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Low-cost soil moisture measurement and parsimonious crop modeling to assist agricultural water management

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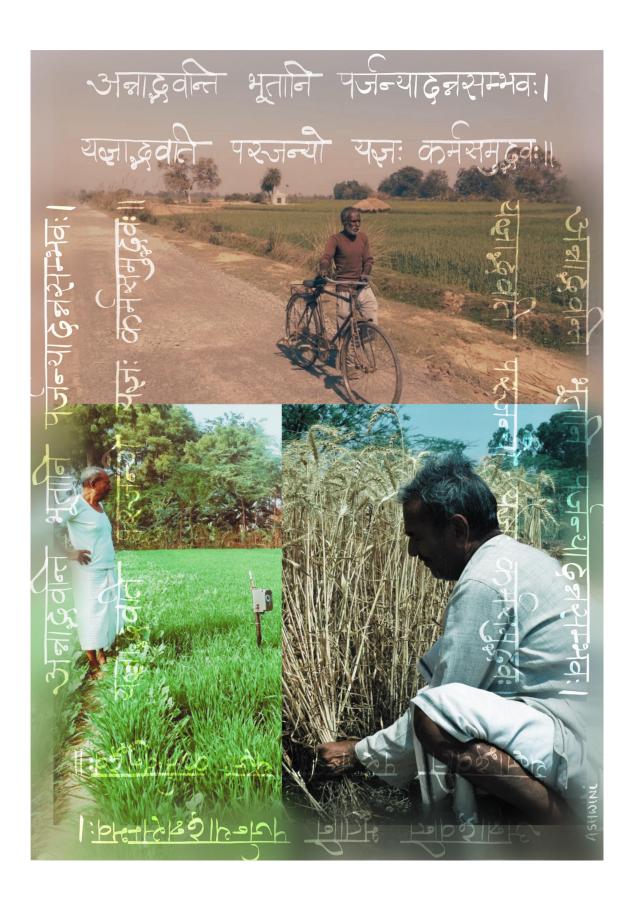
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अन्नाद्भवन्ति भूतानि पर्जन्यादन्नसम्भवः । यज्ञाद्भवति पर्जन्यो यज्ञः कर्मसमुद्भवः। । 3/14 । ।

annād bhavanti bhūtāni parjanyād anna-sambhavaḥ yajñād bhavati parjanyo yajñaḥ karma-samudbhavaḥ || 3/14 ||

All living beings subsist on food, and food is produced by rains. Rains come from sacrifice $(yaj\tilde{n}a)$, and sacrifice is born of action (Bhagavad Gita: Chapter 3, Verse 14).

Abstract

Agricultural production and yields in developing countries have been lower than those of developed countries over the past few decades due to poor agronomy practice, possibly because of (among other reasons) the relative under-utilization of improved agricultural technologies. There is a need to empower agricultural advisories with data-based, farm-specific 'diagnostics' to characterize farm performance and identify the reasons of yield-gaps, leading to more customized advisories and potentially higher adoption of agricultural technologies. Further, cost-effective solutions can be developed to increase water use efficiency and productivity in agriculture, based on the synergies of low-cost soil moisture measurement and parsimonious water-driven crop modeling.

This study proposes a data-based approach to 'diagnose' nutrient and water related agricultural performance quantitatively, to facilitate advisors in developing farm-centric advisories. A user-friendly Farm Agricultural Diagnostics (FAD) tool, developed in Microsoft Excel VBA, uses farmer surveys and soil testing to quantify current agricultural performance, classify farms into different performance categories, and visualize farm performance within a user-friendly interface. The advisory diagnostics approach is tested in Kanpur (India), which represents an intensively managed rural landscape in the Ganga river basin.

Low-cost soil moisture measurements can potentially drive technological tools to improve water management in agriculture. Two low-cost capacitive, and two very low-cost resistive soil moisture sensors were tested in laboratory conditions to characterize their performance in irrigation management applications. Sensors were calibrated in different repacked soils, and tested to evaluate accuracy, precision and sensitivity to variations in temperature and salinity. The capacitive sensors were additionally tested for their performance in liquids of known dielectric constants, and the developed calibration equations were compared with those provided by the manufacturer. While the very low-cost sensors were unsuitable for irrigation management applications, the low-cost SM100 sensor (manufactured by Spectrum Technologies, Inc.) was established as a robust, field ready sensor due to its more consistent performance in soils and reasonable response to variations in temperature and salinity.

Low-cost soil moisture sensing and water-driven crop-growth modeling can be combined to develop irrigation management tools. However, to be applied in data-scarce regions, low-cost soil moisture measurements need to be cost-effective and calibrated, and crop models need to be parsimonious in terms of data requirements. The low-cost SM100 sensor was calibrated in laboratory and field conditions (against a superior sensor, the SMT100 manufactured by UGT GmbH.), revealing that superior calibration was possible in field conditions, using the dry-down curve, and while avoiding over-fitting. The field calibrated piece-wise linear regression function was selected as the best calibration technique to improve SM100 performance in the field. Low-cost sensor data were used with the MATLAB based open-source version of the parsimonious FAO

AquaCrop model, to study the impact of using calibrated soil moisture data to calibrate crop model soil hydraulic properties on crop model performance. This experiment was conducted on an experimental field in Kanpur during the 2018 wheat cropping season. The soil moisture simulation of AquaCrop-OS improved significantly by incorporating calibrated SM100 data. While there were no significant changes in biomass prediction, crop water productivity was significantly improved by using calibrated SM100 data.

Irrigation schedules can be generated under the assumption that no water stress occurs as long as evapotranspirative demand is met. FAO AquaCrop simulates four water stresses and corresponding thresholds which trigger the respective stresses. Irrigation was triggered when these thresholds were reached, and this FAO AquaCrop irrigation strategy was compared with full irrigation conditions in a simulation based study. While no water stress occurred in both strategies, the full irrigation strategy simulated 1.5 times more irrigation applications (equivalent to 111 mm) and lower water productivity than the FAO AquaCrop strategy.

Adopting new irrigation strategies requires behavioral change which may be partly motivated by cost-effectiveness, but it is important to develop solutions with farmers with design considerations based on the socio-economic characteristics, agricultural risk taking attitude and previous experience of the farmers, to steer them towards improved water management practices.

Zusammenfassung

In den letzten Jahrzehnten waren aufgrund schlechter agronomischer Praktiken die landwirtschaftliche Produktion und die landwirtschaftlichen Erträge in den Entwicklungsländern niedriger als die der entwickelten Länder. Möglicherweise lag es (unter anderem) an relativ geringer Nutzung verbesserter landwirtschaftlicher Technologien. Es ist notwendig, landwirtschaftliche Beratungsstellen mit datenbasierten, betriebsspezifischen Diagnosen auszustatten, um die Leistung landwirtschaftlicher Betriebe näher zu charakterisieren und die Gründe für Ertragslücken zu identifizieren, was zu kundenspezifischeren Beratungsangeboten und potenziell höherer Akzeptanz landwirtschaftlicher Technologien führen wird. Darüber hinaus können kostengünstige Lösungen entwickelt werden, um die Wassernutzungseffizienz und Produktivität in der Landwirtschaft zu steigern, basierend auf den Synergien von kostengünstiger Bodenfeuchtemessung und sparsamer wassergesteuerter Nutzpflanzenmodellierung. Diese Studie schlägt einen datenbasierten Ansatz vor, um die nährstoff- und wasserbezogene landwirtschaftliche Leistung quantitativ zu diagnostizieren und somit den Beratungsstellen Entwicklung betriebszentrierter Beratungsangebote zu erleichtern. Ein benutzerfreundliches Farm Agricultural Diagnostics (FAD)-Tool, das in Microsoft Excel VBA entwickelt wurde, verwendet Umfragen der Landwirte und Bodentests, um die aktuelle landwirtschaftliche Leistung zu quantifizieren, landwirtschaftliche Betriebe in verschiedene Leistungskategorien zu klassifizieren und landwirtschaftliche Leistung auf einer benutzerfreundlichen Oberfläche zu visualisieren. Die diagnostische Herangehensweise innerhalb der Beratungsstellen wird in Kanpur (Indien) getestet, das einen intensiv bewirtschafteten ländlichen Naturraum im Flussbecken Ganges darstellt. Potentiell können kostengünstige Bodenfeuchtemessungen technologische Werkzeuge zur Verbesserung des Wassermanagements in der Landwirtschaft vorantreiben. Zwei kostengünstige kapazitive und zwei sehr kostengünstige resistive Bodenfeuchtesensoren wurden unter Laborbedingungen getestet, um ihre Leistung in Bewässerungsmanagementanwendungen zu charakterisieren. Die Sensoren wurden in verschiedenen aufbereiteten Bodenproben kalibriert und getestet, um Genauigkeit, Präzision und Empfindlichkeit gegenüber Temperaturund Salzgehaltschwankungen zu bewerten. Die kapazitiven Sensoren wurden zusätzlich auf ihre Leistungsfähigkeit in Flüssigkeiten bekannter Dielektrizitätskonstanten getestet und die entwickelten Kalibriergleichungen mit den vom Hersteller bereitgestellten verglichen. Während die sehr kostengünstigen Sensoren für Bewässerungsmanagementanwendungen ungeeignet waren, hat sich der kostengünstige SM100-Sensor (hergestellt von Spectrum Technologies, Inc.) aufgrund seiner konsistenteren Leistung in Böden und seiner angemessenen Reaktion auf Schwankungen in Temperatur und Salzgehalt als robuster, einsatzbereiter Sensor bewährt. Kostengünstige Bodenfeuchtemessung und wassergesteuerte Modellierung des Nutzpflanzenwachstums können kombiniert werden, um Bewässerungsmanagement-Tools zu entwickeln, müssen jedoch kalibriert werden und rentabel in Bezug auf die Datenanforderungen für Anwendungen in datenarmen

Regionen sein. Der kostengünstige SM100-Sensor wurde unter Labor- und Feldbedingungen kalibriert (gegenüber einem besseren Sensor, dem SMT100, hergestellt von der UGT GmbH), was zeigte, dass eine bessere Kalibrierung unter Feldbedingungen unter Verwendung der Trockenkurve und Vermeidung einer Überanpassung möglich war. Die feldkalibrierte stückweise lineare Regressionsfunktion wurde als beste Kalibriertechnik ausgewählt, um die Leistung des SM100 auf dem Feld zu verbessern. Kalibrierte Daten von kostengünstigen Bodenfeuchtesensoren wurden verwendet, um die hydraulischen Parameter des Nutzpflanzenmodells zu kalibrieren und die entsprechenden Auswirkungen auf die Effizienz des Nutzpflanzenmodells zu untersuchen. Dies wurde mit der MATLAB-basierten Open-Source-Version des kostengünstigen FAO-AquaCrop-Modells untersucht. Dieses Experiment wurde während der Weizensaison 2018 auf einem Versuchsfeld in Kanpur durchgeführt. Die Bodenfeuchte-Simulation von AquaCrop-OS wurde durch die Einbeziehung kalibrierter SM100-Daten deutlich verbessert. Während es keine signifikanten Änderungen bei der Biomassevorhersage gab, wurde Wasserproduktivität durch die Verwendung kalibrierter SM100-Daten signifikant verbessert. Bewässerungspläne können unter der Annahme erstellt werden, dass kein Wasserstress auftritt, solange der evapotranspirativer Bedarf gedeckt ist. FAO AquaCrop simuliert vier Wasserbelastungen und entsprechende Schwellenwerte, die die jeweiligen Belastungen auslösen. Bewässerung wurde ausgelöst, wenn diese Schwellenwerte erreicht wurden, und diese FAO AquaCrop-Bewässerungsstrategie wurde in einer simulationsbasierten Studie mit vollständigen Bewässerungsbedingungen verglichen. Während bei beiden Strategien kein Wasserstress auftrat, simulierte die vollständige Bewässerungsstrategie 1,5-mal mehr Bewässerungsanwendungen (entspricht 111 mm) und eine geringere Wasserproduktivität als die FAO AquaCrop-Strategie. Die Einführung neuer Bewässerungsstrategien erfordert eine Verhaltensänderung, die teilweise durch Kosteneffizienz motiviert sein kann, aber es ist wichtig, Lösungen mit Landwirten zu entwickeln, wobei Designüberlegungen auf Grundlage der sozioökonomischen Merkmale, der Einstellung zur landwirtschaftlichen Risikobereitschaft und der bisherigen Erfahrung der Landwirte getroffen werden müssen, um sie in Richtung verbesserter Wassermanagementpraktiken zu lenken.

Affidavit

I hereby affirm that I wrote this PhD thesis independently and on my own without illegal assistance of third parties. To the best of my knowledge, all sources that I used to prepare that thesis are labeled as such. This thesis has not been received by any examination board, neither in this nor in a similar form.

New Delhi, 23rd June, 2022

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Research articles and author contributions

1 Research articles and author contributions

This cumulative dissertation is based on three first-author research articles. Two of them (Chapters 2 and 4) have been published in peer reviewed journals and are core to the storyline. Chapter 3 has been submitted to a journal and is under review.

1.1 Article 1

Adla, S., Gupta, S., Karumanchi, S.H., Tripathi, S., Disse, M., Pande, S. 2022. Agricultural Advisory Diagnostics Using a Data-Based Approach: Test Case in an Intensively Managed Rural Landscape in the Ganga River Basin, India. Frontiers in Water 3:798241. DOI: 10.3389/frwa.2021.798241

- 1 of 3 required first author publications.
- Chapter 2
- Author contributions: Soham Adla and Surya Gupta designed the research and analyzed the data. Soham Adla, Surya Gupta, and Sri Harsha Karumanchi performed the research. Soham Adla programmed the software. Soham Adla, Saket Pande, and Surya Gupta wrote the manuscript. Soham Adla, Saket Pande, Shivam Tripathi, and Markus Disse edited the manuscript. Shivam Tripathi, Markus Disse, and Saket Pande provided supervisory support. Shivam Tripathi and Sri Harsha Karumanchi applied for the successful grant which funded the research.

1.2 Article 2

Adla, S., Rai, N.K., Karumanchi, S.H., Tripathi, S., Disse, M., Pande, S. 2020. Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. Sensors 20(2), 363. DOI: 10.3390/s20020363

- 2 of 3 required first author publications.
- Chapter 3
- Author contributions: Soham Adla and Karumanchi Sri Harsha conceived the
 research idea. Soham Adla, Neeraj Kumar Rai, and Karumanchi Sri Harsha
 designed the research methodology. Neeraj Kumar Rai and Soham Adla applied
 software used for the experiments. Soham Adla and Neeraj Kumar Rai validated
 the experimental methodology and generated data. Soham Adla formally analysed
 the data. Soham Adla, Shivam Tripathi, Markus Disse, Karumanchi Sri Harsha
 and Saket Pande investigated the results. Neeraj Kumar Rai and Karumanchi

Sri Harsha mobilized resources used in the study. Soham Adla and Neeraj Kumar Rai curated the data generated during the study. Soham Adla created the visualizations. Soham Adla and Neeraj Kumar Rai wrote the article. All authors reviewed the article. Shivam Tripathi, Karumanchi Sri Harsha, Markus Disse, and Saket Pande supervised the study. Karumanchi Sri Harsha, Neeraj Kumar Rai, and Soham Adla managed the study administration. Karumanchi Sri Harsha, Soham Adla, and Shivam Tripathi acquired the funding for the study.

1.3 Article 3

Adla, S., Bruckmaier, F., Arias-Rodriguez, L.F., Tripathi, S., Pande, S., Disse, M. Impact of calibrating a low-cost capacitance based soil moisture sensor on FAO Aquacrop model performance. Journal of Hydrology, under review.

- 3 of 3 required first author publications (submitted and under review).
- Chapter 4
- Author contributions: Soham Adla conceptualized the research. Soham Adla, Felix Bruckmaier and Leonardo Arias-Rodriguez curated the data. Soham Adla, Leonardo Arias-Rodriguez and Shivam Tripathi were involved in the investigation and methodology. Soham Adla, Shivam Tripathi and Markus Disse were involved in funding acquisition, project administration and resources. Soham Adla, Felix Bruckmaier and Leonardo Arias-Rodriguez used the software and were involved in the validation. Soham Adla designed all the visualizations. Soham Adla, Felix Bruckmaier and Leonardo Arias-Rodriguez wrote the original draft. Shivam Tripathi, Saket Pande and Markus Disse supervised the research, and reviewed and edited the manuscript.

2 Further scientific contributions

2.1 Oral presentations

- Adla S., Bruckmaier F., Arias-Rodriguez L. F., Tripathi S., Disse M. and Pande S. 2022. Analysing the impact of calibrating a low-cost soil moisture sensor on FAO Aquacrop model performance. *Oral presentation at the European Geosciences Union (EGU) General Assembly 2022, Vienna (Austria)*, 23-27 May 2022. DOI: 10.5194/egusphere-egu22-11810
- Bruckmaier F., Adla S., Tripathi S. and Disse M. 2018. Modified AquaCrop-OpenSource tool for data-scarce regions. Oral presentation at the European Geosciences Union (EGU) General Assembly 2022, Vienna (Austria), 23-27 May 2022. DOI: 10.5194/egusphere-egu22-10694
- Adla S., Gupta, S., Karumanchi, S.H., Tripathi S., Disse M. and Pande S. 2021. Agricultural advisory diagnostics using a community driven data-based approach: test case in the Ganga River Basin, India. *Oral presentation at the Delft International Conference on Sociohydrology*, Delft (Netherlands), 7 September 2021.

2.2 Posters

- Adla S., Gupta, S., Karumanchi, S.H., Rai, N.K., Tripathi S., Disse M. and Pande S. 2022. Evaluation/pilot-test of a low-cost monitoring methodology to represent plot-scale soil moisture for wheat cropping in India. *Poster presentation at the European Geosciences Union (EGU) General Assembly 2018, Vienna (Austria)*, 8-13 April 2018. DOI: 10.13140/RG.2.2.29990.83529
- Adla S., Pande, S. and Disse M. 2017. Understanding challenges to smallholder sustainability with surveys in the Ganga river basin. *Poster presentation at the European Geosciences Union (EGU) General Assembly 2017, Vienna (Austria)*, 23-28 April 2017. DOI: 10.13140/RG.2.2.28574.59204

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Abbreviation

CC Canopy Cover

CGC Canopy Growth Coefficient

DAS Days after sowing

DP Deep Percolation

EC Electrical Conductivity

EM Electromagnetic

FAO Food and Agriculture Organization (of the United Nations)

