Ingenieurfakultät Bau Geo Umwelt
Technische Universität München

Data-driven modeling of areas prone to heavy rain-induced floods

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Vollständiger Abdruck der von der Ingenieurfakultät Bau Geo Umwelt der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktor-Ingenieurs (Dr.-Ing.)

genehmigten Dissertation.

Vorsitzender:

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Prüfende der Dissertation:

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Die Dissertation wurde am 31.03.2021 bei der Technischen Universität München eingereicht und durch die Ingenieurfakultät Bau Geo Umwelt am 23.07.2021 angenommen.

Acknowledgment

First of all, I would like to thank my supervisor Prof. Dr.-Ing. Markus Disse for his continuous support and the trust he has placed in me over the past years. I am deeply grateful that he has supported me to explore new ways. I am truly thankful to Prof. Dr. Stephan Günnemann for supervising me and giving me the opportunity to become part of his Data Analytics and Machine Learning Group. His supervision enabled me to work on this interdisciplinary research topic.
Special thanks are also due to Prof. Dr. Axel Bronstert for joining my PhD committee. Furthermore, I want to thank Prof. Dr. Michael Krautblatter for taking over the role as chairman of my PhD defense.
I would like to thank all my colleagues at the Chair of Hydrology and River Basin Management for the great working atmosphere. I owe very special thanks to my roommates Johannes Mitterer, Thomas Pflugbeil and Karl Broich for the many fruitful discussions, chatty lunches, and fun coffee breaks we have had together. It has been a great pleasure working with you for the last 3.5 years.
I am also grateful to my colleagues in Garching, especially Daniel Zügner and Moritz Sichert, who introduced me to the world of machine learning and databases. They were always happy to share their knowledge with me and gave me advice whenever I needed it.
I further want to gratefully acknowledge the Bavarian State Ministry of the Environment and Consumer Protection (StMUV) and the Bavarian Environment Agency (LfU) for the financial support and supervision of the HiOS project. Moreover, I am very grateful to my colleagues from the HiOS project Hai Nguyen, Tahoora Sheikhy, Florian Willkofer, Fabian von Trentini, Qing Lin, Johannes Mitterer, Thomas Pflugbeil and Karl Broich for the exciting time we spent together.
Another thanks goes to Prof. Dr. Marco Borga, with whom I had the opportunity to do a research stay. I am grateful that he shared his knowledge on flash floods with me.
I would also like to take this opportunity to thank the International Graduate School of Science and Engineering, especially Marco Barden. I consider it a great privilege to have been part of the IGSSE family. I am deeply grateful for the IGSSE funding that

allowed me to participate in conferences abroad and a variety of interesting courses.
My special thanks go to my family, who always supported me and believed in me. I am especially grateful for the many discussions with my parents, whether in the car or over coffee, which have given me new perspectives. I am also grateful to my friends for their moral support during the ups and downs of doctoral life. Finally yet importantly, my sincere thanks go to Michael, who had to do without me on many weekends during the last years and who also knew how to motivate me, especially in the last weeks before the deadline.

Abstract

Floods caused by heavy rain pose a threat to people due to their sudden occurrence and destructive power. Flash floods are triggered by small-scale, short but intense precipitation events that are challenging to forecast. Moreover, floods resulting from heavy rain are not necessarily bound to water bodies, which further complicates their prediction. Therefore, identifying areas of particular risk is a critical precautionary measure.

In 2016, the state of Bavaria (Germany) was severely affected by a series of flood events triggered by heavy rain, in which seven people died. The flood events of 2016 underlined the need to identify susceptible areas throughout Bavaria. However, a new approach had to be developed for this purpose, since a nationwide hazard assessment using hydrodynamic modeling was not possible due to the high computational demands.

In the context of this dissertation, a data-driven approach was developed that identifies pluvial and flash flood-prone areas in Bavaria based on historical events and area and catchment characteristics. The developed approach covers all necessary steps from event dataset generation through data management and event analysis to model setup and model evaluation.

First, a dataset comprising nearly 23,800 German pluvial and flash flood events was generated, which forms the basis of the data-driven model. To generate an event dataset suitable for susceptibility modeling, a documentation procedure was developed, ranging from event definition through the identification of sources to the schematic event documentation. The key feature of this procedure is a documentation scheme that specifies what event information to document and how. To create a high-quality event dataset, it is necessary to assess information quality, report event information separated by source, and use predefined categories for attribute description.

Then, a spatial event database was developed to link the event dataset to geodatasets and perform spatiotemporal event analyses. All relevant aspects of database design were exemplified, from database requirements and system architecture to table and attribute design and the definition of keys and relationships. Of particular importance is the consideration of the spatiotemporal and content-related accuracy of the event information. The evaluation of the generated event dataset proved that pluvial and flash floods occur

everywhere in Germany, with northern Germany tending to be affected less frequently. Heavy rain-induced flood events in Germany mostly occur in summer and between midday and late afternoon. Across Germany, seven hotspots (i.e., regions that experience particularly numerous events) were identified, located in both densely populated and mountainous areas.
A machine learning approach was developed for the identification of areas in Bavaria at risk from pluvial and flash flooding. To this end, a CatBoost model was trained using 1,864 affected and unaffected locations and 11 spatially distributed and six catchment-related influencing factors. To achieve good model performance, it proved necessary to ensure good spatial coverage of the Bavarian state territory and to represent the four major landscapes in the training and test set. Particularly susceptible regions were identified in northern Bavaria (metropolitan area of Nuremberg, Würzburg and its surroundings, along the Main River) and southeastern Bavaria (Alpine foothills, Munich and its surroundings, the southern part of the eastern low mountain range).
This dissertation improves the hazard understanding of pluvial and flash floods in Germany and introduces a new data-driven approach to identify areas at risk. Detailed guidance is provided on how to document, process, and evaluate event information for susceptibility modeling and event assessment that extends the methods in flash flood research. In the context of flood risk management and spatial planning, the newly gained knowledge about endangered areas in Bavaria and the spatiotemporal characteristics of pluvial flash floods can be used. An application of the methodology to other (federal) states is possible.

Zusammenfassung

Durch Starkregen verursachte Hochwasser stellen aufgrund ihres plötzlichen Auftretens und ihrer Zerstörungskraft eine Bedrohung für Menschen dar. Sturzfluten werden durch kleinräumige, kurze aber intensive Niederschlagsereignisse ausgelöst, die schwer vorherzusagen sind. Darüber hinaus sind Hochwasser infolge von Starkregen nicht zwingend an Gewässer gebunden, was ihre Vorhersage weiter erschwert. Daher ist die Identifizierung von besonders gefährdeten Gebieten eine entscheidende Vorsorgemaßnahme.
Im Jahr 2016 wurde der Freistaat Bayern (Deutschland) von einer Serie von starkregenbedingten Hochwasserereignissen schwer getroffen, bei denen sieben Menschen starben. Die Hochwasserereignisse von 2016 unterstrichen die Notwendigkeit, gefährdete Gebiete in ganz Bayern zu identifizieren. Dafür musste jedoch ein neuer Ansatz entwickelt werden, da eine landesweite Gefahrenbewertung mittels hydrodynamischer Modellierung aufgrund der hohen Rechenanforderungen nicht möglich war.
Im Rahmen dieser Dissertation wurde ein datengetriebener Ansatz entwickelt, der auf Grundlage von historischen Ereignissen sowie Gebiets- und Einzugsgebietseigenschaften sturzflutgefährdete Gebiete identifiziert. Der entwickelte Ansatz umfasst alle notwendigen Schritte von der Erstellung des Ereignisdatensatzes, dem Datenmanagement und der Ereignisanalyse bis hin zum Modellaufbau und der Modellauswertung.
Zunächst wurde ein Datensatz mit knapp 23.800 deutschen Sturzflut- und pluvialen Hochwasserereignissen erstellt, der die Grundlage für das datengetriebene Modell bildet. Um einen für die Anfälligkeitsmodellierung geeigneten Ereignisdatensatz zu erstellen, wurde ein Dokumentationsverfahren entwickelt, das von der Ereignisdefinition über die Identifikation der Quellen bis hin zur schematischen Ereignisdokumentation reicht. Das zentrale Element dieses Verfahrens ist ein Dokumentationsschema, das festlegt, welche Ereignisinformationen wie zu dokumentieren sind. Um einen qualitativ hochwertigen Ereignisdatensatz zu erstellen, ist es notwendig, die Informationsqualität zu bewerten, die Ereignisinformationen nach Quellen getrennt zu dokumentieren und vordefinierte Kategorien für die Attributbeschreibung zu verwenden.
Anschließend wurde eine räumliche Ereignisdatenbank entwickelt, um den Ereignisdatensatz mit Geodatensätzen zu verknüpfen und um raumzeitliche Ereignisanalysen

durchzuführen. Alle relevanten Aspekte des Datenbankdesigns wurden exemplarisch dargelegt, von den Datenbankanforderungen und der Systemarchitektur über das Tabellen- und Attributdesign bis hin zur Definition von Schlüsseln und Beziehungen. Von besonderer Bedeutung ist die Berücksichtigung der raumzeitlichen und inhaltlichen Auflösung der Ereignisinformationen. Die Auswertung des erstellten Ereignisdatensatzes zeigte, dass pluviale Hochwasser und Sturzfluten überall in Deutschland auftreten, wobei Norddeutschland tendenziell seltener betroffen ist. Starkregenbedingte Hochwasserereignisse treten in Deutschland meist im Sommer und zwischen den Mittagsstunden und dem späten Nachmittag auf. Deutschlandweit wurden sieben Hotspots (d. h. Regionen, in denen besonders viele Ereignisse auftreten) identifiziert, die sowohl in dicht besiedelten als auch in gebirgigen Regionen liegen.

Für die Identifizierung von Gebieten in Bayern, die durch pluviales Hochwasser und Sturzfluten gefährdet sind, wurde ein Machine-Learning-Ansatz entwickelt. Dazu wurde ein CatBoost-Modell mit 1.864 betroffenen und nicht betroffenen Orten und 11 räumlich verteilten und sechs einzugsgebietsbezogenen Einflussfaktoren trainiert. Um eine gute Modellperformance zu erreichen, erwies es sich als notwendig, eine gute räumliche Abdeckung des bayerischen Staatsgebietes zu gewährleisten und die vier Naturräume im Trainings- und Testdatensatz zu berücksichtigen. Besonders gefährdete Regionen wurden in Nordbayern (Großraum Nürnberg, Würzburg und Umgebung, entlang des Mains) und Südostbayern (Alpenvorland, München und Umgebung, südlicher Teil des östlichen Mittelgebirges) identifiziert.

Diese Dissertation verbessert das Gefahrenverständnis von pluvialem Hochwasser und Sturzfluten in Deutschland und führt einen neuen datengetriebenen Ansatz zur Identifizierung gefährdeter Gebiete ein. Es wird eine detaillierte Anleitung zur Dokumentation, Verarbeitung und Auswertung von Ereignisinformationen für die Gefährdungsmodellierung und Ereignisauswertung gegeben, die die Methoden der Sturzflutforschung erweitert. Im Rahmen des Hochwasserrisikomanagements und der Raumplanung können die neu gewonnenen Erkenntnisse über gefährdete Gebiete in Bayern und die raumzeitlichen Charakteristika von pluvialem Hochwasser und Sturzfluten genutzt werden. Eine Anwendung der Methodik auf andere (Bundes-)Länder ist möglich.

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.

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Place, date	Maria Kaiser

Contents

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Author contributions

This cumulative dissertation is based on the following peer-reviewed journal papers. Chapter 2 to 4 in this work have been submitted or are published in a similar form.

Chapter 2

Kaiser, M., Günnemann, S., Disse, M., 2020. Providing guidance on efficient flash flood documentation: an application based approach. *Journal of Hydrology*. 581, 124466. `https://doi.org/10.1016/j.jhydrol.2019.124466`.

Maria Kaiser wrote the manuscript. Stephan Günnemann and Markus Disse took part in conceiving the study and reviewed the manuscript. All authors contributed to the modification of the manuscript.

Chapter 3

Kaiser, M., Günnemann, S., Disse, M., 2021. Spatiotemporal analysis of heavy rain-induced flood occurrences in Germany using a novel event database approach. *Journal of Hydrology*. 595, 125985. `https://doi.org/10.1016/j.jhydrol.2021.125985`.

Maria Kaiser wrote the manuscript. Stephan Günnemann and Markus Disse took part in conceiving the study and reviewed the manuscript. All authors contributed to the modification of the manuscript.

Chapter 4

Kaiser, M., Günnemann, S., Disse, M., 2021. Predicting pluvial and flash flood susceptible areas in the state of Bavaria (Germany) using tree-based classifiers. Submitted to *Journal of Hydrology* (under review).

Maria Kaiser wrote the manuscript. Stephan Günnemann and Markus Disse took part in conceiving the study and reviewed the manuscript. All authors contributed to the modification of the manuscript.

