometrics (Publication 1)

In Publication 1 (Ferrer Velasco et al., 2020), we further obtained relevant results related to the role of drivers of forest cover change across spatial levels, i.e., across interconnected hierarchical jurisdictions (e.g., from provinces to municipalities). In this case, the importance of both population pressure and the land condition for crop production were not only significant across deforestation contexts or countries as already studied (Busch and Ferretti-Gallon, 2017; Hosonuma et al., 2012; Köthke et al., 2013), but also in every studied spatial level. Moreover and in line with the panarchy theory (Allen et al., 2014; Gunderson and Holling, 2002), we observed a strong scale dependency of the analyzed drivers, which presented an increased heterogeneity at the local levels, categorized by a larger and more diverse number of determinants of forest cover. The local levels also presented stronger spatial interactions (i.e., neighbor effects and spatial errors), providing empirical evidence that certain deforestation forces happen independently of the existing official administrative boundaries.

First of all, the drivers that were consistently significant across countries or forest transition stages (i.e., population pressure and land suitability for agriculture) presented the same pattern across the three studied spatial levels. This, again, confirms the important and critical role of both determinants, together with the need to harmonize international, national and subnational policies to anticipate demographic and agricultural development.

Nevertheless, in our study we also found noteworthy cross-scale differences. For instance, we observed an increased heterogeneity of drivers and the need of more sophisticated models to explain the complexity of local levels (e.g., municipalities), when compared to the macro-levels (e.g., provinces). Thus, in both the aggregated and in the country-specific models (for all the three studied countries), the number of predictors contributing significantly increased at more local levels. In addition, the explanatory power of the models decreased with smaller administrative units (despite an increase of their statistical significance), indicating that the heterogeneity of the larger sample size of local levels could not be completely explained by the tested variables. This result is also underpinned by the fact that the micro-level presented more spatial errors, stronger neighbor interactions and larger Moran's Is of the residues, suggesting the omission of relevant spatially-correlated determinants (J. P. LeSage and Pace, 2014). All in all, our finding goes in line with the evidence of existing literature, with plenty of studied cases at local levels, which exemplify the complexity of coupled human and natural systems (Busch and Ferretti-Gallon, 2017; Geist and Lambin, 2001; Liu et al., 2007).

In our publication we also found other interesting scale effects for some specific drivers, which were affecting forest cover at different intensities or even in different directions, depending on the studied spatial levels. For instance, while the drivers related to the agricultural suitability of the land show comparable ranges of intensities across spatial levels, the impacts of population pressure are stronger in the models with smaller administrative units, for both the aggregated and country-specific samples. Interpreting these results is not straightforward, but they suggest that increases in population density have stronger influence in systems with narrower boundaries, putting more direct pressure on forests and other natural resources (Smith et al., 2010). Another peculiar scale-related result is the fact that larger total areas of the studied units had a negative influence on forests at micro-level, in contrast to a positive effect on forest cover at meso-level. This finding was linked to the definition of forest cover used, which was proportional to the potentially vegetated area, excluding build-up land. Therefore, at the micro-level, smaller cities or municipalities had higher forest cover, as their potential vegetation area was typically restricted to natural parks and tree areas, with less probabilities of including pastures, crops, grasslands or other non-forest vegetation types. Despite this example being very model-specific and not really a key finding of our study (due to the very low intensities of this determinant), it exemplifies how the same driver can influence forest cover and condition differently, depending on the scale studied. These results will be further explained with the support of the panarchy theory in Page 88.

Another important aspect to keep in mind while interpreting our findings, is the fact that the impacts of specific drivers of de-/reforestation can be perceived at different spatial levels than at those where they origin. For instance, local decisions based on income, opportunity costs or the establishment of community areas for protecting forest functions, result on land use and land cover changes, which can have an effect at larger regional levels. These decisions can even end up in a conflict with the interests of international and national companies and governments (Edmunds and Wollenberg, 2013; Foley et al., 2005; Wondolleck, 2013). Likewise, but in the reverse direction, the choices and actions of private and/or public stakeholders (e.g., international trade agreements, national conservation policies, regional planning, …) can have clear impacts on forests and agriculture locally, affecting the livelihoods of those dependent on forest resources (Ferraro, 2002; Meyfroidt et al., 2010; Weyerhaeuser et al., 2005). This is not only important while interpreting results, but it is also a methodological challenge when conceptualizing and designing any empirical study related to socioeconomic, political and ecological causes of deforestation. As we put it in our publication: "*... connections between neighbors and hierarchies are not always easy to identify, quantify and weight, as they are a miscellaneous result of geographical, historical, political, economic and even random conditions that may vary from region to region*".

Our work also shows the importance of indirect impacts or effects of neighbors, especially at local levels. In certain samples, the effect of some drivers of the neighboring administrative units was even stronger than the same driver at the unit of analysis itself. For instance, this was the case for the suitability for crop production in Ecuador and in Zambia, for flatness and population pressure in Ecuador and for the potential vegetation area in the Philippines. In other cases (i.e., potential vegetation area and population pressure in the pantropical sample), the same driver acted in opposite directions when comparing the analyzed unit with its neighbors. These results manifest the existence of spillovers or leakages and demonstrate how the interactions between neighbors can release or increase pressure on forest resources, while showing that certain deforestation forces occur independently of de jure governance boundaries (Amin et al., 2019; Gollnow et al., 2018; Kuschnig et al., 2021). Similar effects were observed in our work in Publication 7 (Gordillo et al., 2021), where we assessed deforestation in Sociobosque protected areas and in neighboring rings. According to our findings, such impacts and neighboring effects appear to be stronger in countries or regions with increased connectivity, namely in landlocked countries or regions (i.e., Zambia and partly Ecuador) and especially when analyzing smaller administrative units of local spatial levels.

Overall, the results from Publication 1 reveal that population pressure and the land condition for crop production are influential drivers of forest cover change across interconnected hierarchical jurisdictions, spanning from provinces to municipalities. These factors demonstrate consistent significance not only at the national or regional level but also at finer-grained spatial scales. The study supports the panarchy theory by demonstrating the scale-dependent nature of these drivers, with greater heterogeneity and a wider range of determinants of forest cover observed at the local level. Additionally, the analysis highlights the stronger spatial interactions found at local levels, indicating that certain deforestation forces operate beyond existing administrative boundaries. Overall, these findings underscore the importance of understanding the varying impacts of population pressure and land condition across different spatial levels and the need to account for local-level dynamics and spatial interactions when examining deforestation patterns.

4.2.2 Forest dynamics and map accuracy across spatial levels (Publication 2)

Although in Publication 2 (Ferrer Velasco et al., 2022) we did not conduct an explicit analysis across spatial levels, our work can serve to explore some scale-related issues which affect forest dynamics and the mapping of tropical forests. Thus, we can compare the quality of datasets which were conceived at different scales: (1) our maps, produced using locally obtained data, in landscapes equally distributed in the study regions; (2) the national maps, produced by the official mapping agencies of each country and used for international reporting; and (3) four relevant forest maps conceived at global level. This aspect should be kept in mind when analyzing the results of our study (e.g., when comparing regions or deforestation contexts, Page 70), as each of the maps studied were produced using different sensors (active/passive), temporal/spatial resolutions and processing steps, depending on their specific scale and purpose.

As introduced previously in subsection 4.1.2 (Page 70), our maps delivered the best overall accuracies in the studied regions, when compared to the secondary sources. This should be expected due to the extensive ground verification campaign conducted in the field, which resulted in a substantial number of reference patches collected on the ground and distributed evenly enough across all the targeted regions (Figure 7). Thus, the campaign to collect reference data was carefully designed to map these specific regions and to train the RF classifiers locally, based on up-to-date standards and including, for instance, details on the most relevant local forest and LCLU types (GFOI, 2020; Olofsson et al., 2014). Also critical was the selection of sensors and scenes, which was again done purposely to match the spatial and temporal resolution requirements of the targeted areas. Apart from combining information from both passive and active sensors, our processing framework included the mosaicking of several optical scenes, in order to decrease the impact of cloud cover on our maps, based on the weather history of the studied regions. With this, our work is a demonstration of the potentials to generate improved mapping results for the tropics at local to regional scale with enough technical capabilities and resources (Wang et al., 2019). In smaller areas this can even be done using alternative methods to remote sensing, such as participatory approaches, with which we obtained positive experiences at community and landscape levels in other studies (Fischer et al., 2021; Nansikombi et al., 2020a). As already mentioned, collaborations between researchers and practitioners (e.g., data sharing, common forest databases, harmonized definitions) can help to extend the reach or scale of reliable local mapping projects while maintaining or improving the quality of the generated products.

The overall accuracies of our maps were still very close to those of the national maps in many regions. However, it is important to keep in mind that, despite using local information and carefully considering the conditions of our study areas during all classification steps of our maps, we still used the same standardized methodology for all the research regions, which limited the capacity to optimize the classification process everywhere. In any case, the generally good results of the national maps underpin the progress made by the mapping agencies of the studied countries, regarding the capabilities of their NFM and NFI systems (Murrins Misiukas et al., 2021). Normally, this refers to the accessibility to remotely sensed data and internet/electricity, computer power/software, qualified workforce and enough resources for field assessments. The development of such competences during the last years/decades has followed different pathways in every country (Nesha et al., 2021; Romijn et al., 2015), but it has been mostly linked to the commitments of tropical governments to international reporting (i.e., FAO's FRA, Measurement, Reporting and Verification [MRV] for REDD+). However, other voluntary initiatives within the agricultural and forest sector (e.g., forest certification) have also triggered the need to improve NFM systems in the tropics, often with the assistance of international organizations (Carter et al., 2021).

Regarding the national LCLU maps and the countries included in our work (see subsection in Page 34), Zambia's results were the worst among them. The overall accuracies of the national forest maps were even slightly worse than some of the global datasets in many areas of the African country. This shows some room for improvement in the Zambian forest mapping capacities, which have nevertheless undergone speedy development in the last decade (Phiri et al., 2019a). This progress has been mostly happening under the umbrella of both phases of the ILUA project, coordinated by the Forestry Department of the Ministry of Lands and Natural Resources and supervised by the UN's FAO (ILUA-II, 2016). Further improving Zambia's NFM capabilities might be especially relevant, considering the still high forest cover and the current accelerating deforestation rates in this country (Phiri et al., 2019b). In the case of Ecuador and the Philippines, the NFI and NFM capabilities have a relatively longer history of development, probably explaining the better results of both national LCLU maps when compared to the Zambian ones. Thus, in the studied areas of Ecuador, MAE's maps reported very satisfactory results, in contrast to the recurrent overestimations of forest cover by the global maps. This was also confirmed by other supporting studies, in which the national datasets provided the best LCLU information at smaller spatial levels (Fischer et al., 2021; Gordillo et al., 2021). MAE has produced consistent and regularly updated LCLU and deforestation maps (from 1990), which combine Landsat time series, very high-resolution imagery and field verification for training and validation (MAE-MAGAP, 2015). Similarly, NAMRIA's 2015 maps showed the best overall accuracies in all three studied regions of the Philippines, when compared to the other secondary datasets. The Philippine national mapping agency has been refining the methodologies previously used to generate the 2003 and the 2010 LCLU maps, which presented different challenges related to their applicability (Estoque et al., 2018; Santos, 2018). Our results indicate an effective enhancement of the quality of NAMRIA's products as a result of this work.

Finally, we obtained the worst overall results in our study regions when using the global maps (see subsection in Page 31). This finding was expected as these datasets have been conceived for a larger international scope, thus their applicability at local levels is facing a larger number of challenges, especially in the tropics (GFOI, 2020; Harris et al., 2018; Tropek et al., 2014). These difficulties include the lack of reference/auxiliary data in the focus areas (e.g., in situ validation), cloud cover interferences, inconsistencies between the temporal/spatial coverage and the aims of research, or incongruities between pixel size and the extent of LCLU patches on the ground (Fritz et al., 2011; Hilker et al., 2012). This last point could partly explain the generally better results of the global datasets in Zambia, a country which is characterized by rather larger uniform LCLU patches (Hill, 2021; Smith et al., 2003). In contrast, the global datasets faced more challenges in detecting smaller deforested patches in the studied Ecuadorian landscapes, which are typically surrounded by higher forests with denser canopy cover. Similarly, Zambia was barely affected by cloud cover in comparison to Ecuador and the Philippines, which could also partly explain the better accuracies of the global maps in the African country. Therefore, global maps, due to their larger scope, are affected more strongly by the ecological, biophysical and biochemical dissimilarities (e.g., different seasonality, tree height/canopy, water content) of the vegetation between biomes and geographical areas. In the same manner, larger scopes or scales signify dealing with a larger variety of forest types/definitions, contexts and dynamics of change (i.e., drivers), while increasing the technical burdens associated with matching physical properties to specific LCLU classes, forest disturbance levels and functions. Despite the rapid progress and improvement of global forest monitoring capacities and remote sensing technology, providing valuable and unprecedented insights about the of forest dynamics worldwide (Galiatsatos et al., 2020), these sources of information still have to be used very carefully at the local levels and even in certain larger regions. Our work in this publication and in other supporting studies (Kazungu et al., 2021; Nansikombi et al., 2020a) is a clear example of the usefulness of global forest maps such as the GFC dataset, if used prudently in combination with locally obtained information and accounting for the regional specifics.

Wrapping up, our work in Publication 2 exemplifies the potential of using locally obtained information to generate forest and land cover maps of improved accuracy. Despite the remarkable recent improvements in the quality of national and global forest datasets in the tropics, these sources of information still need to be used very carefully and rather as a reference when deriving estimations of forest cover and forest condition for certain regions and local applications.

4.2.3 Perceptions about future drivers and preferred policy instruments across spatial levels (Publication 3)

In Publication 3, we did not only identify significantly lower alertness about commercial drivers and less confidence in policy instruments in Zambia, when compared to the other studied countries, but also for the respondents of the subnational institutions in relation to those of national and international institutions. At the same time, our cross-scale findings confirmed the overall picture identified in our cross-region analysis (and partly in Publication 1), in which the stakeholders agree about the most important threats to forest (i.e., agriculture) and about the most effective policy instruments (i.e., reforestation) in the coming decade.

The cross-scale analysis in Publication 3 showed that the indicators *Alertness* (about drivers) and *Confidence* (in policy instruments) were significantly lower for the respondents of subnational institutions, when compared to international and national stakeholders. Thus, equally as with Zambian respondents when related to those from Ecuador or the Philippines, we found that subnational stakeholders tend to identify a smaller number of threats to forest as dangerous, while having less trust in a larger number of potential solutions or policy instruments. We interpret this result as a demonstration that sub-national and local institutions usually confront fewer drivers or policies in typically more specific contexts, while being nearer to the consequences of the potentially ineffective policies when implemented on the ground (*de facto*). On the contrary, international and national institutions are normally responsible of the planning and design of these policies (*de jure*), having a stronger interest on the success of their own strategies, while also having a broader overview of possible drivers and protection alternatives. These reasons can explain that their representatives would identify a larger number of threats and policy options as having a strong or very strong influence on forest cover and forest condition (Busch and Amarjargal, 2020; Nansikombi et al., 2020a; Sullivan et al., 2017). Moreover, information about newly designed policy instruments often reaches local levels with a time delay in tropical countries, recurrently accentuated by political instability and weak institutions, apart from other related implementation challenges. Another possible reason for the lower alertness about drivers at local levels might be the fact that deforestation (or the exploitation of forest resources) can be seen as a direct source of income and economic progress by some of the actors on the ground. Namely, income from forest products and from the conversion of forestlands to productive agrosystems, represent a relevant share of the total income for rural populations in the tropics and in the studied countries (Kazungu et al., 2021; Ojeda Luna et al., 2020; Wiebe et al., 2022). In any case, our findings underpin the importance of preventing potential disengagement of local stakeholders regarding national or international forest protection aims. To this regard the design forest policy should not only consider law enforcement, but also the direct dependence of local populations on forest resources, while ensuring economic, logistical and institutional support for local implementation (Fischer et al., 2021; Hoffmann et al., 2018; Nansikombi et al., 2020a).

The findings of Publication 3 concerning the expected importance of specific driver and policy categories were characterized by a general lack of scale-related effects, as only two category groups showed significant differences between spatial levels. First, most of the additional suggestions alternative to the proposed policy instrument categories (or non-categorizable answers) were given by respondents of subnational institutions, typically too detailed or too general responses by academia members (regional universities, for instance) and by other local stakeholders. Second and more interestingly, our study showed a tendency in which the stakeholders of subnational institutions were more aware about the importance of drivers related to the subsistence economy (i.e., woodfuel), whereas respondents from international and national institutions acknowledged a larger number of threats linked to commercial activities (i.e., oil and mining). This influence of the spatial scale on perceptions about commodity trade, can exemplify the existence of distant coupled human and natural system interactions in a globalized economy (Hull and Liu, 2018).

In any case, the overall absence of scale-related effects reveals that the interviewed stakeholders share the same narratives about the most important drivers and policy instruments, independently of the geographical scope of their institutions. Thus, respondents across spatial levels agree about the main trends identified for all studied tropical countries (i.e., agricultural pressure and reforestation) and about the specific national contexts. This was surprising, as we had predicted stronger spatial dependencies, especially regarding the perceived effectiveness of certain policy instruments. For instance, based on our own research in the supporting studies, we had expected that the local stakeholders would manifest a clearer rejection of command-and-control regulation (i.e., protected areas), while favoring measures related to decentralization or positive monetary incentives (i.e., land use rights and financial tools) (Fischer et al., 2021; Nansikombi et al., 2020a, 2020b). Nevertheless, we observed similar levels of acceptance of national narratives of success (e.g., PES program Sociobosque in Ecuador or reforestation measures in Philippines) or failure (e.g., governance issues and ineffectiveness protected areas in Zambia) across the studied spatial levels. This indicated that such discourses are shared by most of the studied stakeholders, probably as most of them belong to formal institutions with strong interactions with each other, while having direct or indirect dependency from the respective central governments. This could also imply that the desired effect of current international protection measures (e.g., European Union's regulation for deforestation-free supply chains) are actually smaller than regarded by certain stakeholders. These possible negative effects related to confirmation biases, should at least be regarded by the planning and communication of such policies. Regardless, this general cross-scale consensus, indicates a solid foundation for future cooperation between actors at different spatial levels, which is needed for effective policy design and implementation of forest-related policies (Seymour and Harris, 2019).

4.3 Synthesis: Main findings and implications for science, policy and practice

The present subsection of the Discussion synthesizes and integrates the most important findings from the three main investigations and the auxiliary scientific papers of this thesis, while discussing some of their interlinkages and their implications for science, policy and practice.

4.3.1 Forest transition theory and sensitivity to deforestation context

Notwithstanding the predominant influence of socio-economic factors, namely demography and agriculture, the primary drivers of tropical deforestation exhibit sensitivity to the national context and the distinct phases of forest transition (Figure 4). This finding, in line with previous literature (Busch and Ferretti-Gallon, 2017; Hosonuma et al., 2012; Köthke et al., 2013) and substantiated by spatial econometric models (Page 66), map accuracy assessment (Page 70), stakeholder perception analysis (Page 72), and supporting studies (Page 59), indicates that a universal solution for addressing tropical deforestation within the framework of international forest policy is not viable. I highlight two main contributions of my research, which shed light on significant aspects related to the forest transition theory and its implications for practice.

Firstly, integrating the results of my different publications, I derive some conclusions about the need for tailored policies in Zambia, which by extension might hold true for other regions in similar stages of early transition (high forest cover, accelerating deforestation rates) and countries with similar contexts in Africa, e.g., Democratic Republic of the Congo, Angola, Gabon or Tanzania (FAO, 2020). Publication 3 shows that stakeholders in Zambia exhibit a lower level of alertness concerning potential commercial threats to forests and a higher level of skepticism towards policy instruments, compared to their counterparts in Ecuador and the Philippines. However, findings in Publications 1, 4 and 5 point out that Zambian deforestation and forest degradation rates have increased dramatically over the last decade, i.e., woodfuel, charcoal (Phiri et al., 2019a). Consequently, it becomes imperative to prioritize awareness-raising efforts and enhance stakeholders' confidence in a diverse range of policy instruments. Such lack of confidence in policy measures can be related to weak governance in the context of forest management, as many examples identified in Publication 4. Weak governance can manifest in various forms, such as corruption, lack of enforcement, or inadequate institutional capacity. These examples underscore the necessity for effective governance structures and policies to combat forest degradation and ensure sustainable practices, particularly in early deforestation contexts. Improving governance frameworks through measures like transparency, accountability, and capacity building is crucial for fostering sustainable forest management (Nansikombi et al., 2020a, 2020b). Furthermore, Publication 2 uncovered that Zambia has a lower level of development in its mapping capabilities. This result underscores the importance of investing in the improvement and advancement of mapping technologies in the country. Enhanced mapping capabilities can enable more accurate and efficient forest monitoring, resource management, and decision-making processes (Carter et al., 2021; Murrins Misiukas et al., 2021; Nesha et al., 2021). In early deforestation contexts, high-resolution imagery can help to identify the initial clearing of forested areas, often involving selective logging or small-scale clearing. Another important capability in early stages are historical analyses to understand the temporal dynamics of deforestation. The lack of reliable information might also partly explain the lower alertness about threats to forest observed in Zambia, when compared to Ecuador and the Philippines. Overall, these findings emphasize the need for targeted awareness-raising initiatives, investment in mapping capabilities (high-resolution satellite imagery and historical/temporal analysis), and improved governance frameworks to effectively address the challenges associated with early forest transition stages and promote sustainable forest management practices in contexts similar to Zambia.

Secondly, my research presents some thought-provoking results related to regions in more advanced deforestation contexts (i.e., late-post forest transition stages). Namely, as demonstrated in Publication 2, state-of-the-art forest datasets (i.e., global and national maps) are prone to much worse estimations of forest cover and forest condition, in areas undergoing early reforestation or advanced deforestation processes. This holds especially true for the accuracy in mapping regrowth forests, when compared to reference or degraded forests. In such regions, the discrepancies between the best existing data sources account for 21% to 41% of the area assessed, which is higher than the discrepancies in early and middle deforestation contexts (10% to 17% and 17% to 26% discrepancy area, respectively) (Weber et al., 2022). Thus, the findings of this study highlight the growing demand and necessity for rigorous methods of forest cover monitoring, implementation, and reporting in advanced deforestation contexts and regrowth forests. This is particularly crucial in light of the current proliferation of reforestation and forest restoration initiatives, driven by global environmental programs (Holl, 2017; Verchot et al., 2018). This is also especially important if taking the results of my other two main publications into account. Publication 3 reveals that stakeholders in advanced deforestation contexts generally exhibit higher levels of confidence in forest protection measures. However, according to Publication 2 these perceptions may occasionally be influenced by biased or incomplete information. Therefore, the development of rigorous monitoring capabilities becomes even more critical to provide objective and transparent data on the actual state of forests and the effectiveness of protection measures. By employing robust monitoring methods, decision-makers and stakeholders can make well-informed choices and ensure that reforestation efforts are based on accurate information. Similarly, the presence of a diverse array of drivers characterizing late and post-forest transition stages, as identified in Publications 1 and 3, underscores the significance of comprehensive monitoring systems. These drivers, which may include socio-economic factors, governance issues, and land-use dynamics, contribute to the complexity of deforestation processes in advanced contexts. Robust monitoring capabilities can help identify and understand these drivers, enabling the formulation of targeted interventions that address the root causes of deforestation effectively. In summary, given the global push for reforestation and forest restoration initiatives in the tropics, there is a growing demand for rigorous methods of forest cover monitoring, implementation, and reporting in advanced deforestation contexts. The results of my investigations, highlight the importance of accurate monitoring systems to provide objective information and counter potential biases in stakeholders' perceptions. Additionally, the presence of a variety of drivers characterizing late and post-forest transition stages emphasizes the need for comprehensive monitoring capabilities to address the complex forest dynamics. By incorporating rigorous monitoring practices, practitioners can enhance the effectiveness and long-term success of reforestation and forest restoration initiatives in these critical contexts.

4.3.2 Panarchy and influence of the spatial scale on forest dynamics

My research also identified some scale-related effects (Page 76), which can be explained with the support of the panarchy theory (Figure 4) (Allen et al., 2014; Gunderson and Holling, 2002). Based on this analytical framework, a driving force can be strong enough to have a positive or negative impact on forest cover at micro-levels (i.e., community, municipality), but if the same driver does not reach certain intensities, its impact will probably not be enough to initiate the “destructive processes” or “revolts” that change the memory of conservative structures at larger slower levels (i.e., national, international).

This framework can explain, for instance, the higher complexity of the models at the local levels observed in Publication 1, where a larger number of determinants were significant when compared to the studied macro-levels, and higher spatial errors (significant omitted variables) were observed. In the same manner, in Publication 3 a larger array of specific drivers was identified as relevant by subnational stakeholders, when compared to national or international ones. This increased heterogeneity of drivers is also observable in the supporting studies (Publications 4 to 8), which focused on more local levels, e.g., household, municipality, landscape (Figure 4 and Table 4). Similarly, some variables in the models of Publication 1 had varying impacts at the different spatial levels. In the case of population pressure, which was clearly the most decisive factor of our models and capable of affecting even the conservative slower structures at macro-levels, the direct impacts at micro-levels were more pronounced.

Within the panarchy framework, this heterogeneity can be explained by the higher likelihood of human-environment interactions at local levels, by the increased demands for land and resources, and by the potential for cascading ecological effects. Local communities and households often rely heavily on forest resources for their subsistence and livelihoods, resulting in increased pressure on forests (Publications 5 and 8). As the population grows, the demands placed on forests can exceed their regenerative capacity, leading to unsustainable levels of deforestation. Additionally, the ecological impacts of deforestation at smaller scales, such as habitat fragmentation, loss of biodiversity, and altered ecosystem functioning, can propagate to regional or global scales over time. These cascading effects further reinforce the notion that addressing population pressure and socio-economic drivers of deforestation at smaller spatial levels is crucial for maintaining the resilience and sustainability of larger-scale social-ecological systems (Kinzig et al., 2006). From a theoretical perspective, these nested processes and interrelated relations have to be regarded when selecting (a) the adequate analytical tools (e.g., multilevel approaches) and (b) suitable models of land use processes.

Related to the higher likelihood of human-environment interactions at local levels, Publication 1 empirically demonstrates that smaller administrative units present stronger spatial interactions with their neighbors. This study clearly shows that that the indirect impacts, or the effects of drivers in neighboring administrative units, play a much more substantial role when analyzing micro-levels. This finding not only demonstrates empirically that human-environment interactions are more probable at local levels, but also the fact that certain deforestation forces act beyond existing de jure limits or official administrative boundaries. This indicates the presence of so-called leakages or spillovers, which can complicate the analysis of effectiveness of protection measures or difficult the identification of the origin or root of deforestation drivers. Such undesired effects have been also identified in both Publications 5 and 7. Ultimately, this finding challenges the effectiveness of jurisdictional approaches, especially at smaller spatial levels (i.e., village, municipality), and suggests the potential appropriateness of more flexible approaches (Gonçalves et al., 2020; Shobe, 2020), which can capture the socioecological characteristics of an area (e.g., Ostrom's framework).

I will highlight two further contributions of my research, which are both a manifestation of this increased heterogeneity and variability of drivers and forest dynamics at local spatial levels. Firstly, my studies identified a large variety of interests of local actors, which play a major role in shaping the environment of their e.g., villages or landscapes. This refers to their direct dependence on agriculture and forest resources (as clearly shown in Publications 5 and 8), the need of enhanced governance mechanisms in local communities (as demonstrated by Publications 4 and 6), environmental education or other types of institutional, logistical or economic support. The lower confidence in policy instruments and the lower alertness about commercial deforestation drivers of local stakeholders, as shown in Publication 3, points to the importance of harmonizing international and national protection aims with the interests of local actors mentioned above. Taking this into consideration is key to design policies that effectively halt deforestation, by achieving long-term resilience in smaller units (e.g., community) and therefore avoiding cascading effects and destructive cycles that result in unsustainable (longer-term) deforestation of larger ecosystems (e.g., at provincial-national level). Secondly, my work in Publication 2 demonstrated the limitations of existing forest datasets in capturing the complexity and contextual aspects of tropical forests locally: e.g., forest extent, degradation levels or species. While progress in the mapping capabilities and in the quality of estimations of forest cover/condition at global or national level are tangible, there is still a lack of accuracy of such maps at local levels (Fritz et al., 2012). Our work in this publication, combined with the results of the participatory mapping exercises of Publications 4 and 6 (Page 38), is a demonstration on the importance of using in situ validation data and locally obtained information to obtain reliable results about forest dynamics. To optimize logistic and economic resources, synergies and collaborations between institutions to develop harmonized global reference databases with information about tropical forests should be created, together with the coherent integration of NFM and NFI systems (Carter et al., 2021; Nesha et al., 2021).

4.3.3 Universal patterns of tropical forest dynamics

My research also identified some universal traits or patterns characteristic of tropical forest dynamics, which were observed independently of the deforestation context or the spatial level analyzed. These findings are relevant, as they can indicate which common entry points are pertinent both for international policies and for the collaboration between institutions operating at different spatial levels.

Firstly, despite the abovementioned regional and contextual differences, my studies suggest that the drivers of tropical deforestation are largely dominated by human pressure and socio-economic factors (i.e., demography, agriculture, wood extraction, infrastructure). This trend goes in line with existing knowledge (Busch and Ferretti-Gallon, 2017; Hosonuma et al., 2012; Köthke et al., 2013) and it confirmed by the work in Publications 1 and 3, together with the observations in the supporting studies. The results of Publication 1, highlight the important role of demographics in determining forest cover in all studied contexts and spatial levels. In Publication 3, the interviewed stakeholders perceived agriculture as the main threat to tropical forests in the coming ten years in all studied contexts and spatial levels. Similar results were observed in the supplementary studies (i.e., Publication 4 and 6), where the role of other socio-economic factors was highlighted, namely agriculture, charcoal and distance to roads and infrastructure. Population density can just be seen as an indicator of human pressure, correlated to other factors such as the expansion of agriculture and infrastructure. However, the strong effects of this variable in Publication 1, when compared to the other studied drivers, can challenge the conventional understanding of tropical deforestation (Geist and Lambin, 2001) and the interpretations of the results of Publication 3 and the supplementary studies. Namely, population density could play a superordinate role as driver of forest cover change, with a stronger contribution to the x-axis of Figure 4a than other underlying factors (i.e., cultural, technological, economic), which are normally studied at the same level as demography (Figure 2). If this holds true, the perceptions of stakeholders in Publication 3 might be missing an important point in this causality relationship. Namely, the demographic trend of a region could explain deforestation and the depletion of forest resources better than any other factor related to land use or agriculture. In any case, my findings imply the need of horizontal policy and cross-sectoral strategies, which address population dynamics, spatial planning, and sustainable land use practices, to ensure effective and sustainable forest management and preservation in the face of expanding human populations. Such integrated approaches that consider population growth, urbanization patterns, and related socio-economic factors, appear to be of high relevance when formulating conservation and natural resource management strategies in all tropical deforestation contexts and at all spatial levels.

It is also worthwhile to explore the implications of the further consensus observed among the stakeholders interviewed in Publication 3, considering the broader framework of the thesis's additional findings. This refers to the shared opinions or perceptions regarding the relevance and effectiveness of policy instruments to protect tropical forests in the coming decade. Contrary to expected, in this study the stakeholders agreed on national narratives (e.g., against protected areas in Zambia, for PES in Ecuador), independently of the spatial level of their institutions. Similarly, a general favoritism for reforestation and forest restoration measures was found across the studied countries, not only in advanced deforestation contexts or late forest transition stages. On the one hand, such unexpected results can indicate potential entry points for the agreement and collaboration between actors of different regions or operating at different spatial levels. On the other hand, such findings are just perceptions and as such they could be biased and not necessarily reflect the needs on the ground or indicative of effective policy. For instance, the consensus might be a result of strongly institutionalized discourses (i.e., official narratives of success or failure) and the confirmation bias of the interviewed actors. Our results, therefore, show possible pathways for future agreements, but such recommendations must be taken cautiously and sustained with trustworthy information. As discussed in Page 85, when considering the additional findings of Publications 1 and 2, the challenges and limitations of the available information about drivers and forest dynamics are especially important at local levels and when analyzing advanced deforestation contexts. Omitting this may lead to misestimations of forest cover and forest condition in certain contexts, especially in tropical regions likely to host current environmental programs, such as the abovementioned reforestation and forest restoration measures, leading to biased conclusions about the success or failure of currently favored international policies.

4.4 Methodological aspects of the main investigations

4.4.1 Innovation

The work in the three main investigations of this thesis covers conceptual and methodological innovations on different fronts. Some of these are described in this subsection.

Our work in Publication 1 constitutes a first empirical attempt in science to generate econometric models that explain forest cover change including cross-scale data (i.e., multiple spatial levels) from three different continents (i.e., pantropical approach). Previous similar attempts (see Page 12) with subnational or multilevel approaches have put their focus on single countries (López-Carr et al., 2012; Loran et al., 2016; Moonen et al., 2016; Yackulic et al., 2011). In this investigation, we could derive highly significant models of deforestation applying a sigmoid function and cross-section data from secondary sources, such as national land cover maps, or official statistics. Moreover, we demonstrated that using spatial models, i.e., considering spatial errors and/or neighbor effects, can improve the explanatory power and the goodness of fit of deforestation models. These models are based on the idea that physical and social events, like those related to forest dynamics, are highly clustered in space, as Tobler's first law of geography suggests (Tobler, 1970). Such approaches had not yet been applied intensively in empirical research about drivers of deforestation. With this, we demonstrated the importance of taking spatial dependencies into account when analyzing econometric models of forest dynamics, to avoid misinterpretations such as wrongly interpreted predictors, biased coefficients or opposite effect directions.

In Publication 2, we were able to develop a consistent and standardized mapping method to obtain highly accurate high-resolution (30 m) forest maps in very different regions across the tropics, covering a wide spectrum of ecological and geographical conditions. We used freely-accessible multi-sensor (active and passive) and multi-temporal satellite images and machine learning methods, together with an extensive validation dataset obtained in situ, building on a series of previous studies (see Page 36). With this, we improved the quality of the existing global and national forest maps in the studied regions (see Pages 12 and 31), while providing a methodology, maps and reference datasets, which can be further employed to analyze forest condition, disturbances or other land use aspects. Furthermore, our study expanded the knowledge about the use of non-parametric classifiers such as random forest algorithms and about the contribution of specific bands, indices and textures for improving LCLU mapping in the tropics. This includes aspects such as the role of elevation in indicating disturbance susceptibility (Fahsi et al., 2000), the relevance of wetness-related indices above greenness-related ones (Schultz et al., 2016), or the recent developments in the field of SAR, by ratifying the potential of using textural data derived from Sentinel-1 backscatter, to map tropical forests, with particularly good results in dry ecosystems (Li et al., 2017; Reiche et al., 2018; Wang et al., 2019). Additionally, by analyzing the quality of multiple forest maps across deforestation contexts or forest transitions, our work constitutes an innovative study design, which can help to reach relevant conclusions with regard to the monitoring and management of particular conservation and forest restoration practices in the tropics.