FC Field Capacity

FDR Frequency Domain Reflectometry

FI Full Irrigation

GSM Global System for Mobile Communications

ICT Information and Communications Technology

IGP Indo-Gangetic Plains

IoT Internet of Things

IS Indian Standard

LC Low-cost

LoRa Long Range

MAD Management Allowed Depletion

MAE Mean Absolute Error

MC Medium-cost

NGO Non-Governmental Organization

PWP Permanent Wilting Point

RAE Relative Absolute Error

RAW Readily Available Water

RFID Radio Frequency Identification

RMSE Root Mean Square Error

RUE Radiation Use Efficiency

RWCS Rice-wheat Cropping System

SAFE Sensitivity Analysis For Everybody

SD Standard Deviation

SHP Soil Hydraulic Properties

SMS Short Messaging Service

SQI Soil Quality Index

SSR Sum of Squared Residuals

TAW Total Available soil Water

TDR Time Domain Reflectometry

TDT Time Domain Transition

USD United States Dollar

VLC Very low-cost

VWC Volumetric Water Content

WP Water Productivity

WSN Wireless Sensor Network

WUE Water Use Efficiency

Nomenclature

```
\theta_{FC} Soil moisture at field capacity (m<sup>3</sup>.m<sup>-3</sup> or %)
\theta_{PWP} Soil moisture at wilting point (m<sup>3</sup>.m<sup>-3</sup> or %)
E_s Soil Evaporation (mm.d<sup>-1</sup>)
ea Irrigation Application Efficiency (%)
ET<sub>a</sub> Actual Evapotranspiration (mm.d<sup>-1</sup>)
ET_{c} Crop Evapotranspiration (mm.d<sup>-1</sup>)
ET<sub>o</sub> Reference Evapotranspiration (mm.d<sup>-1</sup>)
ET Evapotranspiration (mm.d<sup>-1</sup>)
HI_{o} Initial Harvest Index (-)
HI Harvest Index (-)
K_{\mathbf{c}} crop coefficient (-)
Ks<sub>aer</sub> Soil water stress coefficient for water logging (aeration stress) (-)
Ks_{exp,w} Soil water stress coefficient for canopy expansion (-)
Ks_{pol,w} Soil water stress coefficient for pollination (-)
Ks_{sen} Soil water stress coefficient for canopy senescence (-)
Ks<sub>sto</sub> Soil water stress coefficient for stomatal closure (-)
p Soil water depletion fraction (-)
T_r Plant Transpiration (mm.d<sup>-1</sup>)
w_{RZ} Root zone soil water content (mm)
WPET ET Water Productivity (kg.kg<sup>-1</sup> or kg.m<sup>-3</sup>)
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1 Introduction

1.1 Background

The global population is expected to reach almost 10 billion by 2050 (FAO, 2017), which necessitates a commensurate increase in food supply, sustainably (Parra et al., 2020). Simultaneously, water resources are increasingly becoming scarce due to a combination of factors such as climate change, competition from other sectors, and increasing agricultural regulation, which implies an urgent need to develop sustainable production practices (Boretti and Rosa, 2019; Kisekka et al., 2022). Hence, sustainable agricultural intensification is needed to simultaneously manage the resultant situation and mitigate the environmental impacts of agricultural systems (Matson and Vitousek, 2006; Tilman et al., 2011).

Agricultural production and yields in developing countries have been lower than those of developed countries over the past few decades due to poor agronomy practices, possibly because of (among other reasons) the relative under-utilization of improved agricultural technologies (Aker, 2011; George, 2014). For instance, while high yield wheat cultivation in France is mostly rainfed and about 90% of such wheat grown in India is irrigated, the corresponding average yields are 7.7 t/ha and 2.9 t/ha, according to data from 2009 (George, 2014; Sayre, 2002; Tewatia and Chanda, 2005). Similarly, though most of the wheat grown the USA is water limited (Elliott, 2010), it has similar yields to the irrigated wheat in India (George, 2014).

To increase technology adoption, governments and international organizations have attempted to deliver information inputs to farmers via agricultural extension or advisory services (J. Anderson and Feder, 2007; Birner and J. Anderson, 2007; Birner et al., 2009). Extension services disseminate knowledge, new technologies and agricultural information to farmers and rural inhabitants worldwide (Nyarko and Kozári, 2021). They can be crucial to enhance productivity, increase food security, improve rural livelihoods, and promote agriculture as a 'pro-poor economic growth engine' (IFPRI, 2020). Particularly for smallholders, agricultural extension can facilitate a break from the vicious cycle of low productivity, vulnerability, and poverty (Davis and Franzel, 2018).

There has been considerable investment in public extension programs, for e.g., 500,000 personnel engaged in agricultural extension globally in 2005 (J. Anderson and Feder, 2007). Despite this investment and experience over decades, the evidence to support the impact of agricultural extension on agricultural knowledge, technology adoption and improved productivity is limited (Aker, 2011). Agricultural extension is reported to be 'failing' (Government of Malawi, 2000), 'moribund' (Eicher, 2001), or 'in disarray or barely functioning at all' (W. Rivera et al., 2001), particularly in the developing world. More recently, questions have been raised about the ability of farmers to utilize agricultural advisories to enhance productivity and improve agricultural and economic growth due to unsatisfactory experiences among relevant agencies, particularly in the

developing world (Feder et al., 2011).

Public agricultural extension services are associated with disenchantment about the direct provision of such services (Feder et al., 2011). This has been attributed to several limitations of the inherited methods of organizing and managing public extension systems (Birner and J. Anderson, 2007; Feder et al., 2001; Feder et al., 2011). The scale and complexity of, e.g., Indian agriculture, is an impediment to reach geographically scattered, remote, low-literacy farmers with inadequate mass media access. This is further affected by the high and regionally variable farmer-to-agent ratios in most developing countries (Glendenning et al., 2010). Other criticisms include high costs, low accountability, ad-hoc responsibilities of agents, bureaucratic procedures with centralized systems, and the lack of adequate stakeholder interaction (J. Anderson and Feder, 2007; J.R. Anderson et al., 2006; Birner and J. Anderson, 2007).

The provision of private extension services is also limited due to various aspects of market failures (Feder et al., 2011). Ensuring excludability and competitiveness is a challenge considering the public-good like features of information delivery, and farmers may undervalue the benefits of advisories due to insufficient information and short planning horizons (Birner and J. Anderson, 2007).

Hence, there is a need to address some of the limitations of current extension services. Adaptation efforts are effective only when they are locally implemented, and use scientific inquiry supplemented by local knowledge, while incorporating a range of policy development perspectives (Brunner, 2010).

The 'yield gap' (the difference between observed yields and region-specific attainable yields) is a crucial parameter to study prospects of this sustainable intensification (Mueller et al., 2012). Fertilizer use, irrigation and climate are major factors responsible for global yield variability, and balancing food security and sustainability requires substantial changes in nutrient and water management (Mueller et al., 2012). This requirement is reasonable for food crops such as wheat, rice and maize in many developing countries such as India (Mueller et al., 2012). Based on this premise, this study henceforth focuses on improving water management in wheat cropping in India.

Agriculture can potentially contribute to industrial and economic growth (Byerlee et al., 2009). This study is contextualized within the Indian agricultural domain because not only does agriculture contribute to about 17% of India's gross domestic product, it is a source of livelihood for over half of the India's workforce (Department of Economic Affairs, 2019). The focus on water is because of its indispensability to 'human well-being and socio-economic sustainability' (Zhi et al., 2022). Atleast 4 out of the 17 SDGs (i.e., SDG-6, SDG-7, SGD-12, and SDG-13) are related to sustainably using and managing water resources (Pradhan et al., 2017). Contrastingly, nearly half the global population faces severe water scarcity (Schewe et al., 2014). Essentially, sustainable agricultural development requires an adequate supply of freshwater (Ai et al., 2020). Hence, economic development, regional food security, and quality of life are all interlinked with each other and with sustainable water management in agriculture (L.R. Brown and Halweil, 1998; Hanjra and Qureshi, 2010).

The Rice-wheat Cropping System (RWCS) is amongst the largest agricultural production systems in the world, and contributes to global food security substantially (Banjara et al., 2022; Dhanda et al., 2022; Laik et al., 2014). Out of the 13.5 million hectares (Mha) of RWCS practiced in South Asia (J.K. Ladha et al., 2009), around 9.2 Mha are cultivated in India (M.L. Jat et al., 2020), particularly in Indo-Gangetic Plains (IGP) of northwest India, due to its agro-climatic conditions, natural resources and ecology (Dhanda et al., 2022). The major RWCS region of India consists of the states of Punjab, Haryana and Uttar Pradesh, and is called India's 'food basket' because it produces about 50% of India's food grains (Pal et al., 2009). The extensive practice of RWCS occurs due to the availability of short-statured, high-yielding varieties which are irrigation and fertilizer responsive, increased use of sowing and harvesting machinery, irrigation facilities at relatively low prices, the government's guarantee of a minimum support price and established marketing channels (Bhatt et al., 2021; Dhanda et al., 2022). Hence, in addition to ensuring national food security and providing livelihoods to millions of people, the RWCS provides a relatively stable source of income to farmers and other stakeholders (Dhanda et al., 2022).

Policies developed to meet food security demands by increasing food production have generally resulted in expanding harvested area at the cost of low average yields and efficiencies of inputs like water, fertilizer and labor (George, 2014). For instance, though the advent of the Green Revolution in India in the 1970s increased food grain production notably (R.B. Singh, 2000), there is growing evidence that the productivity of the RWCS may be stagnating or plateauing (Dhanda et al., 2022). This could be because of a combination of the depletion of the natural resource base; high labor, water and energy demands; and declining input efficiencies, all aggravated by climate and socio-economic change (Bhatt et al., 2021; Chauhan, 2012; Dhanda et al., 2022; M.L. Jat et al., 2009; Saharawat et al., 2010). The rise in productivity in RWCS cultivation was concurrent with input mismanagement, leading to negative impacts on the environment, biodiversity, air quality, and soil and water resources, thus challenging the sustainability of the system (Chauhan, 2012; Godfray and Garnett, 2014; V. Kumar et al., 2018; Tilman et al., 2011). Moreover, the gaps between overall cultivation costs and the minimum support price of rice and wheat are also increasing, which impacts farm income and profitability (Dhanda et al., 2022). Nevertheless, farmers continue to practice the RWCS due to assured prices, marketing, and relative stability in yields (Bhatt et al., 2021).

The lack of adequate water is a critical limitation for sustainable crop production and maintaining crop yields in semi-arid and arid regions (Yi et al., 2022; C. Zhang et al., 2022a). About 70% freshwater extraction is used for irrigation in agriculture globally (Grafton et al., 2018; Y. Lu et al., 2016); this figure increases to around 82% for India (Sikka et al., 2022). Nearly 68.4 Mha (about 48.8%) of India's net cultivated area (140 MHa) is irrigated (Ministry of Agriculture and Farmers Welfare, 2017). Irrigation has contributed to India's agricultural growth and food security (Sikka et al., 2022), and national wheat yields with irrigation have been reported to be 13% higher by the 2000s than without irrigation (Zaveri and B Lobell, 2019).

The cultivated area under irrigation may increase in the future along with increasing domestic, urban, industrial and environmental demand (Sikka et al., 2022). Major regions in the Indo-Gangetic plains (including the 'food basket') depend on groundwater to fulfil their irrigation demand (Ambast et al., 2006). At the same time, irrigated agriculture, if not managed properly, can lead to environmental degradation and can threaten sustainability (Howell, 2001). For instance, excessive groundwater pumping in the IGP has led to deepening groundwater levels (Hira et al., 2004). Unreasonable irrigation, instead of enhancing crop yield, may cause wastage of water resources and consequently a decline in water productivity (C. Zhang et al., 2022a).

The RWCS needs an improvement in input use efficiencies and natural resource conservation (Dhanda et al., 2022) - critically water. Irrigation water can be saved by applying only that amount of water which is necessary for plant growth, thereby minimizing water losses, potentially leading to a combination of increased productivity and saved water (Dhanda et al., 2022). Within the RWCS, water saving technologies can include the selection of shorter-duration crop varieties to reduce Evapotranspiration (mm.d⁻¹) (ET) losses, laser land leveling, bed planting, direct seeding of rice, applying irrigation at hairline cracking, and more efficient irrigation methods (Dhanda et al., 2022). Surface irrigation, a traditional irrigation method, is inefficient due to deep percolation, non-uniform distribution of water and labor intensiveness (McNabb, 2019; Pramanik et al., 2022; R. Smith et al., 2005). However, surface irrigation was used for around 80% of the total irrigated land in India, as recently as in 2016-17 (Government of India, 2017). It continues to be extensively used due to its low-cost and energy requirements (Bjorneberg, 2013; Pramanik et al., 2022). While micro-irrigation systems (like drip, sprinkler irrigation, etc.) aim to increase irrigation application efficiency by preventing surface runoff (Sidhu et al., 2019), their adoption in India has not increased notably because subsidies by themselves are inadequate in changing farm decision making (Nair and Thomas, 2022). Moreover, the introduction to water saving techniques generally leads to expansion of irrigated area or cultivation of water-intensive crops, referred to as the Jevons' paradox (Alcott, 2005; Nair and Thomas, 2022). Hence any realistic intervention to enhance water management in irrigated agriculture in most of the IGP should be contextualized for current practices including surface or flood irrigation.

In water-limited conditions, agricultural production should optimize net income per unit water rather than net income per unit land (Zhi et al., 2022), hence reiterating the importance of improving water use efficiency and water productivity in agricultural systems (Parra et al., 2020). This challenge requires the development, dissemination and transfer of technology based irrigation solutions (A.K. Singh et al., 2009). Particularly in RWCSs, new technologies are needed to improve input water efficiencies (Dhanda et al., 2022). Though modern irrigation technology like commercial smart irrigation systems are in use, they are expensive and therefore not widely adopted (Bazaluk et al., 2022). Moreover, pressurized irrigation systems can have higher irrigation costs (Bazaluk et al., 2022), which subsequently increases production costs, and reduces profitability (Rodríguez Díaz et al., 2011).

Improved irrigation management requires accurate data as well as an understanding of biophysical processes, such as crop response to water across different crop growth stages (Kisekka et al., 2022). With regards to data, an essential environmental variable which can be measured for agricultural sustainability and precision agriculture is soil moisture or Volumetric Water Content (VWC) (Kisekka et al., 2022). Soil moisture data is important in developing irrigation systems to maximize crop yield, and long-term VWC monitoring combined with climatic information can lead to an improved understanding of agricultural patterns, thresholds and losses (Bastiaanssen et al., 2000; Lin et al., 2018). With regards to understanding biophysical processes and crop growth response, crop models are tools to estimate crop growth and yields as a function of weather, soil conditions and management practices (Guerra et al., 2002). But crop models can be data intensive, requiring multiple input variables and parameter values which may not be easy to obtain for many crop-environment combinations, limiting their practical application in data-scarce regions (Vanuytrecht et al., 2014; Varella et al., 2010) like the Majority World (Graves et al., 2002; J.W. Jones et al., 2012). Hence, any attempt to address water management in agriculture by combining sensor data and crop modeling must not only be cost-effective, but also not be data-intensive, to be applicable to the context of irrigated agriculture in the IGP.

Irrigation scheduling, i.e., applying the 'right amount of water at the right time and place' can help in enhancing the performance of irrigation systems by increasing crop production and conserving water (Sikka et al., 2022). Appropriate irrigation scheduling can lead to benefits like optimal soil water conditions for plant growth, substantial water savings, increased efficiency in fertilizer application (by reducing leaching losses, and even reduced greenhouse gas emissions (Sikka et al., 2022). Irrigation application, like other agricultural management decisions, is often driven by previous observations and experimentation, and discussions with other farmers (Fafchamps and Minten, 2012; Greenwood et al., 2010), particularly in developing countries. However, it is more efficient to schedule irrigation based on the requirement of evapotranspiration (*ET*) or using soil moisture sensors (Irrigation Association, 2011).

1.2 State of the art

1.2.1 Data-based extension services

Recently, traditional extension services have been shifting towards a more data rich paradigm, where farmer-advisor interactions are now based on complex data collation and interpretation at the backend (Eastwood et al., 2019; Nettle et al., 2018). Farm decision-making can be facilitated via smartphones or computers with decision support tools which access data remotely from 'cloud-based' servers (Wolfert et al., 2017).

In developed nations, data-based advisory tools have been applied to cropping and for viticulture management (Bramley, 2009), irrigation scheduling based on evapotranspiration in the USA (Bartlett et al., 2015), and Internet of Things (IoT) enabled automated irrigation scheduling (Severino et al., 2018). In Canada, Australia and New Zealand,

data-driven tools have been applied to the dairy sector (Gargiulo et al., 2018; Rue et al., 2019; Vasseur et al., 2010).

In developing nations like Ethiopia, farm-level data on local weather, input availability and markets have been integrated into advisory platforms such as 'Farmstack' (Digital Green, 2019). In Afghanistan, stakeholders including farmers and extension workers are facilitated to share reliable agricultural information using the Information and Communications Technology (ICT) platform, 'eAfghan' (M. Bell, 2013). In India, farm science centres (*Krishi Vigyan Kendras*) send weekly Short Messaging Service (SMS) alerts to farmers about weather and disease forecasts, and market information (A. Das et al., 2016; Saravanan, 2010). Agriculture related information is also relayed through SMS and voice messages by IFFCO Kissan Sanchar Limited (IKSL) and Reuters Market Light (Fafchamps and Minten, 2012; USAID, 2000). Farmers can raise agricultural and related queries using their mobile phones in every state in India, using the farmer call centre or *Kisan* Call Centre (Ganesan et al., 2013).

However, such initiatives tend to administer generic advisories rather than databased, crop- and plot-specific advisories (Ganesan et al., 2013). This could be one of the major reasons for low-technology adoption through agricultural extension (Aker, 2011). Besides, farmers in developing countries usually take decisions based on their observations, experimentation, or conversations with other farmers (Fafchamps and Minten, 2012).

Since more effect advisory adaptation generally results from scientific enquiry supplemented with local knowledge (Brunner, 2010), some of the limitations of generic extension services can be addressed by empowering advisors with data-based, farm-specific 'diagnoses' to characterize farm performance. This can further help to identify the reasons for sub-optimal performance (or yield-gaps), leading to more customized advisories and potentially higher advisory adoption.

1.2.2 Combining crop-modeling and soil moisture sensing

Many techniques combine data from ground sensor networks (Navarro-Hellín et al., 2015) or satellites (Bastiaanssen et al., 2000) with agro-hydrological modeling (Chiara and Marco, 2022) to augmenting irrigation management. Agro-hydrological modeling generally involves coupled modeling of crop growth and hydrological components/models (Siad et al., 2019).

1.2.2.1 Crop-modeling

Crop models can be classified into empirical models which directly fit one or more equations to observations to estimate crop yield, mechanistic models which explain the mechanisms driving the relationships between weather variables and crop yield, and stochastic models which have probabilities associated with each output (Siad et al., 2019). Based on the method used to estimate biomass production rate from resources like carbon dioxide, solar radiation and water, crop models can be categorized into three crop growth modules: (i) carbon-driven, (ii) radiation-driven and (iii) water-driven

(Azam-Ali et al., 1994; Steduto, 2003; Todorovic et al., 2009).

Carbon-driven models were originally developed based on the approach proposed by Wit (1965), in which crop growth is computed based on carbon assimilation by leaves via the photosynthetic process (Todorovic et al., 2009). These models are hierarchical in structure, since higher-level responses result from the integration of the underlying lower-level processes. This complex structure leads to a larger requirement of parameters. Phenological development and crop growth processes are regulated by radiation, temperature and CO₂ concentration, and limited by water availability. Examples of such models include WOFOST (WOrld FOod STudies, Boogaard et al., 1998; Van Diepen et al., 1989), other Wageningen crop models (Bouman et al., 1996; Ittersum et al., 2003), and the CROPGRO (CROP GROwth) model series (Boote et al., 1998; 2002).

In radiation-driven models, biomass is directly derived from intercepted solar radiation through a conversion coefficient called Radiation Use Efficiency (RUE) (Monteith, 1977; Todorovic et al., 2009). The lower hierarchical processes for biomass accumulation, including photorespiration rate, dark respiration, leaf quantum efficiency per mole of CO₂ fixed, are all incorporated into the RUE synthetically (Monteith, 1977). This reduces the required number and complexity of input variables. Examples of such models include CERES (Crop Environment REsources Synthesis) group of models (J.W. Jones et al., 2003; J. Ritchie et al., 1985), EPIC (Erosion Productivity Impact Calculator; C. Jones et al., 1991), and STICS (Simulator mulTIdisciplinary for Crop Standard; Brisson et al., 2003).

Water-driven models are built on principle that the rate of biomass growth is linearly proportional to transpiration, through a Water Productivity (WP) parameter (De Wit, 1958; Hsiao and Bradford, 1983; Steduto and Albrizio, 2005). Similar to radiation-driven models, water-driven models also avoid hierarchical model structures, and hence require lesser input parameters (Steduto et al., 2007; 2009). Additionally, they have a relative advantage over radiation-driven models since the WP parameter can be normalized for climate (CO₂ concentration and evaporative demand), which extends their spatiotemporal applicability (Hsiao et al., 2007; Steduto and Albrizio, 2005; Steduto et al., 2007). Examples of such models include FAO AquaCrop (Raes et al., 2009; Steduto et al., 2009), and one of the two growth modules of the CropSyst model (Stöckle et al., 2003).

1.2.2.2 Soil moisture sensing

Multiple studies have used soil moisture sensors for irrigation management applications. While some have directly used soil moisture measurements to replenish soil moisture deficit (Pramanik et al., 2022), some actively use measurements to purposely maintain an acceptable level of soil moisture deficit (Benabdelouahab et al., 2016; S.C. Ma et al., 2016; Panda et al., 2003). Soil moisture measurements have been incorporated into crop models to improve model performance (Andarzian et al., 2011; Huang et al., 2022; A. Singh et al., 2013; W. Zhang et al., 2013). Further, soil moisture measurements have been used within the framework of IoT to carry out real-time irrigation management (Cayuela et al., 2022; Pramanik et al., 2022; Vellidis et al., 2008).

However, soil moisture can exhibit variability across both spatial and temporal scales

due to the corresponding variability in soil properties, and therefore sensors measuring soil moisture need site-specific calibration (Peddinti et al., 2020; Vereecken et al., 2014). Calibration of soil moisture sensors can be performed in both laboratory and field conditions. While the advantage of field calibration is that conditions are representative of those that present during field application (including variable environmental factors like temperature, salinity, clay content, organic matter, bulk density) (Kargas and K.X. Soulis, 2012; Matula et al., 2016a), laboratory calibration is generally performed by manufacturers with sieved, repacked soils with controlled VWC and environmental conditions, particularly for coarse homogenous soils including some sands and loams (Feng and Sui, 2020). Previous studies have developed soil moisture sensor calibration equations both in the laboratory (Adla et al., 2020; Bello et al., 2019a; Nagahage et al., 2019; Placidi et al., 2020) and in the field (Rudnick et al., 2015; J. Singh et al., 2018). Most calibration equations reported in the literature are least squares estimates resulting in exponential, hyperbolic, linear, logistic, or polynomial regressions. However, data-driven machine learning approaches can also be used to develop complex soil moisture models without any explicit assumptions made on the governing soil water processes (Kisekka et al., 2022).

Eventually, environmental sensors (including soil moisture sensors), processors and communication components may be available commercially, but their effective application depends on cost-effectiveness, and ease of access and maintenance (Pramanik et al., 2022; Rodríguez-Robles et al., 2020).

1.2.3 Irrigation scheduling

Irrigation scheduling based on soil moisture measurements has been claimed to be ideal (Sikka et al., 2022). For instance, a tensiometer based irrigation scheduling system has been tested for paddy irrigation in Punjab which has resulted in decreased number of irrigations and 13% water savings (Vatta et al., 2018). However, soil moisture sensor based irrigation is not generally practiced in India due to reasons including but not limited to cost (capital, maintenance), cumbersomeness (of installing and upkeeping sensors) and lack of farmers' awareness (Sikka et al., 2022). *ET*-based irrigation scheduling involves estimating Soil Evaporation (mm.d⁻¹) (E_s) and Plant Transpiration (mm.d⁻¹) (T_r) to establish the crop water requirement in the root zone (Zamora-Re et al., 2020). Some experimental studies have used measured or computed Actual Evapotranspiration (mm.d⁻¹) (E_s) for irrigation scheduling (Hunsaker et al., 2015).

Many studies have reported that soils can lose substantial quantities of water without suppressing the rate of crop growth (Bacci et al., 2003; Bailey, 1990; Musick and K.B. Porter, 1990; Panda et al., 2003), and this is fundamental to optimize irrigation without inhibiting growth (Greenwood et al., 2010). This phenomenon has been investigated and quantified extensively (Denmead and Shaw, 1962; J. Ritchie, 1973; W. Rosenthal et al., 1987; V. Sadras and Milroy, 1996; R.B. Thompson et al., 2007b). The Food and Agriculture Organization (of the United Nations) (FAO) Irrigation and Drainage Paper No. 56 (Allen et al., 1998) has comprehensively summarized the subject of *ET*-based crop

water (and irrigation) requirements (Greenwood et al., 2010). Under the assumption that soil water deficit does not affect crop growth unless it limits ET, Allen et al. (1998) define a Soil water depletion fraction (-) (p) and a corresponding estimate of Readily Available Water (RAW), such that if the soil water depletion crosses the threshold of RAW, then ET declines linearly until Permanent Wilting Point (PWP) is reached. However, a limitation of this approach is that the sensitivity of crop growth to soil water deficit (i.e., p) is considered to be constant throughout the growth season (Allen et al., 1998) despite claims that this sensitivity could vary across crop growth stages (Salter and Goode, 1967). For instance, wheat is more sensitive to water stress immediately before and during flowering (Musick and K.B. Porter, 1990). This limitation can be addressed by disaggregating the soil water depletion fraction into multiple fractions which correspond to different crop growth processes and target variables across the various crop growth stages. This is incorporated into the structure of the FAO AquaCrop model (Raes et al., 2009; Steduto et al., 2009; Vanuytrecht et al., 2014).

1.3 Research questions

Based on the background provided in Section 1.1 and the gaps in the state of the art identified in Section 1.2, the following research questions were developed for this study:

- 1. How can agricultural advisories be supported by data-based, plot-scale farm performance diagnostics, to support agricultural extension? Can such a methodology include important yield limiting factors such as soil nutrients and water?
- 2. Focusing on water, can low-cost soil moisture sensors be calibrated and tested in laboratory conditions to improve their overall performance?
- 3. How can low-cost soil moisture sensing and parsimonious crop modeling be combined to improve crop model performance, including water productivity?
- 4. How can soil water stress coefficients be used to simulate improved irrigation schedules without encountering stresses?

1.4 Thesis structure

The research questions were addressed using the structure as described in Table 1.1. Research Question (RQ) 1 is addressed by a data-based farm-specific approach to conduct agricultural performance diagnostics, and is covered in Chapter 2. RQ 2 is addressed by an laboratory based study on low- and very-low cost sensors, which is entailed in Chapter 3. RQ 3 focuses on combining low-cost soil moisture data and parsimonious crop modeling, and is investigated in Chapter 4. Finally, RQ 4 focusing on using soil water stress coefficients to improve irrigation scheduling, water productivity and water savings, and this study is covered in Chapter 5.

Table 1.1: Structure of the cumulative dissertation. RQ stands for Research Question, and Ch. No. is the corresponding Chapter Number.

Objective	RQ (Ch. No.)	Contents	Publication
Farm agricultural performance diagnostics	1 (2)	Data-based approach to quantify nutrient and water related farm performance	Adla et al. 2022. Agricultural Advisory Diagnostics Using a Data- Based Approach: Test Case in an Intensively Managed Rural
		2. Development of the Farm Agricultural Diagnostics tool DOI: 10.5281/zenodo.5195682	Landscape in the Ganga River Basin, India. Frontiers in Water 3:798241. DOI: 10.3389/frwa.2021.798241
		3. Pilot test of the approach in Kanpur (India)	
Laboratory calibration and performance testing of low-cost soil	2 (3)	Low-cost capacitive and very low- cost resistive sensors	Adla et al. 2020. Laboratory calibration and performance evaluation of low-cost capacitive
moisture sensors		2. Calibration using four soils (sands and silty loams); determination of accuracy, precision, sensor to sensor variability; comparison of developed equations with manufacturer's calibration equations	cost and very low-cost resistive soil moisture sensors. Sensors 20(2), 363. DOI: 10.3390/s20020363
		3. Testing of sensors in varying temperature and salinity conditions; testing of capacitive sensors in fluids of known dielectric constants	
3. Combining calibrated low-cost soil moisture sensing and parsimonious crop modeling	3 (4)	Laboratory and field calibration of low-cost capacitive SM100 sensor; comparative analysis of different least squares and machine learning regression models	Adla et al. 2022. Impact of calibrating a low-cost capacitance based soil moisture sensor on FAO AquaCrop model performance. Journal of Hydrology (under review).
		Impact of calibrating FAO AquaCrop model using raw and calibrated low-cost sensor data (relative to the literature) on model outputs	
Using crop modeling for water efficient irrigation scheduling	4 (5)	Conceptualization of crop growth stage dependent critical water stress coefficients in FAO AquaCrop	
		2. Comparison of Full and FAO AquaCrop based irrigation strategies on crop model outputs and water savings	

The titles of the respective chapters are given below:

- Chapter 2: Agricultural advisory diagnostics using a data-based approach
- Chapter 3: Laboratory calibration and performance evaluation of low-cost soil moisture sensors
- Chapter 4: Low-cost soil moisture calibration and parsimonious crop modeling
- Chapter 5: Irrigation scheduling using soil water stress thresholds

A discussion of the results, major conclusions and an outlook on further research are reported in Chapter 6.

2 Agricultural advisory diagnostics using a data-based approach

Adla et al. (2022) 1

Abstract

Low technology adoption through agricultural extension may be a consequence of providing generic information without sufficient adaptation to local conditions. Datarich paradigms may be disruptive to extension services and can potentially change farmer-advisor interactions. This study fills a gap in pre-existing, generic advisory programs by suggesting an approach to "diagnose" farm-specific agricultural issues quantitatively first in order to facilitate advisors in developing farm-centric advisories. A user-friendly Farm Agricultural Diagnostics (FAD) tool is developed in Microsoft Excel VBA that uses farmer surveys and soil testing to quantify current agricultural performance, classify farms into different performance categories relative to a localized performance target, and visualize farm performance within a user-friendly interface. The advisory diagnostics approach is tested in Kanpur, representative of an intensively managed rural landscape in the Ganga river basin in India. The developed open-source tool is made available online to generate data-based agricultural advisories. During the field testing in Kanpur, the tool identifies 24% farms as nutrient-limited, 34% farms as water-limited, 27% farms with nutrient and water co-limitations, and the remaining farms as satisfactory compared to the localized performance target. It is recommended to design advisories in terms of water and nutrient recommendations which can fulfil the farm needs identified by the tool. The tool will add data-based value to pre-existing demand based advisory services in agricultural extension programs. The primary users of the tools are academic, governmental and non-governmental agencies working in the agricultural sector, whose rigorous scientific research, soil testing capacity, and direct stakeholder engagement respectively can be harnessed to generate more data-based and customized advisories, potentially improving farmer uptake of agricultural advisories.

Keywords: agricultural extension, advisory diagnostics, data-based advisory, soil quality index, water use efficiency.

¹Adla, S., Gupta, S., Karumanchi, S.H., Tripathi, S., Disse, M. and Pande, S., 2022. Agricultural Advisory Diagnostics Using a Data-Based Approach: Test Case in an Intensively Managed Rural Landscape in the Ganga River Basin, India. Frontiers in Water 3:798241. https://doi.org/10.3389/frwa.2021.798241

2.1 Introduction

Agricultural production and yields in developing countries have been lower than those of developed countries over the past few decades. Amongst its many reasons is the relative underutilization of improved agricultural technologies (Aker, 2011). Agricultural technologies, along with agricultural knowledge are disseminated using agricultural extension services (or advisories) by governments and international organizations to farmers and rural inhabitants worldwide (J. Anderson and Feder, 2007; Nyarko and Kozári, 2021). Advisories can be crucial to enhance productivity, increase food security, improve rural livelihoods, and promote agriculture as a "pro-poor economic growth engine" (IFPRI, 2020). Particularly for smallholders, agricultural extension can facilitate a break from the vicious cycle of low productivity, vulnerability, and poverty (Davis and Franzel, 2018).

Despite considerable investment and experience over decades (J. Anderson and Feder, 2007), there has been limited evidence to support the impact of agricultural extension on agricultural knowledge, technology adoption and improved productivity (Aker, 2011). Over time, governments of developed countries have reduced direct investments in agricultural extension (Laurent et al., 2006; W.M. Rivera, 2011). Moreover, in the developing world, agricultural extension has been described as "failing" (Government of Malawi, 2000), "moribund" (Eicher, 2001), "in disarray or barely functioning at all" (W. Rivera et al., 2001), or ineffective in responding to farmer demands and technological challenges (Ahikiriza et al., 2021). Factors like wealth, risk preferences, education, access and affordability of information and learning (Aker, 2011) can result in technology adoption slowing down and becoming more discontinuous, further threatening agricultural productivity (Oduniyi, 2021).

Agricultural extension's transfer-of-technology approach, where farmers are "passive recipients" of uniformly administered advisories (Leeuwis and Van den Ban, 2004), has been criticized due to its negligence of the "locally specific nature of knowledge construction" (Klerkx and Jansen, 2010). New data-rich paradigms in agriculture may also be disruptive to extension services (Nettle et al., 2018) as they change traditional farmer-advisor interactions with complex backend processes of data collation and interpretation (Eastwood et al., 2019).

Globally, this shift towards data-driven extension initiatives is quite evident. In developed countries, such as Australia, New Zealand and Canada, data-driven smart farming has been incorporated into dairy farming (Gargiulo et al., 2018; Rue et al., 2019; Vasseur et al., 2010). Data-based tools have been developed for cropping and viticulture management (Bramley, 2009), evapotranspiration-based irrigation scheduling in the western United States (Bartlett et al., 2015), and irrigation scheduling using automated sensors operating within an IoT-framework (Severino et al., 2018). In developing countries like Afghanistan, the Information and Communication Technologies (ICT) platform "eAfghan" enables extension workers, farmers and other stakeholders to share reliable agricultural extension information (M. Bell, 2013). The agricultural advisory platform "Farmstack" integrates farm-level data, local weather, input availability and

market information in Ethiopia (Digital Green, 2019). In India, advisories about weather and disease forecasts, markets and other information are sent by SMS or voice message alerts by agencies such as the farm science centres (*Krishi Vigyan Kendras*) (A. Das et al., 2016; Saravanan, 2010), IFFCO Kissan Sanchar Limited (IKSL) and Reuters Market Light (Fafchamps and Minten, 2012; USAID, 2000).

However, most of these initiatives deliver generic information rather than data-driven advisories customized to the specific farm plot or crop (Ganesan et al., 2013), which is one of the major reasons for low technology adoption through extension services (Aker, 2011). The primary sources that drive decision making about agricultural practices among farmers in developing countries are still their own observations and experimentations, followed by conversations with other farmers (Fafchamps and Minten, 2012). A review of agricultural extension approaches in India reveals that the farmers generally struggle to receive reliable information relevant to them at the right time (Glendenning et al., 2010). Moreover, the lack of adequate interactions between research, extension organizations and the farmers has led to the generation of non-specific advisory services (Feder et al., 2010). Nonetheless, data driven tools utilized for smart farming, including the collection and use of more digital data (Wolfert et al., 2017), sensors measuring animal, plant, soil and water parameters (Eastwood et al., 2019; Hostiou et al., 2017; Neethirajan, 2017; Rutten et al., 2013), and online data platforms, can potentially lead to more effective farmer-advisor interactions through tactical use of data, and administer strategic farm management advisories (Eastwood et al., 2015).

This study aims to address the limitations of generic data-driven extension tools by suggesting an approach to inform advisors to "diagnose" farm-specific agricultural issues more quantitatively. The working assumption for the approach is that yield gaps (the difference between observed yields and region-specific attainable yields) occur either due to nutrient or water related limitation (or co-limitations). This is reasonable for food crops such as wheat, rice and maize in many developing nations such as India (Mueller et al., 2012). Performance related to soil nutrient status can be assessed with soil testing and computing a Soil Quality Index (SQI) indicator which combines multiple soil parameters into a single performance score (Karlen et al., 1997). Performance related to water as a limiting factor to yield gaps can be evaluated using an indicator such as Water Use Efficiency (WUE, in kg/m³) (Van Halsema and Vincent, 2012), which has been applied by irrigation specialists to describe 'how effectively water is delivered to crops' and 'to indicate the amount of water wasted' (Molden et al., 2010).

The proposed approach estimates the respective farm-level performances of soil nutrient and water indicators, and combines the relative performances of multiple farms in a particular region into an integrated visualization. A corresponding user-friendly Farm Agricultural Diagnostics (FAD) tool was developed using Macro-in-Excel feature of Microsoft Office's Excel software to carry out these calculations, generate a performance-based visualization, and automate agricultural advisory diagnostics. The approach is then applied in a pilot study case representative of intensively managed rural landscapes (IMRLs) in the food critical Ganga river basin of North India.

2.2 Materials and methods

2.2.1 Study Area

The diagnostics approach is tested in a smallholder dominated Intensively Managed Rural Landscape (IMRL) representative of the Ganga River Basin in Kanpur (Bilhaur tehsil, Kanpur Nagar district, Uttar Pradesh), India. The study area (Figure 2.1) is part of a Critical Zone Observatory created by the Indian Institute of Technology Kanpur in 2016 in the IMRL (Gupta et al., 2017; Gupta et al., 2019). It lies between the Lower Ganga Canal distribution system and the Pandu river, a tributary of the Ganga river. Agricultural practices are typically monocropping (with alternating monsoon paddy and winter wheat crops), and flood irrigation is carried out using either canal distributaries which flow into the study region, or using groundwater (GW) abstracted by diesel pumps.

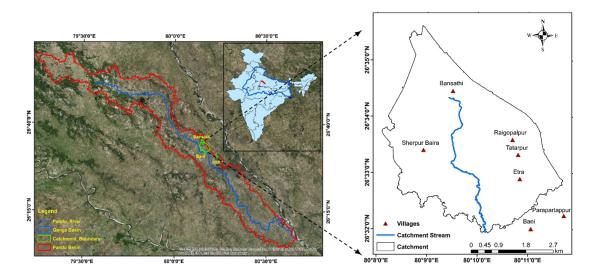


Figure 2.1: The study area (shown within the green 'catchment boundary') for advisory diagnostics approach, in Kanpur (Uttar Pradesh, India). Image modified from Gupta et al., 2019.

2.2.2 Validating the working assumption using farmer surveys

The working assumption that 'yield gaps' can be explained by nutrient-related, water-related limitations, or co-limitations (Mueller et al., 2012) is validated using inferences from an interview-based survey in the study area. 144 farmer-respondents were interviewed in 2018 through random sampling from the five villages of Bani, Bansathi, Etra, Parapratappur, Raigopalpur, Sherpur Baira and Tatarpur, which had a total population

of 8,887 (Government of India, 2011).

Farmers were asked questions about their demands and preferences related to agricultural advisories, to validate whether the impact of nutrient and water limitations on yield gaps (Mueller et al., 2012) is also felt by farmers. Questions aimed to derive the perceived importance of different advisory parameters (input application and irrigation scheduling, weather forecast for rainfall, soil testing), and preferred means of receiving advisory (text message, voice message, phone call). The complete list of questions is included in Section 1 of the Supplementary Material. The developed survey was incorporated into the public domain software package, Census and Survey Processing System (CSPro) (United States Census Bureau, 2000), and the mobile phone application "CSEntry" was used on the field for efficient and convenient data collection.

2.2.3 Selecting indicators to quantify farm performance

The performance indicators used to quantify the current performance are based on the two major factors resulting in yield gaps: soil nutrients and water.

2.2.3.1 Soil related performance indicator: Soil Quality Index (SQI)

Soil Quality Index (SQI) (Karlen et al., 1997) is the performance indicator used to quantify the soil-nutrient status. It is computed as a weighted sum of individual soil parameter scores (or values). The weights are determined based on the literature and expert opinion (C.-H. Lee et al., 2006). The formula of SQI is given below (Wu and M. Wang, 2007):

$$SQI = \sum_{i=1}^{n} W_i \cdot S_i \tag{2.1}$$

where W_i = weight of the *i*th parameter

 S_i = score of the *i*th parameter (here, the normalized parameter value)

n = number of total parameters

Multi-Criteria Decision Making (MCDM) methods are used to assign weights in SQI computation (A.K. Mishra et al., 2015). In this study, the scores and weights are assigned to the soil properties using Analytical Hierarchy Process (AHP) (R.W. Saaty, 1987; T.L. Saaty, 1977). It is a widely used MCDM process (Alharthi et al., 2015; Kil et al., 2016) and has been applied to assess and enhance soil quality through improved soil management practices (Kalambukattu et al., 2018; U. Kumar et al., 2019). AHP can generate indicator weights based on pairwise comparisons of all relevant indicators made by experts, while also reducing biases in the decision-making process by checking for consistency in the decision maker's evaluations. Though the decision maker's subjective involvement in assigning weights or assessing attributes leads to more flexibility, it can lead to different solutions based on different relative prioritizations (A. Kumar et al., 2017a), which reinforces the importance of selecting domain knowledge experts for the approach.

Section 2 in the Supplementary Material describes the AHP methodology in further detail.

2.2.3.2 Water related performance indicator: Water Use Efficiency (WUE)

Water Use Efficiency (WUE, in kg/m³) is defined as the ratio of agricultural production (yield per unit area, kg/ha) to the gross water application or availability at the field (mm), inclusive of both precipitation and irrigation water (Van Halsema and Vincent, 2012).

$$WUE = [agricultural\ production]/[water\ applied]$$
 (2.2)

WUE has been interpreted as a combination of efficiency and productivity ratios (Van Halsema and Vincent, 2012). Its idea is motivated by the need to meet increasing food requirements with limited water resources by maximizing the production per unit of available water (De Fraiture et al., 2010; De Fraiture and Wichelns, 2010; Van Halsema and Vincent, 2012). WUE is used here as a measure of 'localized efficiency' (Van Halsema and Vincent, 2012), which is appropriate in the context of this study, since it focuses on the farmer's perspective of the efficient allocation of input water (and consequently economic inputs).

2.2.4 Data collection to compute performance indicators

The specific villages chosen for the survey and soil testing were Bani, Bansathi, Etra, Parapratappur, Raigopalpur, Sherpur Baira and Tatarpur. The objective was to capture a range of SQIs and WUEs with a systematic sampling methodology (Fowler, 2014). Further, a GIS database was developed to visualize the survey and soil data. This helped in understanding the spatial spread of the current 'problem areas', which can potentially guide applied research, as well as more targeted delivery of the generated advisory.

2.2.4.1 Soil sampling and testing to compute SQI

Soil testing was conducted for 100 farmers in 2018 by the Uttar Pradesh State Agricultural Department. Soil samples were collected in the manner recommended by the Department of Agriculture, Cooperation & Farmers Welfare. Government guidelines recommend sample collection on a grid basis with grid area of 2.5 ha for irrigated areas (Kaur et al., 2020). For this study, the spatial resolution was increased substantially by collecting five soil samples from each farm (instead of each 2.5 ha). Five soil samples were collected from the top 15 cm (four from farm corners and one from the centre). The samples were subsequently mixed to conduct physio-chemical analyses. The parameters which were tested were physical parameters (pH, EC), macronutrients (SOC, N, P and K), and micronutrients (S and Zn).

2.2.4.2 Data for Water Use Efficiency (WUE)

Data regarding wheat yield and number of irrigations, corresponding to the previous winter cropping season (*rabi* 2018, from November to April), were collected from 67 farmers, to generate a database of baseline water related data. Consequently, WUE was computed assuming traditional practices of irrigation depths of 7.5 cm (per irrigation application) for the wheat crop (Prihar et al., 1978) in India. Rainfall over the cropping season was assumed constant for all the farms (since the study area has relatively flat topography with areal coverage of less than 12 km²), and measured monthly rainfall data from November 2017 to April 2018 (total rainfall of 2.2 cm) were used in addition to data about irrigation application and yields reported by farmers during the surveys. WUE was finally computed by dividing the yield values with the gross amount of water applied (total rainfall and cumulative irrigation during the cropping season).

2.2.5 Integrated visualization: quantification and classification of overall farm performance

A scatter plot is generated combining the two performance indicators, resulting in a depiction of localized farm performance (Figure 2.2). The axes limits are determined by the ranges of the respective performance indicators obtained in the survey. The plot is subsequently divided based on the median values of the two indicators (derived from the entire farm dataset generated in Section 2.2.4). There are hence four classes formed, based on their respective performance zones, (i) Zone of satisfactory performance (S, top-right): with both high WUE and SQI, where there is an expectation of high overall performance, (ii) Nutrient limited zone (NL, top-left): with high WUE despite low SQI, and there may be crucial lessons to learn from such farmers, (iii) Water limited zone (WL, bottom-right): low WUE despite high SQI, where there are substantial opportunities to improve the water management practices, and (iv) Zone of co-limitations (NLWL, bottom-left): with both low WUE and SQI, within which there is low overall performance needing more focused advisory dissemination.

The top right corner of the scatter chart (red circle) represents a "Localized Performance Target" corresponding to the highest SQI and WUE indicators from the local farms. The emphasis here is that the result-oriented advisory development should be initially prepared to achieve 'best' performance based on localized characteristics, and not the 'best' performance based on global standards, which is a reasonable approach reported in the literature. For instance, soil quality can only be assessed appropriately within the context of its inherent properties, environmental influences (temperature and precipitation), and of 'what the soil is being asked to do' (Andrews et al., 2004).

Further, the sub-categories of "Best Practice Farms," "Critical Farms" and "Quick Improvement Farms" are proposed (which can be decided subjectively based on the spread of the scatter – here shown in the corners for clear representation). "Best Practice Farms," which despite low SQIs are able to achieve high WUEs through good traditional or modern water management strategies, can be identified to give crucial insights to

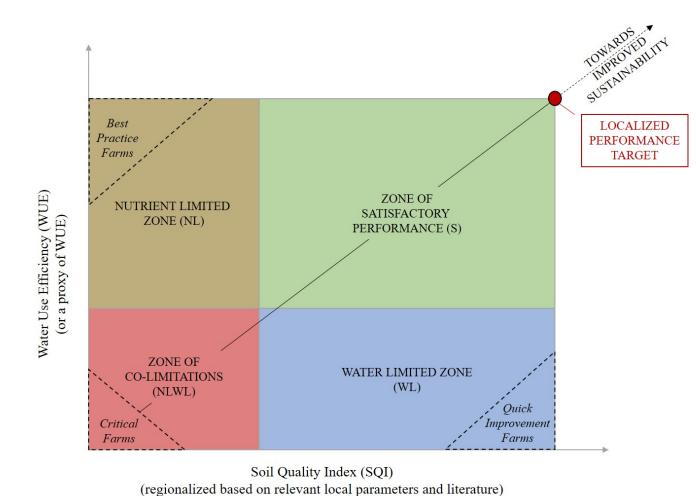


Figure 2.2: Classification of farms based on the two performance indicators (Soil Quality Index and Water Use Efficiency) associated with major yield gap limitations (nutrient, water, or both).

other farmers, to enable community leadership and knowledge exchange. "Critical Farms," with both low WUE and SQI would need immediate assistance, and may be prioritized as part of triage-based critical advisory administration. "Quick Improvement Farms," which have low WUE despite having soils with high SQI, would be expected to show quickest improvements (in WUE) through simple water saving measures due to their pre-existing relative advantage in nutrient status. Additionally, a subjective selection of "High Performance Farms" (the best farms within the S-zone), can help in defining an Intermediate Performance Target which is localized and is based on an average of their respective performance indicators.

A GIS map is created corresponding to this zonal classification which helps in understanding the spatial distribution of the farms.

2.2.6 Recommendations based on 'Farm performance classification' to customize advisories

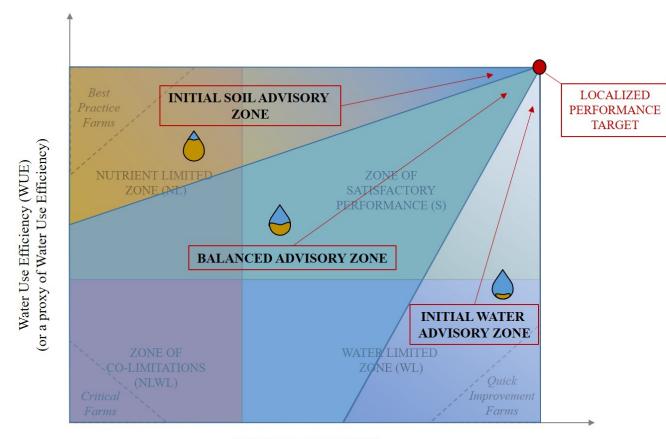
This step is necessary to customize the advisory content to suit a farm's current performance situation (the farm's position in the SQI-WUE plot in Figure 2.3) towards the realistic goal of the Localized Performance Target (top-right corner in Figure 2.3). If this target seems heuristically unrealistic, an Intermediate Target may be suggested, which is the average of "High Performance" farms.

For the sake of simplicity, three basic typologies of advisories based on the ratio of focus between water and nutrient related guidance are proposed. The "Initial soil advisory zone" initially focuses on improving soil nutrient properties, the "Initial water advisory zone" initially contains a higher proportion of water management related content, and the "Balanced advisory zone" has a balance of nutrient and water related advisory contents. Each of the zones tends to become a balanced advisory after observing improvements towards better overall performance, as indicated by the red arrows in Figure 2.3.

2.2.7 Development of the Farm Agricultural Diagnostics (FAD) tool

The motivation for developing the FAD tool (Adla, 2021) is to aid agricultural extension service providers and professionals in allied sectors, such as in a local governments or a Non-Governmental Organization (NGO), with a user-friendly tool for conducting agricultural advisory diagnostics. The tool is developed using the Macro-in-Excel Visual Basic for Applications (MEVBA) feature of Microsoft Office Suite's spreadsheet software MS Excel (Roman, 2002). MEVBA has the ability to incorporate scripts which are easy to maintain and also allow for expansion through its modular framework. Its dynamic formatting can be used to make the user interface more interactive, and yet it is a rather familiar software for collaboration (Yang, Ogunkah, et al., 2013). In the FAD tool (Adla, 2021), MEVBA performs AHP calculations in the back-end by extracting data from dynamic input tables resulting in a well-ordered and tidy user interface.

The FAD tool (Adla, 2021) is free, user-friendly, and accessible in terms of its workflow. Its inputs include data for computing the SQI (results of soil quality testing on relevant parameters), heuristics to conduct relative comparisons between different soil quality parameters, and input data for computing WUE (crop yield, rainfall and applied irrigation during the cropping season). Its GUI can be used to generate a classification of the farm performance based on the diagnostics approach introduced in the study, and provide visual aids to promote a better understanding of the reported results. The resultant chart is easily exportable. The Farm-Agricultural-Diagnostics-tool version 1.0 has been archived as a Github repository (Adla, 2021), alongwith details pertaining to its features and operational instructions described using screenshots of the tool (https://github.com/soham-adla/Farm-Agricultural-Diagnostics-tool/blob/



Soil Quality Index (SQI) regionalized based on relevant local parameters and literature