Aspects of this work have further been presented in the following publications and conference contributions:

1. **Kaiser, M.**, Borga, M., Disse, M., 2020. Occurrence and Characteristics of Flash Floods in Bavaria (Germany). In: W. Leal Filho, G. Nagy, M. Borga, D. Chávez Muñoz, A. Magnuszewski (Editors), Climate Change, Hazards and Adaptation Options. Handling the impacts of a changing climate. Springer International Publishing, Cham. `https://doi.org/10.1007/978-3-030-37425-9_16`.

2. **Kaiser, M.**, Nguyen, H., Sheikhy, T., Hövel, A., Disse, M., 2019. A New GIS-Based Approach to Determining the Flash Flood Hazard in Cities. ESRI User Conference, San Diego, United States.

3. **Kaiser, M.**, Borga, M., Disse, M., 2019. Occurrence and Characteristics of Flash Floods in Bavaria (Germany). Symposium on Climate Change and Natural Hazards: Coping with and managing hazards in the context of a changing climate, Padua, Italy.

4. Disse, M., **Kaiser, M.**, 2018. Flash Floods in Bavaria, Germany: Recording, Exploring, Evaluating – The Project HiOS. AGU Fall Meeting, Washington, D.C., United States.

5. **Kaiser, M.**, Broich, K., Pflugbeil, T., Mitterer, J., Lin, Q., Sheikhy, T., von Trentini, F., Willkofer, F., Nguyen, H., Ludwig, R., Disse, M., 2018. Sturzflutforschung in Bayern – Ziele und Ansätze des Projekts HiOS. *Korrespondenz Wasserwirtschaft* 11, (11), 685-690. `https://doi.org/10.3243/kwe2018.11.005`.

6. Lin, Q., Broich, K., Pflugbeil, T., Mitterer, J., **Kaiser, M.**, Nguyen, H., von Trentini, F., Willkofer, F., Ludwig, R., Disse, M., 2018. Flash Flood Modeling on HPC Systems. EnviroInfo, Garching, Germany.

7. Broich, K., **Kaiser, M.**, Lin, Q., Mitterer, J., Nguyen, H., Pflugbeil, T., von Trentini, F., Willkofer, F., Disse, M., Ludwig, R., 2018. Das Projekt HiOS – Erstellung einer Hinweiskarte für Oberflächenabfluss und Sturzfluten für bayerische Gemeinden. In: M. Disse, **M. Kaiser** (Editors), Starkregen und Sturzfluten – Erfassen, Erforschen, Evaluieren. Beiträge zum Seminar am 6. Juni 2018 an der Technischen Universität München. `https://doi.org/10.14617/for.hydrol.wasbew.40.18`.

8. Handelshauser, E., **Kaiser, M.**, Disse, M., 2018. Erwartungen und Anforderungen an die bayernweite Hinweiskarte Oberflächenabfluss und Sturzflut: eine Untersuchung mittels Stakeholderanalyse und Umfragen. Tag der Hydrologie, Dresden, Germany.

1 Introduction

1.1 Background & motivation

Floods triggered by heavy rain pose a deadly threat to people all over the world. Whether in mountainous or flat terrain, in rural or urban areas – heavy rain-induced floods claim lives worldwide every year and cause millions of dollars in damage. Megacities can be just as affected (e.g., Mumbai 2005, Beijing 2012) as deserts (e.g., Atacama 2015) or mountain regions (e.g., Krasnodar (Russia) 2012, Uttarakhand (India) 2013) (Kron, 2016). Germany is also threatened by heavy rain-induced floods. Between 2002 and 2017, heavy rain events in Germany destroyed residential property values worth about €6.7 billion (GDV, 2019). In the last decade, 2016 was particularly severe for Germany, with 1,025 documented pluvial and flash flood events causing 17 fatalities and 138 injuries (Kaiser et al., 2020b; Kaiser et al., 2021). For 2016, Munich Re (2017) estimated the overall loss from the heavy rain-induced flood events in Germany at €2.6 billion. Although heavy rain-induced floods occur only locally, their average annual overall loss is comparable to a 100-year event on major rivers (Munich Re, 2005). In contrast to heavy rain-induced floods, riverine floods are caused by prolonged, large-scale precipitation and can last for days to weeks.

Due to climate change and ongoing urbanization, the hazard from heavy rain-induced floods in Germany will further increase. Regional climate models suggest that the frequency and intensity of heavy precipitation events will change in many regions of Europe and Germany in the future (Aalbers et al., 2018; Martel et al., 2020; Wood and Ludwig, 2020). Although quantitative statements regarding change signals in heavy precipitation in Germany are subject to greater uncertainty (Kunz et al., 2017), an increase in winter heavy precipitation and a decrease in summer heavy precipitation are expected (Maraun, 2013; Brienen et al., 2020). In addition to climate change, ongoing urbanization will exacerbate the flood hazard. Due to land use/land cover change and the increasing population and infrastructure density in cities, urban areas are becoming more vulnerable to pluvial and flash flooding (e.g., Yang et al., 2013; Q. Huang et al., 2017; Zhou et al., 2019).

Researchers generally distinguish between two types of floods that are triggered by heavy precipitation: flash floods and pluvial floods. Although there is no unified definition of flash floods or pluvial floods in the scientific community (see Kobiyama and Goerl, 2007; Sene, 2013; Bernet et al., 2017), these two flood types can be roughly distinguished as follows. Typically, flash floods are floods that originate from the creek or river, while pluvial floods are characterized by surface water flowing toward the river network stemming from overwhelmed drainage systems, saturation or Hortonian overland flow (Bernet et al., 2017). Pluvial and flash flooding may be promoted by steep slopes, sealed or hydrophobic soils, and high antecedent soil moisture (Bronstert et al., 2018), which favor surface runoff formation. Since both flood types are triggered by short, high-intensity rainfall, pluvial floods and flash floods can occur simultaneously and are thus hard to distinguish.
Besides numerous varying definitions of flash floods and pluvial floods, researchers also use different terms. Flash floods are sometimes referred to as *pluvial flash floods* to specify their origin from heavy rain (e.g., Yin et al., 2016; Zanchetta and Coulibaly, 2020), as opposed to flash floods triggered by dam failures, ice breakups, or snowmelt. Common terms for pluvial flood include *surface water flood* (e.g., Bernet et al., 2017; Gradeci et al., 2019), *urban pluvial flood* (e.g., Löwe et al., 2017; G. Huang et al., 2019), *urban flood* (e.g., Zhao et al., 2019; Wang et al., 2018), and *urban water logging* (e.g., Tang et al., 2019; Q. Zhang et al., 2021). In addition, researchers use the term *urban flash flood*, whereby it is often unclear whether they are referring to a flash flood occurring in an urban area or a pluvial flood (e.g., Portugués-Mollá et al., 2016; Xing et al., 2019; Guillén et al., 2017). The various definitions and terms used in the scientific community illustrate the difficulty in distinguishing between flash floods and pluvial floods. In this thesis, we use the terms flash flood and pluvial flood. We further summarize the two types under the term heavy rain-induced floods as they are hardly to distinguish in nature.
The dangerousness of flash floods results from their suddenness and destructiveness. Within minutes to a few hours, a heavy precipitation event can turn a small creek into a raging torrent. In the literature, a lag time (i.e., the duration between the precipitation onset and the time of peak discharge) of less than 6 hours is often assumed to distinguish flash floods from river floods (e.g., Georgakakos, 1986; Marchi et al., 2010; Gourley et al., 2010). Due to their high flow velocity, flash floods can carry trees, boulders, and debris, turning them into destructive and deadly bodies of water. The power of water could be observed in the Braunsbach flash flood (Baden-Württemberg) in 2016, where layers of debris up to 3 m high covered the roads along the river channel (Laudan et al., 2017).

In post-event analyses, Ozturk et al. (2018) estimated that 42,000 m^3 of coarse sediment was mobilized during the Braunsbach flash flood, of which 1,000 m^3 was woody debris (Lucía et al., 2018).
Although pluvial floods are not characterized by a raging torrent as flash floods, pluvial floods are no less dangerous or damaging. In the recent past, Germany has experienced numerous destructive and deadly pluvial floods. The pluvial flood of Münster is probably among the most known in Germany due to its severe impact. On 28 July 2014, 292 mm poured down on the city of Münster in 7 hours, claiming two lives. Due to the masses of rain, the fire departments in Münster received 13,000 emergency calls within 8 hours. In total, insurers paid €140 million for 30,000 claims caused by the heavy rain, mainly in Münster (Burghoff et al., 2015).
The major issue of pluvial and flash flood risk management is the prediction. Pluvial and flash floods are triggered by small-scale, short convective precipitation that is challenging to forecast and therefore subject to large uncertainties (Collier, 2007). In addition to short-range quantitative precipitation forecasts, flash flood prediction requires a hydrological-hydrodynamic model that delineates potential inundation areas over large spatial scales (Borga et al., 2011). In contrast to riverine flood forecasting, flash flood forecasting has short lead times and must consider every stream within a large region as potentially flash flood-prone (Borga et al., 2011). Although flash flood forecasting has improved significantly in recent decades (see Hapuarachchi et al., 2011; Zanchetta and Coulibaly, 2020), it is still not possible – and may never be possible – to reliably predict when and where heavy rain-induced floods will occur. For these reasons, early identification of areas at particular risk from pluvial and flash flooding is an essential complementary measure to forecasting.
In contrast to the inundation areas of major rivers, the potential pluvial and flash flooding areas in Germany are not identified nationwide. Due to the European Floods Directive (2007/60/EC), all member states must prepare flood hazard maps for rivers with significant flood risk, which indicate humans and assets at risk (see European Union, 2007). However, since the European Floods Directive excludes heavy rain-induced floods and the heavy rain risk management in Germany is the responsibility of the municipalities, pluvial and flash flood risk maps only exist where individual municipalities have already taken measures.
Still, the flash flood susceptibility assessment for areas larger than a municipality poses problems. Generally, researchers use hydrodynamic models to delineate the inundation areas of a study site for different heavy precipitation scenarios (e.g., Li et al., 2019; Hofmann and Schüttrumpf, 2020). However, since the hydrodynamic model setup is

time-consuming and the modeling is computationally expensive, applying hydrodynamic models for vast areas, such as federal states, is not feasible. Therefore, to identify areas at risk from pluvial and flash flooding for large territories, we need a new, fast modeling approach.

1.2 Research objectives & hypotheses

Floods triggered by heavy rain in the state of Bavaria (Germany) were an underestimated natural hazard. According to GDV (2019), 1,866 heavy rain events occurred in Bavaria between 2002 and 2017, causing damages of €1,485 million. However, despite the numerous flood events in the past, the hazard posed by pluvial and flash floods received little attention from the public and those responsible for flood risk management. This is because people tend to underestimate the threat to life posed by an onrushing stream or the force of flowing water. For this reason, and due to the local occurrence of heavy rain-induced floods, authorities, municipalities and citizens are not aware of the risk from heavy rain (Goderbauer-Marchner and Sontheimer, 2015).

It was not until a series of severe pluvial and flash flood events occurred across Bavaria within a few weeks in 2016 that the need for action was recognized. In 2016, over 410 heavy rain-induced flood events were documented, with impacts such as blocked streets, flooded cellars, and destroyed houses (Kaiser et al., 2020b). The Simbach flash flood alone killed seven people and flooded about 5,000 households (Munich Re, 2017). It was this series of heavy rain-induced floods in 2016 that underlined the urgency of investigating and assessing pluvial and flash flood risk in Bavaria.

To support pluvial and flash flood risk management in Bavaria, there is a need to identify areas susceptible to flooding caused by heavy rain within the state. Since the Bavarian state territory covers 70,500 km^2, a state-wide risk assessment using hydrodynamic modeling is not feasible due to the high computational demands. Instead, a faster and easier to implement method for deriving pluvial and flash flood hazard areas is needed. Therefore, the overall objective of this dissertation is to develop a data-driven approach to identify pluvial and flash flood susceptible areas in the state of Bavaria. This data-driven approach should cover all necessary steps from dataset generation through data management and data analysis to model setup and evaluation. This dissertation aims at providing guidance on how to transform pluvial and flash flood event information into a susceptibility map and an improved hazard understanding. From the overall aim, we derive the following five research objectives:

(1) To establish a unified documentation approach for pluvial and flash flood events.

(2) To set up an event database supporting a wide range of analyses.

(3) To analyze the generated event dataset regarding the spatiotemporal characteristics.

(4) To identify pluvial and flash flood susceptible areas in Bavaria.