Finally, Publication 3 fills two main gaps in existing literature. On the one hand, as stated in the introduction of this thesis (Page 12), this investigation explicitly provides an analytical framework to study pantropical perceptions about deforestation across different spatial levels, by linking institutions to the geographical or jurisdictional scope of their work. Such attempts are rather scarce as these frameworks are difficult to design and apply (Bos et al., 2020). On the other hand, this publication uses an empirical approach that combines data on both drivers of deforestation and the suitability or effectiveness of policy instruments. Our framework is applied from a broader conceptual perspective when compared to similar existing research, which typically focuses on specific countries, contexts (Hoffmann et al., 2018; Müller et al., 2013; Tegegne et al., 2016), or on single drivers and policy measures (Fritz et al., 2022; Henders et al., 2018; Salvini et al., 2014). With this, the findings of our article facilitate more general conclusions around the links between the main threats and solutions to tropical deforestation. Moreover, our research constitutes an innovative approach regarding the choice of statistical tools to analyze questionnaire information about deforestation, by implementing concepts of survey analytics (i.e., Top 2 Box scores, ratios) to deal with Likert data and to derive different types of relevant indicators (i.e., confidence, alertness, importance, effectiveness), which are evaluated combining the use of both ANOVAs and PCAs.

4.4.2 Limitations

The following paragraphs showcase some of the most important technical or conceptual limitations of my main articles. Most of these methodological limitations are directly or indirectly related to the general challenges (see ‘Justification & Research gap’, Page 12) behind both objectives (Page 16) of this thesis: (a), conceptualizing and analyzing the role of the spatial scale in forest-related studies and (b), theorizing and applying generalizations on forest cover/condition and forest dynamics in different tropical contexts. It important to acknowledge the following limitations as a critical exercise aimed at enhancing the study rather than as factors that significantly undermine the overall conclusions of the thesis. Although these limitations may impose certain constraints on the scope or generalizability of some findings, they do not fundamentally alter the main conclusions drawn from the research. By identifying and addressing these caveats, the study can be strengthened and its implications better understood.

First, any examination of the findings of Publication 1, should be cautious regarding interpretations of causality or inference within the generated spatial econometric models. The restrictions or assumptions of such complex models must be considered first (Anselin, 2022). For instance, the choice of the studied determinants (i.e., drivers) was influenced by the strong differences regarding the availability and quality of data (e.g., spatial and temporal resolution) in the three countries and at different spatial levels. These strong differences also existed regarding the reliability of the official administrative boundaries themselves in resembling the actual jurisdictional limits on the ground. Moreover, the chosen explanatory variables always present a certain degree of endogeneity. For instance, in the case of the predictors of our models, population pressure can be easily related to potentially omitted variables (e.g., infrastructure), which at the same time have an effect on forest cover, thus biasing the estimations about the influence of demography. A related problem is the collinearity of the potential dependent variables, which is common issue when defining models for complex socioecological processes such as deforestation. In the case of our investigation, the Zambian models were particularly affected by collinearity. Additionally, our study design resulted in nine models with very different sample sizes (e.g., 49 observation units at the macro-level vs. 3,035 at the micro-level), which can affect any comparison between models. Another important aspect directly affecting the outputs of spatial econometric models is the choice or design of an appropriate neighbor matrix, which considers the complex interactions between the analyzed units (J. LeSage and Pace, 2014). These interactions can be very different and difficult to capture depending on the specific geographical and thematical scope of the study (e.g., omitted neighbor countries, remote relationships such as international exports, landlocked territories vs. islands, …). Finally, the selected spatial models were chosen for its ability to quantify spatial dependencies (i.e., error terms, endogenous/exogenous variables) created by externalities or spillovers. However, as discussed in in the next subsection, other types of spatial models can better address further spatial interactions, such as global relationships of the dependent variable or spatial heteroscedasticity issues.

Second, we also have to critically consider some important aspects of the map creation process, when interpreting the findings of Publication 2. For example, any comparison of the relative importance of the variables used in the random forest classifiers (i.e., bands, indices and textures) has to be cautious. Namely, the employed methodology presented the advantage of including several predictors per pixel (increasing the possibilities of accounting for the different biophysical characteristics of the studied regions), but at the cost of potential overfitting problems and biased estimations (Ploton et al., 2020). Similarly, the data used originates from two types of sensors (Landsat-8 and Sentinel-1), with different spatial and temporal availability. The optical information (Landsat-8) conforms a 3-year mosaic with varying quality and quantity of observations per pixel across the different studied regions, mainly because of cloud cover. In contrast, the SAR-derived variables (Sentinel-1) constitute a continuum of pixels across the regions, with information for only two points in time (3 years far from each other) everywhere. Therefore, the still inadequate availability of open or free-of-charge high-resolution (both temporally and spatially) information for the studied areas, has clearly limited the capacity of the generated maps to accurately identify many LCLUs of interest, especially the ones related to recent forest dynamics (Joshi et al., 2016; Schmitt and Zhu, 2016). Furthermore, these aspects and related issues have to be kept in mind when comparing the maps of the different secondary sources as well, as these maps were produced using not only different sensors, temporal and spatial scopes, but also completely different reference datasets and classification methodologies (Foody, 2004; Olofsson et al., 2014).

Third, I will highlight some sample and methodological choices of Publication 3, which could have eventually impacted the results and should therefore be taken carefully, when exploring the interpretations and the implications of our work. For instance, the final categorization of drivers and policy instruments included a relatively small number of classes, in order to allow for general conclusions and comparisons between countries. With this simplified classification system, we could have omitted some relevant sub-categories, or not have accounted for important overlaps or interactions between the studied driver and policy types. Such dependencies between drivers, for example, have been identified in the models of Publication 1, where some variables were removed due to collinearity or endogeneity. In a similar manner, many of the current forest protection programs or initiatives include a mix of different policy instruments (Fischer et al., 2022; Lambin et al., 2014). In any case, our PCA findings suggest the independence of the selected categories and their suitability to describe the studied deforestation processes. Another relevant aspect to consider is the selection and distribution of stakeholders across the studied populations (Fink, 2003). For instance, some imbalances can be seen, especially across spatial levels: e.g., the international level was relatively underrepresented in the overall sample, or the Zambian population included a relatively higher number of regional subnational stakeholders, when compared to Ecuador and Philippines. Also, some stakeholder types are moderately overrepresented at certain spatial levels (e.g., academia regionally, indigenous locally). Thus, the intrinsic characteristics or particular interests of such stakeholder categories might explain some of the results better than just the geographical scope of these institutions. Also related to the characteristics of the selected sample, is the fact that most of the respondents belonged to formal government-dependent institutions and were men over 45 years of age with a university degree. Finally, another important point related to the limitations of Publication 3, is to consider how the data was collected and treated (e.g., compositional data, Likert answers and creation of indicators…), which can clearly condition the interpretations of the study results (Aitchison, 1982; Norman, 2010).

4.4.3 Future research

This subsection will summarize some ideas for further approaches in future research or similar studies, based on the remaining gaps and the limitations of my main investigations.

As already introduced when describing the limitations of Publication 1, further investigations can explore the possibilities of using other complex spatial regression models to explain forest dynamics. For instance, global spatial models use simulation routines to estimate the spatial dependencies related to changes in the dependent variable (Elhorst et al., 2018; Lacombe and McIntyre, 2016). The simulations of global models usually involve cascades of complex interactions with effects happening simultaneously in geographically distant units. In potential future approaches similar to ours, the use of such models would aim to explain how an increase or decrease of forest cover/condition in a specific administrative unit or region, affects forest cover/condition in other observation units separated in space. A second type of models which could be used in further related research are geographically weighted regression models (LeSage, 2004; Wheeler, 2019). These models take into account spatial heteroscedasticity, or the structural instability of the explanatory variables in space. Thus, geographically weighted regression models allow the parameters of determinants (i.e., drivers) and errors to vary spatially and they are typically used as exploratory methods for visualization of non-stationary phenomena. Another option for the improvement of our analysis is the use of panel data to explain historical changes of the drivers of deforestation (Elhorst, 2014). This possibility is however directly linked to the increase in availability and quality of relevant information in developing tropical countries. This would also be a precondition to explore other interesting and relevant dependent variables (e.g., deforestation rates, specific LCLU types or forest condition) or other determinants omitted in our study (e.g., important socioeconomic or political causes).

Regarding Publication 2, future studies or projects can potentially benefit from the created maps and from our reference datasets, to further explore forest-related information in the studied regions or in the tropics in general. Similarly, our field protocols to obtain ground verification data or our mapping approach, can be further applied and adapted to other regions of interest. Furthermore, with the current rapid increase in the availability of free-of-charge high-resolution remote sensing information and the enhancement of computational performance, it should be possible to develop more refined mapping approaches. For instance, one possibility of improvement can be using time series, which could increase data density from a temporal point of view and the possibilities of extending the analysis period and targeting forest dynamics successfully (Caughlin et al., 2021; Hirschmugl et al., 2020; Reiche et al., 2018). In this sense, improving the capacity to process SAR information and to link it to specific LCLU types can play an important role, as this technology is not affected by cloud cover, thus automatically increasing the number of potential observations through the year (Hirschmugl et al., 2020; Murrins Misiukas et al., 2021). Future research can also benefit from the development of data with higher spatial resolution (i.e., very high resolution [VHR] images), involving smaller pixels of sizes below 1 m. Such information can improve the possibilities to accurately classify smaller LCLU patches (e.g., agroforestry, small disturbances), to delineate tree crowns, rivers or other structures, or even to identify specific tree species (Immitzer et al., 2012; Schepaschenko et al., 2019). Finally, the quick progress of information technology tools (e.g., machine learning, artificial intelligence, cloud systems), will probably increase the computational capacity of current information systems drastically. This development should facilitate, not only the more efficient processing of high-resolution information (spatially and temporally), but also improvements regarding the effective fusion of complex and varied multi-sensor data (Meng et al., 2020). One example of application related to our approach, could be the development of efficient methodologies for automatized region-specific sensor and band selection, based on spectral separability and the particular classification goals.

In the case of Publication 3, I will highlight a few aspects which can be considered by similar investigations in the future. The most direct and obvious one would be to conduct our survey in other tropical countries, to increase the sample size and the possibilities to derive conclusions from a broader global perspective. Similarly, our survey could be conducted to particular institution types or stakeholder groups of interest, which might be relatively underrepresented in our study. This can apply, for instance, to international institutions, NGOs, or indigenous associations. Another possibility would be to analyze specific institutional characteristics, such as power, to determine which relationships exist between stakeholders or how they influence the way discourses and interests are built (Sandström et al., 2013). Moreover, further research could focus in exploring the links between the perception about certain drivers and the preferences for specific policy instruments (e.g., the relationship between higher perceived importance of timber extraction vs. the preference of measures against illegal logging). Finally, one more example of potential future approaches, is the linking of existing spatially-explicit forest-related data (e.g., deforestation rates, LCLU shares) with the administrative units where the analyzed institutions operate. Such studies could then contrast empirical data on forest dynamics at different spatial levels with the perceptions of stakeholders of interest, regarding drivers or preferred solutions.

5. Conclusion

This thesis aimed to analyze tropical forest dynamics and their drivers across deforestation contexts and across spatial levels. Based on the empirical research of my three main investigations and five supporting studies, the evidence is clear. It can be concluded that, despite being strongly dominated by human pressure and socio-economic factors (i.e., demography, agriculture, wood extraction, infrastructure), the main drivers of tropical deforestation are sensitive to the deforestation context (or to the different forest transition phases) and to the spatial scale.

Firstly, specific forest dynamics and the drivers of deforestation exhibit connections with distinct forest transition stages observed within regions or countries, suggesting that there is no one-size-fits-all solution for tropical deforestation in international forest policy. For instance, my research in Publications 1 and 2 highlights that Zambia is characterized by underdeveloped monitoring capabilities, while Publications 3 and 4 identified weaker governance, lower alertness about potential threats to forest and lower confidence in policy measures, when compared to Ecuador and Philippines. These findings underscore the significance of initiatives aimed at raising awareness, investing in advanced mapping technologies for early deforestation or forest degradation detection, and enhancing governance frameworks. These measures are crucial in effectively tackling the challenges associated with early forest transition stages and fostering sustainable forest management practices in contexts comparable to Zambia (e.g., Democratic Republic of the Congo, Tanzania, Angola, Gabon). Similarly, patterns were observed for advanced deforestation and early reforestation contexts. Namely, Publication 3 revealed that stakeholders in late/post-transition contexts exhibit heightened awareness of drivers and increased confidence in policy instruments. However, Publication 1 confirmed the presence of greater heterogeneity in drivers within these contexts, while Publication 2 emphasized the limitations of state-of-the-art forest datasets, particularly global and national maps, in accurately estimating forest cover and condition in advanced deforestation and early reforestation contexts. These results combined, point to the need of developing rigorous and comprehensive monitoring capabilities (i.e., detection of young regrowth forests, distinction of multiple drivers) to counter potential biases in stakeholders' perceptions in late/post-transition areas, especially considering the global push for reforestation and forest restoration initiatives in the tropics.

Secondly, the research findings reveal the significance of scale-related effects and the application of the panarchy theory in understanding forest dynamics and drivers of deforestation. For instance, the spatial econometric models of Publication 1 and the analysis of stakeholder perceptions of Publication 3, together with the local investigations of the supplementary studies, demonstrate the increased complexity and heterogeneity of drivers of forest cover change at local levels. Similarly, the research of Publication 1 and 7 highlights the importance of considering indirect impacts and leakages beyond administrative boundaries, especially at local levels, challenging the appropriateness of jurisdictional approaches and pointing to the suitability of broader and flexible system boundaries (i.e., socio-ecological systems). These local effects are both attributed to more likely human-environment interactions and more direct land and resource demands, which can propagate to regional or global scales over time in so-called cascading ecological effects. Overall, these findings emphasize the importance of addressing human pressure and drivers of deforestation at local levels, for the resilience of larger social-ecological systems. Two further important findings of my research can be attributed to this increased heterogeneity of forest dynamics at local levels. To begin with, Publication 3 identified lower confidence in policy instruments and lower alertness about commercial deforestation drivers of local stakeholders. This points to the need of harmonizing international and national protection aims with the interests of local actors: i.e., direct dependence on agriculture and forest resources (Publications 5 and 8), the necessity of enhanced governance mechanisms (Publications 4 and 6), environmental education or other types of institutional, logistical or economic support. In addition, Publication 2 found a clear lack of accuracy of current national and global forest information when applied locally, regarding forest extent and condition. My work in this article and in Publications 4 and 6, demonstrates the importance of using local information to obtain reliable results about forest dynamics, and the need to develop harmonized global reference datasets to be integrated in NFM and NFI systems.

Thirdly, my research has identified universal traits and patterns in tropical forest dynamics, which are independent of the specific deforestation context or spatial level analyzed. Overall, the findings of my publications indicate that human pressure and socio-economic factors, such as demography (e.g., Publication 1), agriculture (e.g., Publication 3, 4, 5, 6), wood extraction (e.g., Publication 3, 4, 6), and infrastructure (Publications 1,4,6), are dominant drivers of tropical deforestation. In particular, the results of the spatial econometric models (Publication 1) challenge the conventional understanding of underlying deforestation drivers and suggest that population density may play a more significant role in forest cover change, when compared to other socio-economic factors. Irrespective of causality interpretations or potential statistical biases, these findings underpin the need for horizontal policies and cross-sectoral strategies to ensure efficient forest management and conservation in the midst of growing human populations. Such comprehensive approaches should address population dynamics, spatial planning, and sustainable land use practices, safeguarding the coherence of agricultural and demographic policies. Furthermore, the analysis of stakeholders' perceptions in Publication 3, revealed a consensus on the relevance and effectiveness of certain policy instruments, such as reforestation and forest restoration initiatives, across different regions and spatial levels. On the one hand, these findings suggest the presence of opportunities for cross-scale and cross-country collaboration among institutions and a paradigm shift from protected areas to a stronger focus on integrative approaches that include reforestation and forest restoration measures. On the other hand, it is important to exercise caution when interpreting this consensus, due to the identified limitations regarding information quality in both Publication 1 and 2. Consequently, it should be noted that these perceptions might be influenced by institutional discourses and confirmation biases.

Overall, the approach of this thesis validates the applicability of the forest transition theory in characterizing countries or regions and in discerning deforestation patterns, to provide valuable insights for scientific inquiry, policy formulation, and practical interventions. By including the spatial scale and the panarchy concept to the analytical framework of the forest transition theory, this thesis addressed a gap in scientific research and contributed to a more comprehensive understanding of tropical forest dynamics. Moreover, this work provides an extensive overview of up-to-date methods on how to obtain and use spatial data to monitor tropical forest dynamics and the drivers of forest cover change. Further research should continue to utilize and refine the presented analytical framework that combines forest transition and panarchy, whether through similar investigations, specific methodological advancements, building on the abovementioned limitations, or application in different tropical countries and contexts.

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Appendix

Complete manuscripts of the three main investigations

Publication 1: Scale and context dependency of deforestation drivers

Ferrer Velasco, R., Köthke, M., Lippe, M., Günter, S., 2020. Scale and context dependency of deforestation drivers: Insights from spatial econometrics in the tropics. PloS one 15, e0226830.

PLOS ONE

RESEARCH ARTICLE

Scale and context dependency of deforestation drivers: Insights from spatial econometrics in the tropics

Rubén Ferrer Velasco[1,2]*, Margret Köthke[2], Melvin Lippe[2], Sven Günter[1,2]

1 Department of Ecology and Ecosystem Sciences, School of Life Sciences Weihenstephan, Technical University of Munich, Freising, Germany, **2** Institute of International Forestry and Forest Economics, Johann Heinrich von Thünen Institute, Hamburg, Germany

* ruben.ferrer@thuenen.de

Abstract

A better understanding of deforestation drivers across countries and spatial scales is a pre-condition for designing efficient international policies and coherent land use planning strategies such as REDD+. However, it is so far unclear if the well-studied drivers of tropical deforestation behave similarly across nested subnational jurisdictions, which is crucial for efficient policy implementation. We selected three countries in Africa, America and Asia, which present very different tropical contexts. Making use of spatial econometrics and a multi-level approach, we conducted a set of regressions comprising 3,035 administrative units from the three countries at micro-level, plus 361 and 49 at meso- and macro-level, respectively. We included forest cover as dependent variable and seven physio-geographic and socioeconomic indicators of well-known drivers of deforestation as explanatory variables. With this, we could provide a first set of highly significant econometric models of pan-tropical deforestation that consider subnational units. We identified recurrent drivers across countries and scales, namely population pressure and the natural condition of land suitability for crop production. The impacts of demography on forest cover were strikingly strong across contexts, suggesting clear limitations of sectoral policy. Our findings also revealed scale and context dependencies, such as an increased heterogeneity at local scopes, with a higher and more diverse number of significant determinants of forest cover. Additionally, we detected stronger spatial interactions at smaller levels, providing empirical evidence that certain deforestation forces occur independently of the existing *de jure* governance boundaries. We demonstrated that neglecting spatial dependencies in this type of studies can lead to several misinterpretations. We therefore advocate, that the design and enforcement of policy instruments—such as REDD+—should start from common international entry points that ensure for coherent agricultural and demographic policies. In order to achieve a long-term impact on the ground, these policies need to have enough flexibility to be modified and adapted to specific national, regional or local conditions.

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1 Introduction

Deforestation processes are related to human activities and endangering forest ecosystem services in many cases [1–3]. These impacts on e.g. carbon sequestration, soil and water quality, species losses or local livelihoods, are widely discussed among the scientific community [4,5]. The discussion is especially recurrent for the pantropics [6,7], where the FAO reported a net annual loss of forest area of about 7 million hectares for the 2000–2010 period [8]. More recent (2003–2014) average net carbon losses in tropical regions have been estimated in 452.2+92.0 Tg C · yr^{-1} globally, of which 59.8% are attributable to America, 23.8% to Africa, and 16.3% to Asia [9]. In parallel, the main drivers behind tropical forest cover (FC) change have been repeatedly studied as well [10–12]. In 2012, Hosonuma et al. [11] related over 80% of global deforestation for the 2000–2010 period to agricultural expansion (both commercial and subsistence), followed by other anthropogenic causes, namely mining, infrastructure and urban expansion. In a more recent study in 2018 [12], Curtis et al. quantified the global forest loss between 2001–2015 and attributed it to permanent land use changes due to commodity production (27%), forestry (26%), shifting agriculture (24%), and wildfire (23%). Busch and Ferretti-Gallon compiled in 2017 [13] "a comprehensive database of 121 spatially explicit econometric studies of deforestation published in peer-reviewed academic journals from 1996 to 2013". In these studies, variables related to population, built infrastructure and market demand for agriculture were consistently associated with high deforestation, while poverty, higher elevations and steeper slopes were regularly identified with lower forest loss. Other variables related to aspects such as ownership and management rights, market demand for timber, or further socioeconomic and biophysical characteristics, showed varying or no influence on FC across the studies included in the meta-analysis.

Gathering knowledge about the drivers of deforestation across different jurisdictional levels is as a precondition for designing effective land use planning and policies at the levels where forest governance takes place. As an example of this, we can highlight the references for the design and implementation of operative and efficient strategies of REDD+ projects [14–16]. Moreover, generalizations about deforestation across pantropical regions and across different jurisdictional levels would help predicting future changes which might occur with or without policy interventions [17]. An area of research that already points in this direction is the classification of tropical countries or regions—and their drivers of deforestation—based on their FC levels and deforestation rates [11,17–19]. This is frequently made under the assumptions of the forest transition theory, which describes the existence of recurrent phases of FC decline and re-expansion [20,21].

Despite the number of studies dealing with the identification, categorization and quantification of the main drivers of FC change in the tropics, no empirical study of global or pantropical focus considered the behavior of these drivers in subnational administrative units across spatial scales and countries so far. On the one hand, some authors have conducted subnational or even multilevel approaches to analyze the causes of deforestation within different interrelated administrative hierarchies, but always putting their focus on single countries (e.g. [22–25]). On the other hand, supranational-regional and global studies have always focused on national and regional aggregations (e.g. [11,12,26]). For instance, from the 121 studies included in Busch and Ferretti-Gallon's meta-analysis [13], only nine included *de jure* administrative entities as their units of observation, and only four studies analyzed data from different tropical regions [27–30]. However, no econometric study of pantropical scope has focused on the drivers of deforestation at sub-national jurisdictions so far.

In order to address this research gap, we made use of spatial econometrics and conducted a multi-level approach with nested jurisdictional units in three tropical contexts of Africa, Asia and South America. Spatial econometrics is a discipline with increasing interest in urban and regional studies [31–34], which can contribute to a better understanding of spatial phenomena and tropical deforestation patterns at different interconnected subnational administrative levels. For instance, with the use of local spatial models, it is possible to estimate the spillovers and the indirect impacts of neighboring units [35]. Furthermore, these models can provide information about omitted variables and on how spatial clusters look like [33,36,37]. So far, these methods have not been widely used in previous studies of tropical deforestation, even if local interactions between neighbor administrative units and omitted spatially correlated parameters exist in real physical deforestation processes. Again, from all the spatially explicit econometric studies included in Busch and Ferretti-Gallon's meta-analysis [13], more than the half of them did not even report any treatment of spatial autocorrelation. Furthermore, only seven of the remaining studies (5.8% of the total) considered spatial lags or the use of a weighting neighbor matrix, but always focusing on one single country or region and at one single level of analysis (e.g. [38,39]). This was also the case in more recently published studies (for instance: [39,40]).

Within this context, our study wants to address the following research questions: Are well-studied *global drivers of tropical deforestation* also *constant across* different subnational *administrative levels*? If not, which *differences* are observable and at which jurisdictional levels? Is this the same for different *tropical contexts*, or are there country/region specific behaviors?

2 Materials and methods

2.1 Selection of study areas and the forest transition theory

With the selection of the study areas we aimed to include three countries that accounted for as much pantropical variability as possible, regarding their FC and deforestation rates, but also considering their biophysical, geographical, socioeconomic and demographic conditions. A key factor behind this selection process was the situation of each country within the forest transition curve [20], when observed at national scale (see S1 Fig). Based on this, we selected the three following countries:

1. Zambia is a land-locked plateau in south-central Africa, which in 2010 was still in the pre-/early stage of the forest transition [11] with a high FC (65.4%) and moderate deforestation rates (-0.3% · yr^{-1}) [41]. Zambia has relatively low population density, life expectancy at birth, GDP per capita and HDI [42–44]. According to Global Forest Watch, the deforestation rates in Zambia have increased and accelerated significantly in the last ten years [1]. While the country lost 850 kha of tree cover extent with canopy larger than 10% during the period 2001–2009, this loss more than doubled to 1.96 Mha in the period 2010–2018. This accelerated deforestation might indicate that Zambia already entered its early transition, reducing its total FC to 62% in 2015 [45]. Following Curtis et al. [12], most of this deforestation was due to shifting agriculture. Other identified relevant drivers of deforestation (and degradation) in Zambia are mining and infrastructure development, wood extraction, charcoal production and wild fires [46].

2. Ecuador is a mega-diversity hotspot that shelters the Andes and the Amazon basin, in the Pacific side of northwestern South America. Ecuador has reduced FC to about 50%, but deforestation is still ongoing since the late nineties at relatively high rates (-0.6% · yr^{-1}) [41,47]. The forest context in the country can thus be a clear example of a "frontier area" ([17]). Ecuador has twice the population density of Zambia, with a share of 63% of urban population, and a relatively high GDP and HDI [42–44]. The key driver of deforestation in

Ecuador is again shifting agriculture [12], together with small-scale ranching and, in a more local manner, commodity-production such as palm oil [48].

3. The Philippines is an archipelago in Southeast Asia consisting of over 7,000 islands. This country is supposed to have achieved a net FC increase of 0.8% $\cdot$ yr^{-1} between 1990 and 2015, with less than 30% of FC left in 2015 [41]. The Philippines is very densely populated, exhibits the highest road density among the three countries, and a share of 41% of agricultural land [42–44]. According to Global Forest Watch and Curtis et al. [1,12], tree cover loss in the Philippines is mostly commodity-driven and related to agriculture expansion. Forestry practices and urbanization also play a bigger role on deforestation than in Zambia and Ecuador. The forest situation on the Philippines is thus an example of a clear "forest-agricultural mosaic" or late-post forest transition phase, when observed at national level [11,17].

2.2 Units of observation and levels of analysis

We subdivided each of the selected countries into three nested spatial levels of analysis (macro-, meso-, and micro-level), related to their hierarchical legal administrative configuration (Fig 1). Each of these three levels of analysis corresponds to an existing *de jure* governance structure, with comparable competences regarding forest policy design and implementation across the three countries [49,50].

For Zambia, 9 provinces comprise the macro-level and 71 districts the meso-level. We downloaded the geo-referenced data for both levels from the GADM database [51]. The third level (micro-) represents approximations of 1,358 ward and constituency boundaries based on printed information from the Election Commission of Zambia (ECZ) for which a polygon file produced by Eubank (2014) [52] was used. The main institution responsible for the management of forest resources in Zambia is the Forestry Department of the Ministry of Lands, Natural Resources and Environmental Protection (MLNREP). Zambia is experiencing a national decentralization process which aims to increase the power and obligations of the districts (meso-level) in order to improve the quality of the service delivery at the subnational level [53–56]. In this line, some changes have happened in the last decade regarding the national legal framework for the forestry sector, like the inclusion of local forest regulations and other forms of local forest management: e.g. Joint Forest Management (JFM) or community forestry [57–60].

In the case of Ecuador, the administrative units selected for the macro-level are the 24 provinces plus the three non-delineated zones as one single unit. The meso-level includes 224 counties and the micro-level 1,024 parishes. We downloaded the data regarding these boundaries from the National Institute of Statistics and Census database [51,61]. Although the main actions regarding forest policy and management in Ecuador are basically planed and coordinated at national level by the Ministry of Environment (MAE) [62], these three levels of territorial organization (provinces, counties, parishes), whose legislative-political role is acknowledged by the current Ecuadorian Constitution [63] and the Organic Code of Territorial Organization, Autonomy and Decentralization [64], participate actively in the implementation of MAEs policies or other forest management programs in line with the national laws.

For the Philippines, the three jurisdictional levels of analysis include 17 regions (macro-level), 81 provinces (meso-level) and 1,652 municipalities (micro-level). The geographic datasets were extracted from the GADM database [51] and are based on official boundaries from NAMRIA (National Mapping and Resource Information Authority), which can be acquired at the Philippine Geoportal System [65]. At a national level, the main governmental body which

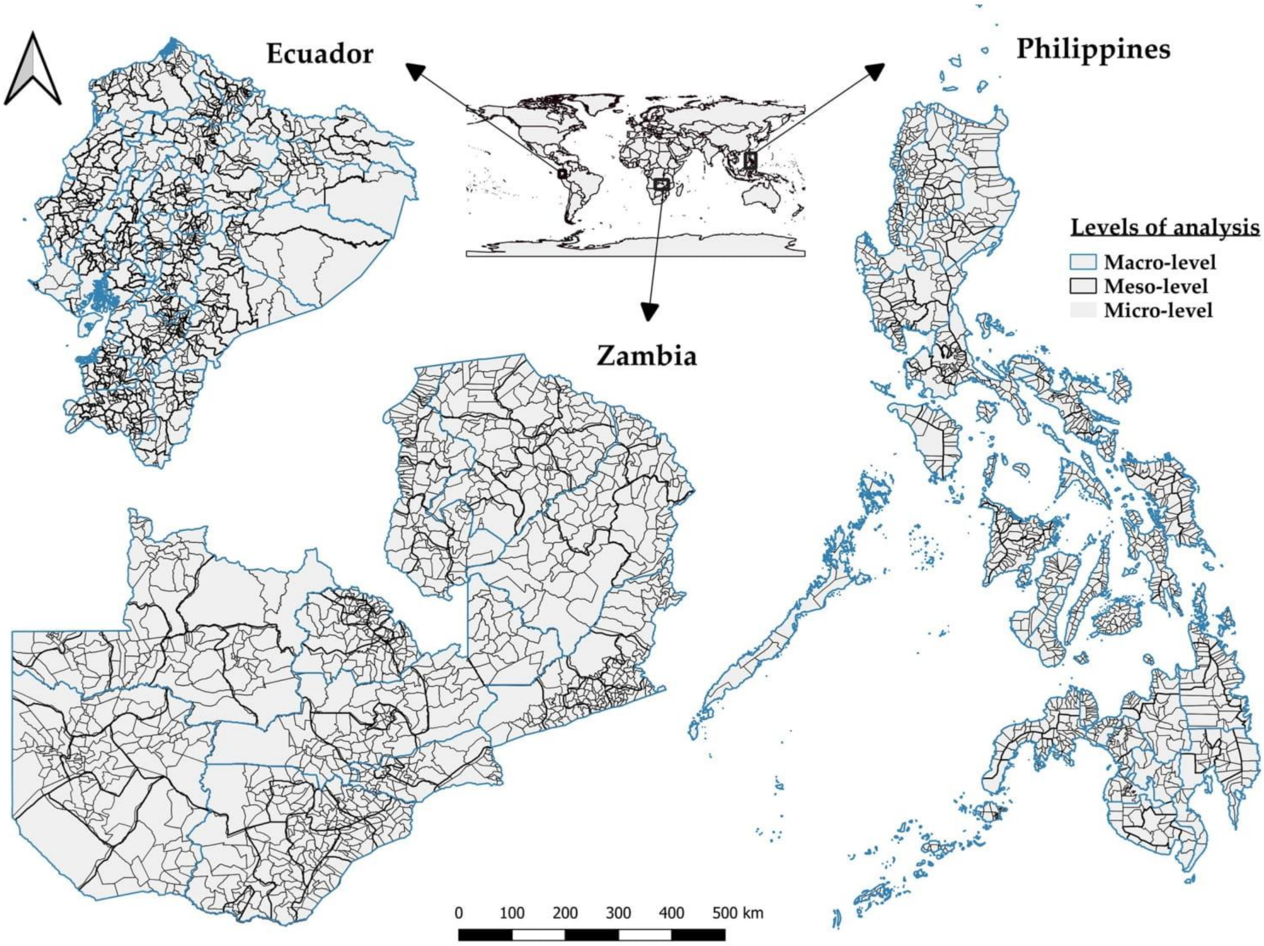

Fig 1. Maps of the three selected countries and their corresponding jurisdictional/spatial levels of analysis. The countries are displayed at the same scale with proportional sizes.

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deals with forest management planning in the Philippines is the Forest Management Bureau (FMB), which belongs to the Department of Environment and Natural Resources (DENR). DENR has offices in all the administrative regions (macro-level), and some offices that operate in most of the provinces (PENROs, at meso-level) and in some cities or municipalities (CENROs, at micro-level) [66,67].

2.3 Selection of variables: Building of a spatial database

We built a geodatabase with the support of Geographic Information System (GIS) software and tools: QGIS 3.4. [68]. This geodatabase (see S1 File) comprised the downloaded spatially explicit boundaries for the three jurisdictional levels in the three countries. In the next steps, we included the information about FC and relevant drivers of de- and reforestation (response and explanatory variables) for each of these units and levels of analysis, as described in the following subchapters.

2.3.1 Response variable: Forest cover (FC). We extracted the FC information for each administrative unit (three countries and three levels) from the most recent national land cover map that was available at the time of performing this study [47,69,70] (Table 1). Therefore, we conducted a cross-sectional analysis, which assumed that patterns of FC development can be detached from the temporal scale, as they are dependent of socioeconomic development [20,21,71]. National land cover maps, contrary to global datasets like [1,72,73], presented advantages such as higher resolution and accuracies for the regions of interest, while considering particular land cover characteristics of each tropical context.

Thus, we post-classified and harmonized forest and land cover definitions, by aggregation of existing tree and FC classes into only three major land cover types: Forest area (FA), Potential forest vegetation area (FApot) and Non-potential forest vegetation area (Non-FApot). We obtained the dependent variable FC by normalizing the forest area (FA) as a fraction of a unit's potential forest area (FApot) (Table 2). FC is, therefore, a proportion of each jurisdictional unit's total forest area on its potentially forested area, rather than on its total surface. The concept of potentially forested area as interpreted in this study is aiming to estimate the maximum forest area that could be reached in a limited period of time, similar to the approach of Köthke et al. (2013) [26]. We calculated this by aggregating all relevant vegetation land cover types, while classes not suitable for forest vegetation were consequently excluded (e.g. water bodies, glaciers or bare areas). Built-up and artificial infrastructures were neither included into this aggregate, assuming that urban areas are rather unlikely to experience rapid land cover dynamics [74,75]. This allows the range for the dependent variable to vary between 0 and 100%.

Table 1. Land cover map sources and FC classification used in this study.

		Zambia	Ecuador	Philippines
	Country:	**Zambia**	**Ecuador**	**Philippines**
	Year and source:	**2016, [69]**	**2014, [47]**	**2010, [70]**
	Sensor(s) Used:	**Sentinel-2**	**LandSat, RapidEye**	**ALOS AVNIR-2, SPOT 5, LandSat**
	Resolution:	**~20m**	**~5-30m**	**~10-30m**
Potential forest area (FA_{pot}[2])	**Forest area (FA[1])**	Tree Cover Areas	Native forest	Closed forest
			Forest plantations	Open forest
				Mangrove forest
	Other non-forest vegetation area (FA_{pot}–FA)	Shrub cover areas	Herbaceous vegetation	Wooded grassland
		Grassland	Shrub vegetation	Grassland
		Cropland	Pasture	Shrubs
		Vegetation aquatic	Agricultural mosaic	Perennial crop
		Lichens	Permanent crop	Annual crop
		Sparse vegetation	Semi-permanent crop	Fallow
			Annual crop	
Non-potential forest area (Non-FApot)		Páramo	Bare areas	Open barren
		Natural (rivers)	Built-up	Marshland
		Infrastructure	Snow or ice	Swamp
		Glacier	Open water	Inland water
		Artificial		Fishpond
		Non-vegetation cover		Built-up
		Settlement		

[1] FA: Forest area [ha]

[2] FApot: Potential forest area [ha]

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2.3.2 Explanatory variables: Drivers of forest cover change. We selected seven explanatory variables, which included elements related to physio-geographic, demographic and socio-economic aspects that we expected to influence FC (Table 2). These variables have been often identified and discussed as mostly influential and uniform across tropical countries by previous authors (see, for instance, [10,13]).