Figure 2.3: Performance class based advisory recommendations (with varying proportions of 'blue' water vs 'brown' soil nutrient advisory 'water droplet' content) based on the current situation relative to the Localized Performance Target (top right corner). Zones of water limitation (WL), nutrient limitation (NL), co-limitation (NLWL) and satisfactory performance (S) are shown within which critical farms, quick improvement farms and best practice farms are special sub-categories (introduced in Section 2.2.5).

main/FAD-v1.0_Instruction-Manual.pdf).

2.3 Results

2.3.1 Validating the working assumption using farmer surveys

In a reconnaissance survey conducted during 2018, farmers expressed concerns on irrigation amounts and timing. In the detailed survey subsequently undertaken, 141 out

Table 2.1: Soil parameters and the respective weights assigned to compute SQI using the AHP.

S. No.	Soil parameter	Weight (%)
1	SOC	35.29
2	рН	15.00
3	EC	15.00
4	N	12.34
5	Р	7.38
6	K	7.38
7	S	3.80
8	Zn	3.80

of 144 farmers expressed their need for an advisory on irrigation scheduling, and all farmers expressed their need for information on rainfall forecast, fertilizer application, and a need to test their soils regularly. This reinforced the working assumption that the major limiting factors to address yield gaps were soil and water related, as they were identified as major advisory requirements by farmers who are the ultimate beneficiaries of agricultural extension services.

2.3.2 Quantifying farm performance

2.3.2.1 Soil related performance indicator: Soil Quality Index (SQI)

The final weights assigned to each soil parameter, based on the AHP methodology, are given in Table 2.1. Once the weights were assigned, the respective parameter values were converted into non-dimensional values lying between 0 and 100%, based on the linear scoring method (U. Kumar et al., 2019; Liebig et al., 2001) described in Section 2 of the Supplementary Material. The weights were then used in combination with the parameter values to compute the SQI of each soil sample collected (based on Equation 2.2).

Figure 2.4 shows the spatial distribution of the farm scale SQI of 100 farms as part of the GIS database that was developed. Higher values of SQI indicate better soil performance or lower nutrient limitations. Soil properties exhibit spatial variability even

at farmland scales (McBratney, 1997), and a comprehensive explanation of this variability would require a historical and current understanding of the physical, chemical and biological processes occurring in the farms (Santra et al., 2008), along with a broad knowledge of land use and management practices (Mouazen et al., 2003). Such a comprehensive database may not be readily available even with advisory institutions. Hence, it is important to conduct soil testing and compute SQI using local expertise as a prerequisite to the proposed advisory diagnostics approach, rather than attempting to address diverse soil quality issues using incomplete information.

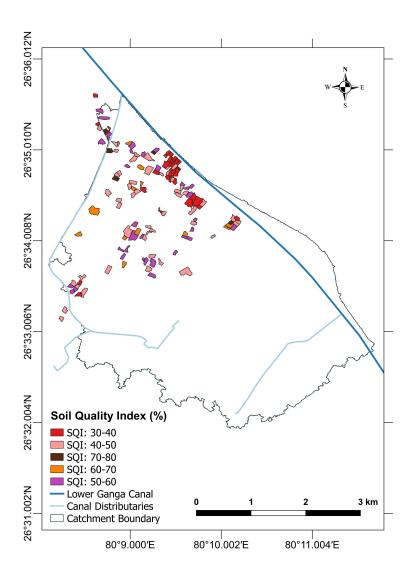


Figure 2.4: Spatial variability of the soil related performance indicator, Soil Quality Index (SQI), computed with the AHP methodology, using the soil testing results of samples collected from 100 farms in the study area.

2.3.2.2 Water related performance indicator: Water Use Efficiency (WUE)

The WUE of wheat (calculated using Equation 2.2) was 1.60 kg/m³ (s = 0.49 kg/m³). Figure 2.5 illustrates the spatial variability of farm scale WUE for 67 farms, as part of the GIS database that was developed. Higher values of WUE indicate a higher localized efficiency in the application of water at the farm level (Van Halsema and Vincent, 2012). A simplistic observation of the proximity to surface water sources (like canal or canal distributaries, shown in bold and light blue colors respectively) would not be sufficient to explain the variability in WUE across the farms, since it is impacted by many management factors including variety, sowing date, planting density and row spacing, soil water content at planting, irrigation method and pest management (Howell, 2001). This again reinforces the need to provide data-driven, farm-specific advisories.

2.3.3 Integrated visualization: quantifying overall farm performance and classification

The scatter plot of the farms' performance, developed using surveys and soil testing, is given in Figure 2.6. Out of the 144 surveyed farms, 100 soil samples were collected, and 67 farmers reported previous year yields and irrigation application data. Hence, 67 farm points are included in the visualization

The extreme values of the SQI were 28.12% and 76.22%, and corresponding values of WUE were 0.61 kg/m^3 and 3.48 kg/m^3 , which represent plot boundaries (X and Y axis extremes respectively). The median values of SQI and WUE were 43.09% and 1.55 kg/m^3 respectively. This led to the Y and X axes passing through these points respectively and to a relatively evenly distributed percentage of farms across the classes: S (14.9%), NL (23.9%), WL (34.3%), and NLWL (26.9%).

The identification of the special sub-categories of "Best Practice Farms", "Critical Farms" and "Quick Improvement Farms" was performed as follows. A visual judgment was taken to categorize only one farm into the category of "Best Practice Farms", whose SQI (39.45%) was 9.5% lower than the median SQI, but WUE (0.28 kg/m³) was 82.5% higher than the median WUE. This may have been due to the fact that though the farm location was relatively upstream to the other farms (and with adequate access to canal irrigation), the farmer chose to irrigate his wheat three times during the season. This was in contrast to the modal and mean values of the number of irrigations in all the farms being 4 and 3.7 respectively. The "Critical Farms" (red diamonds) had both SQI and WUE values below their respective median values within the NLWL region. 4 out of the 18 NLWL farms (22.2%) were identified as "Critical Farms", which could be given prioritized attention through customized advisory services. The "Quick Improvement Farms" (yellow diamonds) had farms whose WUE values were below, and SQI values were above, their respective medians (among the WL datapoints).

The subjectivity in the above categorizations is inherent to model development,

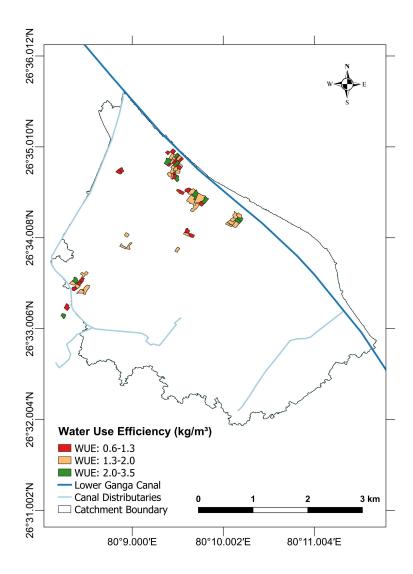


Figure 2.5: Spatial variability of the water related performance indicator, Water Use Efficiency (WUE), computed using data from 67 farms in the study area.

and becomes more explicit when stakeholders are included in the modelling process (Srinivasan et al., 2017). It is recommended that advisors take up this process with the active involvement of stakeholder farmers or farmer groups. The categorization of "Best Practice Farms", "Critical Farms" and "Quick Improvement Farms" has not been incorporated in the corresponding FAD tool (Adla, 2021), and the final outcome of the tool is a visualization with the broader classes (NL, WL, NLWL, and S).

The Localized Performance Target (red circle at the top-right corner of Figure 2.6) seemed distant from any of the farm's performance. The farm with the best SQI = 76.22% had a $WUE = 1.62 \text{ kg/m}^3$, and the farm with the best $WUE = 3.48 \text{ kg/m}^3$ had an SQI = 51.8%. Hence, "High performance farms" were identified through visual

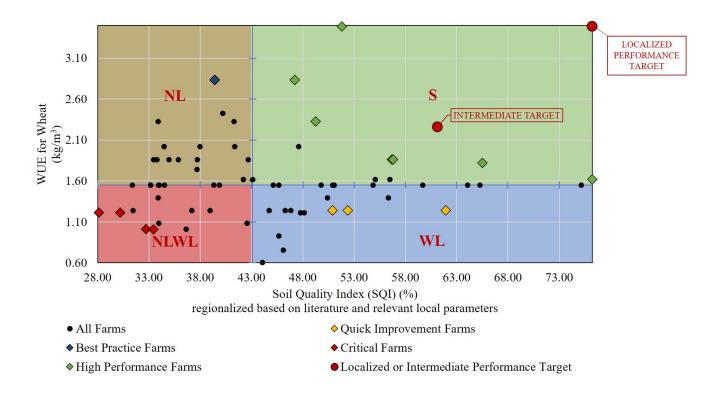


Figure 2.6: Classification of surveyed farmers (n = 67) based on locally relevant Soil Quality Index (%) and Water Use Efficiency (kg/m3) to aid zonal advisory development. S – 'sufficient' farms in terms of limitations to yield gap, WL – 'water limited farms', NL – nutrient limited farms and NLWL – farms with co-limitations of both water and nutrients. Also shown are farms identified as critical, quick improvement, and best practice farms, and the performance targets.

inspection (green diamonds), and their average performance tuple (SQI = 61.24%, WUE = 2.26 kg/m^3) was designated to be an Intermediate Performance Target.

A GIS map of the spatial variation of farms categorized into the four SQI-WUE classes is presented in Figure 2.7. An initial visual analysis did not reveal any clear environmental bases explaining the variability of the farm performance classes within the study area. For example, there both WL and NLWL farms in proximity to the Lower Ganga canal, which is counterintuitive since farms adjoining surface water would generally be expected to not be water limited. The explanation of such patterns may require a deeper analysis of the human-water interactions within social, economic and natural systems (Srinivasan et al., 2017; Van Emmerik et al., 2014) which consequently require more holistic and perhaps new data sources including citizen science, new sensing technologies or satellite data products (Buytaert et al., 2014). Particularly in this case, knowledge of previous and current soil and water management practices, access to farm technology, availability of capital may be useful to make explanatory

interpretations, which are generally available with government or non-governmental agencies working in the agricultural sector, and were not collected for this study.

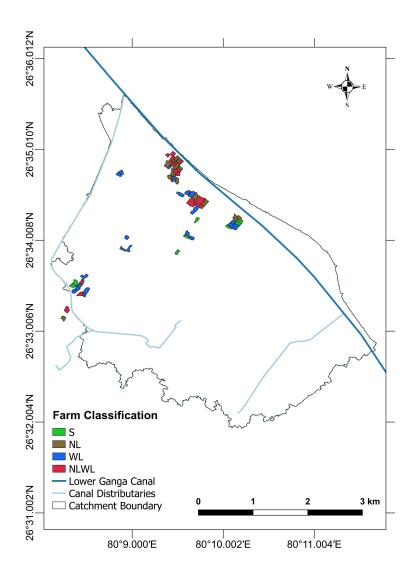


Figure 2.7: GIS map of farm classification using soil nutrients and water as major limitations contributing to yield gap. S – 'satisfactory' farms in terms of limitations to yield gap, NL – nutrient limited farms, WL – water limited farms and NLWL – farms with co-limitations of both nutrients and water.

2.3.4 'Farm performance classification' based recommendations to customize advisories

The SQI-WUE based classification of the different farms in the study area is given in Figure 2.8.

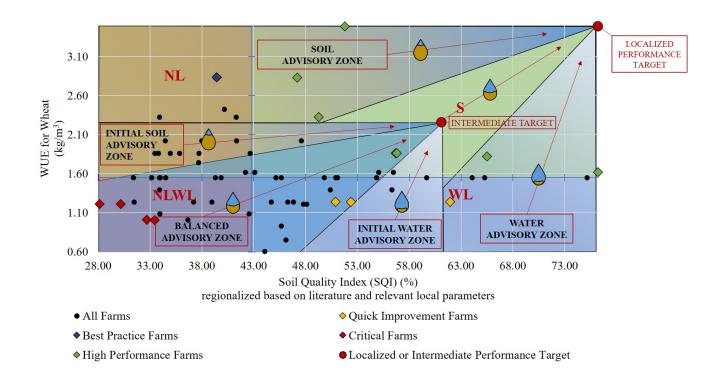


Figure 2.8: Classification based advisory development in the study area. The Intermediate Target is computed using the average of the 'High performance' farms (depicted using green diamonds).

It is desirable to design advisories which would not aim at a performance indicator tuple of SQI = 76.22%, $WUE = 3.48 \text{ kg/m}^3$, but rather aim for a relatively well performing farm in the region. Hence, the average performance of the 'High performance' farms was chosen as an achievable Intermediate Target, e.g., as shown in Figures 2.6 and 2.8. Once a farm achieves this Intermediate Target, it can aim to achieve the Localized Performance Target. Farms that are already better than this Intermediate Target could get advisories which aim at the Localized Performance Target.

The GIS map already generated (Figure 2.7) can be used to implement the designed advisories (three types of advisories each for the Intermediate and the Localized Performance Targets) in the region.

2.4 Discussion

2.4.1 Contextualizing the diagnostics approach using a medical analogy

This study introduces an approach to assess farm performance and diagnose the reasons for yield gaps with a user inspired, data-based approach (Sivapalan et al., 2014; S.E. Thompson et al., 2013). The approach limits itself to advisory diagnostics, and does not make recommendations about advisory content or form. A useful analogy to contextualize this approach is the diagnosis and treatment of a patient by a medical doctor, with the help of diagnostic tests, as illustrated in Figure 2.9.



Figure 2.9: Contextualization of the agricultural diagnostics approach, using a medical analogy, given in parentheses. Image modified from the free-copyright abstract vector created by macrovector (https://www.freepik.com/vectors/abstract)

Every patient is different in terms of their physiological or pathological condition, just like every farm is different in terms of its agricultural condition. A doctor refers their patient to tests conducted by diagnostic laboratories to better ascertain the current state of the patient's physiological condition. An accurate and timely diagnosis, i.e., identification of the patient's problem, leads to 'clinical decision making' tailored to a correct understanding of the patient's health problems (Holmboe and Durning, 2014).

Likewise, this study's approach is a diagnostic method to better quantify the current condition of a farm, so that an advisor can administer advisories which are more customized to the farm in question. Moreover, public health policy is often influenced by diagnostic data, by altering resource allocation decisions and research priorities (Jutel, 2009; WHO, 2012). Similar diagnostic data collection and analysis in agriculture also opens up possibilities for applied research which may inform policy makers and implementing agencies to better serve demand-driven needs.

The tool will add data-based diagnostics value to pre-existing demand based advisory services, if used within already existing agricultural extension programs. The primary users of the tools are advisors (analogous to medical doctors), whom it facilitates, to generate more data-based and hence customized advisories, for farmers. In India, the district-level farm science centres (*Krishi Vigyan Kendras*) are such extension institutions which operate under central or state agricultural universities, the Indian Council of Agricultural Research (ICAR), NGOs, state governments, or public sector undertakings (ICAR, 2015)². It is their mandate to develop advisories, including the disbursement of 'farm advisories using ICT and other media means on varied subjects of interest to farmers' and 'assessment of location specific technology modules in agriculture' (ICAR-IASRI, n.d.)³.

2.4.2 Financial and institutional implications

The financial and institutional implications of this additional diagnostics process are predominantly related to aspects of soil sampling and testing, management of the data generated from soil testing, farmer surveys, and the tool, and human resource skill development for the relevant extension staff. In developing countries such as India, soil testing is a routine function of the Department of Agriculture, Cooperation & Farmers Welfare (Kaur et al., 2020). State agricultural departments are mandated to develop Soil Health Cards (SHCs), launched for Soil Health Management (SHM) by the Department of Agriculture, Cooperation & Farmers Welfare (Ministry of Agriculture and Farmers Welfare) by the Govt. of India⁴. The proposed diagnostics approach can build on the strengths of pre-existing soil testing infrastructure and leverage data collection mechanisms through call centres such as the Kisan Call Centre (Ganesan et al., 2013). The financial investment of the diagnostics approach and tool has two major aspects: the infrastructure to support data storage and processing for the agricultural "big data" thus generated (Hashem et al., 2015), and human resource skill development. The sustainable scaling-up and replication of such data-driven diagnostics will require largescale storage, pre-processing and analysis of data coming from different sources (Hashem et al., 2015; Kamilaris et al., 2017). Though big data management has only recently been incorporated into agriculture (Lokers et al., 2016), the Indian big data analytics

²https://krishi.icar.gov.in/kvk.jsp

³https://kvk.icar.gov.in/aboutkvk.aspx

 $^{^4 \}mathtt{https://soilhealth.dac.gov.in/Content/blue/soil/about.html}$

sector is expected to record a growth rate of 26% and increase by 14 billion USD from 2020 to 2025 (Reghunadhan, 2020). The Government of India has initiated various big data projects in the agricultural sector - Farmers Portal⁵ (portal which delivers relevant village/block/city/state level information through text message/email), Agricultural and Processed Food Products Export Development Authority⁶ (portal which facilitates export of food products, registers farms online, conducts surveys and feasibility studies, aids the collection of test samples, etc.), the Agriculture Portal of www.india.gov.in (database on agricultural products, machinery, research, and knowledge resource for government policies and schemes, market prices, etc.), and the Open Government Data Platform India⁸ (open dataset available for research and analysis) (Shankarnarayan and Ramakrishna, 2020). Additionally, large corporations working in the agri- and allied sector (e.g., Monsanto, Mahindra and Mahindra) have invested substantially in big data in the agribusiness segment (Lane, 2015). However, challenges accompanying big data applications, including privacy, security, data governance, sharing, expense, and data ownership, will also apply to this context, and will need to be addressed appropriately. (Shankarnarayan and Ramakrishna, 2020). The human resource skill development, particularly in subject knowledge and data analytics, can be inculcated through regular ICT trainings, which has been found to improve computer skills and work efficiency (Galanouli et al., 2004), and has been recommended for agricultural extension workers (Nyarko and Kozári, 2021).

2.4.3 Recommendations for advisors using the tool

The advisory content can be supplemented by incorporating knowledge generated through mutual learning through interactions between farmers, among scientists and between farmers and scientists, for more effective translation of scientific information (Feldman and Ingram, 2009). Table 2.2 suggests some key characteristics (or major commonalities) of farms closer to the Localized Performance Target (shown in Figure 2.3). An identification of the key characteristics (or common factors, if they exist) of farms in each of the groups listed in Table 2.2 may help in designing advisories which are more specific than generic advisories. Lessons can be drawn from "Best Practice Farms" about their superior water management practices (despite relatively poor soils), and can be applied with confidence to advise "Critical Farms" and particularly "Quick Improvement Farms" because they are unable to achieve high WUEs despite relatively high SQIs.

⁵https://farmer.gov.in/

⁶http://apeda.gov.in/apedawebsite/

 $^{^{7} \}mathtt{https://www.india.gov.in/topics/agriculture}$

⁸https://data.gov.in

Table 2.2: Template for collecting key characteristics of farm sub-categories to guide a bi-directional flow of information. The examples given are descriptive.

Category	Commonalities/ learnings	Requirements
"Best Practice Farms" (High WUE despite low SQI)	Examples: superior soil conservation techniques, efficient irrigation methods, better educational qualifications etc.	After improvement of nutrient based performance characteristics, incorporating data-based precision farming techniques through experiments.
"Quick Improvement Farms" (Low WUE despite high SQI)	Examples: lack of reliable irrigation sources, poor irrigation practices/water use behaviour, particular low-yielding crop/seed variety etc.	Better water management practices (particularly using lessons from "Best Practice Farms").
"Critical Farms" (Low WUE and SQI)	Examples: poor soil type, poor access to irrigation water, low socio-economic situation etc.	Low-cost, agricultural practices that lead to the quickest initial increase in performance characteristics (towards the Localized Performance Target).

Progressive farmers with the "Best Practice Farms" and "High Performance Farms" could potentially function as community leaders. Several examples of such leadership exists across domains, including the kisan mitras (farmer friends) - educated progressive farmers appointed by the government as village level extension functionaries (Landge and Tripathi, 2006), 'barefoot engineers' - local level para-hydrogeologists employed by the gram panchayat (local village government) to take independent decisions regarding water management programs (Sen et al., 2019), and community health care workers - facilitators in improving health care access and outcomes in poor and deprived communities (E.L. Rosenthal et al., 2010). Also, once a farm is closer to the Localized Performance Target, a customized plan can be designed with modified global best practices, incorporating the potential of precision farming, for enhanced sustainability in the longer run. Ensuring transparency in disseminating performance indicators (with the possibility of farmers to visit vicinal better performing farms) can encourage farmers to visit each other without any immediate need for contacting the external 'scientific' community, inspiring knowledge exchange within the community. Moreover, employees of some agencies in direct and regular communication with farmers (such as grassroots NGOs) have informally appreciated the potential of this tool for improved farm data monitoring and management (particularly of variables causing yield losses), and ultimately developing customized solutions for their farmer beneficiaries.

The form in which advisories are administered may be designed considering preexisting local practices. Farmers have needed graphs and data to be interpreted by trained advisors in some advisory services (Eastwood et al., 2019). Engagement with users in the study area also corroborated this need; farmers suggested that advisories be administered using the local agronomic and agricultural management nomenclature. The corresponding training of advisors could incorporate suggestions from selected local farmers (managing the best practice farms in the region).

2.5 Conclusions

Acknowledging the need for data-driven agricultural extension, a "diagnostics" approach is developed to supplement pre-existing, demand-based, generic advisory programs, particularly in the Indian context. It included the following steps. The current performance of farms is evaluated using soil nutrient and water related performance indicators (Soil Quality Index SQI and Water Use Efficiency WUE respectively). Next, farms are classified into different performance zones to develop more customized advisories. Further special classes of farms are identified; the "Best Practice Farms" which can serve as a source of successful traditional or modern knowledge, "Critical Farms" which perform relatively poorly and would need critical focus urgently, and "Quick Improvement Farms" with low WUE despite relatively better SQI. A corresponding Farm Agricultural Diagnostics (FAD) tool is developed using MS Excel Macros which incorporates the salient features of the approach into a well-ordered, interactive and user-friendly design. The approach and tool are piloted in Kanpur, a region representing a smallholder dominated intensively managed rural landscape in the Ganga river basin (India). Additionally, a GIS database is developed to visualize the diagnostics for improved advisory administration. The approach and tool can be utilized extensively by academia, government and non-government agencies working in the agricultural sector, synergistically harnessing their strengths of rigorous scientific research, soil testing capacity, and direct stakeholder engagement, respectively. However, this effort would require political will, capacity building and cooperation within and between the relevant sectors.

3 Laboratory calibration and performance evaluation of low-cost soil moisture sensors

Adla et al. (2020) 9

Abstract

Soil volumetric water content (VWC) is a vital parameter to understand several ecohydrological and environmental processes. Its cost-effective measurement can potentially drive various technological tools to promote data-driven sustainable agriculture through supplemental irrigation solutions, the lack of which has contributed to severe agricultural distress, particularly for smallholder farmers. The cost of commercially available VWC sensors varies over four orders of magnitude. A laboratory study characterizing and testing sensors from this wide range of cost categories, which is a prerequisite to explore their applicability for irrigation management, has not been conducted. Within this context, two low-cost capacitive sensors - SMEC300 and SM100, manufactured by Spectrum Technologies Inc. (Aurora, IL, USA), and two very low-cost resistive sensors the Soil Hygrometer Detection Module Soil Moisture Sensor (YL100) by Electronicfans and the Generic Soil Moisture Sensor Module (YL69) by KitsGuru - were tested for performance in laboratory conditions. Each sensor was calibrated in different repacked soils, and tested to evaluate accuracy, precision and sensitivity to variations in temperature and salinity. The capacitive sensors were additionally tested for their performance in liquids of known dielectric constants, and a comparative analysis of the calibration equations developed in-house and provided by the manufacturer was carried out. The value for money of the sensors is reflected in their precision performance, i.e., the precision performance largely follows sensor costs. The other aspects of sensor performance do not necessarily follow sensor costs. The low-cost capacitive sensors were more accurate than manufacturer specifications, and could match the performance of the secondary standard sensor, after soil specific calibration. SMEC300 is accurate (Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Relative Absolute Error (RAE) of 2.12%, 2.88% and 0.28 respectively), precise, and performed well considering its price as well as multi-purpose sensing capabilities. The less-expensive SM100 sensor had a better accuracy (MAE, RMSE, and RAE of 1.67%, 2.36% and 0.21 respectively) but poorer precision than the SMEC300. However, it was established as a robust, field ready, low-cost sensor due to its more consistent performance in soils (particularly the field

⁹**Adla, S.**, Rai, N.K., Karumanchi, S.H., Tripathi, S., Disse, M. and Pande, S., 2020. Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. Sensors 20(2), 363. https://doi.org/10.3390/s20020363

soil) and superior performance in fluids. Both the capacitive sensors responded reasonably to variations in temperature and salinity conditions. Though the resistive sensors were less accurate and precise compared to the capacitive sensors, they performed well considering their cost category. The YL100 was more accurate (*MAE*, *RMSE*, and *RAE* of 3.51%, 5.21% and 0.37 respectively) than YL69 (*MAE*, *RMSE*, and *RAE* of 4.13%, 5.54%, and 0.41, respectively). However, YL69 outperformed YL100 in terms of precision, and response to temperature and salinity variations, to emerge as a more robust resistive sensor. These very low-cost sensors may be used in combination with more accurate sensors to better characterize the spatiotemporal variability of field scale soil moisture. The laboratory characterization conducted in this study is a prerequisite to estimate the effect of low- and very low-cost sensor measurements on the efficiency of soil moisture based irrigation scheduling systems.

Keywords: volumetric water content; soil moisture; permittivity; capacitive sensor; SM100 sensor; SMEC300 sensor; resistive sensor; off-the-shelf sensor; calibration; temperature sensitivity, salinity dependence; low-cost sensor; irrigation management; precision agriculture.

3.1 Introduction

The gravimetric method (Gardner, 1986), which is the most accurate method of VWC measurement, is destructive, laborious, and does not provide results in real-time (Kargas and K.X. Soulis, 2012). This has led to the development of non-destructive, indirect methods for the measurement of VWC (Bogena et al., 2017; Hubner et al., 2009; E. Ochsner et al., 2013; Robinson et al., 2008; X. Yu et al., 2013; D. Zhang and G. Zhou, 2016). Examples include neutron thermalization (Greacen, 1981), Time Domain Reflectometry (TDR) (Robinson et al., 2003; Topp et al., 1980), Time Domain Transition (TDT) (e.g., in Blonquist Jr et al., 2005), electrical capacitance (Fares and Polyakov, 2006; Kojima et al., 2016; Ojo et al., 2015) and impedance sensors (e.g., in Gaskin and Miller, 1996; Ojo et al., 2015).

The Electromagnetic (EM) sensors (TDR, TDT, and capacitance sensors) work on the principle that the EM wave propagation in bulk soil is primarily governed by liquid water that has a substantially larger dielectric permittivity (ϵ_r) than the other soil components (gaseous air and solid soil minerals) (Bogena et al., 2017). TDR and TDT sensors operate at higher frequencies (of the order of GHz Blonquist Jr et al., 2005) at which VWC measurements are less sensitive to soil electrical conductivity and imaginary dielectric permittivity (Blonquist Jr et al., 2005). Though the TDR method is regarded as the most accurate EM based VWC measurement technique (Noborio et al., 1994; Robinson et al., 2003), it is limited by its high cost and complex waveform analysis (Kargas and K.X. Soulis, 2012). Capacitance and frequency sensors, developed as alternatives to the TDR technique (Seyfried and Murdock, 2004), operate between 50 and 150 MHz (Bogena et al., 2017). They are similar with respect to repeatability, applicability to a wide range of soil types, and continuous monitoring ability (Dean et al., 1987), but are further advantageous due to significantly lower costs.

The combination of new technologies, stakeholders-cooperation and effective pro-poor institutions, within a larger and enabling policy framework, is considered to be the 'best chance for lasting and sustainable impact on poverty' (Rijsberman, 2003). These factors can result in an improvement of the livelihoods of the the poorest smallholder farmers through a transition towards sustainable agriculture (Rijsberman, 2003; Srbinovska et al., 2015). The lack of supplemental irrigation facilities has been identified as a major exacerbating factor for smallholder farmers facing severe agricultural distress (Besten, 2016; Pande and Savenije, 2016). Therefore, there is a need for sensor based systems for VWC monitoring for applications such as irrigation management (for instance, Wireless Sensor Network (WSN)) (Matula et al., 2016b). The utilization of such technologies is challenged by low awareness and reluctance towards adoption in farmers, and a lack of interest in investment due to the economic pressures of fast returns on investments, which could be countered by developing low-cost and user-friendly systems (Srbinovska et al., 2015).

Soil moisture sensors operating within WSNs can serve various purposes extending beyond irrigation management, such as validating remotely sensed soil moisture products (Cosh et al., 2016), observing ecohydrological processes (Baatz et al., 2015; Bogena et al., 2015), or characterizing spatial soil properties (Qu et al., 2014; 2015). However, WSNs are claimed to be expensive and to require further development (McBratney et al., 2005). To maximize the number of sensor nodes and due to the substantial quantity of VWC measurements from such networks, it is essential to use low-cost sensors with signals which can be interpreted in a straightforward and clear manner (Bogena et al., 2017). This has triggered an increase in the number of low-cost VWC sensors operating within WSNs spread over larger areas (Bogena et al., 2017). The cost of commercially available VWC sensors varies over four orders of magnitude. Capacitance sensors, being comparatively inexpensive and easy-to-use, show promise in measuring VWC within WSNs (González-Teruel et al., 2019; Martini et al., 2015; Qu et al., 2013). However, lowcost sensors may exhibit sensor-to-sensor variability (Rosenbaum et al., 2011), which, if not addressed, affects measurement accuracy (Bogena et al., 2017). In this study, two cost categories are defined: 'low-cost' and 'very low-cost'. These categories are, respectively, approximately one order and three orders of magnitude lower than an expensive, TDR-based sensor (without considering data logger or reader costs).

Tables 7.1 and 7.2 list some representative studies from a large body of work during the past few decades that have focused on the calibration and testing of VWC sensors. The determination of sensor accuracy, precision, sensor-to-sensor variability, volume of influence, and temperature and salinity effects is also vital to understand sensor performance under different conditions encountered in practice (some publications listed in Table 7.1). A list of publications, which have calibrated different capacitance, Frequency Domain Reflectometry (Frequency Domain Reflectometry (FDR)), or impedance soil moisture sensors on various fluids or porous media, using different curve-fitting methods, is given in Table 7.2. The novelty of this study lies in characterizing and testing non-research grade soil moisture sensors (in particular the low-cost capacitive

and very-low cost resistive sensors), which is a prerequisite to assess their irrigation management capabilities. Also, a new approach for holistic visualization of sensor accuracy and precision for multiple sensors and soils is presented.

Partly based on the literature (Czarnomski et al., 2005), and partly motivated by the impact that low-cost soil moisture sensors could have on ecological research and supplemental irrigation, the following questions were used to design the experiments conducted in the study.

- 1. What is the ability of the capacitive sensors to estimate the refractive index (ϵ_r) of various fluids of known ϵ_r values?
- 2. What empirical equation(s) can best explain the relationships between the output of the low- and very low-cost soil moisture sensor instruments tested in the study, and the actual *VWC*, across a variety of soils?
- 3. What is the difference between the respective accuracies of the soil-specific calibration equations developed in-house and the general manufacturer-provided calibration equations?
- 4. What is the accuracy and precision performance of different low- and very low-cost soil moisture sensor instruments tested?
- 5. How is the accuracy and precision of the developed calibration curves affected by variations in (i) temperature and (ii) electrical conductivity, within ranges that are commonly encountered in field conditions?

The results pertaining to the above questions are addressed in Sections 3.3.1.1–3.3.1.3, 3.3.2, and 3.3.3, respectively.

3.2 Materials and Methods

3.2.1 Soil Moisture Sensors

The sensors tested in the study are described in the subsections below. A comparison of the salient features (including prices from quotations) and the corresponding cost-based nomenclature used in the study are presented in Table 3.1. Sensor photographs are given in Figure 3.1.

3.2.1.1 Capacitance Based Low-Cost Sensors: Spectrum SM100 and SMEC300

The WaterScout SM100 Soil Moisture Sensor (manufactured by Spectrum Technologies, Inc.) is a capacitance-based low-cost soil moisture sensor (Spectrum, 2011). The sensor has a pair of electrodes that operates as a capacitor and the surrounding soil functions as the charge storing dielectric medium (Spectrum, 2011). The WaterScout SMEC 300 Soil Moisture Sensor is also a capacitance-based low-cost soil moisture sensor with the additional capability of measuring Electrical Conductivity (EC) and soil temperature (Spectrum, 2012). In both cases, an oscillator operating at 80 MHz drives the



Figure 3.1: The four soil moisture sensors investigated in the study; from left to right (in the order of ascending cost): YL69, YL100, SM100, and SMEC300. The rightmost sensor is the secondary standard sensor, ThetaProbe.

capacitor and the generated output (voltage ratio) is proportional to the soil's dielectric constant (ϵ_r) (Spectrum, 2011). However, the estimated ϵ_r is not available to the user via data loggers or readers as both sensors are calibrated by developing relationships between voltage ratios/raw A/D (analog to digital) values and actual VWC (θ) of a continuously drying soil column (D. Kieffer, personal communication, 5 September 2018). Additionally, the SMEC300 sensor measures EC with a pair of carbon ink electrodes, and temperature using a thermistor potted in the sensor molding (Spectrum, 2012). The SM100 has a reported accuracy of 3% VWC at an EC < 800 mS.m⁻¹, and an operating range of 0.5 °C to 80°C (Spectrum, 2011). The SMEC300 has reported accuracies of 3% for VWC, ± 1 mS.m⁻¹ for EC and 0.6 °C (0.8 °C) for temperatures greater than -30 °C (lesser than -30 °C), and has ranges of operations of 0–1000 mS.m⁻¹ for EC and -50 °C to 85 °C for temperature (Spectrum, 2012).

3.2.1.2 Generic Resistance Based Very Low-Cost Sensors: YL100 and YL69

The Soil Hygrometer Detection Module Soil Moisture Sensor provided by Electronicfans (herein referred to as YL100) and the Generic Soil Moisture Sensor Module by KitsGuru (herein referred to as YL69) are both resistive soil moisture sensors. Both the sensors have two pronged probes operating as variable resistances which are a function of the soil moisture. An increasing soil moisture increases the effective conductivity of soil (Aravind et al., 2015; Saleh et al., 2016). This variation in resistance causes a variation in voltage drop, which is then measured by the electronic module and subsequently returned as an output. However, the measured soil resistivity is also influenced by ion concentration (Bouyoucos and Mick, 1948) and hence careful calibration along with frequent recalibrations (due to variable organic and salt concentrations) are recommended for effective application (Schmugge et al., 1980). Previous studies have developed calibration curves for estimating continuous soil moisture (Saleh et al., 2016) or soil moisture categories (dry, medium, high, etc.) (Aravind et al., 2015) as a compromise between

Measurement Technique	Soil Moisture Sensor (Company)	Price (Quotation)	Nomenclature Used in Study
Capacitance based	SMEC300 Soil Moisture, Temperature and EC sensor (Spectrum Technologies) SM100 Soil Moisture sensor (Spectrum Technologies)	\$ 219.00 \$ 89.00	Low-cost *. Low-cost.
Resistance based	YL100 Soil Hygrometer Detection Module soil moisture sensor (Elec- tronicfans) YL69 Generic Soil Moisture Sensor Module (Kitsguru)	\$ 3.89 \$ 2.11	Very Low-cost. Very Low-cost.
Impedance based	ThetaProbe ML3 Soil Moisture sensor (Delta-T Devices)	\$ 516.33	High-cost, 'true' secondary standard sensor.

Table 3.1: Description of sensors used in the study

sensor accuracy and cost. No records of sensor specifications (including accuracy and operating conditions) could be found in the literature for either of the sensors.

3.2.1.3 Impedance-Based Sensor: Delta-T ThetaProbe ML3

The Delta-T ThetaProbe ML3 (henceforth referred to as the ThetaProbe) measures the soil VWC by responding to the changes in its apparent dielectric constant (Delta-T, 1999). A 100 MHz sinusoidal signal is applied to an internal transmission line extending into the soil by means of a sensing head (Delta-T, 1999). This comprises of an array of four rods: three of them (connected to the instrument ground) behaving as an electrical shield around the central, signal rod. The sensing head operates as an additional section of transmission line and has an impedance which depends on the dielectric constant of the soil (Miller and Gaskin, 1998). The impedance of the rod array subsequently impacts the reflection of the 100 MHz signal at the junction between the internal transmission line and the sensing head (Delta-T, 1999) and the interference of the reflected component with the incident signal causes a standing wave to form on the transmission line (Miller and Gaskin, 1998). The output is an analog voltage proportional to the difference in amplitude of this standing wave at two points—the junction and the starting point of the transmission line (Delta-T, 1999). This amplitude is related to the relative impedance of the probe, and thus the dielectric constant and VWC (Miller and Gaskin, 1998). The VWC sensor has a two-step calibration process; a soil specific linear calibration equation between the actual VWC (θ) and the refractive index

^{*} Considering the additional temperature and EC sensing capabilities.



Figure 3.2: The four different soils used the study. From left to right: Soil 1: Grade I Sand (Bureau of Indian Standards (BIS), 2002), Soil 2: Grade III Sand (Bureau of Indian Standards (BIS), 2002), Soil 3: Silty-loam soil from local field, Soil 4: Graded Silty-loam soil.

 $(\sqrt{\epsilon_r})$ of the dielectric medium, and a sensor specific 6th degree polynomial calibration equation between the output voltage and the refractive index $(\sqrt{\epsilon_r})$, together resulting in a 6th degree polynomial calibration equation between the output voltage and the actual VWC (θ) (Delta-T Devices Ltd., 2017). The ThetaProbe has a reported soil moisture accuracy of $\pm 1\%$, salinity error of $\leq 3.5\%$ VWC over 50-500 mS.m⁻¹ and 0-50% VWC, and soil temperature accuracy of ± 0.5 °C over 0 °C to 40 °C (Delta-T Devices Ltd., 2017). It is considered to provide a sensitive and precise measurement of VWC and soil temperature (Delta-T Devices Ltd., 2017), and is accepted for surface soil water content measurements (Matula et al., 2016b). Therefore, it could be justified to be used as a secondary standard (Nakra and Chaudhry, 2006) for the different experiments conducted in this study.

3.2.2 Description of the Soils Used

The four different soils used in the study are shown in Figure 3.2, and a description of their physical characteristics is tabulated in Table 3.2. These consisted of two Indian Standard sands from Indian Standard (IS) 650:1991 (Bureau of Indian Standards (BIS), 2002) and two silty-loam soils representative of agricultural landuse in the Ganga floodplains. Among the silty-loams, Soil 3 was sampled from a local agricultural field and included without any grading (to purposefully represent local field conditions), as opposed to Soil 4, which was graded with a 2 mm sieve.

3.2.3 Sensor Calibration

3.2.3.1 Calibration of Capacitive Sensors with Fluids

Following the literature (Bogena et al., 2017; Kargas and K.X. Soulis, 2012; 2019; Rosenbaum et al., 2012), fluids of known dielectric properties were used to evaluate (i) sensor accuracy, (ii) sensor precision, and (iii) the comparative performance of the tested capacitive sensors. The motivation behind using fluids was to minimize the variability in measurements arising due to nonuniform contact between the sensor surface and the porous media (Kargas and K.X. Soulis, 2012). The fluids were chosen because their

Table 3.2: Description of physical properties of the 4 soils used in the study (Adla et al., 2018)

	•		
Nomenclature Used in Study	Soil Description	Bulk Density [g/cc]	Soil Texture Classification
Soil 1	Grade I sand (1–2 mm)	1.82	Sand
Soil 2	Grade III sand (0.09–0.5 mm)	1.59	Sand
	Field soil from experimental		
Soil 3	site at IIT Kanpur (Kanpur,	1.23	Silty-Loam
	India)		
Soil 4	Graded Silty-Loam	1.20	Silty-Loam

Table 3.3: Fluids of known relative permittivity (ϵ_r) used in the study.

Fluid	ϵ_r at T = 25 °C (Kargas and K.X. Soulis, 2012)
Air	1.0
Butanol	16.8
Ethanol	24.3
Ethylene-glycol	37.0
De-ionized water (Water)	81.0

respective ϵ_r values were known and those values fall in the range generally encountered in soils of varying VWCs. The fluids selected for the study are shown in Table 3.3. The deionized water is henceforth referred to as "water".

Note that as the ThetaProbe was taken to be a secondary standard, it was included as a standard against which the investigated sensors were tested, rather than being calibrated or tested for performance.

3.2.3.2 Calibration of Sensors with Repacked Soils

In addition to calibrating soil moisture sensors with fluids of different ϵ_r values (which was relevant only for the capacitive sensors), it is essential to calibrate sensors in porous media (such as repacked or natural soils) before effective field application. Although repacking alters the natural soil structure (Czarnomski et al., 2005), using repacked soils for calibration is recommended to achieve better precision (Starr and Paltineanu, 2002). The calibration methodology adopted was based on predetermined uniform soil water content regimes for repacked soils, similar to recent studies (Kargas and K. Soulis, 2019; Matula et al., 2016b). Known quantities of water were added to containers with oven dried soils. The actual VWC (θ) was determined using a weighing machine, and multiple VWC measurements ($\hat{\theta_i}$) were taken with multiple specimens of each of the four sensors tested in the study. This process was repeated for each of the four soils (Table 3.2). The calibration methodology used for the repacked soils

is described in detail on an online database, https://www.protocols.io/ (Adla et al., 2018), to encourage methodological reproducibility and refinement.

3.2.4 Performance Measures for the Sensors

3.2.4.1 Sensor Accuracy

Accuracy is a measure of how close the measured output is to the true value (Morris and Langari, 2012). Accuracy may also be defined as the maximum difference that exists between a measured value and the true value determined by a standard reference procedure (Carr and J. Brown, 2001). In this study, the true value was determined through two approaches: a primary calibration standard (the gravimetric weight) as well as a secondary calibration standard (the impedance-based ThetaProbe soil moisture sensor). Three measures were used to quantify accuracy: mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Relative Absolute Error (RAE, σ). They are described, along with other performance measures, in Section 3.3.

3.2.4.2 Sensor Precision

Precision describes a measurement's repeatability, which indicates the extent to which consecutive measurements of the same input produce the same output (Bloom, 1989). In this study, precision was defined using the Pooled relative standard deviation $(s_{r,p})$, which provides an overall estimate of imprecision by combining the standard deviations around the respective means across a series of measurements (IUPAC, 1997). The multiple series of measurements corresponded to different mean values of measured VWC (for instance, $\theta_m^{\bar{s}}$ for the mth series), and the $s_{r,p}$ is defined in Section 3.3.

3.2.5 Sensor Sensitivity

3.2.5.1 Temperature Sensitivity

Multiple studies have investigated the effect of ambient and soil temperature on VWC measurements (Bello et al., 2019b; Czarnomski et al., 2005; Kargas and K.X. Soulis, 2012; Paltineanu and Starr, 1997; Szypłowska et al., 2019). Further methods have been proposed for correcting errors in VWC measurements arising due to diurnal variations in temperature (Chanzy et al., 2012). For this study, capacitive and resistive soil moisture sensors were tested in a silty-loam soil (Soil-4, described in Table 3.2) with two different values of actual VWC and ambient temperatures ranging from 10 °C to 40 °C (with an error of ± 1 °C), inside a temperature incubator. The soil surfaces were covered with polythene sheets to prevent evaporation. To ensure that the electronic components of the sensors (excluding the sensing element which is inserted in the soil) were not affected by the temperature variations, they were placed outside the incubator.

3.2.5.2 Salinity Sensitivity

The dependence of the measured *VWC* on salinity was determined following the method suggested in the literature (Kargas and K.X. Soulis, 2012; 2019). Varying amounts of water (to cover a range from dry to saturation) with known KCl concentrations were

Table 3.4: Electrical conductivities (*EC*) of the water samples and corresponding *VWC* measurements of the soil samples investigated in the salinity experiment.

EC of the Water Added [mS/cm]	Actual VWC [%]	Symbolic Representation in Figure 3.8
1.7	17.8	Circle (○)
1.7	32.3	
1.7	48.81	
3.02	20.08	Triangle($ riangle$)
3.02	31.12	
3.02	47.32	
6.32	34.09	Square(□)
6.32	38.5	
6.32	49.53	
9.69	17.59	Pentagon(♢)
9.69	34.8	-
9.69	43.53	

added to Grade III sand (Soil-2, Indian standard (Bureau of Indian Standards (BIS), 2002) described in Table 3.2) and *VWC* measurements were made using the different sensors. A total of 12 samples, as described in Table 3.4, were studied.

3.3 Results and Discussion

The performance measures used in developing the results in the study are listed in Table 3.5 along with their respective sources from the literature.

3.3.1 Sensor Calibration

3.3.1.1 Performance of Capacitive Sensors with Fluids

The capacitive sensors SM100 and SMEC300 were first tested with fluids of known ϵ_r (Table 3.3). The secondary standard, ThetaProbe, provides an estimate of the Refractive Index ($\sqrt{\epsilon_r}$), whereas the capacitive sensors do not directly measure ϵ_r but relate raw sensor output to VWC. Therefore, first, the VWC values of the capacitive sensors were converted to $\sqrt{\epsilon_r}$ values using the expression given by Topp et al. (1980):

$$\theta = -5.30 \times 10^{-2} + 2.92 \times 10^{-2} \epsilon_r - 5.50 \times 10^{-4} \epsilon_r^2 + 4.30 \times 10^{-6} \epsilon_r^3$$

where:

 $\theta = VWC$ (%)

 ϵ_r = Dielectric constant (-)

Table 3.5: The list of performance measures used in the study: θ_i denotes an actual VWC value; $\hat{\theta}_i$ represents a raw value measured by the sensor; $\bar{\theta}$ is the average of the actual VWC values; $\bar{\theta}$ is the average of the raw values measured by the sensor; R(x) is the rank of x and n is the number of data points used in the computation. k, n_k , m and s_k are the index of the current series, number of measurements in series k, total number of series, and corresponding standard deviation of the series, respectively, and are used to compute $s_{r,p}$.

Performance Metric	Description/Equation	Range (Ideal Value)
Coefficient of	$R^2 =$	
Determination (R^2)	$\left(n\sum_{i=1}^{n}\hat{\theta_{i}}\theta_{i}\right)-\left(\sum_{i=1}^{n}\hat{\theta_{i}}\right)\left(\sum_{i=1}^{n}\theta_{i}\right)$	0 to 1 (1)
(Moriasi et al., 2007)	$\sqrt{n\sum_{i=1}^{n}(\hat{\theta}_i)^2 - (\sum_{i=1}^{n}\hat{\theta}_i)^2} \sqrt{n\sum_{i=1}^{n}(\theta_i)^2 - (\sum_{i=1}^{n}\theta_i)^2}$	$\frac{1}{(1-\epsilon)^2}$
Mean Absolute Error		0 to ∞
(<i>MAE</i>) (Witten et al., 2011)	$MAE = \left(\sum_{i=1}^{n} \left \theta_i - \hat{\theta}_i \right \right) / n$	(0)
Pooled relative standard deviation $(s_{r,p})$ (IUPAC, 1997)	$s_{r,p} = \sqrt{\frac{\sum_{k=1}^{m} (n_k - 1) s_k^2 (1/\bar{\theta}_k^2)}{\sum_{k=1}^{m} (n_k - 1)}}$	0 to ∞ (0)
Relative Absolute Error (<i>RAE</i>) (Witten et al., 2011)	$RAE = \sum_{i=1}^{n} \left \theta_i - \hat{\theta}_i \right / \sum_{i=1}^{n} \left \hat{\theta}_i - \bar{\theta} \right $	0 to ∞ (0)
Root Mean Squared Error (<i>RMSE</i>) (Witten et al., 2011)	$RMSE = \sqrt{(\sum_{i=1}^{n} (\theta_i - \hat{\theta}_i)^2)/n}$	0 to ∞ (0)
$\sigma_{effective}$	$\sigma_{eff} = \sqrt{(\sigma_{primary})^2 + (\sigma_{secondary})^2}$	0 to ∞ (0)
$\sigma_{primary}$	RAE between in-house calibrated and actual VWC value	0 to ∞ (0)
$\sigma_{secondary}$	RAE between in-house calibrated and ThetaProbe VWC value	0 to ∞ (0)
Spearman's Rank		-1 to 1
Correlation	$r_s = 1 \nabla^n \left(P(\hat{\delta}) \right) P(\hat{\delta}) \left(P(\delta) \right) P(\hat{\delta})$	-1 to 1 (-1 or
Coefficient (r_s)	$\frac{\frac{1}{n}\sum_{i=1}^{n}(R(\hat{\theta}_i)-R(\bar{\theta}))(R(\theta_i)-R(\bar{\theta}))}{(R(\theta_i)-R(\bar{\theta}))}$	= 1)
(Spearman, 1904)	$\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(R(\hat{\theta}_i)-R(\bar{\theta}))^2\right)\left(\frac{1}{n}\sum_{i=1}^{n}R(\theta_i)-R(\bar{\theta})\right)^2}$	2

Table 3.6: Performance metrics of the capacitive (SMEC300 and SM100) and secondary standard (impedance-based ThetaProbe) sensors, in measuring refractive indices ($\sqrt{\epsilon_r}$) of fluids of known ϵ_r at 25 °C.

	SMEC300	SM100	ThetaProbe
MAE	0.87	0.55	0.48
RAE	0.22	0.27	0.24
RMSE	1.08	0.74	0.75
$s_{r,p}$	0.0062	0.0062	0.0405

Further, they was compared with the respective actual values and $\sqrt{\epsilon_r}$ values measured by the ThetaProbe. The results of this analysis are provided in Figure 3.3 and Table 3.6. The estimated $\sqrt{\epsilon_r}$ values (along with their standard errors) for all the three sensors are depicted on the Y-axis, and the actual $\sqrt{\epsilon_r}$ (derived from known ϵ_r values at 25 °C) are plotted on the X-axis of Figure 3.3.

The ThetaProbe sensor has relatively good performance in measuring refractive indices of air, Butanol and Ethanol compared to ethylene glycol and water. The precision values (standard deviations) of the ThetaProbe in measuring $\sqrt{\epsilon_r}$ in air, butanol, ethanol, ethylene glycol, and water were StandardDeviation(SD) = 0.003, 0.053, 0.156, 0.401, and 0.621, respectively. The overall precision of the ThetaProbe was $s_{r,p} = 0.0405$.

Figure 3.3 indicates that the ThetaProbe sensor was more accurate than both the SMEC300 and SM100 sensors in all the fluids except Ethylene Glycol. Both SMEC300 and SM100 have equal precision values when considered till the fourth decimal place ($s_{r,p} = 0.0062$), and are more precise when compared to ThetaProbe.

The comparison of capacitive sensors in fluids suggests that both the sensors were equally precise; however, the inexpensive SM100 sensor outperformed the SMEC300 sensor in terms of MAE and RMSE. Overall, these results were encouraging realizations of the sensing abilities of both the capacitive sensors in general, and the SM100 sensor in particular, under the conditions of uniform contact between the sensor and the dielectric medium.

3.3.1.2 Calibration of All Sensors with Repacked Soils

3.3.1.2.1 Strength of monotonic relationship between measured $(\hat{\theta})$ and actual (θ) VWC

The Spearman's rank correlation coefficient, r_s (Spearman, 1904), was employed to assess the strength of the relationship between $\hat{\theta}$ and θ . The Spearman's rank correlation was selected because it is a nonparametric statistic that measures the strength of a monotonic relationship between paired data without any assumptions made on the distribution of the data or the nature of the relationship existing between them (Hauke and Kossowski, 2011; Mukaka, 2012; Zar, 2005). The number of sensor units of the SMEC300, SM100, YL100 and YL69 sensors used for the experiment were 6, 5, 6, and 5, respectively. Table 3.7 illustrates the r_s values for the four different sensors tested in the

Table 3.7: Spearman's Rank Correlation Coefficient r_s between the sensor readings and the actual soil volumetric water content (VWC) (θ) across the different soils. All the values are significant at $\alpha = 5\%$.

	Low-c Capacitive		,	ow-cost e sensors
	SMEC300	SM100	YL100	YL69
Soil 1	0.93	0.92	0.78	0.91
Soil 2	0.96	0.97	0.89	0.94
Soil 3	0.84	0.94	0.94	0.73
Soil 4	0.95	0.92	0.94	0.85
Average	0.92	0.94	0.89	0.86

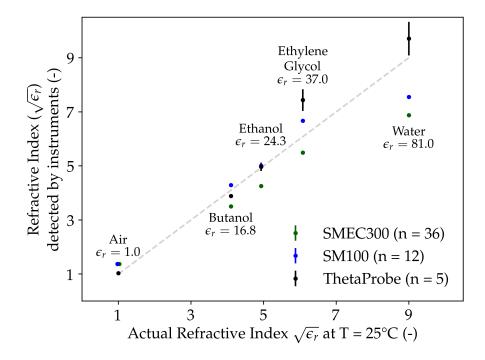


Figure 3.3: Response of the capacitive soil moisture sensors (SMEC300 and SM100) and secondary standard (impedance-based ThetaProbe) to fluids of known ϵ_r at 25 °C. The X- and Y-axis depict the actual and measured refractive indices $(\sqrt{\epsilon_r})$, respectively. Although the ThetaProbe measures $\sqrt{\epsilon_r}$ directly, the VWC values of SM100 and SMEC300 were converted to the corresponding $\sqrt{\epsilon_r}$ values based on the literature (Topp et al., 1980). n is the total number of measurements in the experiment of a fluid, and the error bar shows the mean and standard error of the estimated values.

study. For all the sensors and soils, the Spearman's rank correlation was positive and significant at the 5% level.

The capacitive and the resistive sensors had an average $r_{s,resistive} = 0.93$ and 0.87, respectively, averaged across all soils. Among the capacitive sensors, the SM100 sensor $(r_s = 0.94)$ performed better than the SMEC300 sensor $(r_s = 0.92)$ on average. For each soil, both the sensors had roughly same r_s (within 1 to 3 % of each other) except for Soil 3, in which SM100 ($r_s = 0.94$) substantially outperformed SMEC300 ($r_s = 0.84$). This difference may be attributed to soil characteristics, which was an ungraded field soil purposefully included in the study to represent local field conditions. These results implied that SM100 could outperform the SMEC300 sensor as a robust, field ready capacitive sensor (on the basis of VWC measures in repacked soils). These results advanced the results obtained in Section 3.3.1.1, where the SM100 sensor outperformed the SMEC300 sensor in fluids. Among the resistive sensors, the YL100 sensor ($r_s = 0.89$) performed marginally better on average, compared to the YL69 sensor ($r_s = 0.86$). The YL69 sensor performed better for both the sandy soils Soil 1 (by 16.7%) and Soil 2 (by 5.62%), compared to YL100. However, for the silty-loam soils, YL100 performed better ($r_s = 0.94$ in both cases) than YL69, which itself performed worse in Soil 3 $(r_s = 0.73)$ than in Soil 4 $(r_s = 0.85)$.

Overall, considering only rank correlations, the order of performance was SM100 > SMEC300 > YL100 > YL69. This result could be expected in terms of the capacitive sensors being more accurate compared to the resistive sensors. To further strengthen these inferences, calibration equations were developed for each sensor.

3.3.1.2.2 Calibration equations developed between measured ($\hat{\theta}$) and actual (θ) VWC

The soil-specific calibration equations were piecewise linear regression equations based on the least squares estimate, in which the objective function, Sum of Squared Residuals $SumofSquaredResiduals(SSR) = \sum_{i=1}^{n} (\theta_i - \hat{\theta}_i)^2$, was minimized. The number of line segments were decided using visual inspection, while an open source Python library, pwlf (Jekel, 2017), was used to develop the corresponding piecewise linear equations.

The subsequent sections on sensor testing have used these calibration equations developed for each sensor and soil. Each segment of the piecewise linear equations, outlined in Table 7.3 and illustrated in Figure 3.4, are of the following form,

$$\theta = \beta_0 + (\beta_1 \times \hat{\theta}) \tag{3.1}$$

where,

 $\hat{\theta} = \text{Raw sensor value (-)},$

 $\theta = \text{Actual VWC (\%)}, \text{ and}$

 β_i = Calibration coefficients

The performance of the calibration equations developed for the capacitive sensors was comparable to that of other low-cost capacitive sensors reported in the literature (Kinzli et al., 2012). The SM100 sensor (average overall $R^2 = 0.94$) performed at par with other low-cost capacitive sensors for sandy soils (average $R^2 = 0.95$ compared to $R^2 = 0.97$ from the literature, Kinzli et al., 2012), and surpassed previous work for silty-loams

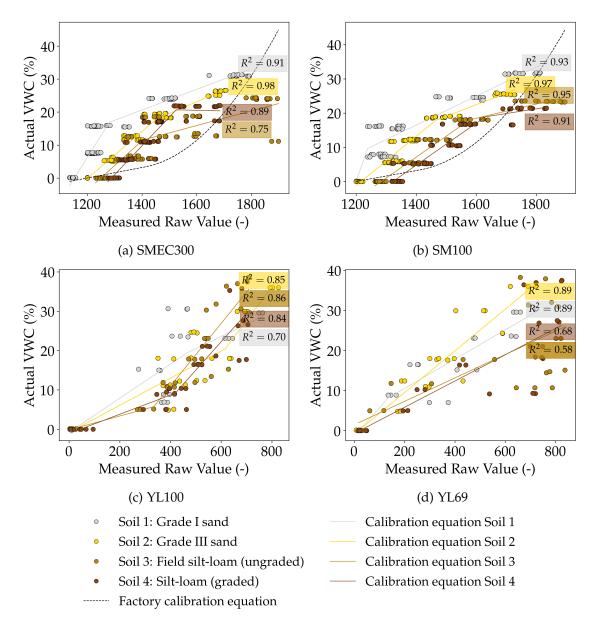