(5) To investigate factors influencing pluvial and flash flood occurrence in Bavaria

There are several research questions associated with the development of the data-driven modeling approach. Since the event dataset is the crucial foundation of a data-driven model, special attention must be paid to its generation. The generation of a pluvial and flash flood event dataset includes not only the collection but also the preparation and homogenization of event information from different sources that are not equally reliable. Therefore, the question is how to structure the documentation of pluvial and flash flood events to generate a high-quality event dataset suitable for hazard evaluation and susceptibility modeling.
In addition, a database for managing and linking the event dataset to geodatasets is essential. The database facilitates the collection of heavy rain-induced flood events, and also supports their spatiotemporal analysis. However, since the table and attribute design has a significant impact on the analysis capabilities, it is necessary to develop a database design that is suitable for pluvial and flash flood event studies.
To support pluvial and flash flood risk management in Bavaria, it is not only crucial to identify endangered areas, but also to enhance our understanding of heavy rain-induced floods. In this context, we still know little about frequency, temporal evolution, spatial distribution and patterns, fatalities and injuries, as well as the seasonality of heavy rain-induced floods in Germany. For effective flood risk management, we further need to know what area and catchment characteristics favor the occurrence of heavy rain-induced flooding.
The following fundamental hypotheses are related to the identification of pluvial and flash flood susceptible areas in Bavaria using a data-driven model:

(1) A standardized documentation procedure is required to generate an event dataset suitable for hazard evaluation and susceptibility modeling.

(2) The design of a database for heavy rain-induced floods must consider the spatiotemporal and content-related accuracy of the event information.

(3) Heavy rain-induced floods in Germany show distinct spatiotemporal characteristics.

(4) Machine learning algorithms can be used to identify pluvial and flash flood susceptible areas in Bavaria.

(5) Area and catchment characteristics influence the occurrence of heavy rain-induced floods in Bavaria.

These hypotheses are addressed in three publications that build on each other. Fig. 1.1 summarizes the research objectives and hypotheses of this dissertation, and assigns them to the corresponding chapters and publications.

Research objective	Hypothesis	Chapter	Publication
Creation of a documentation scheme	A standardized documentation procedure is required to generate an event dataset suitable for hazard evaluation and susceptibility modeling.	Chapter 2	Providing guidance on efficient flash flood documentation: an application based approach
Setup of an event database	The design of a database for heavy rain-induced floods must consider the spatiotemporal and content-related accuracy of the event information.	Chapter 3	Spatiotemporal analysis of heavy rain-induced flood occurrences in Germany using a novel event database approach
Analysis of the event dataset	Heavy rain-induced floods in Germany show distinct spatiotemporal characteristics.	Chapter 3	
Identification of susceptible areas	Machine learning algorithms can be used to identify pluvial and flash flood susceptible areas in Bavaria.	Chapter 4	Predicting pluvial and flash flood susceptible areas in the state of Bavaria (Germany) using tree-based classifiers
Investigation of influencing factors	Area and catchment characteristics influence the occurrence of heavy rain-induced floods in Bavaria.	Chapter 4	

Figure 1.1: Overview of the research objectives, hypotheses, chapters, and publications of this dissertation.

1.3 Thesis outline

This cumulative thesis is divided into five chapters. The introduction is followed by the three main chapters, which are based on the three publications. Chapters 2 through 4 address the research questions and represent the manuscripts that have been published or are currently under review in the peer-reviewed *Journal of Hydrology*.

In **Chapter 2**, we propose a structured documentation procedure for pluvial and flash flood events. To this end, we first review current documentation approaches based on 11 published flash flood datasets. Based on the review findings, we propose a structured 4-step approach for event documentation. We exemplify the proposed documentation approach based on a German pluvial and flash flood dataset. The key feature of the proposed approach is a documentation scheme indicating what event information to report and how.

In **Chapter 3**, we illustrate how an event database for the investigation of heavy rain-induced flood occurrences can be created. Based on the event dataset generated in Chapter 2, we exemplify the database design regarding database requirements and system architecture, table and attribute design, as well as key and relationship definition. By means of the database, we explore the spatiotemporal characteristics of floods caused by heavy rain in Germany. We investigate the collected pluvial and flash flood events regarding the temporal occurrence, spatial distribution, fatalities and injuries, and seasonality.

In **Chapter 4**, we identify the areas in Bavaria that are susceptible to pluvial and flash flooding using a tree-based ensemble model. The ensemble model is trained and validated with a flood inventory extracted from the event database (Chapter 3) and selected influencing factors. Using model-specific and model-agnostic methods, we investigate the interaction of the influencing factors and their impact on the occurrence of pluvial and flash floods in Bavaria.

Chapter 5 discusses the main findings and contributions of this thesis, including practical recommendations and suggestions for future research.

2 Providing guidance on efficient flash flood documentation: an application based approach

This chapter is published as:

Kaiser, M., Günnemann, S., Disse, M., 2020. Providing guidance on efficient flash flood documentation: an application based approach. *Journal of Hydrology.* 581, 124466. `https://doi.org/10.1016/j.jhydrol.2019.124466`.

Abstract Flash flood research crucially relies on historical event information for hypothesis testing. However, flash flood science suffers from data scarcity. Due to the high effort for event data collection, few long-term and comprehensive flash flood datasets exist. Yet, to advance flash flood research, scientists should spend time on creating event datasets. Therefore, to reduce the data collection and preparation effort, this paper takes a first step towards structuring the flash flood documentation procedure. In this context, we first investigate the current documentation approaches by reviewing 11 published flash flood datasets. We found great differences between the flash flood datasets regarding temporal and spatial scope, information density, flash flood definition, and usability by others. Based on the review findings and the cross-industry standard process for data mining, we propose a structured 4-step approach for flash flood documentation. We provide recommendations on efficient flash flood documentation and exemplify a possible implementation based on a German flash flood dataset, starting from flash flood definition through the identification of sources to the schematic event documentation. The key feature of our approach is a documentation scheme specifying what event information to report and how. Within the documentation scheme, it proved particularly helpful to use fixed categories for attribute description, to rate information quality, and to document events separated by source. Following our approach, we were able

to create a comprehensive event dataset composed of a variety of sources. In addition to flash flood events, our dataset also includes surface runoff events triggered by heavy rain, adding up to nearly 23,800 German events. Scientists can employ this approach to document flash floods more efficiently in the future.

2.1 Introduction

Flash flood research starts with a journey into the past. Based on historical flash flood events, we aim to learn for the future. However, being able to learn from past events requires documentation of the generation, course, and impacts of flash flood events. Therefore, event documentation marks the beginning of flash flood research and thus is of fundamental importance. Regardless of whether researchers want to advance flash flood understanding, modeling, or forecasting, they rely on historical event information for their investigations. Recently, researchers used flash flood event datasets for verification of forecasts and warnings (e.g., Creutin et al., 2009; Calianno et al., 2013; Gourley et al., 2017; Auer et al., 2019), for investigations of flash flood characteristics (e.g., Gaume et al., 2009; Marchi et al., 2010; Tarolli et al., 2012; He et al., 2018), for studies on flood risk management (e.g., Einfalt et al., 2009), and for identification of flood prone areas (e.g., Vinet et al., 2016; Saharia et al., 2017).

In recent years, researchers have increasingly used post-flood field surveys and hydrometeorological networks to collect flash flood data. Post-flood investigations help to reproduce the mechanisms and the course of a flash flood event. Besides the reconstruction of the event, the post-flash flood surveys focus on understanding the damage processes (e.g., Laudan et al., 2017), investigating the geomorphic response (e.g., Lucía et al., 2018), analyzing the hydrometeorological forcing (e.g., Marchi et al., 2009; Ruiz-Villanueva et al., 2012; Bronstert et al., 2018), and reconstructing the hydrograph (e.g., Segura-Beltrán et al., 2016; Bačová Mitková et al., 2018). There is also a growing number of scientific papers investigating data collected from radar–rain gauge networks with regard to flash floods (e.g., Bouilloud et al., 2010; Boudevillain et al., 2016; Varlas et al., 2019). In particular, radar images, private rain gauge networks, unmanned aerial vehicles, and citizen science offer new opportunities for data collation (e.g., B. Smith and Rodriguez, 2017; Diakakis et al., 2019; Seibert et al., 2019).

Despite the increasing number of possible data sources, long-term flash flood datasets are still limited (Braud et al., 2016). Therefore, in the editorial of the special issue of Journal of Hydrology entitled “Flash floods, hydro-geomorphic response and risk management”, Braud et al. (2016) call on the community to intensify data collection efforts for advancing knowledge gain. Conceivable reasons for the lack of data inventories are manifold but certainly include (i) the high effort for data collection and preparation, (ii) lack of data, especially weather radar data, (iii) lack of funds, and (iv) lack of recognition. One reason why flash flood documentation is time-consuming is because event information is usually scattered among different sources e.g., agencies, media, and action forces. Furthermore, no documentation guidelines exist describing the dataset generation process. Also, the few published datasets provide little information on how to document flash floods. While lack of funds and lack of recognition are difficult to solve, flash flood science should try to facilitate dataset generation.

To tackle data scarcity in flash flood research, we are convinced that it is necessary to simplify and clarify the process of flash flood documentation. A structured documentation approach, for instance, makes data preparation more efficient, ensures data quality, and facilitates data use by third parties. Therefore, we aim to streamline the process of flash flood documentation to increase the number of available flash flood datasets and thus foster flash flood research.

In this paper, we demonstrate how to document flash flood events by following a structured approach that applies a comprehensive and flexible documentation scheme. First, we prove why a structured approach is needed by highlighting key differences and limitations of existing flash flood datasets and databases (Section 2.2). Subsequently, we propose a structured approach for flash flood documentation to make dataset generation more efficient (Section 2.3). Following, we give recommendations for flash flood documentation based on the conducted dataset review and our experience in flash flood dataset generation (Section 2.4). We exemplify the practical implementation of our recommendations based on a German dataset. Then we shortly present the created flash flood dataset (Section 2.5). Finally, we discuss our findings from dataset creation and review (Section 2.6) and provide concluding remarks (Section 2.7).

2.2 Current flash flood documentation – A review

2.2.1 Comparison of published flash flood datasets and databases

Several published datasets exist that document flash flood and surface runoff events triggered by heavy precipitation. Most of these flash flood datasets are results from scientific studies and projects. However, institutions such as the European Severe Storms Laboratory (ESSL), the National Severe Storms Laboratory (NSSL), or the National Weather Service (NWS) of the United States also operate topical databases. According

to our review, only eleven published flash flood datasets exist (Table 2.1).
The purposes of these eleven flash flood datasets vary greatly. Some datasets serve as a basis for modeling studies and advancing process understanding (cf. EuroMedeFF; FLASH). Other flash flood datasets are created to raise awareness and to improve preparedness and action planning (cf. SINATRA; URBAS; Vennari et al., 2016; Vinet et al., 2016). Also, researchers collect flash flood information to verify warnings and to forecast events (cf. ESWD; HYDRATE; SHAVE; Storm Events Database). Another reason to set up a flash flood dataset is the investigation of flash flood characteristics on a larger scale, e.g. at state level or for a climate region (cf. FLASH; He et al., 2018, HYDRATE). As a result of the different objectives and applications, the flash flood datasets differ regarding structure, accuracy, and scope. A flash flood dataset suitable for historical event modeling, for example, requires detailed and accurate spatial information on precipitation and discharge. For global investigations, in contrast, it may be sufficient to have aggregated and less detailed space-time event information. Hereafter, we will elaborate on the dataset differences in more detail.
We compared the eleven flash flood datasets regarding their spatial and temporal extent, content and event numbers, event definitions, and accessibility (Table 2.1). The flash flood datasets vary regarding to their spatial and temporal extent. Seven of the 11 listed datasets document flash flood events in Europe, three datasets concern the United States, and one dataset covers China (Table 2.1). Most of the European datasets cover the Mediterranean region, where flash floods tend to be more intense than in Continental Europe (Gaume et al., 2009). Furthermore, the flash flood datasets comprise different periods. While the shortest dataset by He et al. (2018) covers 5 years, the most comprehensive dataset by Vennari et al. (2016) starts in 1540.
The datasets also differ in regard to content and number of events. For instance, the smallest dataset, the EuroMedeFF dataset, includes 49 flash flood events, whereas the larger datasets such as the SHAVE dataset and the Storms Event Database comprise several thousand events. As a rule, the fewer entries a flash flood dataset has, the more detailed the event information. Still, the content of the datasets is not completely identical, since some researchers interpret the term flash flood more broadly or tackle the hazard from a different perspective. The Vict-in dataset by Vinet et al. (2016), for instance, reports indirectly about flash floods as it documents flash flood fatalities. Furthermore, the datasets by Archer et al. (2019) and He et al. (2018) comprise more than flash flood events. While Archer et al. (2019) include additionally surface runoff events triggered by heavy rain, He et al. (2018) also consider landslides and debris flows caused by heavy precipitation. Regarding content, the European Severe Weather Database

(ESWD) is also a special case, since the ESWD amongst others reports heavy precipitation events having caused an extreme impact or exceeding a defined threshold amount (Table 2.1). The ESWD therefore covers the entire range from surface runoff through flash flood events to landslides caused by heavy precipitation.
The differences among the flash flood datasets emerge when comparing the applied event definition. Depending on the study objective and climatic region investigated, the applied flash flood definitions vary greatly. Most researchers define event thresholds for considered catchment size (50 to 3,000 km^2) and causative rainfall duration (up to 48 h). Conversely, the FLASH dataset limits the flooding rise time to 6 h and the catchment size to 250 km^2, whereas a flash flood must have posed a potential threat to life or property and moving and standing water must have exceeded 0.15 m and 0.91 m, respectively for inclusion into the Storm Events Database. Overall, the hazard and damage aspect controls the flash flood definition in several datasets (see Storm Events Database; ESWD; URBAS; He et al., 2018; Vinet et al., 2016). However, for some datasets it remains unclear which event definition has been applied since the definition is not stated in the dataset description (cf. Vennari et al., 2016; Vinet et al., 2016; Archer et al., 2019).
With the exception of the datasets by Vinet et al. (2016) and He et al. (2018), the presented flash flood datasets are available either through an online database or a publication. For many datasets, a bulk data download is possible facilitating the use by other researchers. Although the ESWD, URBAS, and SINATRA datasets are online, a download of selected entries or the entire dataset is not possible. This lack of a download possibility severely complicates the dataset use. Researchers can get access to the events of interest only by manual extraction. Alternatively, the ESWD offers event data for sale. However, the ease of use pays off. The HYDRATE, FLASH, and SHAVE datasets, which allow for easy use by third parties, have already served as the basis in several studies.