We tested the influence of total area (A_{TOT}), as different sizes of administrative units might be subject of differences in land pressure, political processes, as well as options for trade and cooperation [26]. We extracted the total extent of each administrative unit from the spatial boundaries used to define the study's units of analysis. We did every calculation of areas or slope degrees (see parameter FL) after re-converting the source spatial files into the corresponding Universal Transverse Mercator (UTM) projected coordinate system. We used UTM zones 35S, 17S and 51N for Zambia, Ecuador and Philippines respectively.

The potential vegetation area (PVA) describes the share of potentially forested area (FA_{POT}) related to the total area (A_{TOT}) of the analyzed administrative unit. PVA can range from 0 to 100% and high values signify a potential for higher forest area in the unit, but not necessarily its existence [26]. For instance, a large region in the Amazon with a lot of its surface share covered by native forest would rank high in PVA. At the same time, a smaller region in a rural province, which has been deforested centuries ago and nowadays mostly comprises pasture- and croplands, would also rank high in PVA. Therefore, and as FC in this study is defined as a proportion on PVA, high PVA values are expected to decrease FC. Units with high PVA will in general have more options to establish productive locations for agricultural land and they are expected to experience an increased need to exploit for food production within the region's borders.

A key driver of deforestation is the role of population density and demographic development [13,87,88]. We expect that higher population density result in higher demand for land and resources with related phenomena putting direct pressure on forest itself, like e.g. agricultural expansion and shifting cultivation, establishment of settlements, roads and other

Table 2. Variables considered in the study (in bold) and related definitions and sources.

	Definition and [unit]	Sources	Year(s) / Country			
Dependent variable			ZAM	ECU	PHI	
FC	**Forest Cover [%]**	FA/FA_{pot} [1]	2016	2014	2010	
	FA: total forest area [ha]	[47,69,70] [1]	2016	2014	2010	
	FA_{pot}: Potential forest area [ha]	[47,69,70] [1]	2016	2014	2010	
Explanatory variables			ZAM	ECU	PHI	Expected impact
A_{TOT}	**Total Area [ha]**	[51,52,61]	2006–10	2010	2010	Positive
PVA	**Share of potential vegetation on surface area [%]**	$[FA_{pot}/A_{TOT}]$ [1]	2016	2014	2010	Negative
PP_{FA}	**Population pressure on remaining forest area [pers./ha]**	$[P_{TOT}/A_{TOT}]$	2015–16	2014–15	2010	Negative
	POP_{TOT}: Total population [pers.]	[76–79]	2015	2015	2010	
RD	**Road density [km/km^2]**	$[RTOT/A_{TOT}]$	2016	2016	2016	Negative
	R_{TOT}: Total road length [km]	[80]	2016	2016	2016	
FL	**Flatness: share of surface with less than 16% steepness [%]**	$[FL_{TOT}/A_{TOT}]$	2008	2008	2008	Negative
	FL_{TOT}: Total area with low slopes (<16%) [ha]	[81]	2008	2008	2008	
CSI	**Crop suitability index [%]**	[82,83]	2005	2005	2005	Negative
CY	**Maximum cereal area yield [kcal/ha]**	[84–86]	2005–15	2004–14	2000–10	Positive

[1] From Table 1

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infrastructures, fuel wood collection and resource extraction. We estimated the total population (P_{TOT}) for each administrative unit by extracting the associated demographic data from worldpop.org.uk [76–79]. We did this for the year closest to the corresponding land cover map used in each country (Table 2). We calculated the density (pressure) on the remaining total forest area (PP_{FA}) by dividing the total population by the forest area (FA).

Similar to population pressure, indicators for accessibility, such as road density or distance to roads, have been widely used as a measure of environmental pressure and economic development [89–92]. The presence of roads can contribute to a range of pressures on forests and on the natural environment in general [13] and thus, we expect that high road densities are likely to affect FC negatively. We downloaded and calculated the total road length (R_{TOT}) in each assessed jurisdictional unit (including highways, roads, paths and railways) from openstreetmap.org and geofabrik.de [80]. The total road length in km (R_{TOT}) was divided by the total area (A_{TOT}) of each respective administrative unit (in km^2), to calculate road density (RD).

Slope at 90m resolution was calculated from the 4.1 version of the SRTM DEM (Shuttle Radar Topographic Mission Digital Elevation Model) produced by the NASA (National Aeronautics and Space Administration) and CGIAR (Consultative Group for International Agricultural Research) [81]. For each analyzed administrative unit, we divided the total area below 16% slope (FL_{TOT}) by its total area (A_{TOT}), thus generating a flatness indicator: FL. We selected land under 16% steepness based on the FAO definition of non- (0–8%) or slightly (8–16%) constrained rain-fed land ([82]). We therefore expect, that regions with a higher share of flatness are more suitable for the clearing of new agricultural land have a lower FC [13]. Cross-country and cross-level differences are also expected depending on each specific physio-geographic condition.

We estimated the crop suitability index (CSI) from FAO's FGGD (Food Insecurity, Poverty and Environment Global GIS Database) data regarding 'suitability of currently available land area for rain-fed crops, using maximizing crop and technology mix' [82,83]. This dataset is a global raster layer displaying values between 0 (not suitable) and 100 (very high CSI). We gave a zero value (no crop suitability) to classes like internal water bodies, urban, closed forest, protected areas, or irrigated land. This concerned a few specific areas like the Galapagos, remote Amazonian forest, or the metropole of Manila in the Philippines. As the pixel resolution was rather coarse (1/12 of degree)—especially when considering the size of some units from the smallest jurisdictional level -, we calculated the area-weighted mean of pixel values situated within the boundaries for each unit of analysis. CSI represents the agricultural potential of the land and is, thus, expected to affect FC negatively [13].

Finally, the cereal area yield (CY) expresses the actually achieved yield at a point or period of time. The CY is supposed to increase over time, fluctuate short-term and maybe saturate in a stage of high intensification. The cereal area yield of a region is an indicator of agricultural productivity and intensification [93,94]. Thus, we expect it to release pressure on FC. We selected two main cereal categories, which represent major crop types in the three selected countries, namely maize and rice. We obtained data for aggregated maize and rice classes area production yields (MY, RY in tons/ha) from official national sources between 1987 and 2015 [84–86], for five of the twelve analyzed samples. For both cereal types, we considered the arithmetic mean of the last 10 years before the production of each particular land cover. We converted the computed means to caloric yields (kcal/ha), using the general conversion factors presented by Cassidy et al. (2013) [95]. For those administrative units with information for both maize and rice, the highest caloric yield was taken into consideration, assuming that this crop type is more likely occurring in the respective region.

2.4 Spatial econometric modelling

We conducted the spatial econometric analysis with the support of the JMP® 13.1.0 and R 3.5.2 statistical software [96,97] and the *spdep* [98,99], *rgdal* [100], *sp* [101], *rgeos* [102] and *RANN* [103] packages. The final product and files used for the analysis (S1 File), together with the associated R script (S2 File), can be found in the online attachments of this article. We defined a total of twelve samples: nine samples present the combinations of the three countries and the three spatial levels of analysis, and three samples present the aggregated data (pantropical) of all countries at the three spatial levels.

We assumed a sigmoidal relationship between the drivers of deforestation and the dependent variable, following the results of other authors [26,88,104,105]. This relationship constitutes a model of FC decline with an inverted growth function approaching 1 as horizontal asymptote at the left side and 0 at the right side (similar to the graph as shown in S1 Fig). Subsequently, the dependent variable needed to be linearized by logistic transformation in order to permit linear regression techniques and the explanatory variables were transformed using a logarithm function:

$$FC_s^* = ln\left(\frac{1}{FC_s} - 1\right) = ln\left(\frac{FA_{POT_s}}{FA_s} - 1\right) \quad \text{(Eq 1)}$$

$$X_{v,s}^* = ln X_{v,s} \quad \text{(Eq 2)}$$

where: * refers to linearized or transformed; *s* is the sample; and *X* is a vector of the seven explanatory variables *v*.

The samples with missing, not linearizable extreme or nil values–in the case of FC, PVA, CSI or RD–were dismissed. This generally consisted of micro- or meso-units from either (a) metropoles with no registered FC (mainly a few big urban centers in Copperbelt and Lusaka in Zambia, highly populated cities in the Philippines and a small number of settlements belonging to the arid Andes, Quito or Guayaquil in Ecuador), or (b) remote areas with almost inexistent human presence (like the Galapagos in Ecuador or the Turtle Islands in Philippines). This implied the exclusion of a total 3.92% of the macro-units, 3.99% of the meso-units and 24.67% of the micro-units from the original sample.

For each of the twelve samples, the provided explanatory variables were standardized individually as follows, in order to later compare or estimate their relative contribution to the model:

$$X_{v,s}^{\wedge} = \frac{X_{v,s}^* - \mu(X_{v,s}^*)}{\sigma(X_{v,s}^*)} = \frac{ln X_{v,s} - \mu(ln X_{v,s})}{\sigma(ln X_{v,s})} \quad \text{(Eq 3)}$$

where: $X^{\wedge}_{v,s}$ is the standardized explanatory variable *v* for sample *s*; $\mu(X^*_{v,s})$ represents the mean value in sample *s* for the transformed explanatory variable *v*; and $\sigma(X^*_{v,s})$ is the standard deviation of the transformed explanatory variable *v* in sample *s*.

In a next step, we tested collinearity between the seven explanatory variables for every sample. Variables with bivariate correlation values of at least 0.6 were considered as highly correlated predictors. We performed simple linear regressions for each of the independent variables. The highly correlated variables with the lower coefficients of determination in their respective linear regressions were not included into the further calculations, assuming they were providing redundant information. Then, we identified the significant explanatory variables per sample, using the non-spatial OLS model following automated stepwise backwards elimination method with the smallest Bayesian information criterion as stop rule. Therefore,

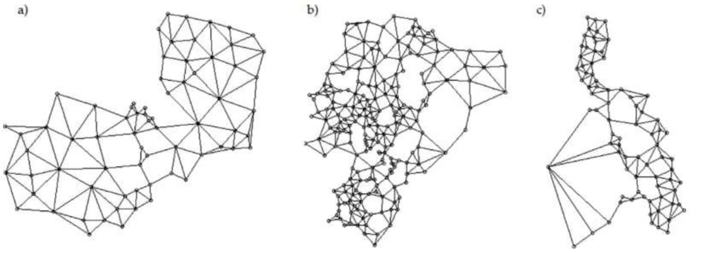

Fig 2. The SOI W diagrams representing the spatial interactions between the meso-level jurisdictional units. a) Zambia b) Ecuador and c) Philippines.

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the OLS model for multivariate analysis is expressed like:

$$\text{OLS Model}: \ FC_s^* = \beta_0 + \beta_v ln\hat{X}_{v,s} + \varepsilon_s \quad \text{(Eq 4)}$$

where β are the respective coefficients and ε is the residual.

Next, we developed a spatial weights matrix (W) for each of the twelve samples. In order to avoid model deficiencies and misapplying spatial econometrics [106–108], this matrix should reflect how spatial units interact with each other and their degree of connectivity. We considered a graph-based—sphere of influence (SOI)—neighbor matrix for the twelve samples of our study (Fig 2). A SOI matrix works "based on Euclidean distances between polygon centroids, where points are neighbors if circles centered on the points, of radius equal to the points' nearest neighbor distances, intersect in two places" [98,109].

We examined the results from each OLS analysis [98] to check for spatial dependency of the model residuals, by performing both Moran test [110] and to explore spatial relationships with the Lagrange Multiplier diagnostic for lag and error models [33,111,112]. We did this in order to reveal spatial autocorrelations and justify the use of the proposed econometric models. Thus, with this, we did not want to explore or discuss the spatial distributions of errors/variables explicitly for each context or scale, but we rather wanted to demonstrate the existence of spatial dependencies among the different samples (different contexts/scales) and justify the use of our spatial econometric models.

Next, to select the most suitable regression model for each sample, we applied the LeSage and Pace method [32,36] for local model specification. Thus, we did likelihood ratio (LHR) tests to select the spatial model that better explained each of the twelve samples. This method tries to demonstrate if a Spatial Durbin Error Model (SDEM) can be restricted to a simpler nested model, such as a spatial error model (SEM), a spatially-lagged X model (SLX), or reduced to the non-spatial OLS model:

Spatial Durbin Error Model (SDEM):

$$FC_s^* = \beta_0 + \beta_v ln\hat{X}_{v,s} + W_{s,n}\theta_{v,s} ln\hat{X}_{v,s,n} + u_s, \ u_s = \lambda W_{s,n} u_s + \varepsilon_s \quad \text{(Eq 5)}$$

if $\theta = 0$, (6) results in Spatial Error Model (SEM):

$$FC_s^* = \beta_0 + \beta_v ln\hat{X}_{v,s} + u_s, \ u_s = \lambda W_{s,n} u_s + \varepsilon_s \quad \text{(Eq 6)}$$

if $\lambda = 0$, (6) results in Spatially Lagged X Model (SLX):

$$FC_s^* = \beta_0 + \beta_v ln\hat{X}_{v,s} + W_{s,n}\theta_{v,s} ln\hat{X}_{v,s} + \varepsilon_s \quad \text{(Eq 7)}$$

if both $\theta = 0$ and $\lambda = 0$, (6) results in OLS Model:

$$FC_s^* = \beta_0 + \beta_v ln\hat{X}_{v,s} + \varepsilon_s \qquad \text{(Eq 8)}$$

where: $W_{s,n}$ represents the row-standardized weight of the neighbor n for a certain sample s; $\theta_{v,s}$ are the neighbors' impacts on a certain variable v and sample s; $ln\,X^{\wedge}_{v,s,n}$ represents the neighbors' values for a certain variable and sample; $\lambda W_{s,n}u_s$ represents the weighted spatial residual error.

Thus, we assigned each sample to an optimal regression model, which could account for either neighbor impacts (SLX model), spatially correlated errors (SEM model), both spatial effects (SDEM model) or none of them (OLS model). Fig 3 summarizes the analytical framework of this research article in the form of a conceptual diagram. This graph also summarizes

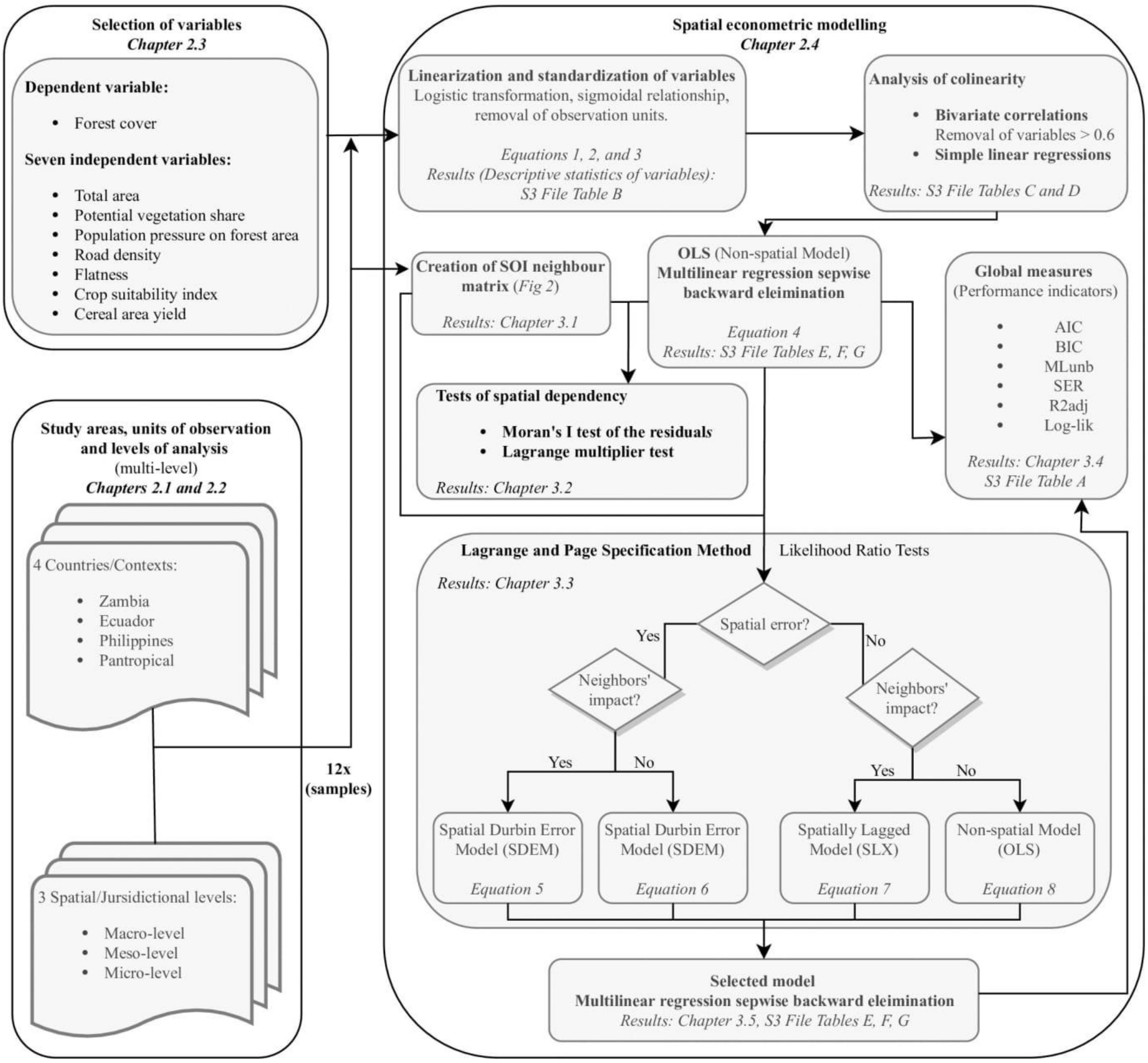

Fig 3. Conceptual diagram summarizing the analytical framework of this research article.

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how the spatial interactions and the different proposed models refer to each other in the specification method.

Finally, in order to justify the specification method, we quantified and compared different performance indicators or global measures for both the OLS and the specified spatial models. First, we considered the (1) Akaike and (2) Bayesian information criterions (AIC, BIC). These are both estimators of relative quality of statistical models, where lower values indicate a better goodness of fit. We also calculated (3) unbiased maximum likelihood estimators of the error variance and (4) standard errors of regression. These two other measures estimate the goodness of fit in percentage, and they tend to decrease (approach zero) if the quality of the regression increases. Finally, we calculated (5) adjusted coefficients of determination (which indicate the percentage of the dependent variable variance explained by the model) and (6) log-likelihoods with maximum likelihood estimators for the regression coefficients. These two last parameters increase with improved model quality. All these measures were calculated following the formulas and definitions proposed by [113].

3 Results

3.1 Spatial weight matrices

Looking at the histograms of the number of neighboring regions (Table 3), we can observe similar distributions across the samples. The smallest matrix consists of 30 links, while the most complex one has 12,890 connections between regions. The matrices provide a relatively low number of sparse non-zero weight connections, especially in the pantropical model and at the smaller levels. These values range from 0.14% to 37.04%, which allowed us to perform the further spatial tests. The associated average links per matrix range from 3.3 (Zambia's macro-level) to 4.6 (Ecuador's micro-level) relations per sample [108].

3.2 Moran's *I* and Lagrange multiplier tests

The Moran's *I* test for the OLS residues was significant (considering a 1% threshold) in at least eight of the twelve samples (Table 4). We detected positive Moran's *I* between 0 and 1 in these

Table 3. Summary of the applied SOI spatial weights matrix (*W*) for each sample [98].

Country	Level	Number of neighboring regions[1]									N[2]	N links[2]	Avg. links[2]	% NZW[2]
		1	2	3	4	5	6	7	8	9				
PAN[3]	Macro-	1	7	13	14	12	0	2	0	0	49	184	3.8	7.66
	Meso-	0	24	75	101	97	48	12	4	0	361	1,566	4.3	1.2
	Micro-	50	250	629	824	711	421	128	18	4	3,035	12,890	4.3	0.14
ZAM[3]	Macro-	0	2	3	3	1	0	0	0	0	9	30	3.3	37.04
	Meso-	0	3	18	16	16	12	2	3	0	70	314	4.5	6.41
	Micro-	7	45	172	287	272	174	49	8	2	1,016	4,590	4.5	0.44
ECU[3]	Macro-	1	4	4	6	7	0	2	0	0	24	94	3.9	16.32
	Meso-	0	15	39	58	60	31	7	2	0	212	930	4.4	2.07
	Micro-	5	35	130	223	264	155	46	6	1	865	3,986	4.6	0.53
PHI[3]	Macro-	0	1	6	5	4	0	0	0	0	16	60	3.8	23.44
	Meso-	0	6	18	26	20	7	2	0	0	79	326	4.1	5.22
	Micro-	39	168	331	309	184	87	30	6	0	1,154	4,304	3.7	0.32

[1] Number of units with a certain number of neighboring regions (1–9).

[2] N: Total sample size; N links: Total number of links per matrix (W); Avg. links: Average number of links per spatial unit in each matrix (W); % NZW: Percentage of links with non-zero weights in the matrix W.

[3] PAN: Pantropical; ZAM: Zambia; ECU: Ecuador; PHI: Philippines.

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Table 4. Results of the Moran's *I* and Lagrange multiplier tests from the OLS models.

			Moran test of the residuals (normal approximation) [110] Alternative hypothesis, greater. [1]					Lagrange Multiplier test [111] [2]							
								SEM		R-SEM		SLX		R-SLX	
Country[4]	Level	N	I	Exp.	Var.	SD	p-val[3]	LM	p-val[3]	LM	p-val[3]	LM	p-val[3]	LM	p-val[3]
PAN	Macro-	49	0.41	-3.95E-2	1.04E-2	4.40	***	14.29	***	16.14	***	0.58	n.s.	2.42	n.s.
	Meso-	361	0.52	-8.96E-3	1.31E-3	14.74	***	203.44	***	174.25	***	37.12	***	7.93	**
	Micro-	3,035	0.58	-1.12E-3	1.71E-4	44.55	***	1,970.20	***	1,753.80	***	355.64	***	139.32	***
ZAM	Macro-	9	-0.18	-1.66E-1	3.84E-2	-0.09	n.s.	0.48	n.s.	0.08	n.s.	2.71	.	2.30	n.s.
	Meso-	70	0.23	-3.06E-2	6.05E-3	3.41	***	8.13	**	4.00	*	4.19	*	0.06	n.s.
	Micro-	1,016	0.58	-3.11E-3	4.63E-4	27.09	***	718.80	***	272.23	***	446.61	***	0.04	n.s.
ECU	Macro-	24	0.13	-8.47E-2	1.71E-2	1.64	.	0.71	n.s.	0.86	n.s.	0.02	n.s.	0.17	n.s.
	Meso-	212	0.29	-1.47E-2	2.17E-3	6.58	***	37.31	***	23.80	***	15.16	***	1.64	n.s.
	Micro-	865	0.35	-3.97E-3	5.28E-4	15.49	***	231.56	***	135.61	***	105.66	***	9.72	**
PHI	Macro-	16	-0.15	-7.53E-2	2.69E-2	-0.48	n.s.	0.68	n.s.	0.88	n.s.	0.03	n.s.	0.92	n.s.
	Meso-	79	0.10	-2.27E-2	5.88E-3	1.59	.	1.54	n.s.	2.87	.	0.40	n.s.	1.73	n.s.
	Micro-	1,154	0.40	-2.82E-3	5.21E-4	17.48	***	299.24	***	259.71	***	39.54	***	0.01	n.s.

[1] I: Moran's *I*; Exp.: Moran's *I* expected value under null hypothesis; Var.: *I* variance; SD: *I* Standard Deviate.

[2] LM: Lagrange Multiplier Test; R-: Robust LM Test; SEM: Spatial Error Model; SLX: Spatially Lagged X Model.

[3] p-val (p-values)

***: $<10^{-3}$

**: $<10^{-2}$

*: $<5.10^{-2}$;.: $<10^{-1}$; n.s.: $>10^{-1.}$

[4] PAN: Pantropical; ZAM: Zambia; ECU: Ecuador; PHI: Philippines.

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samples. At smaller administrative levels with bigger samples, *I* increases together with its standard deviation. Simultaneously, *I*s expected value and variance get closer to 0. Significances also reflect an increase in the tests with the smaller jurisdictional units within each country-specific sample. The aggregated pantropical models had the highest *I* values ranging from 0.41 to 0.58, just like the model for Zambia at the micro-level.

The Lagrange multiplier (LM) tests (Table 4) reported strongly significant results (considering a 1% threshold) for eight of the twelve samples as well. The eight samples showed significant coefficients for the error model (SEM) test. Six of the samples also described significant results for the lagged X model (SLX). Moreover, seven and three samples were also significant at the robust tests for SEM and SLX, respectively. Significance for both error (SEM) and lagged-X (SLX) models increased at smaller administrative units in the different country samples. The significant values of LM for error models were always higher than those for lagged-X models in all of the studied samples, for both normal and robust tests. More specifically, for both Moran's *I* and Lagrange Multiplier tests, the non-significant models were those of the macro-level in individual countries, with the smallest sample size, but also the model for the meso-level in the Philippines.

3.3 Model specification

We could specify a spatial model in nine of the twelve samples following the LeSage and Pace method. Table 5 shows the results of likelihood-ratio tests for the reduction of complex nested models, as described in Eqs 5 to 8.

We could not ratify the need of a spatial model in the samples at the macro-level for individual countries, but this was confirmed for the other nine samples (5%-significance

Table 5. Results of the spatial model specification, following the LeSage & Pace [32,36] method by Likelihood Ratios (LHR) and nested model restriction.

			SEM[1]		SLX[1]		OLS[1]		
Country[3]	Level	N	LHR	p-val[2]	LHR	p-val[2]	LHR	p-val[2]	Selected Spatial Model [1]
PAN	Macro-	49	0.56	n.s.	10.21	*	12.71	**	SEM
	Meso-	361	3.02	n.s.	172.50	***	188.98	***	SEM
	Micro-	3,035	133.63	***	1,804.10	***	2,000.90	***	SDEM
ZAM	Macro-	9	1.70	n.s.	0.08	n.s.	2.78	n.s.	None (OLS)
	Meso-	70	0.12	n.s.	7.36	**	7.90	*	SEM
	Micro-	1,016	37.59	***	686.60	***	808.74	***	SDEM
ECU	Macro-	24	5.41	n.s.	0.22	n.s.	6.04	n.s.	None (OLS)
	Meso-	212	10.82	*	36.63	***	48.89	***	SDEM
	Micro-	865	36.31	***	199.33	***	226.20	***	SDEM
PHI	Macro-	16	1.59	n.s.	0.73	n.s.	2.69	n.s.	None (OLS)
	Meso-	79	12.73	**	0.77	n.s.	15.52	**	SLX
	Micro-	1,154	14.43	**	265.63	***	281.91	***	SDEM

[1] SEM: Spatial Error Model; SLX: Spatially Lagged X Model; OLS: Ordinary Least Squares regression; SDEM: Spatial Durbin Error Model; LHR: Likelihood Ratio.
[2] p-val (p-values)
***: $<10^{-3}$
**: $<10^{-2}$
*: $<5.10^{-2}$;.: $<10^{-1}$; n.s.: $>10^{-1}$.
[3] PAN: Pantropical; ZAM: Zambia; ECU: Ecuador; PHI: Philippines.

https://doi.org/10.1371/journal.pone.0226830.t005

threshold). In five of them, the existence of neighbor interactions (spatially lagged X) was demonstrated and either SLX or SDEM was selected as the best model. This was the case for all the micro- and meso-level specifications for Ecuador and the Philippines. Furthermore, in eight of the twelve samples, a model which accounts for spatially dependent errors was selected, namely SEM or SDEM. These eight cases include all the specifications for the aggregated pantropical models (at the three spatial levels), and all the specifications at meso- and micro-level for individual countries excluding the Philippines' meso-level. In summary, from the twelve samples: three were not specified to any spatial model (and thus remained as OLS), one was assigned to a SLX model, three were acknowledged as a SEM model, and five were specified as a more complex SDEM model (all the micro-level samples and Ecuador's meso-level sample).

3.4 Model performance

Table A in S3 File provides a detailed list of global measures for the OLS and the spatial models. The OLS models have an adjusted R^2 between 0.70 and 0.95 and high statistical significances according to the results of the F-test. Just one sample, Zambia's macro-level, with only nine sample units, presented lower (but still significant) F statistics. In the case of the nine selected spatial models, the adjusted coefficients of determination range between 0.74 and 0.94, the highest being Philippines' micro-level and the lowest being the meso-level of Zambia. Only samples at Zambian meso- and micro- levels have a lower explanatory power (adjusted R^2) compared to the respective tests including data from all countries. The number of degrees of freedom of the spatial models was reduced with respect to the OLS models, in a number equal to the newly introduced parameters (one degree for the lambda error—in SEMs and SDEMs- and one degree for each variable of the model—in the SDEMs and SLXs-). The ranges for standard regression errors (SER) in the spatial models vary from 0.37 in Philippines meso-

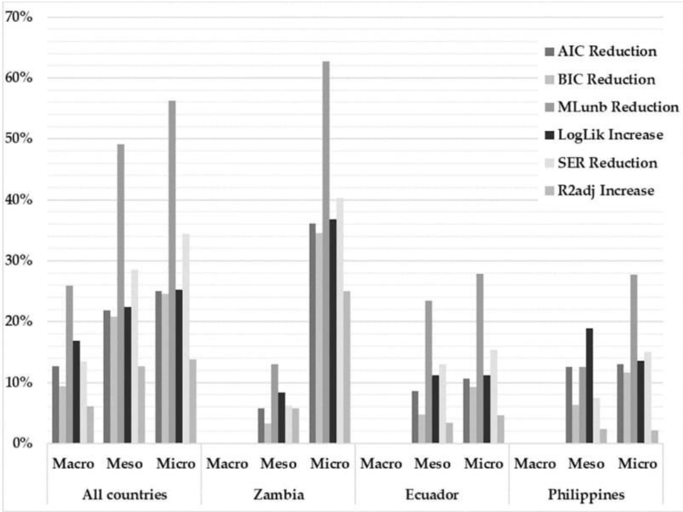

Fig 4. Improvement of the global measures for the spatial models compared to the respective OLS models: relative (in %) increase or reduction.

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level until a maximum of 0.66 in Ecuador's micro-level. The values for the inversed logarithmic likelihoods (logLik), for the Akaike and Bayesian information criterions (AIC, BIC), for the unbiased estimator of the error variance (ML_{unb}) and for the SERs increased gradually at smaller spatial levels within each countries' samples. By this, we can see that the models at smaller spatial levels perform better. The only exception to this was the ML_{unb} and SER values for Zambia's spatial model at micro-level, which decreased when compared to the meso-level.

Fig 4 shows how all the global measures were improved by the nine selected spatial models. This is displayed as relative increase or decrease of the original OLS parameter values. It is clearly noticeable that most of these proportional improvements gradually grow at the lower levels. This growth is especially strong in the micro-level SDEM in Zambia, where the highest values are observed for all the measures, while the SEM for the meso-level presented some of the lowest relative improvements. The models with the smallest improvements were the ones at the meso-level for individual countries (SEM in Zambia, SDEM in Ecuador, and SLX in Philippines) and the country-specific models at the macro-level by omission of spatial specification.

3.5 Spatial regression models

Tables 6 and 7 show the regression results of the specified models for the pantropical samples cross-scale and for the micro-level samples cross-country, respectively. In order to interpret the influence of the regression determinants on FC, all coefficient signs have to be reversed due to the transformation of the dependent variable (FC*).

Fig 5 provides a visual summary of the coefficients (and standard errors) of the seven variables in the selected models for the twelve samples (across level and country). Only the results of the determinants, which showed a significant contribution (considering a p-value threshold of 10%), are shown.

Only significant parameters (p-value threshold of 10%) are shown. Variables are linearized and standardized. In the case of non-spatial and spatial error models, the coefficients or effects

Table 6. Impacts for aggregated pantropical samples in specified spatial models.

		Macro-level (SEM)				Meso-level (SEM)				Micro-level (SDEM)			
		N = 49				N = 361				N = 3,035			
		Coef	SE	z-Val	P> |z|	Coef	SE	z-Val	P> |z|	Coef (Total)	SE	z-Val	P> |z|
Pantropical models	**λ(Err)**	0.51	0.13	3.97	***	0.72	0.04	18.99	***	0.72	0.01	56.18	***
	Inter	0.70	0.13	5.59	***	1.08	0.10	10.46	***	1.57	0.04	41.65	***
	A_{TOT}^	x	x	x	x	-0.09	0.05	-1.87	*	0.08	0.04	2.07	*
	PVA^	-	-	-	-	0.19	0.04	4.76	***	0.03	0.03	0.94	n.s.
	PP_{FA}^	1.19	0.09	14.01	***	1.63	0.05	31.90	***	1.89	0.04	45.96	***
	RD^	-	-	-	-	-	-	-	-	-	-	-	-
	FL^	x	x	x	x	x	x	x	x	x	x	x	x
	CSI^	0.27	0.07	3.97	***	0.21	0.04	5.37	***	0.28	0.36	7.87	***
	CY^	x	x	x	x	xx	xx	xx	xx	xx	xx	xx	xx

Coef: Coefficient; SE: Standard Error; x: variable eliminated by de model; xx: not applicable in this model; -: Collinearity > 0.6

^: linearized and standardized–variable

***: $<10^{-4}$

**: $<10^{-2}$

*: <10–1; n.s.: $>10^{-1}$.

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are displayed as total impacts. (Dir: Direct impacts. Ind: Indirect impacts (neighbors). Tot: Total impacts.) (ATOT: Total Area [ha]. PVA: Share of potential vegetation on surface area [%]. PPFA: Population pressure on remaining forest area [pers./ha]. RD: Road density [km/km2]. FL: Flatness: share of surface with less than 16% steepness [%]. CSI: Crop suitability index [%]. CY: Maximum cereal area yield [kcal/ha].)

Additionally, we provide Tables B-G in S3 File to assist during the analysis of this study's results. Namely, we compiled a detailed and comprehensive table on the descriptive statistics for all the variables used in each of the samples (Table B in S3 File), the results of the collinearity check (Table C in S3 File), the results for the simple regressions (Table D in S3 File), and the results for all OLS models and the non-significant spatial models for macro-, meso- and micro-level (Tables E, F and G in S3 File, respectively).

We can observe that the number of significant explanatory variables, the values of error term parameters (λ), and neighboring effects (θ), tend to increase at smaller administrative levels, in both the aggregated (Table 6) and country-specific models (Tables F and G in S3 File and Table 7).

Across all spatial sales and countries, PP_{FA} always depicts the strongest contribution to all models with the highest coefficients (around three to ten times larger than the other variables) and a negative influence on FC. The relative contribution of PP_{FA} to the models is gradually increasing at smaller levels, both in the pantropical models (from 1.19 to 2.14) and in the country-specific models. Together with PP_{FA}, either CSI or PVA are also present in the models for all the samples. On the one hand, CSI is significant in all pantropical samples, but with slightly smaller coefficients at lower spatial levels. This determinant always has a negative contribution to FC in all the models were it is significant (nine out of the twelve). On the other hand, PVA was significant in eight of the twelve samples (mostly meso- and micro-levels) with negative influence on FC in seven of those. The other variables showed a more differentiated pattern across scale and contexts. A_{TOT} presented smaller but significant impacts on FC with varying signs in only three of the twelve models. FL was included in all Ecuador-specific models only, where it influences FC positively. From the five samples where CY was available, it only had a

Table 7. Impacts for country-specific (and aggregated) samples at micro-level.