Figure 3.4: Calibration of capacitive sensors (a) SMEC300 and (b) SM100, and resistive sensors (c) YL100 and (d) YL69, in repacked soil using piecewise linear equations. The raw values correspond to either the raw readings from the Spectrum's FieldScout reader (for capacitive sensors), or the raw outputs generated using the Arduino setup developed in-house (for resistive sensors). The coefficient of determination, R^2 , for each soil, is illustrated adjacent to the corresponding line.

(average $R^2 = 0.93$ compared to $R^2 = 0.88$ from the literature, Kinzli et al., Kinzli et al., 2012). The SMEC300 performed equally well as the SM100 in sands (average $R^2 = 0.95$), but not in silty-loam soils (average $R^2 = 0.82$); nevertheless, being comparable to previous literature, Kinzli et al., 2012). Overall, the calibration results reinforce the inference that the SM100 sensor is more robust (due to its superior performance in a field soil) compared to the SMEC300 sensor.

Understandably, the resistive sensors did not perform as well as the capacitive sensors. However, considering the fact that they were very-low cost sensors, the average performances of both the YL100 (average $R^2 = 0.81$) and the YL69 sensors (average $R^2 = 0.76$) were notable. Though a literature-based comparison to previous calibrations of low-cost resistive sensors was not possible, it emerged that the YL69 sensor performed reasonably well for sands (average $R^2 = 0.89$) and the YL100 performed well for silty-loam soils (average $R^2 = 0.85$).

Considering the extent to which the calibration equations could explain the variation in the measured data (through the R^2), the order of performance was SM100 > SMEC300 > YL100 > YL69. This is identical to the order of performance based on the Spearman's rank correlation (r_s). These results are encouraging as all the sensors perform well compared to the results reported in the literature, where applicable.

3.3.1.3 Comparison of Manufacturer and In-house Calibration Equations: Capacitive Sensors

Figure 3.5 compares the performance of the calibration equations developed in-house during the study and provided by the manufacturer, for the capacitance sensors (calibration equation were not available for the very low-cost resistive sensors). Additionally, Table 3.8 compares accuracy measures *MAE*, *RMSE* and *RAE* for manufacturer's and in-house calibration equations for the four soils. The manufacturer calibration equations for the capacitance sensors were made available from Spectrum Technologies, Inc. (D. Kieffer, personal communication, 5.9.2018). The number of SMEC300 and SM100 sensors used for this experiment are six and five, respectively.

From Figure 3.5, it was observed that for both the sensors, the manufacturer's equations had a tendency to underpredict the actual VWC (θ), with the exception of Soil 3 (ungraded silty-loam soil) at higher VWC (θ) values. Sensor accuracy increased substantially, overall as well as in each soil, after soil specific calibration equations were developed. From Table 3.8, it could be inferred that the sensor accuracy without calibration, for both the capacitive sensors, was lower than the accuracy specified by the manufacturer, 3% (for both SMEC300 (Spectrum, 2012) and SM100 (Spectrum, 2011)). This observation was in line with the claim that it is "optimistic" to expect such levels of accuracy for many EM sensors (K. Soulis et al., 2015). After soil specific calibrations, there were substantial improvements in sensor accuracy. The MAE (and RMSE) of the calibrated SMEC300 and SM100 sensors were 2.12% and 1.67% (2.88% and 2.36%) respectively, which were better than the manufacturer reported accuracy values.

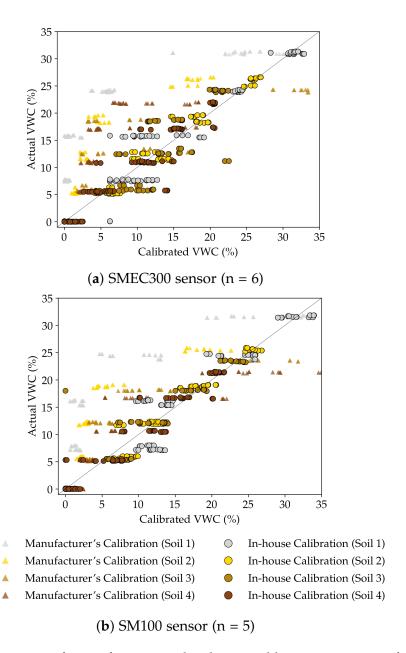


Figure 3.5: Comparison of manufacturer and in-house calibration equations for capacitive sensors (a) SMEC300 and (b) SM100 for the four different experimental soils.

It was hence evident that more effective overall performance can be ensured with soil-specific calibration equation development and installation based on the soil texture established in the field, which supports the previous literature (Kargas and K.X. Soulis, 2012). This performance enhancement would ideally compensate for the resources (financial, human) incurred in the exercise.

Table 3.8: Accuracy performance indicators of the tested sensors, with in-house calibration and manufacturer calibration

0.39	4.45	3.18	4.13 5.54 0.41 3.18 4.45	5.54	4.13	0.37	5.21	3.51 5.21	0.21	2.36	1.67	0.78	7.86	6.23	0.28	2.88	2.12 2.88	0.97	9.57	7.59 9.57	Average
0.42	4.23	3.07	0.46	6.65	4.60	0.31	4.45	2.90	0.26	2.27	1.74	0.63	5.27	4.18	0.28	2.61	1.90	0.96	7.90	6.44	Soil 4
0.39	4.29	2.98	0.61	8.09	6.38	0.35	5.99	3.41	0.21	2.55	1.54	0.80	7.74	5.82	0.47	4.20	3.33	1.00	9.99	7.17	Soil 3
0.34	4.46	2.88	0.29	3.90	2.95	0.35	4.54	3.42	0.14	1.63	1.12	0.87	8.23	6.75	0.12	1.39	0.96	0.89	8.63	7.13	Soil 2
0.40	4.84	3.79	0.28	3.53	2.58	0.47	5.88	4.31	0.23	2.97	2.27	0.84	10.22	8.17	0.24	3.34	2.28	1.01	11.76	9.63	Soil 1
$\sigma_{primary}$			$\sigma_{primary}$			$\sigma_{primary}$			$\sigma_{primary}$			$\sigma_{primary}$			$\sigma_{primary}$			$\sigma_{primary}$			
RAE	MAE RMSE	MAE	RAE	MAE RMSE RAE	MAE		MAE RMSE RAE	MAE	RAE	MAE RMSE	MAE	RAE	MAE RMSE	MAE	RAE	MAE RMSE RAE	MAE	RAE	MAE RMSE	MAE	
Manufacturer Calibration	acturer C	Manuf	bration	In-house Calibration	In-ho	bration	In-house Calibration	In-h	ibration	In-house Calibration		Manufacturer Calibration	facturer (Manut	bration	In-house Calibration		Manufacturer Calibration	facturer C	Manu	
be	ThetaProbe			YL 69			YL100				SM100	NS.					SMEC300	SME			
andard	Secondary Standard	Seco		Sensors	Cost Resistive Sensors	Very Low-Cost 1	Very l						ensors	acitive S	Low-Cost Capacitive Sensors	Low					
			ped).	evelop	ere d	ions w	equat	ation	calibr	ch no	r whi	provided for the secondary standard sensor (for which no calibration equations were developed).	rd ser	tanda	dary s	secono	r the	ded for	provi		
s are	icator	e ind	rmanc	perfo	same	. The	nless)	ensio	" dim	r primarı	E or c	in % VWC), and Relative Absolute Error (RAE or $\sigma_{primary}$, dimensionless). The same performance indicators are	e Errc	solut	ive Ak	Relat	, and	VWC)	in %		
MSE,	or (R)	d Err	Square	Iean !	₹oot №	WC), I	1 % V	AE, in	or (M_{λ})	te Err	bsolu	(applicable only to capacitive sensors): Mean Absolute Error (MAE , in $\%~VWC$), Root Mean Squared Error ($RMSE$	ors): N	senso	acitive	o capa	only t	icable ((appl		

3.3.2 Performance Measures for the Sensors

Figure 3.6 illustrates the accuracy (σ_{eff}) and precision ($s_{r,p}$) of the tested sensors together in a bubble plot in a 2-D Euclidean space. Although the primary accuracy ($\sigma_{primary}$) evaluates sensor performance with actual VWC values (θ), secondary accuracy ($\sigma_{secondary}$) compares the sensor to the ThetaProbe, which was considered as the secondary standard due to its superior measurement technique (Delta-T Devices Ltd., 2017). The relevant performance indicators for effective accuracy (σ_{eff}), component accuracies ($\sigma_{primary}$ and $\sigma_{secondary}$) and precision ($s_{r,p}$) are described in Table 3.5.

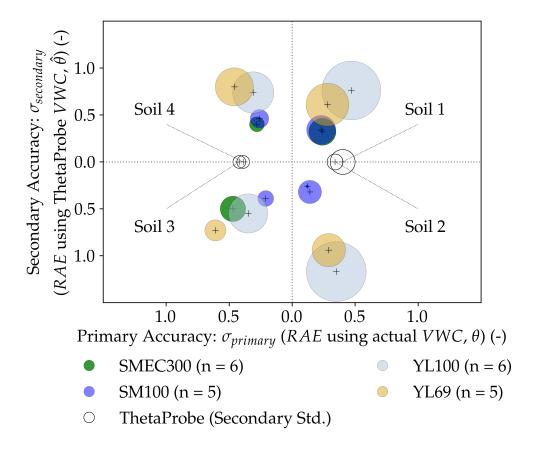


Figure 3.6: Accuracy (primary and secondary) and precision of different soil moisture sensors (SMEC300, SM100, YL69, YL100), in 4 different soils (corresponding to four quadrants). Overall accuracy, σ_{eff} (Table 3.5), is the Euclidean distance of the bubble cross-hairs from the origin. The closer the bubble is to the origin, the more accurate the sensor is. Precision is indicated by the size of the bubbles ($radius = 100 \times s_{r,p}$); the smaller the bubble, the more precise the sensor. 'n' is the number of sensor units per sensor used in the experiment.

Each accuracy component is represented by the distance from the origin to the cross-hair centers of the bubbles in the respective directions ($\sigma_{primary}$ along the X-axis and

 $\sigma_{secondary}$ along the Y-axis). Therefore, the effective accuracy (σ_{eff}) can be described as the Euclidean distance of the cross-hair centers of the bubbles (i.e. the closer the bubble center from the origin, the more accurate the sensor is). As the $\sigma_{secondary} = 0$ for the ThetaProbe as it is computed with respect to itself, $\sigma_{eff} = \sigma_{primary}$ and its accuracy is defined only by the distance of the cross-hairs along the X-axis direction. The performance of all the sensors in each soil is represented in different quadrants (i.e. each soil has a corresponding quadrant, labeled in the figure). Precision is represented by the radius of the bubble graphs, which are proportional to $s_{r,p}$; $radius = 100 \times s_{r,p}$). Therefore, the bubbles with smaller radii are more precise in their VWC estimates ($\hat{\theta}$).

3.3.2.1 Sensor Accuracy

An analysis of metrics related to accuracy revealed the order of performance as SM100 > SMEC300 > YL100 > YL69, which was identical to the results in Section 3.3.1.2. The metrics included Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the primary Relative Absolute Error ($\sigma_{primary}$ values, reported in Table 3.8). As shown in Figure 3.6, the effective accuracy (σ_{eff}) computed after including the secondary standard sensor measurements, gave rise to a slightly different order of performance, i.e., $SM100 > SMEC300 > YL69 \gtrsim YL100$. The capacitive sensors outperformed the resistive sensors by a factor of 2 on average ($MAE_{capacitive} = 1.90\%$, $MAE_{resistive} = 3.82\%$; $RMSE_{capacitive} = 2.62\%$, $RMSE_{resistive} = 5.38\%$; $RAE_{capacitive}$ or $\sigma_{capacitive,primary} = 0.25$, $RAE_{resistive}$ or $\sigma_{resistive,primary} = 0.39$).

Both capacitive sensors had accuracy measures comparable to the previous literature pertaining to low-cost capacitive sensors, in terms of MAE and RMSE (González-Teruel et al., 2019; Kinzli et al., 2012). In terms of RAE, the SMEC300 sensor was accurate across all soils (average $\sigma_{eff} = 0.47$, Standard Error $SE_{\sigma_{eff}} = 0.07$) barring Soil 3, in which the σ_{eff} reduced to 0.69. The SM100 was also accurate across all the soil types (average $\sigma_{eff} = 0.43$ with a lower $SE_{\sigma_{eff}}$ of 0.03). Comparatively, the SM100 sensor outperformed the SMEC300 sensor in terms of overall effective accuracy (σ_{eff}), but largely due to the substantially better performance in Soil 3, supporting the results in Section 3.3.1.2. The SMEC300 was more accurate than the SM100 in both the sands and in Soil 4.

The MAE and RMSE values of the resistive sensors could not be compared with the existing literature on resistive sensors, but were poorer than the specified accuracy values (3%) of most EM sensors (K. Soulis et al., 2015). In terms of RAE, their accuracy values were enhanced by 56% (average $\sigma_{primary} = 0.39$, varying between 0.32 and 0.48) when only primary accuracies were considered, which implied that they were able to capture variations in actual VWC better than the variations taking into account the secondary standard VWC. Comparatively, though the overall accuracies of both the resistive sensors across all the soils were similar, it could be remarked that each sensor complemented the other's performance in a particular soil texture category. YL100 performed better in silty-loam soils while YL69 performed better in sandy soils.

Overall, it can be remarked that the low-cost sensors, when calibrated, could match (or exceed) the accuracy performance of the secondary standard sensor. YL100 was \sim 10% less accurate than the secondary standard ThetaProbe in terms of MAE, while

Table 3.9: Comparison of precision performance of the tested sensors, based on pooled relative standard deviation, $s_{r,p}$ (% VWC). In-house calibration equations were used for the capacitive and resistive sensors, and Manufacturer calibration was used for the secondary standard sensor (for which no calibration equations were developed).

	Low-C Capacitive		•	ow-Cost e Sensors	Secondary Standard
	SMEC300	SM100	YL100	YL69	ThetaProbe
Soil 1	0.51	0.55	1.11	0.81	0.47
Soil 2	0.05	0.44	1.13	0.63	0.30
Soil 3	0.48	0.30	0.74	0.40	0.24
Soil 4	0.28	0.35	0.78	0.72	0.24
Average	0.33	0.41	0.94	0.64	0.31

its *RMSE*, and both *MAE* and *RMSE* values of YL69 were poorer when compared to the ThetaProbe.

3.3.2.2 Sensor precision

The precision performance of each sensor across all four tested soils, along with the performance of the secondary standard sensor, is given in Table 3.9. The order of overall precision (averaged across all soils) nearly followed the order of the cost of the sensors, i.e., SMEC300 > SM100 > YL69 > YL100 with the ThetaProbe being the most precise (as well as expensive) sensor ($s_{r,p} = 0.31$). Capacitive sensors were about twice as precise as the resistive sensors ($s_{r,p(resistive)} = 0.79$, $s_{r,p(capacitive)} = 0.37$). Additionally, the lowest precision achieved by the capacitive sensors was only 18% poorer than the precision of the ThetaProbe.

Both the capacitive sensors had a consistently high precision across all soils. The SMEC300 had a higher precision overall than the SM100 and also across all soils barring Soil 3. However, the SM100 was more consistent in terms of its precision performance across the different soils ($SD_{s_{r,p,SM100}} = 0.11$) when compared to SMEC300 ($SD_{s_{r,p,SMEC300}} = 0.21$). The SMEC300 sensor was reasonably precise compared to the ThetaProbe in Soils 1, 2, and 4, and even exceeded the ThetaProbe performance in Soil 2 (in which it had a very high precision of $s_{r,p} = 0.05$). It was more precise in the soils with the finer grained soils within the two categories (Soil 2 and Soil 4 in the sandy and silty-loam soils, respectively), which was an indicator of the need for better packing around the sensing material during installation. The SM100 sensor also had comparable precision performance vis-à-vis the ThetaProbe (it performed within 31.2% of the ThetaProbe on average). Its performance increased with better packing in the sandy soils (Soil 2 is 20% more precise than Soil 1), but it performed well in both the silty-loams, with its performance being more precise in the ungraded silty-loam field Soil 3 than that in Soil

4 by 16.7%. The consistent precision performance of SM100 across soils in general and in the field Soil 3 in particular suggests that SM100 is a robust and field ready sensor.

Both the resistive sensors were reasonably imprecise compared to the ThetaProbe. The YL69 sensor was a more precise sensor compared to YL100, both overall and also in each soil. YL69 was almost as precise as the capacitive sensors in Soil 3. This was also an encouraging result for field application. Otherwise, the YL69 is within 85.8% and 58.9% of the performance of the capacitive sensors in sandy and silt-loam soils, respectively. YL100 also had better performance (by 32.1%) in silt-loam soils compared to the sandy soils, but was equally imprecise in both the sands and silty-loam soils. It was quite imprecise compared to the ThetaProbe (3 times as imprecise) as well as the capacitive sensors (2.54 times as imprecise).

3.3.3 Sensor sensitivity

3.3.3.1 Temperature Sensitivity

The subfigures of Figure 3.7 show the results of the temperature sensitivity experiments conducted for all sensors in Soil 4 for two different values of actual VWC (θ), depicted by the dashed and solid horizontal lines. The hollow circles and filled squares represent the average VWC estimated by each sensor (based on the corresponding calibration equations in Table 7.3) along with their respective standard errors. The temperature variation is plotted for each sensor on the X-axis. The SMEC300, SM100, YL69 and YL100 sensors had, on average, 6, 211, 276, and 276 data points, respectively, for each VWC-temperature combination. The data from SM100, YL100 and YL69 sensors were automatically read using open source Arduino (https://www.arduino.cc/) electronics while the hand-held FieldScout soil sensor reader was used for SMEC300 readings. The lower number of readings for the SMEC300 was a result of the effort to minimize the number of times the incubator door was opened, to consequently lower the variation in the incubator temperature.

The capacitive sensors showed a positive temperature effect (larger temperature leading to a higher estimated VWC), which is characteristic of capacitance sensors in soils with fine textures due to the release of bound water from clay minerals at higher temperatures (Kargas and K.X. Soulis, 2012). The SMEC300 sensor followed the positive temperature effect at the lower actual VWC of 9.36%, with an overall average estimated VWC change of 9.34% responding to a 36.8 °C temperature increase. However, though the temperature effect was not visible at the higher actual VWC of 21.39%. This is justified through the corresponding fitted calibration curve (Soil 4; indicated in dark brown in Figure 3.4a and Table 7.3) which flattens out at higher raw values (> 1525), and subsequently limits the increase in estimated VWC as a consequence of increasing raw values. Therefore, the positive temperature effect not being visible at the higher actual VWC value is due to the calibration curve and not the physical changes in the measurement. Similarly, the SM100 sensor followed an expected positive temperature effect, for both the levels of actual VWC. At the actual VWC values of 7.63% and 18.38%, respectively, an increase of 30 °C resulted in an increase of estimated VWC by 7% and

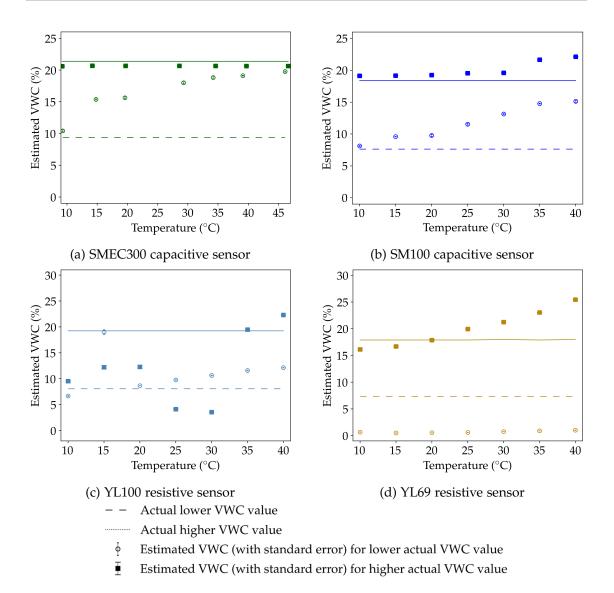


Figure 3.7: Temperature sensitivity of estimated VWC for different sensors: (a) capacitive SMEC300, (b) capacitive SM100, (c) resistive YL100, and (d) resistive YL69. The horizontal lines represent the actual VWC according to the legend. The hollow circular and solid square markers, along with their error bars, represent the average and standard deviations of the calibrated/estimated sensor readings corresponding to the fixed lower and higher actual VWC values, respectively. Positive temperature effects are seen to different extents in all sensors, with the resistive sensors' performance being limited by relatively lower accuracy and precision.

2.99%, respectively. The results suggest that the temperature response of the capacitive sensors SMEC300 and SM100 could be predicted and consequently corrected.

The resistive sensors responded in dissimilar manners to the change in temperature at different actual VWC conditions. The YL100 sensor showed a temperature effect which was seen across larger temperature ranges, but there was a relatively large amount of variability which was seen at smaller temperature differences. Since this variability in measurements dominated the temperature sensitivity, characterizing the temperature sensitivity was difficult in the case of YL100. The YL69 sensor responded with a positive temperature effect, which was less pronounced in the lower actual VWC compared to the higher actual VWC. The YL69 under-estimated the lower value of the actual VWC (7.32%) for all the temperatures. Though this was due to its low accuracy compared to the capacitive sensors and the resultant calibration equation, which underpredicted the actual lower VWC, there was actually a small increase of the estimated VWC by 0.36% over 30 °C. The sensor response to the higher actual VWC (of 17.89%) was substantially closer to what was expected, with a positive temperature effect translating to a rise in 9.33% over the same 30 °C rise in temperature. If the calibration equation was not used, the positive temperature effects were more clearly seen, with increases of 11.03 and 284.98 in the raw values corresponding to actual VWC values of 7.32% and 17.89%, over the same rise in temperatures. The overall behavior implied that notwithstanding the lower accuracy performance, the temperature response of the YL69 sensor was reasonable and would hence be possible to correct.

3.3.3.2 Salinity Sensitivity

Figure 3.8 plots the calibrated *VWC* (based on the equations developed in Section 3.3.1.2, listed in Table 7.3) and the actual *VWC* with changing salinity in water. The corresponding EC values were 1.70, 3.02, 6.32, and 9.69 mS/cm, represented by circular, triangular, square, and pentagonal shapes, respectively.

Based on the coefficients of determination (R^2 values), the order of performance was SM100 > SMEC300 > YL69 > YL100, i.e., SM100 results were least sensitive to changes in salinity. The corresponding R^2 values were 0.85, 0.79, 0.63 and 0.13, respectively. These results are encouraging as the SM100 sensor, despite being the relatively less-expensive capacitive sensor, outperformed the more expensive SMEC300 by 7.6%, and the very low-cost resistive YL69 was only 20.5% less effective compared to the performance of the SMEC300 in response to salinity variations. However, YL100 was almost completely unable to capture any variation, and estimates more or less the same value (SD = 0.57%) irrespective of the actual VWC or the EC of the added water. Additionally, the bulk soil EC values measured by the SMEC300 sensors (median values based on the manufacturer calibration) are plotted in Figure 3.8e. As expected, an increase in the EC of the added water led to an increase in the bulk soil EC measured by SMEC300. The best-fit which minimized SSR was significantly linear (at $\alpha = 5\%$) and had an $R^2 = 0.92$.

However, these results were inferred from an experiment with the sandy Soil 2, and further testing would be necessary to extend the results for each of these sensors to more generalized applications.

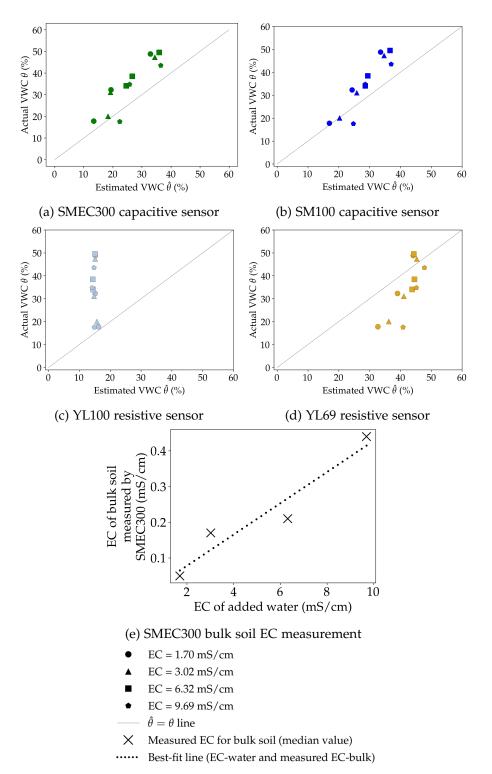


Figure 3.8: Effect of water of different electrical conductivity (EC) values on VWC measured ($\hat{\theta}_i$) by different sensors: (a) capacitive SMEC300, (b) capacitive SM100, (c) resistive YL100, and (d) resistive YL69. (e) shows the relationship between the median values of the bulk soil EC measured by SMEC300 and the EC of water (with the corresponding best-fit line).

3.3.4 Further Discussion

The drawbacks of the experiment included and were not limited to experimental and human errors, as well as the choice of piecewise linear calibration functions. Further, the possibilities to represent more natural variability (by incorporating more soils), and introducing the packing density as an experimental variable (which has shown to have an impact in similar experiments (Matula et al., 2016b)) were not integrated due to resource constraints. Moreover, it was assumed that a laboratory characterization is an essential precursor to field trials and experiments, especially since such a laboratory study involving these particular sensors had not been conducted earlier. Another aspect which was not tested, either in the laboratory or field conditions, was the durability of the sensors.

Having quantified the operations of these sensors, a case can be developed, within the larger framework of low-cost technological tools in agricultural water management, to propose the use of such sensors based on an understanding of the required precision of the problem as well as harness the complementary strengths of the sensors in different aspects of performance. For example, within the resistive sensors, there was a differentiation among the sensors in accuracy estimates across the grain size of the soils (YL69 and YL100 respectively outperformed the other resistive sensor in coarser and finer grained soils respectively). Such a characterization is valuable in choosing the correct sensor for a particular application case.

The efficiency of soil moisture based irrigation scheduling systems is dependent strongly on the sensor accuracy, with 3% errors in soil moisture sensors possibly leading to 'critical' effects on irrigation efficiency (K. Soulis et al., 2015). Therefore, although the capacitive sensors tested in this study had accuracy levels (<2% VWC on average) possibly leading to 'limited' effects on irrigation efficiency, using resistive sensors independently (with an accuracy of <4% VWC on average) could have potentially critical effects. The actual effect of these sensors on irrigation water use efficiency can be determined with comprehensive field experiments.

Field scale soil moisture distribution exhibits high spatial and temporal variability (Vereecken et al., 2014). Instead of a sparse network of capacitive sensors, a dense network combining capacitive and resistive sensors could help better characterize the spatiotemporal variability of soil moisture, which may potentially improve irrigation management. Such a characterization using a combination of low- and very-low cost soil moisture sensors has not been attempted, as per the knowledge of the authors.

3.4 Summary and Conclusions

Four soil moisture sensors, i.e., two low-cost capacitive sensors (SMEC300 and SM100) and two very low-cost resistive sensors (YL100 and YL69), were tested in laboratory conditions to characterize their performance for application in low-cost irrigation management. Based on the literature, five research questions were developed and addressed with specific laboratory experiments. Piecewise linear calibration equations were developed.

oped for each sensor in four different repacked soils to explain the relationship between sensor measurements and actual VWC values. In the case of the capacitive sensors, the manufacturer-provided calibration equations were compared with the calibration equations developed in-house in terms of accuracy measures. Such a comparative analysis could not be performed for the resistive sensors due to the unavailability of manufacturer calibration equations. An evaluation of sensor accuracy and precision was conducted for all the studied sensors in all the tested soils and a novel approach to visually represent the combined performance characteristics is proposed. The sensitivities of the sensors were evaluated for temperature and salinity ranges commonly encountered in field conditions. Additionally, only for the capacitance-based sensors, the performance of the sensors was tested in fluids of known dielectric permittivity (ϵ_r) . The impedance-based ThetaProbe sensor was used as the secondary standard to contextualize the performance of the tested sensors in some of the experiments.

The overall value for money of the sensors is reflected in their precision performance, i.e., the precision performance, on average, of the sensors followed the order of SMEC300 > SM100 > YL69 > YL100, which was almost the same as that of sensor costs, particularly considering that the ThetaProbe sensor was highest in precision. The accuracy of the sensors, on average, followed the order of SM100 > SMEC300 > YL100 > YL69.

It was found that the low-cost capacitive sensors, with soil-specific calibration, can match the performance of the secondary standard and could possibly be used for irrigation management with 'limited' effects on irrigation efficiency (in the context of accuracy). Among the two capacitive sensors, the less-expensive SM100 sensor can be inferred as a more robust and field ready low-cost soil moisture sensor. This is due to its strong performance in fluids (which is a proxy to its measurement technique), consistent precision across soils, accurate performance particularly in the field soil, and reasonable sensitivity to variations in temperature and salinity conditions. The SMEC300 sensor was accurate (except in field silty-loam soil), more precise than the SM100 sensor, and was reasonable in its response to temperature and salinity variations. With its additional capabilities of measuring temperature and electrical conductivity (the results of which have been purposely left out in lieu of being out of the framework of soil 'moisture' sensor comparison), it also presents itself as a useful multipurpose low-cost sensor.

The resistive sensors perform well considering their price category. Both the sensors are less precise and less accurate than the capacitive sensors. The YL100 has limited accuracy and precision, particularly when operating in temperature sensitive conditions, and fails in varying salinity conditions. The YL69 sensor, on average, is as accurate but more precise than the YL100, and is additionally able to operate with expected response to variability in temperature and salinity (comparable even to the capacitive sensors), establishing it as a robust, very low-cost soil moisture sensor. Though neither of the resistive sensors can be recommended as a standalone soil moisture sensor for irrigation management solutions (due to their limited accuracy), they may be used in combination with more accurate soil moisture sensors to better characterize the spatiotemporal variability of field scale soil moisture.

Despite the limitations of the current experiments and having acknowledged the need for more comprehensive investigation (including field experiments), this study, which describes the laboratory performance evaluation and characterization of low and very low-cost soil moisture sensors, is a precondition for the realization of tangible progress within the larger framework of improving low-cost data-driven agricultural water management solutions.

4 Low-cost soil moisture calibration and parsimonious crop modeling

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Abstract

Sensor data and agro-hydrological modeling have been combined to improve irrigation management. Crop water simulation models simulate crop growth and production in response to the soil-water environment but are needed not to be data intensive (i.e., inputs and parameters) to be applicable for data scarce regions. Soil moisture sensors in precision agriculture are needed to be site-calibrated, low-cost, and maintainable. Therefore, there is a need for parsimonious crop modeling combined with low-cost soil moisture sensing without losing predictive power.

This study calibrated the low-cost capacitance-based Spectrum Inc. SM100 soil moisture sensor with both laboratory and field data to investigate the impact of soil moisture calibration on performance in the field. The best calibration technique, field-based piece-wise linear regression, was used with the parsimonious FAO AquaCrop Open Source (AquaCrop-OS) model to study the impact of using raw and calibrated soil moisture sensor data to calibrate crop model soil hydraulic properties on crop model performance.

This approach was tested during the wheat cropping season in 2018, in Kanpur (India), in the Indo-Gangetic plains. Some best practices regarding sensor calibration were developed as a result. The soil moisture sensor was calibrated best in field conditions against a medium-cost secondary standard sensor (UGT GmbH. SMT100), followed by dry-down and then wet-up calibration in laboratory conditions against gravimetric soil moisture. Moreover, model overfitting with machine learning algorithms led to poorer field validation performance. The soil moisture simulation of AquaCrop-OS improved significantly by incorporating both raw and even further by calibrated low-cost SM100 data. There were non-significant improvements in biomass prediction, but water productivity was significantly improved by using calibrated low-cost soil moisture sensor data. The latter was not the case for the raw low-cost sensor data. The results suggest the use of calibrated low-cost soil moisture sensors and crop modeling to improve crop water productivity.

¹⁰**Adla, S.**, Bruckmaier, F., Arias-Rodriguez, L.F., Tripathi, S., Pande, S., and Disse, M., 2020. Impact of calibrating a low-cost capacitance-based soil moisture sensor on FAO AquaCrop model performance. Journal of Hydrology, under review.

4.1 Introduction

The growing world population, expected to rise to nearly 10 billion by 2050 (FAO, 2017), requires a sustainable increase in food production (Parra et al., 2020). Since agriculture consumes around 70% of the global freshwater resources (Zhi et al., 2022), there are serious risks that the food production system may face, due to water availability, quantity and quality (Sikka et al., 2022). Additionally, the growing water demand from competing sectors (Sikka et al., 2022), combined with the effect of climate change and contamination on water supplies, are leading to water scarcity in most regions globally (E. Jones et al., 2019; Pereira et al., 2002). This implies unprecedented challenges in ensuring adequate agricultural water supply (Grafton et al., 2018; Y. Lu et al., 2016; Zheng et al., 2020).

Agriculture is the least efficient user of global freshwater resources (Chiara and Marco, 2022). The increasing difference between irrigation water supply and water demand continues to threaten food security (Dinar et al., 2019; Zhi et al., 2022). The RWCS has seen "phenomenal growth" in South Asia (Kataki et al., 2001), and contributes considerably to global food security (Banjara et al., 2022; Laik et al., 2014). Within South Asia, it is practiced primarily in the Indo-Gangetic plains out of which 9.2 million ha lies within India (Banjara et al., 2021). The major RWCS region in India, comprising the states of Punjab, Haryana and Uttar Pradesh, is called the "food basket" region because it produces about 50% of the national food grains (Pal et al., 2009). The production of food grains had increased significantly since the Green Revolution in the 1970s (R.B. Singh, 2000). However, a stagnation or decline in the system yields has been observed more recently (Bhatt et al., 2021; Chauhan, 2012) due to the natural resource base getting exhausted (Pathak et al., 2003), high demand for labor, water and energy (Bhatt et al., 2021; M.L. Jat et al., 2009; Saharawat et al., 2010), declining input efficiencies, and has been exacerbated by climate change and socio-economic conditions (Dhanda et al., 2022).

Irrigation has led India towards agricultural growth and food security, with around 82% of the total freshwater withdrawals in India being used for agriculture (Sikka et al., 2022). A large part of the Indo-Gangetic plains (including the "food basket") depends on groundwater for irrigation (Ambast et al., 2006). Excessive groundwater pumping, which was a component of the Green Revolution, has led to declining groundwater levels in these regions (Hira et al., 2004). Surface irrigation, like other traditional irrigation methods, is inefficient, but may continue to remain the most extensively used irrigation method due to its low-cost and energy requirements (Bjorneberg, 2013). It is associated with low irrigation application efficiency due to deep percolation and non-uniform distribution of water (Pramanik et al., 2022). Simultaneously, the adoption of micro-irrigation methods (such as drip, sprinkler irrigation etc.) has not increased remarkably in India since subsidies by themselves are inadequate to affect a change in farm decision making, and farmers equipped with water saving techniques tend to expand the area under irrigation or grow more water-intensive crops (Nair and Thomas, 2022), exemplifying the Jevons' paradox (Alcott, 2005). Hence, such technological solutions need to atleast be cost-effective, particularly when they are to be used by smallholder farmers, who tend to be more economical in technology adoption (A.K. Singh et al., 2009).

Techniques aiming at improving irrigation management have combined either data from satellites (Bastiaanssen et al., 2000) or ground sensor networks (Navarro-Hellín et al., 2015) with agro-hydrological modeling (Chiara and Marco, 2022). Precise irrigation water management requires accurate data as well as a comprehensive understanding of biophysical processes related to crop response to water at different crop growth stages (Kisekka et al., 2022). Crop water simulation models have been developed that describe the crop growth and production responses to the soil-water environment (C. Zhang et al., 2022a). Such models are often data intensive as they require numerous input variables and parameter values which may not be available for different crops and environments (Vanuytrecht et al., 2014). Similarly, though commercial sensors, processors, actors and communication components may be available, they need to be cost-effective, easy to access and maintainable to be applied effectively in agriculture (Pramanik et al., 2022; Rodríguez-Robles et al., 2020).

Soil moisture or VWC information is one such key variable involved in precision agriculture and agricultural sustainability (Kisekka et al., 2022). For similar reasons as stated above, the technologies to sense soil moisture can have low-utilization due to farmers' reluctance in investment due to economic limitations (Srbinovska et al., 2015). Further, soil moisture sensors need to be calibrated at each site because of the effects of the variability in soil properties on the sensor outputs (Peddinti et al., 2020). The advantage of field calibration is that undisturbed soil samples can be most representative of field conditions where the sensors might be used. However, soil moisture sensing can be sensitive to environmental factors like temperature, salinity, bulk density, organic matter and clay content, and the gap between the probe sensor body and soil (Kargas and K.X. Soulis, 2012; Matula et al., 2016a). Though researchers have highlighted the importance of field calibration (Robinson et al., 2008), it is generally performed (also by manufacturers) indoors with sieved, uniformly packed, homogenous soil at regulated VWCs and temperature conditions, particularly for homogeneous coarse soils like some sands and loams (Feng and Sui, 2020).

To summarize, the challenge is to combine accurate (calibrated) soil moisture sensing at low costs and parsimonious crop models without losing predictive power (Landau et al., 2000). There are studies on irrigation scheduling with calibrated low-cost capacitance sensors (R.B. Thompson et al., 2007a) with thresholds computed using indices based on VWC data (R.B. Thompson et al., 2007b). Other studies have used relatively higher cost sensors in combination with crop modeling (Y. Lu et al., 2021b). However, the combination of calibrating a low-cost capacitance based soil moisture sensor (using different least squares and machine learning algorithms) and robust crop modeling, has yet to be studied, to the best of the authors' knowledge.

This paper addresses this gap by answering the following research questions:

1. How much impact does the calibration of Low-cost (LC) soil moisture sensors, against some primary standard or Medium-cost (MC) sensor, have on the accuracy of soil moisture sensing applied in a field? What is the difference in the perfor-

mance of laboratory and field calibrated LC soil moisture sensors on independent field validation data?

- 2. What is the effect of using soil moisture data to calibrate the Soil Hydraulic Properties (SHP) of a parsimonious crop model on model outputs such as canopy cover, soil moisture, biomass and crop water productivity/water use efficiency?
- 3. What is the effect of using calibrated LC soil moisture data to calibrate the crop model's SHPs instead of raw LC soil moisture data on the above crop model outputs?

4.2 Material and methods

4.2.1 Study area and wheat cropping season

4.2.1.1 Experimental site

The questions are explored for the wheat cropping season of 2018 in Kanpur, which is representative of an intensively managed rural region with RWCS in the Indo-Gangetic plains (Gupta et al., 2019). The experiments were conducted in a 20 m \times 30 m field (Figure 4.1) at the Indian Institute of Technology Kanpur, Kanpur, India ($26^{\circ}30'56.8''N$ $80^{\circ}13'47.3''E$ and altitude of about 126 m above mean sea level). The experimental site falls within the sub-tropical climate zone with an average annual rainfall of 833.5 mm, 92.5% of which falls within the monsoon season (June to September); the other two seasons are the cold season from November-February and the hot season from March-June (Sankararamakrishnan et al., 2008).

4.2.1.2 Description of the wheat cropping season

The Indian spring wheat variety K7903 (improved Halna) (Dwivedi et al., 2019; S. Kumar et al., 2012) was sown in check basins (hence referred to as 'plots', each 3 m \times 3 m) on 5 January 2018. The seeds were sown at a row-spacing of 10 cm, at a depth of 5 cm and with a planting density of 363 plants/sq.m. Halna is a very late sown, short duration, drought tolerant variety of wheat (Dwivedi et al., 2019; S. Kumar et al., 2017b).

Agricultural management was performed based on local farming practices, that included fertilizer (urea) application during tillering, 27 Days after sowing (DAS), and 4 irrigation applications (25 DAS, 45 DAS, 59 DAS and 74 DAS, given in Table 7.5) totaling 220.2 mm, to supplement the 50.4 mm rainfall during the cropping season. There was a flooding event which occurred just following the final irrigation, totalling 262.5 mm of water. Hence, the total water input was 533.1 mm. The crop was harvested on 15 April 2018 (101 DAS).

4.2.2 Literature review

4.2.2.1 Selecting appropriate soil moisture sensing techniques

The different techniques for soil moisture sensing include neutron thermalization (Chanasyk and Naeth, 1996), TDR (Robinson et al., 2003; Topp et al., 1980), TDT

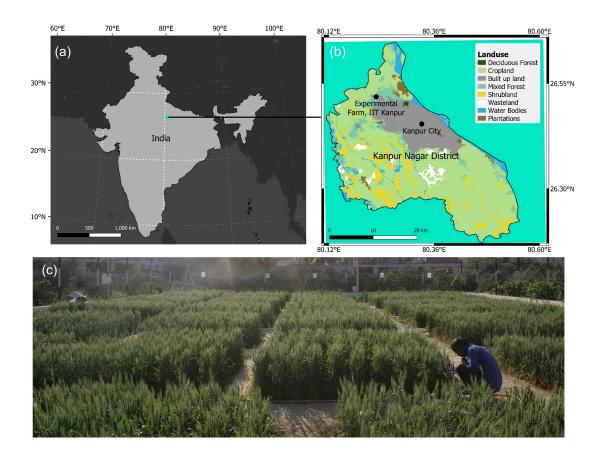


Figure 4.1: (a) Location of Kanpur in India, (b) Location of the Indian Institute of Technology (IIT) Kanpur in the Kanpur district (landuse map shown here), (c) Experimental wheat farm in IIT Kanpur, with multiple check-basins (hence referred to as 'plots') irrigated using flood irrigation. 6 plots with soil moisture monitoring using both MC and LC sensors were chosen for the study.

(Blonquist Jr et al., 2005), electrical impedance (Cosh et al., 2005; Gaskin and Miller, 1996), FDR (Ojo et al., 2015), electrical capacitance (Zotarelli et al., 2011), and sensing using electrical resistance blocks (Cummings and Chandler Jr, 1941) or tensiometers (Muñoz-Carpena et al., 2005).

Capacitance-type soil moisture sensors are more widely used for decision support systems in irrigated agriculture (Fares and Alva, 2000; Gallardo et al., 2020) due to their lower cost, robustness, precision, and low power and maintenance requirements (S.B. Jones et al., 2005; Rosenbaum et al., 2011; Spelman et al., 2013; Visconti et al., 2014). However, despite performing well in laboratory conditions, they may exhibit sensor-to-sensor variability in field conditions (Bogena et al., 2017; Rosenbaum et al., 2010; Spelman et al., 2013), and consequently require site-specific calibration to be able to provide reliable VWC measurements (Kisekka et al., 2022; Peddinti et al., 2020).

4.2.2.1.1 TDR-FDR based medium-cost (MC) sensor: SMT100

The SMT100 sensor (manufactured by Umwelt-Geräte-Technik GmbH, Müncheberg, Germany) was chosen as the secondary standard soil moisture sensor (UGT, 2017), henceforth called the 'medium-cost (MC)' sensor. This nomenclature comes from previous research which characterized the performance low-cost (capacitance) and very-low cost (resistance) sensors against high-cost (impedance) sensors (Adla et al., 2020) The cost of the SMT100 sensor is intermediate between the low-cost and high-cost sensors (see Figure 4.3). The SMT100 incorporates the higher accuracy of a TDR system with the cost effectiveness of FDR sensing (UGT, 2017). The sensor head containing the sensor electronics emits a steep pulse which travels along a closed transmission line which is buried in the soil. However, instead of directly measuring the time for the pulse to return (e.g., in TDT or TDR), the pulse is inverted and fed back into the line driver input, resulting in an "oscillation" frequency which is a function of the soil dielectric permittivity (Bogena et al., 2017). Also, unlike the FDR which is based on a capacitor, the SMT100 uses a ring oscillator to generate the pulse and transform the travel time to frequency (Bogena et al., 2017; UGT, 2017). The oscillation frequency is around 340 MHz in air and 150 MHz in water (Bogena et al., 2017). This resultant frequency is high enough to not be influenced by the high clay content, electrical conductivity or imaginary dielectric permittivity of the soil (Blonquist Jr et al., 2005; UGT, 2017). The outputs of SMT100 are relative permittivity, volumetric water content computed using the relative permittivity (Blonquist Jr et al., 2005) and soil temperature. The accuracy for VWC is 3% (which can be improved to 1% with calibration), and the accuracy for temperature is ± 0.2 °C within a temperature range of -40 °C to 80 °C, as reported by the manufacturer (UGT, 2017). Sensor specific calibration in the laboratory with (non-soil) materials of known apparent dielectric permittivity can improve the VWC accuracy (RMSE, Raes et al., 2018) to range between 0.21% to 1.30%, for different materials (Bogena et al., 2017). The MC SMT100 sensor was assumed to be relatively more accurate due to its superior sensing technique, and was thus used as a secondary standard (Nakra and Chaudhry, 2006) to calibrate the low-cost (LC) SM100 sensor (see Section 4.2.4.1.2).

4.2.2.1.2 Capacitance based low-cost (LC) sensor: SM100

The WaterScout SM100 soil moisture sensor (Spectrum Technologies, Inc., Plainfield, IL, USA) was chosen as the capacitance based low-cost (LC) soil moisture sensor (Spectrum, 2011). The sensor operates with a pair of electrodes behaving as a capacitor and the soil surrounding the sensor behaving as the charge storing dielectric medium. An oscillator operating at 80 MHz drives the capacitor, and generates an output (voltage ratio) which is proportional to the dielectric permittivity of the soil-water system. The sensor output (voltage ratio/raw value) is then converted to a VWC value using the factory calibration equation (Kieffer, personal communication, 5 September 2018). The accuracy of SM100 is reported to be 3% (for EC < 800 mS.m-1) and it has an operating range of 0.5 °C to 80 °C (Spectrum, 2011). Calibration in the laboratory (with repacked sands and silty

loams) has improved the VWC accuracy (*RMSE*) to range between 1.63% to 2.97% (Adla et al., 2020). The LC SM100 sensor was calibrated using a primary standard as well as the MC SMT100 sensor as the secondary standard (see Section 4.2.4.1).

4.2.2.2 Selecting calibration techniques for the LC capacitance sensor

4.2.2.2.1 Least squares estimate based regression

Studies have calibrated capacitance-based soil moisture sensors, both in laboratories (Adla et al., 2020; Bello et al., 2019a; Nagahage et al., 2019; Placidi et al., 2020; 2021) and in the field (Rudnick et al., 2015; J. Singh et al., 2018), to improve performance. Most of the calibration equations reported in the literature for the low-cost sensors are least-squares estimates and are either linear, logistic, hyperbolic, logarithmic, exponential, or polynomial. Based on a visual inspection of the data, piecewise linear regression, power law regression and polynomial regressions (both degree 2 and 3) were used to calibrate the LC capacitance based SM100 sensor.

4.2.2.2.2 Machine learning based regression

Diverse machine learning algorithms were applied to calibrate and evaluate a predictive model. The focus was on standard algorithms for regression applications: linear regression (LR), support vector regression (SVR), random forest regression (RFR) and multilayer perceptron neural networks (MLP). LR models have been applied extensively earlier in soil moisture applications (Qiu et al., 2003; Teng et al., 1993); and are still relevant due to their simplicity and easy interpretation (García et al., 2016; Y. Lee et al., 2019). The Support Vector Machine (SVM) algorithm defines optimal hyperplanes in a high or infinite dimensional space which can be used for classification or regression (Vapnik et al., 1996). SVR has been applied in soil moisture related studies (Gill et al., 2006; D. Liu et al., 2010; Z. Yu et al., 2012). The RFR algorithm (Breiman, 2001) is based on averaging non-correlated decision trees for variance reduction and avoidance of overfitting. Its simplicity in training and tuning has made it popular in current regression applications of soil moisture (Carranza et al., 2021; Qingling et al., 2019; Srivastava et al., 2021; H. Zhang et al., 2022b). However, calibration hyperparameters can be computationally expensive due to its many possibilities. The MLP is an algorithm based on the typical architecture of a neural network, hence it is a nonlinear statistical model which has unknown parameters (weights) meant to be tuned to make the model well fit to training data using back-propagation equations in multiple hidden layers. It has also been applied in soil moisture applications extensively (Chai et al., 2009; Gu et al., 2021; F. Yu et al., 2012). All the algorithms were applied using the Scikit-learn tool library (v.10.2) (Pedregosa et al., 2011) in Python (v.3.8.5). Hyperparameters of each algorithm were calibrated with default values available in Scikit-learn and evaluated with a cross validation of 10 folds (CV, k = 10). This process avoided skewing results in validation due to random sampling in the training process. The controlling metrics were the coefficient of determination (R^2 , Raes et al., 2018) and the root mean squared

error (*RMSE*). A detailed definition of all the machine learning models applied here can be found in (Hastie et al., 2009), and an example of this application can be found in (Arias-Rodriguez et al., 2021).

4.2.2.3 Selecting a parsimonious crop model

Crop growth models can simulate physiological processes (Chenu et al., 2009; Yin et al., 2003), and crop growth behavior in the field (J.W. Jones et al., 2003; Keating et al., 2003; Steduto et al., 2009). Modeling has been used to quantify yield gaps (Schils et al., 2018; Van Ittersum et al., 2016), highlight gaps regarding food security (Keating et al., 2014), quantify land area needed (currently and into the future) to feed the population (Gerten et al., 2020), and discuss the possible need to expand agricultural lands into natural habitats (Stehfest et al., 2019). In the past few decades, crop models have been refined and updated by incorporating the influence of various water-fertilizer conditions and field management practices on the variables of interest (C. Zhang et al., 2022a). As a result, crop models have informed management decisions regarding water and nutrients, identified optimal sowing dates, and explored the feasibility of new cropping systems (Asseng et al., 2014; Silva et al., 2017). The more popular models that have recently been used for simulating crop growth and yield production of wheat under different soil water conditions and irrigation scenarios are: APSIM (Ahmed et al., 2016; Chen et al., 2010), DSSAT-CERES-Wheat (Attia et al., 2016; L.-l. Zhou et al., 2018) FAO AquaCrop (Iqbal et al., 2014; Toumi et al., 2016) RZWQM2 (Saseendran et al., 2015; Zheng et al., 2020), and SWAP (Eitzinger et al., 2004; X. Wang et al., 2021).

Crop modeling environments like DSSAT and APSIM can require 211 and 292 parameter inputs respectively (Soltani and T.R. Sinclair, 2015), which enables such models to address complex research questions linking crop development to long-term nitrogen balances, greenhouse gas emissions, or climate variability (Todorovic et al., 2009). The incorporation of all possible processes and integration levels amplifies errors and uncertainties (Silva and Giller, 2020). Moreover, data intensive models with numerous inputs and parameter requirements may not be practical in data-scarce regions (Vanuytrecht et al., 2014; Varella et al., 2010) like the Majority World (Graves et al., 2002; J.W. Jones et al., 2012).

The water-driven FAO AquaCrop model has been developed with the vision to balance simplicity, accuracy and robustness (Vanuytrecht et al., 2014). Consequently, it relies on considerably fewer (about 19, according to Raes, 2017), and relatively easier to measure inputs, such as the percentage of green Canopy Cover (CC) instead of the leaf area index (LAI) (Kulshreshtha and Elshorbagy, 2017; Steduto et al., 2012; Steduto et al., 2009; Todorovic et al., 2009; Vanuytrecht et al., 2014). Model comparison studies have confirmed that despite the reduced number of inputs data and parameters, FAO AquaCrop's performance can be similar or only slightly inferior compared to data-intensive models (Babel et al., 2019; Quintero and Díaz, 2020; Todorovic et al., 2009). Moderate to good simulation results have also been reported for wheat and regions of water scarcity (Andarzian et al., 2011; Huang et al., 2022; A. Singh et al., 2013; W. Zhang et al., 2013).

4.2.2.4 Description of the crop-water model FAO AquaCrop

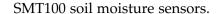
AquaCrop is freely distributed stand-alone software distributed by the Food and Agriculture Organization of the United Nations (FAO). Open-source versions of the FAO AquaCrop model have been developed using both proprietary and open-source software environments (Camargo Rodriguez and Ober, 2019; T. Foster et al., 2017; Kelly and T. Foster, 2021). This study uses the MATLAB-based AquaCrop OpenSource (AquaCrop-OS) v.6.1 tool (T. Foster et al., 2017).

Evolving from the approach of (Doorenbos and Kassam, 1979), AquaCrop simulates daily yield loss in response to soil water depletion in the root zone. The improvements include using a simple canopy growth and senescence model to compute transpiration, consequently partitioning evapotranspiration (ET) into crop transpiration and soil evaporation, and estimating yield from biomass and Harvest Index (-) (HI) (Steduto et al., 2009). Four main variables are calculated consecutively and on a daily basis through individual equations; i.e., accumulated canopy cover (CC), daily plant transpiration, accumulated aboveground biomass, and accumulated final dry yield. These model variables are mainly interconnected by empirical factors, such as the water productivity (WP) and harvest index (HI), to convert transpiration to biomass and biomass to yield, respectively. Water productivity only incorporates plant transpiration to account for the confounding effect of the nonproductive consumptive water use (Steduto et al., 2009). Moreover, WP is normalized for atmospheric CO2 concentration and climate (Raes et al., 2018), and hence makes the model more robust and generalizable (Steduto et al., 2009). AquaCrop also differentiates the effect of water stress into 4 components: canopy growth, canopy senescence, transpiration and harvest index (Steduto et al., 2009). AquaCrop-OS v.6.1 integrates the adverse effects of water excess or deficiency, and extreme temperatures on crop development by calculating daily reductive factors which then impact the model equations that compute the corresponding variables (Raes et al., 2018; Steduto et al., 2012). The separate modeling of water deficiency stresses depending on their impact pathway is expected to give AquaCrop a competitive advantage over other water-driven models (Foster et al., 2017).

Model set-up requires user input for climate parameters, 'non-conservative' (i.e., temporally and spatially variable) model parameters, and, where applicable, an irrigation schedule and the groundwater water table. Climate parameters include precipitation, reference evapotranspiration, and minimum and maximum temperature, which are to be specified on a daily scale for the entire growing season. Non-conservative model parameters relate to crop phenology, soil conditions, and field management practices (Raes et al., 2018; Steduto et al., 2012).

4.2.3 Measurements

Figure 4.2 illustrates the seasonal evolution of the daily water demand (depicted by weather parameters combined into the FAO-56 reference ETo, from Allen et al., 1998), water supply (depicted by rainfall and applied irrigation during the season), and soil moisture (VWC) monitoring by both low-cost (LC) SM100 and medium-cost (MC)



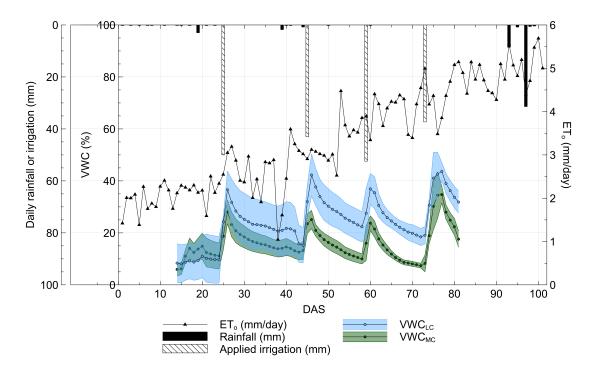


Figure 4.2: Variation of daily values of FAO-56 reference evapotranspiration Reference Evapotranspiration (mm.d $^{-1}$) ($ET_{\rm o}$), input water through rainfall or irrigation application, and soil moisture measurements (both medium-cost SMT100 and low-cost SM100 sensor) during the wheat cropping season. Soil moisture averages over the field are depicted as bubbles, with their standard deviations as ranges.

An automatic weather station at the experimental field measured precipitation, barometric pressure, relative humidity, global solar radiation, wind speed and direction, and air temperature at two different heights (2 m and 3 m above the ground), all at 15-minute intervals aggregated to daily values. During the cropping season, the average daily temperature and relative humidity (both at 2 m) ranged from 9.3°C to 30.7°C and from 35.3% to 93.9%, respectively.

The soil texture components of the experimental plot were found to be 15.4% sand, 66.3% silt and 18.2% clay, classifying it as silty-loam (USDA classification). The soil texture classification was conducted by the UGT Sedimat 4-12 instrument, which determines the particle size distribution in mineral soils based on the Köhn method (König et al., 2005). Moreover, the soil was relatively homogenous in depth and the groundwater table is deep enough to prevent capillary rise from influencing soil moisture measurements.

Surface soil moisture was determined at the center of each plot at 15-minute intervals

by the TDR-FDR based MC SMT100 sensor (manufactured by Umwelt-Geräte-Technik GmbH), and the capacitance based LC SM100 (manufactured by Spectrum Technologies, Inc.), and both datasets were aggregated to the daily time-step.