Table 2.1: Comparison of published datasets and databases on flash flood events triggered by heavy precipitation. The comparison reveals major differences between the datasets regarding content, event number, event definition, spatial and temporal extent, and accessibility.

Organization/ project/study	Name of database/ dataset	State, region	Documented time	Content and number of datasets	Definition of event	URL	Applications/ studies using the dataset
European Severe Storms Laboratory (ESSL)	European Severe Weather Database (ESWD)	Europe	varies depending on country and event type	heavy precipitation events, wind gusts, tornadoes, hail, funnel clouds, gustnadoes, whirlwinds; number of events differs from country to country	• heavy precipitation event must have caused an extreme impact OR • a measurement of extreme rainfall must be given: $P \geq 2\sqrt{5 \cdot d}$ P = precipitation amount [mm], d = duration [min] $0.5\,\text{h} < \text{d} < 24\,\text{h}$ Excluded are: • flooding along rivers • flooding due to thaw and rain • falling rocks to which the rainfall may have contributed • events with $P < 25\,\text{mm}$ or $d < 30\,\text{min}$	`http://www.eswd.eu/`	Dotzek et al., 2009; Groenemeijer et al., 2017; Llasat et al., 2010
He et al., 2018	–	China	2011–2015	782 flash floods, including river floods, landslides and debris flows caused by heavy precipitation	• causative rainfall $< 6\,\text{h}$ • catchment $< 400\,\text{km}^2$ • flash floods, including river floods, landslides and debris flows caused by heavy precipitation that caused fatalities	–	He et al., 2018; Ma et al., 2018
Hydrometeorological Data Resources And Technologies for Effective flash flood forecasting (HYDRATE) project	HYDRATE	Europe	1946–2007	578 flash flood events	• causative rainfall $< 24\,\text{h}$ • catchment $< 500\,\text{km}^2$ (with some exceptions)	`http://www.hydrate.tesaf.unipd.it/`	Creutin et al., 2009; Gaume et al., 2009; Marchi et al., 2010; Borga et al., 2011; Tarolli et al., 2012
HYdrological cycle in the Mediterranean EXperiment (HyMeX)	EuroMedeFF database	Europe, Mediterranean Region	1991–2015	49 flash flood events	• storm duration $\leq 48\,\text{h}$ • catchment $\leq 3{,}000\,\text{km}^2$ • unit peak discharge $\geq 0.5\,\text{m}^3\,\text{s}^{-1}\,\text{km}^{-2}$	`https://doi.org//10.6096/MISTRALS-HyMeX.1493` (Amponsah et al., 2018b)	Amponsah et al., 2018a

Table 2.1: *Continued.*

Organization/ project/study	Name of database/ dataset	State, region	Documented time	Content and number of datasets	Definition of event	URL	Applications/ studies using the dataset
National Severe Storms Laboratory (NSSL)	Flooded Locations And Simulated Hydrographs (FLASH)	United States	1927–2010 streamflow data, 2006–2011 NWS storm reports, 2008–2010 SHAVE dataset	• SHAVE dataset • NWS Storm data • event-based streamflow measurements from USGS	• flooding rise time $< 6\,\mathrm{h}$ • catchment $< 250\,\mathrm{km}^2$	`https://blog.nssl.noaa.gov/flash/database/`	Gourley et al., 2013; Špitalar et al., 2014; Saharia et al., 2017; Gourley et al., 2017
National Severe Storms Laboratory (NSSL)	Severe Hazards Analysis and Verification Experiment (SHAVE)	United States	2008–2015	9,369 flash flood reports of no flooding, non severe flooding, and severe flooding	A flash flood survey was conducted, if any of the following criteria were met: • 6 h precipitation accumulation exceeded flash-flood guidance values less than 24 h ago • a flash flood warning or urban/small stream advisory was issued by an NWS forecast office during the past 24 h • a survey for a different severe weather threat indicated flash flooding was a problem	`https://www.nssl.noaa.gov/projects/shave/`	Ortega et al., 2009; Gourley et al., 2010; Gourley et al., 2012; Calianno et al., 2013
National Weather Service (NWS)	Storm Events Database	United States	2006–2010	15,999 flash flood reports	• a flash flood event begins within minutes to multiple hours of the causative event such as moderate to heavy rain, dam break, or ice jam release. Indicators for flash floods: • flash flood posed a potential threat to life or property • moving water $> 0.15\,\mathrm{m}$ • standing water $> 0.91\,\mathrm{m}$	`https://www.ncdc.noaa.gov/stormevents/`	Gourley et al., 2012; Calianno et al., 2013; Marjerison et al., 2016; Schroeder et al., 2016; Terti et al., 2017
Susceptibility of catchments to intense rainfall and flooding (SINATRA) project	–	England, northern and south-western region	1700–2013	3,706 flash flood events including surface water and fluvial flooding	• no information about the used flash flood definition	`http://ceg-fepsys.ncl.ac.uk/fc`	Archer et al., 2019

Table 2.1: *Continued.*

Organization/ project/study	Name of database/ dataset	State, region	Documented time	Content and number of datasets	Definition of event	URL	Applications/ studies using the dataset
Urbane Sturzfluten (URBAS) project	URBAS	Germany	1954–2008	350 flash flood events	• causative rainfall $< 6\,\mathrm{h}$ • catchment $< 50\,\mathrm{km}^2$ • within the period from April to September • flash flood event must have caused damage in urban area	`http://www.urbanesturzfluten.de/ereignisdb/ereignisse/ereignisse_view`	BMBF, 2008; Einfalt et al., 2009
Vennari et al., 2016	–	Italy, Campania region	1540–2015	477 flash flood events	• no information about the used flash flood definition	–	Vennari et al., 2016
Vinet et al., 2016	Vict-in	France, Mediterranean region	1988–2015	244 fatalities due to flash floods	• direct and indirect fatalities caused by flash floods: causal relation between flooding and death must exist • no information about the used flash flood definition	–	Vinet et al., 2016

2.2.2 Collected event information

The investigated flash flood datasets contain differently detailed event information depending on the purpose of use. While some datasets include a wide range of facts, others only provide basic information about event time and location, as well as an event description. However, the event description usually focuses on the damage aspect indicating the occurred losses and the number of injured and killed people. Except for the US-American datasets and the dataset by Vinet et al. (2016), all datasets provide quantitative information about the triggering precipitation such as amount and duration. However, some flash flood datasets go beyond that precipitation information, specifying, for example, the peak amount and duration, 6 h, 12 h, and 24 h accumulated rainfall (cf. ESWD) or the number of rain gauges and the spatial extent (cf. HYDRATE) if available. Furthermore, the FLASH, SHAVE, HYDRATE, and EuroMedeFF datasets report about the flooding and discharge of the event. While the SHAVE and the FLASH dataset provide estimated values for water depth and bank overflow, the HYDRATE and EuroMedeFF databases indicate mostly modeled flood hydrographs and reconstructed peak discharges, as well as measurements from gauging stations. Moreover, the FLASH and HYDRATE datasets specify catchment characteristics such as concentration time, average slope, or land use.

Typically, flash flood datasets are of qualitative, descriptive information referring to a point, namely the impacted town or city. Event reports therefore usually provide no information on affected areas or event extent. The only exceptions to this are the Storm Events Database, which has been specifying bounding polygons of flash flood impact and the SHAVE dataset, which estimates the spatial event extent since 2008 (Calianno et al., 2013). The HYDRATE and EuroMedeFF datasets do not provide event extents but indicate peak discharge estimations for various locations in the catchment. However, spatially distributed precipitation and discharge information as provided by the HYDRATE and EuroMedeFF datasets remain the exception.

The ESWD dataset is distinguished from the other investigated datasets, since the ESWD rates the quality of the event reports. Each event entry submitted via the public ESWD interface undergoes quality control (QC) by the ESSL. According to the QC-levels, the ESSL classifies the event report “as received” (QC0), “plausibility checked” (QC0+), “report confirmed” (QC1), or “event fully verified” (QC2) (Dotzek et al., 2009).

2.2.3 Concluding remarks on the available flash flood datasets

The available flash flood datasets reveal large differences regarding scope, content, and usability. However, the greatest difference is the spatiotemporal resolution of the provided precipitation and runoff information. Among the eleven flash flood datasets, the precipitation-runoff information ranges from no information through aggregated point information to spatially distributed estimates and measurements. It generally applies the more detailed and higher the resolution of the hydro-meteorological data, the smaller the dataset.

Flash flood records underestimate reality by nature, as they only cover a subset of occurred events. Furthermore, flash flood documentation naturally focuses on urban areas, since this is where the damage occurs and where the events are witnessed. As a result, flash flood events outside of settlements or without damages are often less documented. Overall in flash flood documentation, we report positive events rather than false alarms. However, the investigation of events, where no flash flood occurred despite enough heavy precipitation, could improve the process understanding of flash floods.

Another dataset issue is the inherent uncertainty in event information due to subjectivity in reporting. In particular, the perception of affected persons may be distorted (Gourley et al., 2013; Calianno et al., 2013). Therefore, Gourley et al. (2013) consider reports from the general public as unreliable. According to Dotzek et al. (2009), media reports are sometimes exaggerated and should thus be treated with caution. Since these uncertainties can hardly be eliminated, researchers have to consider them in the evaluation of the datasets.

In order to advance flash flood research, scientists rely on using existing datasets in particular since available flash flood datasets are still rare. However, due to differences in event definition and collected event information, investigating existing datasets or combining several datasets for further research is challenging. Besides, data integration is hampered by the different focuses of the datasets and resolutions of the information. Furthermore, flash floods are highly region and climate dependent, which complicates the merging of datasets as temporal and spatial scales of the flash floods may vary. Nevertheless, dataset pooling across climate regions is possible but requires documentation of the hydro-meteorological differences of the flash flood events in the database. Using existing flash flood datasets is further complicated by the fact that simple reuse of datasets by third parties is often not foreseen by the authors. Following a consistent and structured approach of flash flood documentation would however facilitate dataset use by others.

2.3 A structured approach for flash flood documentation

Data collection and preparation are of fundamental importance for knowledge gain. Before researchers gain insights from a dataset, they must perform many preparatory steps. However, these preparatory steps, such as data gathering, cleaning, and transformation, require a considerable amount of time. It is assumed that data collection and preparation take 70 to 90 % of the total investigation time. Consequently, the time scientists spend on analyses leading to findings is comparatively low. Scientists therefore lay the foundation for future results during the data collection and preparation process.
To support the entire process from data preparation to data insights, we propose a structured, step-by-step approach. Our approach is based on the first three steps of the cross-industry standard process for data mining, known as CRISP-DM (Chapman et al., 2000). We adapted the approach to the processes of flash flood documentation. Our process model consists of four steps, with no strict order of the steps (Fig. 2.1). The result of each step determines which step, or which task of a step, must be carried out next.

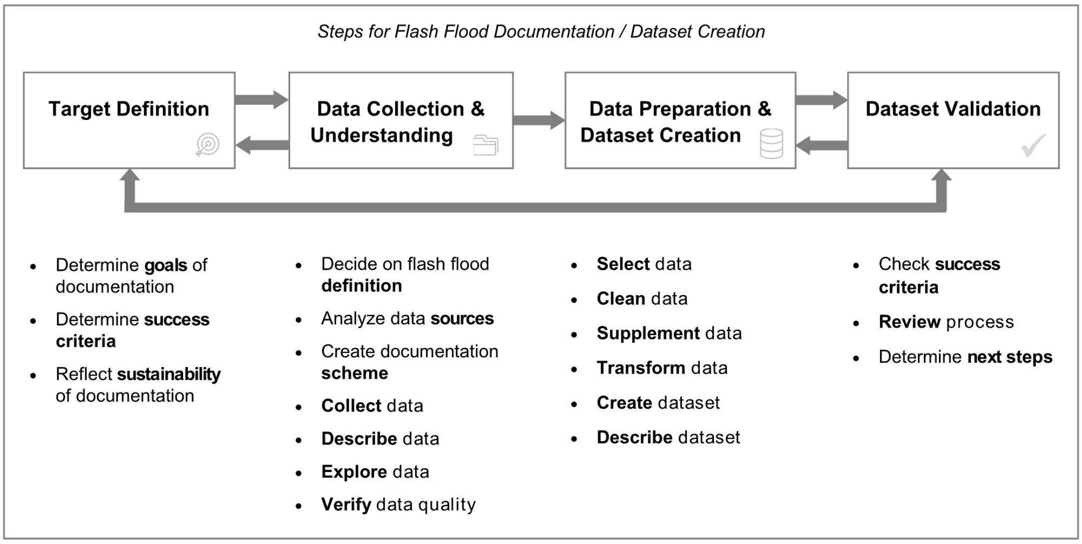

Figure 2.1: Proposed 4-step approach for structured documentation of flash flood events adapted from the cross-industry standard process for data mining, known as CRISP-DM (Chapman et al., 2000).