		SDEM—Spatial Durbin Error Model											
		Direct impacts: observed unit				Indirect impacts: neighboring units (lag X)				Total impacts			
		Coef	SE	z-Val	P>|z|	Coef	SE	z-Val	P>|z|	Coef	SE	z-Val	P>|z|
Zambia N = 1,016	Inter	0.87	0.06	13.70	***				λ(Err)	0.79	0.02	40.04	***
	A_{TOT}^	x	x	x	x	x	x	x	x	x	x	x	x
	PVA^	-0.09	0.02	-4.45	***	-0.04	0.05	-0.77	n.s.	-0.13	0.05	-2.45	*
	PP_{FA}^	1.21	0.03	35.16	***	-0.09	0.06	-1.63	n.s.	1.11	0.06	18.45	***
	RD^	0.01	0.02	0.47	n.s.	-0.12	0.05	-2.55	*	-0.11	0.06	-1.91	*
	FL^	x	x	x	x	x	x	x	x	x	x	x	x
	CSI^	0.15	0.02	7.09	***	0.22	0.05	4.48	***	0.37	0.06	6.59	***
	CY^	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx
Ecuador N = 865	Inter	1.26	0.05	25.62	***				λ(Err)	0.54	0.04	15.58	***
	A_{TOT}^	x	x	x	x	x	x	x	x	x	x	x	x
	PVA^	0.21	0.03	6.58	***	-0.14	0.06	-2.49	*	0.07	0.06	1.15	n.s.
	PP_{FA}^	1.86	0.04	49.84	***	0.25	0.06	4.27	***	2.12	0.06	37.33	***
	RD^	-	-	-	-	-	-	-	-	-	-	-	-
	FL^	-0.09	0.05	-1.61	n.s.	-0.15	0.07	-2.04	*	-0.23	0.05	-4.29	***
	CSI^	0.09	0.03	2.72	**	0.28	0.06	4.62	***	0.36	0.06	5.86	***
	CY^	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx
Philippines N = 1,154	Inter	2.44	0.03	81.80	***				λ(Err)	0.50	0.03	18.42	***
	A_{TOT}^	0.21	0.02	9.37	***	0.11	0.04	3.23	**	0.32	0.04	8.03	***
	PVA^	0.40	0.02	19.34	***	-0.04	0.02	-1.91	*	0.35	0.03	12.05	***
	PP_{FA}^	2.32	0.02	96.96	***	0.04	0.04	1.07	n.s.	2.36	0.04	54.17	***
	RD^	-0.31	0.02	-13.18	***	0.07	0.04	1.75	*	-0.24	0.04	-5.71	***
	FL^	x	x	x	x	x	x	x	x	x	x	x	x
	CSI^	x	x	x	x	x	x	x	x	x	x	x	x
	CY^	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx
Pantropical N = 3,035	Inter	1.57	0.04	41.65	***				λ(Err)	0.72	0.01	56.18	***
	A_{TOT}^	0.01	0.02	0.79	n.s.	0.07	0.03	2.10	*	0.08	0.04	2.07	*
	PVA^	0.18	0.02	11.07	***	-0.15	0.02	-6.16	***	0.03	0.03	0.94	n.s.
	PP_{FA}^	2.14	0.02	101.87	***	-0.26	0.04	-7.13	***	1.89	0.04	45.96	***
	RD^	-	-	-	-	-	-	-	-	-	-	-	-
	FL^	x	x	x	x	x	x	x	x	x	x	x	x
	CSI^	0.12	0.02	7.34	***	0.17	0.03	5.66	***	0.28	0.36	7.87	***
	CY^	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx

Coef: Coefficient; SE: Standard Error; x: variable eliminated by de model; xx: not applicable in this model; -: Collinearity > 0.6

^: linearized and standardized–variable

***: $<10^{-4}$

**: $<10^{-2}$

*: <10–1; n.s.: $>10^{-1}$.

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significant (negative) effect on FC in the macro-level OLS model for Ecuador. We detected a strong collinearity (correlation above 0.6, see Table C in S3 File) between RD and PP_{FA} in ten of the twelve samples. Thus, this variable was only included (and found significant) in two country-specific samples at the micro-level. The samples for Zambia's macro and meso-levels further showed strong collinearity between other variables, for instance between A_{TOT} and CSI, PP_{FA} or RD and between RD and CSI.

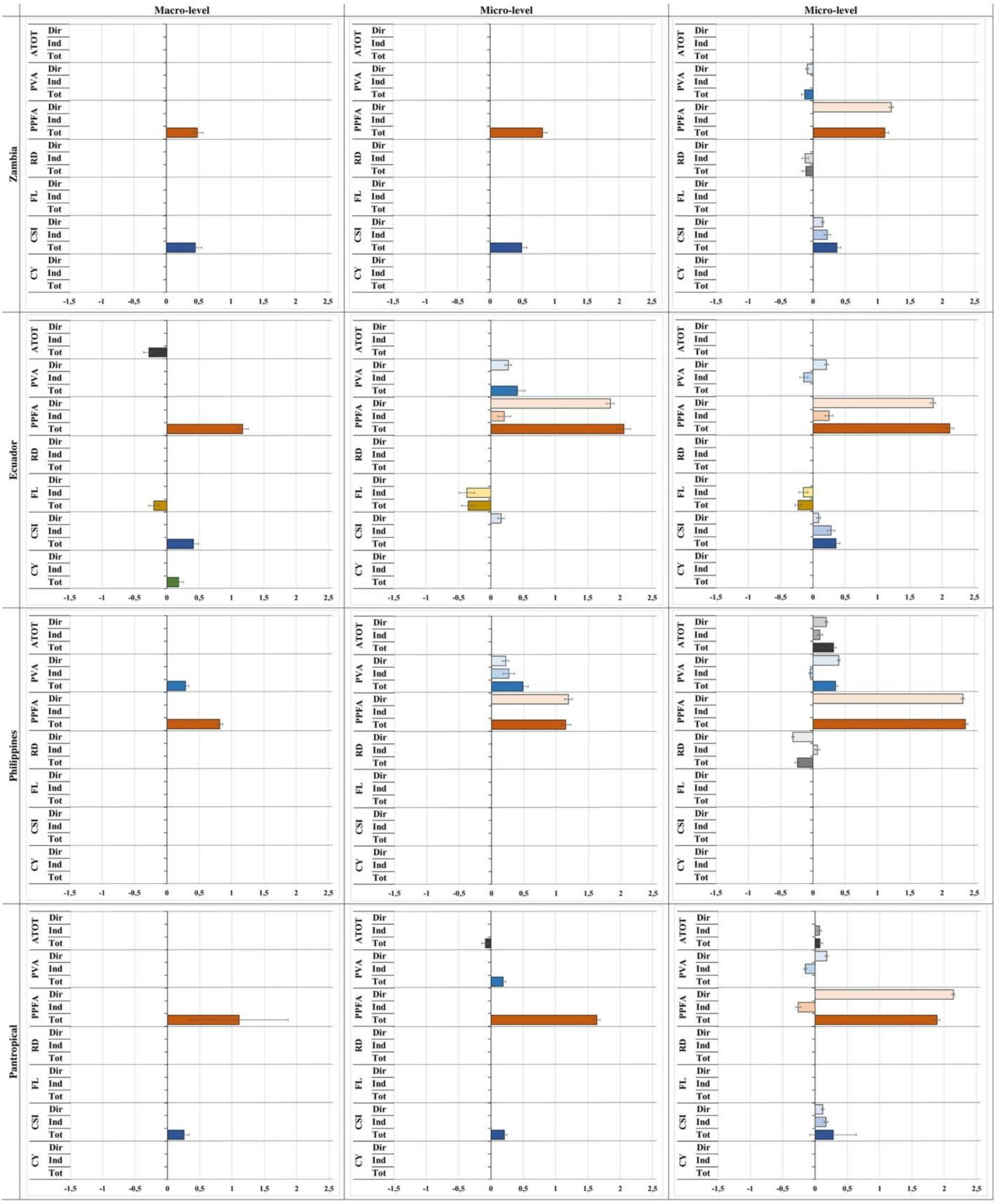

Fig 5. Coefficients and standard errors of the seven explanatory variables (drivers of deforestation) of the selected models for the twelve samples, across spatial level and country context.

https://doi.org/10.1371/journal.pone.0226830.g005

When observing the results for the micro-level analysis, where a SDEM including spatial errors and indirect impacts from neighbors was always specified (Table 7), we can identify more context dependencies. Neighbor effects are also observed in Philippines' and Ecuador's meso-level results. Although in general the total effects of the spatial models are similar, in direction and intensity, to those of the OLS models, we can see some particular exceptions. The variable RD in Zambia's micro-level, for example, loses its high significance in the SDEM model. In other cases, the indirect effects of the neighbors represent a relatively large or even more significant contribution to a variables' behavior than the direct effects. We can see this in Ecuador's results, for CSI and FL, and for Zambia's CSI as well as for the pantropical results' CSI and A_{TOT}. This is also true for Ecuador's FL and for Philippines PVA at meso-level. In some other cases, even the direction of the indirect impacts differs from the direct effects, while still in notable intensities and significance. This happens for PVA in Ecuador's and in the aggregated results, PP_{FA} in the aggregated model, and RD in the Philippines sample; all of them, at the micro-level. At the micro-level, the strongest and most significant effect of neighboring regions is observed in Ecuador and in the pantropical model.

In general, the error coefficients were higher in the pantropical models (0.51 to 0.72) compared to the respective country-specific models (0.43 to 0.54). The only exception to this is the highest spatial error coefficient (λ), which was identified in Zambia's micro-level sample (0.79). Moreover, the spatial error terms are relatively large in all SEM and SDEM models if compared to the other variable coefficients (except PP_{FA}).

4 Discussion

4.1 Insights from spatial econometrics

4.1.1 Econometric models of pantropical deforestation and spatial dependencies. We calculated highly significant econometric models with cross-section data applying a sigmoid function for different spatial levels and tropical contexts. This represents a first empirical attempt in scientific research on basis of an aggregated pantropical study. Both non-spatial and spatial regressions resulted in significant models of deforestation for different countries and jurisdictional levels (see Table A in S3 File).

However, we demonstrated spatial dependency and consequently, the use of spatial models was justified in at least nine of the twelve studied samples (Tables 4 and 5). Our results support Tobler's first law of geography [114], which implies that social and physical events are highly clustered in space. In these nine cases (all except for the country-specific macro-levels), the inclusion of spatial errors and/or spatially lagged Xs improved the explanatory power and the goodness of fit of the spatial models significantly. The application of this theory to drivers of deforestation has not yet been addressed intensively in empirical research. Our results indicate that neglecting spatial effects in this kind of studies can lead to several problems and misinterpretation, e.g. bias of coefficients, falsely classified predictors, or even opposite change of effect directions.

Before discussing our general findings into detail, we will highlight some of the methodological limitations and the potential for innovation of this study.

4.1.2 Methodological limitations and innovation. Understanding the influence of the spatial scale on drivers of deforestation constitutes a methodological and conceptual challenge. Especially, if generalizations on FC and deforestation rates are to be used as a framework for operationalizing adequate forest policies like REDD+ [115,116]. First, the assumptions and restrictions of complex spatial econometric models require cautiousness when interpreting causality or inference. For example, the chosen variables related to the most common drivers of deforestation can have some degree of endogeneity ([13,117]). Increasing population needs more roads, agricultural land and thus, results in reduced FC. But, at the same time, in areas with middle to high FC, as deforestation increases, more roads can be built, more land can be cleared and, thus, the number of people that can be supplied increases as well. Moreover, we detected and treated persistent collinearity (especially strong in Zambian samples), mostly between population and other variables, like road density. This warns us to be especially careful with the analysis of these cases and suggests the thorough exploration of the relations between selected determinants in similar approaches. Besides, due to the nested multi-level design of our study, our samples had very different sizes ranging from 9 to over 3,000 units, which has to be kept in mind again when comparing the respective results.

As often discussed, the results of spatial models can be very different depending on the neighbor matrix and the specified model [118]. The spatial weights matrices (*W*s) based on the SOI method resulted to be an improved alternative to reflect the spatial interactions in the twelve very heterogeneous samples [118,119]. As with other graph-based matrices such as Delaunay triangulation or Gabriel *W*, SOI presented advantages to other–and more commonly used–contiguity (e.g. rook, queen) or distance-based *W*s. For instance, all the resulting *W*s were symmetric (if *i* is neighbor of *j*, *j* is neighbor of *i*), and row standardization allowed for proportional weights when features had unequal number of neighbors. Moreover, this type of spatial weight does not need a common border between units, which allowed us to work with close island regions as neighbors like in the case of the Philippines. Moreover, this type of matrix enabled working with separated blocks, for instance treating and comparing different countries in the aggregated sample. The SOI matrix and a local model specification fulfilled the purposes of our study providing relevant answers to our research questions.

Our proposed econometric models deal with the issue of spatial autocorrelation or spatial dependency of the observations (endogenous/exogenous variables or error terms). Spatial autocorrelation exists due to a diversity of phenomena related to measurement (choice of observation unit), externalities or spillovers. Our selected nested models allowed us to compare impacts between parameters and provide generalized spatial models of deforestation, which could be compared to each other as well. However, further studies with similar approaches could explore other types of commonly used spatial regression models, which present other advantages or possibilities for the analysis. For example, gobal spatial models (such as the classical Spatial Durbin Model) are based on simulations and imply more complex interactions, as the changes in neighbors' FC affect the FC in all the system units [120,121]. Another option are geographically weighted regression (GWR) models, which deal with another kind of spatial phenomena–although related to autocorrelation-, namely: spatial heterogeneity, heteroscedasticity, spatial non-stationary or structural instability in space. Therefore, in GWR models, the explanatory variables can have different effects or parameters at different points, and the error term may vary spatially as well. This is why GWR models are normally considered as a good exploratory method to visualize non-stationary phenomena [122–124].

Other options for further analysis could be the use of spatial panel data models or laying the focus on deforestation rates as dependent variable [120,125]. An analysis of this type could reflect the forest trajectory of each particular administrative unit, but it would imply further methodological compromises. For instance, it would need harmonized information about land (forest) cover and its drivers for the three countries at different points in time. Including more variables or indicators for drivers of deforestation could also brighten the opportunities for further analyses. On the one hand, the availability and the quality of the existing information vary significantly across spatial and jurisdictional levels. Some of this information is normally missing or problematic to obtain at subnational levels, especially in developing tropical countries. For instance: economic, agricultural or land use data are normally collected and summarized at national or regional level for international reporting, or sometimes available but in different formats or quality standards (e.g. CSI and CY). Another example is the reliability of the available administrative boundaries themselves in resembling the actual political scenarios on the ground. Normally, official governmental boundaries do not acknowledge customary management and governance schemes, such as chiefdoms in Zambia, indigenous territories in Ecuador or ancestral domains in the Philippines [126,127]. Moreover, this boundaries are frequently unsure or inaccurate, due to a combination of an on-going modernization of the technical mapping capacities of the relevant institutions, and in some cases, regional tensions and disputed boundaries [128,129]. But on the other hand, the existing data on global deforestation and related drivers (e.g. [1,72,130]) is constantly increasing and more new sources are regularly updated at medium to high resolution. This fact creates promising room for innovative approaches and new research directions.

4.2 Scale and context dependency of deforestation drivers

4.2.1 Constant leading impact of population pressure and land suitability for agriculture. As expected and in line with previous studies [13,26], we empirically identified population pressure (i.e. PP_{FA}) and land suitability for agriculture (CSI or PVA) as the main recurrent pantropical drivers of deforestation. While previous studies have been focusing on specific administrative levels or specific countries, our models show that this phenomenon occurs across all jurisdictional levels and different tropical contexts.

Moreover, demographic pressure, which expresses the need for agricultural land and infrastructure at the expense of natural resources, has by far the highest (negative) influence on FC. Its standardized impacts are five to ten times larger than those for the other significant determinants. Thus, our study not only confirms the constant negative impact of population pressure on FC, but it empirically demonstrates its leading influence across different regions and jurisdictional levels. These results suggest, that it is the best 'stand-alone' indicator for FC change across contexts and scales [30,131,132].

The influence of demographics is combined and intensified by the natural conditions of the land, expressed by the crop suitability index and the share of potential vegetation area. Constantly influential across scale and context, higher land suitability for agricultural production triggers the conversion of forests to such. This highlights the importance of competition for land between different forest and alternative land uses–and their respective opportunity costs–as a recurrent universal phenomenon in forest-agriculture frontiers [133,134].

4.2.2 Scale dependency: Heterogeneity at local levels. We could recognize recurrent and clear differences across spatial levels. In general, the number of explanatory variables increases at more local scopes, in both the aggregated and country-specific results. Moreover, the quality and the statistical significance of the models increases with smaller administrative units, while their explanatory power decreases. This is due to the heterogeneity and the larger sample size of the lower levels, which is not yet completely explained by the tested variables. In addition, strong spatial errors and larger Moran's *I*s of the residues, suggest that important spatially correlated variables might have been omitted, especially at the lower levels. Smaller jurisdictional units require more complex models, which account for both larger spatial errors and stronger neighbor interactions [37]. Our results confirm the evidence from the literature and previous studies, which is rich in local-scale cases that exhibit complex patterns and processes of coupled human and natural systems [10,13,135].

Furthermore, the studied drivers influence FC with varying intensities and directions depending on scale and the regional context. The impact of demographics, for instance, gains strength at smaller administrative units across contexts, while the variables associated with agricultural suitability (CSI for Ecuador, Zambia and pantropical models, PVA for Philippines' model), present similar ranges of intensities across scales. This could be representing a more direct pressure on the natural resources and signifying the human competition for land in systems with narrower limits [136]. Likewise, when analyzing the results of the pantropical models, the area size of the administrative unit apparently has a negative influence on forest at the micro-level, but positive at the meso-level. Although this impact is relatively little if compared with the ones of other determinants, it is related to the existence of small units within urban areas at the micro-level. According to our definitions, these areas result in high FC as most of its limited potential vegetation area comprises natural parks and tree areas, but little pastures, crops or grasslands.

4.2.3 Context dependency: Particularities of the countries. Some context-specific findings of our study can be highlighted. The larger error coefficients (λ) of the pantropical models indicate the importance of some omitted variables that account for these contextual differences. The missing factors could be related to regional, geographic or ecological dissimilarities of the three countries.

In the case of Zambia, the variable potential vegetation area had a positive influence on FC. This might be representing the relevance of woodland areas and shrubs and their compensation effect when being used or classified as forests [126,137]. Another possible explanation could be the land cover information used, which is generalized for Africa and does not distinguish between the varying and complex forest ecosystems in the country, ranging from evergreen closed forests to open miombo or mopane woodlands and bushlands [58,138,139]. Furthermore, the lower quality and explanatory power of the models, together with their higher spatial errors (especially at the micro-level), clearly suggest that the models could not capture another determinant, which is less relevant at district or province level. As suggested by other authors [46,58], this could be related to the existence of more local events such as fire occurrence or wood extraction for charcoal and fuel production. Furthermore, we observe a less important role of demographics in comparison to Ecuador and Philippines, most likely due to the lower population density.

Besides, Ecuador has the models with the most significant independent variables, explaining the heterogeneity of the country at all spatial levels from an ecological and socio-economic perspective. Flatness, for example, was positively correlated with deforestation at all spatial levels, only in this country. This might be due to the more diverse geographic conditions and the larger differences between the steep Andean slopes with historical deforestation and the lowland areas as a current deforestation frontier [140,141]. Similarly, cereal yield was significant at the macro-level of Ecuador only, and associated with deforested provinces. At this large-scale picture of the country, cereal yields for maize and rice are much higher in the coastal and central areas, where the cultivation of these crops is more extended and more commercially oriented [142]. In these provinces, relatively little or almost none forest is left. At the same time, indigenous groups with a more subsistence oriented crop production inhabit large areas of the Amazon with lower agricultural yields [142,143]. These results might reflect the importance of effective and conscious territorial organization [144], like the particular governance schemes taking place at the different spatial levels in the country [127,145].

The models for the Philippines included the smallest number of significant explanatory variables, and population pressure is apparently explaining FC change almost exclusively. It is important to understand the archipelago condition of this highly populated country, plus its late/post- transition context, in which massive deforestation has already taken place resulting in the actual national forest-agriculture mosaic [146,147]. This might also be the reason why factors like the crop suitability index are not significant, in contrast to the other countries where higher deforestation rates are still observed. However, the uniform and substantial contribution of the share of potential vegetation area to the model might be capturing this influence of key deforestation and degradation drivers, such as agricultural expansion or forest product extraction [148]. A last remark must be made regarding the omission of flatness in the three spatial levels. This is observed despite the biophysical heterogeneity of the Philippines, a country which has even been using a slope threshold to legally define forestland [149]. For decades, all areas above 18% of slope have been classified by the Philippine institutions as forestland regardless of whether any tree cover was present, because of their location in mountain ranges or in hardly accessible areas where forest was (usually) found [150].

4.2.4 The impacts of neighbors: Defining the system limits. It is important to understand that the effects of many socioeconomic, political and ecological drivers of de- and reforestation are often perceived at other spatial levels or at different jurisdictional units than those ones where the actual causes are being generated [17]. For example, national, regional or global decisions from private and/or public actors regarding forests and agriculture (e.g. trade agreements or conservation policies), might help intentionally or not in halting or increasing deforestation at different smaller geographical contexts [151–153]. Similarly, but on the opposite direction, both community decisions referring to priority areas for protecting forest functions, as well as land use/cover changes related to local income or opportunity costs, might turn relevant on provincial, national or international levels, sometimes even in conflict with private or governmental interests [2,154,155]. These connections between neighbors and hierarchies are not always easy to identify, quantify and weight, as they are a miscellaneous result of geographical, historical, political, economic and even random conditions that may vary from region to region.

The results for the indirect impacts provided by the spatial models at the smaller levels offer some interesting insights and room for discussion. For instance, the neighbors' suitability for crop production (in Ecuador and Zambia) even has a stronger influence on FC than the unit of analysis itself. We can observe the exact same behavior between adjacent units (stronger impacts of neighbors) in Ecuador with other variables of higher resolution, like flatness or population. Moreover, we also identified these interactions in the results for the potential vegetation area in the Philippines' at meso-level. In some other cases, the neighbors influence FC with inverse directions. If we analyze the pantropical model, for example, larger potential vegetation areas and population densities in the neighboring units apparently release the pressure on forest. Furthermore, the influence of neighboring units on deforestation at meso-level appears to be more significant in Ecuador and Philippines than in Zambia. Perhaps, because the smaller size of the counties (Ecuador) and provinces (Philippines) allows these interactions to happen, if compared with the larger districts in Zambia. Other reasons could be the contrasting geography of the countries, the obvious differences on connectivity (e.g. islands vs. landlocked) and infrastructure, or other data-driven explanations such as the use of a non-realistic neighboring matrix and the quality of Zambia's unofficial boundary dataset [52]. Moreover, these neighbor interactions between provinces and administrative regions do not seem to be relevant at the macro-level in any of the countries, individually or aggregated.

In any case, our results are empirical evidence that certain deforestation forces occur independently of de jure governance boundaries; thus, they should be addressed setting broader and more flexible system limits, which consider the complex socio-ecological characteristics of each particular landscape.

4.3 Policy implications: The scale of REDD+

Policy design usually takes place on different interacting levels, such as international conventions, national laws, regional policy programs and local on the ground initiatives. The degree of federalism and decentralization differs among countries. Developing countries often have highly complex laws and regulations, which are, however, frequently inconsistent among concurring policy resorts or governance hierarchies and therefore unclear. Additionally, low capacities and weak law enforcement impede the governance process [156,157]. A clear example of this are the challenges and difficulties often faced during the design and implementation of REDD+ programs on the ground [158–160]. In order to ensure the success of such measures and reach both global and local objectives, there is a need for coordinated coherent policy design [14,160,161].

Our results indicate that anticipating demographic development and harmonizing forest and agricultural policies with increasing population pressure are of highest priority at all spatial levels and across countries. However, the strikingly strong relationship between demography and FC could indicate clear limitations of sectoral policy far beyond forestry, agriculture or even beyond bioeconomy. Although the main drivers of tropical deforestation are strongly dominated by socio-economic factors (e.g. demographic and infrastructure development), they are sensitive to the context and spatial scale, thus being case specific. Our findings stress the importance of taking context-specific factors into account, especially at smaller spatial scales. The varying spatial interactions between neighbors and drivers suggest a demand for flexibility when setting system boundaries in forest-related policy. Thus, depending on the specific tropical context and scale, a different spatial focus (beyond the existing *de jure* governance configurations) might be needed, in order to design effective measures, which halt deforestation.

Our results highlight the need for coherence between forest conservation and management policy implementation from national to local level on the one side. On the other side, they signalize the need for suitable demographic and agricultural policies across scales and countries. These raises some questions in line with frequent discussions [16,160], such as how sustainable and efficient conservation and restoration measures can be in highly populated areas or in societies with weak governance.

5 Conclusions

Our study represents a first attempt of generating econometric models of pantropical deforestation that consider subnational administrative units. We were successful in providing highly significant models that quantify the influence of commonly identified drivers of deforestation for different tropical contexts and spatial levels. We also demonstrated that neglecting spatial effects in this type of studies can lead to several problems or misinterpretations.

We conclude from our findings that the enforcement of policy instruments should start from common entry points at the international level and has to be then modified and adapted to particular national, regional or local conditions. International and national policy makers should focus on addressing demographic/infrastructure development and overcoming conflicts with agricultural purposes, while designing the framing conditions for efficient land use planning and policies. This can only be effective if global, national (large scale) REDD+ policy leaves enough flexibility for smaller scale adaptation of the policy frameworks to the respective socio-ecological conditions. Some successful examples of this are decentralization efforts such as 'landscape approaches' or participatory and community-based forest management, as long as broader national and international political commitment is present [162,163].

Supporting information

S1 Fig. Forest transition phases according to different categorizations and expected situation of the selected countries within the forest transition curve. Forest Cover (FC) vs. Socio-economic development (above). Annual Forest Change Rate (AFCR) vs. Socio-economic

development (behind): (a) FAO (2015)–FC: Forest cover; AFCR: Annual forest change rate. (b) Angelsen and Rudel (2013)–Quote: "The FT framework suggests that over time a country (or region) moves through three stages: (1) high forest cover and low deforestation ("core forests"), (2) accelerated deforestation and shrinking forest cover ("frontier forests"), and (3) stabilization and eventual reversal of the deforestation process ("forest-agricultural mosaics")". (c) da Fonseca et al. (2007)–HFLD: High FC (>50%), Low Deforestation rate (AFCR > -0.22%/yr.)–HFHD: High FC (>50%), High Deforestation rate (AFCR < -0.22%/yr.)–LFHD: Low FC (<50%), High Deforestation rate (AFCR < -0.22%/yr.)–LFHD: Low FC (<50%), Low Deforestation rate (AFCR > -0.22%/yr.). (d) Hosonuma et al. (2012) Pre-transition: FC>50% and AFCR > -0,25%, Late transition: FC < 15% or AFCR = 0% or decreasing AFCR, Post-transition: FC < 50%, Early transition: Remaining cases.
(TIF)

S1 File. Geodatabase. Compressed file including Excel tables and ESRI shapefiles with the variables for all the samples.
(7Z)

S2 File. R Script used for statistical analysis.
(R)

S3 File. Supporting information. Table A: Global measures of the models. Table B: Descriptive statistics. Table C: Multi-collinearity results. Table D: Simple linear regressions. Tables E, F, G: Impacts for the additional OLS and spatial models.
(PDF)

S4 File. Executive summary of the main findings.
(PDF)

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Author Contributions

Conceptualization: Rubén Ferrer Velasco, Margret Köthke, Melvin Lippe, Sven Günter.

Formal analysis: Rubén Ferrer Velasco.

Funding acquisition: Sven Günter.

Investigation: Rubén Ferrer Velasco, Margret Köthke, Melvin Lippe, Sven Günter.

Methodology: Rubén Ferrer Velasco, Margret Köthke, Sven Günter.

Project administration: Sven Günter.

Resources: Rubén Ferrer Velasco, Sven Günter.

Software: Rubén Ferrer Velasco.

Supervision: Margret Köthke, Melvin Lippe.

Validation: Margret Köthke, Sven Günter.

Writing – original draft: Rubén Ferrer Velasco, Margret Köthke.

Writing – review & editing: Rubén Ferrer Velasco, Margret Köthke, Melvin Lippe, Sven Günter.

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Publication 2: Forest mapping across pantropical deforestation contexts

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Towards accurate mapping of forest in tropical landscapes: A comparison of datasets on how forest transition matters

Rubén Ferrer Velasco [a,b,*], Melvin Lippe [b], Fabián Tamayo [c,1], Tiza Mfuni [d,2], Renezita Sales-Come [e], Cecilia Mangabat [f], Thomas Schneider [g], Sven Günter [a,b]

[a] Ecosystem Dynamics and Forest Management Group, School of Life Sciences, Technical University of Munich (TUM), 85354 Freising, Germany
[b] Institute of Forestry, Johann Heinrich von Thünen Institute, 21031 Hamburg, Germany
[c] Departamento de Ciencias de la Tierra, Universidad Estatal Amazónica (UEA), 160101 Puyo, Ecuador
[d] Center for International Forestry Research (CIFOR), 50977 Lusaka, Zambia
[e] Department of Forest Science, Visayas State University (VSU), Baybay City, 6521, Leyte, Philippines
[f] College of Forestry and Environmental Management, Isabela State University (ISU), 3328 Cabagan, Isabela, Philippines
[g] Institute of Forest Management, School of Life Sciences, Technical University of Munich (TUM), 85354 Freising, Germany

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ABSTRACT

Tropical forests represent half of the Earth's remaining forest area, but they are shrinking at high rates, which poses a threat to their multiple ecosystem services. As a response, international environmental agreements and related programs require information about tropical forested landscapes. Despite the increasing quantity and quality of remote sensing-based data, the effective monitoring of forests in the tropics still faces operational challenges: (a) applicability at local levels, with lack of reference or cloud-free information; (b) overcoming geographical, ecological, or biophysical variability; (c): stratification, distinguishing forest categories related to functionality and disturbance history.

We conducted an extensive ground verification campaign through 36 landscapes in 9 regions of Zambia, Ecuador and Philippines, which constitute a gradient of pantropical deforestation contexts or forest transitions. We collected over 16,000 ground control points and digitized over 18,000 ha with details on land use and forest disturbance history. We trained a random forest algorithm and generated high-resolution (30 m) binary forest maps covering ~15 Mha, building on 39 optical (Landsat-8), radar (Sentinel-1) and elevation bands, indices and textures. We validated the quality of the outputs across the studied deforestation gradient and compared them to (a): 3 national land cover maps used for international reporting, (b): 4 global forest datasets (Global Forest Change, Copernicus Land Cover, JAXA and TanDEM-X Forest/Non-Forest).

Our method generated highly accurate (92%) forest maps for the studied regions when compared to the global datasets, which generally overestimated forest cover. We achieved accuracies similar to the national maps, following a standardized method for all countries. The difficulties in delineating forest increased in more advanced stages of deforestation, with recurring struggles to distinguish non-forest tree-based systems (e.g. perennials, palms, or agroforestry), shrublands and grasslands. Regrowth forests were repeatedly misclassified across contexts, countries and datasets, in contrast to reference or degraded forests. Our results highlight the importance of in situ verification as accompanying method to establish efficient forest monitoring systems, especially in areas with higher rates of forest cover change and in tropical regions of advanced deforestation or early reforestation stages. These are precisely the areas where current REDD+ or Forest Landscape Restoration initiatives take place.

* Corresponding author at: Institute of Forestry, Johann Heinrich von Thünen Institute, 21031 Hamburg, Germany.
E-mail address: ruben.weber@thuenen.de (R. Ferrer Velasco).
[1] Current Affiliation: The Nature Conservancy, Ecuador office, 170135 Quito, Ecuador.
[2] Current Affiliation: Department of Geography, College of Earth and Mineral Sciences, Pennsylvania State University, PA 16801, USA.

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1. Introduction

Tropical forests represent almost half of the Earth's remaining forest area, but continue to shrink at relatively rapid rates (FAO and UNEP, 2020), while suffering processes of degradation and landscape fragmentation (Taubert et al., 2018; Vancutsem et al., 2021). The drivers of these dynamics, which are mostly anthropogenic and related to land use (LU) (Curtis et al., 2018; Seymour and Harris, 2019), pose a threat to the multiple ecosystem services and functions provided by tropical forests (Wilson et al., 2017). With the objective of tackling these pressures, several international environmental agreements (e.g. Agenda 2030 for Sustainable Development, Paris Agreement) currently promote numerous programs for the conservation, rehabilitation and sustainable use of forests in tropical landscapes. Some globally relevant examples of established initiatives are the Forest Landscape Restoration (FLR) projects within the Bonn Challenge, or arrangements supported by the Reducing Emission from Deforestation and forest Degradation program (REDD+).

In order to appraise the achievement of international environmental objectives fairly and effectively, forest cover (FC) and its change have to be coherently analyzed across territories, with certifiable methodologies and common metrics (GFOI, 2020; Harris et al., 2018). This is a precondition for drawing sound conclusions about the contributions of these programs to sustainable development. The field of remote sensing offers a low-cost, ready and reliable source of information for individual countries to meet their reporting needs. During the last decades, the availability, quantity and quality of satellite sensors and FC or Land Cover (LC) and LU (LCLU) maps with enhanced spatial and temporal resolution has improved drastically (Galiatsatos et al., 2020; Grekousis et al., 2015). Yet, establishing such operational systems of Measurement, Reporting and Verification (MRV) or National Forest Monitoring (NFM) is particularly challenging in tropical countries. Some known reasons are the lack of national forest inventories or frequently-updated national LCLU maps, limited technical expertise and resources, or the absence of good governance and administrative capacity (Ochieng et al., 2016).

Global forest datasets grant methodological comparability between regions and contexts by considering a larger spatial scope. Thus, they are often presented as an inestimable basis to establish REDD+ reference levels, or to quantify FC and its change at national or regional scales. For instance, the Global Forest Change (GFC) dataset (Hansen et al., 2013), Globeland30 (Chen et al., 2015), or the Copernicus Global Land Service LC Layers (CGLS-LC100) (Buchhorn et al., 2020), are commonly mentioned in MRV or NFM guidelines (Finegold et al., 2016; GFOI, 2020). However, global and regional FC maps must be used cautiously and only under certain circumstances (Tropek et al., 2014). Namely, as a cross-check to the national mapping capacities (if extant), or as a temporary step to developing such proficiencies (Harris et al., 2018; GFOI, 2020). We summarize the technical limitations of global forest datasets in the following interrelated operational challenges.

First, global FC datasets are not always accurate at local spatial levels. The low accuracies in specific landscapes are partly related to a lack of reference/auxiliary data, such as reliable and detailed in situ information (Fritz et al., 2011). Additionally, inconsistencies may occur between the temporal or the spatial coverage of regional or global maps and the scope of local analysis, together with incongruities between the pixel size of global maps (sometimes of medium to low resolution) and the size of the targeted LCLU patches on the ground. Moreover and especially in the tropics, areas with permanent cloud cover result in low quality or non-existing observations (Hilker et al., 2012). In this respect, Synthetic Aperture Radar (SAR) is a promising technology, as its observations are not affected by sunlight or cloud presence. Its potential for regional forest monitoring (alone or in combination with optical sources) is being explored by current research (Joshi et al., 2016), and the first SAR-based global forest maps have been published already (Martone et al., 2018; Shimada et al., 2014).