The observations used for model parameterization included the following. Phenological parameters which were observed included days to emergence, start of flowering, start of senescence and maturity, length of flowering (days). VWC related observed parameters were maximum rooting depth, The observed parameters plant population density was related to crop management. The observations compared with simulated outputs for crop modeling calibration were leaf area index and above ground biomass. Leaf Area Index (LAI) was measured eight times during the season (36, 44, 55, 59, 68, 83, 90 and 101 DAS) using the LAI-2200C plant canopy analyzer manufactured by LI-COR Biosciences. It was converted into Canopy Cover values (which is the direct crop model output) using an empirical exponential equation for wheat (Nielsen et al., 2012). Above ground dry biomass was measured conducting a crop cutting experiment (M. Singh, 2014) from a representative 1 sq. m section for each plot. Moreover, actual evapotranspiration ET_a was measured using microlysimeters which was part of another study (Kumar, 2019). These measurements were used to calculate the ET Water Productivity (kg.kg⁻¹ or kg.m⁻³) (WP_{ET}), introduced in Section 4.2.5.2.

There were six plots which had simultaneous measurements by both MC and LC soil moisture sensors as well as the observations required for crop modeling, and were used for the analyses. Overall, VWC measurements for both the sensors were available on average for 61.2 days (s=3.0 days) out of the 100 day cropping season across the six plots.

4.2.4 Calibration of low-cost soil moisture sensors

4.2.4.1 Strategy to calibrate-validate soil moisture data

Capacitance based soil-moisture sensors have been calibrated both with repacked (Adla et al., 2020; Nagahage et al., 2019; Placidi et al., 2020) or undisturbed (Bello et al., 2019a) soil samples inside the laboratory, as well as in the field (Rudnick et al., 2015; J. Singh et al., 2018). In the laboratory, calibration of soil moisture sensors is generally carried out either using the substantially faster 'wet-up' or wetting (downward or upward infiltration, taking <1 day) or slower 'dry-down' or drying (taking about 1-2 weeks) processes (Burns et al., 2014).

Figure 4.3 describes the overall workflow of this study. The sensors used are displayed at the top-left corner of the figure. Throughout the study, the data corresponding to the LC SM100 and MC SMT100 sensors are represented in blue and green colors respectively. The simulations corresponding to the calibrated LC soil moisture sensor data are represented in a deeper blue compared to the raw LC sensor data.

The workflow related to the LC soil moisture sensor (SM100) calibration is illustrated in the inset "Soil moisture sensor calibration", in Figure 4.3. The LC sensor data is calibrated against either a primary standard (gravimetric water content, Section 4.2.4.1.1) or a secondary standard (the MC SMT100 data, Section 4.2.4.1.2) - this is mentioned in the respective bubbles, "Lab Cal." (laboratory calibration) and "Field Cal." (field calibration).

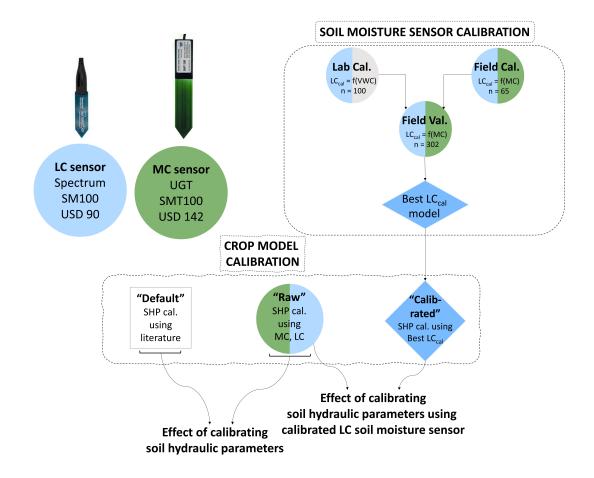


Figure 4.3: Overview of the strategy to calibrate LC soil moisture sensor and crop model. The sensors used are displayed at the top-left corner of the figure, along with information about the manufacturer and cost (US dollars). The "Soil moisture sensor calibration" of the LC SM100 sensor was conducted in the laboratory "Lab Cal.") using gravimetrically determined VWC, and in the field ("Field Cal.") using the MC SMT100 sensor as a secondary standard. All the developed models were then validated in the field ("Field Val.) to select the best model, "Best LC_{cal} model". The "Crop model calibration" either used the literature ("Default"), raw VWC values from both MC and LC sensors ("Raw"), or the Best LC_{cal} model ("Calibrated") to calibrate the SHP of the AquaCrop model. The Best LC_{cal} rhombus in "Soil moisture sensor calibration" is a flowchart decision, whereas, the "Calibrated" diamond in "Crop model calibration" is not a decision, but a representation that is followed in Figure 4.5.

The number of paired data points (sensor and primary/secondary standard) used in both calibration approaches is also mentioned (n=100 for laboratory calibration, n=65 for field calibration). The objective of the following process was to select the "best"

calibration algorithm (across laboratory and field calibration schemes) to be used in a crop modeling scenario (Section 4.2.5.2).

4.2.4.1.1 Laboratory calibration of LC SM100 sensor

The laboratory calibration of repacked soils using the LC SM100 sensor had already been undertaken in a previous study (Adla et al., 2020); piece-wise linear regression functions (PWLFs, Jekel, 2017) were used to fit the LC VWC values of five LC SM100 sensors against gravimetric VWC (primary standard), for four soils (number of data points, n=400). The study had calibrated five sensors in controlled laboratory conditions with the wet-up curve (similar to Matula et al., 2016a) to account for sensor-to-sensor-variability and improve cost-effectiveness in terms of saved time and energy resources (Burns et al., 2014). For this study, the data (n=100) corresponding to the soil sampled from the current study site (silty-loam soil referred to as Soil 3 in Adla et al., 2020), were used to fit the LC sensor values against gravimetric VWC, using the different algorithms described in Section 4.2.2.2. The coefficient of determination (R^2) and root mean squared error (RMSE) were used to quantify the calibration performance in all cases.

4.2.4.1.2 Field calibration of LC SM100 sensor

Out of the six plots used for the study, the plot with the highest (significant) linear correlation between the aggregated daily values of MC SMT100 and LC SM100 sensor ($r^2 = 0.76$) was used for calibration (n=65), and the five remaining plots were used for validation (n=302). The TDR-FDR based MC SMT100 sensor was taken as the secondary standard based on the evidence of superior performance compared to the capacitance based LC SM100 sensor (Section 4.2.2.1). Consequently, the daily aggregated LC SM100 data were calibrated using the daily aggregated MC SMT100 data, using all the algorithms listed in Section 4.2.2.2. Similar to the laboratory calibration, the calibration performance in each case was quantified using the coefficient of determination (R^2) and root mean squared error (RMSE).

4.2.4.1.3 Field validation of laboratory and field calibrations

The data from the five validation plots (n=302) were used to validate the performance of each calibration algorithm developed using both laboratory or field data. These data were independent of the calibration datasets of the laboratory and field. Moreover, since the aim of the calibration process is eventually to use the calibrated LC SM100 sensors in the field, it was decided to use field data to validate all the developed calibration algorithms. The MC SMT100 data measurements were taken as the secondary standard used for calibrating or validating the field data. The square of the Pearson correlation coefficient (r^2 , Raes et al., 2018), and the *RMSE* were used as the performance indicators for the validation process.

4.2.5 Crop model calibration scenarios

4.2.5.1 AquaCrop calibration procedure/method

The official AquaCrop calibration guidelines propose calibrating all non-conservative and non-observed model parameters in a sequential process with appropriate objective functions (Raes et al., 2018; Steduto et al., 2012). Accordingly, model simulation was sequentially improved using intermediately computed model variables like canopy cover (CC), volumetric water content (VWC) and biomass (BM) by adjusting different sets of model parameters, until the simulation of the harvested yield agreed with observations within an acceptable error range. The model performance regarding intermediate variables can be evaluated and interpreted by visually and statistically comparing the respective simulated and observed curves (Raes et al., 2018).

In this study, eight (non-conservative) crop growth parameters of the AquaCrop-OS model were calibrated: phenological parameters (initial canopy size of the emergent seedling CC_o , maximum canopy cover CC_x , and Canopy Growth Coefficient (CGC)) similar to Vanuytrecht et al. (2014), and soil hydraulic parameters (readily available water REW, saturated soil hydraulic conductivity Ksat, VWC at wilting point θ_{PWP} , field capacity θ_{FC} and saturation θ_s).

4.2.5.2 Different calibration scenarios used in the study (default, raw and calibrated)

The inset 'Crop model calibration" in Figure 4.3 illustrates the crop modeling scenarios to address the second and third research questions defined for the study. The soil hydraulic properties (SHPs) of FAO AquaCrop which were calibrated within the scenarios were: θ_{PWP} (%), θ_{FC} (%), θ_s (%), Ksat (mm/day), and REW (mm). A trial-and-error method (Liang et al., 2017; H. Ma et al., 2020) was used to calibrate the canopy cover (CC) curve to maximize the r^2 and minimize the RMSE between the observed (estimated) and simulated CC values for each plot. The calibration of the crop model SHPs was done, to optimize the same performance indices, under the following scenarios (refer to Figure 4.3):

- The "Default" scenarios (for both MC and LC sensor): The SHPs were calibrated based on average values from the literature (Gupta et al., 2021; Rawls and Brakensiek, 1989), corresponding to the classified soil texture (silty-loam). The soil moisture data for both the MC SMT100 and LC SM100 sensors were only used to observe model performance, and had no effect on the SHPs.
- The "Raw" scenarios (for both MC and LC sensor): The AquaCrop SHPs were calibrated using the raw (uncalibrated) LC and MC soil moisture data. The calibration was done using a trial-and-error method of Liang et al. (2017) and H. Ma et al. (2020). The difference between "Raw" and "Default" scenarios quantified the respective impacts of calibrating the SHPs on the crop model performance (research question 2).
- The "Calibrated" scenario (only for LC sensor): The SHPs were calibrated using the "best" LC soil moisture sensor calibration technique. The difference between

the "Calibrated" and "Raw" model performance (both for the LC sensor) quantifies the additional impact of using calibrated soil moisture data (as compared to raw data) on crop model performance (research question 3).

Another simulated output of the AquaCrop model, the above ground dry biomass (BM) was compared with the observed biomass, using the indicators mean absolute error (MAE, Witten et al., 2011), RMSE, NRMSE (normalized RMSE, Raes et al., 2018), and percentage bias (PBIAS, Sorooshian et al., 1993). The recommendations of NRMSE for qualitative performance, of $NRMSE \leq 5\%$ for very good performance, NRMSE between 6%-15%, 16%-25%, 26%-35%, 36%-45% for good, moderately good, moderately poor, and poor performance respectively, and $NRMSE \geq 45\%$ implying very poor performance (Raes et al., 2018), were used to evaluate the BM simulations.

Also, in the context of food and water security, Water Productivity was used to understand the "efficacy of the crop production processes in relation to their required water consumption" (Van Halsema and Vincent, 2012). Water productivity is a critical element in irrigated agriculture to evaluate the enhancement of agricultural production without majorly increasing fresh water allocation to agriculture (De Fraiture and Wichelns, 2010; Molden et al., 2010). There are many alternative terms used to denote this concept water productivity (Van Halsema and Vincent, 2012; Vanuytrecht et al., 2014), water use efficiency used in the agronomic context (Ai et al., 2020; Andarzian et al., 2011), ET water productivity (Raes et al., 2018). This study uses Water Productivity or $WP_{\rm ET}$ (kg.m⁻³, or kg.kg⁻¹), defined as the following (Van Halsema and Vincent, 2012):

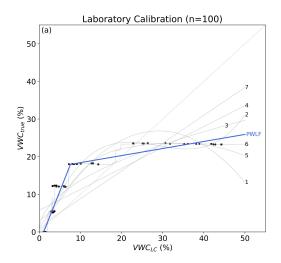
$$WP_{ET} = Yield/ET_a \tag{4.1}$$

where Yield is the final (simulated or observed) crop yield (kg/m2) and ET_a (m) is the cumulative actual evapotranspiration during the cropping season. The simulated $WP_{\rm ET}$ was computed by extracting the yield and simulated seasonal evaporation and transpiration (sum of daily values), generated by AquaCrop. The observed $WP_{\rm ET}$ values were computed using the observed biomass, the default Initial Harvest Index (-) (HI_o) for wheat, and ET_a estimated on the field using microlysimeters (A. Kumar, 2019).

4.3 Results and discussion

4.3.1 Calibration of low-cost soil moisture sensors

Table 4.1 details the results of the calibration and validation procedure used for the LC SM100 soil moisture sensor described in Section 4.2.4. The sub-table on the left and right describe the calibration-validation performance in the laboratory and field respectively, using coefficient of determination (R^2) or square of Pearson's correlation coefficient (r^2), and the root mean squared error (RMSE) as the performance indicators. The validation in both cases is done on the same independent field data (n=302). Figure 4.4 plots all the calibration curves preserving the index from Table 4.1, highlighting the selected "best" calibration technique.



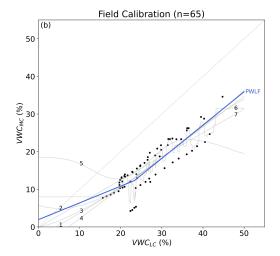


Figure 4.4: Comparison of the different calibration equations developed using (a) lab and (b) field data. The index numbers correspond to Table 4.1. The "Best" model identified in both cases is the PWLF algorithm. The respective data used for calibration are shown as points.

During both laboratory and field calibrations, the performance of the machine learning algorithm Random Forest Regression (RFR) was quantitatively the best among all the algorithms included in the study, based on the chosen performance indicators. In laboratory calibration, the coefficient of determination R^2 =0.98 and RMSE=1.26%, and during field calibration, R^2 =0.93 and RMSE=1.67%.

Table 4.1: Overview of the performance indices for calibrating the LC sensor in the laboratory (left) and in the field (right). The different calibration techniques are 0. Piecewise linear function (PWLF), 1. polynomial of degree 2, 2. polynomial of model (number 0), highlighted in bold. n is the number of data points, R^2 is the coefficient of determination for degree 3, 3. Power law, 4. Linear regression (LR), 5. Support Vector Regression (SVR), 6. Random Forest Regression (RFR), 7 Multi-Layer Perceptron regression (MLP). Laboratory and field models 0 to 7 use the wet-up and dry-down curves respectively to calibrate the LC sensor. Models 8 and 9 correspond to laboratory calibrations from independent research with the dry down curve. Gedilu (2012) calibrated the LC sensor using the same field's soil, and Rai (2012) calibrated a slightly different silty-loam soil, both using dry-down curves. The Best LC_{cal} model was the PWLF-field model development, r^2 is the square of the Pearson correlation coefficient, and RMSE is the root mean square error.

			$\overline{\cdot}$						4.	3 I	Resi	ults	an	d d	iscu
pu		Field Validation	(against MC sensor)	RMSE (%)	11.99	4.57	5.09	4.66	4.97	5.43	5.84	4.87	4.7		
field a	e field	ield Va	ainst N	r^2	0.62	0.67	0.64	99.0	0.65	0.62	0.47	0.62	0.62		
n the	in the	H	(ag	и	302	302	302	302	302	302	302	302	302		
Calibration in the field and	validation in the field	Field Calibration	(against MC sensor)	RMSE (%)	11.49	3.13	3.18	3.18	3.18	3.19	3.97	1.67	3.5		
		eld Ca	ainst 🛚	\mathbb{R}^2	0.76	92.0	0.76	0.76	0.76	0.76	0.62	0.93	0.71		
		臣	(ag	и	65	65	65	65	65	65	65	65	65		
pu		Field Validation	(against MC sensor)	RMSE (%)	11.99	7.98	11.28	69.6	7.31	6.29	9.12	8.88	6.85	90.9	5.26
tory, a	ple	eld Va	inst N	r ²	0.62	0.42	0	0.12	0.54	0.62	0.1	0.2	0.62	0.61	99.0
labora	the fi	臣	(age	и	302	302	302	302	302	302	302	302	302	302	302
Calibration in the laboratory, and	validation in the field	y Calibration	vimetric VWC)	RMSE (%)	7.58	1.96	2.92	2.16	3.67	4.93	3.09	1.26	5.97	dent studies	with dry-down curve
Ca		Laboratory	(against gravir	\mathbb{R}^2	99.0 00	0.95	0.88	0.93	0.81	99.0	0.87	86.0	0.5	Independent	ith dry
		Lal	(agai	и	100	100	100	100	100	100	100	100	100	Ir	W
				Calibration models	Manufacturer's calibration	Best LCcal: PWLF	Polynomial (d=2)	Polynomial (d=3)	Power Law	LR	SVR	RFR	MLP	Gedilu (2020)	Rai (2012)
						0	1	7	\mathcal{C}	4	R	9	^	∞	6

However, plotting the curve (index 6 in Figure 4.4) revealed evidence of overfitting. Even when RFR avoids overfitting from the original decision trees, a lack of generalization is still possible (Hastie et al., 2009). Particularly, generalization error variance decreases as more trees are added to the algorithm, without a change in the bias of the generalization. This study used the default n_estimators = 100 (Pedregosa et al., 2011), however, different options of decision trees should be examined, particularly searching for lower n_estimators using a GridSearch. Overfitting is likely a consequence of the limited tuning of the hyperparameters and the need of more computation resources. As a consequence, the validation of the RFR-laboratory model worsened the performance substantially (r^2 =0.20, RMSE=8.88%). The RFR-field and RFR-laboratory models were not monotonic and monotonically non-decreasing functions respectively, which implied that the calibrated LC VWC values could also decrease (or not increase, respectively) with increasing MC VWC. Both the model behaviors were not realistic. Hence, the RFR algorithm was not chosen for further analyses.

The piece-wise linear regression function had the next best performance during calibration: laboratory R^2 =0.95, RMSE=1.96%; and field R^2 =0.76, RMSE=3.13%. Further, during both the respective validation cases, the PWLF performed adequately well when compared to the relative performances of the RFR models (PWLF-laboratory: r^2 =0.42, RMSE=7.98%, PWLF-field: r^2 =0.67, RMSE=4.57%). The piece-wise (segmented) behavior is also a feature of the manufacturer's calibration equation; its segments are linear and quadratic (Kieffer, personal communication, 5 September 2018). A comparison of the calibration equations developed by the manufacturer (Spectrum Technologies, Inc.) and in-house has been studied earlier (Adla et al., 2020).

Scatter plots between the measured/calibrated LC SM100 values and the measured MC SMT100 values are presented in Figure 4.5, for (a) laboratory calibration, (b) validation of the laboratory-calibrated model, (c) field calibration, and (d) validation of the field-calibrated model. The cyan bubbles depict the scatter plots for the original data, i.e. raw LC SM100 vs. raw MC SMT100 data, and the deeper blue diamonds represent the scatter of the data after the respective calibration, i.e. calibrated LC SM100 vs. raw MC SMT100 data, except for Figure 4.5(a) laboratory calibration, where the Y-axis is gravimetrically determined VWC.

The comparison of calibration approaches provided an opportunity to generate some best practices for soil moisture sensor calibration. These would correspond more specifically to silty-loam soils in agricultural fields monitored by capacitance based sensors. The derived best practices were:

• Field calibration of less sensors may be more robust than laboratory calibration of more sensors, for field application: The performance of the laboratory-calibrated models is significantly poorer than the field-calibrated models, when applied to the field validation set, in terms of both r^2 and RMSE values. This supports the previous literature which recommends calibration on-site or on undisturbed soil-specific calibration (Feng and Sui, 2020). Field calibrations with undisturbed soils may be more robust for field applications. This can be observed

by the difference in performance moving from the laboratory calibrations to the validation, and from field calibrations to the validation.

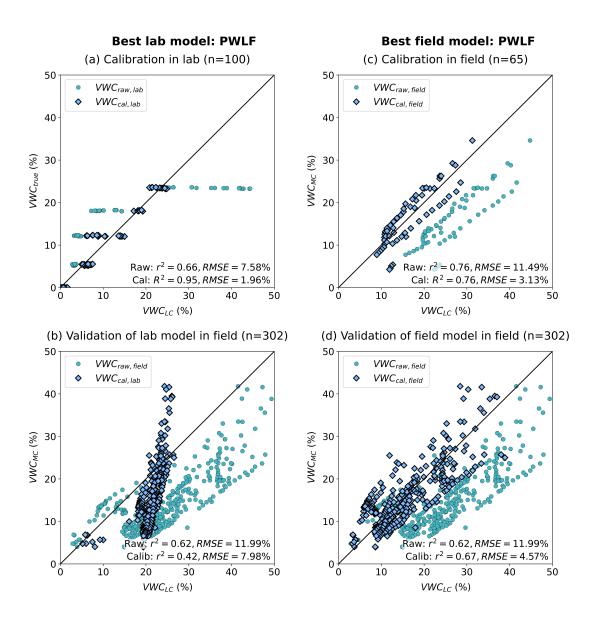


Figure 4.5: Soil moisture calibration in the lab (top-left) and the field (top-right), validated on an independent, identical field dataset (bottom left and right respectively). R^2 represents the coefficient of determination, and r^2 represents the square of the Pearson correlation coefficient. The best performing model in both cases is PWLF, and data generated using the PWLF-field-calibration model was used to calibrate the soil hydraulic parameters of the AquaCrop-OS crop model.

- If field calibration is not possible, calibration should be done using the drydown curve, for field applications: Calibrating LC sensors in the laboratory using the dry-down curve rather than the wet-up curve leads to superior performance for field applications. This corroborates with previous literature which claimed superior laboratory calibration accuracy using dry-down curves, particularly for finer textured soils (Burns et al., 2014). In this study, the validation performances of all the field-calibrated models were significantly better than that of laboratorycalibrated models. Moreover, capturing the drying curve is more apt to capture the dynamics on the field in dry non-monsoonal *rabi* crop conditions in northern India, where most of the annual rainfall occurs in the monsoons (Sankararamakrishnan et al., 2008). Calibration using the dry-down curve in the laboratory may partly address the loss of representativeness when soils are repacked, may apply for soils that are similar in texture and structure, and also compensate for sensor-tosensor variability. Calibration of the dry-down curve using 3 LC SM100 sensors in an earlier study was found to have the best validation performance among all laboratory calibrated models (r^2 =0.66, and the best RMSE=5.26%), despite a slightly different silty-loam soil (around 10% more sand and 10% less silt than this study) being used for it (Rai, 2012). Similarly, a linear equation developed by calibrating one LC SM100 sensor in the laboratory (without environmental representativeness) using repacked soil from the experimental site, had nearly the best r^2 =0.61 and RMSE=6.06% (Gedilu, 2012). This seemed to compensate for the sensor-to-sensor variability even for repacked soils inside the laboratory, since it performed better than the laboratory models (models 0 to 7) calculated using the wet-up curve with five LC sensors.
- Overfitting during calibration can lead to loss in robust application: Overfitting was observed in the poor validation performance of both laboratory and field RFR models compared to the respective calibration performance. Machine learning models, applied to non-linear hydrological processes have been found to exhibit issues such as overfitting and difficulties explaining results (Elshorbagy et al., 2010). Soil moisture calibration curves that are monotonic (preferably "gently sloped") are more robust for field application, as the data in this study seems to suggest. This is reiterated by previous studies with capacitance sensors, which mainly report calibration equations such as linear and polynomial (Bello et al., 2019a; Deng et al., 2020; Gedilu, 2012; Nagahage et al., 2019; Placidi et al., 2020; Rudnick et al., 2015; J. Singh et al., 2018; R.B. Thompson et al., 2007a,b).

Overall, the PWLF model calibrated using field data was chosen as the "best" model for further analysis. This strengthens the choice of piece-wise linear regression that was also selected in a previous study with the same capacitance sensor in the same field soil (Adla et al., 2020). It combines the flexibility of multiple segments without compromising on physical realities through monotonicity which should result from the soil moisture sensing of two electromagnetic sensors in the same soil.

4.3.2 Crop model calibration scenarios

4.3.2.1 Intermediate crop model outputs: canopy cover and volumetric water content

Table 4.2 details performance indices computed between simulated and observed crop model outputs for each calibration scenario (4.2.5.2) for the five modeled plots taken together. Table 7.4 outlines the default values of all non-conservative parameters, which were either fixed using either secondary literature or observations, or calibrated under the different calibration scenarios (Section 4.2.5.2). Figure 7.1 shows the respective mean and standard deviation values of only the parameters which were calibrated under the different scenarios (subset of Table 7.4). Figure 4.6 illustrates the time series of the simulated and observed canopy cover (CC) (a-e) and volumetric water content (VWC) (f-j) for the same scenarios, as averages and standard error of the mean (SEM) for all the plots taken together. Tables 4.2 and 7.4, and Figures 4.6 and 7.1 are used together for the following discussion of the results.

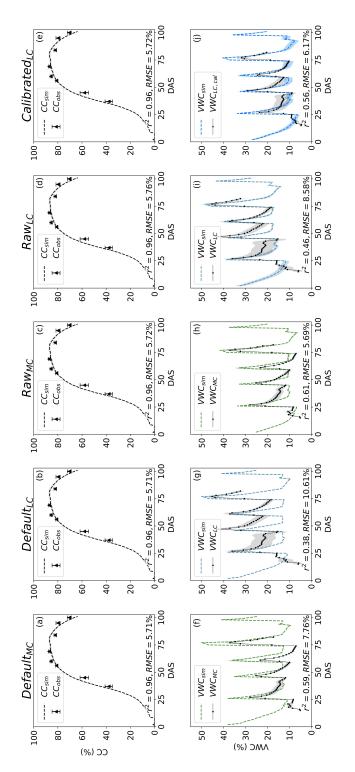
In the Def_{MC} and Def_{LC} scenarios, only the parameters related to the CC development were altered to improve the fit of the simulated CC curve with the observations, i.e., SeedSize (CCo), CCx and CGC (descriptions in Section 4.2.5.1 and Table 7.4). The SHPs which would impact the VWC curve fitting were chosen from (the average of) default values from literature (as given in Table 7.4). Hence, neither the MC nor the LC soil moisture sensor observations were used to fit these parameters, and were rather only used to infer how well SHPs calibrated using the literature would be able to predict the VWC.

In both the default scenarios, CC was predicted very well, with r^2 =0.96 and RMSE=5.71%, which was satisfactory based on the previous literature with AquaCrop modeling on wheat (Huang et al., 2022; Kale et al., 2018). The canopy growth parameters related to the Raw_{MC} and Raw_{LC} were identical to those developed for the 2 default scenarios, and hence the performance indicators were also nearly equal. The same CC parameters were also carried over to the Cal_{LC} scenario, leading to non-significant differences in the respective r^2 and RMSE values.

In the Def_{MC} and Def_{LC} scenarios, the SHPs were calibrated using the literature, and the simulated VWC values were modeled significantly better for the Def_{MC} scenario (r^2 =0.59, RMSE=7.76%) relative to Def_{LC} (r^2 =0.38, RMSE=10.61%). These results would help in serving as a reference to compare with the results of including the VWC observations in the process of calibrating the SHPs, addressing research question 2. When the SHPs were modified based on the raw daily aggregated MC and LC sensor values (in the Raw_{MC} and Raw_{LC} scenarios respectively), the RMSE for both Raw_{MC} (5.69%) and Raw_{LC} (8.58%) scenarios both showed significant improvement compared to the respective default scenarios (Def_{MC} RMSE=7.76%, Def_{LC} RMSE=10.61%), and the r^2 value improved significantly in the case of the Raw_{LC} scenario (Raw_{LC} r^2 =0.46, Raw_{LC} r^2 =0.38). Since the r^2 value for the Raw_{MC} (r^2 =0.61) was non-significant.

water content (VWC) and biomass (BM), across the five crop model calibration scenarios. The effect of calibrating Table 4.2: Overall performance indices for major outputs of the AquaCrop-OS crop model - canopy cover (CC), volumetric Soil Hydraulic Parameters (SHPs) on crop model performance of the crop model shows that calibrated LC sensor data ("Cal_{LC}" scenario) gives nearly as good results as raw MC data (Raw_{MC}" scenario).

Crop model	Performance	$\mathbf{Default}_{\mathbf{MC}}$	$Default_{LC}$	Rawmc	Raw _{LC}	$Calibrated_{LC}$
output	Index	$({ m Def}_{ m MC})$	(Def_{LC})	(Raw_{MC})	(Raw_{LC})	(Cal_{LC})
		SHPs calik	SHPs calibrated using	SHPs calib	SHPs calibrated using	CUD, colibrated
Sce	Scenario	default lite	default literature values,	raw VWC n	raw VWC measurements	Srirs camprated
defi	definitions	and VWC	and VWC performance	from M	from MC and LC	using Dest Legal
		evaluated aga	evaluated against MC or LC	sensor re	sensor respectively	model, r w Lr-neid
CC (%)	r ² (%)	96:0	96:0	96.0	96.0	96:0
	RMSE (%)	5.71	5.71	5.72	5.76	5.72
(/0) ()/()/()	r ² (%)	0.59	0.38	0.61	0.46	0.56
(%)) M A	RMSE (%)	7.76	10.61	5.69	8.58	6.17
	$MAE (kg/m^2)$	0.11	0.11	0.11	0.109	0.111
PM (Lalm2)	$RMSE (kg/m^2)$	0.145	0.145	0.145	0.143	0.145
DIM (RB/IIII)	NRMSE (%)	13.417	13.417	13.416	13.289	13.496
	PBIAS (%)	-0.63	-0.63	-0.63	-0.57	-0.5



averaged over 5 field plots, for the 5 different AquaCrop-OS crop modeling scenarios (DefaultMC, DefaultLC, Raw_{MC}, Raw_{LC} and Calibrated_{LC}). Error bars and ranges in all figures represent the standard error of the respective Figure 4.6: Comparison of observed and AquaCrop-OS simulated ('sim') (a)-(e): Canopy cover (%) and (f)-(j): VWC (%) mean values across the five validation plots. DAS implies days after sowing.

When the SHPs were modified using the calibrated LC soil moisture data (in the Cal_{LC} scenario), there was an improvement in r^2 values (Raw_{LC} r^2 =0.46 to Cal_{LC} r^2 =0.56), as well as RMSE (Raw_{LC} RMSE=8.58% to Cal_{LC} RMSE=6.17%), which performs closer to the Raw_{MC} performance in general. This indicates the utility of calibrating LC sensors using MC sensors in terms of improving VWC simulation performance of AquaCrop. The VWC performance of this study was not as good as previous studies which employed either cumbersome gravimetric VWC measurements or highly accurate (and costly) neutron probes (Huang et al., 2022; Kale et al., 2018; W. Zhang et al., 2013). However, it was promising to note that significant improvements were obtained in the VWC simulations by calibrating the LC capacitance-based sensor even against an uncalibrated, medium cost (TDR-FDR) sensor.

4.3.2.2 Final crop model outputs: crop model yield and water productivity

Figure 4.7 illustrates the simulated aboveground crop Water Productivity ($WP_{\rm ET}$) for all the scenarios, as averages and standard error of the mean (SEM) for all the plots taken together. Table 4.2 also lists the MAE, RMSE and PBIAS for the respective BM values. AquaCrop-OS overestimated the observed biomass by an average of 0.11 kg/m2, and an average RMSE of 0.145 kg/m2, and NRMSE of 13.41%, which is considered to be a 'good' simulation performance (Jamieson et al., 1991; Raes et al., 2018).

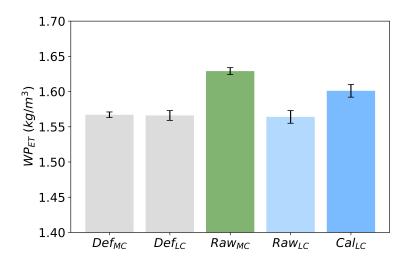


Figure 4.7: Comparison of AquaCrop-OS simulated Water Productivity ($WP_{\rm ET}$) averaged over 5 field plots, for the 5 different AquaCrop-OS crop modeling scenarios (Default_{MC}, Default_{LC}, Raw_{MC}, Raw_{LC} and Calibrated_{LC}). Error bars in all figures represent the standard error of the respective mean values.

In the context of the differences between the simulations of BM across scenarios, most of the observed differences were not significant. Hence, there were no significant differences in the simulated BM across the five scenarios irrespective of the strength of VWC simulation, indicating that the FAO AquaCrop simulation of biomass relied

primarily on the canopy curve development.

However, the effect of the different SHP calibration schemes could be seen through the water productivity WP_{ET} comparison across all scenarios. There was a significant improvement in WP_{ET} when the SHPs were calibrated using the MC sensor data as compared to the default literature (WP_{ET} for Def_{MC} = 1.566 \pm 0.009 kg/m³, WP_{ET} for $Raw_{MC} = 1.629 \pm 0.006 \text{ kg/m}^3$), due to significantly lower ET in Raw_{MC} compared to Def_{MC}. Comparing Def_{LC} and Raw_{LC}, there was a non-significant change in WP when LC sensors were used to calibrate the SHPs: $(WP_{ET} \text{ for Def}_{LC} = 1.566 \pm 0.009 \text{ kg/m}^3)$ $WP_{\rm ET}$ for Raw_{LC} = 1.564 \pm 0.011 kg/m³), which corresponded to the non-significant differences in simulated ET between the two scenarios, in addition to the non-significant difference in computed yield. This implies that incorporating the raw LC SM100 sensor data to calibrate SHPs was not significantly more useful compared to the taking literature values, and did not address any water saving objectives. However, when the LC sensors were calibrated using the MC sensors, there was a significant improvement in WP_{ET} $(WP_{\rm ET} \text{ for Raw}_{\rm LC} = 1.564 \pm 0.011 \text{ kg/m}^3, WP_{\rm ET} \text{ for Cal}_{\rm LC} = 1.601 \pm 0.010 \text{ kg/m}^3), due$ to the significant differences between simulated ET between both the scenarios. This implies that the raw LC SM100 sensors do not increase $WP_{\rm ET}$, but if they are calibrated using a higher quality sensor, they lead to significant improvements in $WP_{\rm ET}$.

4.3.3 Further discussion

This study focused on low-cost soil moisture measurements and calibration without accounting for other soil related factors to remain relevant in the context of irrigation management applications in the Majority World. Capacitance based sensing is affected by environmental factors including salinity, clay and temperature, which can be measured and compensated for, to improve performance at lower frequencies of soil moisture sensing (Deng et al., 2020). Hence, although the SMT100 measures temperature, these data were not included in the analyses. Machine learning algorithms may have performed better by incorporating more data and variables (e.g., weather), but this was also not done to keep the least squares and machine learning algorithms comparable in terms of the input data. The validations of the different soil moisture calibration models performed poorly than the recommended 3% sensor accuracy for soil moisture sensor based irrigation scheduling systems (K. Soulis et al., 2015). However, since this study was aimed at analyzing the effect of sensor calibration on relevant crop model outputs, this was not a valid concern within this context, and would need further investigation.

4.4 Conclusions

A set of best practices of calibrating capacitance based low-cost (LC) soil moisture sensors (Spectrum SM100 used in this study) was developed using two calibration approaches: calibrating against gravimetric water content in the using wet-up curve laboratory conditions, and calibrating against a TDR-FDR medium-cost (MC) soil moisture sensor (UGT SMT100) in the field. Different least squares and machine

learning approaches were used to calibrate the LC sensor. Field calibration was observed to be more robust than calibration in the laboratory. Calibration of the dry-down curve was found to be more accurate, and even calibrations using the dry-down curve in the laboratory were robust enough to perform similarly well as the superior field calibrations. Overfitting during calibration can lead to loss in robustness on the field, and hence, should be avoided. The best calibration model, considering the above issues, was the field calibrated piece-wise linear regression function (PWLF-field).

The soil hydraulic parameters (SHPs) of the FAO AquaCrop model were calibrated under different calibration schemes to understand the effect of using raw soil moisture sensor data, and the additional effect of calibrating the capacitance LC sensor, on model outputs. While VWC estimation improved significantly on incorporating the sensor data in calibrating SHPs compared to deriving them from the literature (except SMT100, where the default parameters also resulted in a good model performance), there were non-significant improvements in biomass simulation performance. However, the water productivity ($WP_{\rm ET}$) improved significantly while incorporating raw MC sensor data to calibrate SHPs. This was not seen while incorporating raw LC data, but on transforming the data using the best calibration model, a significant improvement was seen in the $WP_{\rm ET}$ compared to both the raw and default scenarios.

These experiments and modeling reveal that while the default SHPs from the literature may result in better simulations than using raw LC capacitance sensor measurements, calibrating the LC sensors using a higher-quality secondary standard sensor in the field may give rise to not only better VWC simulations by the crop model, but also significant improvements in water productivity.

5 Irrigation scheduling using soil water stress thresholds

5.1 Introduction

The Sustainable Development Goal 6 (UN, 2017), in particular, SDG Target 6.4, aims to: "By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity." This goal is particularly relevant to irrigation, which is the largest global consumer of freshwater resources, and is often cited for its profligate and inefficient water usage (Grafton et al., 2018; Y. Lu et al., 2016; C. Perry et al., 2017). Irrigation scheduling aims to provide plants with the appropriate quantity of water at the appropriate time, and can help in enhancing the performance of irrigation systems by increasing crop production and conserving water (Gu et al., 2020; Sikka et al., 2022).

Water is essential to plants since it supports photosynthesis, regulates temperature through evaporative cooling, maintains cell turgor pressure, and transports nutrients into and within the plant, consequently supporting plant growth (Gu et al., 2020). Both the lack and excess of adequate (irrigation) water can be detrimental, in terms of crop water stress at critical plant growth stages, and water losses through ponding, waterlogging, runoff and deep percolation leading to nurient leaching and pollution, respectively (Gu et al., 2020). Increasing the efficiency of irrigation can result from allowing plants to use the water stored in the entire root zone, and reducing water lost through soil evaporation and minimizing water leached beyond the root zone (Greenwood et al., 2010).

Irrigation scheduling has been classified into four major categories, based on the mechanism used for decision making: (i) evapotranspiration (*ET*) and soil water balance based, (ii) soil moisture based, (iii) plant water status based, and (iv) simulation model based (Gu et al., 2020). All four methods are centered around soil volumetric water content VWC, which connects crop water requirements and irrigation management.

In the evapotranspiration-water balance based method, the main consumptive component, i.e., Crop Evapotranspiration (mm.d⁻¹) (ET_c) is estimated, and then daily soil water deficit is computed using the soil water balance equation. Irrigation is scheduled when soil water depletion in the root zone exceeds the Readily Available Water (RAW). Any further increase in the soil water depletion leads to the inhibition of ET, which then inhibits crop growth (Greenwood et al., 2010). The Management Allowed Depletion (MAD) fraction (i.e., p), is the fraction of the Total Available soil Water (TAW) that RAW represents, i.e. p = RAW/TAW (Allen et al., 1998). Since the direct measurement of ET_c is costly and labor intensive (e.g., with lysimeters), ET_c is generally estimated using the two-step crop coefficient-reference evapotranspiration approach (Pereira et al.,

2015). This combines the Reference Evapotranspiration (mm.d⁻¹) (ET_o), which represents weather driven effects on water consumption, and the crop coefficient (-) (K_c), which is a crop-specific scaling factor depending on the variation of the crop-based influences during the cropping season (Pereira et al., 2015). Details of this approach are reported in the FAO Irrigation and Drainage Paper No. 56 (Allen et al., 1998). This method requires weather data, crop K_c curve, crop-specific MAD fraction, and soil properties, and is limited by the availability of such data and the cumulative errors which can result in a mismatch between the required and supplied irrigation water (Gu et al., 2020; H.G. Jones, 2004).

Soil moisture based irrigation scheduling compares measured soil moisture or volumetric water content (VWC) to a soil moisture threshold to trigger irrigation, so that VWC in the root zone can be maintained within ranges beneficial for crop growth, yield and quality (Gu et al., 2020; Viani, 2016). Soil water tension or soil matric potential measurements (by tensiometers) can also be used instead of soil moisture measurements to quantify the availability of soil water for plant use, and thereby irrigation requirements (Gu et al., 2020). Different methods have been reported in the literature to determine irrigation timings using either soil moisture thresholds (Haley and Dukes, 2012; Zotarelli et al., 2011), or soil water tension thresholds (Hoppula and Salo, 2007; Migliaccio et al., 2010; R.B. Thompson et al., 2007a). These threshold values are generally optimized for specific locations and crop species, due to their variation across soil properties and crops, respectively (Gu et al., 2020). Thresholds can be estimated either through field experiments (Hoppula and Salo, 2007; Migliaccio et al., 2010; J. Wang et al., 2017) or secondary literature (Haley and Dukes, 2012). This method requires sensor systems and verified soil moisture thresholds, but can be limited by their respective accuracies, and the non-representativeness of soil moisture measurements due to spatio-temporal soil moisture variability (Gu et al., 2020).

Plant based irrigation scheduling methods use indices describing plant water status to relate crop water stress and soil water deficit (Gu et al., 2020). Such methods have been reviewed by H.G. Jones (2004). While they do not directly indicate water requirement (Greenwood et al., 2010), they need a conversion of plant water status to an optimum VWC level for crop growth, which can vary across plant species, plant tissues and phenological stages due to variable sensitivity to water deficit (Gu et al., 2020). Thermal imaging is an extensively used approach which is based on measuring the drop in canopy temperature as a result of evaporation via the stomata, along with evaporative conditions in the surrounding atmosphere (H.G. Jones, 2004). This method requires a monitoring system with sensors and validated threshold conditions, and is limited by the requirement of relatively higher expertise of the operator, sensitivity of the measured parameters, and the challenge to remove the noise in the measured data (Greenwood et al., 2010; Gu et al., 2020).

Model based irrigation scheduling methods use either process-based or regression models which use optimization algorithms developed based on the soil water balance equation to determine irrigation timing and amount (Gu et al., 2020). This is similar to

the evapotranspiration-water balance method since both work essentially with models, but these models are more complex in terms of the crop growth processes and outputs that are incorporated into the model structure. Process based models investigate crop growth responses to different irrigation management strategies and can recommend irrigation schedules (Gu et al., 2020). Alternatively, regression models can be used by viewing the irrigation planning problem as optimal control problem with objective functions which minimize the total irrigation volume during the growing season (Lopes et al., 2016), or maximize the crop water productivity for a given total irrigation volume (Seidel et al., 2015). This method requires a calibrated model (based on previous field experiments), weather data and a developed code for the scheduling procedure, and can be limited by its crop- and site-specific results which may not be easily generalizable (Ortega Álvarez et al., 2004).

In this study, the evapotranspiration-water balance based method is used with a modified strategy to determine the MAD fraction(s) - as defined by the FAO AquaCrop model (Raes et al., 2009; Steduto et al., 2009; Vanuytrecht et al., 2014). Previously, FAO Aquacrop has been used to develop optimized irrigation frequencies during sensitive crop growth stages to develop easy-to-use charts for farmers (Geerts et al., 2010), without recommending the corresponding irrigation amounts (Gu et al., 2020). This study quantifies the effect of simulated irrigation schedules (i.e., timing and amount) using the soil water stress thresholds defined by FAO AquaCrop (Raes et al., 2009; Steduto et al., 2009), on the resultant water productivity, total irrigation, and water savings, and compares the corresponding results with the 'full irrigation' strategy.

5.2 Methodology

5.2.1 Study area

The study area was the experimental plot in IIT Kanpur where the wheat cropping experiment was conducted in 2018, as described in detail in Chapter 4. A model study was conducted to critically analyze the difference between the FAO AquaCrop irrigation scheduling approach (via its MAD conceptualization) and Full Irrigation (FI) conditions, using the FAO Aquacrop model (Raes et al., 2009; Steduto et al., 2009). FI maintains Field Capacity (FC) conditions in the root zone, a practice which stores sufficient water for plant uptake, but can lead to excessive water losses through soil evaporation and drainage beyond the root zone (Greenwood et al., 2010). Section 5.2.2 describes the FAO Aquacrop's conceptualization of MAD fractions (or p) (Raes et al., 2009; Steduto et al., 2009).

5.2.2 Soil water depletion threshold for no stress/soil water stress coefficients defined by FAO Aquacrop

The Total Available Water (TAW) is defined as the capacity of a soil to retain water for plants, ranging between the Soil moisture at field capacity (m³.m⁻³ or %) (θ_{FC}) and the Soil moisture at wilting point (m³.m⁻³ or %) (θ_{PWP}). Water is theoretically available until

the PWP but binds more strongly to the soil matrix as the water content in the root zone decreases (Allen et al., 1998).

The soil water content threshold below which soil water cannot be uptaken by roots quickly enough to satisfy the transpiration demand (resulting in crop water stress) is called the Readily Available Water (RAW), expressed as a fraction of the TAW:

$$RAW = p * TAW (5.1)$$

where *p* is the the soil water depletion fraction corresponding to the management allowed deficit (MAD). Values of *p* for different crops are listed in FAO56 (Allen et al., 1998). FAO56 assumes that a single MAD factor can be used to schedule irrigations, by keeping the soil water depletion below the RAW threshold (Greenwood et al., 2010). However, the sensitivity of crop growth to soil water deficit can vary across different crop growth stages (Salter and Goode, 1967). For example, wheat is more sensitive to water stress immediately before and during flowering (Musick and K.B. Porter, 1990). FAO Aquacrop disaggregates soil water stress coefficients into different components which affect different crop model variables, thus resulting in multiple MAD values corresponding to the most sensitive water stress in a particular growth stage (Raes et al., 2009; Steduto et al., 2009; Vanuytrecht et al., 2014).

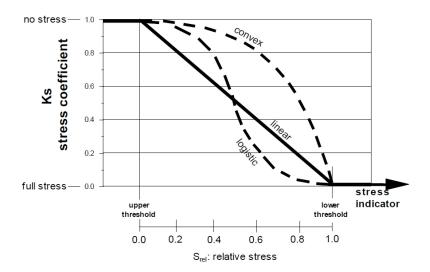


Figure 5.1: Conceptualization of individual stress response functions in FAO Aquacrop (Raes et al., 2009). The upper threshold corresponds to the level of the stress indicator at no stress (i.e., relative stress, $S^{\rm rel}$ =0 and $K^{\rm s}$ =1) and the lower threshold corresponds to fully stressed conditions (i.e., relative stress, $S_{\rm rel}$ =1 and $K_{\rm s}$ =0).

Table 5.1: Description of different soil water stresses defined in FAO AquaCrop, along with their direct effect, target AquaCrop variable, upper and lower thresholds. Table is modified from Raes et al. (2009).

Soil water stress coefficient	Direct effect	Target model parame- ter	Upper threshold (p_up)	Lower thresh- old (p_lo)
Soil water stress coefficient for canopy expansion (-) $(Ks_{exp,w})$	Reduced canopy expansion; possible positive effect on harvest index (depending on time and strength of stress)	CGC, HI	0.2	0.65
Soil water stress coefficient for pollination (-) (Ks _{pol,w})	Affects pollination; possible negative effect on harvest index (depending on duration and strength of stress)	HI_{o}	0.8	0.1
Soil water stress coefficient for canopy senescence (-) (Ks _{sen})	Reduced green canopy cover	CC	0.7	1
Soil water stress coefficient for stomatal closure (-) (Ks_{sto})	Reduced crop transpiration and root zone expansion; possible negative effect on harvest index (depending on timing and strength of stress)	Tr _x , HI, dZ	0.65	1

CC - Canopy Cover; CGC - Canopy Growth Coefficient; dZ - root zone growth rate $\mathrm{HI_0}$ - initial Harvest index; HI - Harvest Index; $\mathrm{Tr_x}$ - potential transpiration

FAO Aquacrop defines four stresses overall - soil water stress, air temperature stress, soil fertility stress and soil salinity stress (Raes et al., 2009; Steduto et al., 2009). Bruckmaier (2021) presents a detailed overview on the description of the soil water stresses in FAO AquaCrop; each stress is computed using the approach depicted in Figure 5.1 (Raes et al., 2009). Out of the four stresses, this study focused on (preventing) soil water stresses. In FAO AquaCrop, soil water stress has impacts on canopy cover development, root zone expansion rate, stomatal closure and consequently a reduction in crop transpiration rate. It can also alter harvest index and, if severe, can lead to failure in pollination which can trigger early canopy senescence.

FAO AquaCrop's soil water stresses are differentiated into the following stresses which are defined in Table 5.1, along with their respective effects, target model parameter and

upper and lower thresholds. They include Soil water stress coefficient for water logging (aeration stress) (-) (Ks_{aer}), Soil water stress coefficient for canopy expansion (-) ($Ks_{exp,w}$), Soil water stress coefficient for pollination (-) ($Ks_{pol,w}$), Soil water stress coefficient for canopy senescence (-) (Ks_{sen}) and Soil water stress coefficient for stomatal closure (-) (Ks_{sto}). The upper threshold (p_{up}) is the higher VWC (lower soil water depletion) where the respective water stress coefficient starts to fall below 1, and the lower threshold (p_{lo}) is the lower VWC at which the water stress coefficient reduces to zero.

5.2.3 Irrigation scheduling in FAO AquaCrop

With an understanding of the four different FAO AquaCrop water stresses ($Ks_{\text{exp,w}}$, $Ks_{\text{pol,w}}$, Ks_{sen} and Ks_{sto}) and their p_{up} values across the four crop growth stages (initial, crop development, mid-season and late-season), a daily time-series of the overall critical p_{up} values was developed, to avoid all water stresses across the entire cropping season. This is depicted in Figure 5.2.

Figure 5.2 (a) depicts the same stress response function to changing soil water depletion (as presented in Figure 5.1). The representational image of the crop and root zone in Figure 5.2 (b) illustrates the same response function in terms of root zone depths with indicative root zone depletion values shown on the left. The non-stressed region (between root zone depletion values of zero and $p_{up} * TAW$) and fully stressed region (between depletion values of $p_{lo} * TAW$ and TAW) are highlighted with blue and yellow shading respectively.

Figure 5.2 (c) presents a time series of the four different water stresses across the 100-day cropping season with their active operational periods (out of the crop growth stages printed on the top) with their respective p_{up} and p_{lo} thresholds.

The canopy expansion stress ($Ks_{exp,w}$) has the critical p_{up} value (0.2, from Table 5.1) during the initial and crop development stage as vegetative growth is driven by canopy expansion. Since the end of the crop development stage coincides with the achievement of maximum canopy cover (or effective full cover, Allen et al., 1998), the remainder of the $Ks_{exp,w}$ period is shaded in a lighter green color, and is not critical to avoid stress. In the mid- and late-season stages, stomatal closure is the critical water stress (Ks_{sto}) since the primarily reproductive growth is limited by transpiration which drives biomass accumulation via AquaCrop's water productivity parameter (Steduto et al., 2009). The corresponding critical p_{up} value is 0.65.

In Figure 5.2 (c), the $p_{up,all}$ threshold, which is depicted with the thicker black line, is the upper soil water depletion threshold (or MAD fraction) which avoids all four soil water stresses. Subsequently, the critical p_{up} values not to be exceeded to prevent water stress are 0.2, 0.2, 0.65 and 0.65 during the initial, crop development, mid-season and late-season stages, respectively.

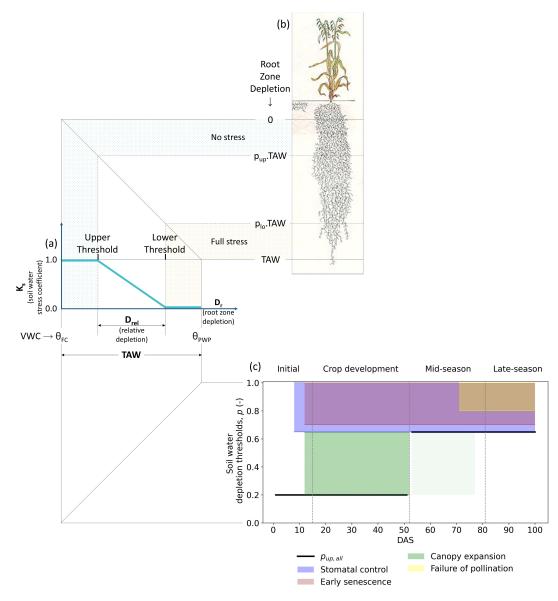


Figure 5.2: (a) General stress response function for individual water stresses in FAO AquaCrop. (b) Representational image of root zone with soil water depths corresponding to the stress response function. (c) Time series of individual stress response functions. The upper threshold corresponds to the level of the stress indicator at no stress (i.e., relative stress, $S_{\rm rel}$ =0 and $K_{\rm s}$ =1) and the lower threshold corresponds to fully stressed conditions (i.e., relative stress, $S_{\rm rel}$ =1 and $K_{\rm s}$ =0). The overall level of $p_{up,all}$ to avoid all stresses is given as a thick black line in the time series. Figures (a) and (b) are modified from Raes et al. (2009).

AquaCrop-OS provides the option of scheduling irrigation with soil moisture thresholds (T. Foster et al., 2017; Raes, 2017). The soil moisture values corresponding to these soil water depletion thresholds were inserted as thresholds to trigger irrigation while avoiding any water stress. In the FI scenario, AquaCrop-OS was programmed in a manner that irrigation was triggered every time the soil moisture went below θ_{FC} . In both cases, irrigation was applied to bring the VWC to θ_{FC} .

These simulation experiments were conducted in the five validation plots calibrated with the best performing model parameters, the MC_{raw} parameters, as defined in Chapter 4. The results compare model outputs such as ET water productivity (WP_{ET}), total irrigation (mm), and other explanatory soil water balance components to analyze the difference between FI and FAO AquaCrop based stress-avoiding irrigation strategies.

5.3 Results and Discussion

The FI and FAO Aquacrop irrigation strategies were simulated on the five validation plots referred to in Chapter 4. A comparison of the relevant AquaCrop outputs over the entire season is given in Table 5.2.

Table 5.2: Comparison between the seasonal values (mean \pm standard error) of relevant variables for Full Irrigation and FAO AquaCrop irrigation strategies.

Relevant variables	Full Irrigation	FAO AquaCrop
Rainfall (mm)	50.4	50.4
Total irrigation (mm)	537.28 ± 0.17	426.06 ± 5.02
Total soil evaporation, E_s (mm)	100.33 ± 1.51	86.95 ± 1.68
Total plant transpiration, $T_{\rm r}$ (mm)	250.53 ± 1.46	250.53 ± 1.46
Total evapotranspiration, ET (mm)	350.86 ± 2.1	337.48 ± 2.23
Total deep percolation, Deep Percolation (DP) (mm)	13.14 ± 0.21	0
Final biomass (kg/m²)	1.09 ± 0.06	1.09 ± 0.06
Potential biomass (kg/m²)	1.09 ± 0.07	1.09 ± 0.07
Yield (kg/m²)	0.51 ± 0.03	0.51 ± 0.03
ET Water Productivity, WP _{ET} (kg/m ³)	1.44 ± 0.01	1.50 ± 0.01

Across both strategies, average canopy growth and root zone development were identical, and canopy growth was not limited and was always equal to the potential canopy growth (in all the plots). The average total transpiration over the entire season was also identical across both the strategies (250.53 \pm 1.46 mm) Moreover, the average biomass accumulated with both strategies were equal to each other (10.85 kg/m²) and were equal to the respective potential biomass values (also 10.85 kg/m²). Principally, the yield values generated by both strategies were 5.13 \pm 0.03 t/ha (or 0.513 \pm 0.003 kg/m²). These results imply that both the strategies didn't result in any stresses which may have limited any of these variables from obtaining their potential growth.

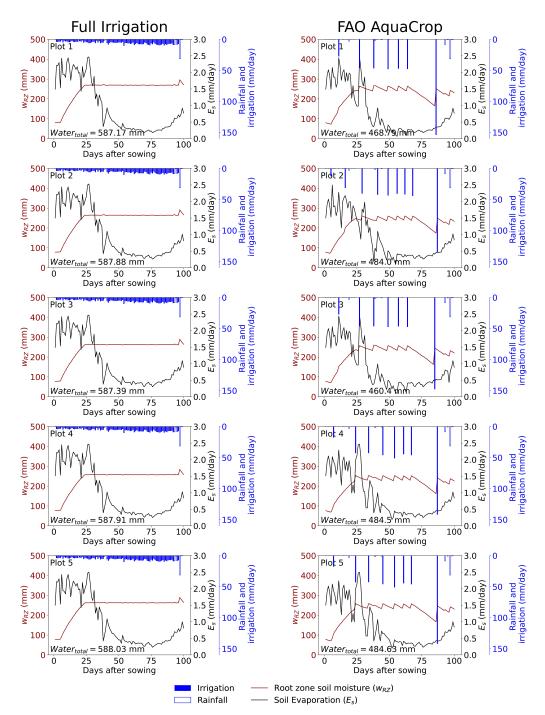


Figure 5.3: Key water balance components of the Full (left) and FAO AquaCrop based irrigation (right) strategies for the five validation plots (mentioned at the top left of each panel). Rainfall and irrigation are plotted as inverted bar graphs, and soil evaporation (E_s) and root zone soil moisture (Root zone soil water content (mm) (w_{RZ})) are illustrated with line graphs. Total applied water (rainfall and irrigation), $Water_{total}$, is printed on the bottom left of each panel.

The differences between the strategies were seen in the Root zone soil water content (mm) (w_{RZ}), soil evaporation (E_s), which along with the different soil water depletion thresholds, led to the differences in irrigation schedules and eventually total irrigation. A time series of these variables across all plots and both the strategies is given in Figure 5.3.

The total irrigation applied in the FI strategy was 537.28 ± 0.17 mm, as opposed to 426.06 ± 5.02 mm applied in the FAO AquaCrop strategy, and the difference between the two was statistically significant. The FI irrigations were triggered on 91 days during the 100 day season, with an average amount of 5.42 ± 0.26 mm. The only days when irrigation wasn't triggered was on the day of sowing (since the initial water content was set to θ_{FC}), and the days when there was rainfall which was greater than 3 mm. On 96 DAS (days after sowing), there was a rainfall event of 31.4 mm, which led to no irrigation till the end of the season. Comparatively, the FAO AquaCrop strategy simulated 7-9 irrigations, with higher number of irrigations in plots with lower TAW. The average irrigation amounts increased from 12.7-17.8 mm (within the first 10 DAS) to a maximum of 144.29 mm (averaged across the plots) for the last irrigation application. The average irrigation amount for the non-terminal irrigation applications was 45.02 mm (across all plots).

The difference between the irrigation application amounts could be explained by the differences in root zone soil water storage (w_{RZ}), soil evaporation (E_s) and Deep Percolation (DP). The higher irrigation application led to a higher overall E_s in the FI strategy (100.33 \pm 1.51 mm) compared to the FAO AquaCrop strategy (86.95 \pm 1.68 mm). Additionally, there was 13.14 \pm 0.21 mm of deep percolation that occurred in the FI as opposed to no DP in the FAO AquaCrop strategy. The w_{RZ} at the end of the cropping season was significantly higher for FI (272.51 \pm 2.05 mm) compared to FAO AquaCrop (232.34 \pm 2.31 mm). Most of this difference in w_{RZ} was accumulated during the mid-season stage, after 53 DAS. This is because FAO AquaCrop's critical soil water depletion fraction (i.e., p_{up}) changed from 0.20 to 0.65, allowing the root zone to become more depleted without resulting in any stresses. This also led to the relatively higher irrigation application amount during the last irrigation which occurred just following the stage change from mid-season to late-season stage.