The first step is to **define the study targets**. To this end, we determine as precisely and as measurably as possible what the documentation goals are and how we measure the target achievement. The purposes and applications of flash flood datasets are manifold, ranging from modeling studies through action planning to verification of forecasts (cf. Section 2.2.1). Depending on the study target, the requirements for the structure, resolution, and scope of the dataset change. Furthermore, we reflect on how to ensure the sustainability of the dataset. What needs to be considered so that other researchers can understand and use the dataset subsequently? What needs to be considered if the dataset should be published later? Data journals support the scientifically recognized publication of datasets today, which not only acknowledges data collection efforts but also fosters research progress.

The second step is to **collect and** to **understand the data**. First, in order to ensure dataset consistency, we must establish a flash flood definition considering the local conditions of the study region. For example, flash floods in the Mediterranean region tend to have a greater spatial extent and a longer duration compared to the Continental flash floods (Gaume et al., 2009). Thus, climatic differences lead to different flash flood thresholds in studies (e.g., Gaume et al., 2009; Marchi et al., 2010; Braud et al., 2014; Amponsah et al., 2018a). In addition, it should be defined how flash floods are distinguished from river floods (cf. Section 2.4.1). After the definition has been set, possible data sources must be identified (cf. Section 2.4.2). Prior to data collection however, a documentation scheme must be developed (cf. Section 2.4.3). A documentation scheme supports targeted data collection by listing attributes of interest and their respective units. After the required data has been collected and described, the data is explored. The process of data exploration is crucial for scientific knowledge gain, since it helps to understand content and characteristics of the dataset. Furthermore, researcher should verify the quality of the collected data, so that erroneous values or other inconsistencies can be eliminated from the dataset. In addition, the uncertainty of the data should be quantified, e.g. using a range of values (cf. Section 2.4.4).

In the third step, the collected **data is prepared** and the flash flood **dataset is created**. For this purpose, the data required for the documentation scheme is selected and cleaned. An important task in data preparation is data supplementation (cf. Section 2.4.6), since data supplementation often enables more detailed and complex analyses. For instance, catchment information or derived discharge parameter could be used to enrich the event dataset. Subsequently, the selected data is transformed into the format or structure needed by the documentation scheme. A dataset description ensures that other researchers, who may want to use the dataset in the future, can understand the data and the processes undertaken.

During the last of the four steps, the created **flash flood dataset is validated**. It is assessed if and to what degree the determined success criteria were achieved. At the end, the entire process is reviewed to check dataset quality. If necessary, individual steps are repeated and further data is requested and processed. After completing the flash flood dataset, the next steps are planned.

2.4 Exemplified recommendations for efficient flash flood documentation

Documentation is an important task in flash flood research, since we improve our understanding by studying historical events. To improve scientific knowledge gain, we provide recommendations on how to document flash flood events efficiently. By efficient documentation, we mean the creation of a high-quality dataset created in a reasonable amount of time and with a reasonable amount of effort that is reusable by other researchers. Our recommendations are based on the conducted dataset review and our experience from creating a flash flood dataset. We first explain every recommendation theoretically and then exemplify a possible implementation based on our created dataset. Our dataset was created in the framework of the HiOS (**Hi**nweiskarte **O**berflächenabfluss und **S**turzflut, engl. Reference Map for Surface Runoff and Flash Floods) project and comprises German flash flood and surface runoff events triggered by heavy rain. The primary goal of the HiOS dataset is the geostatistical investigation of flash flood characteristics and triggering factors in Germany with a focus on Bavaria. We plan to publish the HiOS dataset at the end of the project. Previously, however, publication rights must be clarified, as the HiOS dataset combines event information from different sources for which different legal restrictions may apply.

2.4.1 Recommendation 1: Clearly state the flash flood definition applied

A clear event definition is of crucial importance to enable dataset use by third parties, since the event definition clarifies when a flash flood event was included or discarded from the dataset. Frequently used thresholds in the event definitions concern catchment size, triggering rainfall duration and amount, as well as time to peak. However, these thresholds are guiding values, since the transition between flash floods and river floods is seamless. In addition, the strong regional dependence of flash floods makes it difficult to define thresholds that can be uniformly applied over large spatial scales. Investigating European flash floods, for instance, requires different thresholds for Continental than for

Mediterranean flash floods (cf. Gaume et al., 2009). Therefore, the study objective and spatial scope are decisive for the definition of flash flood. However, a clear flash flood definition not only supports dataset reuse by other researchers but also ensures dataset consistency.

The first step in flash flood documentation is the determination of an event. A critical point hereby is the decision whether a past flood event has been a flash flood or a river flood, particularly since the transition is seamless. Nevertheless, flash floods and river floods differ in their generation and spatiotemporal spread. We have therefore based our distinction between a flash flood and river flood on (i) event trigger, (ii) event speed, and (iii) catchment size, although, the most important distinguishing feature is the event trigger, i.e. the precipitation event. Here, we distinguish whether a short, intense or a long-lasting precipitation caused a flood event. Since we are using the ESWD dataset for Germany, we are applying the ESWD precipitation threshold (ESSL, 2014). Accordingly, we consider heavy precipitation events lasting between 30 minutes and 24 h and apply the following as the precipitation threshold:

$$P \geq 2\sqrt{5 \cdot d} \tag{2.1}$$

where P is the precipitation amount in mm and d is the duration in min.

Since it is not always possible to classify the precipitation event by means of newspaper articles or measurements, we are using two additional criteria, namely event speed and catchment size. Therefore, when flooding occurs within a few hours, we consider this as an indication for a flash flood or surface runoff event triggered by heavy rain. In case the flooding rise time of the event is unknown, we are using little to no early warning time as a flash flood indicator. In addition, when the affected catchment is small, the event is likely to have been a flash flood. As upper threshold, we are applying a catchment size of $500\,\text{km}^2$. We are further assuming an occurrence period for flash floods in Germany from April to October. Kaiser et al. (2020a) demonstrated by means of a discharge investigation that these spatiotemporal thresholds are reasonable for Bavaria. We are supposing that these thresholds are transferable to all of Germany. To summarize, we are defining a flash flood as a sudden flood event triggered by heavy precipitation, which lasted no longer than 24 h and exceeded a given minimum precipitation amount, in a catchment up to $500\,\text{km}^2$ within the period from April to October.

Besides flash flood events, our dataset also contains surface runoff events due to heavy precipitation, which follow the thresholds defined in the previous paragraph. We documented debris flows and landslides as cascading effects of a flash flood event but not as

standalone events.
In our dataset, we uniquely define a flash flood event based on event date and affected settlement area, with settlement size ranging from a village through a small town to a city. According to our event definition, only one event per day and affected settlement area can be documented. Since it is highly unlikely that two flash flood events occur on the same day in the same city, our definition is consistent. However, the event linkage to the affected settlement area results in a concentration on urban areas.

2.4.2 Recommendation 2: Combine event information from different sources

To obtain a comprehensive picture of past events, we recommend compiling information from a variety of sources. As in most countries, and also in Germany, the documentation of flash floods is still unregulated and required event information is scattered among various sources. Consequently, no government agencies exist that centralize and schematically document flash flood events. To facilitate the search for data, we listed possible starting points (Table 2.2). Conceivable sources range from agencies through action force archives to insurance companies and media. However, the sources differ considerably in regard to accessibility, preparation effort, and information quality. Newspaper articles, archives of storm spotter networks and weather services are usually readily available online. To get access to event information from ministries, municipalities, or non-public archives of action forces is typically more complicated, since it requires a personal contact. Furthermore, access to the most valuable information, namely high-resolution insurance data, is usually denied. Regarding the applied preparation effort, the less structured the event information is, the more complex is information extraction. This is especially true for continuous text like articles or surveys and interviews.
For generation of the HiOS dataset, we requested various sources for flash flood information. We requested information from agencies and institutions at state and federal level in Germany, as well as from institutions at the European level. In addition, we requested information from the German Weather Service and insurance companies. In total, we sent out 37 requests and obtained flash flood information in about 20 % of the cases. However, the returned event information varied greatly in scope and quality and was therefore not uniformly useful. Among the obtained information, the data of the ESWD, the Bavarian Environment Agency, the SV SparkassenVersicherung, and the URBAS project was particularly extensive.
The spatiotemporal scope of the used event datasets varies widely. While many flash

flood events of the HiOS dataset are available from the 2000s, the first entry of the ESWD dataset, for instance, dates to the year 346 (Table 2.3). Although our dataset comprises all of Germany, some datasets only cover certain federal states. As a result, some federal states are overrepresented in regard to the event numbers. This applies, for instance, to the federal states covered by the SV SparkassenVersicherung dataset, which contains by far the most events with 16,900 entries. In addition, Bavarian flash flood events may also be slightly overrepresented, since HiOS is a Bavarian project, and we therefore collected more information on Bavaria. In total, we generated a dataset with 23,752 German flash flood and surface runoff events triggered by heavy precipitation. For 1,462 events, information originates from more than one source.

Table 2.2: List of possible sources on flash flood event information assessed regarding accessibility and preparation effort.

Possible source	Accessibility	Access via	Preparation effort	Annotations
Agencies, institutions, ministries (e.g., agriculture/forestry, environment, finance, infrastructure, emergency management)	with effort, barely/no	internet, personal contact	low to high	• event information often scattered between agencies depending on area of responsibility • access eventually to highly aggregated information with little benefit
Archives of action forces (e.g., fire department, technical relief organization)	easy, with effort	internet, personal contact	medium to high	• quality of report and event type must be checked • often only operation description, little event information
General public, affected residents	with effort	surveys, interviews	high	• great effort to gain information, which is subjective • uncertain information due to perceptions and occasional embellishment
Insurance companies	barely/no	personal contact	low	• access to high-resolution information on damages usually denied • access eventually to highly aggregated information with little benefit
Media (e.g., newspaper, TV, YouTube)	easy	internet	high	• quality of report event type must be checked • accuracy of reports varies strongly from highly aggregated to very detailed informatio
Municipalities (e.g., department of urban planning, civil protection, waste water management)	with effort	personal contact	high	• sometimes event reports from water management offices or engineering companies available with high quality
Scientific literature and projects	easy, barley/no	internet	low to medium	• acquisition of information may be difficult to impossible due to different underlying event definitions and access restrictions
Storm spotter networks	easy	internet, personal contact	high	• quality of report and event type must be checked • event description varies strongly depending on spotter
Weather services (national, private)	easy, with effort	internet, personal contact	medium	• great effort for precipitation interpolation for one event • sometimes annual reports include prepared precipitation information for extreme events

Table 2.3: Sources used to compose a dataset of German flash flood and surface runoff events triggered by heavy precipitation.

Source	Temporal resolution	Spatial resolution	Description of dataset	Number of events	Accessibility	Access via	Preparation effort
Annual reports of the German Weather Service, the Deutsche Rückversicherung (reinsurance)	2007–2016	Germany	Review of the most important natural hazards of the past year	17	easy	internet	high
Archive of the Federal Agency for Technical Relief	2016–2017	Germany	Extract from the mission archive in connection with severe weather operations	163	with effort	personal contact	high
Bavarian Environment Agency	2016	Bavaria (Germany)	Collection of reports, newspaper articles, and photos of flash flood events	224	easy	personal contact	high
Deutsche Rückversicherung (reinsurance)	2007–2017	Germany	Collection of reports and newspaper articles of flash flood events	143	with effort	personal contact	medium
European Severe Weather Database (ESWD)	346–2017	Germany	Database on heavy precipitation events having caused extreme impact or exceeded a given threshold	6,349	easy	internet, personal contact	medium
Historische Analyse von Naturgefahren (HANG) project	1905–2017	Bavaria (Germany)	Database on past natural hazards in the Bavarian Alps	70	easy	internet, personal contact	medium
SV SparkassenVersicherung (insurance)	2002–2017	Thuringia, Baden-Wuerttemberg, Hesse, Rhineland-Palatinate (Germany)	Reimbursed damages due to flooding caused by heavy precipitation	16,900	with effort	personal contact	low
Urbane Sturzfluten (URBAS) project	1954–2009	Germany	Database on urban flash flood events	2,318	with effort	internet	medium

2.4.3 Recommendation 3: Use a sophisticated documentation scheme

Setting up a sophisticated documentation scheme before data collection, makes dataset generation more efficient. Since a documentation scheme determines what information is collected, what units the information has, and how the information is categorized, it helps to focus on the required data. Data collection and preparation are more targeted that way. However, the elaboration of a documentation scheme strongly depends on the study purpose. Nonetheless, it is helpful to determine the required mandatory information for the documentation of an event independent of the study purpose. In this regard, the defined flash flood definition facilitates the decision of whether an event is included or discarded.