Second, the accuracy of global forest datasets varies regionally due to ecological, biophysical and biochemical dissimilarities (e.g. different seasonality, tree height/canopy, water content) of the vegetation between biomes and geographical areas (Crowther et al., 2015; Yang et al., 2017). Distinct forest definitions (based on the minimum size of forest extent, canopy cover and tree height thresholds, or the level of detail of LU) are adequate and accepted in each country or territory depending on the reporting purposes (Harris et al., 2018). Matching remote sensing derived classes, which are based on physical thresholds, with national surveys built on definitions of countries or organizations, can be burdensome. For instance, very different tree cover (TC) thresholds of the GFC match the specific forest characteristics of different territories (Galiatsatos et al., 2020; Hansen et al., 2013). Moreover, the change dynamics and the drivers of deforestation often differ strongly between regions (e.g. industrial crops/plantations vs. smallholding) (Curtis et al., 2018; Ferrer Velasco et al., 2020). All these contextual differences make it challenging to establish consistent methods of forest classification and definition, which are equally accurate and reliable across the globe.

Third, the accurate differentiation of forest types over large geographic extents still faces some technical burdens. Certain physical variables (e.g. biomass, tree height/cover) have been estimated and mapped globally, but still with issues regarding their validity in the tropics (Hansen et al., 2013; Potapov et al., 2021; Spawn et al., 2020). It is even more challenging to make classification methods match forest definitions, which are based on LU and distinguish between disturbance levels or forest functions (Putz and Redford, 2010; Vancutsem et al., 2021). Similarly, improving the capacity to identify forest stands or certain tree species (e.g. invasive, commercially interesting or selectively logged) could be applied for the effective monitoring of forest degradation or disturbance levels (Fassnacht et al., 2016). These limitations worsen when mapping multifunctional tropical landscapes, which are characterized by mixed fast-growing types of forest and non-forest tree-based systems (Caughlin et al., 2020). A promising application is time series analysis, which can provide valuable insights on LCLU history (Winkler et al., 2021; Woodcock et al., 2020) or on the ecological characteristics of the forest (Jha et al., 2020).

In this study we use data collected in situ across thirty-six tropical landscapes in Africa, South America and Southeast Asia, to generate forest cover maps that combine information from active and passive remote sensing systems. We test the accuracies of such maps and those of other secondary sources which are commonly used for NFM or MRV in the studied regions. With this, we aim to explore the ability to accurately delineate forest in the tropics with up-to-date methods, while studying the influence of different deforestation contexts and LCLUs s on the quality of forest mapping outputs.

2. Conceptual framework and objectives

2.1. Hypothesis

We hypothesize that the deforestation contexts and the associated forest disturbance regimes have an impact on the classification accuracies of forest maps, because they are an exemplification of the problems of geographical variability and the separation of vegetation types. We theorize that this influence might be mostly related to the degree of deforestation/degradation and to the number and proportion of land cover classes, independently of the classification method/dataset or the analyzed region. The framework of how we conceptualize deforestation contexts and forest disturbance regimes is presented in the following subsection, which is then followed by the research questions of this study.

2.2. Forest transition: deforestation contexts and forest disturbance regimes

The forest transition theory describes a process of net forest area decline and re-expansion as a result of socio-economic development

(Mather, 1992), which has been reported for several nations and regions worldwide (Köthke et al., 2013; Meyfroidt and Lambin, 2011). One of the most common uses of this theory has been the classification of territories into different transition stages based on their FC and deforestation rates, to analyze the related drivers and design effective polices correspondingly, such as the specific regulations related to REDD+ (Angelsen and Rudel, 2013; Hosonuma et al., 2012).

Based on the aforesaid literature, regions passing through these phases build a gradient of what we call *deforestation contexts*, characterized by specific forest disturbance regimes and pertinent policies:

(a) In an *initial* deforestation context, also known as 'pre-transition' or 'before the frontier', FC is high (close to the potential natural vegetation) and deforestation is still low or inexistent. In this phase, mature forests are abundant, while conservation measures and sustainable concession policies are encouraged. Measures based on timber certification, control of imports/exports, such as the EU's FLEGT Action Plan (Forest Law Enforcement, Governance and Trade), aim to operate at this level.
(b) At some point, deforestation and degradation increase and accelerate, in what is known as 'early transition' or 'frontier area' phases, eventually entering a *middle* deforestation context. These stages are characterized by an increased proportion of disturbed and degraded forests and by the suitability of direct regulation measures (e.g. protected areas, LU zoning) and efforts to reduce the extensive agriculture rent. Gradually, FC decreases at the expense of deforested vegetation (e.g. crops or grasslands), reaching what is typically known as 'late transition' or 'forest-agricultural mosaics'.
(c) Eventually in an *advanced* deforestation context, deforestation rates decrease and are ultimately reversed into net positive reforestation rates. This results on an increased proportion of natural (forest succession) or artificial (forest plantations) forest regrowth, occurring in areas which had previously been clearfelled and converted to other LCLUs. This shift into the so-called 'post-transition' phase can be catalyzed by different drivers, such as (a) the abandonment of forest lands due to forest scarcity or diminished agricultural rent, or (b) by structural and policy changes due to economic development. Regions in these advanced stages are also appropriate for direct regulation (e.g. LU zoning and active reforestation: FLR measures) and for environmental policies to increase forest rent and its capture, together with the intensification of the agricultural sector.

2.3. Research questions

Building on the forest transition theory as conceptual framework and considering the challenges of using earth observation approaches in tropical forest areas as described above, we focus on the following research questions, which will later serve as structure to organize the discussion section:

(1) Can we develop a methodology for the accurate delineation of FC in different tropical regions?
(2) How good are the classification accuracies of our forest maps and other global sources in the selected countries/regions, when compared to the existing NFM used for international reporting?
(3) How do the different deforestation contexts and their associated forest disturbance regimes influence the results of regional forest mapping in tropical landscapes?

The first two questions are methodological steps to address the main research problem: exploring the influence of de−/reforestation stages on the produced forest maps. Our results can help to establish pathways towards coherent LU planning and sustainable forest management, while improving the knowledge about monitoring of forest disturbance regimes. We want to further understand how to produce consistent forest maps and achieve satisfactory accuracies for the effective monitoring with both conservation and restoration purposes. Such improvements can facilitate the establishment of forest strata to meet the activity data requirements of REDD+ and to efficiently monitor FC in FLR projects. We test our hypothesis in multifunctional landscapes with LCLU dynamics representative of very diverse tropical regions, aiming to establish conclusions and generalizations at pantropical level.

3. Materials and methods

3.1. Study design: selection of landscapes, regions and countries

Our research is based on data collected through thirty-six landscapes of approximately 10,000 ha each (Fig. 1), distributed in equal number among nine regions of three tropical countries in Africa (Zambia), South America (Ecuador) and Southeast Asia (Philippines). These landscapes are all study sites of the larger research project Landscape Forestry in the Tropics (LaForeT: www.la-foret.org), coordinated by Germany's federal research organization Thünen Institute of International Forestry and Forest Economics. Each of the landscapes was positioned within the boundaries of an independent jurisdictional unit (chiefdom, parish or municipality in Zambia, Ecuador and Philippines, respectively) to ensure homogeneous formal administration. They were all selected as multifunctional landscapes, thus capturing a diversity of forest and LCLUs of the corresponding region representatively, together with characteristic LCLU change dynamics. The nine selected regions comprise a diversity of biophysical, geographical, socioeconomic and demographic settings, in order to facilitate generalizations from a broader pantropical perspective.

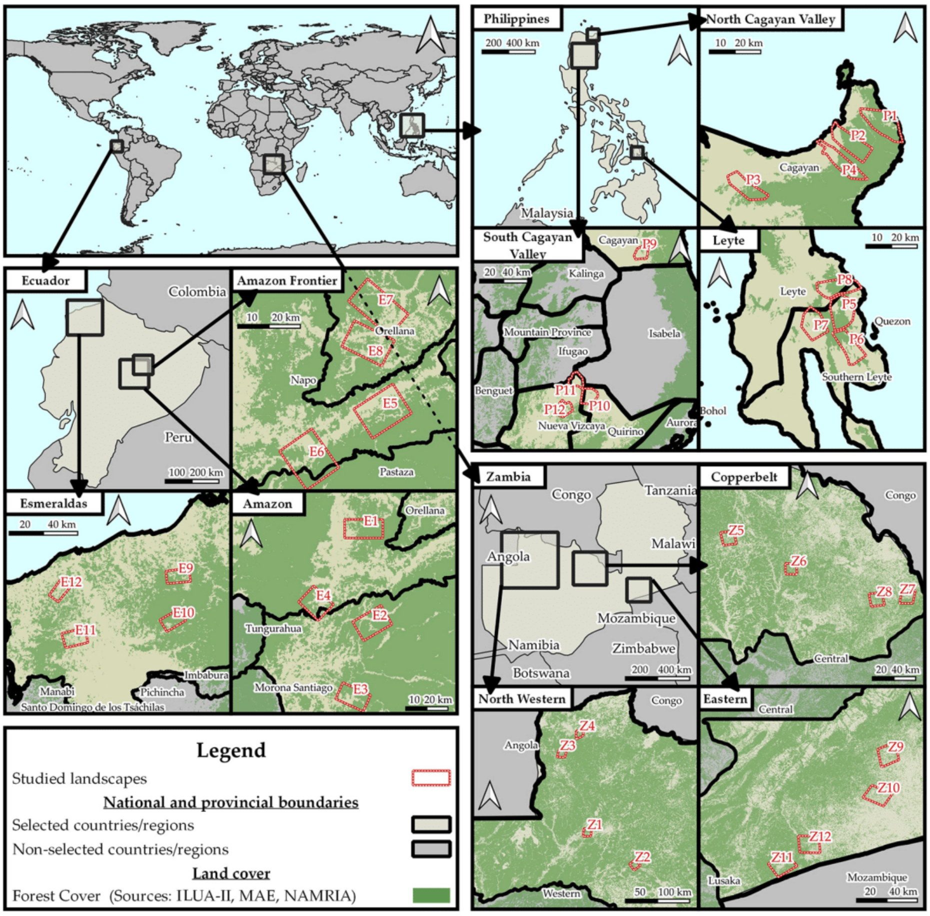
Our study design aimed to obtain a selection of landscapes that depict different forest transition stages, thus a gradient of pantropical deforestation contexts and a variety of the associated forest disturbance regimes (Table 1). The three regions of each country comprise three different deforestation contexts (initial, middle, and advanced) within the respective national perspective. Previously, the three countries had been selected and classified into the same three categories, considering their situation within the forest transition curve at national level. In order to classify both countries and regions, we estimated FC and average annual change rates from the most up-to-date national LCLU maps used for NFMs and international reporting (FAO, 2020). Thus, we relied on information from the second phase of the Integrated LU Assessment (ILUA-II) between 2000 and 2014 for Zambia (ILUA-II, 2016), from the Ministry of Environment (MAE) between 2000 and 2016 for Ecuador (MAE, 2017) and from the National Mapping Agency (NAMRIA) between 2003 and 2015 for the Philippines (NAMRIA, 2017).

3.2. Ground (in situ) verification

3.2.1. Data collection

We collected ground verification information across the thirty-six research landscapes between September 2016 and October 2019 (Fig. S1). Field teams were composed by two to five researchers familiar with the locally prevailing forest and LCLU types, together with local guides familiar with a particular landscape. They spent approximately one month and a half in each landscape, in which georeferenced ground control points (GCPs) and photographs (GCPhotos) with LCLU information were obtained, following a standardized field protocol (Annex S1) based on existing good practice guidelines (GFOI, 2020; Olofsson et al., 2014).

We conducted a stratified sampling approach to capture the main forest and LCLU types in each landscape. These strata were identified by the expert teams on the ground, through related activities within the larger LaForeT project (e.g. scoping visits, key informant interviews, community workshops, participatory mapping exercises, household interviews, forest inventories). The delineation of relevant strata and the



Landscapes	Name (Parishes, Ecuador)
E1	Rukullakta
E2	Arajuno
E3	Canelos
E4	Carlos Julio Arosemena Tola
E5	Chontapunta
E6	Ahuano
E7	Avila Huirino
E8	San Jose de Dahuano
E9	San Francisco Onzole
E10	Santo Domingo Onzole
E11	Cube
E12	Tabiazo

Landscapes	Name (Municipalities, Philippines)
P1	Santa Ana
P2	Gonzaga I
P3	Lal-lo
P4	Gonzaga II
P5	Silago
P6	Hinunangan
P7	Sogod
P8	Abuyog
P9	Penablanca
P10	Diffun
P11	Diadi
P12	Quezon

Landscapes	Name (Chiefdoms, Zambia)
Z1	Chizera
Z2	Mushima
Z3	Chibwika
Z4	Sailunga
Z5	Shibuchinga
Z6	Lumpuma
Z7	Nkambo
Z8	Mushili
Z9	Nyampande
Z10	Mumbi
Z11	Nyalugwe
Z12	Ndake

Fig. 1. Location of the thirty-six landscapes where ground verification data was collected, with the corresponding selected regions and countries.

design of the field sampling campaign built on visual interpretation of existing satellite images (Google Earth imagery) or auxiliary maps, such as those produced in participatory mapping workshops. A 4-Tier cross-country harmonized classification scheme was used to categorize LCLUs (Table S1), based on FAOs FRA forest definitions and on IPCC categories (Di Gregorio, 2005; FAO, 2018). This scheme was modified to include typical LCLUs of the regions, such as particular agroforestry systems (Huxley, 1999). Additionally, the classification system included details on forest disturbance and regeneration history, namely about the type (human/natural) and the age (up to 20 years) of the last disturbance and the type of regeneration (human/ natural). This information was determined by researchers and inhabitants familiar with the locally prevailing forest and LCLU types.

The teams covered every pertinent class with a representative number of GCPs, spatially distributed across each landscape (Fig. 2). A minimum distance of 100 m between points was required, together with homogeneous LCLU within a radius of 10 m around the GCPs. Additionally, photo sequences or GCPhotos, consisting of four pictures in a clockwise direction of compass, were collected for a number of GCPs belonging to the main LCLU classes. In total (Table S2), 16,676 GCPs were collected, with an average of 463 GCPs per landscape: 245, 597 and 548 in Zambia, Ecuador and Philippines, respectively. In addition, more than 14,000 GCPhotos (over 2800 sequences) were collected, with an average of 79 sequences per landscape: 40, 120 and 80 in Zambia, Ecuador and Philippines, respectively.

3.2.2. Digitization of the training & validation dataset

After cleaning the collected GCPs and GCPhotos (removing duplicates and inconsistent data), we harmonized the dataset to fulfil a cross-country LCLU classification scheme based on forest disturbance regimes (Tables 2, S1 and S2).

First, *reference forest* represents forests with none or slight disturbances before the ground verification took place. This class includes mostly mature old-growth forests or intact primary forests, but also (in more deforested landscapes) secondary forests, which had the last disturbance at least 10 years ago, without being completely clearfelled. Second, *degraded forest* comprises areas of forest with a more recent disturbance shorter than 10 years (mostly human impact in the form of logging), leading to a current state of degradation: reduction of forest canopy cover but not completely clearfelled. Next, *forest regrowth* includes forests which had been completely clearfelled and converted to other LCLUs, but which have subsequently undergone a recovery process either spontaneously (succession) or actively by humans (plantations). The rest of forests with no information on disturbance history (mostly areas of forest identified visually in the satellite images) were categorized as *undefined forest*.

We consider four classes of deforested vegetation. First, *tree-based system* covers the most relevant non-forest tree vegetation types: agroforestry systems (e.g. traditional 'chackras' in Ecuador, trees on crops in Philippines), palms (e.g. coconut, oil) or other perennial crops (e.g. cacao plantations, orchards). This category had no observations in Zambian landscapes. Second, *annual cropland* comprises deforested

Table 1
Selected landscapes, regions and countries and their respective deforestation context, FC in 2016 and average annual forest area change (AFC) for the 2000–2016 period.

					Deforestation context (regional level, national perspective)								
					Initial			Middle			Advanced		
		Country	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]	Regions & *Landscapes*[2]	FC[1] [%]	AFC[1] [%]
Deforestation context (national level, pantropical perspective)	Initial	Zambia	61	−0.20	North Western	67	−0.17	Copperbelt	70	−0.41	Eastern	55	−0.54
					Chizera	73	−0.61	*Shibuchinga*	62	−0.35	*Nyampande*	42	−2.60
					Mushima	81	−0.16	*Lumpuma*	77	−0.80	*Mumbi*	37	−2.69
					Chibwika	77	−0.15	*Nkambo*	59	−0.51	*Nyalugwe*	73	−0.13
					Sailunga	76	−0.14	*Mushili*	68	−0.59	*Ndake*	56	−0.63
	Middle	Ecuador	51	−0.44	Amazon	86	−0.13	Amazon frontier	74	−0.60	Esmeraldas	53	−0.97
					Rukullakta	72	0.46	*Chontapunta*	50	−0.63	*San Francisco*	62	−0.54
					Arajuno	82	−0.50	*Ahuano*	65	−0.49	*Santo Domingo*	88	−0.46
					Canelos	73	−0.67	*Avila Huirino*	62	−0.84	*Cube*	31	−0.14
					Carlos Julio AT	58	−0.56	*San Jose Dahuano*	49	−1.39	*Tabiazo*	24	−1.83
	Advanced	Philippines	24	−0.22	North Cagayan Valley	59	−1.19	Leyte	18	0.25	South Cagayan Valley	46	0.54
					Santa Ana	80	−0.35	*Silago*	57	1.89	*Penablanca*	11	−6.23
					Gonzaga I	77	−0.18	*Hinunangan*	42	5.83	*Diffun*	4	8.70
					Lal-lo	53	−0.35	*Sogod*	28	1.63	*Diadi*	4	100.00
					Gonzaga II	63	−1.32	*Abuyog*	49	−0.11	*Quezon*	36	−3.06

[1] FC: Percentage of total land area covered by forests. AFC: Average annual net forest area change. National results for 2016 and 2000–2016 period, respectively, as reported in FAOs FRA2020. Regional and landscape results obtained from LCLU maps used for international reporting: Zambia 2000–2014 (ILUA-II, 2016), Ecuador 2000–2016 (MAE, 2017), and Philippines 2003–2015 (NAMRIA, 2017).

[2] Landscape boundaries cover areas within chiefdoms, parishes and municipalities where ground verification data was collected. Region boundaries: North Western (Mufumbwe and Mwinilunga district), Copperbelt (Lufwanyama and Masaiti district), Eastern (Petauke and Nyimba district), Amazon (Pastaza and Napo provinces, excluding Ahuano and Chontapunta parishes), Amazon frontier (Ahuano and Chontapunta parish plus Loreto in Orellana province), Esmeraldas (Esmeraldas province), North Cagayan Valley (Selected municipalities in Cagayan province), Leyte (Southern Leyte province plus Abuyog municipality), South Cagayan Valley (Quirino and Nueva Vizcaya province).

areas with irrigated or rainfed cropping fields (mostly cereals such as rice or maize) and land prepared for agriculture. Third, *shrubland* (woody), which was only relevant in Zambia. Fourth, *grassland* includes mainly pastures, but also other grassland types such as abandoned croplands or grass-covered river banks in Zambia (locally referred to as 'dambos').

Last, representing non-vegetation classes, *built-up* covers mostly settlements and roads, while *waterbody* comprises rivers, marshlands and aquaculture, but also oceans in coastal regions.

We digitized polygons containing homogeneous information of the abovementioned LCLU categories with Quantum GIS v3.10 (Fig. 2), based on the collected GCPs, GCPhotos and using up-to-date satellite images (Google Earth imagery) as a reference. Altogether (Table 2), we digitized 23,880 ha (2136 polygons) of forest, from which 6193 ha (1636 patches) included information about forest disturbance and regeneration history. 4987 polygons of 20,528 ha were digitized for the non-forest categories. To minimize overoptimistic assessment due to overfitting problems (Ploton et al., 2020), these polygons were split randomly into two independent training and validation datasets, which included 70% and 30% of the total number of polygons, respectively, preserving the share of the LCLU classes per region.

3.3. Creation of LaForeT forest maps

The processing steps to create the LaForeT maps and the subsequent analysis were performed with Quantum GIS v3.10, SNAP v8.0, ENVI v5.6 and PyCharm v2019.3. Further details on the selection and the processing of scenes, bands, indices and textures can be found in Tables S3 to S6.

3.3.1. Remote sensing data

The fusion of optical and radar remote sensing data is commonly used in LCLU applications (Joshi et al., 2016), including the mapping and monitoring of FC in tropical regions (Hirschmugl et al., 2020; Reiche et al., 2016). Some known advantage, when compared to the use of single sensors, is the yield of additional information, increasing the chances of targeting specific LCLU types.

We created seven multi-sensor composites (stacked raster layers) co-registered to 30 m resolution, which included thirty-nine variables per pixel each:

- Seven mosaicked Landsat-8 bands and seven related vegetation indices.
- Twenty-four Sentinel-1-derived bands, consisting on one sigma nought and three texture values for two points in time and three different polarizations.
- One elevation band (height above sea level), obtained from the Shuttle Radar Topography Mission (SRTM)-1Sec digital elevation model.

These seven composites cover the nine studied regions, as two regions in Ecuador (Amazon) and two in Philippines (Cagayan Valley) are geographically close to each other. Regional spectrograms of the chosen variables for the analyzed LCLU classes can be found in Figs. S2 to S4.

- *Landsat-8*

Landsat-8 offered a higher number of available scenes and the best spatial and temporal coverage for our regions, when compared to other high-resolution optical sensors (e.g. Sentinel-2). However, as obtaining cloud-free information was still challenging in Ecuador and Philippines, we created multi-temporal seasonal mosaics, similarly to previous approaches (Hansen et al., 2013; Potapov et al., 2012).

A best period of three to four months with cloud-free coverage was

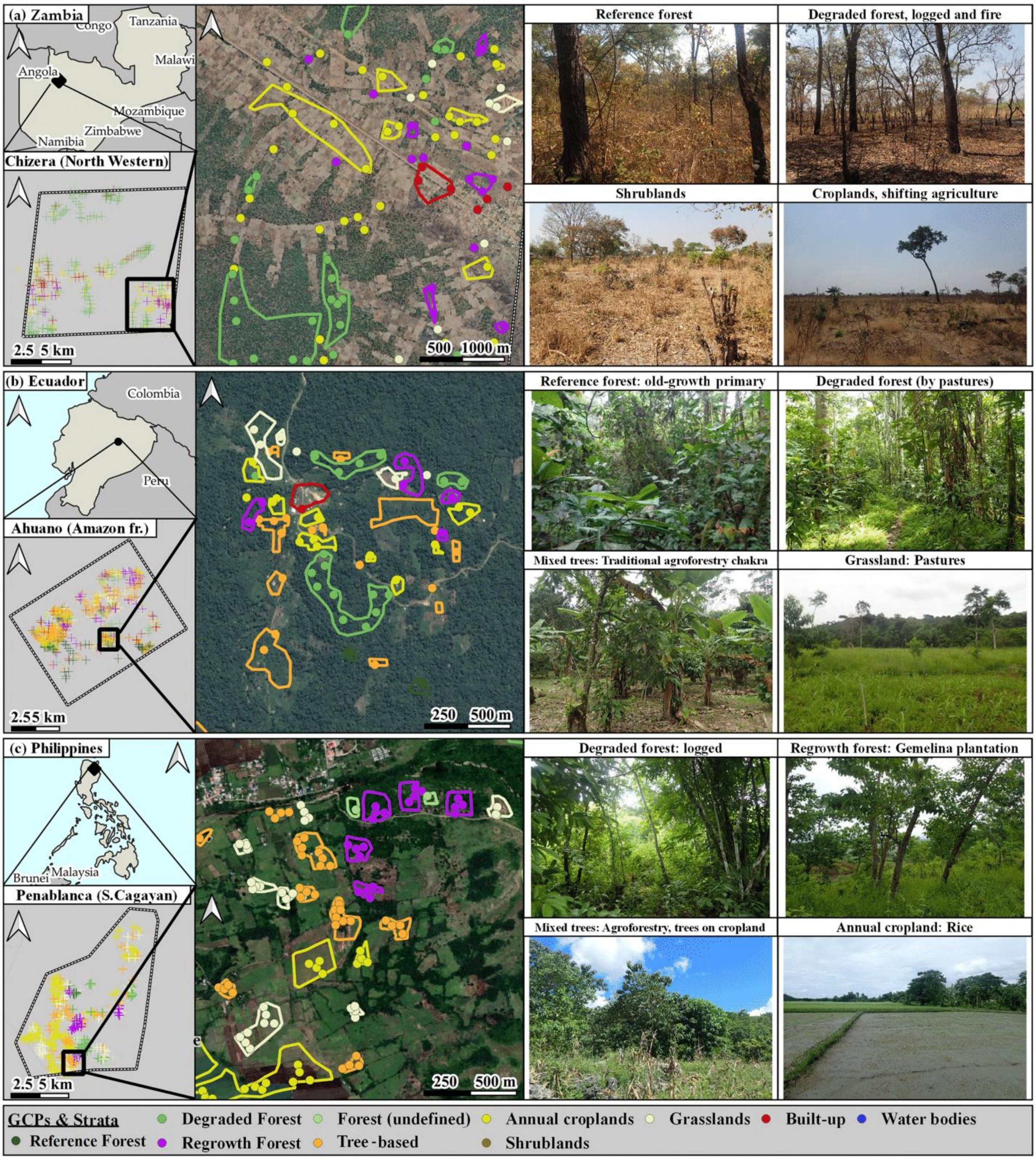


Fig. 2. GCPs spatial distribution in three landscapes, delineation of strata and GCPhotos for selected areas. (a): Chizera, North Western, Zambia. (b): Ahuano, Amazon frontier, Ecuador. (c): Penablanca, South Cagayan Valley, Philippines.

selected in each region, usually coinciding with the respective dry season (Table S3). In total, we used 269 scenes from nineteen different Landsat tiles, downloaded using the on-demand service of the United States Geological Survey (USGS) and its ESPA Bulk Downloader. This included all the available Landsat-8 Level-2 Surface Reflectance images (Collection 1 OLI/TIRS Combined) for the selected months within the year of the ground verification and the two previous years. This three-year period permitted almost cloud-free mosaics and was acceptable considering the defined thresholds between forest classes (ten years from the last disturbance) and under the observed LCLU change dynamics. We created and applied a cloud mask to each of the downloaded scenes, based on the Quality Assessment bands and, in the case of Ecuador (where the preliminary results were unsatisfactory) on the 'Fmask' method (Zhu and Woodcock, 2012). Finally, we created 30 m

Table 2
LCLU classes, forest disturbance regimes (FDR, highlighted in grey) and number of polygons (with corresponding total hectares) per class in the training/validation dataset.

LCLU	FDR	Detailed LCLU class	Digitized polygons (Training/Validation dataset)							
			Zambia		Ecuador		Philippines		Total	
			N	Area [ha]	N	Area [ha]	N	Area [ha]	N	Area [ha]
Forest	Reference forest		48	297	165	762	99	336	312	1,394
	Degraded forest		342	2,423	250	597	176	823	768	3,843
	Forest regrowth		130	271	284	531	142	154	556	956
	-	Forest undefined	51	9,296	306	2,919	143	5,473	500	17,687
Non-forest	Deforested vegetation	Tree-based system	0	-	1,038	1,881	766	1,733	1,804	3,614
		Annual cropland	222	1,001	387	553	527	3,093	1,136	4,648
		Shrubland	122	214	0	-	12	3	134	218
		Grassland	137	682	451	2,202	432	697	1,020	3,581
	-	Built-up	88	1,123	316	2,595	214	1,837	618	5,556
		Waterbody	32	335	91	834	152	1,742	275	2,911

resolution mosaics by co-registering the masked scenes and clipping them to the bounding coordinates of each region (Table S4), with every pixel containing the average cloud-free value for each of the seven Landsat-8 bands (Table S5 and Fig. S5).

We then calculated a group of seven vegetation indices for each of the mosaics (Table S6). This selection was derived from Schultz et al. (2016) and it includes indices based on wetness (NDMI, TCw) and greenness (EVI, GEMI, NDVI, SAVI, TCg), which are commonly used in deforestation monitoring.

- *Sentinel-1*

We included information derived from Sentinel-1C-band SAR imagery, which can contribute to map FC or LCLU, independently from clouds or luminosity (Abdikan et al., 2016; Hirschmugl et al., 2020). With the aim of capturing short-term LCLU changes, we included scenes from two points in time within the selected season of each region: one close to date of in situ verification (last) and another point two years before (first). In total, we selected thirty-two scenes of Level-1 high-resolution Ground Range Detected (GRD) Interferometric Wide (IW) swath data with Dual VV/VH Polarization, and downloaded them from the Copernicus Open Access Hub.

We used a standardized pre-processing workflow to treat our scenes, following good practice recommendations (Palazzo et al., 2018). First, we applied updated orbit files to the downloaded scenes. Second, thermal noise (background energy generated by the receiver) was removed, using the noise lookup tables. Next, we applied radiometric calibration, thus converting pixel values to normalized radar cross-section or backscatter coefficient (sigma nought). As a fourth step, we removed the speckle from our images, by applying the improved Lee sigma filter (Lee et al., 2009). Following, we converted our data from slant to ground range geometry (terrain correction) using bilinear interpolation of the SRTM-1Sec digital elevation model and Universal Transverse Mercator (UTM) as a map projection. The pre-processed bands were then clipped to the bounding coordinates of each region (Table S4), creating two mosaics (first and last) per region. This process was repeated for three polarizations: VV, VH and for the absolute difference between VV and VH's sigma noughts (VV-VH), which had reported improved accuracies in previous studies (Abdikan et al., 2016).

Finally, we converted the original sigma nought values to integer numbers and then calculated three Grey Level Co-occurrence Matrix (GLCM)-derived texture features (Haralick et al., 1973): GLCM-mean, GLCM-variance and contrast (Table S7). Textures account for neighbor pixels and are commonly used in forest monitoring applications (Numbisi et al., 2019; Herold et al., 2004). We used a 9 × 9-pixel window and repeated the process for each polarization and point in time.

3.3.2. *Supervised classification and post-processing*

We performed a supervised classification for each of our seven composites, using the corresponding regional training datasets (70% of the digitized polygons) and a random forest (RF) classifier (Breiman, 2001). RF is a machine learning method, which has been widely used to classify LCLU (Gislason et al., 2006; Pal, 2005). As a non-parametric method, RF presents the advantage of omitting distribution assumptions and thus, working with multisource information such as our composites. Moreover, RF permits to rate the relative importance or contribution of the different variables to the classification output. Considering the computational time and the accuracy of our regional models, we used a maximum of 1000 trees and 50,000 pixels as training samples; only pixels with valid data (e.g. cloud-free) for all the variables were included in the model and later classified.

In total, we built eight independent RF models to generate eight LaForeT forest maps, which covered an extent of approximately 15 million hectares. The Cagayan Valley composite (Philippines), was classified separately for the two regions of analysis: North and South. For each of the outputs, confidence maps were generated and further analyzed (Table S8 and Fig. S6). Moreover, the bands were ranked based on how much the accuracy decreased when the variable was excluded (Fig. S7). Isolated groups of less than five pixels, considering 8-connectivity, were reclassified as no forest, as they did not reach a minimum size of 0.5 ha. Lastly, an ocean mask was applied to the maps before clipping them to the bounding boundaries of the respective region of analysis (Table S4).

3.4. *Secondary sources: national and global forest datasets*

Next, we selected up-to-date national maps and relevant global forest datasets of high to medium resolution, ranging from 25 to 100 m (Table 3). All the secondary sources were converted to binary Forest/Non-Forest (FNF) maps, clipped to our areas of interest and co-registered to spatially match our own maps. The national sources were the LCLU maps used for NFMs and international reporting of reference levels in the respective countries, which were the closest to the date of our data collection (ILUA-II, 2016; MAE, 2017; NAMRIA, 2017). Regarding the global forest datasets, we first selected two sources based on optical data: the GFC dataset (Hansen et al., 2013) and the CGLS-

Table 3
Overview of the national and global forest datasets used for comparison of results.

Dataset	Coverage	Type	Year used	Spatial resolution	Source	Main sensor	Reference
ILUA-II-LC	Zambia	LCLU	2014	30 m	Optical	Landsat-8	(ILUA-II, 2016)
MAE-LC	Ecuador	LCLU	2016	~50 m [3]	Optical	Landsat-8	(MAE, 2017)
NAMRIA-LC	Philippines	LCLU	2015	~25 m [3]	Optical	Landsat-8	(NAMRIA, 2017)
GFC [1]	Global	TC	2010	30 m	Optical	Landsat	(Hansen et al., 2013)
CGLS-LC100	Global	LCLU	2017–2019 [2]	100 m	Optical	PROVA-V	(Buchhorn et al., 2020)
JAXA-FNF	Global	FC	2017	25 m	SAR	PALSAR-2, PALSAR	(Shimada et al., 2014)
TanDEM-X-FNF	Global	FC	2011–2016	50 m	SAR	TanDEM-X, TerraSAR-X	(Martone et al., 2018)

[1] Different TC thresholds used in every region, as shown in Fig. S8.
[2] 2017 in Ecuador and Philippines. In Zambia: 2018 in North Western and Copperbelt, 2019 in Eastern.
[3] ~50 m resolution = 1:100,000 scale. ~25 m resolution = 1:50,000 scale.

LC100 layers (Buchhorn et al., 2020). Additionally, we selected two recent SAR-derived global FNF maps: one produced by the Japan Aerospace Exploration Agency (JAXA) based on the ALOS-2 PALSAR-2 information (Shimada et al., 2014) and one created by the German Aerospace Center (DLR) based on data from the TanDEM-X satellite (Martone et al., 2018).

The GFC dataset is not a forest map itself (it depicts TC) and it provides older estimations (2000,2010) than the period covered by our maps (2016–2019). However, we selected it for its relevance, as it is widely used as a reference for global forest monitoring. In order to generate FNF maps, we defined TC thresholds from GFC's 2010-dataset that matched FC in our regions (Fig. S8), based on Galiatsatos et al. (2020). Regarding CGLS-LC100, a forest map between 2017 and 2019 was selected, depending on the year when the most GCPs were collected in each region. In the case of JAXA, information from 2017 was used everywhere, as it was the most up-to-date dataset available.

3.5. Quality analysis

Finally, we analyzed the quality of our map outputs and the selected secondary sources, grouping the results by region, country and deforestation context. We generated error matrices (Olofsson et al., 2014) for all datasets in each of the study regions, by measuring the number of correctly classified pixels within the validation dataset (30% of the digitized polygons). We used the zonal histogram tool of QGIS, which appends fields representing counts of each unique value from a raster layer (i.e. LCLU classes) contained within zones (i.e. validation polygons). We then obtained thematic accuracy measures (user, producer and overall accuracies) for all the compared FNF sources, together with producer accuracies of LCLU subclasses, as the probability of correctly being classified as forest or no-forest (Tables S9 to S14). The main steps related to data collection and processing, as input for the accuracy assessment, are summarized in Fig. 3. Moreover, we analyzed the differences in FC estimation for the different sources, at regional and landscape level (Table S15 and Figs. S9 to S44). In addition, we did a per-pixel spatial comparison based on Yang et al. (2017), in which the overall and the individual-class spatial agreements for every unique pair-combination of datasets were determined in each region, after resampling the datasets to the lowest resolution of each pair by nearest neighbor interpolation (Tables S16 and S17).