Finally, despite the same yield obtained across both strategies, the ET water productivity ($WP_{\rm ET}$) was significantly higher for the FAO AquaCrop strategy ($1.5 \pm 0.01~{\rm kg/m_3}$) compared to the FI strategy ($1.44 \pm 0.01~{\rm kg/m_3}$), due to the significant differences in the $E_{\rm s}$. These results imply that changing irrigation strategy from full irrigation to one where soil water depletion thresholds are not crossed can lead to significant irrigation water savings and increase in $WP_{\rm ET}$ without incurring losses in yield, due to reduction in soil water storage in the root zone, soil evaporation and deep percolation while satisfying the crop transpiration demand.

5.3.1 Further discussion

This study focused on comparing the impact of reducing irrigation input to avoid water stresses as conceptualized by FAO AquaCrop with full irrigation conditions. Hence, deficit irrigation as a scheduling strategy was not within the scope of the study. Deficit irrigation is an optimization strategy where irrigation is applied to water-sensitive growth stages of a crop to maximize WP_{ET} rather than avoiding reductions in yields (H. Zhang and Oweis, 1999). However, this is also dependent on the farmer's strategy and constraints, which can vary based on a combination of factors like socio-economic condition, farm size, and availability of resources. A smallholder farmer may want to maximize yield if there is no dearth of irrigation water supply, and may only resort to maximizing WP_{ET} in case of water limiting conditions. Similarly, larger commercial farms with higher input investment (including water) may need to optimize resource efficiency to maintain profit margins. Nonetheless, the FAO AquaCrop irrigation strategy was able to save 111.22 mm of irrigation water on average, which constitutes around 1.5 irrigations (assuming an average irrigation application amount of 75 mm, Prihar et al., 1978) without incurring any biomass or yield losses. Also, maintaining conditions of field capacity is cumbersome as there were 91 days of irrigation application in the FI strategy as opposed to 7-9 days in the FAO AquaCrop strategy. This can be especially labor intensive for smallholder farms which may not have mechanization to automate irrigation management, and need the supervision of farmers during irrigation application, as well as access to reliable water sources and withdrawal techniques (diesel or electrical irrigation pumps etc.). Another limitation of this study is that the results were obtained using simulation modeling of experimentally calibrated field plots. Hence they can be generalized further only after validation through appropriately designed experiments combining both simulation modeling and field experimental components. Further studies on irrigation scheduling can investigate soil moisture management based on an improved understanding of the effects of soil moisture on crop growth, either by integrating different irrigation scheduling methods, or developing new methods using intelligent algorithms (Gu et al., 2020).

5.4 Conclusions

A simulation study was conducted using the FAO AquaCrop model, to compare two different irrigation scheduling strategies - 'full irrigation' which implies constant conditions of field capacity, and the FAO AquaCrop strategy, which avoids the generation of soil water stresses by not crossing critical soil water stress thresholds as defined by the model. The study was conducted for the spring wheat crop during the winter cropping season (2018) in Kanpur, India, based on five plots previously calibrated using the AquaCrop model. There were no changes across the irrigation strategies on the final model output variables like biomass, yield, and the intermediate model outputs like canopy cover, root zone development and total plant transpiration for the growing season, which implied identical (non-stressed) crop development across both strategies.

There was a significant reduction in total applied irrigation of 111.22 mm on average moving from the FI to FAO AquaCrop irrigation strategy, corresponding to the average value of 1.5 irrigation application amounts of 75 mm each. Also, ET water productivity increased significantly from the FI to FAO AquaCrop strategy, due to a reduction in root zone soil water storage, soil evaporation and deep percolation. Also, the number of irrigation applications was about 10 times higher for FI strategy, increasing input costs particularly in the context of smallholdings. The results highlight the utility of irrigation scheduling using the FAO AquaCrop strategy to avoid water stresses, to reduce water input without reducing yields, hence increasing water productivity.

6 Discussion, conclusions and outlook

The importance of improving water use efficiency and water productivity, particularly in intensive and subsistence agriculture, to ensure food security without compromising either crop productivity or environmental sustainability, cannot be overstated. One strategy to address this problem is by first diagnosing the limitations in farm performance using a data-based, plot-scale approach, and then developing cost-effective tools which combine soil water measurements and parsimonious crop modeling to recommend techniques to improve irrigation management. This study employed a four step approach to address the above problem (see also Chapter 1): (i) developing a data-based approach for plot-scale farm performance diagnostics, (ii) calibrating and testing low-cost soil moisture sensors in the laboratory, (iii) combining calibrated soil moisture sensor data with parsimonious crop modeling, and (iv) scheduling irrigation to avoid stresses and improve water savings and water productivity. For each of these topics, research questions were proposed and addressed in a series of methodologies (see Chapters 2 to 5). In this chapter, the results of each of these studies are critically discussed in Section 6.1, major conclusions drawn from each study are summarized in Section 6.2, and an outlook on possible research which could be attempted in the future is described in Section 6.3. All of these descriptions generally pertain to spring wheat cultivation in the intensively managed rural landscape of Kanpur, India.

6.1 Discussion

Agricultural extension providers usually administer generic advisories which are not customized at a plot-scale. Though there is a paradigm shift towards data-based advisories, they are still rather generic. Cost effective advisories that are data-based and farm-specific can potentially improve farmer-advisor relations and extension services in a disruptive manner. The data-based agricultural advisory diagnostics approach proposed in Chapter 2 focused on two factors which have been identified as most critical to yield gaps, nutrients and water, and incorporated both objective and subjective elements, potentially resulting in a robust solution that can support advisory development. Its objective elements included the laboratory testing of different soil (nutrient) parameters. Subjectivity was introduced both from the perspective of the farmer, via surveys seeking data on self-reported yields and number of irrigation applications, and the advisor, via heuristic expert knowledge regarding which soil parameters (relevant to the region in question) should be included in the analysis and the relative importances of each parameter pair (as an input to the Analytic Hierarchy Process). Naturally, this diagnostics approach has financial and logistical implications related to regular soil sampling and testing, data management, and skill development of the extension staff, which can become economically impractical for NGOs or farmer organizations to sustain independently. However, the current focus of the Government of India on improving

overall soil quality under various schemes, through initiatives such as regular soil testing and distribution of soil health cards (Kaur et al., 2020), may provide a favorable environment for such a tool to be adapted and applied extensively. Though the proposed approach was tested on farm data, and classified and visualized farm performance, there were no follow-up studies conducted with either farmers or advisors to test whether these diagnostics could quantitatively improve farm performance. This would involve more intensive and concerted testing with different stakeholders. Also, the demand from citizens to be engaged as stakeholders in planning related to decisions that impact them and their communities, has recently increased (Voinov et al., 2016). This reinforces the importance of stakeholder interaction as a prerequisite to 'understand, negotiate, and mediate the variable of interest' (Srinivasan et al., 2017). While this study was motivated by some of the authors' field surveys in same study area in Kanpur for various research projects (Adla et al., 2017; Gupta et al., 2017; Gupta et al., 2019; Hossain et al., 2020b), there was no focused effort to carry out stakeholder interaction directly regarding this study.

This study consequently concentrated on soil moisture or volumetric water content (VWC) as a key parameter to the overall problem statement of agricultural water use efficiency and water productivity. Supplemental irrigation facilities have been identified as a major challenge for smallholder farmers who face severe agricultural distress, and sensor based systems for VWC monitoring for irrigation management and other applications can be one way to address this challenge, provided the developed solutions are cost-effective. Soil moisture sensors determine VWC indirectly by measuring some soil property which is a proxy of the moisture content (such as resistance, interaction with neutrons, or dielectric constant ϵ_r), and sensors may also exhibit variability from one sensor to another, and across different soils. Hence, it is essential to calibrate soil moisture sensors and test them for different environmental conditions before applying them on the field. In Chapter 3, two Low-cost (LC) and two Very low-cost (VLC) soil moisture sensors were calibrated and tested in laboratory conditions to characterize their applicability for low-cost irrigation management. The LC capacitance based sensors were the Spectrum SM100 sensor (costing about United States Dollar (USD) 90), and the Spectrum SMEC300 sensor which had additional temperature and salinity sensing ability (costing about USD 220). The two VLC resistive sensors were the Electronic fans Soil Hygrometer Detection Module Soil Moisture sensor YL100 (about USD 4), and the KitsGuru Generic Soil Moisture Sensor Module YL69 (about USD 2). The sensors were calibrated with repacked soils to develop soil-specific calibration equations for four soils, to determine the accuracy, precision and sensor-to-sensor-variability, and to compare the performance of the equations developed in-house with those provided by the manufacturer (only for LC sensors). Testing in the laboratory was conducted with the objectives to understand the ability of capacitance based sensors to estimate the ϵ_r values of various standard fluids, and to analyze how variations in temperature and electrical conductivity (EC) modified the sensors' performance. Piece-wise linear calibration functions were developed for all the sensors.

Repacked soils were used for many of the experiments (in Chapter 3). However, different studies report contrasting claims about the reliability of repacked soils for soil moisture sensor calibration. Studies use both repacked (Nagahage et al., 2019; Placidi et al., 2020) and undisturbed (Bello et al., 2019a) soils for laboratory calibration. While studies have recommended calibration on-site or on undisturbed soils (Feng and Sui, 2020) because repacking alters natural soil structure (Czarnomski et al., 2005), repacked soils have also been recommended for better precision (Starr and Paltineanu, 2002). Notwithstanding this academic debate, many manufacturers perform calibration in the laboratory with sieved, uniformly packed, homogeneous soils (particularly some sands and loams), with regulated environmental conditions (Feng and Sui, 2020). Although soil moisture is also sensitive to factors such as bulk density and gap between the sensor body and soil (Kargas and K.X. Soulis, 2012; Matula et al., 2016a), packing density could not be introduced as an experimental variable due to resource constraints. Another contentious issue regarding soil moisture sensor calibration is whether to use the drydown or the wet-up curve for calibration. Dry-down curves may be more representative to field conditions as well as superior in terms of calibration accuracy (Burns et al., 2014). However, it is claimed that wet-up curves (with either upward or downward infiltration) are faster to calibrate (taking < 1 day) than dry-down curves which can sometimes take even more than 1-2 weeks to calibrate (Burns et al., 2014). In Chapter 3, wet-up curves were calibrated following the methodology suggested by Matula et al. (2016a) to calibrate and test multiple LC and VLC sensors manually with limited resources.

Several methods have been developed which combine data from ground sensor networks with agro-hydrological modeling to improve irrigation water management. For such methods to be effective, it is necessary to obtain accurate data as well as understand biophysical processes of crop response to water at different crop growth stages. Water-driven crop models, which simulate crop growth and production as a response to the soil-water environment, need to be parsimonious in terms of their data and parameter requirements, to be applicable in data scarce regions like the Majority World. Additionally, soil moisture sensors being combined with such models need to be cost-effective, maintainable, and site-calibrated to be effective. Chapter 4 combined the previously investigated LC SM100 soil moisture sensor with the parsimonious AquaCrop model developed by the Food and Agricultural Organization (FAO) of the United Nations to test the impact of different laboratory and field calibration techniques on crop model performance in the field. The soil hydraulic parameters (SHPs) of the FAO AquaCrop model were calibrated under different calibration schemes to understand the effect of using raw soil moisture sensor data, and the additional effect of calibrating the capacitance based LC sensor, on model outputs.

The study undertaken in Chapter 4 had the following implicit assumptions. The field soil moisture measurements were assumed to capture the plot-scale spatio-temporal soil moisture variability. Measurements were carried out using two sensors (one each of LC and MC) per plot (of size 3 m \times 3 m), placed at the center of the plot at a depth of 5 cm from the soil surface with a measurement frequency of 15 minutes. While this was

reasonable in capturing the temporal variation after aggregation to daily values (since crop model computations were conducted at a daily time step), there was no explicit incorporation of the spatial variability within the plot. Soil hydraulic properties may exhibit considerable spatial variability, also within parameters which may be assumed to be homogeneous (K.R. Bell et al., 1980). The spatial variability of soil moisture can have characteristic length scales from a few centimeters to several kilometers (Vereecken et al., 2014). Plot-scale spatial variability of soil moisture has been analyzed by previous studies (K.R. Bell et al., 1980). Quantitative methods such as geostatistics, wavelet and spectral analysis, multi-fractal analysis, fuzzy set analysis and state-space analysis have been used to understand the spatio-temporal patterns and dynamics of soil properties across a range of scales (B.C. Si, 2008). A study was conducted using the soil moisture sensor data during the 2018 cropping season to comparatively analyze the impact of varying spatial resolution of soil moisture data on plot scale soil moisture variability using deterministic and geostatistical soil moisture interpolation techniques (Ghimire, 2020). Simulating crop heterogeneity accurately ideally requires incorporating the spatial variability in soil moisture as well (J.T. Ritchie, 1981; V.O. Sadras et al., 2016; Verhagen and Bouma, 1997). However, FAO AquaCrop carries out daily computations at the point scale, and while this is accepted as a limitation of current crop models, it has received limited attention (Ahuja et al., 2014; J.W. Jones et al., 2017). Hence, spatio-temporal variability could not be incorporated into Chapters 4 or 5, both of which used FAO AquaCrop for their model simulations. The optimum placement and number of soil moisture sensors is also a factor to consider to improve irrigation scheduling (including automation, performance and cost-effectiveness) (Pramanik et al., 2022).

The FAO AquaCrop model is calibrated on a trial-and-error basis (Liang et al., 2017; H. Ma et al., 2020; Raes, 2017; Steduto et al., 2012). This technique (as opposed to more systematic methods) can challenge the replication of the model calibration, preclude the achievement of the global optima of the objective function (Wallach et al., 2001), and can make the model calibration process cumbersome for complex systems or multiple measured locations (Tolson and Shoemaker, 2007). Some tools have been developed for automating and systematizing the process of sensitivity analysis and model calibration - such as the propeitary SWAT-CUP software for the SWAT (Soil & Water Assessment Tool) hydrological model (Abbaspour, 2015), or the Dockerized Job Scheduler for the National Water Model of the USA (Raney et al., 2022). Such tools are intended to 'lower the model usage entry barrier' by automating simulation runs and model calibration (Raney et al., 2022). While some studies have investigated sensitivity analysis and model calibration in FAO AquaCrop (Y. Lu et al., 2021a; 2022; Silvestro et al., 2017; Xing et al., 2017), a comprehensive yet user-friendly sensitivity analysis and calibration tool is not yet available for the model, which limits its functionality and replicability. This limitation has been addressed to an extent by the recently developed Automated AquaCrop OS tool (Bruckmaier, 2022b) which is based on the coupling of AquaCrop-OS (T. Foster et al., 2017) and the Sensitivity Analysis For Everybody (SAFE) toolbox (Pianosi et al., 2015). However, this effort requires further investigation and development.

Model calibration resulting in single-valued parameter sets (i.e., each parameter in the calibrated model parameter has one 'effective ' value) may not account for model equifinality, i.e., the possibility of multiple parameter sets resulting in the same model output (Abbaspour, 2015; Beven and Freer, 2001; Khatami et al., 2019). Using such single-valued optimal parameter sets for model application may limit the effectiveness of any subsequent decision making (He et al., 2009; Sheng et al., 2019). Hence, there is a need to quantify the uncertainty associated with model structure, parameters, and input data (Moges et al., 2020). Several approaches have been developed for parameter estimation and uncertainty analysis, including the Sequential Uncertainty Fitting (SUFI-2, Abbaspour et al., 2004; 2015), Parameter Solution (ParaSol), and Bayesian methods (Beven and Binley, 1992; Kuczera and Parent, 1998; D. Lu et al., 2017; McMillan and M. Clark, 2009; Tao et al., 2009; Vrugt et al., 2009). While some research has focused on analyzing the uncertainty in crop modeling systems (He et al., 2009; Sheng et al., 2019; Yan et al., 2020), an extensive study to quantify uncertainty for FAO AquaCrop is yet to be reported. Some progress was made on sensitivity analysis and understanding uncertainty in AquaCrop (Bruckmaier, 2022a), but there is still a need for more comprehensive studies which quantify uncertainty and address the equifinality problem within the AquaCrop model.

Crop water requirement can also be computed empirically using indirect estimation techniques such as the two-step crop-coefficient-reference-evapotranspiration (K_c - ET_o) approach (Pereira et al., 2015), described in the FAO56 paper (Allen et al., 1998). The ET_o represents the weather driven effects on water consumption, and the crop coefficient (K_c) is a scaling factor specific to the crop, which represents the variation of the crop's influence on crop water requirement across the crop growth stages (Pereira et al., 2015). Subsequently, irrigation can be scheduled to either replenish the crop water requirement (accounting for precipitation), or triggered when the depletion equals readily available water (RAW), both of which avoid any soil water stresses (Allen et al., 1998). This approach was also attempted within an unpublished study developed during the study period. The study utilized microlysimeter based estimates of soil evaporation (E_s) and plant transpiration (E_s) (A. Kumar, 2019) and the two-step E_c - ET_o method to develop empirical crop coefficients for the spring wheat variety (E_s) used in this study. However, since the FAO AquaCrop model disaggregates soil water stress coefficients into different components, it was selected to simulate irrigation scheduling in Chapter 5.

Applications of crop model simulation include yield forecasting, adaptation to and impact assessment of climate change, crop breeding, yield prediction, support to policy makers, and strategic management decision making (Ewert et al., 2015; Rosenzweig et al., 2013; R. Rötter et al., 2015). Chapter 5 focused on irrigation scheduling with the objective to prevent water related stresses from occurring during the cropping season. The study compared two different irrigation scheduling strategies, 'full irrigation' (FI) and the FAO AquaCrop strategy which avoided all water stresses (related to canopy expansion $Ks_{\rm exp,w}$, canopy senescence $Ks_{\rm sen}$, stomatal closure $Ks_{\rm sto}$ and pollination $Ks_{\rm pol,w}$).

In water-limited regions, agriculture should optimize net income (or yield) per unit

water instead of net income (or yield) per unit land (Zhi et al., 2022). Hence, deficit irrigation, which aims at stabilizing yields and maximizing water productivity (H. Zhang and Oweis, 1999), can be used as an irrigation scheduling strategy instead of scheduling supplemental irrigation while avoiding stresses as proposed by Allen et al. (1998) and FAO AquaCrop (Raes et al., 2009). Deficit irrigation applies water below ET requirements (Fereres and Soriano, 2007), and optimizes irrigation scheduling within the drought-sensitive crop growth stages, with less or no irrigation applied to drought-tolerant, vegetative or late ripening phenological stages (Geerts and Raes, 2009). There have been numerous experimental studies which have explored the effect of deficit irrigation on wheat cropping systems (Kang et al., 2002; Tari, 2016; Thapa et al., 2019), some of which proposed soil moisture thresholds resulting in acceptable levels of soil water deficit (Benabdelouahab et al., 2016; S.C. Ma et al., 2016; Panda et al., 2003). Further, optimization algorithms have also been used to simulate irrigation strategies under deficit irrigation, and consequently develop tools such as the Deficit Irrigation Toolbox (Schütze and Mialyk, 2019; Seidel et al., 2015), which is also coupled with AquaCrop-OS. It has been applied to simulate different irrigation strategies under hydroclimatic variability (Gadédjisso-Tossou et al., 2018; Orduña Alegría et al., 2019), or extend the scope to study economic effects of such irrigation strategies on crop production (Gadedjisso-Tossou et al., 2019). However, the study in Chapter 5 aimed at quantifying the water savings for an irrigation strategy which avoided water stresses, which was also found to be significant. Also, subsistence farmers may still prioritize yield rather than water productivity, which is behaviourally similar to the inclination of farmers to keep practising rice-wheat cropping system because it provides more stable incomes despite stagnating productivity (George, 2014).

6.2 Conclusions

The main conclusions from the thesis are summarized in Table 6.1, and outlined below:

• Data-based, farm-scale agricultural performance diagnostics can supplement pre-existing, demand-based, generic advisory programs, particularly in the Indian context: a methodology was proposed to balance the trade-off between data-based plot-scale farm performance diagnostics and upscaling the applicability of such a tool by contextualization its outputs to a region. The diagnostics approach first quantified farm performance based on soil and water indicators, i.e., a localized Soil Quality Index (SQI) and Water Use Efficiency (WUE), respectively. It subsequently classified farms into different performance categories, and visualized this classification on a two-dimensional plane (of performance). A user-friendly, freely available, open-source tool, the Farm-Agricultural-Diagnostics-toolbox, was developed using Microsoft Excel-VBA, which can automate this process. Field testing of this tool in Kanpur classified 24% farms as nutrient-limited, 34% farms as water-limited, 27% farms as having nutrient and water co-limitations, and the remaining 15% farms as satisfactory, based on a localized performance target.

Further, farms were divided into "Best Practice Farms" which could potentially be model farms, "Quick Improvement Farms" which had low WUE despite having high SQI performance, and "Critical Farms" which perfomed poorly in terms of both nutrient and water performances. Additionally, a GIS database was developed to provide visual support for these diagnostics, to potentially lead to more efficiently administered advisories. This conceptualization could assist not only agricultural advisors, but also academia, government and non-government agencies working in agriculture to harness their respective strengths to suggest customized advisories and strategically establish connections between different types of farmers to encourage co-learning by exchanging knowledge, experiences, and best practices in agricultural management.

- Laboratory calibration and testing of low-cost capacitance based sensors can lead to improved, robust performance: The LC capacitance sensors (SM100 and SMEC300) had acceptable performance in terms of accuracy and precision, as well as sensitivity to temperature and salinity, establishing them as prospective sensors to be investigated for field experiments associated with irrigation management. In particular, the Spectrum SM100 sensor was recognized as a robust, cost effective sensor which could be calibrated and tested for field application. However, VLC resistive sensors (YL69 and YL100) were deemed unsuitable for irrigation management due to either their poor performance in high EC conditions or their lower than acceptable accuracy (threshold of acceptability was 3% VWC, K. Soulis et al., 2015) for field application. The cost of the sensor is generally proportional to the precision performance of the sensor, i.e., higher cost implied more precise sensing.
- Field calibration results in superior soil moisture sensor calibration for irrigation management, followed by laboratory calibration using dry-down curve (provided that overfitting is avoided in both cases): A set of best practices of calibrating capacitance based LC soil moisture sensors was developed using two calibration approaches: calibrating against gravimetric water content in laboratory conditions using wet-up curve, and calibrating against a TDR-FDR medium-cost (MC) soil moisture sensor (UGT SMT100) in the field. Sensor calibration was carried out using various least squares regression methods (like piece-wise linear regression, quadratic, cubic, power law) as well as machine learning algorithms (like linear regression, support vector regression, random forest regression and multilayer perceptron neural networks). Field calibration was observed to be more robust than calibration in the laboratory. Calibration of the dry-down curve was found to be more accurate, and even calibrations using the dry-down curve in the laboratory were robust enough to perform similarly well as the superior field calibrations. Overfitting during calibration led to loss in robustness on the field, and hence, should be avoided. The best calibration model that was selected for crop model calibration was the field calibrated piece-wise linear regression function (PWLF-field).

- FAO AquaCrop soil hydraulic parameters (SHPs) should ideally be calibrated using calibrated LC soil moisture data, or directly using default values from the literature. Using raw LC soil moisture data is not effective: VWC simulation generally improved significantly on incorporating the raw LC sensor data in calibrating SHPs compared to deriving them from the literature, which improved further on incorporating calibrated LC sensor data (nearly to the level of the medium-cost SMT100 sensor). There were non-significant improvements in biomass simulation performance in all cases. However, the water productivity (WP_{ET}) improved significantly by incorporating calibrated LC sensor data to calibrate SHPs, which was not observed while calibrating the crop model with the raw LC sensor data. These experiments and modeling revealed that while the default SHPs from the literature may result in better simulations than using raw LC capacitance sensor measurements, calibrating the LC sensors using a higher-quality secondary standard sensor in the field may give rise to not only better VWC simulations by the crop model, but also significant improvements in water productivity.
- Irrigation scheduling with the FAO AquaCrop strategy to avoid critical water stress coefficients across the crop growth season can lead to significant increase in water productivity and reduction in total irrigation amount and number of events, relative to full irrigation (FI) conditions: The FAO AquaCrop strategy simulated significantly lower total irrigation, significantly lower evaporation, root zone soil water storage, and deep percolation, which led to a significant increase in WP_{ET}. The irrigation schedule calculated for the FI strategy had a higher total irrigation input than the FAO AquaCrop by an amount corresponding to 1.5 irrigation applications or 111.22 mm (assuming an irrigation application depth of about 75 mm), and had 10 times more irrigation events (during one cropping season) respectively. The results also indicated that there were no differences between the FI and FAO AquaCrop strategy in any of the variables directly contributing to crop yield, such as canopy cover development, rootzone development, transpiration, which indicated the absence of any water stresses in both the strategies (since FI by definition is fully non-stressed).

6.3 Outlook

Acknowledging the demand from citizens to be engaged in decision making which impacts their communities (Srinivasan et al., 2017; Voinov et al., 2016), stakeholder interaction is a prerequisite to any studies aiming at supporting advisory development. Future studies to support advisory development could include stakeholder interaction with farmers (or farmer groups) as well as agricultural advisors through interactive and regular workshops. Follow-up studies could be conducted over multiple cropping seasons to verify the impact of using data-driven approaches on actual adoption of the advisories by the farmers. Also, the strengths of academia, government and

Table 6.1: Summary of the conclusions from the thesis.

Conclusion No.	Conclusion	Chapter No. and publication
1	Data-based, farm-scale agricultural performance diagnostics can supplement pre-existing, demand-based, generic advisory programs	Chapter 2, Adla et al. 2022. Frontiers in Water. DOI: 10.3389/frwa.2021.798241
2	Laboratory calibration and testing of low-cost capacitance based sensors can lead to improved, robust performance	Chapter 3, Adla et al. 2020. Sensors. DOI: 10.3390/s20020363
3	Field calibration results in the best calibration performance, followed by laboratory calibration using dry-down curve (it is important to avoid overfitting in both)	Chapter 4, Adla et al. 2022. Journal of Hydrology (under review).
4	If low-cost soil moisture sensors are being used to calibrate FAO AquaCrop model, they should necessarily be calibrated. If calibration is not possible, it is better to use default values of soil hydraulic parameters to calibrate FAO AquaCrop	Chapter 4, Adla et al. 2022. Journal of Hydrology (under review).
5	Irrigation scheduling with the FAO AquaCrop strategy to avoid critical water stress coefficients across the crop growth season can lead to significant increase in water productivity and reduction in total irrigation amount and number of events, relative to full irrigation conditions	Chapter 5

non-governmental agencies, i.e., scientific research and data management, soil testing capacity, and direct stakeholder engagement, respectively, could be synergistically combined to maximize the utility of such approaches.

Since soil moisture is sensitive to bulk density, gap between the sensor body and soil (i.e., packing density), and sensor calibration results depend on whether dry-down or wet-up curves are used, future studies on soil moisture sensor testing could carefully investigate and critically analyze the marginal effects of each of these variables on sensor performance. The performance of soil moisture sensors could be determined both within the laboratory and in the field, with both dry-down and wet-up curves, with repacked and undisturbed soils, along with other experiments already conducted in this study.

Crop modeling studies in the future using the parsimonious FAO AquaCrop model should ideally incorporate more systematic approaches for sensitivity analysis, and an addressal of model equifinality via the quantification of the associated uncertainty arising from model structure, input data, and more importantly, model parameters. Also, it is also important to investigate how this uncertainty can be communicated to the end-user farmer, whose primary interest is to apply a certain irrigation depth at

the right time, and may not be able to incorporate uncertainty directly into irrigation decision-making. Alternatively, the scope of reporting uncertainty in crop modeling can be explored, in terms of its relevance to particular applications (such as yield forecasting or climate adaptation) and avenues (such as policy development).

Studies combining soil moisture data and crop modeling can also investigate the difference in irrigation application performance between soil moisture being input as a continuous variable and a category variable. Low-cost soil moisture sensors may be limited in terms of their ability to predict true soil moisture exactly, but they may have more potential in predicting categorical soil moisture values more accurately. The different categories could include a 'no stress' category (with soil water depletion under RAW), an 'intermediate' category between no stress and full stress (with depletion between RAW and TAW), and a 'full stressed' category (with higher depletions). This calibration could be attempted using categorical regression (or classification) techniques such as logistic regression, support vector classification, etc.

In addition to commercially available systems, more studies are being conducted which aim at real-time, wireless irrigation automation using soil moisture sensors within the IoT framework. For instance, Vellidis et al. (2008) tested a real-time smart sensor array consisting of granular resistive soil water tension sensors and thermocouples to measure canopy temperature to trigger variable rate irrigation based on established soil water tension thresholds in a cotton crop. Communication between the sensors and the smart sensor circuit board was established using a Radio Frequency Identification (RFID) tags. The cost for the 20-sensor node system was about USD 2400. Similarly, Pramanik et al. (2022) deployed capacitance based soil moisture sensors along the length of a field, and established a wireless communication network between these sensors and an automatic check gate (which could be opened remotely based on soil moisture sensor values, to release water). This wireless communication was established using Long Range (LoRa) and Global System for Mobile Communications (GSM) modules. They measured field Irrigation Application Efficiency (%) (ea) as the irrigated water stored in the rootzone as a fraction of the total water applied, and were on average able to achieve increases in ea by upto 86.6% across nine irrigation events with different soil moisture thresholds. The cost of this system, including the check gate and controller unit, solar charging module, gateway and one soil moisture sensor, was around USD 160. It is not clear whether this would increase proportionally for multiple sensors.

Nevertheless, it is equally important to understand the scope and effectiveness of such purely technological water management interventions. There are usually two major challenges to farmers, particularly smallholders, in adoption water efficient irrigation technologies. Firstly, information regarding effective irrigation strategies must be provided to the farmers, and secondly, there needs to be a behavioural change towards adopting such technology. The first challenge involves verifying the accuracy of such technology and contextualizing it to local conditions, which has been addressed to an extent in Chapters 4 and 5. Further, the information should be disseminated through extension services - this issue has been partly discussed in Chapter 2. Information and

Communications Technologies (ICTs) are gaining popularity as a means of communication to disseminate advisories (Baumüller, 2018; Steinke et al., 2021), particularly mobile phone-enabled services. One such service had also been tested in the study region of Kanpur during this period, which provided satellite and model based recommendations for irrigation application, during the wheat cropping season of 2019 (Hossain et al., 2020a,b). However, such mobile phone enable services see disappointingly low uptake by farmers in terms of impact on their decision making (Baumüller, 2018; Rose et al., 2018). This poor adoption is reported to occur due to gaps between the information needs and technological capabilities/habits of the farmer, and the advisory delivered by the tool in question (Lindblom et al., 2017; Parker and M. Sinclair, 2001; Rose et al., 2018). While there is a need to involve end-users in developing such solutions using a user-centered design approach (Kragt and Llewellyn, 2014; Oliver et al., 2017; 2012; Rose et al., 2018; Rossi et al., 2014), the information should be administered in a way which can influence a change in the decision making behaviour of the farmer (Mosler, 2012), which is the second challenge in widespread adoption of such irrigation strategies.

Since adopting new irrigation strategies result from a change in behaviour, 'understanding, predicting, and influencing' this behaviour would then require an understanding of the motivations behind behaviour, which may not only be limited to utility maximization and may also include cognitive and social parameters (Weersink and Fulton, 2020). The key factors which govern the adoption of agricultural technologies have been classified into four categories: (i) weather and agro-climatic conditions, (ii) farm characteristics, (iii) socio-economic characteristics of the (head of the) household, and (iv) farmers' attitude towards risk (Bahinipati and Viswanathan, 2019). Moreover, psychological frameworks have to used to understand the adoption of water technologies in low-middle income countries (Daniel et al., 2019; Dessart et al., 2019; Gamma et al., 2017). For instance, Daniel et al. (2019) identify socio-economic and psychosocial factors as key determinants to technology adoption. Contextualizing this body of research to this study, it is possible that despite the low-cost sensor and crop modeling technology having been verified, there would be additional important factors which may influence farmer uptake, such as socio-economic characteristics (which includes income, educational level and previous experience with farm technology), perceptions about resource efficiency in agriculture, and agricultural risk-taking attitude. For instance, an educated farmer who has had some previous experience with sensors (say through visits to or by agricultural extension centres, research universities or NGOs) may be more inclined to attempt such technological interventions on their field. Further, some farmers may experiment with different management strategies within their fields as well, to test out new varieties of inputs (like fertilizers), and such risk-taking farmers may be more inclined to attempt experiments with such innovations. This intervention may also be more suitable for more economically affluent farmers (who can afford some losses as a result of negative results) as compared to marginal subsistence farmers. While these factors and their relative weights in influencing farmer behaviour may be specific to the local conditions (Knowler and Bradshaw, 2007), contextualizing these factors in the local

context can help design solutions in a way which is suited to behaviour change towards improved water management practices.

7 Article Appendices

7.1 Appendix to Chapter 3

Table 7.1: Publications relevant to sensor testing studies.

Category	Relevant publications		
Sensor accuracy	Czarnomski et al. (2005), Kargas and Soulis (2012), González- Teruel et al. (2019)		
Sensor precision	Czarnomski et al. (2005)		
Sensor-to-sensor variability	Sakaki et al. (2008), Rosenbaum et al. (2010), Kargas and Soulis (2012), Bogena et al. (2017), González-Teruel et al. (2019)		
Temperature effects	Paltineanu and Starr (1997), Baumhardt et al. (2000), Czarnomski (2005), Chanzy (2012), Kargas and Soulis (2012), Fares et al. (2016), Bello et al. (2019b), Szypłowska et al. (2019), Zhu et al. (2019)		
Salinity effects	Baumhardt et al. (2000), Kargas and Soulis (2012), Matula et al. (2016b), Kargas and Soulis (2019)		
Volume of influence/sensitivity	Paltineanu and Starr (1997), Sakaki et al. (2008), Sun et al. (2012)		

Table 7.2: Publications relevant to sensor calibration studies.

Publication	Sensor Name (Company Name)	Sensor Type	Soils Used	Calibration Curve Details
Paltineanu and Starr (1997)	Multisensor Capacitance probe: MCAP (Enviroscan)	Capacitance sensor	Mattaplex silt loam (fine-silty, mixed, mesic, Aquic Hapludult)	Scaled frequency
Baumhardt et al. (2000)	Multisensor Capacitance probe: MCAP (Enviroscan)	Capacitance sensor	2 soil materials: Surface and calcic horizons of an Olton soil	Scaled frequency
Czarnomski et al (2005)	ECH2O (Decagon), CT l.1502C (Tektronix Inc.), WCR CS615 Campbell Scientific)	Capacitance sensors	Alluvial soils of volcanic origin (sandy loam to sandy clay loam)	Linear (for capacitance sensor)
Sakaki et al. (2008)	ECH2O (Decagon)	Capacitance sensor	4 sands	Linear, quadratic, 2-point alpha mixing model
Kargas and Soulis (2012)	10HS (Decagon Devices)	Capacitance sensor	Liquids and porous media of known dielectric permittivity	2-point calibration equation
Matula et al. (2016b)	ThetaProbe ML2x (Delta-T Devices Ltd.), ECH2O EC10 (Decagon), ECH2O EC 20 (Decagon), ECH2O EC5 (Decagon), ECH2O TE (Decagon)	Impedance sensors, FDR sensors	Silica sand and loess	Comparison between manufacturer and developed linear calibration equations
Kargas and Soulis (2019)	CS655 (Campbell Scientific)	Water Content Reflectometer	Liquids of known dielectric permittivity and 10 soils (sand, sandy-loam, sandy-clay-loam, loam, clay-loam, clay)	2-point, multi-point calibration equations; calibration equation for non-conductive soils using Kelleners'(2005) method
González- Teruel et al. (2019)	Self-developed soil moisture sensor with SDI-12 communication	Capacitance based	3 soils (clay-loams and sand)	Exponential equations

Table 7.3: Coefficients of the calibration equations for repacked soil samples, of the form indicated in Equation (3.1). The segment limits indicate the [lower, upper] limits of the fitted piecewise linear segments.

Sensor Name	Soil Type	Equation Characteristics	Segment 1	Segment 2
	Soil-1	Segment limits Slope (β_1) Intercept (β_0)	[1135, 1280) 0.13 -152.65	[1280, 1792) 0.03 -23.21
SMEC300	Soil-2	Segment limits Slope (β_1) Intercept (β_0)	[1200, 1451) 0.07 -85.91	1451, 1707) 0.04 -34.23
	Soil-3	Segment limits Slope (β_1) Intercept (β_0)	[1231, 1402) 0.08 -94.19	[1402, 1899) 0.02 -19.71
	Soil-4	Segment limits Slope (β_1) Intercept (β_0)	[1275, 1525) 0.09 -112.50	[1525, 1685) 0.00 23.58
	Soil-1	Segment limits Slope (β_1) Intercept (β_0)	[1200, 1238) 0.25 -303.95	[1238, 1812) 0.04 -42.88
SM100	Soil-2	Segment limits Slope (β_1) Intercept (β_0)	[1200, 1464) 0.07 -87.61	[1464, 1728) 0.03 -32.15
	Soil-3	Segment limits Slope (β_1) Intercept (β_0)	[1263, 1578) 0.06 -78.57	[1578, 1895) 0.02 -14.80
	Soil-4	Segment limits Slope (β_1) Intercept (β_0)	[1319, 1630) 0.06 -81.29	[1630, 1833) 0.01 -3.56

Table 7.3 Continued from previous page

Sensor Name	Soil Type	Equation Characteristics	Segment 1	Segment 2
	Soil-1	Segment limits	[2, 467.5)	[467.5, 763)
		Slope (β_1)	0.04	0.03
		Intercept (β_0)	-0.80	5.01
		Segment limits	[6, 615.5)	[615.5, 826)
	Soil-2	Slope (β_1)	0.03	0.09
YL100		Intercept (β_0)	-0.81	-32.32
		Segment limits	[5, 333.5)	[333.5, 709)
	Soil-3	Slope (β_1)	0.02	0.08
		Intercept (β_0)	-0.17	-20.81
	Soil-4	Segment limits	[6, 418.5)	[418.5, 705)
		Slope (β_1)	0.02	0.07
		Intercept (β_0)	-1.08	-21.08
	Soil-1	Segment limits	[11, 134)	[134, 724)
		Slope (β_1)	0.07	0.04
		Intercept (β_0)	-1.35	3.24
		Segment limits	[7, 722]	
	Soil-2	Slope (β_1)	0.05	
YL69		Intercept (β_0)	-0.87	
		Segment limits	[18, 838]	
	Soil-3	Slope (β_1)	0.03	
		Intercept (β_0)	1.48	
		Segment limits	[14, 824)	
	Soil-4	Slope (β_1)	0.03	
		Intercept (β_0)	-0.71	

7.2 Appendix to Chapter 4

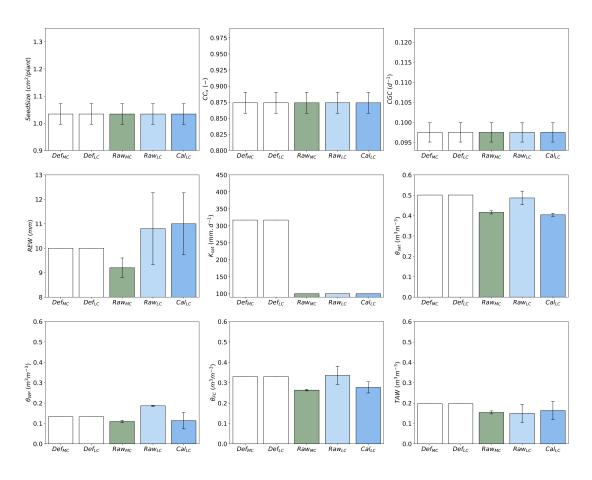


Figure 7.1: Mean and standard deviation values for non-conservative parameters across all crop model calibration scenarios. The parameters related to CC that were calibrated: Soil surface covered by an individual seedling at 90% emergence (SeedSize), maximum canopy cover (CC_x), and canopy growth coefficient (CGC). The soil hydraulic parameters (SHPs) related to the VWC that were calibrated: readily evaporable water (REW), saturated hydraulic conductivity (K_{sat}), VWC at saturation (θ_s), VWC at permanent wilting point (θ_{PWP}), VWC at field capacity (θ_{FC}), and total available water content ($TAW = \theta_{FC} - \theta_{PWP}$). For more details like parameter descriptions, please see Table 7.5

Table 7.4: Non-conservative model parameters and their default values before calibrating the AquaCrop model. The target variable indicates which intermediate AquaCrop output is affected by a change in the corresponding parameter. (i) Raes et al. (2018), (ii) Brouwer et al. (1989), (iii) Taghavaeian (2017), (iv) Allen et al. (2005), (v) Rawls and Brakensiek (1989), (vi) Gupta et al. (2021), (vii) USDA-NRCS (2017)

Parameter	Description	Target	Unit	Default value (range)
	Soil surface covered by an			
SeedSize	individual seedling at 90%	CC	cm²/plant	1.5^{i}
	emergence			
CCx	Maximum canopy cover	CC	$m^2 m^{-2}$	0.80 - 0.99 ⁱ
CGC	Canopy growth coefficient	CC	d^{-1} or °C- d^{-1}	$0.0930 - 0.1235^{i}$
CDC	Canopy decline coefficient	CC	d^{-1} or °C- d^{-1}	0.0925^{i}
Emergence	Time from sowing to emergence	CC	d	8
HIstart	Time from sowing to start of build-up of Harvest Index			70
Flowering	Length of the flowering stage	CC	d	14
Senescence	Time from sowing to start of senescence	CC	d	81
Maturity	Time from sowing to maturity, i.e., length of crop cycle	CC	d	100
Zmin	Minimum effective rooting depth	VWC	m	$0.2 \text{-} 0.3^{\mathrm{i}}$
Zmax	Maximum effective rooting depth	VWC	m	1.5
AppEff	Irrigation Application Efficiency	VWC	%	60 ^{ii, iii}
REW	Readily Evaporable Water	VWC	mm	9-12 ^{iv}
K_sat	Saturated hydraulic conductivity	VWC	mm-d ⁻¹	96-446 ^{iv, vi}
th_wp	VWC at Permanent wilting point	VWC	$m^3 m^{-3}$	0.133 (0.078-0.188) ^v
th_fc	VWC at Field Capacity	VWC	$m^3 m^{-3}$	0.330 (0.258-0.402) ^v
th_sat	VWC at Saturation	VWC	$\mathrm{m}^3~\mathrm{m}^{-3}$	0.501 (0.42-0.582) ^v
CN	Curve Number for antecedent moisture class II	VWC	-	69-75 ^{vii}
HI	Reference Harvest Index	Yield	%	0.48 (0.45-0.50) ⁱ

Table 7.5: Details of agricultural management during the experiment

	U	0	<u> </u>
		Managament day	Management quantification
Management practice	Management date	Management day	(irrigation depth in mm,
		(DAS) (DAS) or quantity in	or quantity in kg/ha)
Fertilizer application	01-Feb-18	27 (at tillering)	347 kg/ha
Irrigation – 1	29-Jan-18	25	50
Irrigation – 2	18-Feb-18	45	43
Irrigation – 3	04-Mar-18	59	52.4
Irrigation – 4	19-Mar-18	74	37.3

Bibliography

Abbaspour, K.C., 2015. SWAT calibration and uncertainty programs: A User Manual [Online]. Eawag - Swiss Federal Institute of Aquatic Science and Technology. Available from: https://swat.tamu.edu/media/114860/usermanual_swatcup.pdf (cit. on pp.104, 105).

Abbaspour, K.C., Johnson, C., and Van Genuchten, M.T., 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone Journal* [Online], 3(4), pp.1340–1352. Available from: https://doi.org/10.2136/vzj2004.1340 (cit. on p.105).

Abbaspour, K.C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., and Kløve, B., 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology* [Online], 524, pp.733–752. Available from: https://doi.org/10.1016/j.jhydrol.2015.03.027 (cit. on p.105).

Adla, S., Pande, S., and Disse, M., 2017. Understanding challenges to smallholder sustainability with surveys in the Ganga river basin. *European Geosciences Union General Assembly* 2017 [Online]. Vienna, Austria: European Geosciences Union. Available from: https://doi.org/10.13140/RG.2.2.28574.59204 (cit. on p.102).

Adla, S., 2021. Farm-Agricultural-Diagnostics-tool (v.1.0.0) [Online]. Available from: https://doi.org/10.5281/zenodo.5195682 (cit. on pp.21, 26).

Adla, S., Rai, N., Harsha, K.S., Tripathi, S., Disse, M., and Pande, S., 2018. *Laboratory calibration of soil moisture sensors in porous media (repacked soils)* v2 [Online]. protocols.io. Available from: https://doi.org/10.17504/protocols.io.swnefde (cit. on pp.42, 43).

Adla, S., Rai, N.K., Karumanchi, S.H., Tripathi, S., Disse, M., and Pande, S., 2020. Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. *Sensors* [Online], 20(2), p.363. Available from: https://doi.org/10.3390/s20020363 (cit. on pp.8, 68, 69, 73, 75, 80, 82).

Ahikiriza, E., Wesana, J., Gellynck, X., Van Huylenbroeck, G., and Lauwers, L., 2021. Context Specificity and Time Dependency in Classifying Sub-Saharan Africa Dairy Cattle Farmers for Targeted Extension Farm Advice: The Case of Uganda. *Agriculture* [Online], 11(9), p.836. Available from: https://doi.org/10.3390/agriculture11090836 (cit. on p.14).

Ahmed, M., Akram, M.N., Asim, M., Aslam, M., Hassan, F.-u., Higgins, S., Stöckle, C.O., and Hoogenboom, G., 2016. Calibration and validation of APSIM-Wheat and CERES-Wheat for spring wheat under rainfed conditions: Models evaluation and application. *Computers and Electronics in Agriculture* [Online], 123, pp.384–401. Available from: https://doi.org/10.1016/j.compag.2016.03.015 (cit. on p.70).

Ahuja, L., Ma, L., Lascano, R.J., Saseendran, S., Fang, Q., Nielsen, D.C., Wang, E., and Colaizzi, P.D., 2014. Syntheses of the current model applications for managing water and needs for experimental data and model improvements to enhance these applications. *Practical applications of agricultural system models to optimize the use of limited water* [Online], 5, pp.399–437. Available from: https://doi.org/10.2134/advagricsystmodel5.c15 (cit. on p.104).

Ai, Z., Wang, Q., Yang, Y., Manevski, K., Yi, S., and Zhao, X., 2020. Variation of gross primary production, evapotranspiration and water use efficiency for global croplands. *Agricultural and Forest Meteorology* [Online], 287, p.107935. Available from: https://doi.org/10.1016/j.agrformet.2020.107935 (cit. on pp.2, 77).

Aker, J.C., 2011. Dial "A" for agriculture: a review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics* [Online], 42(6), pp.631–647. Available from: https://doi.org/10.1111/j.1574-0862.2011.00545.x (cit. on pp.1, 6, 14, 15).

Alcott, B., 2005. Jevons' paradox. *Ecological Economics* [Online], 54(1), pp.9–21. Available from: https://doi.org/10.1016/j.ecolecon.2005.03.020 (cit. on pp.4, 64).

Alharthi, H., Sultana, N., Al-Amoudi, A., and Basudan, A., 2015. An Analytic Hierarchy Process-based Method to Rank the Critical Success Factors of Implementing a Pharmacy Barcode System. *Perspectives in Health Information Management* [Online], 12(Winter). Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4700872/ (cit. on p.17).

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., et al., 1998. Crop evapotranspiration-Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. *FAO*, *Rome*, 300(9), p.D05109 (cit. on pp.8, 9, 71, 89, 90, 92, 94, 105, 106).

Allen, R.G., Pereira, L.S., Smith, M., Raes, D., and Wright, J.L., 2005. Fao-56 dual crop coefficient method for estimating evaporation from soil and application extensions. *ASCE Journal of Irrigation and Drainage Engineering* [Online], 131(1). Available from: https://doi.org/10.1061/(ASCE)0733-9437(2005)131:1(2) (cit. on p.118).

Ambast, S., Tyagi, N., and Raul, S., 2006. Management of declining groundwater in the Trans Indo-Gangetic Plain (India): some options. *Agricultural Water Management* [Online], 82(3), pp.279–296. Available from: https://doi.org/10.1016/j.agwat.2005.06.005 (cit. on pp.4, 64).

Andarzian, B., Bannayan, M., Steduto, P., Mazraeh, H., Barati, M., Barati, M., and Rahnama, A., 2011. Validation and testing of the AquaCrop model under full and deficit irrigated wheat production in Iran. *Agricultural Water Management* [Online], 100(1), pp.1–8. Available from: https://doi.org/10.1016/j.agwat.2011.08.023 (cit. on pp.7, 70, 77).

Anderson, J. and Feder, G., 2007. Agricultural Extension. *Handbook of Agricultural Economics*. [Online]. Vol. 3. Elsevier B.V., pp.2343–2378. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1574007206030441 (cit. on pp.1, 2, 14).

Anderson, J.R., Feder, G., and Ganguly, S., 2006. The rise and fall of training and visit extension: an Asian mini-drama with an African epilogue. In: *Changing Roles of Agricultural Extension in Asian Nations*. (cit. on p.2).

Andrews, S.S., Karlen, D.L., and Cambardella, C.A., 2004. The soil management assessment framework: A quantitative soil quality evaluation method. *Soil Science Society of America Journal* [Online], 68(6). Available from: https://doi.org/10.2136/sssaj2004. 1945 (cit. on p.19).

Aravind, P., Gurav, M., Mehta, A., Shelar, R., John, J., Palaparthy, V.S., Singh, K.K., Sarik, S., and Baghini, M.S., 2015. A wireless multi-sensor system for soil moisture measurement. 2015 IEEE SENSORS [Online]. IEEE, pp.1–4. Available from: https://doi.org/10.1109/ICSENS.2015.7370444 (cit. on p.39).

Arias-Rodriguez, L.F., Duan, Z., Díaz-Torres, J.d.J., Basilio Hazas, M., Huang, J., Kumar, B.U., Tuo, Y., and Disse, M., 2021. Integration of remote sensing and mexican water quality monitoring system using an extreme learning machine. *Sensors* [Online], 21(12), p.4118. Available from: https://doi.org/10.3390/s21124118 (cit. on p.70).

Asseng, S., Zhu, Y., Basso, B., Wilson, T., Cammarano, D., and Van Alfen, N.K., 2014. Simulation modeling: applications in cropping systems. In: *Encyclopedia of Agriculture and Food Systems* (cit. on p.70).

Attia, A., Rajan, N., Xue, Q., Nair, S., Ibrahim, A., and Hays, D., 2016. Application of DSSAT-CERES-Wheat model to simulate winter wheat response to irrigation management in the Texas High Plains. *Agricultural Water Management* [Online], 165, pp.50–60. Available from: https://doi.org/10.1016/j.agwat.2015.11.002 (cit. on p.70).

Azam-Ali, S., Crout, N., and Bradley, R., 1994. Perspectives in modelling resource capture by crops. *Resource capture by crops*. Nottingham University Press Nottingham, pp.125–148 (cit. on p.7).

Baatz, R., Bogena, H., Hendricks Franssen, H.-J., Huisman, J., Montzka, C., and Vereecken, H., 2015. An empirical vegetation correction for soil water content quantification using cosmic ray probes. *Water Resources Research* [Online], 51(4), pp.2030–2046. Available from: https://doi.org/10.1002/2014WR016443 (cit. on p.37).

Babel, M.S., Deb, P., and Soni, P., 2019. Performance evaluation of AquaCrop and DSSAT-CERES for maize under different irrigation and manure application rates in the Himalayan region of India. *Agricultural Research* [Online], 8(2), pp.207–217. Available from: https://doi.org/10.1007/s40003-018-0366-y (cit. on p.70).

Bacci, L., Battista, P., Rapi, B., Sabatini, F., and Checcacci, E., 2003. Irrigation control of container crops by means of tensiometers. *Acta Horticulturae: International Symposium on Managing Greenhouse Crops in Saline Environment* [Online], 609, pp.467–474. Available from: https://doi.org/10.17660/ActaHortic.2003.609.72 (cit. on p.8).

Bahinipati, C.S. and Viswanathan, P., 2019. Incentivizing resource efficient technologies in India: Evidence from diffusion of micro-irrigation in the dark zone regions of Gujarat. *Land use policy* [Online], 86, pp.253–260. Available from: https://doi.org/10.1016/j.landusepol.2019.04.017 (cit. on p.111).

Bailey, R., 1990. Irrigated crops and their management. Farming Press Books (cit. on p.8).

Banjara, T.R., Bohra, J.S., Kumar, S., Singh, T., Shori, A., and Prajapat, K., 2021. Sustainable alternative crop rotations to the irrigated rice-wheat cropping system of Indo-Gangetic plains of India. *Archives of Agronomy and Soil Science* [Online], pp.1–18. Available from: https://doi.org/10.1080/03650340.2021.1912324 (cit. on p.64).

Banjara, T.R., Bohra, J., Kumar, S., Ram, A., and Pal, V., 2022. Diversification of rice—wheat cropping system improves growth, productivity and energetics of rice in the Indo-Gangetic Plains of India. *Agricultural Research* [Online], 11(1), pp.48–57. Available from: https://doi.org/10.1007/s40003-020-00533-9 (cit. on pp.3, 64).