Within the HiOS project, we followed a comprehensive and flexible scheme for the documentation of an event. Our goal was to develop a documentation scheme that supports as many analyses as possible while minimizing the loss of event information. Therefore, our documentation scheme must be able to handle the different accuracy of the information, such as descriptions, estimates, and measurements. In addition, our scheme covers a wide range of possible event information. By supporting the preprocessing of event information, our documentation scheme also simplifies later analyses.

For each event, we gathered comprehensive event information on space and time, meteorology, hydrology, and damage (Table 2.4). By specifying the attributes to collect, the scheme supported targeted data collection. Therefore, it was already known during information retrieval that e.g. the start of the flooding and the type of flotsam is of interest. In total, we defined five mandatory attributes for an event entry: date, village/town/city, ZIP code, source, and information quality.

For attribute description, we used free text and fixed categories. Overall, we utilized three types of fixed categories: the description with (i) yes, no, or null, (ii) default options, and (iii) text blocks. In our documentation scheme, we omitted free text options whenever possible. For several reasons, free text information is disadvantageous in event documentation. On the one hand, there is the risk of information loss if the editor does not write down all of the relevant information. For instance, it is easy to forget to document non-occurrences. On the other hand, it is difficult to evaluate free text information automatically since texts do not follow rules. The evaluation of descriptive texts therefore often remains a time-consuming human task. However, to document information that does not fit given categories or to have an additional option, we used free text entries for the “Comment” fields.

The yes-no-null category records the occurrence or non-occurrence of attributes such as landslides, hail, or disaster alert. By stating “null”, we recorded that the needed information is unknown. To report false alarms (meaning heavy precipitation events of sufficient magnitude that did not cause surface runoff or a flash flood), we documented the non-occurrence by indicating “no” flooding. In addition, we described some attributes with default options. This for example includes the attribute “highest affected floor”, for which the default options are basement, first floor, second floor, and third floor.

In the meteorology section of the documentation scheme, we suggest a set of attributes to describe the triggering processes of a flash flood. In addition to heavy rain events, we document occurrences of further weather phenomena such as storm, lightning, and hail. In summer, heavy rain events are often accompanied by hail, which can cause major damage to cars and buildings. For damage estimation, we therefore document the maximum and average hail diameter, as well as the layer thickness of the hail. Furthermore, we record precipitation information derived from weather radar and rain gauge measurements. If available, we recommend documenting the precipitation start and end, which is valuable information combined with the flooding onset to determine the response time of the catchment. The visual assessment or automated procedure applied to determine the start and end of the rain event can be described in the comment field. Besides total precipitation amount and duration, we record precipitation sums for different time steps as well as the amount and duration of the precipitation peak. For a flash flood event, either an interpolated value or multiple station values can be specified. In any case, we recommend describing relevant information such as the interpolation method applied in the “comment on precipitation”. Furthermore, the convection of the rain event and the weather condition are valuable event information that should be characterized.

With regard to hydrological impacts, we propose to describe occurring cascade effects and technical failures as well as the flooding. Flash floods and cascade effects such as debris flows, landslides, and sediment transport often occur together. Further possible consequences of flash floods are sewer overflow, water pollution, and dike breaks. We therefore recommend documenting these event impacts with regard to potential damage assessments and event classifications. For hydrological investigations, it is crucial to consider the initial condition of the catchment, as snow cover, ground frost, and initial soil moisture can strongly influence flood behavior. As with precipitation, we also document the flooding onset and end in the affected town with regard to the response time of the catchment. Furthermore, we recommend describing in the “comment on flooding” whether the event was a pluvial flood or rather a flood wave originating from the catchment. Besides this qualitative information, we also document measurements and estimates of peak discharges and water levels at gauging stations or cross-sections, whereby the estimation method applied should be stated in the comment field. Furthermore, measurements from flood marks can be reported.

Table 2.4: Documentation scheme for flash flood events. The documentation scheme facilitates data collection and preparation by prescribing the needed information and its format. Mandatory attributes for event description are asterisked.

	Attribute	Possible entries/unit
Time-Space	Date*	DD-MM-YYYY
	Village/town/city*	
	Affected city district(s)	
	ZIP code*	
	UTM coordinates	
	Municipality	
	Administrative district	
	Federal state	
	Temporal accuracy	5 min, 15 min, 30 min, 1 h, 3 h, 6 h, 12 h, 1 d
	Spatial accuracy	1 km, 3 km, 10 km, 20 km, 100 km
	Event extent	very local, local, regional, supraregional, national
	Source*	
	Information quality*	QC0, QC0+, QC1, QC2
	Comment on event	free text
Meteorology	Storm	yes/no/null
	Lightning	yes/no/null
	Rain on snow	yes/no/null
	Hail	yes/no/null
	Max. diameter of hail	[cm]
	Average diameter of hail	[cm]
	Layer thickness of hail	[cm]
	Comment on meteorology	free text
	Date of precipitation	DD-MM-YYYY
	Start of precipitation	HH:MM

Table 2.4: *Continued.*

	Attribute	Possible entries/unit
	End of precipitation	HH:MM
	Return period of precipitation	
	Comment on precipitation	free text
	Precipitation measurement	yes/no/null
	Rain gauge/radar station	free text
	Precipitation duration	[h]
	Precipitation amount	[mm]
	Convection	uncertain, convective, partly convective, non-convective
	Max. 30 min precipitation	[mm]
	Max. 1 h precipitation	[mm]
	Max. 3 h precipitation	[mm]
	Max. 6 h precipitation	[mm]
	Max. 12 h precipitation	[mm]
	Max. 24 h precipitation	[mm]
	Amount of precipitation peak	[mm]
	Duration of precipitation peak	[h]
	Weather condition	free text
Hydrology	Flooding	yes/no/null
	Start of flooding	DD-MM-YY HH:MM
	End of flooding	DD-MM-YY HH:MM
	Duration of flooding	[h]
	Comment on flooding	free text
	Cause	free text
	Debris flow	yes/no/null
	Landslide	yes/no/null
	Sedimentation	yes/no/null
	Type of contamination	oil, sewage, chemicals, other
	Flotsam	yes/no/nulll

Table 2.4: *Continued.*

	Attribute	Possible entries/unit
	Type of flotsam	green waste, wood, trees, debris, silage bales, oil tanks, vehicles, container, hail, other
	Log jam	yes/no/null
	Comment on log jam	free text
	Dike failure	yes/no/null
	Traffic congestion	yes/no/null
	Sewerage system overload	yes/no/null
	Catchment	free text
	Initial condition of catchment	snow cover, ground frost, high soil moisture, dry
	River	free text
	Gauging station	free text
	Measured max. water level at gauge	[m]
	Estimated max. water level at gauge	[m]
	Measured peak discharge at gauge	$[\mathrm{m}^3\,\mathrm{s}^{-1}]$
	Estimated peak discharge at gauge	$[\mathrm{m}^3\,\mathrm{s}^{-1}]$
	Flood mark coordinates	
	Max. water level at flood mark	[m]
	Cross-section coordinates	
	Estimated peak discharge at cross-section	$[\mathrm{m}^3\,\mathrm{s}^{-1}]$
	Comment on estimation method	free text
	Highest affected floor	basement, first floor, second floor, third floor
Damage	Description of damage	low/average/serious/exceptional total damage
	Comment on damage	free text
	Total damage	€
	Number of fatalities	
	Number of casualties	

Table 2.4: *Continued.*

Attribute	Possible entries/unit
Evacuation	yes/no/null
Advance warning	yes/no/null
Disaster alert	yes/no/null
Damage of buildings	€
Number of claims	
Description of building damages	text blocks
Comment on building damages	free text
Damage of forestry/agriculture	€
Description of forestry/agricultural damages	text blocks
Damage of infrastructure	€
Description of infrastructural damages	text blocks
Comment on infrastructural damages	free text
Damage of business	€
Description of business damages	text blocks
Comment on business damages	free text
Other damages	€
Description of other damages	text blocks
Comment on other damages	free text

We documented event damages using text blocks consisting of an adjective and a noun. To be more precise, the text block specifies the damage degree with the adjective and the damaged object with the noun (Fig. 2.2). The damage degree ranges from minor over medium to severe. However, we consider minor damages to be temporary restrictions stated by adjectives such as “flooded”, “overloaded”, and “blocked”. When medium damage occurs, buildings need to be partially rebuilt or renovated, which we expressed with the adjective “damaged”. In contrast, severe damage means that buildings e.g. were completely “destroyed” and need to be rebuilt. Following this concept, possible damage descriptions are, for instance “flooded basements”, “damaged stores”, or “eroded agricultural land”. We documented damages in the categories of buildings, forestry and agriculture, infrastructure, business, and others. Damage information not fitting the text blocks is recorded in the comment column.

Damage degree	Damage description	Descriptive adjectives
minor	temporary restriction	flooded, overloaded, blocked, etc.
medium	partially to rebuild, to renovate	damaged, eroded, injured, etc.
severe	to rebuild, unusable, uninhabitable	destroyed, killed

Category	Possible objects
buildings	basement, garage, house, underground car park
forestry and agriculture	agricultural land, forestry land, farm building, livestock, harvest
infrastructure	sewerage, street, bridge, railway station, railroad, gas pipe, dike, subway, tram, etc.
business	industrial building, store
other	vehicle, road traffic, air traffic, rail transport, heating oil tank, etc.

Adjective +	Noun
flooded	streets
damaged	vehicles
destroyed	houses

Figure 2.2: Damage categorization by using text blocks consisting of an adjective and a noun. Whereas the adjective describes the damage degree and the noun specifies the affected object.

For our documentation scheme, we adopted some attributes and default options from the ESWD. For instance, we took over the attributes 'temporal accuracy', 'spatial accuracy', and information quality as well as their default options. The attribute spatial accuracy specifies in which radius of the reported settlement area the event has occurred, for example within 10 km. The specification of the temporal accuracy works similarly. Here, the indicated time states the period in which the event had likely occurred. The time of one hour implies that the event has likely occurred up to 30 minutes earlier or later than the indicated time. Furthermore, we inherited most of the meteorological attributes from the ESWD.
In addition to the information contained in the scheme, we recommend saving all available original and describing data of the documented flash flood events. This concerns hydrological data such as measured and modeled hydrographs, estimated peak discharges, and water levels at gauging stations or cross-sections. Concerning the precipitation information, we recommend the storage of radar images, rainfall maps, and rain gauge measurements. Newspaper articles, database extracts, and reports from engineering companies and agencies should be stored as well. To ensure sustainable documentation of internet sources, we recommend offline storage or export as PDF. Photos and videos also provide valuable insights into the course and extent of the documented flash flood

event. Videos of flash floods, for example, are suitable for estimating flow velocity, sediment transport, and flotsam. Pictures, in turn, help to document flood marks, culverts, and damages. Several papers exist that can provide guidance on post-flash flood field investigations. Gaume and Borga (2008), for example, propose steps for data collation and data analysis after a flash flood event. In addition, there are numerous examples of photographs of (i) slope failures and erosion rills (e.g., Gaume and Borga, 2008; Santo et al., 2017), (ii) sediment transport and debris processes (e.g., Segura-Beltrán et al., 2016; Bronstert et al., 2018; Lucía et al., 2018), (iii) channel-bed widening (e.g., Marchi et al., 2009; Lucía et al., 2018), and (iv) bridges and flood marks (e.g., Gaume and Borga, 2008; Segura-Beltrán et al., 2016; Bačová Mitková et al., 2018). Moreover, Marchi et al. (2009) describe the evaluation of a flash flood video for flow velocity estimation.

2.4.4 Recommendation 4: Rate information quality and data uncertainty

Since information quality can differ strongly depending on the source, we recommend rating the reliability of the event information. Particularly, newspaper and eyewitness reports can be subjective and exaggerated as pointed out by Dotzek et al. (2009). Regarding later analyses, it is thus advisable to assess the information quality, e.g. similar to the QC-levels of the ESWD (Section 2.2.2), leaving the option to exclude uncertain information. In addition, event documentation separated by source prevents accuracy loss due to information aggregation, since it has to be decided, for instance, which reported damage sum of which source is more reliable or how to summarize the different given damage information when aggregating event information. In addition to the verification of the event information, uncertainties, especially concerning hydrometeorological data, should be quantified and reported. Flood damage, which is commonly estimated, is often reported as a range of values reflecting uncertainty. Overall, the quantification of the data uncertainty already during the documentation is beneficial for the later evaluation and use of the flash flood dataset.