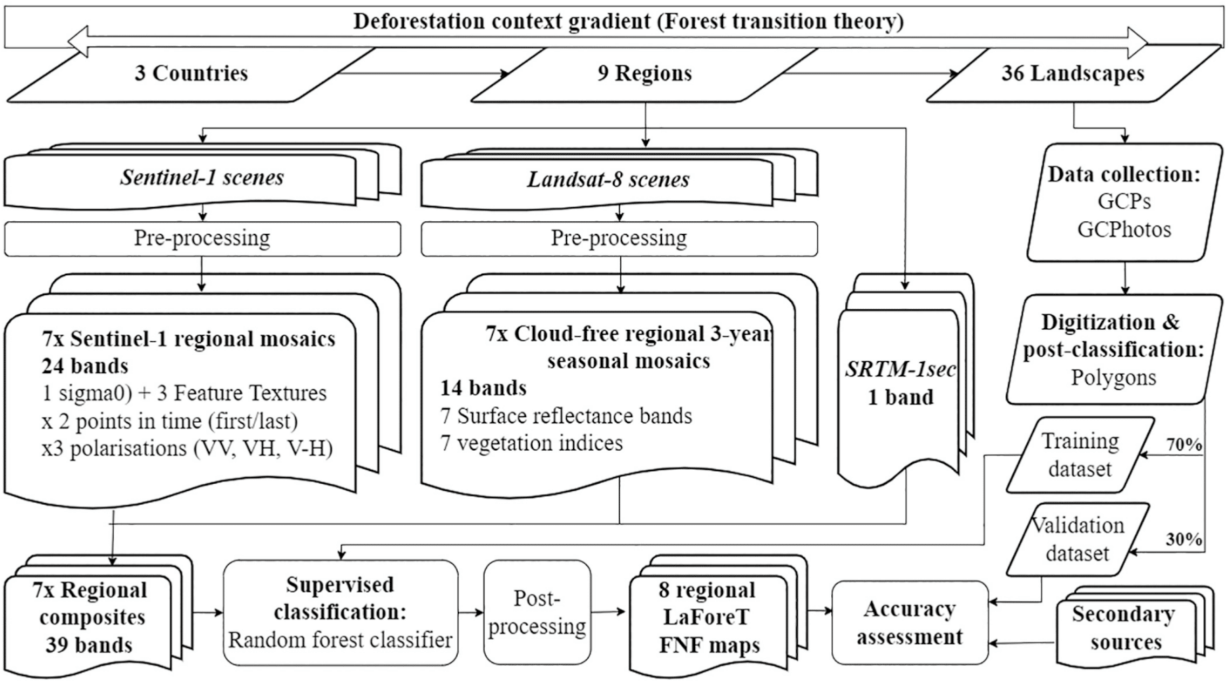


Fig. 3. Flowchart diagram of the main steps of data collection and processing, as input for the accuracy assessment.

4. Results

4.1. Creation of LaForeT forest maps

4.1.1. Cloud-cover and confidence maps

In total, only 2% of the pixels in the analyzed regions (1.25% within the studied landscapes) presented no Landsat-8 data in any scene after mosaicking (Table S5 and Fig. S5). This was mostly due to clouds, cirrus or shadows presence, but also (in a smaller number) waterbodies, settlements or pixels with no data. Altogether, the treated pixels had an average of ten observations (9.97), with regional averages between 15 and 18 scenes in Zambia, 2 and 7 scenes in Ecuador, and 7 and 12 scenes in Philippines. While the Zambian regions were almost completely cloud-free, the availability of optical data in the selected areas of Ecuador and Philippines was more problematic, which justified the use of the mosaics. The region of Esmeraldas in Ecuador presented a relatively high percentage of pixels without information (21.78% of the total area, 4.25% within the landscapes), after mosaicking. The rest of regions had lower number of pixels with no data after mosaicking, with values between 0% and 3.36% (0% and 1.55% within in the landscapes).

The overall standardized average confidence values did not vary strongly across regions, with results between 32% (Esmeraldas) and 46% (North Cagayan) (Table S8 and Fig. S6). FC-specific confidences ranged from 30% (Esmeraldas) to 47% (North Western and North Cagayan). Non-FC-specific confidences were especially low (35–36%) in all the Ecuadorian regions and the highest in both North and South Cagayan Valley regions in the Philippines (44% and 46%, respectively). The maps in Zambia and the Philippines provided the highest average total confidence values (42% and 44%), when compared to Ecuador (38%). Regions in earlier deforestation contexts resulted in better overall confidences (45%) than regions in middle (40%) and advanced (39%) ones, related to decreasing specific confidences of the forest class (46%, 39% and 37%).

4.1.2. Relative importance of variables

Elevation was the most decisive variable across the study regions (Fig. S7). The contribution of this band to the accuracy of the classification algorithm ranked within the five more important variables in every region.

Among the Landsat-derived variables, moisture-related indices (NDMI and TCw) ranked generally better than greenness-related ones. However, some greenness variables, such as NDVI and TCg, were still very relevant in the classification of certain regions (e.g. Southern Cagayan Valley, Esmeraldas, Copperbelt and Leyte). The individual Landsat bands were also relatively important to the classification outputs, with all of them contributing in specific regions. The ultra-blue band (coastal/aerosol) ranked the highest across regions, while the green, red and SWIR bands were also relevant in specific areas.

The Sentinel-1-derived variables also contributed importantly to improve the accuracy of the different classifications. Overall, the textures ranked better than the backscatter signal (sigma0) across polarizations and points in time. For instance, the mean GLCM of the last image ranked second among all the studied variables. In general, the VH polarization reported the best results, in both the first and the last scenes. The VV-bands of the old (first) scenes contributed more relevantly to the accuracy of the classifications than the ones of the new (last) images. The difference polarization (VV-VH) showed the worst results when compared to VV and VH.

4.2. Quality analysis

4.2.1. Thematic accuracy assessment

The detailed error matrices of all the analyzed maps, with the results for LCLUs grouped by country and deforestation context, can be found in the supplementary material (Tables S9 to S14).

- *Overall accuracies*

Our produced forest maps (Table 4) had an overall accuracy of 92%. User accuracies (precisions) of 92% and 93% were observed for forest and no-forest, respectively. Our maps presented better producer accuracies (sensitivities) for the forest class (96%) than for the no-forest category (85%).

From all the analyzed sources (Fig. 4), our maps and the national datasets presented the highest overall accuracies for the total sample (92%). Within the secondary global sources, the GFC dataset exhibited the best overall accuracies (91%). The other three global maps reported overall accuracies of 88% (JAXA-FNF), 86% (TanDEM-X-FNF) and 85% (CGLS-LC100).

Our forest maps showed better overall accuracies in Zambia and in the Philippines (96% for both) than in Ecuador (79%). The same pattern was observed in all the analyzed global sources. In Zambia, the national LCLU maps presented the lowest overall accuracies (89%), in relation to the global datasets (with values ranging from 92% to 96%). The classification results in Zambia were characterized by lower overall accuracies in the Eastern Province. In Ecuador, the national LCLU maps also provided the best overall accuracies (93%). In general, the five global datasets (including our maps) presented relatively unsatisfactory overall accuracies across the three Ecuadorian regions (ranging from 48% to 87%). In the Philippines, the national datasets and our maps reported the best results (95% and 96% overall accuracy, respectively) in contrast to a range of accuracies between 79% and 91% in the secondary global datasets. The classification results in the Philippines were repeatedly affected by lower overall accuracies for Leyte. Philippines was also the only subsample where another secondary global dataset different than GFC provided the highest accuracy, namely the JAXA-FNF dataset.

The overall accuracies of our forest maps were better in regions with initial deforestation contexts (96%) than in regions with middle or advanced ones (89% and 90%, respectively). We observed a similar trend in all the secondary sources, with exception of the national and the TanDEM-X-FNF maps.

- *Sensitivity of LCLU classes and forest disturbance regimes*

Reference forests showed the highest sensitivities (producer accuracies) among the analyzed forest disturbance regimes in three datasets:

Table 4
Error matrix with the overall results of the produced LaForeT FC maps (total sample).

		Reference dataset[1]			
		Forest	No-Forest	Row Total	User Accuracy
LaForeT Forest Map	Forest	174,772	14,382	189,154	92%
	No-Forest	6701	82,605	89,398	93%
	Column Total	181,473	96,987	278,552	
	Producer Accuracy	96%	85%		
			Overall accuracy		92%

[1] Count refers to the pixels of 30 m resolution within the validation polygons.

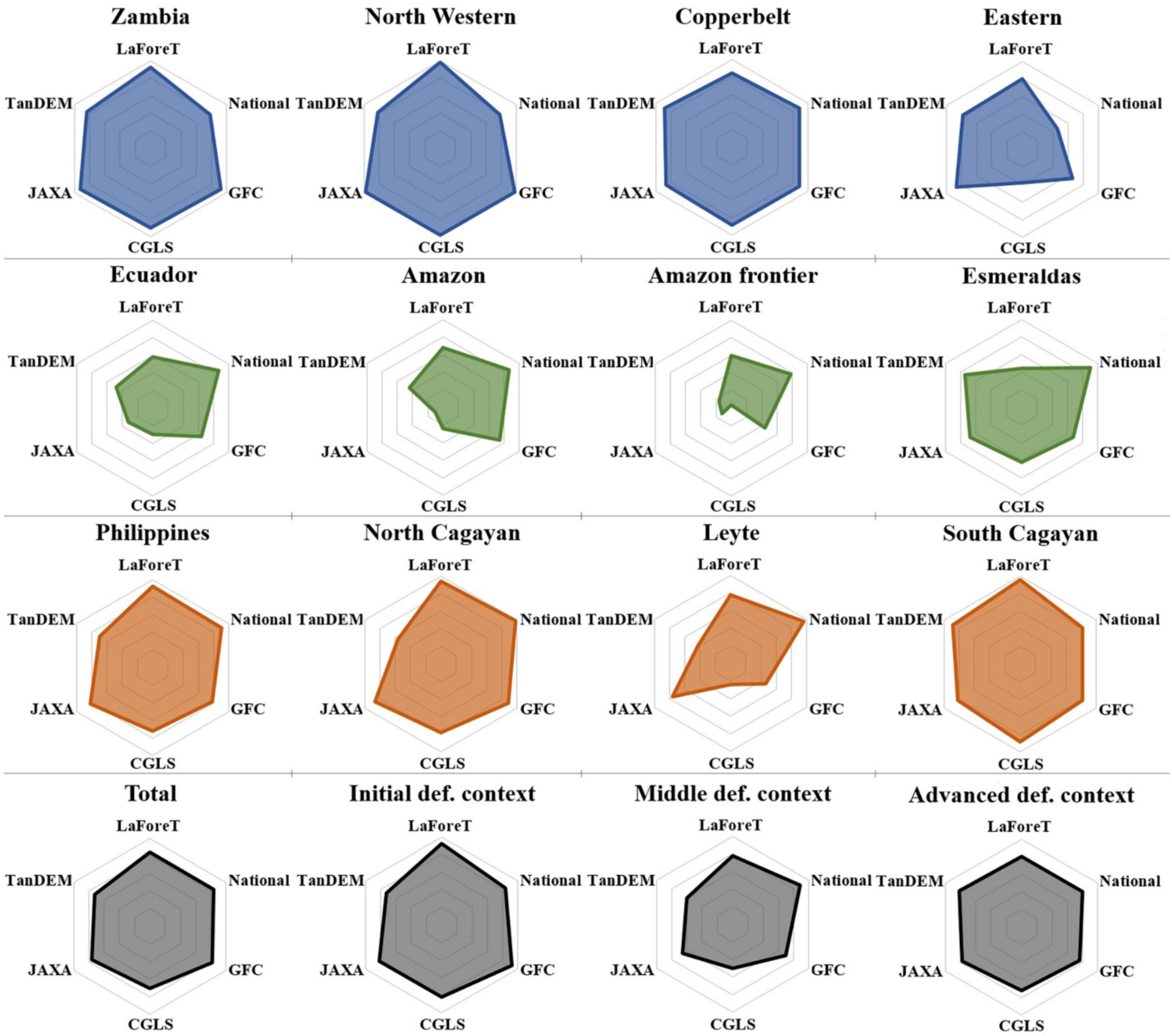


Fig. 4. Overall accuracies (range 50–100%, with the 100% value corresponding to the outer ring of the presented hexagons) of the different compared regional maps for the total sample and the different subsamples (countries, regions and deforestation contexts).

LaForeT (93%), national (92%) and JAXA-FNF (93%) (Fig. 5). The other three maps reported higher sensitivity of degraded forests, which averaged 90% when considering all the studied datasets. Regrowth forests was the forest class with the lowest sensitivities (75% average of all maps). Even the national LCLU maps, which showed relatively high overall accuracies, reported the lowest sensitivity among the sources (49%) for regrowth forests. The best sensitivities for a forest subclass were observed in forests with no disturbance history (between 92% and 98%), thus in forest areas that had been identified visually in satellite images.

Considering deforested vegetation, the best results were obtained by the national, LaForeT and GFC datasets (94%, 85% and 85%, respectively), while the other sources presented lower sensitivities (between 55% and 74%). The CGLS-LC100 dataset and the two SAR-derived global maps (JAXA-FNF and TanDEM-X-FNF) reported very low sensitivities, even in non-vegetation areas (i.e. built-up and waterbodies). All the sources showed higher sensitivities for annual croplands, with values between 84% and 94%. Worse were the results for other deforested vegetation subclasses, namely for non-forest tree-based systems (e.g. agroforestry, palms and perennials) and for grasslands. The worst results were observed in shrublands (mainly in Zambian landscapes with presence of degraded forests), which always reported very low accuracies below 65%.

In general, the sensitivities of all the forest subclasses decreased in regions and countries with more advanced deforestation contexts, while the opposite trend was observed for deforested vegetation (Fig. 6). Overall, the maps show higher sensitivities for all forest subclasses in Zambia and Ecuador. In contrast, we can observe better results for deforested vegetation in the Philippines. The secondary global forest maps were particularly inaccurate in mapping deforested vegetation, while the national maps delivered the best sensitivities in all the analyzed deforestation contexts and countries. On average, the sensitivities of regrowth forests were the lowest among the forest subclasses independently of the analyzed country or deforestation context.

4.2.2. FC estimations

Details on the estimations of FC for all the landscapes (individually and grouped by region, countries or deforestation context), can be found

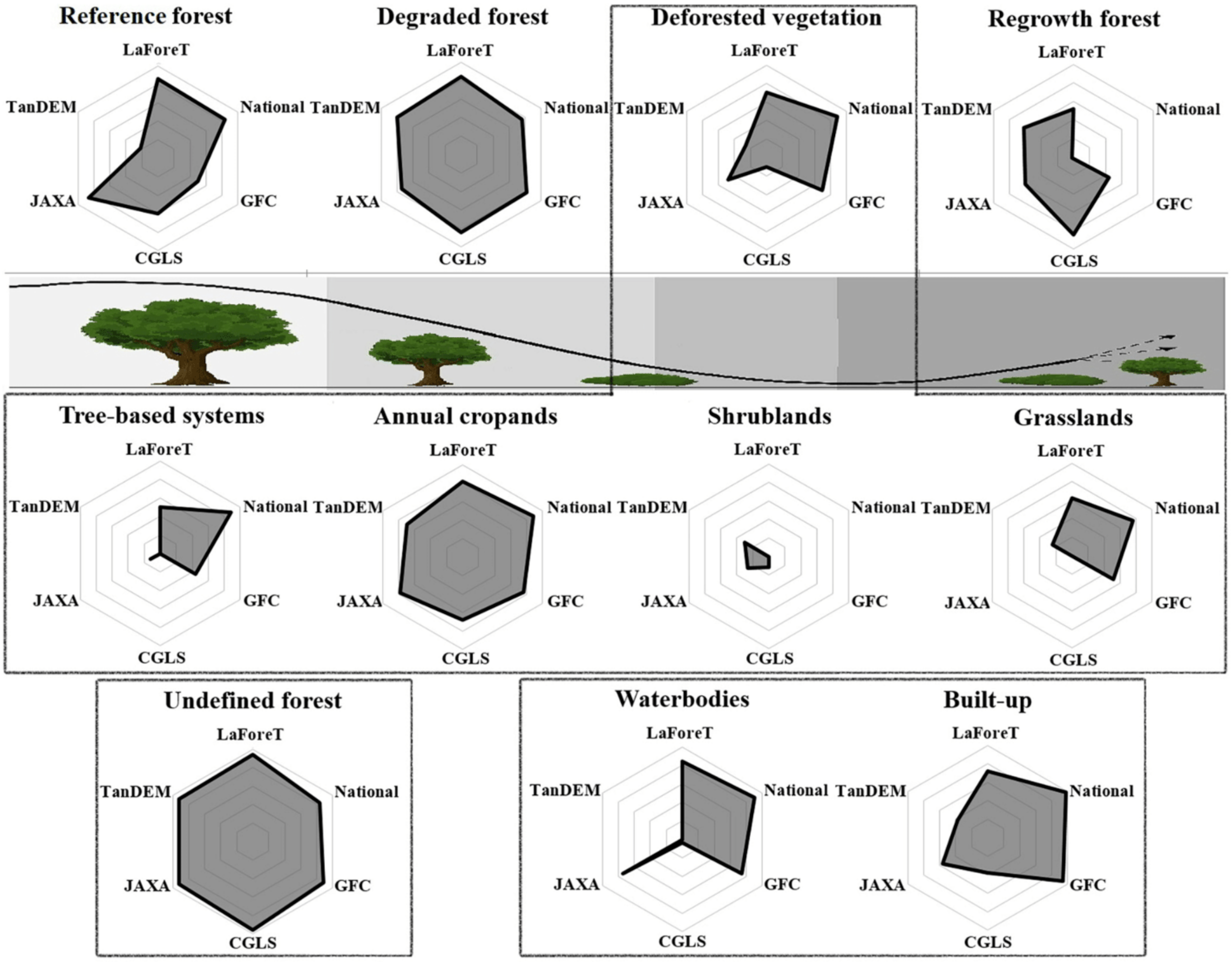


Fig. 5. Sensitivity or producer accuracies (range 50–100%, with the 100% value corresponding to the outer ring of the presented hexagons) of the specific LCLU types and forest disturbance regimes (based on the forest transition theory) in the analyzed datasets for the total sample. Note: The first row depicts forest disturbance regimes, represented by the different stages related to the forest transition. The second row shows the results for the specific LCLU types within the deforested vegetation category. The third row includes LCLU classes not included in the analysis of the forest disturbance regimes.

in Table S15 and Figs. S9 to S44. The national LCLU maps reported the lowest FC estimations (57%) for our landscapes (Fig. 7). The highest estimations were the ones of CGLS-LC100 (75%) and TanDEM-X-FNF (74%), followed by our maps (66%), JAXA-FNF (64%) and GFC (62%). According to our study design, estimations of FC decreased gradually in regions with middle and advanced deforestation contexts for all the compared datasets. At the same time, discrepancies between maps increased along this gradient (Fig. 8).

In Zambia, all the sources provided similar estimations of FC for the landscapes in North Western (from 78% to 89%) and Copperbelt (from 59% to 71%). In contrast, the estimations of FC for the landscapes in the Eastern region varied substantially, between 9% (CGLS-LC100) and 59% (GFC). In Ecuador, the estimations of FC by the global sources were much higher, from 76% (LaForeT) to 95% (CGLS-LC100), than the ones by MAE's maps (61%). These discrepancies were stronger in Esmeraldas and in the Amazon frontier. Similarly, CGLS-LC100 (71%) and TanDEM-X-FNF (76%) provided higher estimations of FC in the Philippines, when compared to the other sources (36% to 48%). These discrepancies were particularly strong in Leyte and South Cagayan.

4.2.3. Spatial agreements

Fig. 9 shows the spatial agreements between our maps and the secondary sources in all the studied regions. The extended results for all dataset combinations and different subsamples are depicted in Table S17. The overall spatial agreements between the different sources had little variation, with values ranging from 76% to 83% and similar results in the three countries. In general, the specific spatial agreements for forests (ranging from 82% to 88%) were higher than the ones for the no-forest class (between 62% and 74%), which were particularly low in Ecuador (32% to 65%). Only in Philippines, the specific spatial agreements for the no-forest class were similar and even higher (68% to 92%) than the ones for the forest class (58% to 85%).

We observed that the overall and forest-class specific agreements gradually decreased in regions with more advanced deforestation contexts. Thus, overall agreements ranged from 83% to 90% in initial, from 74% to 83% in middle and from 59% to 78% in advanced deforestation contexts, respectively. In contrast, no-forest class-specific agreements remained similar across deforestation contexts or even increased in later forest transition stages, ranging from 60% to 72%, 60% to 74% and 61% to 81% for initial, middle and advanced deforestation contexts, respectively.

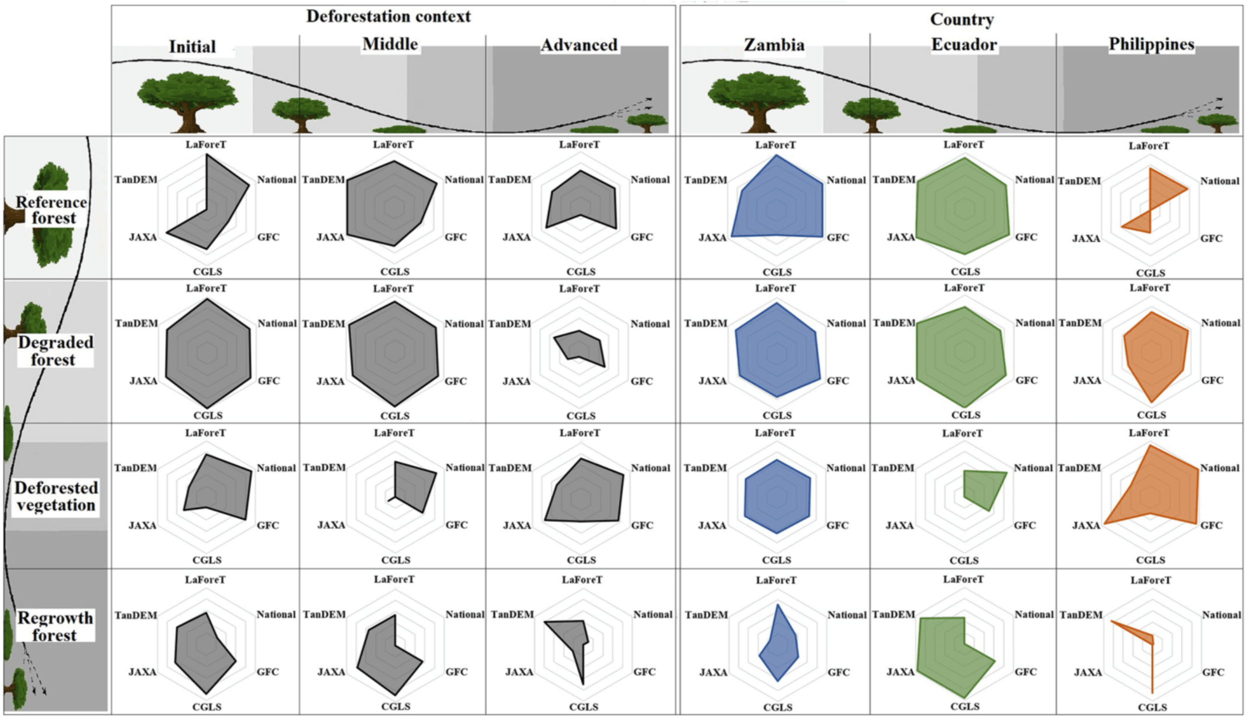


Fig. 6. Sensitivity or producer accuracies (range 50–100%, with the 100% value corresponding to the outer ring of the presented hexagons) of the forest disturbance regimes in the analyzed datasets, grouped by deforestation contexts (left) and countries (right) Note: Deforestation contexts, countries and forest disturbance regimes are represented by the different stages related to the forest transition.

5. Discussion

5.1. Mapping of tropical forest

We were successful in developing a standardized and consistent methodology to generate accurate high-resolution (30 m) forest maps for various tropical regions across three continents. Overall, our findings reaffirm the potential of using innovative machine learning techniques together with the fusion of freely-accessible multi-sensor and multi-temporal satellite information, in order to improve the outputs of tropical forest mapping (Li et al., 2017; Reiche et al., 2018; Wang et al., 2019). Our reference dataset, along with the produced maps and methods, can be used in future studies to analyze additional forest disturbance or LCLU aspects in the tropics.

The application of a non-parametric classifier such as the RF algorithm presented the advantage of dealing with several bands, indices and textures per pixel, capturing the physical and spectral differences of forest between the analyzed regions (Figs. S2 to S4 and S8).

Elevation was the only variable that strongly enhanced the map outputs in all the studied regions. This highlights the potential of DEMs as valuable auxiliary information to improve LCLU classification accuracies by, for example, reducing the relief effect of satellite images or by predicting disturbance susceptibility (Fahsi et al., 2000). We also interpret that elevation acted as an indicator of accessibility, which is s key determinant of deforestation in the tropics, observed across the studied landscapes. Moreover, our findings reaffirm the relevance of wetness-related indices for the effective monitoring of FC in the tropics, when compared to greenness-related ones (Schultz et al., 2016). Similarly, the importance of the ultra-blue band could be related to mist/haze and other fine aerosol particles, which are characteristic of areas with continuous rain and cloud coverage (Pöschl et al., 2010). In further studies, it might be opportune to incorporate more complex indices related to canopy density (e.g. Normalized Difference Fraction Index) or leaf surface properties (e.g. Leaf Area Index), which have reported satisfactory results in the past (Souza et al., 2013). Finally, our findings expand the recent developments in the field of SAR, by ratifying the advantages of using textural information, derived from Sentinel-1 backscatter (i.e. recurring importance of GCLM-mean of the VH polarization across regions), to map FC (Numbisi et al., 2019). Additionally, better contributions of certain variables in older scenes (i.e. VV polarization) ratify the importance of including multi-temporal information to capture historical LCLU and FC changes (Pulella et al., 2020).

However, we have to be cautious when interpreting the relative importance of variables in RF models, especially if a large number of predictors are used. This behavior may lead to serious overfitting problems and biased estimations, due to unaccounted spatial correlation between variables (Ploton et al., 2020). This can also be the reason for the region-specific results and for the unexpected contribution of certain variables (e.g. ultra-blue band), which may be correlated to other predictors like elevation (Fig. S7). Further studies should consider a pre-selection of variables in every region, based on expert knowledge or spectral separability.

Furthermore, comparisons of the results for the studied sensors (Landsat-8, Sentinel-1) need to be addressed critically, due to the substantial differences on the type and availability of temporal data used. For instance, the creation of Landsat-8 seasonal mosaics using a relatively long 3-year period, lead to very different timestamps per map, depending on regional cloud cover. Additionally, the quality and density of these mosaics decreased drastically in areas with poor availability of data (i.e. Ecuador). In contrast, Sentinel-1 uses single observations for only two points in time. Further studies could try to increase data density and ideally perform a time-series approach by extending the analysis period or the number of sensors. This could improve the poor results obtained for certain LCLUs, which suffered recent changes. In addition,

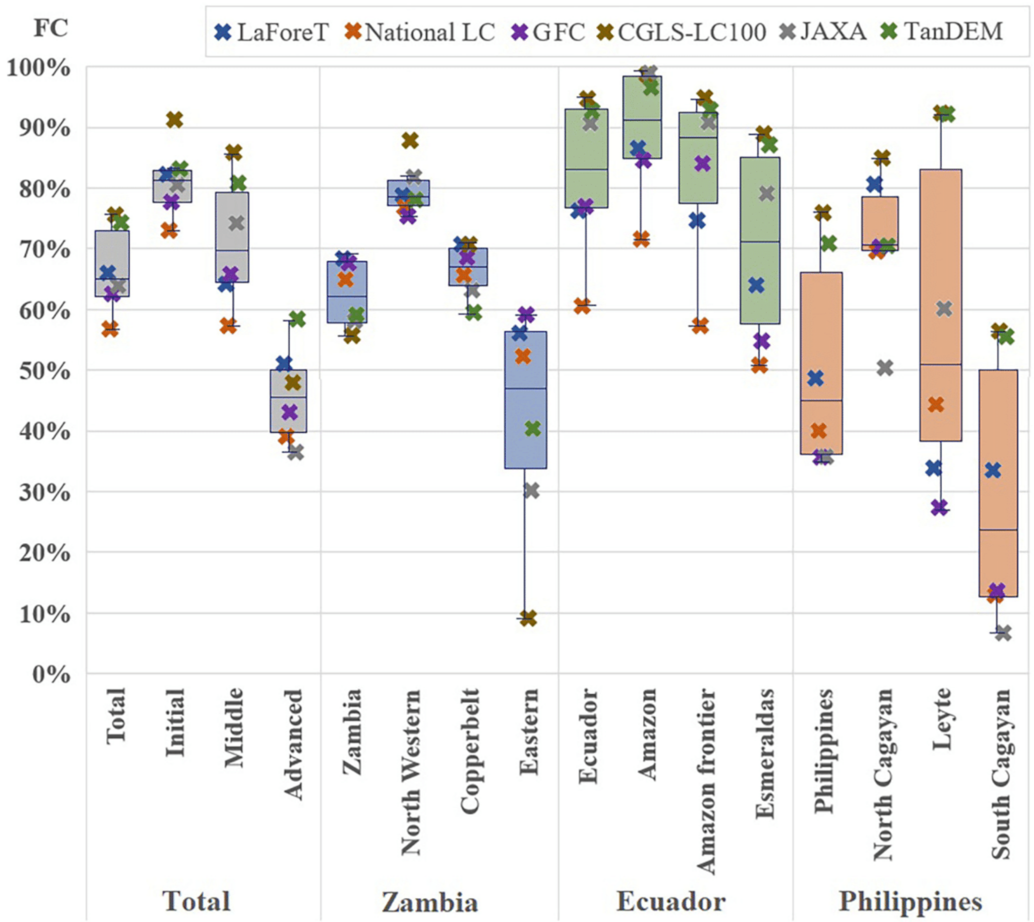


Fig. 7. Forest Cover (FC) within the studied landscapes ($n = 36$; $n = 12$ per country) according to different sources, grouped by regions, countries and deforestation contexts.

some processing steps may be optimized, such as the use of median (instead of average) to reduce the blur of the optical mosaics, or the use of multi-temporal speckle filters for the SAR scenes (Wang et al., 2019; Woodcock et al., 2020).

5.2. Comparing tropical forest maps

Our extensive field campaign to collect training and validation data in situ allowed us to achieve satisfactory classification outputs, which generally outperformed the results of the global secondary maps (Fig. 4). This emphasizes the importance of using updated reference data from the ground, which ideally should include detailed and standardized information about the different forest strata. Similarly, the relatively high accuracies of JAXA-FNF in the Philippines are probably related to the fact that the country was used for the training of the map's classifier (Shimada et al., 2014). Undefined forests (identified visually in the satellite images), reported the highest producer accuracies in all the compared datasets and contexts (Fig. 5). We argue that only relying on this type of information for training and validation might omit relevant forest types and lead to wrong estimations of FC (Figs. 7 and 8). Certainly, there is a trade-off between reducing economic and logistic costs of implementing such an extensive field campaign and improving the quality of the generated maps. Regarding this, the synergetic development of collaborative and harmonized global reference databases and the integration of both NFM and Inventory systems in tropical countries are still highly desired (Fritz et al., 2011).

The generally high accuracies of the maps produced by the national mapping agencies (Fig. 4) are promising, as we analyzed three countries with very different capacities regarding their MRV/NFM systems and their commitments to international reporting (e.g. participation in REDD+ program) (Nesha et al., 2021). In Zambia (Phiri et al., 2019), where NFM agencies are still undergoing phases of development and capacity building, the recently produced ILUA-II maps performed well but still slightly worse than the global datasets. In Ecuador, MAE's relatively long-established inventory and mapping capabilities delivered satisfactory overall accuracies, in contrast to the disconcerting results of all other datasets, which noticeably overestimated FC (Fig. 7). In order to produce their regularly updated national LCLU and deforestation maps, MAE uses a combination of Landsat time-series and very high resolution imagery for training and validation (i.e. RapidEye and aerial photographs) (MAE-MAGAP, 2015). In Philippines, where again global secondary sources generally overestimated FC (Fig. 7), NAMRIA's 2015 maps reported the best accuracies in the three studied regions. This suggests an improvement of the quality of previous LCLU datasets by the Philippine national mapping agency (Estoque et al., 2018; Santos, 2018).