Bartlett, A., Andales, A., Arabi, M., and Bauder, T., 2015. A smartphone app to extend use of a cloud-based irrigation scheduling tool. *Computers and Electronics in Agriculture* [Online], 111, pp.127–130. Available from: https://doi.org/10.1016/j.compag.2014.12.021 (cit. on pp.5, 14).

Bastiaanssen, W.G., Molden, D.J., and Makin, I.W., 2000. Remote sensing for irrigated agriculture: examples from research and possible applications. *Agricultural Water Management* [Online], 46(2), pp.137–155. Available from: https://doi.org/10.1016/S0378-3774(00)00080-9 (cit. on pp.5, 6, 65).

Baumhardt, R., Lascano, R., and Evett, S., 2000. Soil Material, Temperature, and Salinity Effects on Calibration of Multisensor Capacitance Probes. *Soil Science Society of America Journal* [Online], 64, pp.1940–1946. Available from: https://doi.org/10.2136/sssaj2000.6461940x (cit. on pp.113, 114).

Baumüller, H., 2018. The little we know: an exploratory literature review on the utility of mobile phone-enabled services for smallholder farmers. *Journal of International Development* [Online], 30(1), pp.134–154. Available from: https://doi.org/10.1002/jid.3314 (cit. on p.111).

Bazaluk, O., Havrysh, V., Nitsenko, V., Mazur, Y., and Lavrenko, S., 2022. Low-Cost Smart Farm Irrigation Systems in Kherson Province: Feasibility Study. *Agronomy* [Online], 12(5), p.1013. Available from: https://doi.org/10.3390/agronomy12051013 (cit. on p.4).

Bell, K.R., Blanchard, B., Schmugge, T., and Witczak, M., 1980. Analysis of surface moisture variations within large-field sites. *Water Resources Research* [Online], 16(4), pp.796–810. Available from: https://doi.org/10.1029/WR016i004p00796 (cit. on p.104).

Bell, M., 2013. e-Afghan Ag. Content is just part of the story. Presentation at CTA's ICT4Ag International Conference, Kigali, Rwanda. (cit. on pp.6, 14).

Bello, Z.A., Tfwala, C.M., and Rensburg, L.D. van, 2019a. Evaluation of newly developed capacitance probes for continuous soil water measurement. *Geoderma* [Online], 345, pp.104–113. Available from: https://doi.org/10.1016/j.geoderma.2019.03.030 (cit. on pp.8, 69, 73, 82, 103).

Bello, Z.A., Tfwala, C.M., and Rensburg, L.D. van, 2019b. Investigation of temperature effects and performance evaluation of a newly developed capacitance probe. *Measurement* [Online], 140, pp.269–282. Available from: https://doi.org/10.1016/j.measurement.2019.03.062 (cit. on pp.43, 113).

Benabdelouahab, T., Balaghi, R., Hadria, R., Lionboui, H., Djaby, B., and Tychon, B., 2016. Testing Aquacrop to Simulate Durum Wheat Yield and Schedule Irrigation in a Semi-Arid Irrigated Perimeter in Morocco. *Irrigation and Drainage* [Online], 65(5), pp.631–643. Available from: https://doi.org/10.1002/ird.1977 (cit. on pp.7, 106).

Besten, N. den, 2016. *The socio-hydrology of smallholders in Marathwada, Maharashtra state (India)*. Master's Thesis. Delft University of Technology (cit. on p.37).

Beven, K. and Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrological Processes* [Online], 6(3), pp.279–298. Available from: https://doi.org/10.1002/hyp.3360060305 (cit. on p.105).

Beven, K. and Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology* [Online], 249(1-4), pp.11–29. Available from: https://doi.org/10.1016/S0022-1694(01)00421-8 (cit. on p.105).

Bhatt, R., Singh, P., Hossain, A., and Timsina, J., 2021. Rice—wheat system in the northwest Indo-Gangetic plains of South Asia: Issues and technological interventions for increasing productivity and sustainability. *Paddy and Water Environment* [Online], 19(3), pp.345–365. Available from: https://doi.org/10.1007/s10333-021-00846-7 (cit. on pp.3, 64).

Birner, R. and Anderson, J., 2007. *How to make agricultural extension demand driven? The case of India's agricultural extension policy*. Vol. 729. International Food Policy Research Institute (IFPRI) (cit. on pp.1, 2).

Birner, R., Davis, K., Pender, J., Nkonya, E., Anandajayasekeram, P., Ekboir, J., Mbabu, A., Spielman, D.J., Horna, D., Benin, S., et al., 2009. From best practice to best fit: a framework for designing and analyzing pluralistic agricultural advisory services worldwide. *Journal of Agricultural Education and Extension* [Online], 15(4), pp.341–355. Available from: https://doi.org/10.1080/13892240903309595 (cit. on p.1).

Bjorneberg, D., 2013. *Irrigation Methods*. (Reference Module in Earth Systems and Environmental Sciences). Elsevier Inc. (cit. on pp.4, 64).

Blonquist Jr, J., Jones, S.B., and Robinson, D.A., 2005. Standardizing characterization of electromagnetic water content sensors: Part 2. Evaluation of seven sensing systems. *Vadose Zone Journal* [Online], 4(4), pp.1059–1069. Available from: https://doi.org/10.2136/vzj2004.0141 (cit. on pp.36, 67, 68).

Bloom, A., 1989. Principles of instrumentation for physiological ecology. In: *Plant Physiological Ecology: Field Methods and Instrumentation* [Online]. Available from: https://doi.org/10.1007/978-94-009-2221-1_1 (cit. on p.43).

Bogena, H., Bol, R., Borchard, N., Brüggemann, N., Diekkrüger, B., Drüe, C., Groh, J., Gottselig, N., Huisman, J., Lücke, A., et al., 2015. A terrestrial observatory approach to the integrated investigation of the effects of deforestation on water, energy, and matter fluxes. *Science China Earth Sciences* [Online], 58(1), pp.61–75. Available from: https://doi.org/10.1007/s11430-014-4911-7 (cit. on p.37).

Bogena, H., Huisman, J., Schilling, B., Weuthen, A., and Vereecken, H., 2017. Effective calibration of low-cost soil water content sensors. *Sensors* [Online], 17(1), p.208. Available from: https://doi.org/10.3390/s17010208 (cit. on pp.36, 37, 41, 67, 68, 113).

Boogaard, H., Diepen, C. van, Rötter, R., J.M.C.A., C., and Laar, H. van, 1998. *User's guide for the WOFOST 7.1 crop growth simulation model and WOFOST Control Center 1.5.* (Tech. Doc. 52.). DLO-Winand Staring Centre (cit. on p.7).

Boote, K.J., Jones, J.W., Hoogenboom, G., and Pickering, N., 1998. Simulation of crop growth: CROPGRO model. In: *Agricultural systems modeling and simulation*. Vol. 651 (cit. on p.7).

Boote, K.J., Mínguez, M.I., and Sau, F., 2002. Adapting the CROPGRO legume model to simulate growth of faba bean. *Agronomy Journal* [Online], 94(4), pp.743–756. Available from: https://doi.org/10.2134/agronj2002.7430 (cit. on p.7).

Boretti, A. and Rosa, L., 2019. Reassessing the projections of the world water development report. *NPJ Clean Water* [Online], 2(1), pp.1–6. Available from: https://doi.org/10.1038/s41545-019-0039- (cit. on p.1).

Bouman, B., Van Keulen, H., Van Laar, H., and Rabbinge, R., 1996. The 'School of de Wit' crop growth simulation models: a pedigree and historical overview. *Agricultural Systems* [Online], 52(2-3), pp.171–198. Available from: https://doi.org/10.1016/0308-521X(96)00011-X (cit. on p.7).

Bouyoucos, G. and Mick, A., 1948. A comparison of electric resistance units for making a continuous measurement of soil moisture under field conditions. *Plant Physiology* [Online], 23(4), p.532. Available from: https://doi.org/10.1104/PP.23.4.532 (cit. on p.39).

Bramley, R.G., 2009. Lessons from nearly 20 years of Precision Agriculture research, development, and adoption as a guide to its appropriate application. *Crop and Pasture Science* [Online], 60(3), pp.197–217. Available from: https://doi.org/10.1071/CP08304 (cit. on pp.5, 14).

Breiman, L., 2001. Random forests. In: Machine learning. Vol. 45, pp.5–32 (cit. on p.69).

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., et al., 2003. An overview of the crop model STICS. *European Journal of Agronomy* [Online], 18(3-4), pp.309–332. Available from: https://doi.org/10.1016/S1161-0301(02)00110-7 (cit. on p.7).

Brouwer, C., Prins, K., and Heibloem, M., 1989. *Annex I: Irrigation efficiencies, in: Irrigation Water Management: Irrigation Scheduling.* Food and Agricultural Organization of the United Nations (cit. on p.118).

Brown, L.R. and Halweil, B., 1998. China's water shortage could shake world food security. *World Watch* [Online], 11(4), pp.10–21. Available from: https://pubmed.ncbi.nlm.nih.gov/12348868/ (cit. on p.2).

Bruckmaier, F., 2022a. *Development of a Matlab tool for automatic sensitivity and uncertainty analysis of the AquaCrop-OS model in data-scarce regions*. (Master's Thesis). Technical University of Munich (cit. on p.105).

Bruckmaier, F., 2021. *Quantification of yield loss due to water and temperature stress with AquaCrop for wheat in Northern India* [Online]. (Master's Study Project). Technical University of Munich. Available from: https://doi.org/10.13140/RG.2.2.15557.93920 (cit. on p.93).

Bruckmaier, F., 2022b. *Automated AquaCrop-OpenSource (AAOS)* [Online]. Available from: https://github.com/felixbruckmaier/aquacrop (cit. on p.104).

Brunner, R.D., 2010. Adaptive governance as a reform strategy. *Policy Sciences* [Online], 43(4), pp.301–341. Available from: https://doi.org/10.1007/s11077-010-9117-z (cit. on pp.2, 6).

Bureau of Indian Standards (BIS), 2002. Standard sand for testing cement-specifications. In: *IS 650:1991 (Second Revision)* (cit. on pp.41, 44).

Burns, T.T., Adams, J.R., and Berg, A.A., 2014. Laboratory calibration procedures of the Hydra Probe soil moisture sensor: infiltration wet-up vs. dry-down. *Vadose Zone Journal* [Online], 13(12). Available from: https://doi.org/10.2136/vzj2014.07.0081 (cit. on pp.73, 75, 82, 103).

Buytaert, W., Zulkafli, Z., Grainger, S., Acosta, L., Alemie, T.C., Bastiaensen, J., De Bièvre, B., Bhusal, J., Clark, J., Dewulf, A., et al., 2014. Citizen science in hydrology and water resources: opportunities for knowledge generation, ecosystem service management, and sustainable development. *Frontiers in Earth Science* [Online], 2, p.26. Available from: https://doi.org/10.3389/feart.2014.00026 (cit. on p.27).

Byerlee, D., De Janvry, A., and Sadoulet, E., 2009. Agriculture for development: Toward a new paradigm. *Annu. Rev. Resour. Econ.* [Online], 1(1), pp.15–31. Available from: https://doi.org/10.1146/annurev.resource.050708.144239 (cit. on p.2).

Camargo Rodriguez, A.V. and Ober, E.S., 2019. Aquacropr: crop growth model for r. *Agronomy* [Online], 9(7), p.378. Available from: https://doi.org/10.3390/agronomy9070378 (cit. on p.71).

Carr, J. and Brown, J., 2001. Basic Theories of Measurement. In: *Introduction to Biomedical Equipment Technology* (cit. on p.43).

Carranza, C., Nolet, C., Pezij, M., and Ploeg, M. van der, 2021. Root zone soil moisture estimation with Random Forest. *Journal of hydrology* [Online], 593, p.125840. Available from: https://doi.org/10.1016/j.jhydrol.2020.125840 (cit. on p.69).

Cayuela, C.M.F., Perea, R.G., Poyato, E.C., and Montesinos, P., 2022. An ICT-based decision support system for precision irrigation management in outdoor orange and greenhouse tomato crops. *Agricultural Water Management* [Online], 269, p.107686. Available from: https://doi.org/10.1016/j.agwat.2022.107686 (cit. on p.7).

Chai, S.-S., Walker, J.P., Makarynskyy, O., Kuhn, M., Veenendaal, B., and West, G., 2009. Use of soil moisture variability in artificial neural network retrieval of soil moisture. *Remote Sensing* [Online], 2(1), pp.166–190. Available from: https://doi.org/10.3390/rs2010166 (cit. on p.69).

Chanasyk, D. and Naeth, M.A., 1996. Field measurement of soil moisture using neutron probes. *Canadian Journal of Soil Science* [Online], 76(3), pp.317–323. Available from: https://doi.org/10.4141/cjss96-038 (cit. on p.66).

Chanzy, A., Gaudu, J.-C., and Marloie, O., 2012. Correcting the temperature influence on soil capacitance sensors using diurnal temperature and water content cycles. *Sensors* [Online], 12(7), pp.9773–9790. Available from: https://doi.org/10.3390/s120709773 (cit. on pp.43, 113).

Chauhan, B.S., 2012. Weed ecology and weed management strategies for dry-seeded rice in Asia. *Weed Technology* [Online], 26(1), pp.1–13. Available from: https://doi.org/10.1614/WT-D-11-00105.1 (cit. on pp.3, 64).

Chen, C., Wang, E., and Yu, Q., 2010. Modelling the effects of climate variability and water management on crop water productivity and water balance in the North China Plain. *Agricultural Water Management* [Online], 97(8), pp.1175–1184. Available from: https://doi.org/10.1016/j.agwat.2008.11.012 (cit. on p.70).

Chenu, K., Chapman, S.C., Tardieu, F., McLean, G., Welcker, C., and Hammer, G.L., 2009. Simulating the yield impacts of organ-level quantitative trait loci associated with drought response in maize: a "gene-to-phenotype" modeling approach. *Genetics* [Online], 183(4), pp.1507–1523. Available from: https://doi.org/10.1534/genetics.109.105429 (cit. on p.70).

Chiara, C. and Marco, M., 2022. Irrigation efficiency optimization at multiple stakeholders' levels based on remote sensing data and energy water balance modelling. *Irrigation Science* [Online], pp.1–19. Available from: https://doi.org/10.1007/s00271-022-00780-4 (cit. on pp.6, 64, 65).

Cosh, M.H., Jackson, T.J., Bindlish, R., Famiglietti, J.S., and Ryu, D., 2005. Calibration of an impedance probe for estimation of surface soil water content over large regions. *Journal of Hydrology* [Online], 311(1-4), pp.49–58. Available from: https://doi.org/10.1016/j.jhydrol.2005.01.003 (cit. on p.67).

Cosh, M.H., Ochsner, T.E., McKee, L., Dong, J., Basara, J.B., Evett, S.R., Hatch, C.E., Small, E.E., Steele-Dunne, S.C., Zreda, M., et al., 2016. The soil moisture active passive marena, oklahoma, in situ sensor testbed (smap-moisst): Testbed design and evaluation of in situ sensors. *Vadose Zone Journal* [Online], 15(4), vzj2015–09. Available from: https://doi.org/10.2136/vzj2015.09.0122 (cit. on p.37).

Cummings, R.W. and Chandler Jr, R., 1941. A field comparison of the electrothermal and gypsum block electrical resistance methods with the tensiometer method for estimating soil moisture in situ. *Soil Science Society of America Journal* [Online], 5(C), pp.80–85. Available from: https://doi.org/10.2136/sssaj1941.036159950005000C0015x (cit. on p.67).

Czarnomski, N., Moore, G., Pypker, T., Licata, J., and Bond, J., 2005. Precision and accuracy of three alternative instruments for measuring soil water content in two forest soils of the Pacifie Northwest. *Canadian Journal of Forest Research* [Online], 35(8), pp.1867–1876. Available from: https://doi.org/10.1139/x05-121 (cit. on pp.38, 42, 43, 103, 113, 114).

Daniel, D., Diener, A., Pande, S., Jansen, S., Marks, S., Meierhofer, R., Bhatta, M., and Rietveld, L., 2019. Understanding the effect of socio-economic characteristics and psychosocial factors on household water treatment practices in rural Nepal using Bayesian Belief Networks. *International Journal of Hygiene and Environmental Health* [Online], 222(5), pp.847–855. Available from: https://doi.org/10.1016/j.ijheh.2019.04.005 (cit. on p.111).

Das, A., Basu, D., and Goswami, R., 2016. Accessing agricultural information through mobile phone: lessons of IKSL services in West Bengal. *Indian Research Journal of Extension Education*, 12(3), pp.102–107 (cit. on pp.6, 15).

Davis, K. and Franzel, S., 2018. *Extension and Advisory Services in 10 Developing Countries: A Cross-country Analysis*. (technical report). USAID (cit. on pp.1, 14).

De Fraiture, C., Molden, D., and Wichelns, D., 2010. Investing in water for food, ecosystems, and livelihoods: An overview of the comprehensive assessment of water management in agriculture. *Agricultural Water Management* [Online], 97(4), pp.495–501. Available from: https://doi.org/10.1016/j.agwat.2009.08.015 (cit. on p.18).

De Fraiture, C. and Wichelns, D., 2010. Satisfying future water demands for agriculture. *Agricultural Water Management* [Online], 97(4), pp.502–511. Available from: https://doi.org/10.1016/j.agwat.2009.08.008 (cit. on pp.18, 77).

De Wit, C., 1958. Transpiration and Crop Yields: Agricultural Research Reports 64.6. *Wageningen: PUDOC* (cit. on p.7).

Dean, T., Bell, J., and Baty, A., 1987. Soil moisture measurement by an improved capacitance technique, Part I. Sensor design and performance. *Journal of Hydrology* [Online], 93(1-2), pp.67–78. Available from: https://doi.org/10.1016/0022-1694(87)90194-6 (cit. on p.36).

Delta-T, 1999. *ThetaProbe Soil Moisture Sensor Type ML2x User Manual ML2-UM-1*. (Manual). Delta-T Devices Ltd. (cit. on p.40).

Delta-T Devices Ltd., 2017. *User Manual for the ML3 ThetaProbe ML3-UM-2.1.* (Manual). Delta-T Devices (cit. on pp.41, 53).

Deng, X., Gu, H., Yang, L., Lyu, H., Cheng, Y., Pan, L., Fu, Z., Cui, L., and Zhang, L., 2020. A method of electrical conductivity compensation in a low-cost soil moisture sensing measurement based on capacitance. *Measurement* [Online], 150, p.107052. Available from: https://doi.org/10.1016/j.measurement.2019.107052 (cit. on pp.82, 87).

Denmead, O.T. and Shaw, R.H., 1962. Availability of soil water to plants as affected by soil moisture content and meteorological conditions 1. *Agronomy Journal* [Online], 54(5), pp.385–390. Available from: https://doi.org/10.2134/agronj1962.00021962005400050005x (cit. on p.8).

Department of Economic Affairs, 2019. *Economic Survey 2018-2019*. Economic Division, Ministry of Finance, Government of India (GoI) (cit. on p.2).

Dessart, F.J., Barreiro-Hurlé, J., and Bavel, R. van, 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics* [Online]. Available from: https://doi.org/10.1093/erae/jbz019 (cit. on p.111).

Dhanda, S., Yadav, A., Yadav, D.B., and Chauhan, B.S., 2022. Emerging Issues and Potential Opportunities in the Rice–Wheat Cropping System of North-Western India. *Frontiers in Plant Science* [Online], 13. Available from: https://doi.org/10.3389/fpls.2022.832683 (cit. on pp.3, 4, 64).

Digital Green, 2019. Farm stack. A digital green web publication [Online]. Available from: https://farmstack.co/(cit. on pp.6, 15).

Dinar, A., Tieu, A., and Huynh, H., 2019. Water scarcity impacts on global food production. *Global Food Security*, 23, pp.212–226 (cit. on p.64).

Doorenbos, J. and Kassam, A.H., 1979. *Yield response to water*. (FAO Irrigation and Drainage Paper No. 33). Food and Agricultural Organization of the United Nations (cit. on p.71).

Dwivedi, S., Kumar, S., Mishra, J., Haris, A., Singh, S., Srivastava, A., Kumar, A., Kumar, V., Singh, S., and Bhatt, B., 2019. Effect of moisture regimes and sowing dates on wheat physiological process and yield attributes under rain-fed ecosystem in Eastern Indo Gangetic Plain. *Plant Physiology Reports* [Online], 24(1), pp.46–53. Available from: https://doi.org/10.1007/s40502-018-0406-4 (cit. on p.66).

Eastwood, C., Ayre, M., Nettle, R., and Rue, B.D., 2019. Making sense in the cloud: Farm advisory services in a smart farming future. *NJAS-Wageningen Journal of Life Sciences* [Online], 90, p.100298. Available from: https://doi.org/10.1016/j.njas.2019.04.004 (cit. on pp.5, 14, 15, 34).

Eastwood, C., Jago, J., Edwards, J., and Burke, J., 2015. Getting the most out of advanced farm management technologies: roles of technology suppliers and dairy industry organisations in supporting precision dairy farmers. *Animal Production Science* [Online], 56(10), pp.1752–1760. Available from: https://doi.org/10.1071/AN141015 (cit. on p.15).

Eicher, C.K., 2001. *Africa's unfinished business: building sustainable agricultural research systems* [Online]. (Staff paper 2001-10, technical report 1099-2016-89172). East Lansing: Department of Agricultural Economics, Michigan State University, p.44. Available from: https://doi.org/10.22004/ag.econ.11802 (cit. on pp.1, 14).

Eitzinger, J., Trnka, M., Hösch, J., Žalud, Z., and Dubrovskỳ, M., 2004. Comparison of CERES, WOFOST and SWAP models in simulating soil water content during growing season under different soil conditions. *Ecological Modelling* [Online], 171(3), pp.223–246. Available from: https://doi.org/10.1016/J.ECOLMODEL.2003.08.012 (cit. on p.70).

Elliott, N., 2010. Introduction-wheat production in the Great Plains. In: Wheat production and pest management for the Great Plains region (cit. on p.1).

Elshorbagy, A., Corzo, G., Srinivasulu, S., and Solomatine, D., 2010. Experimental investigation of the predictive capabilities of data driven modeling techniques in hydrology-part 1: concepts and methodology. *Hydrology and Earth System Sciences* [Online], 14(10), pp.1931–1941. Available from: https://doi.org/10.5194/hess-14-1931-2010 (cit. on p.82).

Ewert, F., Rötter, R.P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K.C., Olesen, J.E., Ittersum, M.K. van, Janssen, S., Rivington, M., et al., 2015. Crop modelling for integrated assessment of risk to food production from climate change. *Environmental Modelling & Software* [Online], 72, pp.287–303. Available from: https://doi.org/10.1016/j.envsoft.2014.12.003 (cit. on p.105).

Fafchamps, M. and Minten, B., 2012. Impact of SMS-based agricultural information on Indian farmers. *The World Bank Economic Review*, 26(3), pp.383–414 (cit. on pp.5, 6, 15).

FAO, 2017. The future of food and agriculture–Trends and challenges. *Annual Report*, 296, pp.1–180 (cit. on pp.1, 64).

Fares, A. and Polyakov, V., 2006. Advances in crop water management using capacitive water sensors. *Advances in Agronomy* [Online], 90, pp.43–77. Available from: https://doi.org/10.1016/S0065-2113(06)90002-9 (cit. on p.36).

Fares, A. and Alva, A.K., 2000. Evaluation of capacitance probes for optimal irrigation of citrus through soil moisture monitoring in an entisol profile. *Irrigation Science* [Online], 19(2), pp.57–64. Available from: https://doi.org/10.1007/s002710050001 (cit. on p.67).

Fares, A., Safeeq, M., Awal, R., Fares, S., and Dogan, A., 2016. Temperature and probe-to-probe variability effects on the performance of capacitance soil moisture sensors in an Oxisol. *Vadose Zone Journal* [Online], 15(3), vzj2015–07. Available from: https://doi.org/10.2136/vzj2015.07.0098 (cit. on p.113).

Feder, G., Anderson, J.R., Birner, R., and Deininger, K., 2011. Promises and realities of community-based extension. In: *Community, Market, and State in Development, a Festschrift in Honour of Professor Y. Hayami*. (cit. on p.2).

Feder, G., Willett, A., and Zijp, W., 2001. Agricultural extension: Generic challenges and the ingredients for solutions. In: *Knowledge Generation and Technical Change: Institutional Innovation in Agriculture*. (cit. on p.2).

Feder, G., Anderson, J.R., Birner, R., and Deininger, K., 2010. Promises and realities of community-based agricultural extension. In: K. Otsuka and K. Kaliranjan, eds. *Community, market and state in development* [Online]. London: Palgrave Macmillan, pp.187–208. Available from: https://doi.org/10.1057/9780230295018_12 (cit. on p.15).

Feder, G., Birner, R., and Anderson, J.R., 2011. The private sector's role in agricultural extension systems: potential and limitations. *Journal of Agribusiness in Developing and Emerging Economies* [Online]. Available from: https://doi.org/10.1108/20440831111131505 (cit. on p.2).

Feldman, D.L. and Ingram, H.M., 2009. Making science useful to decision makers: Climate forecasts, water management, and knowledge networks. *Weather, Climate, and Society* [Online], 1(1), pp.9–21. Available from: https://doi.org/10.1175/2009WCAS1007.1 (cit. on p.32).

Feng, G. and Sui, R., 2020. Evaluation and calibration of soil moisture sensors in undisturbed soils. *Transactions of the ASABE* [Online], 63(2), pp.265–274. Available from: https://doi.org/10.13031/trans.13428 (cit. on pp.8, 65, 80, 103).

Fereres, E. and Soriano, M.A., 2007. Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany* [Online], 58(2), pp.147–159. Available from: https://doi.org/10.1093/jxb/erl165 (cit. on p.106).

Foster, T., Brozović, N., Butler, A., Neale, C., Raes, D., Steduto, P., Fereres, E., and Hsiao, T.C., 2017. Aquacrop-os: an open source version of fao's crop water productivity model. *Agricultural Water Management* [Online], 181, pp.18–22. Available from: https://doi.org/10.1016/j.agwat.2016.11.015 (cit. on pp.71, 96, 104).

Fowler, F.J.J., 2014. Survey research methods. 5th. SAGE Publications, Inc. (cit. on p.18).

Gadedjisso-Tossou, A., Avellán, T., and Schütze, N., 2019. An Economic-Based Evaluation of Maize Production under Deficit and Supplemental Irrigation for Smallholder Farmers in Northern Togo, West Africa. *Resources* [Online], 8(4), p.175. Available from: https://doi.org/10.3390/resources8040175 (cit. on p.106).

Gadédjisso-Tossou, A., Avellán, T., and Schütze, N., 2018. Potential of deficit and supplemental irrigation under climate variability in northern Togo, West Africa. *Water* [Online], 10(12), p.1803. Available from: https://doi.org/10.3390/w10121803 (cit. on p.106).

Galanouli, D., Murphy, C., and Gardner, J., 2004. Teachers' perceptions of the effectiveness of ICT-competence training. *Computers & Education* [Online], 43(1-2), pp.63–79. Available from: https://doi.org/10.1016/j.compedu.2003.12.005 (cit. on p.32).

Gallardo, M., Elia, A., and Thompson, R.B., 2020. Decision support systems and models for aiding irrigation and nutrient management of vegetable crops. *Agricultural Water Management* [Online], 240, p.106209. Available from: https://doi.org/10.1016/j.agwat.2020.106209 (cit. on p.67).

Gamma, A.E., Slekiene, J., Medeazza, G. von, Asplund, F., Cardoso, P., and Mosler, H.-J., 2017. Contextual and psychosocial factors predicting Ebola prevention behaviours using the RANAS approach to behaviour change in Guinea-Bissau. *BMC Public Health* [Online], 17(1), pp.1–12. Available from: https://doi.org/10.1186/s12889-017-4360-2 (cit. on p.111).

Ganesan, M., Karthikeyan, K., Prashant, S., and Umadikar, J., 2013. Use of mobile multimedia agricultural advisory systems by Indian farmers: Results of a survey. *Journal of Agricultural Extension and Rural Development* [Online], 5(4), pp.89–99. Available from: https://doi.org/10.5897/JAERD13.0466 (cit. on pp.6, 15, 31).

García, G., Brogioni, M., Venturini, V., Rodriguez, L., Fontanelli, G., Walker, E., Graciani, S., and Macelloni, G., 2016. Soil moisture estimation using multi linear regression with terrasar-x data. *Revista de Teledetección*, (46), pp.73–81 (cit. on p.69).

Gardner, W., 1986. Water Content. In: *Methods of Soil Analysis. Part 1. Physical and Mineralogical Methods* [Online]. Available from: https://doi.org/10.2136/sssabookser5.1.2ed.c21 (cit. on p.36).

Gargiulo, J., Eastwood, C., Garcia, S., and Lyons, N., 2018. Dairy farmers with larger herd sizes adopt more precision dairy technologies. *Journal of Dairy Science* [Online], 101(6), pp.5466–5473. Available from: https://doi.org/10.3168/jds.2017-13324 (cit. on pp.6, 14).

Gaskin, G. and Miller, J., 1996. Measurement of soil water content using a simplified impedance measuring technique. *Journal of Agricultural Engineering Research* [Online], 63(2), pp.153–159. Available from: https://doi.org/10.1006/jaer.1996.0017 (cit. on pp.36, 67).

Gedilu, E.Y., 2012. Soil Moisture Dynamics in Agricultural Fields with Heterogeneous Unsaturated Soils. (PhD Thesis). Indian Institute of Technology Kanpur (cit. on pp.79, 82).

Geerts, S. and Raes, D., 2009. Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. *Agricultural Water Management* [Online], 96(9), pp.1275–1284. Available from: https://doi.org/10.1016/j.agwat.2009.04.009 (cit. on p.106).

Geerts, S., Raes, D., and Garcia, M., 2010. Using AquaCrop to derive deficit irrigation schedules. *Agricultural Water Management* [Online], 98(1), pp.213–216. Available from: https://doi.org/10.1016/j.agwat.2010.07.003 (cit. on p.91).

George, T., 2014. Why crop yields in developing countries have not kept pace with advances in agronomy. *Global Food Security* [Online], 3(1), pp.49–58. Available from: https://doi.org/10.1016/j.gfs.2013.10.002 (cit. on pp.1, 3, 106).

Gerten, D., Heck, V., Jägermeyr, J., Bodirsky, B.L., Fetzer, I., Jalava, M., Kummu, M., Lucht, W., Rockström, J., Schaphoff, S., et al., 2020. Feeding ten billion people is possible within four terrestrial planetary boundaries. *Nature Sustainability* [Online], 3(3), pp.200–208. Available from: https://doi.org/10.1038/s41893-019-0465-1 (cit. on p.70).

Ghimire, K., 2020. *Geostatistic and deterministic interpolation for generating plot scale soil moisture maps*. (Master's Study Project). Technical University of Munich (cit. on p.104).

Gill, M.K., Asefa, T., Kemblowski, M.W., and McKee, M., 2006. Soil moisture prediction using support vector machines 1. *JAWRA Journal of the American Water Resources Association* [Online], 42(4), pp.1033–1046. Available from: https://doi.org/10.1111/j.1752-1688.2006.tb04512.x (cit. on p.69).

Glendenning, C.J., Babu, S., and Asenso-Okyere, K., 2010. *Review of agricultural extension in India: Are farmers' information needs being met?* (Discussion paper 01048, technical report). International Food Policy Research Institute (IFPRI) (cit. on pp.2, 15).

Godfray, H.C.J. and Garnett, T., 2014. Food security and sustainable intensification. *Philosophical transactions of the Royal Society B: Biological Sciences* [Online], 369(1639), p.20120273. Available from: https://doi.org/10.1098/rstb.2012.0273 (cit. on p.3).

González-Teruel, J.D., Torres-Sánchez, R., Blaya-Ros, P.J., Toledo-Moreo, A.B., Jiménez-Buendía, M., and Soto-Valles, F., 2019. Design and calibration of a low-cost SDI-12 soil moisture sensor. *Sensors* [Online], 19(3), p.491. Available from: https://doi.org/10.3390/s19030491 (cit. on pp.37, 54, 113, 114).

Government of India, 2011. Census of India (cit. on p.17).

Government of India, 2017. *Pocketbook of Agricultural Statistics*. Dept. of Agriculture, Cooperation and Farmers Welfare, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare (cit. on p.4).

Government of Malawi, 2000. *Agriculture Extension in the New Millennium: Towards Pluralistic and Demand-Driven Services in Malawi*. (technical report). Department of Agricultural Extension Services, Ministry of Agriculture and Irrigation (cit. on pp.1, 14).

Grafton, R.Q., Williams, J., Perry, C.J., Molle, F., Ringler, C., Steduto, P., Udall, B., Wheeler, S., Wang, Y., Garrick, D., et al., 2018. The paradox of irrigation efficiency. *Science* [Online], 361(6404), pp.748–750. Available from: https://doi.org/10.1126/science.aat9314 (cit. on pp.3, 64, 89).

Graves, A., Hess, T., and Matthews, R., 2002. Using models as tools in education and training. *Crop-soil simulation models: applications in developing countries*, pp.151–182 (cit. on pp.5, 70).

Greacen, E., 1981. *Soil Water Assessment by the Neutron Method*. Commonwealth Science Industrial Research Organization (cit. on p.36).

Greenwood, D.J., Zhang, K., Hilton, H.W., and Thompson, A.J., 2010. Opportunities for improving irrigation efficiency with quantitative models, soil water sensors and wireless technology. *The Journal of Agricultural Science* [Online], 148(1), pp.1–16. Available from: https://doi.org/10.1017/S0021859609990487 (cit. on pp.5, 8, 9, 89–92).

Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., and Xu, J., 2020. Irrigation scheduling approaches and applications: A review. *Journal of Irrigation and Drainage Engineering* [Online], 146(6), p.04020007. Available from: https://doi.org/10.1061/(ASCE) IR. 1943-4774.0001464 (cit. on pp.89–91, 99).

Gu, Z., Zhu, T., Jiao, X., Xu, J., and Qi, Z., 2021. Neural network soil moisture model for irrigation scheduling. *Computers and Electronics in Agriculture* [Online], 180, p.105801. Available from: https://doi.org/10.1016/j.compag.2020.105801 (cit. on p.69).

Guerra, L.C., Hoogenboom, G., Boken, V.K., Hook, J.E., Thomas, D.L., and Harrison, K.A., 2002. Estimating water demand for irrigation using a crop simulation model. 2002 *ASAE Annual Meeting*. American Society of Agricultural and Biological Engineers, p.1 (cit. on p.5).

Gupta, S., Tripathi, S., Sinha, R., Sri Harsha, K., Paul, D., Tripathi, S., Sen, I., and Dash, S., 2017. Setting Up a New CZO in the Ganga Basin: Instrumentation, Stakeholder Engagement and Preliminary Observations. *American geophysical union general assembly* 2017 [Online]. New Orleans: American Geophysical Union. Available from: https://doi.org/10.1002/essoar.bfe245c93cb55808.b3f3df49a9514dcb.1 (cit. on pp.16, 102).

Gupta, S., Hengl, T., Lehmann, P., Bonetti, S., and Or, D., 2021. SoilKsatDB: global database of soil saturated hydraulic conductivity measurements for geoscience applications. *Earth System Science Data*, 13(4), pp.1593–1612 (cit. on pp.76, 118).

Gupta, S., Karumanchi, S.H., Dash, S.K., Adla, S., Tripathi, S., Sinha, R., Paul, D., and Sen, I., 2019. Monitoring ecosystem health in India's food basket. *Eos* [Online], 100(March). Available from: https://doi.org/10.1029/2019E0117683 (cit. on pp.16, 66, 102).

Haley, M.B. and Dukes, M.D., 2012. Validation of landscape irrigation reduction with soil moisture sensor irrigation controllers. *Journal of Irrigation and Drainage Engineering* [Online], 138(2), pp.135–144. Available from: https://doi.org/10.1061/(ASCE)IR. 1943-4774.0000391 (cit. on p.90).

Hanjra, M.A. and Qureshi, M.E., 2010. Global water crisis and future food security in an era of climate change. *Food Policy* [Online], 35(5), pp.365–377. Available from: https://doi.org/10.1016/j.foodpol.2010.05.006 (cit. on p.2).

Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A., and Khan, S.U., 2015. The rise of "big data" on cloud computing: review and open research issues. *Information Systems* [Online], 47, pp.98–115. Available from: https://doi.org/10.1016/j.is.2014.07.006 (cit. on p.31).

Hastie, T., Tibshirani, R., and Friedman, J., 2009. *The Elements of Statistical Learning 2nd ed Springer Series in Statistics*. Springer New York (cit. on pp.70, 80).

Hauke, J. and Kossowski, T., 2011. Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Set of Data. *Quaestiones Geographicae* [Online], 30(2), pp.87–93. Available from: https://doi.org/10.2478/v10117-011-0021-1 (cit. on p.46).

He, J., Dukes, M., Jones, J., Graham, W., and Judge, J., 2009. Applying GLUE for estimating CERES-Maize genetic and soil parameters for sweet corn production. *Transactions of the ASABE* [Online], 52(6), pp.1907–1921. Available from: https://doi.org/10.13031/2013.29218 (cit. on p.105).

Hira, G., Jalota, S., and VK, A., 2004. *Efficient Management of Water Resources for Sustainable Cropping in Punjab*. (Research Bulletin no. 20). Department of Soils, Punjab Agricultural University (cit. on pp.4, 64).

Holmboe, E.S. and Durning, S.J., 2014. Assessing clinical reasoning: moving from in vitro to in vivo. *Diagnosis* [Online], 1(1), pp.111–117. Available from: https://doi.org/10.1515/dx-2013-0029 (cit. on p.30).

Hoppula, K.I. and Salo, T.J., 2007. Tensiometer-based irrigation scheduling in perennial strawberry cultivation. *Irrigation Science* [Online], 25(4), pp.401–409. Available from: https://doi.org/10.1007/s00271-006-0055-7 (cit. on p.90).

Hossain, F., Karumanchi, S.H., Goyal, S., Ahmad, S.K., Lohani, B., Balaji, N., and Tripathi, S., 2020a. Towards Affordable and Sustainable Water-Smart Irrigation Services. *Water Resources IMPACT* (cit. on p.111).

Hossain, F., Tripathi, S., Ahmad, S.K., Adla, S., Lohani, B., Goyal, S., and Karumanchi, S.H., 2020b. *Improving Irrigation Services for Marginal Farmers in India* [Online]. Available from: https://www.agrilinks.org/post/improving-irrigation-services-marginal-farmers-india/(cit. on pp.102, 111).

Hostiou, N., Fagon, J., Chauvat, S., Turlot, A., Kling-Eveillard, F., Boivin, X., and Allain, C., 2017. Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. *Biotechnologie*, *Agronomie*, *Société et Environnement/Biotechnology*, *Agronomy*, *Society and Environment*, 21(4), pp.268–275 (cit. on p.15).

Howell, T., 2001. Enhancing water use efficiency in irrigated agriculture. *Agronomy Journal* [Online], 93, pp.281–289. Available from: https://doi.org/10.2134/agronj2001.932281x (cit. on pp.4, 25).

Hsiao, T.C. and Bradford, K.J., 1983. Physiological consequences of cellular water deficits. Limitations to efficient water use in crop production [Online], pp.227–265. Available from: https://doi.org/10.2134/1983.limitationstoefficientwateruse.c15 (cit. on p.7).

Hsiao, T.C., Steduto, P., and Fereres, E., 2007. A systematic and quantitative approach to improve water use efficiency in agriculture. *Irrigation Science* [Online], 25(3), pp.209–231. Available from: https://doi.org/10.1007/s00271-007-0063-2 (cit. on p.7).

Huang, M., Wang, C., Qi, W., Zhang, Z., and Xu, H., 2022. Modelling the integrated strategies of deficit irrigation, nitrogen fertilization, and biochar addition for winter wheat by AquaCrop based on a two-year field study. *Field Crops Research* [Online], 282, p.108510. Available from: https://doi.org/10.1016/j.fcr.2022.108510 (cit. on pp.7, 70, 83, 86).

Hubner, C., Cardell-Oliver, R., Becker, R., Spohrer, K., Jotter, K., and Wagenknecht, T., 2009. Wireless soil moisture sensor networks for environmental monitoring and vineyard irrigation. *Wireless soil moisture sensor networks for environmental monitoring and vineyard irrigation*. Helsinki University of Technology, pp.408–415 (cit. on p.36).

Hunsaker, D., French, A., Waller, P.M., Bautista, E., Thorp, K., Bronson, K., and Andrade-Sanchez, P., 2015. Comparison of traditional and ET-based irrigation scheduling of surface-irrigated cotton in the arid southwestern USA. *Agricultural Water Management* [Online], 159, pp.209–224. Available from: https://doi.org/10.1016/j.agwat.2015.06.016 (cit. on p.8).

ICAR, 2015. KVK: A brief overview. [Online]. Available from: https://krishi.icar.gov.in/kvk.jsp (cit. on p.31).

ICAR-IASRI, n.d. *About KVK*. [Online]. Available from: https://kvk.icar.gov.in/aboutkvk.aspx (cit. on p.31).

IFPRI, 2020. Agricultural extension [Online]. Available from: https://www.ifpri.org/topic/agricultural-extension (cit. on pp.1, 14).

Iqbal, M.A., Shen, Y., Stricevic, R., Pei, H., Sun, H., Amiri, E., Penas, A., and Rio, S. del, 2014. Evaluation of the FAO AquaCrop model for winter wheat on the North China Plain under deficit irrigation from field experiment to regional yield simulation. *Agricultural Water Management* [Online], 135, pp.61–72. Available from: https://doi.org/10.1016/j.agwat.2013.12.012 (cit. on p.70).

Irrigation Association, 2011. Irrigation. Irrigation ASsociation, Virginia (cit. on p.5).

Ittersum, M.K. van, Leffelaar, P.A., Keulen, H. van, Kropff, M.J., Bastiaans, L., and Goudriaan, J., 2003. On approaches and applications of the Wageningen crop models. *European Journal of Agronomy* [Online], 18(3-4), pp.201–234. Available from: https://doi.org/10.1016/S1161-0301(02)00106-5 (cit. on p.7).

IUPAC, 1997. Compendium of Chemical Terminology. Blackwell Scientific Publications Oxford. Available from: https://doi.org/10.1351/goldbook.P04758 (cit. on pp.43, 45).

Jamieson, P., Porter, J., and Wilson, D., 1991. A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand. *Field Crops Research* [Online], 27(4), pp.337–350. Available from: https://doi.org/10.1016/0378-4290(91)90040-3 (cit. on p.86).

Jat, M.L., Gathala, M., Ladha, J., Saharawat, Y., Jat, A., Kumar, V., Sharma, S., Kumar, V., and Gupta, R., 2009. Evaluation of precision land leveling and double zero-till systems in the rice—wheat rotation: Water use, productivity, profitability and soil physical properties. *Soil and Tillage Research* [Online], 105(1), pp.112–121. Available from: https://doi.org/10.1016/j.still.2009.06.003 (cit. on pp.3, 64).

Jat, M.L., Chakraborty, D., Ladha, J.K., Rana, D.S., Gathala, M.K., McDonald, A., and Gerard, B., 2020. Conservation agriculture for sustainable intensification in South Asia. *Nature Sustainability* [Online], 3(4), pp.336–343. Available from: https://doi.org/10.1038/s41893-020-0500-2 (cit. on p.3).

Jekel, C., 2017. Fitting a Piecewise Linear Function to Data (cit. on pp.48, 75).

Jones, C., Dyke, P., Williams, J., Kiniry, J., Benson, V., and Griggs, R., 1991. EPIC: an operational model for evaluation of agricultural sustainability. *Agricultural Systems* [Online], 37(4), pp.341–350. Available from: https://doi.org/10.1016/0308-521X(91) 90057-H (cit. on p.7).

Jones, E., Qadir, M., Vliet, M.T. van, Smakhtin, V., and Kang, S.-m., 2019. The state of desalination and brine production: A global outlook. *Science of the Total Environment* [Online], 657, pp.1343–1356. Available from: https://doi.org/10.1016/j.scitotenv.2018.12.076 (cit. on p.64).

Jones, H.G., 2004. Irrigation scheduling: advantages and pitfalls of plant-based methods. *Journal of Experimental Botany* [Online], 55(407), pp.2427–2436. Available from: https://doi.org/10.1093/jxb/erh213 (cit. on p.90).

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., et al., 2017. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems* [Online], 155, pp.269–288. Available from: https://doi.org/10.1016/j.agsy.2016.09.021 (cit. on p.104).

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L., Wilkens, P.W., Singh, U., Gijsman, A.J., and Ritchie, J.T., 2003. The DSSAT cropping system model. *European Journal of Agronomy* [Online], 18(3-4), pp.235–265. Available from: https://doi.org/10.1016/S1161-0301(02)00107-7 (cit. on pp.7, 70).

Jones, J.W., Naab, J., Fatondji, D., Dzotsi, K., Adiku, S., and He, J., 2012. Uncertainties in simulating crop performance in degraded soils and low input production systems. *Improving soil fertility recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT)*. Springer, pp.43–59 (cit. on pp.5, 70).

Jones, S.B., Blonquist Jr, J., Robinson, D.A., Rasmussen, V.P., and Or, D., 2005. Standardizing characterization of electromagnetic water content sensors: part 1. methodology. *Vadose Zone Journal* [Online], 4(4), pp.1048–1058. Available from: https://doi.org/10.2136/vzj2004.0140 (cit. on p.67).

Jutel, A., 2009. Sociology of diagnosis: a preliminary review. *Sociology of Health & Illness* [Online], 31(2), pp.278–299. Available from: https://doi.org/10.1111/j.1467-9566.2008.01152.x (cit. on p.31).

Kalambukattu, J.G., Kumar, S., and Ghotekar, Y.S., 2018. Spatial variability analysis of soil quality parameters in a watershed of Sub-Himalayan Landscape-A case study. *Eurasian Journal of Soil Science* [Online], 7(3), pp.238–250. Available from: https://doi.org/10.18393/ejss.427189 (cit. on p.17).

Kale, S., Madenoğlu, S., and Sonmez, B., 2018. Evaluating aquacrop model for winter wheat under various irrigation conditions in turkey. *Tarim Bilimleri Dergisi*, 24, pp.205–217 (cit. on pp.83, 86).

Kamilaris, A., Kartakoullis, A., and Prenafeta-Boldú, F.X., 2017. A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture* [Online], 143, pp.23–37. Available from: https://doi.org/10.1016/j.compag.2017.09.037 (cit. on p.31).

Kang, S., Zhang, L., Liang, Y., Hu, X., Cai, H., and Gu, B., 2002. Effects of limited irrigation on yield and water use efficiency of winter wheat in the Loess Plateau of China. *Agricultural Water Management* [Online], 55(3), pp.203–216. Available from: https://doi.org/10.1016/S0378-3774(01)00180-9 (cit. on p.106).

Kargas, G. and Soulis, K.X., 2012. Performance analysis and calibration of a new low-cost capacitance soil moisture sensor. *Journal of Irrigation and Drainage Engineering* [Online], 138(7), pp.632–641. Available from: https://doi.org/10.1061/(asce)ir.1943-4774.0000449 (cit. on pp.8, 36, 41–43, 51, 56, 65, 103, 113, 114).

Kargas, G. and Soulis, K., 2019. Performance evaluation of a recently developed soil water content, dielectric permittivity, and bulk electrical conductivity electromagnetic sensor. *Agricultural Water Management* [Online], 213, pp.568–579. Available from: https://doi.org/10.1016/j.agwat.2018.11.002 (cit. on pp.41–43, 113, 114).

Karlen, D.L., Mausbach, M., Doran, J.W., Cline, R., Harris, R., and Schuman, G., 1997. Soil quality: a concept, definition, and framework for evaluation (a guest editorial). *Soil Science Society of America Journal* [Online], 61(1), pp.4–10. Available from: https://doi.org/10.2136/sssaj1997.03615995006100010001x (cit. on pp.15, 17).

Kataki, P.K., Hobbs, P., and Adhikary, B., 2001. The rice-wheat cropping system of South Asia: Trends, constraints and productivity—A prologue. *Journal of Crop Production* [Online], 3(2), pp.1–26. Available from: https://doi.org/10.1300/J144v03n02_01 (cit. on p.64).

Kaur, S., Kaur, P., and Kumar, P., 2020. Farmers' knowledge of soil health card and constraints in its use. *Indian Journal of Extension Education*, 56(1), pp.28–32 (cit. on pp.18, 31, 102).

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N., Meinke, H., Hochman, Z., et al., 2003. An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy* [Online], 18(3-4), pp.267–288. Available from: https://doi.org/10.1016/S1161-0301(02)00108-9 (cit. on p.70).

Keating, B.A., Herrero, M., Carberry, P.S., Gardner, J., and Cole, M.B., 2014. Food wedges: framing the global food demand and supply challenge towards 2050. *Global Food Security* [Online], 3(3-4), pp.125–132. Available from: https://doi.org/10.1016/j.gfs.2014.08.004 (cit. on p.70).

Kelleners, T., Seyfried, M., Blonquist Jr, J., Bilskie, J., and Chandler, D., 2005. Improved interpretation of water content reflectometer measurements in soils. *Soil Science Society of America Journal* [Online], 69(6), pp.1684–1690. Available from: https://doi.org/10.2136/sssaj2005.0023 (cit. on p.114).

Kelly, T. and Foster, T., 2021. AquaCrop-OSPy: Bridging the gap between research and practice in crop-water modeling. *Agricultural Water Management* [Online], 254, p.106976. Available from: https://doi.org/10.1016/j.agwat.2021.106976 (cit. on p.71).

Khatami, S., Peel, M.C., Peterson, T.J., and Western, A.W., 2019. Equifinality and flux mapping: A new approach to model evaluation and process representation under uncertainty. *Water Resources Research* [Online], 55(11), pp.8922–8941. Available from: https://doi.org/10.1029/2018WR023750 (cit. on p.105).

Kil, S.-H., Lee, D.K., Kim, J.-H., Li, M.-H., and Newman, G., 2016. Utilizing the analytic hierarchy process to establish weighted values for evaluating the stability of slope revegetation based on hydroseeding applications in South Korea. *Sustainability* [Online], 8(1), p.58. Available from: https://doi.org/10.3390/su8010058 (cit. on p.17).

Kinzli, K.-D., Manana, N., and Oad, R., 2012. Comparison of laboratory and field calibration of a soil-moisture capacitance probe for various soils. *Journal of Irrigation and Drainage Engineering* [Online], 138(4), pp.310–321. Available from: https://doi.org/10.1061/(ASCE)IR.1943-4774.0000418 (cit. on pp.48, 50, 54).

Kisekka, I., Peddinti, S.R., Kustas, W.P., McElrone, A.J., Bambach-Ortiz, N., McKee, L., and Bastiaanssen, W., 2022. Spatial–temporal modeling of root zone soil moisture dynamics in a vineyard using machine learning and remote sensing. *Irrigation Science* [Online], pp.1–17. Available from: https://doi.org/10.1007/s00271-022-00775-1 (cit. on pp.1, 5, 8, 65, 67).

Klerkx, L. and Jansen, J., 2010. Building knowledge systems for sustainable agriculture: supporting private advisors to adequately address sustainable farm management in regular service contacts. *International Journal of Agricultural Sustainability* [Online], 8(3), pp.148–163. Available from: https://doi.org/10.3763/ijas.2009.0457 (cit. on p.14).

Knowler, D. and Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy* [Online], 32(1), pp.25–48. Available from: https://doi.org/10.1016/j.foodpol.2006.01.003 (cit. on p.111).

Kojima, Y., Shigeta, R., Miyamoto, N., Shirahama, Y., Nishioka, K., Mizoguchi, M., and Kawahara, Y., 2016. Low-cost soil moisture profile probe using thin-film capacitors and a capacitive touch sensor. *Sensors* [Online], 16(8), p.1292. Available from: https://doi.org/10.3390/s16081292 (cit. on p.36).

Kragt, M.E. and Llewellyn, R.S., 2014. Using a choice experiment to improve decision support tool design. *Applied Economic Perspectives and Policy* [Online], 36(2), pp.351–371. Available from: https://doi.org/10.1093/aepp/ppu001 (cit. on p.111).

Kuczera, G. and Parent, E., 1998. Monte Carlo assessment of parameter uncertainty in conceptual catchment models: the Metropolis algorithm. *Journal of Hydrology* [Online], 211(1-4), pp.69–85. Available from: https://doi.org/10.1016/S0022-1694(98)00198-X (cit. on p.105).

Kulshreshtha, S. and Elshorbagy, A., 2017. *Current Perspective on Irrigation and Drainage* [Online]. InTech. Available from: https://doi.org/10.5772/63177 (cit. on p.70).

Kumar, A., 2019. *Partitioning of evapotranspiration using hydrometric methods* [Online]. (Master's Thesis). Indian Institute of Technology Kanpur. Available from: http://172.28.64.70:8080/jspui/handle/123456789/18076 (cit. on pp.77, 105).

Kumar, A., Sah, B., Singh, A.R., Deng, Y., He, X., Kumar, P., and Bansal, R., 2017a. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews* [Online], 69, pp.596–609. Available from: https://doi.org/10.1016/j.rser.2016.11.191 (cit. on p.17).

Kumar, S., Dwivedi, S., Kumar, R., Mishra, J., Singh, S., Prakash, V., Rao, K., and Bhatt, B., 2017b. Productivity and energy use efficiency of wheat (Triticum aestivum) genotypes under different tillage options in rainfed ecosystem of middle Indo-Gangetic Plains. *Indian Journal of Agronomy*, 62(1), pp.31–38 (cit. on p.66).

Kumar, S., Sharma, V., Chaudhary, S., Tyagi, A., Mishra, P., Priyadarshini, A., and Singh, A., 2012. Genetics of flowering time in bread wheat Triticum aestivum: complementary interaction between vernalization-insensitive and photoperiod-insensitive mutations imparts very early flowering habit to spring wheat. *Journal of Genetics* [Online], 91(1), pp.33–47. Available from: https://doi.org/10.1007/s12041-012-0149-3 (cit. on p.66).

Kumar, U., Kumar, N., Mishra, V., and Jena, R., 2019. Soil Quality Assessment Using Analytic Hierarchy Process (AHP): A Case Study. *Interdisciplinary Approaches to Information Systems and Software Engineering*. IGI Global, pp.1–18 (cit. on pp.17, 23).

Kumar, V., Jat, H.S., Sharma, P.C., Gathala, M.K., Malik, R.K., Kamboj, B.R., Yadav, A.K., Ladha, J.K., Raman, A., Sharma, D., et al., 2018. Can productivity and profitability be enhanced in intensively managed cereal systems while reducing the environmental footprint of production? Assessing sustainable intensification options in the breadbasket of India. *Agriculture, Ecosystems & Environment* [Online], 252, pp.132–147. Available from: https://doi.org/10.1016/j.agee.2017.10.006 (cit. on p.3).

Ladha, J.K., Kumar, V., Alam, M.M., Sharma, S., Gathala, M., Chandna, P., Saharawat, Y.S., and Balasubramanian, V., 2009. Integrating crop and resource management technologies for enhanced productivity, profitability, and sustainability of the rice-wheat system in South Asia. *Integrated crop and resource management in the rice-wheat system of South Asia*, pp.69–108 (cit. on p.3).

Laik, R., Sharma, S., Idris, M., Singh, A., Singh, S., Bhatt, B., Saharawat, Y., Humphreys, E., and Ladha, J., 2014. Integration of conservation agriculture with best management practices for improving system performance of the rice—wheat rotation in the Eastern Indo-Gangetic Plains of India. *Agriculture, Ecosystems & Environment* [Online], 195, pp.68–82. Available from: https://doi.org/10.1016/j.agee.2014.06.001 (cit. on pp.3, 64).

Landau, S., Mitchell, R., Barnett, V., Colls, J., Craigon, J., and Payne, R., 2000. A parsimonious, multiple-regression model of wheat yield response to environment. *Agricultural and Forest Meteorology* [Online], 101(2-3), pp.151–166. Available from: https://doi.org/10.1016/S0168-1923(99)00166-5 (cit. on p.65).

Landge, S. and Tripathi, H., 2006. Training needs of *kisan mitras* in agriculture and allied areas. *Indian Research Journal of Extension Education*, 6(3), pp.54–58 (cit. on p.33).

Lane, J., 2015. Digital Soil: The Four Secrets of the New Agriculture. Biofuels Digest [Online]. Available from: https://www.biofuelsdigest.com/bdigest/2015/03/09/the-four-secrets-of-the-new-agriculture/ (cit. on p.32).

Laurent, C., Cerf, M., and Labarthe, P., 2006. Agricultural extension services and market regulation: learning from a comparison of six eu countries. *Journal of Agricultural Education and Extension* [Online], 12(1), pp.5–16. Available from: https://doi.org/10.1080/13892240600740787 (cit. on p.14).

Lee, C.-H., Wu, M.-Y., Asio, V.B., and Chen, Z.-S., 2006. Using a soil quality index to assess the effects of applying swine manure compost on soil quality under a crop rotation system in Taiwan. *Soil Science* [Online], 171(3), pp.210–222. Available from: https://doi.org/10.1097/01.ss.0000199700.78956.8c (cit. on p.17).

Lee, Y., Jung, C., and Kim, S., 2019. Spatial distribution of soil moisture estimates using a multiple linear regression model and Korean geostationary satellite (COMS) data. *Agricultural Water Management* [Online], 213, pp.580–593. Available from: https://doi.org/10.1016/j.agwat.2018.09.004 (cit. on p.69).

Leeuwis, C. and Van den Ban, A., 2004. Communication for rural innovation: rethinking agricultural extension. Blackwell Publishing Ltd. (cit. on p.14).

Liang, H., Qi, Z., DeJonge, K.C., Hu, K., and Li, B., 2017. Global sensitivity and uncertainty analysis of nitrate leaching and crop yield simulation under different water and nitrogen management practices. *Computers and Electronics in Agriculture* [Online], 142, pp.201–210. Available from: https://doi.org/DOI:10.1016/j.compag.2017.09.010 (cit. on pp.76, 104).

Liebig, M.A., Varvel, G., and Doran, J., 2001. A simple performance-based index for assessing multiple agroecosystem functions. *Agronomy Journal* [Online], 93(2), pp.313–318. Available from: https://doi.org/10.2134/agronj2001.932313x (cit. on p.23).

Lin, B.B., Egerer, M.H., Liere, H., Jha, S., and Philpott, S.M., 2018. Soil management is key to maintaining soil moisture in urban gardens facing changing climatic conditions. *Scientific Reports* [Online], 8(1), pp.1–9. Available from: https://doi.org/10.1038/s41598-018-35731-7 (cit. on p.5).

Lindblom, J., Lundström, C., Ljung, M., and Jonsson, A., 2017. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precision Agriculture* [Online], 18(3), pp.309–331. Available from: https://doi.org/10.1007/s11119-016-9491-4 (cit. on p.111).

Liu, D., Yu, Z.-b., and Hai-shen, L., 2010. Data assimilation using support vector machines and ensemble Kalman filter for multi-layer soil moisture prediction. *Water Science and Engineering* [Online], 3(4), pp.361–377. Available from: https://doi.org/10.3882/j.issn.1674-2370.2010.04.001 (cit. on p.69).

Lokers, R., Knapen, R., Janssen, S., Randen, Y. van, and Jansen, J., 2016. Analysis of Big Data technologies for use in agro-environmental science. *Environmental Modelling & Software* [Online], 84, pp.494–504. Available from: https://doi.org/10.1016/j.envsoft.2016.07.017 (cit. on p.31).

Lopes, S.O., Fontes, F.A., Pereira, R., Pinho, M. de, and Gonçalves, A.M., 2016. Optimal control applied to an irrigation planning problem. *Mathematical Problems in Engineering* [Online], 2016. Available from: https://doi.org/10.1155/2016/5076879 (cit. on p.91).

Lu, D., Ricciuto, D., Walker, A., Safta, C., and Munger, W., 2017. Bayesian calibration of terrestrial ecosystem models: a study of advanced Markov chain Monte Carlo methods. *Biogeosciences* [Online], 14(18), pp.4295–4314. Available from: https://doi.org/10.5194/bg-14-4295-2017 (cit. on p.105).

Lu, Y., Chibarabada, T.P., McCabe, M.F., De Lannoy, G.J., and Sheffield, J., 2021a. Global sensitivity analysis of crop yield and transpiration from the FAO-AquaCrop model for dryland environments. *Field Crops Research* [Online], 269, p.108182. Available from: https://doi.org/10.1016/j.fcr.2021.108182 (cit. on p.104).

Lu, Y., Chibarabada, T.P., Ziliani, M.G., Onema, J.-M.K., McCabe, M.F., and Sheffield, J., 2021b. Assimilation of soil moisture and canopy cover data improves maize simulation using an under-calibrated crop model. *Agricultural Water Management* [Online], 252, p.106884. Available from: https://doi.org/10.1016/j.agwat.2021.106884 (cit. on p.65).

Lu, Y., Wei, C., McCabe, M.F., and Sheffield, J., 2022. Multi-variable assimilation into a modified AquaCrop model for improved maize simulation without management or crop phenology information. *Agricultural Water Management* [Online], 266, p.107576. Available from: https://doi.org/10.1016/j.agwat.2022.107576 (cit. on p.104).

Lu, Y., Zhang, X., Chen, S., Shao, L., and Sun, H., 2016. Changes in water use efficiency and water footprint in grain production over the past 35 years: a case study in the North China Plain. *Journal of Cleaner Production* [Online], 116, pp.71–79. Available from: https://doi.org/10.1016/j.jclepro.2016.01.008 (cit. on pp.3, 64, 89).

Ma, H., Malone, R.W., Jiang, T., Yao, N., Chen, S., Song, L., Feng, H., Yu, Q., and He, J., 2020. Estimating crop genetic parameters for DSSAT with modified PEST software. *European Journal of Agronomy* [Online], 115, p.126017. Available from: https://doi.org/10.1016/j.eja.2020.126017 (cit. on pp.76, 104).

Ma, S.C., Duan, A.-W., Ma, S.-T., and Yang, S.-J., 2016. Effect of early-stage regulated deficit irrigation on stem lodging resistance, leaf photosynthesis, root respiration and yield stability of winter wheat under post-anthesis water stress conditions. *Irrigation and Drainage* [Online], 65(5), pp.673–681. Available from: https://doi.org/10.1002/ird.2022 (cit. on pp.7, 106).

Martini, E., Wollschläger, U., Kögler, S., Behrens, T., Dietrich, P., Reinstorf, F., Schmidt, K., Weiler, M., Werban, U., and Zacharias, S., 2015. Spatial and temporal dynamics of hillslope-scale soil moisture patterns: Characteristic states and transition mechanisms. *Vadose Zone Journal* [Online], 14(4), vzj2014–10. Available from: https://doi.org/10.2136/vzj2014.10.0150 (cit. on p.37).

Matson, P.A. and Vitousek, P.M., 2006. Agricultural intensification: will land spared from farming be land spared for nature? *Conservation Biology* [Online], 20(3), pp.709–710. Available from: https://doi.org/10.1111/j.1523-1739.2006.00442.x (cit. on p.1).

Matula, S., Bát'ková, K., and Legese, W.L., 2016a. Laboratory performance of five selected soil moisture sensors applying factory and own calibration equations for two soil media of different bulk density and salinity levels. *Sensors* [Online], 16(11), p.1912. Available from: https://doi.org/10.3390/s16111912 (cit. on pp.8, 65, 75, 103).