Regarding quality estimation of event information, we adopted the four levels “as received” (QC0), “plausibility checked” (QC0+), “report confirmed” (QC1), and “event fully verified” (QC2) presented by Dotzek et al. (2009). The HiOS dataset consists mainly of already quality-controlled datasets. We verified questionable events reported in the media or indicated in the archive of the Federal Agency for Technical Relief based on trusted sources when possible. Overall, two-thirds of the HiOS dataset (67 %) are fully verified and conform to the highest quality level QC2. More than a quarter of the dataset (27 %) is verified by a trusted source. However, only 6 % of the dataset meets either the low-quality level of QC0 (as received) or QC0+ (plausibility checked). Regarding data uncertainty, a range of values indicates possible values for quantitative attributes such as “max. discharge”, “precipitation amount”, or “damage of buildings”. Further information concerning data uncertainty can be specified in the comment fields.

2.4.5 Recommendation 5: Report false alarms and minor events

To study the rainfall–runoff process in its entirety, researchers should not focus only on extreme cases but document the entire event spectrum including false alarms. However, researchers naturally concentrate on positive events, especially catastrophic flash flood events. Yet, studies should also include negative events, meaning heavy precipitation events of sufficient magnitude that did not cause surface runoff or flash floods since studying negative events will help us understand why no flash flood was caused in certain catchments or under certain conditions. Contrasting positive and negative events will give researchers the greatest insight into causative processes. In addition to false alarms, researchers should also document minor flash flood events, not only disasters. Flash floods cover a wide range of possible magnitudes and impacts. The question of when one refers to a flash flood therefore plays an important role, particularly for early warning. From the perspective of protection planning, minor events are especially relevant, since much damage can be prevented by self-provision.

In accordance with our documentation scheme, we documented false alarms by indicating “no” flooding. However, this was only the case for five heavy rain events. Since we did not have access to flash flood warnings, finding out about heavy rain events sufficient to trigger flash flooding was virtually impossible. In addition, the data was often not accurate enough to determine with certainty that no flash flood had occurred. Since we also documented surface runoff events triggered by heavy rain, our dataset contains a large number of minor events.

2.4.6 Recommendation 6: Supplement the dataset

Data supplementation is an important step in data mining, since it extends analysis options and thus increases knowledge gain. Several ways exist to supplement an event dataset that describes space, time, and impacts of past flash floods. On the one hand, it is possible to supplement discharge attributes of the flash flood events. Since the event hydrograph contains a lot of information, it is crucial for flash flood investigation to include this information when available. To obtain a robust flash flood classification,

it is advisable to derive additional descriptive parameters from the event hydrograph besides the return period. For instance, the time to peak and the specific peak discharge help to classify the flash flood event.
Precipitation data also improve the information value of a flash flood dataset. In addition to precipitation data such as sum and intensity, the return period and the convective storm trajectory might be of interest. Precipitation, especially in combination with discharge, adds a lot of information. With precipitation and discharge data, it is possible to determine the runoff coefficient and to investigate the catchment response to the triggering rain.
Flash flood classification facilitates the estimation of event magnitude and event comparison in the dataset. Currently, there are two ways to classify flash floods. The classification either uses parameters derived from event discharge and precipitation (e.g., Bhaskar et al., 2000; B.-S. Kim and H.-S. Kim, 2014; Saharia et al., 2017) or the classification categorizes flash flood impacts (e.g., Schroeder et al., 2016).
In addition, supplementation of spatial data is crucial for flash flood investigation. In particular, catchment information is needed to understand the catchment response to heavy rain. In this regard, data describing catchment characteristics such as soil and land use distribution as well as catchment parameters such as average slope, river density, or basin shape are valuable.
We supplemented our event dataset by administrative data, catchment information (e.g., boundaries, streams and gauges) and catchment characteristics, as well as soil and land use maps. In addition, we derived discharge attributes (time to peak, specific peak discharge, volume, gradient, peak to volume) from the event hydrographs as described by Kaiser et al. (2020a). Overall, the supplementation of event information by measurement and catchment data gives us the opportunity to link different datasets and perform holistic analyses.

2.5 The HiOS flash flood dataset

2.5.1 Occurrence of flash flood events in Germany from 2000

The amount of documented events increases steadily towards recent decades, with most events documented from the 2000s. This is probably due to the internet, which has drastically simplified the search for past flash flood events. In addition, there has been a marked increase in public interest in natural hazards over the past decade, not least because of recurring severe events.

Figure 2.3 states the flash flood and surface runoff events collected per year and by federal state. However, it has to be noted that Bavarian events are probably slightly overrepresented in Fig. 2.3, since two datasets that we used only cover Bavaria (cf. Table 2.3). To obtain a reasonably comparable dataset throughout Germany, we excluded the insurance dataset (~ 16,900 events) from the figure, which covers only 4 out of 16 federal states. Furthermore, the size of the insurance data would skew the color bar. Figure 3 highlights that some federal states such as Baden-Wuerttemberg and Bavaria in the South, and North Rhine-Westphalia in the West of Germany have been affected more often than others. In addition, eventful years like 2007, 2011, 2014, and 2016 are striking. Yet, not all federal states were equally affected in those eventful years. In 2007 and 2014, North Rhine-Westphalia and Hesse were hit particularly hard with more than 150 events each. However, in 2011, large parts of Germany were affected with five federal states having experienced more than 100 events. For Bavaria, the year 2016, for which we documented 410 flash flood and surface runoff events, was particularly severe.

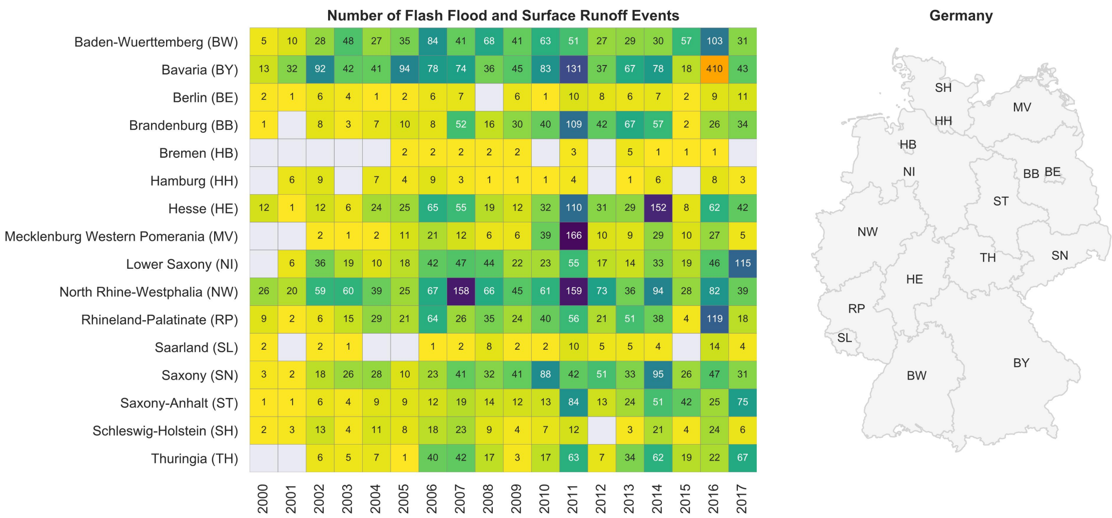

Figure 2.3: Number of flash flood and surface runoff events collected per year and federal state of Germany from the 2000s. (Data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

2.5.2 Relationship between watershed area and unit peak discharge

The watershed area significantly influences the peak discharge. Therefore, the investigation of the peak discharge–watershed area relationship provides insights into the catchment behavior. For reasons of comparison, the unit peak discharge (as the ratio

of the peak discharge and the upstream catchment area) and the watershed area are plotted in a log-log diagram. In literature, the upper limit of this relationship is usually described by empirically derived envelope curves (e.g., Marchi et al., 2009; Borga et al., 2011; Amponsah et al., 2018a).
Figure 2.4 shows 50 measured flash flood events of Bavaria, which are contained in the HiOS database. For classification into the climatic regions of Europe, we also plot the envelope curves for Mediterranean, Alpine-Mediterranean, and Inland Continental flash floods derived by Amponsah et al. (2018a). We further display the envelope curve for Bavarian flash floods derived from a discharge study by Kaiser et al. (2020a). The reported flash flood events have mostly unit peak discharges less than $1\,\mathrm{m^3\,s^{-1}\,km^{-2}}$ and are thus far from the upper limit of the Mediterranean and Alpine-Mediterranean flash floods. According to Borga et al. (2011), these differences in intensity can be explained by the different spatial and temporal resolution of the generating heavy rain events in the different climatic and orographic regions. Therefore, it is not surprising that the upper bounds for Bavarian and Inland Continental flash floods lie close together. Overall, a decline in unit peak discharge with increasing watershed area is noticeable for the Bavarian events.

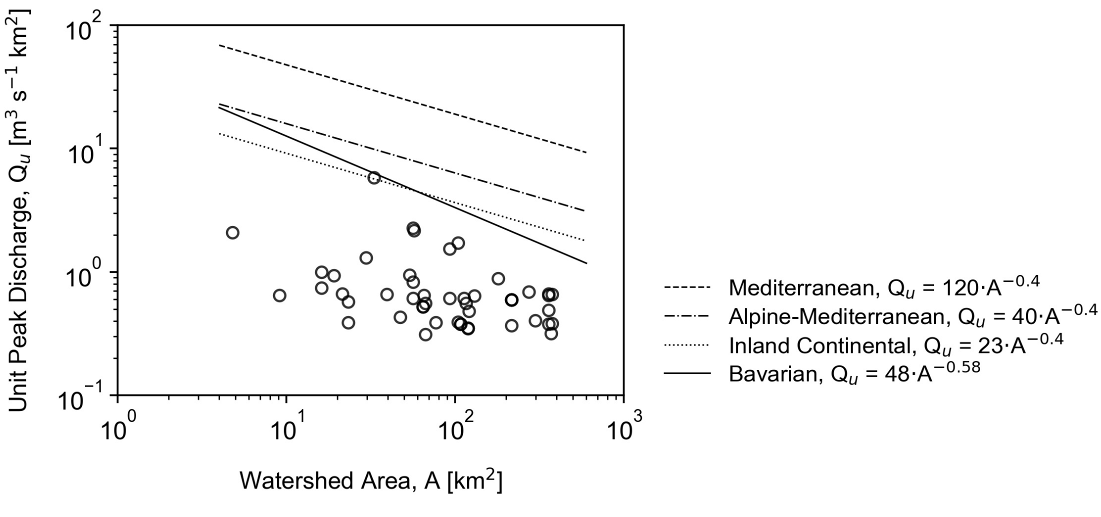

Figure 2.4: Unit peak discharges versus watershed areas for measured flash flood events in Bavaria (Germany). The envelope curves for Mediterranean, Alpine-Mediterranean, and Inland Continental flash floods are reported by Amponsah et al. (2018a). The envelope curve for Bavarian flash floods is reported by Kaiser et al. (2020a).

2.6 Discussion

2.6.1 Insights from flash flood dataset creation

Data request and collection proved to be more tedious and difficult than expected. Since flash flood documentation is not regulated in Germany, we requested flash flood documentation from relevant federal offices, as well as from all environment ministries and agencies of the 16 German federal states. However, the data return was sobering. Only two federal states could provide a list of a few flash flood events. The main reasons given for the lack of documentation were unclear responsibility and lack of funds.

Particularly time-consuming was information extraction from reports, archive entries, and newspaper articles. In contrast, data migration was less time-consuming when datasets stemmed from databases and were thus preprocessed, such as the ESWD or the SV SparkassenVersicherung dataset. In addition, event validation was a complex matter. Overall, we spent more than one year on data request, collection, and preparation.

Furthermore, the level of detail of the event descriptions varies widely. The event descriptions range from mere event naming to detailed event information on damage and hydro-meteorological conditions. For 6 % of the collected flash flood events, we do not know more than the place and date. On average, five describing attributes per event have been collected additionally to place and date in which damage descriptions are usually available. However, half of the events (53 %) are described with 2 to 5 additional attributes, less than a third (28 %) with 6 to 10 attributes. Only 1 % of the events are described with at least 11 additional attributes.

By documenting event information separated by information quality and source, we maintain flexibility for later analyses. Separation by source allows us to easily remove information from the HiOS dataset, such as the confidential insurance record. Furthermore, we can exclude data from less trusted sources from analyses. This flexibility, however, is no longer assured once event information is mixed. The indication of information quality offers similar benefits. The HiOS dataset contains event information of different quality levels. We included uncertain event information (QC0) because we believe that insecure information can also provide valuable indications on event course and magnitude. Since scientists have to deal with data uncertainty regularly, we are convinced that scientific users can be offered uncertain event information. Moreover, by indicating information quality, scientists can decide for themselves whether they include uncertain event information or not. Non-expert users, however, should only be provided with fully verified event information (QC2).