Nevertheless, any comparison of results between regions or between map sources should be made critically. For instance, the quality of the different maps depends on their scale and purpose, but also on the sensors used (active vs. passive) and the related resolutions and

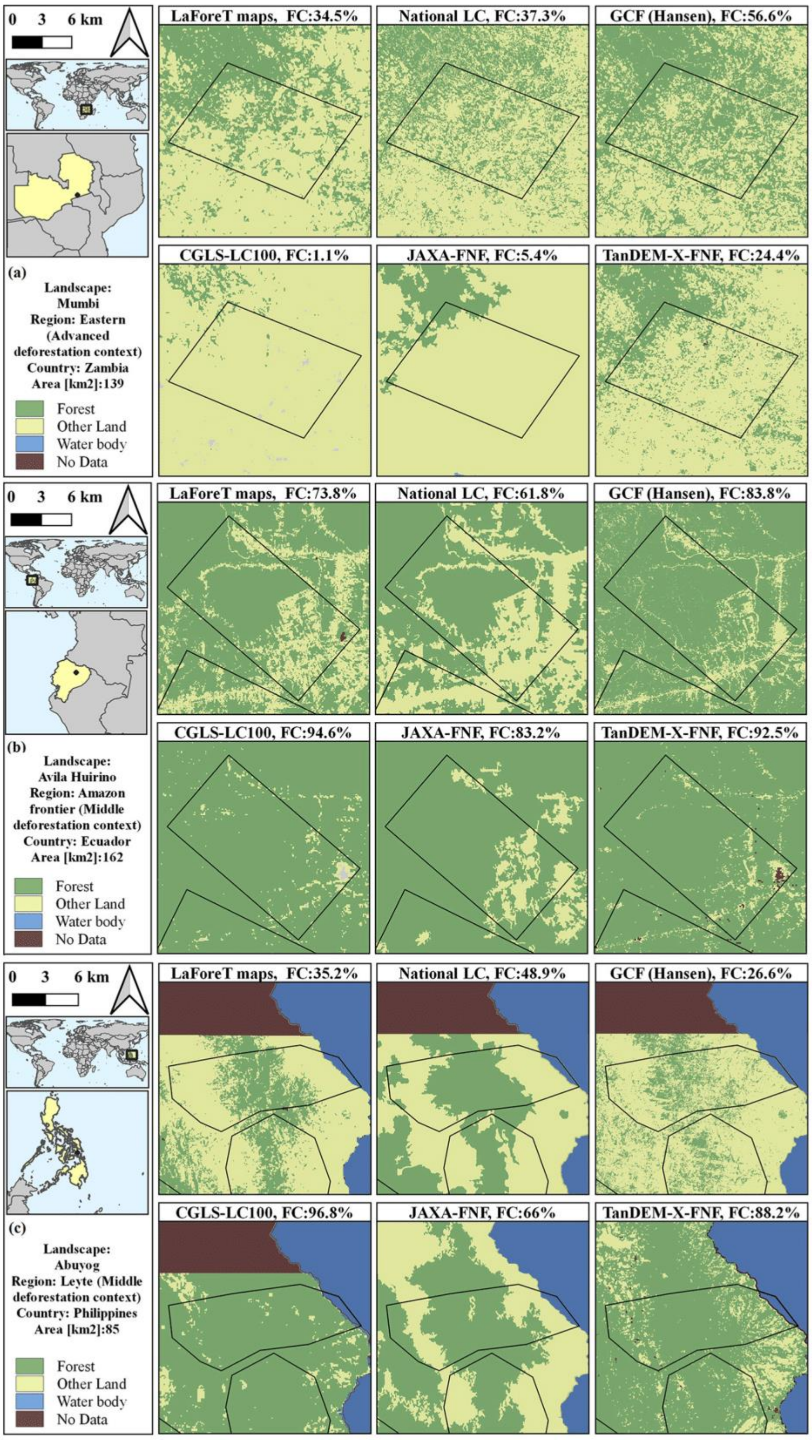


Fig. 8. Examples of three landscapes with strong discrepancies in Forest Cover (FC) estimations between the selected datasets: (a): Mumbi, Eastern, Zambia; (b): Avila, Amazon, Ecuador; (c): Abuyog, Leyte, Philippines. Note: Comparisons for all 36 landscapes can be found in the supplementary material (Figs. S9 to S44).

processing steps. Related to this, the size of the uniform LCLU patches observed on the ground, which should match the minimum mapping unit required by the resolution of the used satellite sensors, is region-dependent (Table 2). This could explain the generally better results in Zambia, where larger patches were observed, and the difficulties to detect smaller deforested vegetation patches in Ecuador (Smith et al., 2003), usually surrounded by forests of greater heights and denser canopy cover (Fig. S8). Furthermore, cloud cover clearly affected the

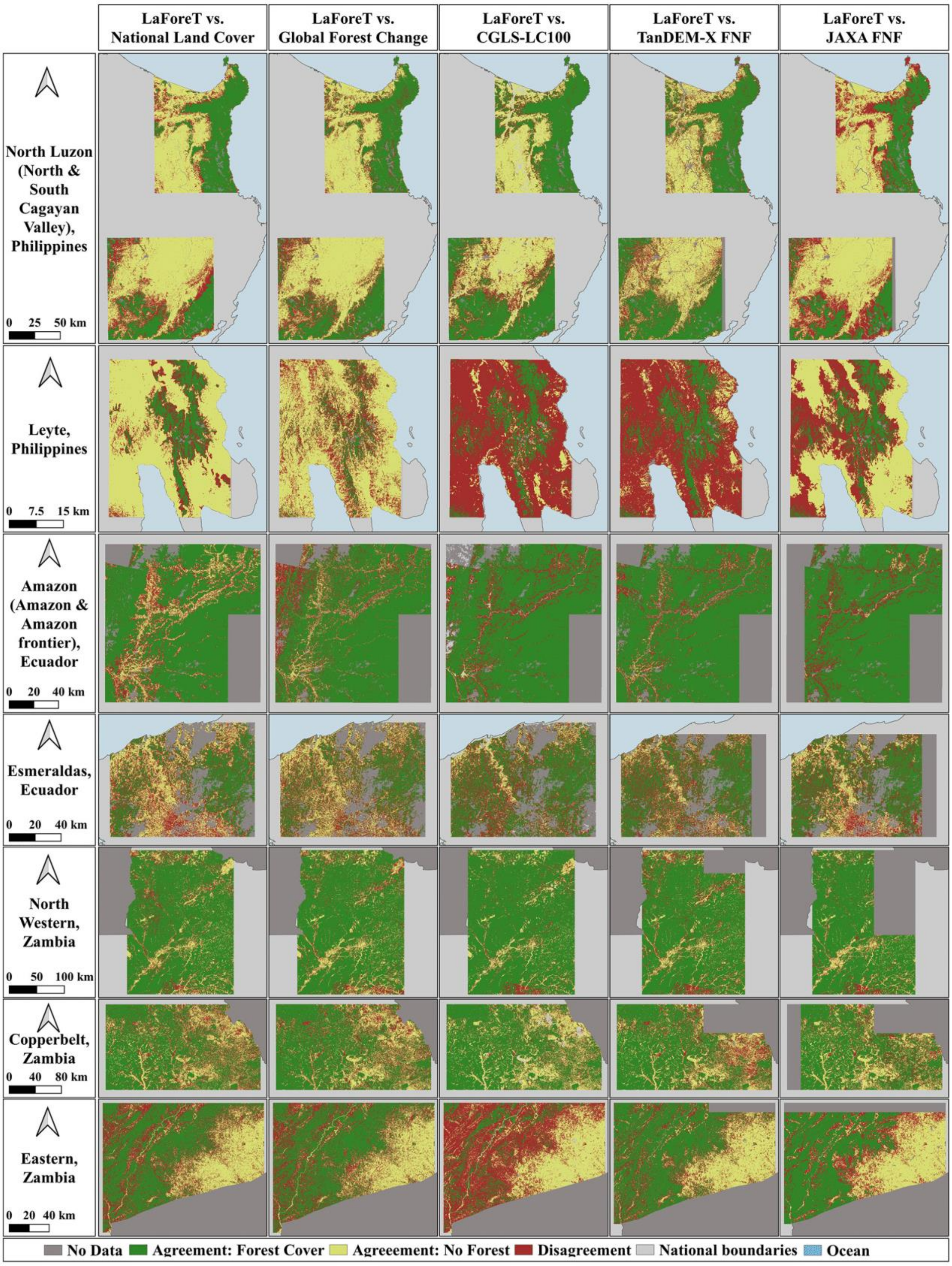


Fig. 9. Spatial agreements between LaForeT maps and the selected secondary forest datasets. See Fig. 1 for reference.

confidences of our maps and the overall accuracies of the global maps in Philippines and especially in Ecuador, but barely in Zambia. Additionally, the temporal gap between data collection and scene acquisition (Fig. S1 and Table S3) or map production (Table 3), might explain better accuracies of datasets in specific regions (e.g. JAXA-FNF in Philippines). Further studies can try to optimize this caveat by using auxiliary information to improve outdated maps, such as the GLAD alerts in the case of GFC (Hansen et al., 2016). Regarding this dataset, our findings confirmed how a preliminary definition of a TC threshold, can match the diverse forest definitions and deliver improved classification accuracies

(Galiatsatos et al., 2020), even if there is a temporal gap with the validation data. The GFC analysis (Fig. S8) also underpins the strong regional dependency of ecological features (i.e. TC) and the high sensitivity of map outputs to these biological aspects. For instance, the presence of other tree-based systems commonly misclassified as forest (Fig. 5) has probably influenced the classifications of certain regions negatively. The clearest examples are Esmeraldas in Ecuador, with large oil palm plantations, and Leyte in the Philippines, characterized very steep mountains and historical expansion of coconut palms to take part of degraded forest in the last decades (Estomata, 2014). Furthermore, the worse results in the Eastern province of Zambia can be related to the known challenges in mapping sparse forests of dry ecosystems associated with woodlands or savannas (Feng et al., 2016; Hill, 2021). These ecosystems are characterized by lower canopy densities, slower growth rates, less greenness or water content and problematic LCLUs, such as shrublands (Fig. 5). The better accuracies of our method and SAR-based global sources in this region suggest potential advantages of using SAR-derived observations (alone or combined with optical data) to accurately map forests and deforestation in dry tropical areas, as previously demonstrated by other studies (Li et al., 2017; Reiche et al., 2018).

5.3. Monitoring tropical forest across forest transitions

Our initial hypothesis, that the different deforestation contexts and their associated forest disturbance regimes strongly influence the classification outputs of regional forest maps in the tropics, finds empirical evidence in our analysis. We observed a tendency of increased difficulties in distinguishing FC by global maps in more developed stages of our deforestation contexts gradient. This was manifested as progressively worse classification outputs in regions with middle and advanced deforestation contexts, regarding not only the confidences of our maps (Table S8) and their overall accuracies (Fig. 5), but also the accuracies of the secondary global datasets and the overall and forest-specific spatial agreements among map sources (Table S17). Generally, all the studied forest types, reported worse producer accuracies in middle and advanced deforestation contexts, independently of the analyzed dataset (Fig. 6). Consequently, the estimation of FC in these regions presented wider ranges or variances, associated with larger uncertainties and errors (Figs. 7, 8 and 9).

Apart from the specific methodological limitations of each region or dataset, as discussed in the previous subsections, these findings can also be explained by our general hypothesis. Namely, accelerated LU dynamics in advanced deforestation contexts result in more diverse and complex LC patches of smaller size, with increased difficulties to map forest correctly (Smith et al., 2003): i.e. tree-based systems (i.e. perennial crops, palms and other agroforestry arrangements), shrublands and grasslands (Fig. 5). Accelerated LU dynamics also result in more degraded and sparse forests, which again increase the uncertainties of FC measurements and disturbance detections (Feng et al., 2016; Vancutsem et al., 2021). This would also explain why regrowth forests presented worse producer accuracies than reference and degraded forests across datasets, countries and deforestation contexts (Fig. 6); thus, confirming the challenges to identify relatively young (less than 20 years) tropical tree plantations and succession forests, grown in areas which have been completely clearfelled (Caughlin et al., 2020; Li et al., 2017).

The number of rehabilitation and reforestation initiatives in tropical landscapes is growing, as forests are a specific target within Goal 15 of the Sustainable Development Goals for 2030 (SDGs) (Holl, 2017). For instance, FLR projects within the Bonn Challenge have 350 million hectares pledged worldwide, together with country-led partnerships, such as Initiative 20 × 20 or AFR100. Other examples are afforestation and reforestation projects within the Clean Development Mechanism (CDM) or the Great Green Wall project in Africa, which aims to restore 100 million hectares of currently degraded land by 2030. The goals of these initiatives (increasing vegetation cover, biodiversity recovery and recovery of ecological processes) often synergize with those of other relevant programs in place, like REDD+ (Verchot et al., 2018). Yet, as forest protection and rehabilitation measures continue to bloom in the tropics, so does the need for rigorous monitoring and improved implementation and reporting mechanisms (Murcia et al., 2016; Stanturf et al., 2019).

Our findings suggest that the recommendation of using forest datasets carefully and rather as a reference, is especially relevant in regions with more advanced stages of degradation/deforestation or for the case of reforested areas. We argue that these regions with higher rates of FC change also have a greater need to use stratified in situ information for training/validation and to develop improved classification approaches which can be linked to forest condition and landscape multifunctionality. These are precisely the regions where most of the abovementioned environmental programs (e.g. REDD+ or FLR) are likely to take place. Omitting this may lead to wrong estimations of FC and therefore to biased conclusions about the success or failure of such international policies.

6. Conclusion

Our study represents an innovative attempt to analyze forest classification accuracies at pantropical level on basis of the forest transition theory. In the context of the international Agenda 2030 for Sustainable Development and the Paris Agreement, numerous measures and programs for the conservation, rehabilitation and sustainable use of forests are being implemented worldwide (e.g. FLR, REDD+). Although the goals of these initiatives might be well-intended and desirable, there is a need to improve the technical capacity to measure their success or effectivity, in order to draw sound conclusions on their contributions to sustainable development. This includes the ability to monitor tropical FC accurately and derive precise estimations of the quality and quantity of the associated ecosystem services. Our pantropical study clearly demonstrated how all the compared national and global forest maps struggled to differentiate forests with a disturbance history from other vegetation types, often resulting in wrong FC estimations. We empirically proved that these complications are accentuated in regions with higher rates of FC change (in advanced stages of deforestation or reforestation) and particularly for forests grown in previously deforested areas. We therefore interpret our findings as evidence that the deliberations regarding the applicability of secondary forest maps and the establishment of forest monitoring systems should be especially critical in these contexts. Our results also indicate the importance of in situ verification as accompanying method for MRV in regions of advanced stages of deforestation and early stages of reforestation. This should be relevant for upcoming policy making and research, as these are also the areas where forest protection and rehabilitation measures are required the most.

CRediT authorship contribution statement

Rubén Ferrer Velasco: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Supervision, Writing – original draft, Writing – review & editing. **Melvin Lippe:** Conceptualization, Methodology, Resources, Data curation, Supervision, Writing – original draft, Writing – review & editing, Project administration. **Fabián Tamayo:** Resources, Data curation, Supervision, Project administration. **Tiza Mfuni:** Resources, Data curation, Supervision, Project administration. **Renezita Sales-Come:** Resources, Supervision, Project administration. **Cecilia Mangabat:** Resources, Supervision, Writing – review & editing, Project administration. **Thomas Schneider:** Validation, Writing – review & editing. **Sven Günter:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2022.112997.

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Publication 3: Cross-scale analysis of stakeholder perceptions on drivers and policies

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Reconciling policy instruments with drivers of deforestation and forest degradation: cross-scale analysis of stakeholder perceptions in tropical countries

Rubén Ferrer Velasco[1,2]✉, Melvin Lippe[2], Richard Fischer[2], Bolier Torres[3], Fabián Tamayo[3], Felix Kanungwe Kalaba[4], Humphrey Kaoma[4], Leonida Bugayong[5] & Sven Günter[1,2]

Cross-scale studies combining information on policy instruments and on drivers of deforestation and forest degradation are key to design and implement effective forest protection measures. We investigated the scale and country dependency of stakeholder perceptions about future threats to tropical forests (e.g. agriculture, logging, woodfuel) and preferred policy instruments (e.g. reforestation, protected areas, combat illegal logging), by interviewing 224 representatives of forest-related institutions. We conducted analysis of variance and principal component analysis for eighteen variables across three countries (Zambia, Ecuador and the Philippines) and four spatial levels (from international to local). We found that the overall alertness about commercial drivers and the confidence in policy instruments are significantly lower at subnational levels and also in Zambia. Stakeholder expectations about the most important drivers and the most effective policies in the coming decade follow regional narratives, suggesting that there are no one-size-fits-all solutions in international forest policy. However, we found an unexpected consensus across scales, indicating potential for collaboration between institutions operating at different geographical levels. Overall, agriculture remains the driver with the highest expected influence (43%), while a strong favoritism for reforestation and forest restoration (38%) suggests a paradigm shift from protected areas to a stronger focus on integrative approaches.

Although current tropical deforestation rates (9.3 million ha/yr between 2015 and 2020) have slowed down when compared to previous decades (e.g. 13.8 million ha/yr between 1990 and 2000)[1], tropical forests still account for more than 90% of the total forest loss worldwide. This deforestation trend, linked to processes of forest fragmentation and degradation[2,3], poses a threat to the multiple ecosystem services of tropical forests, which are essential for human well-being[4,5]. This wide range of ecosystem services provided by tropical forests has profound impacts both locally and globally (e.g. on weather patterns, water cycle, natural catastrophes, biodiversity or food and human health)[5,6].

The drivers behind this trend have been well studied[7]. Already in the early 2000's forest scholars and practitioners identified pantropical patterns and distinguished between proximate and other underlying driving forces[8–10]. This classification had been introduced in the early nineties in the context of anthropogenic global environmental change[11,12] and it has been widely accepted and used[7,13–15]. More recently, further investigations have used econometric and spatial analyses and survey or remote sensing data to quantify and characterize the main direct causes of deforestation and forest degradation in the tropics[16–20]. These drivers are complex and region-dependent[16,17,20], but they are mostly related to land-use and anthropogenic pressure[19,20]: e.g. expansion

[1]Ecosystem Dynamics and Forest Management Group, School of Life Sciences, Technical University of Munich (TUM), 85354 Freising, Germany. [2]Institute of Forestry, Johann Heinrich von Thünen Institute, 21031 Hamburg, Germany. [3]Life Sciences Department, Universidad Estatal Amazónica (UEA), 160101 Puyo, Ecuador. [4]School of Natural Resources, Copperbelt University, 21692 Kitwe, Zambia. [5]Forestry Development Center, College of Forestry and Natural Resources, University of the Philippines Los Baños, 4031 Laguna, Philippines. ✉email: ruben.weber@tum.de

of commercial and subsistence agriculture, legal and illegal logging, fuelwood collection, charcoal production, expansion of timber plantations, oil extraction, surface mining, urban and infrastructure, and wildfires or other natural disasters.

As a response to these threats, an increasing number and variety of policy instruments for the protection and conservation of forests have been implemented in tropical landscapes over the last decades[21,22]. Some examples include: protected areas, reforestation activities, measures against logging or land tenure reforms. Conventionally, such policy instruments are classified into regulatory (command and control), economic and informational (sermons), while they imply a set of enabling, positive (carrots) or negative (sticks) incentives and regulations[21–23]. Nevertheless, the effectiveness of these instruments is very context-dependent and usually well-designed mixes of policies are recommended[21,22,24]. More recently, market-based and demand-led policy instruments involving public and private actors (e.g. payments for ecosystem services [PESs] such as the "Reducing emissions from deforestation and forest degradation" program [REDD +], certification or supply-chain initiatives), have shown their potential (and limitations) to be effective in halting deforestation with favorable institutional and governance contexts[21,25,26].

Our work addresses two main gaps in existing empirical research. First, there is a lack of pantropical studies which combine both information on drivers of deforestation and the suitability or effectiveness of different policy instruments. Improving the knowledge about such interrelations is important, because the design and implementation of effective forest protection measures requires addressing the specific forces that drive forest loss in a particular context. Most of the previous literature focuses on single countries and circumstances[27–29] or on specific drivers and/or policy options[30–33]. However, broader approaches can orientate us towards more general conclusions and provide useful insights on the links between the main threats and solutions related to tropical deforestation. Secondly, pantropical cross-scale studies about the drivers of deforestation and/or policy instruments are even scarcer (i.e. across spatial levels related to interconnected geographical jurisdictions, from global to local: e.g. international, national, provinces, districts, municipalities…). Despite previous studies examining the cross-scale effects of tropical deforestation[34,35], research has largely focused on single countries[36–40]. Deriving meaningful empirical findings from cross-scale information is a challenging task, which implies overcoming a number of mismatches between data of varying nature, quality and very different acquisition methods[20,32]. For instance, many relevant statistics are, if available, collected at provincial or national levels (e.g. land cover maps, commodity production, exports or agricultural yields). Thus, the majority of pantropical studies still work with national or regional aggregations[18,41,42]. The information at local levels usually relies on perceptions and on disaggregated estimations[32,43,44]. Nevertheless, integrated analyses that consider the circumstances of each jurisdiction across the spatial scale where both drivers of deforestation and policy instruments act, can support more comprehensive deliberations over the appropriate mix of policy tools and strategies needed to successfully combat deforestation[24].

In our work, we aim to shed some light on the abovementioned gaps by answering the following research questions:

- Are perceptions of relevant key informants and stakeholders in the tropics the same across countries (Zambia, Ecuador and the Philippines) and across scales (spatial levels or geographical jurisdictions, i.e. international, national, regional [subnational] and local) regarding:

  (a) Future drivers of deforestation and forest degradation and
  (b) Preferred policy instruments for forest protection?

To address these questions, we use data from a questionnaire conducted between 2018 and 2019 with 224 representatives of forest-related institutions in Zambia, Ecuador and the Philippines. We analyze responses across the three countries and four spatial levels (geographical jurisdictions from international to local), by conducting analysis of variance (ANOVA) and principal component analysis (PCA) for eighteen relevant variables. The studied variables are indicators of the stakeholders' general perception (i.e. alertness about commercial/subsistence drivers and confidence in policy measures), as well as expected relative importance and effectiveness of specific cross-country driver and policy instrument categories, respectively.

We hypothesize that clear country and scale dependencies can be identified among the interviewed stakeholders, as both drivers and policy instruments vary strongly across regions and scales[20]. For instance, a higher prevalence of commodity-driven deforestation over shifting agriculture has been identified in South America and South East Asia, when compared to Sub-Saharan Africa[16,17,33]. Similarly, certain policy instruments, such as PES schemes, count with a longer history of implementation in specific regions[45], with most of the research on their effectiveness being conducted in South America[22]. Another current example of such regional differences is the prioritization of Africa within the Bonn Challenge, where 130 million hectares of degraded forest have been pledged to be restored by 2030 (roughly 20% of total forest extent in Africa), in contrast to 47 million hectares in Latin America and the 29 million hectares in Asia and the Pacific (5 and 4% of total forest area, respectively)[46]. Likewise, we expect cross-scale differences because deforestation drivers and policy instruments act at different spatial levels or interconnected geographical jurisdictions, from global (e.g. international trade of commodities or internationally-funded protection schemes) and national (e.g., planning of infrastructure development or national protected areas), to subnational and local (e.g. subsistence agriculture and forest resource extraction or community-based forestry). A further reason to expect country and scale dependencies in our findings, is the existence of different stakeholder configurations in each context. Stakeholders have specific responsibilities or management roles and perceptions based on particular interests and experiences of success or failure in the past. For instance, national stakeholders (e.g. ministry representatives) are usually involved in the design of de jure practices, considering the threats to forest and potential protection mechanisms from a broader perspective. In contrast, local stakeholders (e.g. municipality officers) are typically closer to the implementation on the field and de facto practices[47–49].

Our hypothesis can be underpinned theoretically by some of the frameworks used in research on forest-related conflicts[50]. Forest conflicts have been defined as "differing views of reality and underlying cultural biases"[51] or "incompatibility of interests over the same territory or resource"[52]. Such conflicts, not necessarily involving dramatic confrontations or negative changes, are intrinsic to forest governance/management and happen at a range of geographical levels[53]. The theoretical approaches of literature[50] are typically classified into structural–functional (i.e. related to economic and political distribution of power over forest resources), neo-institutionalism (i.e. considering the influence of formal and informal rules on the behavior of individuals and groups or public/private actors) and perceptional–ideational (i.e. contrasting storylines, narratives, values-beliefs, discourses or frames). Our work is a clear example of how these frameworks overlap in practice and how they can help to explain the country and scale dependencies of stakeholder perceptions as described in the previous paragraph.

Results

Sample and answers. Our sample included a comparable number of observations per country, ranging from 66 and 73 key informant questionnaires in Ecuador and Zambia respectively, to 85 in the Philippines (Table 1). Most of the institutions of the interviewed stakeholders belonged to the national and regional levels (82 and 72 respectively), whereas 52 were local institutions. The international level was represented by 18 observations. The distribution across spatial levels was similar between countries, but Zambia had a slightly higher share of regional institutions (48%, versus 27% and 22% in Ecuador and the Philippines, respectively). Ecuador and the Philippines had a relatively larger proportion of national institutions (28% and 38%, respectively, versus 16% in Zambia). Further details about the respondents and their institutions constituting our sample are included in Supplementary Table S1.

We include a comprehensive list of the answers provided by the respondents in each country, grouped by driver and policy instrument categories, as Supplementary Tables S2 and S3 online. Additionally, we summarize the Likert scores and ranking answers grouped by country and spatial level (see Supplementary Figs. S1–S8). Details on the descriptive statistics and the distributions of the studied variables can also be found as Supplementary Tables S4 to S7 online. Table 2 lists the eighteen variables included in our study and their definition.

One-way analysis of variance (ANOVA). Table 3 depicts the results (levels of significance) of the non-parametric one-way ANOVAs for the eighteen studied variables across countries and spatial levels, overall and between groups. In this table and in the following subsections, we will show the results of the non-parametric tests, as we could not demonstrate univariate and multivariate normality of our sample. However, we also conducted parametric tests (with stronger statistical power) as an additional support of the validity of our findings. Thus, for all variables, the significance of the parametric and non-parametric tests was identical, regarding the overall results across countries and spatial levels. Only a few disagreements occurred at the specific group comparisons. On the one hand, the parametric ANOVA (Tukey test) detected statistically significant differences between Ecuador and the Philippines for three variables, and between the national and the local level for one variable. On the other hand, the non-parametric Dunn test detected statistically significant differences between four pair combinations of spatial levels, concerning two variables. The extended results of both parametric and non-parametric analyses are included as Supplementary Tables S8 to S11 online.

Overall alertness about drivers and confidence in policy instruments. For both overall alertness about deforestation drivers (*Alertness*) and overall confidence in policy instruments (*Confidence*), we could detect significant differences across countries and spatial levels (Table 3, Fig. 1). In the case of *Alertness*, the differences were related to the drivers connected to the commercial economy (*AlertnessCom*). No significant differences across countries or spatial levels were observed regarding the alertness about drivers linked to subsistence economy (*AlertnessSub*).

When compared to the other two countries, Zambia showed significantly lower *Alertness* (14% average, vs. 24% and 22% in Ecuador and the Philippines, respectively), *AlertnessCom* (12% vs. 35% and 30%) and *Confidence* (19% vs. 33% and 34%). *AlertnessSub* was generally lower than *AlertnessCom* (overall 14% vs. 26%), with the exception of Zambia (16% vs. 12%).

		Spatial level				Total
		International	National	Regional	Local	
Country	Zambia	6	16	35	16	73
	Ecuador	7	28	18	13	66
	Philippines	5	38	19	23	85
Total		18	82	72	52	224

Table 1. Number of interviews conducted per country and spatial level of the participants' institutions.

Variable	Definition/classification
Overall perceptions	
Alertness	Share (%) of total answers on drivers of deforestation with "strong" (4) or "very strong" (5) influence
AlertnessCom	Share (%) of total answers on drivers of deforestation related to commercial economy with "strong" (4) or "very strong" (5) influence
AlertnessSub	Share (%) of total answers on drivers of deforestation related to subsistence economy with "strong" (4) or "very strong" (5) influence
Confidence	Share (%) of total answers on policy instruments with "strong" (4) or "very strong" (5) influence
Expected importance of drivers of deforestation and forest degradation (future 10 years)	
Agriculture	Expected importance (%) of drivers related to expansion of agriculture (includes commercial and subsistence, crops/pastures/agroforestry, shifting cultivation…)
Logging	Expected importance (%) of drivers related to logging and extraction of timber and other forest resources involving tree cutting (both legal/illegal activities)
Woodfuel	Expected importance (%) of drivers related to firewood/woodfuel collection and charcoal production
Oilmining	Expected importance (%) of drivers related to oil and mining activities (e.g. exploration)
Infrastructure	Expected importance (%) of drivers related to expansion of urban areas and infrastructure development (road construction, bridges…)
Plantations	Expected importance (%) of drivers related to the expansion of timber plantations
Naturaldisasters	Expected importance (%) of drivers related to natural disasters (e.g. drought, fires, flooding, landslides, earthquakes…)
Otherdrivers	Expected importance (%) of other drivers mentioned by the participants (mostly underlying drivers, e.g. political and tenure conflicts, lack of education)
Expected effectiveness of policy instruments (future 10 years)	
Reforestation	Expected effectiveness (%) of policy instruments related to reforestation, regrowth of natural forest, passive/active forms of forest restoration or establishment of agroforestry areas
Protectedareas	Expected effectiveness (%) of policy instruments related to protected areas restricting access or use of forest, including state reserves, indigenous or private forests
AntiLogging	Expected effectiveness (%) of policy instruments related to measures against illegal logging, including different forms of banning, moratoriums, stronger controls (e.g. patrolling, rangers, regulating timber exports)
Financialtools	Expected effectiveness (%) of policy instruments related to financial mechanisms, including certification, business-funded incentives or PESs (e.g. REDD+)
Landuserights	Expected effectiveness (%) of policy instruments related to improved and secured land titling, decentralization, local participation, community-based and integrated forest management
Otherpolicies	Expected effectiveness (%) of other policy instruments mentioned by the participants, e.g. improving education, sensitization, promoting alternative livelihood/energy sources, international involvement, better governance, less political interference

Table 2. Variables included in the statistical analysis and their definition (observation unit: respondent).

We also observed that *Alertness* and *AlertnessCom* decreased gradually from the international to the local institutions. The average *Alertness* was 27% at the international level, 24% at the national level, 17% at the regional (subnational) level and 15% at the local one. Concerning *AlertnessCom*, the average values for the different spatial levels were 36%, 32%, 22% and 18%, respectively. According to the non-parametric Dunn test, all the differences between groups were significant for both variables, except for the pairs international-national and regional-local. *Confidence* showed a similar decreasing trend, with average values of 34%, 33%, 24% and 26% for the international, national, regional and local levels, respectively. However, we could only demonstrate statistically significant differences between the national and the regional (subnational) level.

Expected future importance of drivers of deforestation and forest degradation. *Agriculture* was expected to be the most important driver category in the three countries: i.e. overall, 43% importance (Fig. 2). In Ecuador (Fig. 3 and Table 3), the importance of *Agriculture* was significantly higher (54%) than in Zambia (40%) and the Philippines (38%). *Logging* was identified as the second most important driver overall (15% importance), but with significantly lower relative importance in Zambia (10%) than in Ecuador (18%) and the Philippines (17%). Instead, Zambia had significantly higher importance (34%) for *Woodfuel*, which stayed below 5% in the Philippines and was not mentioned by the participants in Ecuador. The rest of drivers showed lower relevance overall,

Variables	Across countries				Across spatial levels						
	Country	Zmb-Ecu	Zmb-Phl	Ecu-Phl	Spatial level	Int-Nat	Int-Reg	Int-Loc	Nat-Reg	Nat-Loc	Reg-Loc
Overall perceptions											
Alertness	***	***	***	ns	***	ns	<u>*</u>	<u>**</u>	**	***	ns
AlertnessCom	***	***	***	<u>ns</u>	***	ns	<u>*</u>	**	<u>**</u>	***	ns
AlertnessSub	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Confidence	***	***	***	ns	**	ns	ns	ns	**	<u>ns</u>	ns
Expected importance of drivers											
Agriculture	***	**	ns	**	ns	ns	ns	ns	ns	ns	ns
Logging	**	**	**	ns	ns	ns	ns	ns	ns	ns	ns
Woodfuel	***	***	***	<u>ns</u>	**	ns	ns	ns	**	ns	ns
OilMining	***	***	ns	<u>ns</u>	**	ns	ns	ns	ns	**	**
Infrastructure	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Plantations	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Naturaldisasters	***	ns	***	***	ns	ns	ns	ns	ns	ns	ns
Otherdrivers	**	ns	**	ns	ns	ns	ns	ns	ns	ns	ns
Expected effectiveness of policy instruments											
Reforestation	***	***	ns	**	ns	ns	ns	ns	ns	ns	ns
Protectedareas	***	***	***	ns	ns	ns	ns	ns	ns	ns	ns
AntiLogging	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Financialtools	***	***	ns	***	ns	ns	ns	ns	ns	ns	ns
Landuserights	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Otherpolicies	***	***	***	ns	***	ns	ns	ns	***	ns	*

Table 3. Results of non-parametric ANOVAs for the eighteen studied variables, with overall cross-country and cross- 'spatial level' significances (***: < 0.001, **: < 0.01, *: < 0.05, *ns* not significant [> 0.05], underlined: disagreement between parametric and non-parametric methods) and results for group comparisons (*Zmb* Zambia, *Ecu* Ecuador, *Phl* Philippines, *Int* International, *Nat* National, *Reg* Regional, *Loc* Local).

but still with some significant differences between countries. For instance, *OilMining* was significantly higher in Ecuador (15% importance), while *NaturalDisasters* was significantly more important in the Philippines (11% vs. 1% and 2% in Zambia and Ecuador, respectively). The Philippines also showed higher results for *Infrastructure* (15% vs. 7% and 8%), although these differences were not statistically significant. In Zambia, the importance of *OtherDrivers* was also significantly higher but still relatively low (2%). Finally, no cross-country differences were detected for the generally low importance (2% overall) of *Plantations*.

Across spatial levels, however, we only detected two statistically significant differences (Fig. 3 and Table 3). First, we found significantly lower importance of *OilMining* at local levels (5%) when compared to national (13%) and regional (13%) stakeholders. Second, *Woodfuel* was significantly more important at regional (subnational) levels (17%) than at national levels (7%).

Expected future effectiveness of policy instruments. We could further detect country dependencies on the expected effectiveness of policy instruments (Fig. 4 and Table 3). *Reforestation* (Fig. 2) was the favorite category overall (38%), with statistically higher effectiveness assigned by the stakeholders in Zambia (45%) and the Philippines (41%) than in Ecuador (26%). The second most effective instrument was *ProtectedAreas* (19% overall), which had significantly lower results in Zambia (5%). Third in preference was *AntiLogging* (16% effectiveness overall*)*, with no statistically significant differences among countries. The three remaining policy instrument categories had overall effectiveness scores below 10%. Among these, *FinancialTools* showed significantly higher results in Ecuador (25%), *OtherPolicies* had significantly higher effectiveness in Zambia (19%) and *LandUseRights* showed no statistically significant differences between countries.

Concerning the expected effectiveness of policy instrument categories across scales, we could only detect a significantly higher preference for *OtherPolicies* in the regional (subnational) level (14%), when compared to the national (2%) and local levels (6%) (Fig. 4 and Table 3).

Principal component analysis (PCA). When conducting PCA with all the eighteen studied variables (Supplementary Figs. S9–S11), the first principal component (PC) explained 18.4% of the variance, twice as much as the second PC. The first nine PCs had eigenvalues higher than 1 (Kaiser rule) and explained similar variances ranging from 9.2 (second PC) to 5.9% (eighth PC). Twelve PCs were needed to explain a cumulative variance over 90%. The first PC (Fig. 5) was (strongly) negatively influenced by *Alertness* (overall and for commercial drivers), *Confidence*, *ProtectedAreas* and *FinancialTools*, and positively by *Woodfuel* and *OtherPolicies*. The scores for a number of PCs revealed strong cross-country differences. Specifically, the first two PCs distinguished Zambia from the other two countries, while the third and sixth PCs accounted for variations between

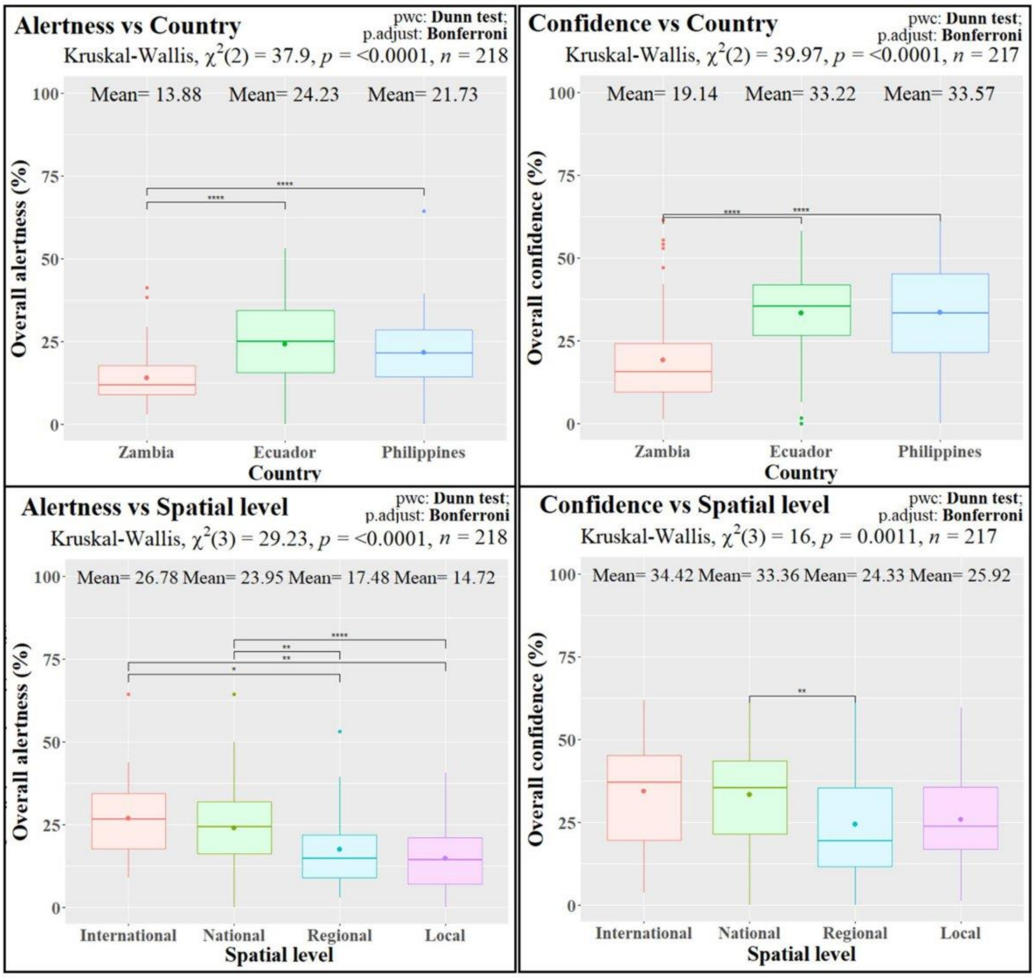

Figure 1. Results of the Kruskal–Wallis and Dunn tests across countries and spatial levels for *Alertness* (overall alertness about deforestation drivers) and *Confidence* (overall confidence in policy instruments). Boxplots including mean values (Mean), chi square statistic (χ^2), p-values (p) and number of observations (n) of the Kruskal–Wallis tests and p-adjustment (p. adjust) and p-scores (sign, ****: < 0.0001, ***: < 0.001, **: < 0.01, *: < 0.05, *ns* not significant [> 0.05]) for the Dunn pairwise comparisons (pwc).