Matula, S., Bát'ková, K., and Legese, W.L., 2016b. Laboratory performance of five selected soil moisture sensors applying factory and own calibration equations for two soil media of different bulk density and salinity levels. *Sensors* [Online], 16(11), p.1912. Available from: https://doi.org/10.3390/s16111912 (cit. on pp.37, 41, 42, 60, 113, 114).

McBratney, A., 1997. Spatial variability in soil-implications for precision agriculture. *Proc. of Precision Agriculture* 1997, pp.3–31 (cit. on p.24).

McBratney, A., Whelan, B., Ancev, T., and Bouma, J., 2005. Future directions of precision agriculture. *Precision Agriculture* [Online], 6(1), pp.7–23. Available from: https://doi.org/10.1007/s11119-005-0681-8 (cit. on p.37).

McMillan, H. and Clark, M., 2009. Rainfall-runoff model calibration using informal likelihood measures within a Markov chain Monte Carlo sampling scheme. *Water Resources Research* [Online], 45(4). Available from: https://doi.org/10.1029/2008WR007288 (cit. on p.105).

McNabb, D.E., 2019. Agriculture and inefficient water use. *Global pathways to water sustainability*. Springer, pp.99–115 (cit. on p.4).

Migliaccio, K.W., Schaffer, B., Crane, J.H., and Davies, F.S., 2010. Plant response to evapotranspiration and soil water sensor irrigation scheduling methods for papaya production in south Florida. *Agricultural Water Management* [Online], 97(10), pp.1452–1460. Available from: https://doi.org/10.1016/j.agwat.2010.04.012 (cit. on p.90).

Miller, J. and Gaskin, G., 1998. *ThetaProbe ML2x. Principles of operation and applications*. *Technical Note*. (Manual). UK Macaulay Land Use Research Institute (cit. on p.40).

Ministry of Agriculture and Farmers Welfare, 2017. *Irrigation statistical year book*. Directorate of Economics and Statistics, Government of India (cit. on p.3).

Mishra, A.K., Deep, S., and Choudhary, A., 2015. Identification of suitable sites for organic farming using AHP & GIS. *The Egyptian Journal of Remote Sensing and Space Science* [Online], 18(2), pp.181–193. Available from: https://doi.org/10.1016/j.ejrs.2015.06.005 (cit. on p.17).

Moges, E., Demissie, Y., Larsen, L., and Yassin, F., 2020. Sources of hydrological model uncertainties and advances in their analysis. *Water* [Online], 13(1), p.28. Available from: https://doi.org/10.3390/w13010028 (cit. on p.105).

Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A., and Kijne, J., 2010. Improving agricultural water productivity: Between optimism and caution. *Agricultural Water Management* [Online], 97(4), pp.528–535. Available from: https://doi.org/10.1016/j.agwat.2009.03.023 (cit. on pp.15, 77).

Monteith, J.L., 1977. Climate and the efficiency of crop production in Britain. *Philosophical Transactions of the Royal Society of London. B, Biological Sciences* [Online], 281(980), pp.277–294. Available from: https://doi.org/10.1098/rstb.1977.0140 (cit. on p.7).

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., and Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* [Online], 50(3), pp.885–900. Available from: https://doi.org/10.13031/2013.23153 (cit. on p.45).

Morris, A. and Langari, R., 2012. Instrument Types and Performance Characteristics. In: *Measurement and Instrumentation: Theory and Application* [Online]. Available from: https://doi.org/10.1016/B978-0-12-381960-4.00002-4 (cit. on p.43).

Mosler, H.-J., 2012. A systematic approach to behavior change interventions for the water and sanitation sector in developing countries: a conceptual model, a review, and a guideline. *International Journal of Environmental Health Research* [Online], 22(5), pp.431–449. Available from: https://doi.org/10.1080/09603123.2011.650156 (cit. on p.111).

Mouazen, A.M., Dumont, K., Maertens, K., and Ramon, H., 2003. Two-dimensional prediction of spatial variation in topsoil compaction of a sandy loam field-based on measured horizontal force of compaction sensor, cutting depth and moisture content. *Soil and Tillage Research* [Online], 74(1), pp.91–102. Available from: https://doi.org/10.1016/S0167-1987(03)00123-5 (cit. on p.24).

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., and Foley, J.A., 2012. Closing yield gaps through nutrient and water management. *Nature* [Online], 490(7419), pp.254–257. Available from: https://doi.org/10.1038/nature11420 (cit. on pp.2, 15–17).

Mukaka, M.M., 2012. A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal* [Online], 24(3), pp.69–71. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3576830/ (cit. on p.46).

Muñoz-Carpena, R., Li, Y.C., Klassen, W., and Dukes, M.D., 2005. Field comparison of tensiometer and granular matrix sensor automatic drip irrigation on tomato. *HortTechnology* [Online], 15(3), pp.584–590. Available from: https://doi.org/10.21273/HORTTECH. 15.3.0584 (cit. on p.67).

Musick, J.T. and Porter, K.B., 1990. Wheat. In: *Irrigation of agricultural crops* (cit. on pp.8, 9, 92).

Nagahage, E.A.A.D., Nagahage, I.S.P., and Fujino, T., 2019. Calibration and validation of a low-cost capacitive moisture sensor to integrate the automated soil moisture monitoring system. *Agriculture* [Online], 9(7), p.141. Available from: https://doi.org/10.3390/agriculture9070141 (cit. on pp.8, 69, 73, 82, 103).

Nair, J. and Thomas, B.K., 2022. Why is adoption of micro-irrigation slow in India? a review. *Development in Practice* [Online], pp.1–11. Available from: https://doi.org/10.1080/09614524.2022.2059065 (cit. on pp.4, 64).

Nakra, B.C. and Chaudhry, K.K., 2006. Introduction to Instruments and Their Representation. In: *Instrumentation, Measurement and Analysis* (cit. on pp.41, 68).

Navarro-Hellín, H., Torres-Sánchez, R., Soto-Valles, F., Albaladejo-Pérez, C., López-Riquelme, J.A., and Domingo-Miguel, R., 2015. A wireless sensors architecture for efficient irrigation water management. *Agricultural Water Management* [Online], 151, pp.64–74. Available from: https://doi.org/10.1016/j.agwat.2014.10.022 (cit. on pp.6, 65).

Neethirajan, S., 2017. Recent advances in wearable sensors for animal health management. *Sensing and Bio-Sensing Research* [Online], 12, pp.15–29. Available from: https://doi.org/10.1016/j.sbsr.2016.11.004 (cit. on p.15).

Nettle, R., Crawford, A., and Brightling, P., 2018. How private-sector farm advisors change their practices: an Australian case study. *Journal of Rural Studies* [Online], 58, pp.20–27. Available from: https://doi.org/10.1016/j.jrurstud.2017.12.027 (cit. on pp.5, 14).

Nielsen, D.C., Miceli-Garcia, J.J., and Lyon, D.J., 2012. Canopy cover and leaf area index relationships for Wheat, Triticale, and Corn. *Agronomy Journal* [Online], 104(6), pp.1569–1573. Available from: https://doi.org/10.2134/agronj2012.0107n (cit. on p.73).

Noborio, K., McInnes, K., and Heilman, J., 1994. Field measurements of soil electrical conductivity and water content by time-domain reflectometry. *Computers and Electronics in Agriculture* [Online], 11(2-3), pp.131–142. Available from: https://doi.org/10.1016/0168-1699(94)90003-5 (cit. on p.36).

Nyarko, D.A. and Kozári, J., 2021. Information and communication technologies (ICTs) usage among agricultural extension officers and its impact on extension delivery in Ghana. *Journal of the Saudi Society of Agricultural Sciences* [Online], 20(3), pp.164–172. Available from: https://doi.org/10.1016/j.jssas.2021.01.002 (cit. on pp.1, 14, 32).

Ochsner, E., Cosh, M.H., Cuenca, R., Hagimoto, Y., Kerr, Y.H., Njoku, E., Zreda, M., et al., 2013. State of the art in large-scale soil moisture monitoring. *Soil Science Society of America Journal* [Online], pp.1–32. Available from: https://doi.org/10.2136/sssaj2013.03.0093 (cit. on p.36).

Oduniyi, O.S., 2021. Factors Driving the Adoption and Use Extent of Sustainable Land Management Practices in South Africa. *Circular Economy and Sustainability* [Online], pp.1–20. Available from: https://doi.org/10.1007/s43615-021-00119-9 (cit. on p.14).

Ojo, E.R., Bullock, P.R., L'Heureux, J., Powers, J., McNairn, H., and Pacheco, A., 2015. Calibration and evaluation of a frequency domain reflectometry sensor for real-time soil moisture monitoring. *Vadose Zone Journal* [Online], 14(3). Available from: https://doi.org/10.1006/jaer.1996.0017 (cit. on pp.36, 67).

Oliver, D.M., Bartie, P.J., Heathwaite, A.L., Pschetz, L., and Quilliam, R.S., 2017. Design of a decision support tool for visualising E. coli risk on agricultural land using a stakeholder-driven approach. *Land Use Policy* [Online], 66, pp.227–234. Available from: https://doi.org/10.1016/j.landusepol.2017.05.005 (cit. on p.111).

Oliver, D.M., Fish, R.D., Winter, M., Hodgson, C.J., Heathwaite, A.L., and Chadwick, D.R., 2012. Valuing local knowledge as a source of expert data: farmer engagement and the design of decision support systems. *Environmental Modelling & Software* [Online], 36, pp.76–85. Available from: https://doi.org/10.1016/j.envsoft.2011.09.013 (cit. on p.111).

Orduña Alegría, M.E., Schütze, N., and Niyogi, D., 2019. Evaluation of hydroclimatic variability and prospective irrigation strategies in the US corn belt. *Water* [Online], 11(12), p.2447. Available from: https://doi.org/10.3390/w11122447 (cit. on p.106).

Ortega Álvarez, J.F., Juan Valero, J.A. de, Tarjuelo Marti*n-Benito, J.M., and López Mata, E., 2004. MOPECO: an economic optimization model for irrigation water management. *Irrigation Science* [Online], 23(2), pp.61–75. Available from: https://doi.org/10.1007/s00271-004-0094-x (cit. on p.91).

Pal, D., Bhattacharyya, T., Srivastava, P., Chandran, P., and Ray, S., 2009. Soils of the Indo-Gangetic Plains: their historical perspective and management. *Current Science* [Online], pp.1193–1202. Available from: https://www.jstor.org/stable/24105408 (cit. on pp.3, 64).

Paltineanu, I. and Starr, J., 1997. Real-time soil water dynamics using multisensor capacitance probes: Laboratory calibration. *Soil Science Society of America Journal* [Online], 61(6), pp.1576–1585. Available from: https://doi.org/10.2136/sssaj1997.03615995006100060006x (cit. on pp.43, 113, 114).

Panda, R., Behera, S., and Kashyap, P., 2003. Effective management of irrigation water for wheat under stressed conditions. *Agricultural Water Management* [Online], 63(1), pp.37–56. Available from: https://doi.org/10.1016/S0378-3774(03)00099-4 (cit. on pp.7, 8, 106).

Pande, S. and Savenije, H.H., 2016. A sociohydrological model for smallholder farmers in Maharashtra, India. *Water Resources Research* [Online], 52(3), pp.1923–1947. Available from: https://doi.org/10.1002/2015WR017841 (cit. on p.37).

Parker, C. and Sinclair, M., 2001. User-centred design does make a difference. The case of decision support systems in crop production. *Behaviour & Information Technology* [Online], 20(6), pp.449–460. Available from: https://doi.org/10.1080/01449290110089570 (cit. on p.111).

Parra, L., Botella-Campos, M., Puerto, H., Roig-Merino, B., and Lloret, J., 2020. Evaluating irrigation efficiency with performance indicators: A case study of citrus in the east of Spain. *Agronomy* [Online], 10(9), p.1359. Available from: https://doi.org/10.3390/agronomy10091359 (cit. on pp.1, 4, 64).

Pathak, H., Ladha, J., Aggarwal, P., Peng, S., Das, S., Singh, Y., Singh, B., Kamra, S., Mishra, B., Sastri, A., et al., 2003. Trends of climatic potential and on-farm yields of rice and wheat in the Indo-Gangetic Plains. *Field Crops Research* [Online], 80(3), pp.223–234. Available from: https://doi.org/10.1016/S0378-4290(02)00194-6 (cit. on p.64).

Peddinti, S.R., Hopmans, J.W., Abou Najm, M., and Kisekka, I., 2020. Assessing effects of salinity on the performance of a low-cost wireless soil water sensor. *Sensors* [Online], 20(24), p.7041. Available from: https://doi.org/10.3390/s20247041 (cit. on pp.8, 65, 67).

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al., 2011. Scikit-learn: Machine learning in Python. *The Journal of Machine Learning Research* [Online], 12, pp.2825–2830. Available from: https://doi.org/10.48550/arXiv.1201.0490 (cit. on pp.69, 80).

Pereira, L.S., Allen, R.G., Smith, M., and Raes, D., 2015. Crop evapotranspiration estimation with FAO56: Past and future. *Agricultural Water Management* [Online], 147, pp.4–20. Available from: https://doi.org/10.1016/j.agwat.2014.07.031 (cit. on pp.89, 90, 105).

Pereira, L.S., Oweis, T., and Zairi, A., 2002. Irrigation management under water scarcity. *Agricultural Water Management* [Online], 57(3), pp.175–206. Available from: https://doi.org/10.1016/S0378-3774(02)00075-6 (cit. on p.64).

Perry, C., Steduto, P., and Karajeh, F., 2017. Does improved irrigation technology save water? A review of the evidence. *Food and Agriculture Organization of the United Nations, Cairo* [Online], 42. Available from: https://www.fao.org/3/I7090EN/i7090en.pdf (cit. on p.89).

Pianosi, F., Sarrazin, F., and Wagener, T., 2015. A Matlab toolbox for global sensitivity analysis. *Environmental Modelling & Software* [Online], 70, pp.80–85. Available from: https://doi.org/10.1016/j.envsoft.2015.04.009 (cit. on p.104).

Placidi, P., Gasperini, L., Grassi, A., Cecconi, M., and Scorzoni, A., 2020. Characterization of low-cost capacitive soil moisture sensors for IoT networks. *Sensors* [Online], 20(12), p.3585. Available from: https://doi.org/10.3390/s20123585 (cit. on pp.8, 69, 73, 82, 103).

Placidi, P., Morbidelli, R., Fortunati, D., Papini, N., Gobbi, F., and Scorzoni, A., 2021. Monitoring soil and ambient parameters in the iot precision agriculture scenario: an original modeling approach dedicated to low-cost soil water content sensors. *Sensors* [Online], 21(15), p.5110. Available from: https://doi.org/10.3390/s21155110 (cit. on p.69).

Pradhan, P., Costa, L., Rybski, D., Lucht, W., and Kropp, J.P., 2017. A systematic study of sustainable development goal (SDG) interactions. *Earth's Future* [Online], 5(11), pp.1169–1179. Available from: https://doi.org/10.1002/2017EF000632 (cit. on p.2).

Pramanik, M., Khanna, M., Singh, M., Singh, D., Sudhishri, S., Bhatia, A., and Ranjan, R., 2022. Automation of soil moisture sensor-based basin irrigation system. *Smart Agricultural Technology* [Online], 2, p.100032. Available from: https://doi.org/10.1016/j.atech.2021.100032 (cit. on pp.4, 7, 8, 64, 65, 104, 110).

Prihar, S., Sandhu, B., Khera, K., and Jalota, S., 1978. Water use and yield of winter wheat in northern India as affected by timing of last irrigation. *Irrigation science* [Online], 1(1), pp.39–45. Available from: https://doi.org/10.1007/BF00269006 (cit. on pp.19, 99).

Qingling, B., Jianli, D., and Jingzhe, W., 2019. Prediction of soil moisture content by selecting spectral characteristics using random forest method. *Laser & Optoelectronics Progress* [Online], 55(11), p.113002. Available from: https://doi.org/10.11766/trxb201507020256 (cit. on p.69).

Qiu, Y., Fu, B., Wang, J., and Chen, L., 2003. Spatiotemporal prediction of soil moisture content using multiple-linear regression in a small catchment of the Loess Plateau, China. *Catena* [Online], 54(1-2), pp.173–195. Available from: https://doi.org/10.1016/S0341-8162(03)00064-X (cit. on p.69).

Qu, W., Bogena, H., Huisman, J., and Vereecken, H., 2013. Calibration of a novel low-cost soil water content sensor based on a ring oscillator. *Vadose Zone Journal* [Online], 12(2), vzj2012–0139. Available from: https://doi.org/10.2136/vzj2012.0139 (cit. on p.37).

Qu, W., Bogena, H., Huisman, J.A., Martinez, G., Pachepsky, Y., and Vereecken, H., 2014. Effects of soil hydraulic properties on the spatial variability of soil water content: Evidence from sensor network data and inverse modeling. *Vadose Zone Journal* [Online], 13(12), vzj2014–07. Available from: https://doi.org/10.2136/vzj2014.07.0099 (cit. on p.37).

Qu, W., Bogena, H., Huisman, J.A., Vanderborght, J., Schuh, M., Priesack, E., and Vereecken, H., 2015. Predicting subgrid variability of soil water content from basic soil information. *Geophysical Research Letters* [Online], 42(3), pp.789–796. Available from: https://doi.org/10.1002/2014GL062496 (cit. on p.37).

Quintero, D. and Díaz, E., 2020. A comparison of two open-source crop simulation models for a potato crop. *Agronomía Colombiana* [Online], 38(3), pp.382–387. Available from: https://doi.org/10.15446/agron.colomb.v38n3.82525 (cit. on p.70).

Raes, D., 2017. AquaCrop training handbook I. Understanding AquaCrop, FAO. [Online]. (Training handbook). Food and Agricultural Organization of the United Nations. Available from: https://www.fao.org/documents/card/en/c/ec22b063-15ed-4ad1-b57f-%2074b047e4e0cb (cit. on pp.70, 96, 104).

Raes, D., Steduto, P., Hsiao, T.C., and Fereres, E., 2018. *AquaCrop Version* 6.0 – 6.1, *Reference Manual* [Online]. (Reference Manual). Food and Agricultural Organization of the United Nations. Available from: https://www.fao.org/aquacrop/resources/referencemanuals/en/ (cit. on pp.68, 69, 71, 75–77, 86, 118).

Raes, D., Steduto, P., Hsiao, T.C., and Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: II. Main algorithms and software description. *Agronomy Journal* [Online], 101(3), pp.438–447. Available from: https://doi.org/10.2134/agronj2008.0140s (cit. on pp.7, 9, 91–93, 95, 106).

Rai, P.K., 2012. *Calibration of Soil Moisture Capacitance Probe*. (Master's Thesis). Indian Institute of Technology Kanpur (cit. on pp.79, 82).

Raney, A., Maghami, I., Feng, Y., Mandli, K., Cohen, S., and Goodall, J., 2022. An Open-Source Python Library for Varying Model Parameters and Automating Concurrent Simulations of the National Water Model. *JAWRA Journal of the American Water Resources Association* [Online], 58(1), pp.75–85. Available from: https://doi.org/10.1111/1752-1688.12973 (cit. on p.104).

Rawls, E.J. and Brakensiek, D.L., 1989. Estimation of soil water retention and hydraulic properties. In: *Unsaturated flow in hydrologic modeling* (cit. on pp.76, 118).

Reghunadhan, R., 2020. Big data, climate smart agriculture and India–Africa relations: a social science perspective. *IoT and Analytics for Agriculture* [Online]. Springer, pp.113–137. Available from: https://doi.org/10.1007/978-981-13-9177-4_6 (cit. on p.32).

Rijsberman, F., 2003. Can development of water resources reduce poverty? *Water Policy* [Online], 5(5-6), pp.399–412. Available from: https://doi.org/10.2166/wp.2003.0025 (cit. on p.37).

Ritchie, J.T., 1981. Water dynamics in the soil-plant-atmosphere system. *Plant and Soil* [Online], pp.81–96. Available from: https://www.jstor.org/stable/42933782 (cit. on p.104).

Ritchie, J., 1973. Influence of Soil Water Status and Meteorological Conditions on Evaporation from a Corn Canopy 1. *Agronomy Journal* [Online], 65(6), pp.893–897. Available from: https://doi.org/10.2134/agronj1973.00021962006500060014x (cit. on p.8).

Ritchie, J., Godwin, D., and Otter-Nacke, S., 1985. *CERES-Wheat. A simulation model of wheat growth and development*. Texas A & M Univ. Press College Station (cit. on p.7).

Rivera, W., Qamar, K., and Crowder, L., 2001. *Agricultural and rural extension worldwide: Options for institutional reform in developing countries*. (technical report). Rome: Food and Agriculture Organization of the United Nations. (cit. on pp.1, 14).

Rivera, W.M., 2011. Public sector agricultural extension system reform and the challenges ahead. *Journal of Agricultural Education and Extension* [Online], 17(2), pp.165–180. Available from: https://doi.org/10.1080/1389224X.2011.544457 (cit. on p.14).

Robinson, D., Campbell, C., Hopmans, J., Hornbuckle, B.K., Jones, S.B., Knight, R., Ogden, F., Selker, J., and Wendroth, O., 2008. Soil moisture measurement for ecological and hydrological watershed-scale observatories: A review. *Vadose Zone Journal* [Online], 7(1), pp.358–389. Available from: https://doi.org/10.2136/vzj2007.0143 (cit. on pp.36, 65).

Robinson, D., Jones, S.B., Wraith, J.M., Or, D., and Friedman, S.P., 2003. A review of advances in dielectric and electrical conductivity measurement in soils using time domain reflectometry. *Vadose Zone Journal* [Online], 2(4), pp.444–475. Available from: https://doi.org/10.2136/vzj2003.0444 (cit. on pp.36, 66).

Rodríguez Díaz, J., Camacho Poyato, E., and Blanco Pérez, M., 2011. Evaluation of water and energy use in pressurized irrigation networks in Southern Spain. *Journal of Irrigation and Drainage Engineering* [Online], 137(10), pp.644–650. Available from: https://doi.org/10.1061/(ASCE)IR.1943-4774.0000338 (cit. on p.4).

Rodríguez-Robles, J., Martin, Á., Martin, S., Ruipérez-Valiente, J.A., and Castro, M., 2020. Autonomous sensor network for rural agriculture environments, low cost, and energy self-charge. *Sustainability* [Online], 12(15), p.5913. Available from: https://doi.org/10.3390/su12155913 (cit. on pp.8, 65).

Roman, S., 2002. Writing Excel macros with VBA. O'Reilly Media, Inc. (cit. on p.21).

Rose, D.C., Parker, C., Fodery, J., Park, C., Sutherland, W.J., and Dicks, L.V., 2018. Involving stakeholders in agricultural decision support systems: Improving user-centred design. *International Journal of Agricultural Management* [Online], 6(1029-2019-924), pp.80–89. Available from: https://doi.org/10.5836/ijam/2017-06-80 (cit. on p.111).

Rosenbaum, U., Huisman, J., Vrba, J., Vereecken, H., and Bogena, H., 2011. Correction of temperature and electrical conductivity effects on dielectric permittivity measurements with ECH2O sensors. *Vadose Zone Journal* [Online], 10(2), pp.582–593. Available from: https://doi.org/10.2136/vzj2010.0083 (cit. on pp.37, 67).

Rosenbaum, U., Huisman, J., Weuthen, A., Vereecken, H., and Bogena, H., 2010. Sensorto-sensor variability of the ECH2O EC-5, TE, and 5TE sensors in dielectric liquids. *Vadose Zone Journal* [Online], 9(1), pp.181–186. Available from: https://doi.org/10.2136/vzj2009.0036 (cit. on pp.67, 113).

Rosenbaum, U., Bogena, H.R., Herbst, M., Huisman, J.A., Peterson, T.J., Weuthen, A., Western, A.W., and Vereecken, H., 2012. Seasonal and event dynamics of spatial soil moisture patterns at the small catchment scale. *Water Resources Research* [Online], 48(10). Available from: https://doi.org/10.1029/2011WR011518 (cit. on p.41).

Rosenthal, E.L., Brownstein, J.N., Rush, C.H., Hirsch, G.R., Willaert, A.M., Scott, J.R., Holderby, L.R., and Fox, D.J., 2010. Community health workers: part of the solution. *Health Affairs* [Online], 29(7), pp.1338–1342. Available from: https://doi.org/10.1377/hlthaff.2010.0081 (cit. on p.33).

Rosenthal, W., Arkin, G., Shouse, P.e., and Jordan, W., 1987. Water Deficit Effects on Transpiration and Leaf Growth 1. *Agronomy Journal* [Online], 79(6), pp.1019–1026. Available from: https://doi.org/10.2134/agronj1987.00021962007900060014x (cit. on p.8).

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., et al., 2013. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. *Agricultural and Forest Meteorology* [Online], 170, pp.166–182. Available from: https://doi.org/10.1016/j.agrformet.2012.09.011 (cit. on p.105).

Rossi, V., Salinari, F., Poni, S., Caffi, T., and Bettati, T., 2014. Addressing the implementation problem in agricultural decision support systems: the example of vite. net®. *Computers and Electronics in Agriculture* [Online], 100, pp.88–99. Available from: https://doi.org/10.1016/j.compag.2013.10.011 (cit. on p.111).

Rötter, R., Tao, F., Höhn, J., and Palosuo, T., 2015. Use of crop simulation modelling to aid ideotype design of future cereal cultivars. *Journal of Experimental Botany* [Online], 66(12), pp.3463–3476. Available from: https://doi.org/10.1093/jxb/erv098 (cit. on p.105).

Rudnick, D.R., Djaman, K., and Irmak, S., 2015. Performance analysis of capacitance and electrical resistance-type soil moisture sensors in a silt loam soil. *Transactions of the ASABE* [Online], 58(3), pp.649–665. Available from: https://doi.org/10.13031/trans.58.10761 (cit. on pp.8, 69, 73, 82).

Rue, B.D., Eastwood, C., Edwards, J., and Cuthbert, S., 2019. New Zealand dairy farmers preference investments in automation technology over decision-support technology. *Animal Production Science* [Online], 60(1), pp.133–137. Available from: https://doi.org/10.1071/AN18566 (cit. on pp.6, 14).

Rutten, C.J., Velthuis, A., Steeneveld, W., and Hogeveen, H., 2013. Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science* [Online], 96(4), pp.1928–1952. Available from: https://doi.org/10.3168/jds.2012-6107 (cit. on p.15).

Saaty, R.W., 1987. The analytic hierarchy process—what it is and how it is used. *Mathematical modelling* [Online], 9(3-5), pp.161–176. Available from: https://doi.org/10.1016/0270-0255(87)90473-8 (cit. on p.17).

Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology* [Online], 15(3), pp.234–281. Available from: https://doi.org/10.1016/0022-2496(77)90033-5 (cit. on p.17).

Sadras, V.O., Villalobos, F.J., Orgaz, F., and Fereres, E., 2016. Effects of water stress on crop production. *Principles of Agronomy for Sustainable Agriculture* [Online]. Springer, pp.189–204. Available from: https://doi.org/10.1007/978-3-319-46116-8_14 (cit. on p.104).

Sadras, V. and Milroy, S., 1996. Soil-water thresholds for the responses of leaf expansion and gas exchange: A review. *Field Crops Research* [Online], 47(2-3), pp.253–266. Available from: https://doi.org/10.1016/0378-4290(96)00014-7 (cit. on p.8).

Saharawat, Y., Singh, B., Malik, R., Ladha, J.K., Gathala, M., Jat, M.L., and Kumar, V., 2010. Evaluation of alternative tillage and crop establishment methods in a rice—wheat rotation in North Western IGP. *Field Crops Research* [Online], 116(3), pp.260–267. Available from: https://doi.org/10.1016/j.fcr.2010.01.003 (cit. on pp.3, 64).

Sakaki, T., Limsuwat, A., Smits, K.M., and Illangasekare, T.H., 2008. Empirical two-point α -mixing model for calibrating the ECH2O EC-5 soil moisture sensor in sands. *Water Resources Research* [Online], 44(4). Available from: https://doi.org/10.1029/2008WR006870 (cit. on pp.113, 114).

Saleh, M., Elhajj, I.H., Asmar, D., Bashour, I., and Kidess, S., 2016. Experimental evaluation of low-cost resistive soil moisture sensors. 2016 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET) [Online]. IEEE, pp.179–184. Available from: https://doi.org/10.1109/IMCET.2016.7777448 (cit. on p.39).

Salter, P.J. and Goode, J.E., 1967. Crop responses to water at different stages of growth. Commonwealth Agricultural Bureaux (cit. on pp.9, 92).

Sankararamakrishnan, N., Sharma, A.K., and Iyengar, L., 2008. Contamination of nitrate and fluoride in ground water along the Ganges Alluvial Plain of Kanpur district, Uttar Pradesh, India. *Environmental Monitoring and Assessment* [Online], 146(1), pp.375–382. Available from: https://doi.org/10.1007/s10661-007-0085-5 (cit. on pp.66, 82).

Santra, P., Chopra, U., and Chakraborty, D., 2008. Spatial variability of soil properties and its application in predicting surface map of hydraulic parameters in an agricultural farm. *Current Science* [Online], pp.937–945. Available from: https://www.jstor.org/stable/24103193 (cit. on p.24).

Saravanan, R., 2010. *ICTs for agricultural extension: Global experiments, innovations and experiences*. New Delhi: New India Publishing, pp.115–168 (cit. on pp.6, 15).

Saseendran, S., Trout, T., Ahuja, L., Ma, L., McMaster, G., Nielsen, D., Andales, A., Chávez, J., and Ham, J., 2015. Quantifying crop water stress factors from soil water measurements in a limited irrigation experiment. *Agricultural Systems* [Online], 137, pp.191–205. Available from: https://doi.org/http://dx.doi.org/10.1016/j.agsy.2014.11.005 (cit. on p.70).

Sayre, K., 2002. Management of irrigated wheat. In: *Bread Wheat: Improvement and Production*. (cit. on p.1).

Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N.W., Clark, D.B., Dankers, R., Eisner, S., Fekete, B.M., Colón-González, F.J., et al., 2014. Multimodel assessment of water scarcity under climate change. *Proceedings of the National Academy of Sciences* [Online], 111(9), pp.3245–3250. Available from: https://doi.org/10.1073/pnas.1222460110 (cit. on p.2).

Schils, R., Olesen, J.E., Kersebaum, K.-C., Rijk, B., Oberforster, M., Kalyada, V., Khitrykau, M., Gobin, A., Kirchev, H., Manolova, V., et al., 2018. Cereal yield gaps across Europe. *European Journal of Agronomy* [Online], 101, pp.109–120. Available from: https://doi.org/10.1016/j.eja.2018.09.003 (cit. on p.70).

Schmugge, T., Jackson, T., and McKim, H., 1980. Survey of methods for soil moisture determination. *Water Resources Research* [Online], 16(6), pp.961–979. Available from: https://doi.org/10.1029/WR016i006p00961 (cit. on p.39).

Schütze, N. and Mialyk, O., 2019. *Deficit Irrigation Toolbox (DIT)* [Online]. Technical University of Dresden. Available from: https://tu-dresden.de/bu/umwelt/hydro/ihm/hydrologie/ressourcen/dateien/services/DITUserGuide.pdf (cit. on p.106).

Seidel, S.J., Schütze, N., Fahle, M., Mailhol, J.-C., and Ruelle, P., 2015. Optimal irrigation scheduling, irrigation control and drip line layout to increase water productivity and profit in subsurface drip-irrigated agriculture. *Irrigation and Drainage* [Online], 64(4), pp.501–518. Available from: https://doi.org/10.1002/ird.1926 (cit. on pp.91, 106).

Sen, S.M., Singh, A., Varma, N., Sharma, D., and Kansal, A., 2019. Analyzing Social Networks to Examine the Changing Governance Structure of Springsheds: A Case Study of Sikkim in the Indian Himalayas. *Environmental Management* [Online], 63(2), pp.233–248. Available from: https://doi.org/10.1007/s00267-018-1128-0 (cit. on p.33).

Severino, G., D'Urso, G., Scarfato, M., and Toraldo, G., 2018. The IoT as a tool to combine the scheduling of the irrigation with the geostatistics of the soils. *Future Generation Computer Systems* [Online], 82, pp.268–273. Available from: https://doi.org/10.1016/j.future.2017.12.058 (cit. on pp.5, 14).

Seyfried, M.S. and Murdock, M.D., 2004. Measurement of soil water content with a 50-MHz soil dielectric sensor. *Soil Science Society of America Journal* [Online], 68, pp.394–403. Available from: https://doi.org/10.2136/sssaj2004.0394 (cit. on p.36).

Shankarnarayan, V.K. and Ramakrishna, H., 2020. Paradigm change in Indian agricultural practices using Big Data: Challenges and opportunities from field to plate. *Information Processing in Agriculture*, 7(3), pp.355–368 (cit. on p.32).

Sheng, M., Liu, J., Zhu, A.-X., Rossiter, D.G., Liu, H., Liu, Z., and Zhu, L., 2019. Comparison of GLUE and DREAM for the estimation of cultivar parameters in the APSIM-maize model. *Agricultural and Forest Meteorology* [Online], 278, p.107659. Available from: https://doi.org/10.1016/j.agrformet.2019.107659 (cit. on p.105).

Si, B.C., 2008. Spatial scaling analyses of soil physical properties: A review of spectral and wavelet methods. *Vadose Zone Journal* [Online], 7(2), pp.547–562. Available from: https://doi.org/10.2136/vzj2007.0040 (cit. on p.104).

Siad, S.M., Iacobellis, V., Zdruli, P., Gioia, A., Stavi, I., and Hoogenboom, G., 2019. A review of coupled hydrologic and crop growth models. *Agricultural Water Management* [Online], 224, p.105746. Available from: https://doi.org/10.1016/j.agwat.2019.105746 (cit. on p.6).

Sidhu, H., Jat, M., Singh, Y., Sidhu, R.K., Gupta, N., Singh, P., Singh, P., Jat, H., and Gerard, B., 2019. Sub-surface drip fertigation with conservation agriculture in a rice-wheat system: A breakthrough for addressing water and nitrogen use efficiency. *Agricultural Water Management* [Online], 216, pp.273–283. Available from: https://doi.org/10.1016/j.agwat.2019.02.019 (cit. on p.4).

Sikka, A.K., Alam, M.F., and Mandave, V., 2022. Agricultural water management practices to improve the climate resilience of irrigated agriculture in India. *Irrigation and Drainage* [Online]. Available from: https://doi.org/10.1002/ird.2696 (cit. on pp.3–5, 8, 64, 89).

Silva, J.V. and Giller, K.E., 2020. Grand challenges for the 21st century: what crop models can and can't (yet) do. *The Journal of Agricultural Science* [Online], 158(10), pp.794–805. Available from: https://doi.org/10.1017/S0021859621000150 (cit. on p.70).

Silva, J.V., Reidsma, P., Laborte, A.G., and Van Ittersum, M.K., 2017. Explaining rice yields and yield gaps in Central Luzon, Philippines: An application of stochastic frontier analysis and crop modelling. *European Journal of Agronomy* [Online], 82, pp.223–241. Available from: https://doi.org/10.1016/j.eja.2016.06.017 (cit. on p.70).

Silvestro, P.C., Pignatti, S., Yang, H., Yang, G., Pascucci, S., Castaldi, F., and Casa, R., 2017. Sensitivity analysis of the Aquacrop and SAFYE crop models for the assessment of water limited winter wheat yield in regional scale applications. *PloS One* [Online], 12(11), e0187485. Available from: https://doi.org/10.1371/journal.pone.0187485 (cit. on p.104).

Singh, A., Saha, S., and Mondal, S., 2013. Modelling irrigated wheat production using the FAO AquaCrop model in West Bengal, India, for sustainable agriculture. *Irrigation and Drainage* [Online], 62(1), pp.50–56. Available from: https://doi.org/10.1002/ird.1722 (cit. on pp.7, 70).

Singh, A.K., Rahman, A., Sharma, S., Upadhyaya, A., and Sikka, A., 2009. Small holders' irrigation—Problems and options. *Water Resources Management* [Online], 23(2), pp.289–302. Available from: https://doi.org/10.1007/s11269-008-9275-3 (cit. on pp.4, 64).

Singh, J., Lo, T., Rudnick, D., Dorr, T., Burr, C., Werle, R., Shaver, T., and Muñoz-Arriola, F., 2018. Performance assessment of factory and field calibrations for electromagnetic sensors in a loam soil. *Agricultural Water Management* [Online], 196, pp.87–98. Available from: https://doi.org/10.1016/j.agwat.2017.10.020 (cit. on pp.8, 69, 73, 82).

Singh, M., 2014. Techniques of crop cutting experiment. In: *Recent Advances in Survey Design and Analysis of Survey Data Using Statistical Software* (cit. on p.73).

Singh, R.B., 2000. Environmental consequences of agricultural development: a case study from the Green Revolution state of Haryana, India. *Agriculture, Ecosystems & Environment* [Online], 82(1-3), pp.97–103. Available from: https://doi.org/10.1016/S0167-8809(00)00219-X (cit. on pp.3, 64).

Sivapalan, M., Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C., Wescoat, J., and Rodríguez-Iturbe, I., 2014. Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. *Earth's Future* [Online], 2(4), pp.225–230. Available from: https://doi.org/10.1002/2013EF000164 (cit. on p.30).

Smith, R., Raine, S.R., and Minkevich, J., 2005. Irrigation application efficiency and deep drainage potential under surface irrigated cotton. *Agricultural Water Management* [Online], 71(2), pp.117–130. Available from: https://doi.org/10.1016/j.agwat.2004.07.008 (cit. on p.4).

Soltani, A. and Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: simulation in a temperate, sub-humid environment. *Field Crops Research* [Online], 175, pp.37–46. Available from: https://doi.org/10.1016/j.fcr.2014.10.019 (cit. on p.70).

Sorooshian, S., Duan, Q., and Gupta, V.K., 1993. Calibration of rainfall-runoff models: Application of global optimization to the Sacramento Soil Moisture Accounting Model. *Water Resources Research* [Online], 29(4), pp.1185–1194. Available from: https://doi.org/10.1029/92WR02617 (cit. on p.77).

Soulis, K., Elmaloglou, S., and Dercas, N., 2015. Investigating the effects of soil moisture sensors positioning and accuracy on soil moisture based drip irrigation scheduling systems. *Agricultural Water Management* [Online], 148, pp.258–268. Available from: https://doi.org/10.1016/j.agwat.2014.10.015 (cit. on pp.50, 54, 60, 87, 107).

Spearman, C., 1904. The Proof and Measurement of Association between Two Things. *The American Journal of Psychology* [Online], 15, pp.72–101. Available from: https://doi.org/10.2307/1412159 (cit. on pp.45, 46).

Spectrum, 2011. Waterscout SM100 Soil Moisture Sensor Product Manual. (Manual). Available at https://www.specmeters.com/assets/1/22/6460_SM1002.pdf. Spectrum Technologies, Inc. (cit. on pp.38, 39, 50, 68).

Spectrum, 2012. Waterscout SMEC 300 Soil Moisture Sensor Product Manual. (Manual). Available at https://www.specmeters.com/assets/1/22/6470_SMEC3004.pdf. Spectrum Technologies, Inc. (cit. on pp.38, 39, 50).

Spelman, D., Kinzli, K.-D., and Kunberger, T., 2013. Calibration of the 10hs soil moisture sensor for southwest florida agricultural soils. *Journal of Irrigation and Drainage Engineering* [Online], 139(12), pp.965–971. Available from: https://doi.org/10.1061/(ASCE) IR. 1943-4774.0000647 (cit. on p.67).

Srbinovska, M., Gavrovski, C., Dimcev, V., Krkoleva, A., and Borozan, V., 2015. Environmental parameters monitoring in precision agriculture using wireless sensor networks. *Journal of Cleaner Production* [Online], 88, pp.297–307. Available from: https://doi.org/10.1016/j.jclepro.2014.04.036 (cit. on pp.37, 65).

Srinivasan, V., Sanderson, M., Garcia, M., Konar, M., Blöschl, G., and Sivapalan, M., 2017. Prediction in a socio-hydrological world. *Hydrological Sciences Journal* [Online], 62(3), pp.338–345. Available from: https://doi.org/10.1080/02626667.2016.1253844 (cit. on pp.26, 27, 102, 108).

Srivastava, P.K., Petropoulos, G.P., Prasad, R., and Triantakonstantis, D., 2021. Random forests with bagging and genetic algorithms coupled with least trimmed squares regression for soil moisture deficit using smos satellite soil moisture. *ISPRS International Journal of Geo-Information* [Online], 10(8), p.507. Available from: https://doi.org/10.3390/ijgi10080507 (cit. on p.69).

Starr, J. and Paltineanu, I., 2002. Methods for measurement of soil water content: Capacitance devices. In: *Methods of Soil Analysis: Part 4 Physical Methods* (cit. on pp.42, 103).

Steduto, P., Hsiao, T.C., Fereres, E., and Raes, D., 2012. *Crop yield response to water*. (FAO Irrigation and Drainage Paper No. 66). Food and Agricultural Organization of the United Nations (cit. on pp.70, 71, 76, 104).

Steduto, P., 2003. Biomass water-productivity. Comparing the growth-Engines of Crop Models. FAO expert consultation on crop water productivity under deficient water supply, pp.26–28 (cit. on p.7).

Steduto, P. and Albrizio, R., 2005. Resource use efficiency of field-grown sunflower, sorghum, wheat and chickpea: II. Water use efficiency and comparison with radiation use efficiency. *Agricultural and Forest Meteorology* [Online], 130(3-4), pp.269–281. Available from: https://doi.org/10.1016/j.agrformet.2005.04.003 (cit. on p.7).

Steduto, P., Hsiao, T.C., and Fereres, E., 2007. On the conservative behavior of biomass water productivity. *Irrigation Science* [Online], 25(3), pp.189–207. Available from: https://doi.org/10.1007/s00271-007-0064-1 (cit. on p.7).

Steduto, P., Hsiao, T.C., Raes, D., and Fereres, E., 2009. AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal* [Online], 101(3), pp.426–437. Available from: https://doi.org/10.2134/agronj2008.0139s (cit. on pp.7, 9, 70, 71, 91–94).

Stehfest, E., Zeist, W.-J. van, Valin, H., Havlik, P., Popp, A., Kyle, P., Tabeau, A., Mason-D'Croz, D., Hasegawa, T., Bodirsky, B.L., et al., 2019. Key determinants of global landuse projections. *Nature Communications* [Online], 10(1), pp.1–10. Available from: https://doi.org/10.1038/s41467-019-09945-w (cit. on p.70).

Steinke, J., Etten, J. van, Müller, A., Ortiz-Crespo, B., Gevel, J. van de, Silvestri, S., and Priebe, J., 2021. Tapping the full potential of the digital revolution for agricultural extension: an emerging innovation agenda. *International Journal of Agricultural Sustainability* [Online], 19(5-6), pp.549–565. Available from: https://doi.org/10.1080/14735903. 2020.1738754 (cit. on p.111).

Stöckle, C.O., Donatelli, M., and Nelson, R., 2003. CropSyst, a cropping systems simulation model. *European Journal of Agronomy* [Online], 18(3-4), pp.289–307. Available from: https://doi.org/10.1016/S1161-0301(02)00109-0 (cit. on p.7).

Sun, Y., Sheng, W., Cheng, Q., Chai, J., Yun, Y., Zhao, Y., Xue, X., Lammers, P.S., Damerow, L., and Cai, X., 2012. A novel method to determine the volume of sensitivity for soil moisture sensors. *Soil Science Society of America Journal* [Online], 76(6), pp.1987–1991. Available from: https://doi.org/10.2136/sssaj2012.0063n (cit. on p.113).

Szypłowska, A., Lewandowski, A., Jones, S.B., Sabouroux, P., Szerement, J., Kafarski, M., Wilczek, A., and Skierucha, W., 2019. Impact of soil salinity, texture and measurement frequency on the relations between soil moisture and 20 MHz–3 GHz dielectric permittivity spectrum for soils of medium texture. *Journal of Hydrology* [Online], 579, p.124155. Available from: https://doi.org/10.1016/j.jhydrol.2019.124155 (cit. on pp.43, 113).

Taghavaeian, S., 2017. *Surface Irrigation Systems*. (Fact Sheet No. BAE-1527, Oklahoma Cooperative Extension Fact Sheets). Oklahoma State University (cit. on p.118).

Tao, F., Zhang, Z., Liu, J., and Yokozawa, M., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection. *Agricultural and Forest Meteorology* [Online], 149(8), pp.1266–1278. Available from: https://doi.org/10.1016/j.agrformet.2009.02.015 (cit. on p.105).

Tari, A.F., 2016. The effects of different deficit irrigation strategies on yield, quality, and water-use efficiencies of wheat under semi-arid conditions. *Agricultural Water Management* [Online], 167, pp.1–10. Available from: https://doi.org/10.1016/j.agwat. 2015.12.023 (cit. on p.106).

Teng, W., Wang, J., and Doraiswamy, P., 1993. Relationship between satellite microwave radiometric data, antecedent precipitation index, and regional soil moisture. *International Journal of Remote Sensing* [Online], 14(13), pp.2483–2500. Available from: https://doi.org/10.1080/01431169308904287 (cit. on p.69).

Tewatia, R. and Chanda, T., 2005. Fertilizer use by crop in India. Food and Agriculture Organization of the United Nations (cit. on p.1).

Thapa, S., Xue, Q., Jessup, K.E., Rudd, J.C., Liu, S., Marek, T.H., Devkota, R.N., Baker, J.A., and Baker, S., 2019. Yield determination in winter wheat under different water regimes. *Field Crops Research* [Online], 233, pp.80–87. Available from: https://doi.org/10.1016/j.fcr.2018.12.018 (cit. on p.106).

Thompson, R.B., Gallardo, M., Valdez, L.C., and Fernández, M.D., 2007a. Using plant water status to define threshold values for irrigation management of vegetable crops using soil moisture sensors. *Agricultural Water Management* [Online], 88(1-3), pp.147–158. Available from: https://doi.org/10.1016/j.agwat.2006.10.007 (cit. on pp.65, 82, 90).

Thompson, R.B., Gallardo, M., Valdez, L.C., and Fernández, M., 2007b. Determination of lower limits for irrigation management using in situ assessments of apparent crop water uptake made with volumetric soil water content sensors. *Agricultural Water Management* [Online], 92(1-2), pp.13–28. Available from: https://doi.org/10.1016/j.agwat.2007.04.009 (cit. on pp.8, 65, 82).

Thompson, S.E., Sivapalan, M., Harman, C.J., Srinivasan, V., Hipsey, M., Reed, P., Montanari, A., and Blöschl, G., 2013. Developing predictive insight into changing water systems: use-inspired hydrologic science for the Anthropocene. *Hydrology and Earth System Sciences* [Online], 17(12), pp.5013–5039. Available from: https://doi.org/10.5194/hess-17-5013-2013 (cit. on p.30).

Tilman, D., Balzer, C., Hill, J., and Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences* [Online], 108(50), pp.20260–20264. Available from: https://doi.org/10.1073/pnas.1116437108 (cit. on pp.1, 3).

Todorovic, M., Albrizio, R., Zivotic, L., Saab, M.-T.A., Stöckle, C., and Steduto, P., 2009. Assessment of AquaCrop, CropSyst, and WOFOST models in the simulation of sunflower growth under different water regimes. *Agronomy Journal* [Online], 101(3), pp.509–521. Available from: https://doi.org/10.2134/agronj2008.0166s (cit. on pp.7, 70).

Tolson, B.A. and Shoemaker, C.A., 2007. Dynamically dimensioned search algorithm for computationally efficient watershed model calibration. *Water Resources Research* [Online], 43(1). Available from: https://doi.org/10.1029/2005WR004723 (cit. on p.104).

Topp, G.C., Davis, J., and Annan, A., 1980. Electromagnetic determination of soil water content: Measurements in coaxial transmission lines. *Water Resources Research* [Online], 16(3), pp.574–582. Available from: https://doi.org/10.1029/WR016i003p00574 (cit. on pp.36, 44, 47, 66).

Toumi, J., Er-Raki, S., Ezzahar, J., Khabba, S., Jarlan, L., and Chehbouni, A., 2016. Performance assessment of AquaCrop model for estimating evapotranspiration, soil water content and grain yield of winter wheat in Tensift Al Haouz (Morocco): Application to irrigation management. *Agricultural Water Management* [Online], 163, pp.219–235. Available from: https://doi.org/10.1016/j.agwat.2015.09.007 (cit. on p.70).

UGT, 2017. 01/2017/EN Catalog [Online]. Umwelt-Geräte-Technik GmbH. Available from: https://www.ugt-online.de/fileadmin/Public/downloads/Produkte/Catalog_en.pdf (cit. on p.68).

UN, 2017. The Sustainable Development Goals Report. United Nations (cit. on p.89).

United States Census Bureau, 2000. Census and Survey Processing System (CSPro) [Online]. Available from: https://www.census.gov/data/software/cspro.html (cit. on p.17).

USAID, 2000. ICTFSECBP (Information Communication Technology For Small Enterprise Capacity Building Program) [Online]. Available from: https://www.census.gov/data/software/cspro.html (cit. on pp.6, 15).

USDA-NRCS, 2017. Hydrologic Soil-Cover Complexes. In: *National Engineering Handbook* (cit. on p.118).

Van Diepen, C.A., Wolf, J., Van Keulen, H., and Rappoldt, C., 1989. WOFOST: a simulation model of crop production. *Soil Use and Management* [Online], 5(1), pp.16–24. Available from: https://doi.org/10.1111/j.1475-2743.1989.tb00755.x (cit. on p.7).

Van Emmerik, T., Li, Z., Sivapalan, M., Pande, S., Kandasamy, J., Savenije, H., Chanan, A., and Vigneswaran, S., 2014. Socio-hydrologic modeling to understand and mediate the competition for water between agriculture development and environmental health: Murrumbidgee River basin, Australia. *Hydrology and Earth System Sciences* [Online], 18(10), pp.4239–4259. Available from: https://doi.org/10.5194/hessd-11-3387-2014 (cit. on p.27).

Van Halsema, G.E. and Vincent, L., 2012. Efficiency and productivity terms for water management: A matter of contextual relativism versus general absolutism. *Agricultural Water Management* [Online], 108, pp.9–15. Available from: https://doi.org/10.1016/j.agwat.2011.05.016 (cit. on pp.15, 18, 25, 77).

Van Ittersum, M.K., Van Bussel, L.G., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., Claessens, L., De Groot, H., Wiebe, K., Mason-D'Croz, D., et al., 2016. Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences* [Online], 113(52), pp.14964–14969. Available from: https://doi.org/10.1073/pnas.1610359113 (cit. on p.70).

Vanuytrecht, E., Raes, D., Steduto, P., Hsiao, T.C., Fereres, E., Heng, L.K., Vila, M.G., and Moreno, P.M., 2014. AquaCrop: FAO's crop water productivity and yield response model. *Environmental Modelling & Software* [Online], 62, pp.351–360. Available from: https://doi.org/10.1016/j.envsoft.2014.08.005 (cit. on pp.5, 9, 65, 70, 76, 77, 91, 92).

Vapnik, V., Golowich, S., and Smola, A., 1996. Support vector method for function approximation, regression estimation and signal processing. *Advances in Neural Information Processing Systems*, 9 (cit. on p.69).

Varella, H., Guérif, M., and Buis, S., 2010. Global sensitivity analysis measures the quality of parameter estimation: The case of soil parameters and a crop model. *Environmental Modelling & Software* [Online], 25(3), pp.310–319. Available from: https://doi.org/10.1016/j.envsoft.2009.09.012 (cit. on pp.5, 70).

Vasseur, E., Rushen, J., De Passillé, A., Lefebvre, D., and Pellerin, D., 2010. An advisory tool to improve management practices affecting calf and heifer welfare on dairy farms. *Journal of Dairy Science* [Online], 93(9), pp.4414–4426. Available from: https://doi.org/10.3168/jds.2009-2586 (cit. on pp.6, 14).

Vatta, K., Sidhu, R., Lall, U., Birthal, P., Taneja, G., Kaur, B., Devineni, N., and MacAlister, C., 2018. Assessing the economic impact of a low-cost water-saving irrigation technology in Indian Punjab: the tensiometer. *Water International* [Online], 43(2), pp.305–321. Available from: https://doi.org/10.1080/02508060.2017.1416443 (cit. on p.8).

Vellidis, G., Tucker, M., Perry, C., Kvien, C., and Bednarz, C., 2008. A real-time wireless smart sensor array for scheduling irrigation. *Computers and Electronics in Agriculture* [Online], 61(1), pp.44–50. Available from: https://doi.org/10.1016/j.compag.2007.05.009 (cit. on pp.7, 110).

Vereecken, H., Huisman, J., Pachepsky, Y., Montzka, C., Van Der Kruk, J., Bogena, H., Weihermüller, L., Herbst, M., Martinez, G., and Vanderborght, J., 2014. On the spatiotemporal dynamics of soil moisture at the field scale. *Journal of Hydrology* [Online], 516, pp.76–96. Available from: https://doi.org/10.1016/j.jhydrol.2013.11.061 (cit. on pp.8, 60, 104).

Verhagen, J. and Bouma, J., 1997. Modeling soil variability. *The state of site specific management for agriculture* [Online], pp.55–67. Available from: https://doi.org/10.2134/1997.stateofsitespecific.c3 (cit. on p.104).

Viani, F., 2016. Experimental validation of a wireless system for the irrigation management in smart farming applications. *Microwave and Optical Technology Letters* [Online], 58(9), pp.2186–2189. Available from: https://doi.org/10.1002/mop.30000 (cit. on p.90).

Visconti, F., Paz, J.M. de, Martinez, D., and Molina, M.J., 2014. Laboratory and field assessment of the capacitance sensors Decagon 10HS and 5TE for estimating the water content of irrigated soils. *Agricultural Water Management* [Online], 132, pp.111–119. Available from: https://doi.org/10.1016/j.agwat.2013.10.005 (cit. on p.67).

Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., Pierce, S.A., and Ramu, P., 2016. Modelling with stakeholders—next generation. *Environmental Modelling & Software* [Online], 77, pp.196–220. Available from: https://doi.org/10.1016/j.envsoft.2015.11.016 (cit. on pp.102, 108).

Vrugt, J.A., Ter Braak, C., Diks, C., Robinson, B.A., Hyman, J.M., and Higdon, D., 2009. Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling. *International Journal of Nonlinear Sciences and Numerical Simulation* [Online], 10(3), pp.273–290. Available from: https://doi.org/10.1515/IJNSNS.2009.10.3.273 (cit. on p.105).

Wallach, D., Goffinet, B., Bergez, J.-E., Debaeke, P., Leenhardt, D., and Aubertot, J.-N., 2001. Parameter estimation for crop models: a new approach and application to a corn model. *Agronomy Journal* [Online], 93(4), pp.757–766. Available from: https://doi.org/10.2134/agronj2001.934757x (cit. on p.104).

Wang, J., Huang, G., Li, J., Zheng, J., Huang, Q., and Liu, H., 2017. Effect of soil moisture-based furrow irrigation scheduling on melon (Cucumis melo L.) yield and quality in an arid region of Northwest China. *Agricultural Water Management* [Online], 179, pp.167–176. Available from: https://doi.org/10.1016/j.agwat.2016.04.023 (cit. on p.90).

Wang, X., Li, L., Ding, Y., Xu, J., Wang, Y., Zhu, Y., Wang, X., and Cai, H., 2021. Adaptation of winter wheat varieties and irrigation patterns under future climate change conditions in Northern China. *Agricultural Water Management* [Online], 243, p.106409. Available from: https://doi.org/10.1016/j.agwat.2020.106409 (cit. on p.70).

Weersink, A. and Fulton, M., 2020. Limits to profit maximization as a guide to behavior change. *Applied Economic Perspectives and Policy* [Online], 42(1), pp.67–79. Available from: https://doi.org/10.1002/aepp.13004 (cit. on p.111).

WHO, 2012. International Classification of Diseases (ICD). Geneva (cit. on p.31).

Wit, C.T. de, 1965. Photosynthesis of leaf canopies. In: *Agricultural Research Report 663* (cit. on p.7).

Witten, I., Frank, E., and Hall, M., 2011. Credibility: Evaluating What's Been Learned. In: *Data Mining: Practical Machine Learning Tools and Techniques* (cit. on pp.45, 77).

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.-J., 2017. Big data in smart farming - a review. *Agricultural Systems* [Online], 153, pp.69–80. Available from: https://doi.org/10.1016/j.agsy.2017.01.023 (cit. on pp.5, 15).

Wu, Q. and Wang, M., 2007. A framework for risk assessment on soil erosion by water using an integrated and systematic approach. *Journal of Hydrology* [Online], 337(1-2), pp.11–21. Available from: https://doi.org/10.1016/j.jhydrol.2007.01.022 (cit. on p.17).

Xing, H.-m., Xu, X.-g., Li, Z.-h., Chen, Y.-j., Feng, H.-k., Yang, G.-j., and Chen, Z.-x., 2017. Global sensitivity analysis of the AquaCrop model for winter wheat under different water treatments based on the extended Fourier amplitude sensitivity test. *Journal of Integrative Agriculture* [Online], 16(11), pp.2444–2458. Available from: https://doi.org/10.1016/S2095-3119(16)61626-X (cit. on p.104).

Yan, L., Jin, J., and Wu, P., 2020. Impact of parameter uncertainty and water stress parameterization on wheat growth simulations using CERES-Wheat with GLUE. *Agricultural Systems* [Online], 181, p.102823. Available from: https://doi.org/10.1016/j.agsy.2020.102823 (cit. on p.105).

Yang, J., Ogunkah, I.C.B., et al., 2013. A multi-criteria decision support system for the selection of low-cost green building materials and components. *Journal of Building Construction and Planning Research* [Online], 1(04), p.89. Available from: https://doi.org/10.4236/jbcpr.2013.14013 (cit. on p.21).

Yi, J., Li, H., Zhao, Y., Zhang, H., Liu, M., et al., 2022. Assessing soil water balance to optimize irrigation schedules of flood-irrigated maize fields with different cultivation histories in the arid region. *Agricultural Water Management* [Online], 265, p.107543. Available from: https://doi.org/10.1016/j.agwat.2022.107543 (cit. on p.3).

Yin, X., Stam, P., Kropff, M.J., and Schapendonk, A.H., 2003. Crop modeling, qtl mapping, and their complementary role in plant breeding. *Agronomy Journal* [Online], 95(1), pp.90–98. Available from: https://doi.org/10.2134/agronj2003.9000a (cit. on p.70).

Yu, F., Zhao, Y.-S., Li, H.-T., et al., 2012. Soil moisture retrieval based on GA-BP neural networks algorithm. *Journal of Infrared and Millimeter Waves* [Online], 31(3), pp.283–288. Available from: https://doi.org/10.3724/SP.J.1010.2012.00283 (cit. on p.69).

Yu, X., Wu, P., Han, W., and Zhang, Z., 2013. A survey on wireless sensor network infrastructure for agriculture. *Computer Standards & Interfaces* [Online], 35(1), pp.59–64. Available from: https://doi.org/10.1016/j.csi.2012.05.001 (cit. on p.36).

Yu, Z., Liu, D., Lü, H., Fu, X., Xiang, L., and Zhu, Y., 2012. A multi-layer soil moisture data assimilation using support vector machines and ensemble particle filter. *Journal of Hydrology* [Online], 475, pp.53–64. Available from: https://doi.org/10.1016/j.jhydrol.2012.08.034 (cit. on p.69).

Zamora-Re, M.I., Dukes, M., Hensley, D., Rowland, D., and Graham, W., 2020. The effect of irrigation strategies and nitrogen fertilizer rates on maize growth and grain yield. *Irrigation Science* [Online], 38(4), pp.461–478. Available from: https://doi.org/10.1007/s00271-020-00687-y (cit. on p.8).

Zar, J., 2005. Spearman Rank Correlation. In: Encyclopedia of Biostatistics (cit. on p.46).

Zaveri, E. and B Lobell, D., 2019. The role of irrigation in changing wheat yields and heat sensitivity in India. *Nature Communications* [Online], 10(1), pp.1–7. Available from: https://doi.org/10.1038/s41467-019-12183-9 (cit. on p.3).

Zhang, C., Xie, Z., Wang, Q., Tang, M., Feng, S., and Cai, H., 2022a. AquaCrop modeling to explore optimal irrigation of winter wheat for improving grain yield and water productivity. *Agricultural Water Management*, 266, p.107580 (cit. on pp.3, 4, 65, 70).

Zhang, D. and Zhou, G., 2016. Estimation of soil moisture from optical and thermal remote sensing: A review. *Sensors* [Online], 16(8), p.1308. Available from: https://doi.org/10.3390/s16081308 (cit. on p.36).

Zhang, H. and Oweis, T., 1999. Water–yield relations and optimal irrigation scheduling of wheat in the Mediterranean region. *Agricultural Water Management* [Online], 38(3), pp.195–211. Available from: https://doi.org/10.1016/S0378-3774(98)00069-9 (cit. on pp.99, 106).

Zhang, H., Wang, S., Liu, K., Li, X., Li, Z., Zhang, X., and Liu, B., 2022b. Downscaling of AMSR-E soil moisture over north China using random forest regression. *ISPRS International Journal of Geo-Information* [Online], 11(2), p.101. Available from: https://doi.org/10.3390/ijgi11020101 (cit. on p.69).

Zhang, W., Liu, W., Xue, Q., Chen, J., and Han, X., 2013. Evaluation of the AquaCrop model for simulating yield response of winter wheat to water on the southern Loess Plateau of China. *Water Science and Technology* [Online], 68(4), pp.821–828. Available from: https://doi.org/10.2166/wst.2013.305 (cit. on pp.7, 70, 86).

Zheng, H., Shao, R., Xue, Y., Ying, H., Yin, Y., Cui, Z., and Yang, Q., 2020. Water productivity of irrigated maize production systems in Northern China: a meta-analysis. *Agricultural Water Management*, 234, p.106119 (cit. on pp.64, 70).

Zhi, Y., Zhang, F., Wang, H., Qin, T., Tong, J., Wang, T., Wang, Z., Kang, J., and Fang, Z., 2022. Agricultural Water Use Efficiency: Is There Any Spatial Correlation between Different Regions? *Land* [Online], 11(1), p.77. Available from: https://doi.org/10.3390/land11010077 (cit. on pp.2, 4, 64, 106).

Zhou, L.-l., Liao, S.-h., WAng, Z.-m., Pu, W., Zhang, Y.-h., YAN, H.-j., Zhen, G., Si, S., LIANG, X.-g., WANG, J.-h., et al., 2018. A simulation of winter wheat crop responses to irrigation management using ceres-wheat model in the north china plain. *Journal of Integrative Agriculture* [Online], 17(5), pp.1181–1193. Available from: https://doi.org/10.1016/S2095-3119(17)61818-5 (cit. on p.70).

Zhu, Y., Irmak, S., Jhala, A.J., Vuran, M.C., and Diotto, A., 2019. Time-domain and frequency-domain reflectometry type soil moisture sensor performance and soil temperature effects in fine-and coarse-textured soils. *Applied Engineering in Agriculture* [Online], 35(2), pp.117–134. Available from: https://doi.org/10.13031/aea.12908 (cit. on p.113).

Zotarelli, L., Dukes, M., Scholberg, J., Femminella, K., and Munoz-Carpena, R., 2011. Irrigation scheduling for green bell peppers using capacitance soil moisture sensors. *Journal of Irrigation and Drainage Engineering* [Online], 137(2), pp.73–81. Available from: https://doi.org/10.1061/(ASCE)IR.1943-4774.0000281 (cit. on pp.67, 90).