Ecuador and the Philippines (Fig. 5). The cross-scale differences were less distinct but still noticeable, especially when observing the scores of the two first PCs (Supplementary Fig. S7).

Discussion

Our findings indicate that stakeholders in Zambia and those from institutions of subnational levels tend to be less alert about the number of possible commercial threats to forests and are skeptical about the effectiveness of more policy instruments (Table 3 and Fig. 1). However, stakeholders agree across scales about the most important drivers (i.e. agriculture) and about the most effective policy instruments (i.e. reforestation) in the coming decade, which follow regional trends (Table 3 and Figs. 3, 4).

Consistent with our hypothesis, the ANOVA results revealed that *Alertness* and *Confidence* differ across countries (Table 3 and Fig. 1). The PCA ratified the relevance of these two indicators, as they both contributed strongly to the first PC explaining most of the variance and clearly differentiating the Zambian observations (Fig. 5). The differences observed for *Alertness* were attributable to drivers related to the demands of commercial economy. These perceptions align with the regional trends of the last decades, where commercial operators (e.g. agriculture, logging) have been playing a major role in South America and South East Asia, when compared to Africa[17,24]. The fact that Ecuador and especially the Philippines are in a more advanced stage of deforestation[20,43], could have conditioned the perceptions of their stakeholders to be more alert about potential threats, resulting in a higher perceived need for policy instruments. This is remarkable, as historical deforestation, if related to inefficient policies, can be rather expected as a reason for lower *Confidence*. Ecuador has lost a large share of its native forests since the sixties, catalyzed by agrarian reforms and laws incentivizing land-use conversion and

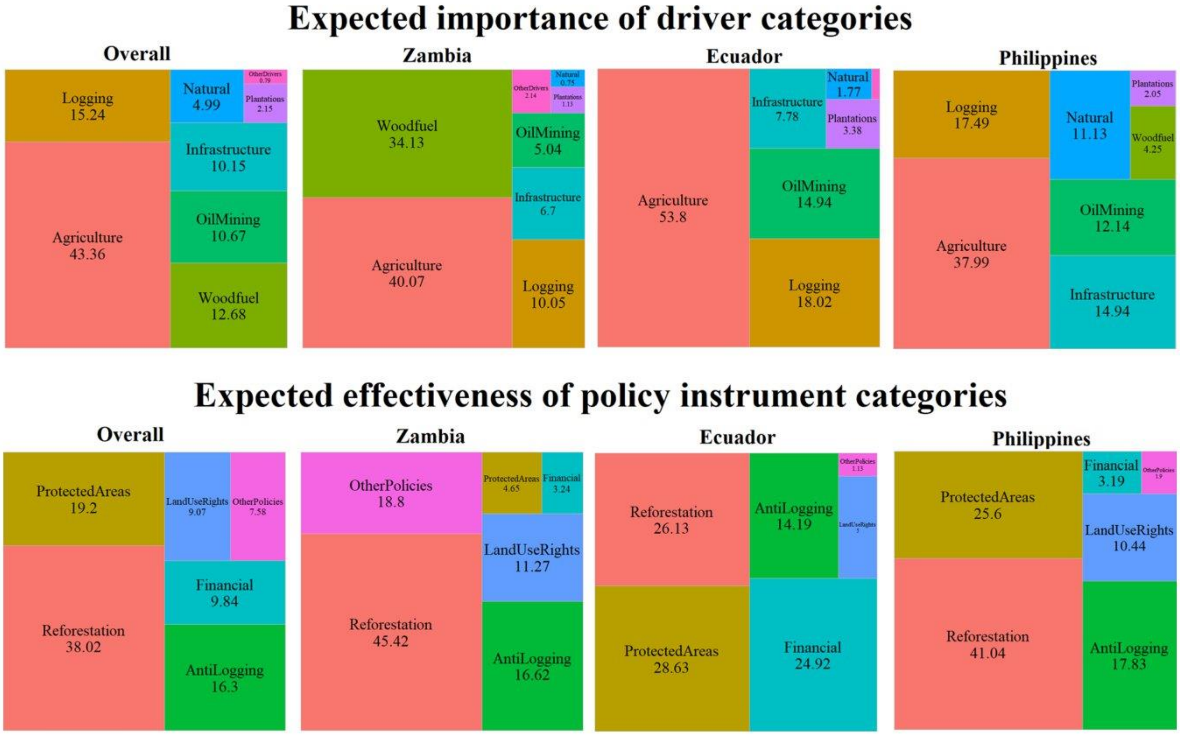

Figure 2. Tree maps representing the overall expected importance of the driver categories and the expected effectiveness of the policy instrument categories in the total sample and in the country subsamples. Natural refers to *NaturalDisasters*, Financial refers to *FinancialTools*.

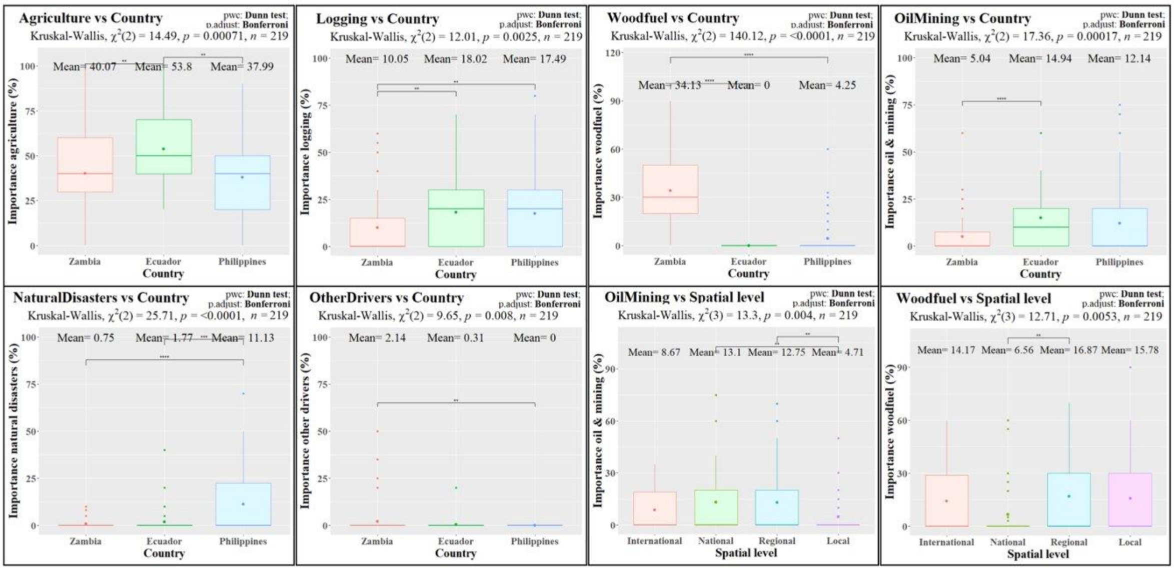

Figure 3. Results of the Kruskal–Wallis and Dunn tests across countries and spatial levels for the variables related to the expected importance of driver categories. Only tests with statistically significant results are shown. Boxplots including mean values (Mean), chi square statistic (χ^2), p-values (p) and number of observations (n) of the Kruskal–Wallis tests and p-adjustment (p.adjust) and p-scores (sign, ****: < 0.0001, ***: < 0.001, **: < 0.01, *: < 0.05, *ns* not significant [> 0.05]) for the Dunn pairwise comparisons (pwc).

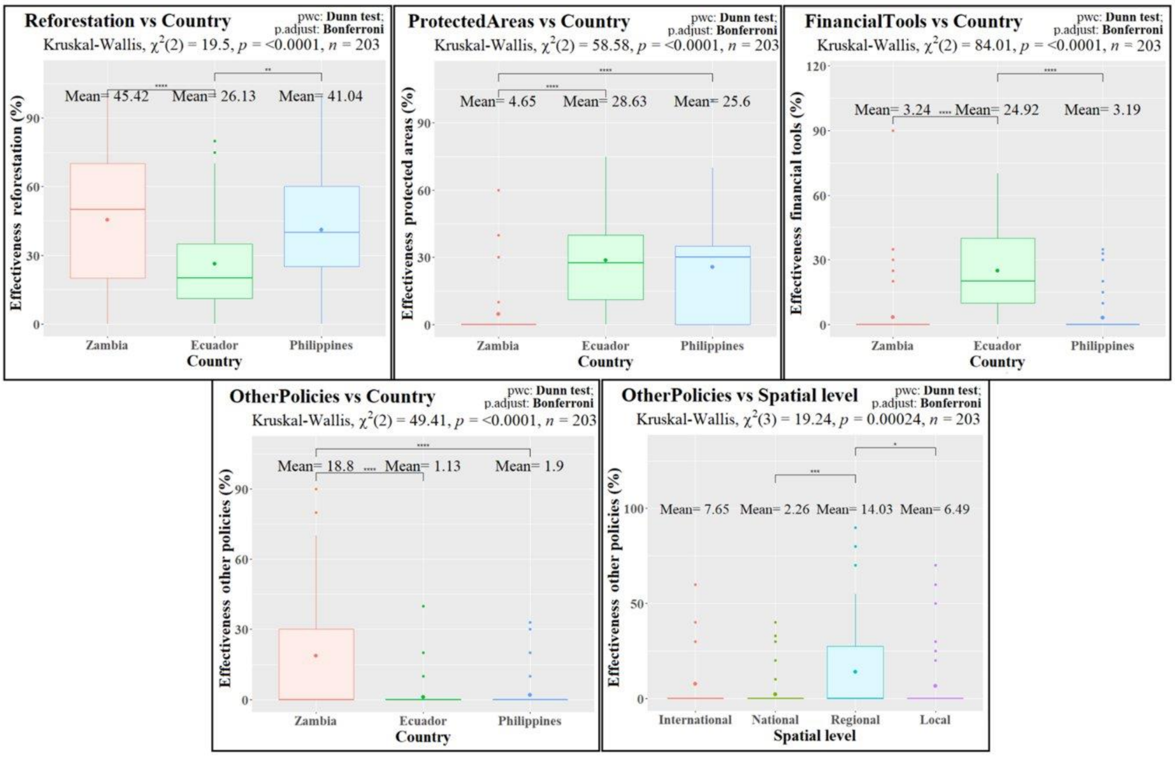

Figure 4. Results of the Kruskal–Wallis and Dunn tests across countries and spatial levels for the variables related to the expected effectiveness of policy instrument categories. Only tests with statistically significant results are shown. Boxplots including mean values (Mean), chi square statistic (χ^2), p-values (p) and number of observations (n) of the Kruskal–Wallis tests and p-adjustment (p. adjust) and p-scores (sign, ****: < 0.0001, ***: < 0.001, **: < 0.01, *: < 0.05, *ns* not significant [> 0.05]) for the Dunn pairwise comparisons (pwc).

by road construction for the oil industry[54,55]. Similarly, forest cover in the Philippines has decreased drastically from approximately 70% to less than 25% during the twentieth century, mostly due to massive commercial timber harvesting, leading to a nationwide logging moratorium, net wood imports and numerous reforestation and forest restoration programs[56–58]. In contrast, a large share of Zambian primary forests have been degraded since the seventies, but the relatively high forest cover of the country has been decreasing at slower rates[59]. This probably explains the lower *Alertness* in Zambia, while the lower *Confidence* could be rather related to a lack of trust in governance mechanisms, which was recurrently mentioned by the respondents and has been identified by previous research in the region[47,60]. These results may characterize contexts of pre- or early forest transition, when forest areas are still abundant and slow deforestation rates accelerate[17]. This may be seen as a warning sign and point to a need for precautionary measures such as environmental education or the improvement of governance structures[60], before reaching lower levels of forest cover in Zambia or in countries of the region with similar characteristics (e.g. Gabon, Angola, Tanzania, Liberia, Congo, Democratic Republic of the Congo)[1]. Our results in Ecuador and the Philippines indicate that opposing views are possible, in which the importance of drivers and potential solutions are more strongly taken into consideration by all actors. However, it remains unclear whether this change in perspective can be achieved before assuming uncontrolled deforestation rates and low levels of forest cover in later forest transition stages.

Similarly, lower *Alertness* and *Confidence* detected in institutions of subnational levels (Table 3 and Fig. 1) suggests that international and national stakeholders, normally involved in and responsible for planning and policy design (de jure), would have a broader overview of possible threats and protection mechanisms. Therefore, they would identify a larger set of drivers and policies as having a strong or very strong effect when compared to sub-national and local stakeholders. In contrast, the latter would typically experience a lower number of specific drivers, while being closer to the sometimes-ineffective policy measures being implemented on the ground (de facto)[48,49,60]. Such challenges are especially common in tropical countries characterized by political instability and weak institutions[61], where the information and rules about political instruments and forest management often reach the local levels with a time delay[62]. Avoiding potential disengagement of local stakeholders regarding national forest protection goals is particularly relevant, as those actors are closer to the effects of deforestation on the ground and closer to reverse such trends with direct action[29,47]. This points to the importance of law enforcement and ensuring economic, logistical and institutional support to local organizations for achieving effective policy implementation[63]. We also interpret that the lower *Alertness* of local stakeholders is related to the fact that they do not perceive deforestation necessarily as a threat, but rather as a potential source of revenue

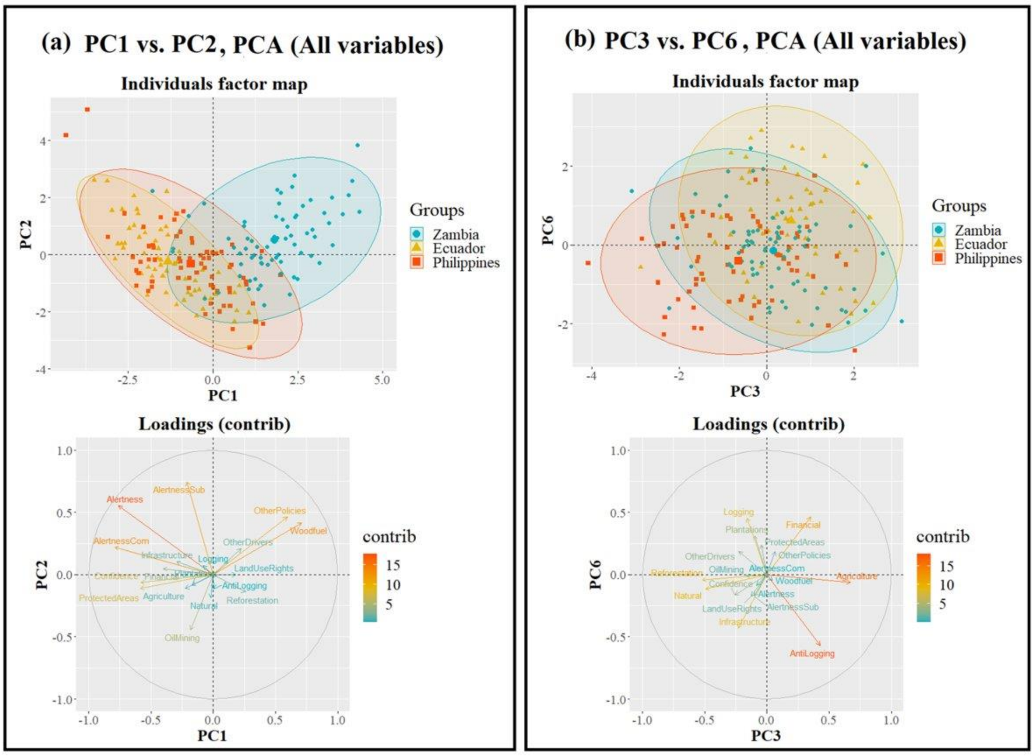

Figure 5. Results of the PCA with all the eighteen studied variables: biplots of the individuals grouped by country (ellipse of 95% confidence) and loadings of the variables for the two first components (**a**) and for the third and sixth component (**b**).

and economic development. Forest products can represent a significant share of total rural household income in the tropics, averaging roughly from 15 to 50% in the studied countries[56,64,65]. This could also be viewed as an explanation for the lower *Alertness* in Zambia, where forest-related share of income was the highest among the target countries[66]. Thus, our results suggest that forest policies or strategies to combat deforestation in the tropics should consider the direct dependence of local, usually rural, populations on forests, to avoid further challenges during implementation.

As hypothesized and supported by the PCA (Fig. 5), the ANOVAs detected significant differences among the three countries regarding the expected importance of the driver categories (Table 3, Figs. 2 and 3). Our findings confirm the higher importance of agricultural expansion and cattle ranching in South America in general[17,24] and in Ecuador in particular, where they have been responsible for approximately 95% of the forest loss between 1990 and 2018[54]. Similarly, Ecuadorian respondents expected a significantly higher importance for mining and oil extractions. In addition to the historical link between oil development and deforestation[54,55], recent governmental concessions for such purpose overlap with about 24% of all official indigenous territories and protected areas in the Amazon basin[67]. In Zambia, the higher importance of woodfuel and charcoal production was anticipated in a country where these sources comprise over 70% of the national energy consumption, as they are seen as cheap, accessible and reliable alternatives to electricity[68]. Respondents in Zambia provided a larger number of additional answers, mentioning governance issues as threats to forests in line with previously reported results[47,60]. Zambian stakeholders also reported a significantly lower importance of timber extraction (mostly selective logging leading to degradation[59]) when compared to Ecuador and the Philippines. These two countries present a longer history of combating illegal logging and allowing or prohibiting timber extraction in both private and public lands[69–71]. The responses in the Philippines were relatively high for a larger variety of driver categories, which can also be explained by their history of a nationwide and large-scale deforestation over the twentieth century[56,58,72]. Apart from the mentioned drivers (i.e. *Agriculture*, *Logging* and *OilMining*), the Philippine respondents also highlighted the role of other known threats to forests[72,73], namely natural disasters (i.e. typhoons, landslides and floods) and infrastructure expansion, the latter without being statistically significant. Thus, our findings indicate that stakeholders expect the currently-relevant drivers to remain important in the future decade, pointing to the continuation of the well-known regional trends and providing hints on which drivers to anticipate and where to do it.

We also observed significant differences among the studied countries regarding the expected effectiveness of policy measures (Table 3, Figs. 2 and 4). In line with current international agenda (e.g. 1 Trillion Trees initiative, Bonn Challenge or the UN Decade on Ecosystem Restoration), reforestation and forest restoration initiatives are the favorite policy instruments overall. The Philippines have reversed the trend of deforestation to a net gain of forest area in the last decade, partly attributed to tree plantings, natural regeneration and high government investments on reforestation projects, such as the National Greening Program[56–58]. The respondents in Ecuador reported a relatively lower effectiveness of *Reforestation* when compared to the Philippines and Zambia, despite several ambitious reforestation plans aiming to convert 300,000 hectares of pastureland to agroforestry systems in the Amazon[74]. This is due to a larger preference for financial instruments, linked to positive experiences regarding the national PES scheme of Socio Bosque[75]. Although protected areas are the second favorite policy instrument overall, their expected effectiveness is half that of reforestation. The Zambian respondents showed a much lower preference for protected areas, likely related to a historic ineffectiveness of such regulatory measures in the country[76]. Policies against illegal logging play a relevant intermediate role and land use rights were less preferred, both without significant differences across countries. Finally, the Zambian respondents (especially the regional subsample), highlighted the importance of other policies, i.e. related to improving governance mechanisms and facilitating energy and livelihood alternatives. Previous results when evaluating the national subsample of our dataset, had already pointed to a similar overall picture about the effectiveness of policy instruments in the tropics[77].

Overall, the astonishingly high scores of *Reforestation* may indicate a paradigm shift from protected areas to a stronger focus on reforestation and integrative approaches. This points to the importance of including reforestation and forest restoration measures in the design, promotion and management of protected areas and other effective area-based conservation measures (OECMs), which are currently promoted by policy, especially related to biodiversity conservation[78,79]. Reforestation can encompass different forms of natural regrowth, passive/active forest restoration or the establishment of agroforestry areas. These approaches can be relevant in the current context of transformative change towards climate-resilient socioecological systems and the proliferation of fragmented and degraded forests[2,80]. However, we should highlight that this strong preference for reforestation over other policy instruments does not necessarily imply that prioritizing such measures always constitutes sound policy[81,82]. This interesting finding could reflect the widely extended narratives of the current international forest agenda promoting reforestation measures, e.g., in the context of the Bonn Challenge. Similarly, the preference of reforestation measures could point to negative experiences regarding other financial or regulatory policies. For instance, despite positive evidence for the effectiveness of protected areas, these have been found to not always avoid clearing within the boundaries (or to increase the risk in neighbor areas), and to highly depend on monitoring and law enforcement[83–85].

Surprisingly, we observed very few significant cross-scale differences regarding both the expected importance of deforestation drivers and the expected effectiveness of policy instruments (Table 3, Figs. 3 and 4). First, our findings suggest that subnational stakeholders are more aware of the importance of subsistence activities, such as firewood collection, while national institutions identify commercial and industrial threats of higher importance, such as oil and mining operations. This finding is an example of how scale affects the perception of telecoupled commodities or agricultural trade flows in a globalized economy[86]. Apparently, high-level stakeholders are more concerned about the impacts of such commodities on forests than local actors. Nevertheless, local actors are often both producers and consumers of such commercial products as well. Second, most of the respondents providing suggestions for other policy instruments belonged to the regional level, due to the more detailed recommendations of respondents in academia.

However, the general lack of effects across scales indicates that most of the forest representatives follow the same narratives regarding the main future threats to tropical forests and the favored strategies to combat them, independently of the geographical jurisdiction of their institutions. This contradicts our hypothesis that different stakeholder configurations and interests would result in particular preferences. Concerning policy instruments, for instance, we had expected a favoritism of decentralization measures (i.e. *LandUseRights*) and positive financial incentives (i.e. *FinancialTools*) at local levels, together with a rejection of command-and-control measures such as *ProtectedAreas*, based on our previous work at landscapes of the studied countries[47,60,63]. A possible explanation for this result is the strong influence of the national narratives of success (e.g. Sociobosque in Ecuador) or failure (e.g. protected areas in Zambia) for specific policy instruments, which showed similar degrees of acceptance across spatial levels. This idea would be supported by the fact that most of the interviewed institutions have strong interactions with each other within the national setting, rather than internationally. However, this fact alone would not explain if such dominating and broadly accepted discourses are created unidirectionally and thus dictated by the one or the other stakeholder group (e.g. top-down or bottom-up approaches); or, in contrast, if they are rather the result of a bi-directional exchange of complementary storylines. To achieve these type of conclusions, more complex analysis including the role of power (both over institutions and forest resources) would be needed. In any case, this finding indicates a potential of agreements for future collaboration between actors at different spatial levels, in particular needed for effective policy design and cross-scale implementation of forest conservation measures and forest landscape restoration[24].

The interpretations and implications of our findings must nonetheless be taken cautiously, as the reliability of this data is impacted by the sample and methodological choices. For instance, the distribution of observations across spatial levels is not perfectly balanced (e.g. less international institutions, more regional stakeholders in Zambia). Also relevant is how the institutions were selected and distributed across spatial levels. The majority of the interviewed stakeholders were representatives (typically men over 45 years of age with university education) of formal government-related institutions. Additionally, the way the answers of importance and effectiveness were collected as compositional data, or the analysis of Likert answers as Top 2 Box scores, conditions the potential for interpretation[87,88]. Another important point is the simplification of categories conducted to generalize our results and make them comparable across countries. In reality, such categories might present strong overlaps or interactions. For instance, drivers of deforestation often act in a conjoint manner, which includes subtle interrelations and dependencies[20]. Similarly, most environmental programs and policies nowadays include a mix or combination of instruments[21,22], which makes it challenging to assign them or their effects to a specific category. However, the fact that most of PCs explained a similar share of the variance, had eigenvalues close to or higher than 1 and were mostly loaded with one or few variables (Supplementary Fig. S9–S11), indicates that the dimensions could not be reduced easily and that most of the PCs were relevant and related to the included variables. This suggests the independence of the chosen driver and policy categories based on existing literature, confirming their appropriateness in describing distinct deforestation processes and recommending further studies to use similar classifications. Further studies could expand this sample to other tropical countries or extend the representativity of certain stakeholder types. Likewise, we see additional potential in analyzing institutional characteristics such as power, exploring the direct relationships between drivers and policies, or linking perceptions with spatially-explicit data on deforestation for different countries or administrative units.

While the role of the drivers of tropical deforestation and forest degradation in reshaping the Earth's surface is by now common knowledge, policy instruments often fail to address these drivers effectively across countries and scales. The evidence is clear: local stakeholders and also actors in certain contexts (i.e. Zambia and potentially other African countries with high forest cover) are less alert about a larger number of future commercial threats to tropical forests. In addition, these stakeholders are more skeptical about the effectiveness of existing policy instruments. At the same time, our investigation clearly shows that the national context matters for the perception of both deforestation threats and effective policies, suggesting that there is no one-size-fits-all solution to improve forest policy at a global scale. Despite these differences, actors across scales agree about the most important drivers (i.e. agriculture) and about the most effective policy instruments (i.e. reforestation) in the coming decade. This unexpected consensus confirms the existence of common entry points for collaboration between institutions operating at different spatial levels, which is a precondition for effective policy design and implementation. For instance, the overwhelming favoritism for reforestation and forest restoration initiatives is particularly relevant, as it points to the potential of integrating different forms of reforestation as a complementary component of area-based conservation measures.

Methods

Study design. The study was conducted in three tropical countries of Africa (Zambia), South America (Ecuador) and South East Asia (Philippines), as part of the project Landscape Forestry in the Tropics (LaForeT: www.la-foret.org). The country selection aimed to include different continents and a gradient of forest transitions contexts, from early in Zambia (with still a relatively high forest cover and accelerating deforestation rates), middle in Ecuador and late in the Philippines (with historical deforestation resulting in low forest cover and recent reforestation efforts)[43].

Between November 2018 and December 2019, a total of 224 representatives of forest-related institutions (key informants or stakeholders) were interviewed following a standardized questionnaire. The study sample included respondents from local and central governments, national and international organizations, private enterprises, indigenous associations and academia. An extended list of characteristics of the respondents and their institutions can be found as Supplementary Table S1 online. Additionally, a list of the institutions taking part on the survey, as well as anonymized detailed information on the respondents (i.e. gender, position within the institution, …) and on the institutions themselves (number of workers, type of institution, …) can be found attached to this manuscript as a Supplementary File online (spreadsheet 'Data Questionnaire', sheets 'Institutions' and 'Respondents').

Each of the participants was assigned to one of four spatial levels (Table 1) depending on the nature or main scope of work of the stakeholder's institution. These spatial levels were related to the different levels of geographical jurisdictions or administrative units located across the spatial scale, i.e. (i) international (e.g. Food and Agriculture Organization or development agencies), (ii) national (e.g. central ministry units or national forestry/environmental departments), (iii) regional (e.g. Provincial offices or sub-national departments/Universities) and (iv) local (e.g. municipal government/offices or traditional leaders). Thus, the regional level captures all subnational jurisdictional units larger or equal to Districts in Zambia, Counties in Ecuador and Provinces in the Philippines. The local level comprises institutions with a scope at smaller jurisdictional units (e.g. Chiefdoms in Zambia, Parishes in Ecuador, Municipalities or Barangays in the Philippines).

Questionnaire. The protocol of the questionnaire study was approved through research permits signed by all participating scientific institutions, namely the Thünen Institute in Hamburg (Germany), the Universidad Estatal Amazónica in Puyo (Ecuador), the University of the Philippines in Los Baños (Philippines) and the Copperbelt University in Kitwe (Zambia). The methods were carried out in accordance with the guidelines of good scientific practice from the German Research Foundation (DFG) and relevant regulations. Informed consent was obtained from all participants, who were all over eighteen years of age at the time of conducting the interviews.

Our questionnaire included two sections: (i) one, asking about the influence of different proximate drivers on deforestation and forest degradation in the next 10 years; and (ii) a second one, asking about the influence of policy measures on stopping deforestation/degradation and increasing forest areas, again in the future 10 years. Based on existing literature and expert knowledge[47,58,63,89–91], we provided a list of nationally relevant drivers and policy instruments for each section respectively and gave the respondents the opportunity to add their own answers. In the case of the drivers, we focused on proximate or direct drivers, while the policy instruments included regulatory (i.e. spatial planning direct regulation), economic (i.e. land tenure, positive/negative incentives, market mechanisms) and information instruments. We further aggregated all the drivers and policy instruments into eight and six cross-country categories, respectively. These categories were defined based on the literature mentioned in the introduction[8,17,21,22] and to be broad enough to include a sufficiently high number of answers for comparison across countries and spatial levels. Thus, the aggregated results for cross-country categories included a varying number of answers for multiple national drivers and policy instruments. A detailed list of questions/answers for both sections of the questionnaire in the three countries, grouped by cross-country categories, are included as supplementary information (see Supplementary Tables S2, S3 online).

The respondents could score each national driver or policy instrument based on a Likert scale[92], from 1 (no effect) to 5 (very strong effect). In the case of the first section, the participants could also distinguish if the drivers were related to the demands of subsistence or commercial economy. Additionally, the respondents listed their top three to five important national drivers and policies, respectively, each with a share of relative relevance adding up to 100. An extended version of these results can be found as Supplementary Figs. S1 to S8. All the answers were collected in digital format and included in a common database for the three countries by the project staff. The complete list of responses for all the drivers and policies with details on national and cross-country categories, including the Likert and rank/percentage answers, can be found attached to this manuscript as a Supplementary File online (spreadsheet 'Data Questionnaire', sheet 'Responses').

Variables. Based on the answers of the respondents, we derived a total of eighteen variables per questionnaire (Table 2), which were further used in the statistical analyses. We include descriptive statistics of all these variables for the total sample and for the country and spatial level subsamples as Supplementary Tables S4, S5 online. The complete list of values for all the variables and observation units (respondents) can be found as a Supplementary File online (spreadsheet 'Data Questionnaire', sheet 'Variables').

Overall alertness about deforestation drivers and overall confidence in policy instruments. From the Likert answers we derived two variables: (i) "Overall alertness about deforestation drivers" (*Alertness*) and (ii) "Overall confidence in policy measures" (*Confidence*). These two variables were defined as the share of answers with "strong" (4) or "very strong" (5) influence in each section of the questionnaire, respectively (Top 2 Box scores [T2B] in percentage[93]). We included these variables as indicators of the stakeholders' general perception about the influence of drivers and policy instruments. As described above, in the case of the driver categories (*Alertness*), we could also further distinguish between the answers related to the demands of subsistence (*AlertnessSub*) or commercial (*AlertnessCom*) economy.

Expected importance of deforestation drivers and expected effectiveness of policy instruments. By adding up the answers on relative relevance in percentage, we derived fourteen further variables, related to the expected relative importance and effectiveness of the specific cross-country driver and policy instrument categories, respectively. Thus, we calculated the expected relative importance of the following eight drivers: (i) Expansion of agriculture (*Agriculture*), (ii) Logging, timber and resource extraction (*Logging*), (iii) Firewood, woodfuel and charcoal (*Woodfuel*), (iv) Oil and mining (*OilMining*), (v) Infrastructure and urbanization (*Infrastructure*), (vi) Expansion of timber plantations (*Plantations*), (vii) Natural disasters (*NaturalDisasters*) and (viii) Other drivers (*OtherDrivers*). Correspondingly, we calculated the expected relative effectiveness of the following six policy instruments: (i) Reforestation, restoration and agroforestry (*Reforestation*), (ii) Protected areas (*ProtectedAreas*), (iii) Measures against logging (*AntiLogging*), (iv) Financial instruments (*FinancialTools*), (v) Land-use rights (*LandUseRights*) and (vi) Other policy instruments (*OtherPolicies*).

Statistical analysis. For all the steps described in this section we used R[94] packages rstatix[95] and factoextra[96], as well as multiple helper functions[97–104]. The complete R script used for the analysis can be found as a Supplementary File, attached to this manuscript online.

First, we checked the distribution of each variable by analyzing visually the histograms and boxplots, before and after centering, scaling and selecting a transformation (square-root, log or inverse), which brought the skewness the closest to 0. We confirmed the visual interpretations by performing Shapiro–Wilk tests[105] of univariate normality and Mardia[106] tests of multivariate normality (see Supplementary Tables S6, S7).

We could not find significant evidence of multivariate or univariate normality for most of the selected variables. This was expected due to the type of survey data used (i.e. Likert scores and compositional data), known for presenting particular properties (e.g. presence of zeroes, not enough observations for particular answers, ordinal scales) which result in mathematical challenges when applying parametric methods[87,88].

In addition, we removed questionnaires with errors, missing entries or outliers before each of the specific statistical analysis. From the original 224 interviews, this resulted in 218 observations including valid responses about alertness, 217 about confidence and 219 and 203 questionnaires including valid answers about the importance of driver and policy categories, respectively (Supplementary Tables S4, S5).

One-way analysis of variance (ANOVA). We conducted parametric and non-parametric one-way ANOVA for all the studied variables across countries and across spatial scales, to test whether the different samples originated from the same distribution. As we could not confirm normality, we relied on the results of the non-parametric Kruskal–Wallis one-way ANOVA[107], accompanied by Dunn's test[108] and pairwise Mann–Whitney tests with Bonferroni correction[109] (Supplementary Tables S8, S9). Nevertheless, we also conducted parametric one-way ANOVAs (by generalizing the t statistic[110] to three [country] and four [spatial level] samples) and pairwise Tukey test[111], in order to compare and support the validity of our results (Supplementary Tables S10, S11).

Principal component analysis (PCA). We conducted PCA[112] with all the eighteen studied variables (scaled), in order to find relationships and correlations within them and further support the interpretation of the ANOVAs across countries and spatial levels. With this approach, we also aimed to explore if the number of pre-selected categories could be reduced and still capture most of the variation in the answers The extended results for these tests, including spree plots, proportions of variance explained, eigenvalues, loadings and biplots of the first components (PCs) are included as supplementary information (see Supplementary Figs. S9–S11).

Data availability

Data supporting the results reported in the manuscript (without breaching participant confidentiality) is freely available to any researcher wishing to use them for non-commercial purposes, in the Supplementary Information files of these article (Spreadsheet file 'Data Questionnaire').

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Author contributions
R.F.V. prepared the data, conducted the statistical analysis and wrote the manuscript draft. M.L. and R.F. designed the different sections of the questionnaire and supervised the collection of data and its digitalization. B.T., F.T. F.K.K., H.K. and L.B. supervised the collection of data and reviewed the final version of the manuscript. S.G. administered the project, supervised the study and acquired funding. R.F.V., M.L., R.F. and S.G. participated in the conceptualization of the study and reviewed different versions of the manuscript.

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Correspondence and requests for materials should be addressed to R.F.V.

List of all publications and contributions of the author

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