After completing the HiOS dataset, we have to summarize that only scarce and vague information exists about most events. While information comes from several detailed reports of water management offices and engineering companies for a few events, most events are described rudimentarily in newspaper articles. Furthermore, estimated losses given in newspaper articles are often aggregated for the entire affected county. Therefore, loss allocation to individual cities is usually uncertain or impossible. In addition, the evaluation of damage descriptions causes problems when several affected cities are described together in articles. Frequently vague are also the documented times for precipitation and flooding onset and end.

We estimate that the HiOS dataset from the 2000s is roughly comprehensive and representative for Germany. Still, we do not consider the HiOS dataset to be suitable for studies or statements on climate change, since comprehensive data collection has only taken place in the last two decades. The collected German flash flood events show a pronounced Inland Continental character. With most of the reported events having unit peak discharges smaller than $1\,\mathrm{m^3\,s^{-1}\,km^{-2}}$, German flash floods are much less intense than Alpine-Mediterranean and Mediterranean flash floods.

2.6.2 Findings from flash flood dataset review

In the context of data scarcity and the simultaneously growing importance of flash flood research, discussing and defining documentation standards for flash floods becomes increasingly important. However, as the comparison of existing datasets proves, current flash flood documentation does not follow a uniform approach. Depending on the objective of the planned investigations, flash flood datasets vary with regard to information quantity, quality, and resolution.

Regarding current literature, our proposed documentation scheme is more comprehensive in terms of number and variability of attributes than many existing flash flood datasets. By collecting information about space and time, meteorology, hydrology, and damage, we cover the entire flash flood event from its origins to its impacts. While some available flash flood datasets provide comprehensive event information (e.g., EuroMedeFF, HYDRATE), others only document the information required for the study objective (e.g., Vinet et al., 2016, SHAVE) or give a rudimentary event overview (e.g., SINATRA, Storm Events Database). In contrast, our scheme specifies exactly which attributes should be reported and how. Despite the attribute specifications, our approach can be flexibly applied to different types of reports and information. In addition, the documentation scheme also supports the evaluation of qualitative information by using default options and text blocks for attribute description. Overall, we believe it is necessary to document flash floods as comprehensively as possible in terms of knowledge gain and dataset sustainability.

There are several potential applications and users of our proposed approach. One target group are environmental agencies that want to establish a central flash flood documentation. Provided that the information is available, the agency can use our approach to create a comprehensive dataset that is useful for various stakeholders. Furthermore, the detailed attribute specifications make it easier for less experienced users and non-experts to collect and prepare flash flood information. Other potential users are scientists who want to create a comprehensive dataset that can serve multiple study purposes as well as interdisciplinary investigations. Our documentation scheme allows for damage assessments but does not support damage modeling at house level. In addition, hydrological modeling of past events is only possible if measured rainfall-runoff measurements are available.

The findings of this study however have to be seen in the light of some limitations. The primary limitation of our proposed approach is the use of a documentation scheme applying fixed categorical descriptions. While our documentation scheme facilitates collection and preparation of event data by its specifications, it simultaneously fosters information loss. Although standardizing of event information is beneficial for later analyses, unification reduces the information content. Using categorical descriptions for attributes may further lead to misclassification due to inappropriate class boundaries. Especially outliers and information with seamless transitions can hardly be categorized adequately. Consequently, the inflexibility of categorical descriptions regarding complex information is disadvantageous. We have therefore added comment fields in which we documented relevant information not fitting the default categories to reduce information loss.

To summarize, the application of a documentation scheme for flash flood events implies both advantages and disadvantages. However, to further improve the proposed scheme, the tradeoff between unifying information on the one hand, and necessary complexity on the other should be investigated. Furthermore, the proposed documentation scheme needs to be applied and adapted to different climatic conditions to reach generalizability and especially damage categorization.

2.7 Conclusion

Historical event documentation is the starting point of flash flood research. However, flash flood science still suffers from data scarcity, increasing the need of researchers for structured, high-quality event datasets. Yet, there are few published flash flood datasets, of which only some allow reuse by other researchers. Furthermore, the existing flash flood datasets differ significantly in flash flood definition to dataset content, since a consistent documentation approach is missing. To support the process of data collection and preparation, we suggest a 4-step approach for flash flood documentation based on the cross-industry standard process for data mining. The key aspects of our approach include determination of the documentation goals, definition of a flash flood event, and application of a documentation scheme. In this paper, we demonstrated application of the proposed approach based on the generation of a German flash flood and surface runoff event dataset. We developed a documentation scheme indicating the attributes to be collected in regard to space and time, meteorology, hydrology, and damage. By using yes-no-null categories, default options and text blocks for the attribute description, we simplify and structure event documentation. Furthermore, indicating information quality and uncertainty, and keeping information separated by source helps to generate a high-quality dataset. Due to the internet and increasing interest in natural hazards, it is easier to collect event information from the 2000s. Nonetheless, the collection of flash flood information remains an arduous task that often ends with little and vague event information, especially for minor events. Reviewing our experiences from dataset comparison and dataset generation, we can make the following recommendations to improve future documentation of flash floods: (1) follow a clearly defined flash flood definition, (2) compose event information from different sources, (3) apply a sophisticated documentation scheme, (4) estimate information quality and data uncertainty, (5) include false alarms and minor events in your documentation, and (6) enrich your event dataset with measurement and catchment data.

To enhance sustainability and knowledge gain, future work should focus on a unification of flash flood datasets. For this purpose, we need to discuss the documentation process and define standards. To push the generation of event datasets, we further have to simplify data collection by e.g. publishing peer reviewed data articles or contributing to topical open data platforms. In the end, flash flood science will benefit from these well-organized and structured event datasets. With this paper, we hope to establish a discussion on data collection in flash flood science, which will further clarify the importance of event documentation for flash flood research.

3 Spatiotemporal analysis of heavy rain-induced flood occurrences in Germany using a novel event database approach

This chapter is published as:

Kaiser, M., Günnemann, S., Disse, M., 2021. Spatiotemporal analysis of heavy rain-induced flood occurrences in Germany using a novel event database approach. *Journal of Hydrology.* 595, 125985. https://doi.org/10.1016/j.jhydrol.2021.125985.

Abstract Flash floods are a worldwide threat to humans, which is why they are being intensively studied using historical event records. As measurements and event data increase, databases are becoming increasingly important for flash flood research. However, the recent literature on flood databases lacks technical details as well as discussions about a suitable database design for scientific investigations. In this paper, we thus show how an event database for the investigation of heavy rain-induced flood occurrences can be created. Based on the HiOS dataset (a German dataset with ~23,800 flash flood and pluvial flood events), we exemplify the database design and explore the spatiotemporal characteristics of floods caused by heavy rain in Germany. We outline all aspects relevant to database setup: from database requirements and system architecture through table and attribute design to a key and relationship definition. Furthermore, we clarify why a spatial database with interfaces for GIS softwares should be chosen, why a damage-based event definition is preferable to a hydrometeorological definition, and how table attributes support differentiated analyses. By means of the database, we investigated frequency, temporal evolution, spatial distribution and patterns, fatalities and injuries, as well as the seasonality of heavy rain-induced floods in Germany. The results indicate that floods caused by heavy rain occur throughout Germany but with a tendency toward

fewer events in the northern direction. Across the country, we identified seven hot spots in urbanized and mountainous regions. Although heavy rain-induced floods in Germany take place mostly between noon and late afternoon, most people are injured and killed in events starting in the evening. Our investigation indicates an increased incidence of flash flood and pluvial flood-related injuries and fatalities in the identified hot spots. Overall, we observe a pronounced summer seasonality of the heavy rain-induced flood events. This study highlights the importance of event databases for flash flood research and advances our understanding of heavy rain-induced flood occurrences in Germany.

3.1 Introduction

Flash flood research requires a comprehensive documentation of past events. With the help of measurements, photos, and witness statements, researchers reconstruct the initial conditions, course, and intensity of flash flood events (e.g., Santo et al., 2017; Varlas et al., 2019; Bačová Mitková et al., 2018). In flash flood research, event data is used to test hypotheses or to calibrate and validate models. Therefore, flash flood event data forms the basis for research on, e.g., forecasting and warning (e.g., Bouilloud et al., 2010; Boudevillain et al., 2016), controlling factors (e.g., Diakakis et al., 2019; Xiong et al., 2019), data-driven spatial prediction (e.g., Khosravi et al., 2019; Bui et al., 2019a), geomorphological processes (e.g., Ozturk et al., 2018; Segura-Beltrán et al., 2016) and damage modeling (e.g., Arrighi et al., 2020; Alipour et al., 2020).
Due to the need for event data, more and more researchers and institutions have begun to compile flash flood inventories during the last decade. Some thematic event databases and inventories already exist, such as ESWD (Dotzek et al., 2009), SHAVE (Ortega et al., 2009), FLASH (Gourley et al., 2017), and HYDRATE (Gaume et al., 2009). However, the existing flash flood datasets differ greatly regarding scope, content and usability, and not all of them are accessible (Kaiser et al., 2020b).
Although most existing flash flood inventories are organized in databases, little or nothing is known about their underlying database designs. As the current literature on flash flood datasets primarily focuses on dataset evaluation, data management is scarcely addressed. In addition, database setup is probably considered known, not relevant or not of interest. Furthermore, the enormous effort required to generate an event dataset and build a database is seldom recognized (Llasat et al., 2013; Kaiser et al., 2020b). These reasons probably explain the knowledge gap regarding scientific flash flood database design.
Databases are crucial for effectively collecting and analyzing flash flood events. Not only

do databases facilitate data collection and management, but they also support data investigation. By linking event information and geodata, databases enable spatiotemporal analyses and damage assessments. Since the database design affects data preparation and aggregation, its design significantly influences the analysis. However, despite its influence, the table and attribute design of event databases has hardly been discussed in the literature so far.

Although Germany has been affected by flash floods in the past, the frequency, temporal occurrence, spatial distribution, and seasonality of floods caused by heavy rain in Germany have not yet been investigated. So far, only a few event-specific studies have been conducted for Germany, e.g., for the Braunsbach (Bronstert et al., 2018; Laudan et al., 2017; Lucía et al., 2018; Vogel et al., 2017) or Simbach flash flood events (Hübl, 2018; Mayr et al., 2020) and the Starzel river basin (Ruiz-Villanueva et al., 2012). Further studies have examined individual pluvial flood events in Germany (e.g., Rözer et al., 2016; Spekkers et al., 2017). In a joint project, the German Insurance Association (GDV) and the German Weather Service (DWD) recently investigated the relationship between insured losses and small-scale heavy rain events in Germany (GDV and DWD, 2020). In this project context, Lengfeld et al. (2019) evaluated radar data regarding the characteristic spatial extent of hourly and daily rain events in Germany. To answer these fundamental questions about the spatiotemporal occurrence of heavy rain-induced floods in Germany and thus provide background information for a better risk assessment, we need a database for flood events caused by heavy rain.

In this paper, we illustrate how to design a database for heavy rain-induced floods that supports the systematic collection of event information and a wide range of spatiotemporal analyses to enhance the understanding of the flood hazards from extreme precipitation in Germany. By means of the HiOS database (a German event database with ~23,800 flood events caused by heavy rain; abbreviation for ***Hi****nweiskarte* ***O****berflächenabfluss und* ***S****turzflut*), we explain the database structure and illustrate the database's use for flood hazard evaluation in Germany. First, we specify the database purpose and requirements, as well as the system architecture of the HiOS database (Section 3.2). Then, we outline the database design considerations (Section 3.3) and the methods applied (Section 3.4). Subsequently, we perform spatiotemporal analyses on heavy rain-induced flood occurrences in Germany using the HiOS database (Section 3.5). Finally, we discuss our findings from database design and spatiotemporal investigations (Section 3.6) and give concluding remarks (Section 3.7).

3.2 The HiOS database

In May and June 2016, a series of extreme flash flood events occurred in southern and central Germany causing a flood loss of €2.6 billion (Munich Re, 2017). The German state of Bavaria experienced a multitude of events, which claimed seven lives (LfU, 2017e). The loss of the worst affected administrative district in Bavaria was estimated at €1.25 billion (LfU, 2017e). As a consequence of these flash flood events, the Bavarian State Ministry of the Environment and Consumer Protection funded the HiOS project (***Hi****nweiskarte* ***O****berflächenabfluss und* ***S****turzflut*, Reference Map for Surface Runoff and Flash Floods). The main project objective is the creation of a reference map for Bavaria, which indicates possible hazards from pluvial floods and flash floods triggered by heavy rain. For the investigation of the characteristics and triggering factors of heavy rain-induced floods, we compiled a dataset comprising about 23,800 German flash flood and pluvial flood events (cf. Kaiser et al., 2020b). To enable spatiotemporal analyses that improve our understanding of the hazards from heavy precipitation in Germany, we designed a database that effectively manages event information and geodata. It is planned to publish the HiOS dataset after the end of the project. Prior to the publication, however, publication rights of the individual datasets have to be checked as varying legal restrictions may apply.

3.2.1 Database purpose and required data

We pursue two goals with the HiOS database: the systematic collection and the scientific evaluation of past flood events triggered by heavy rain. The database must therefore support the systematic documentation and organization of event data from sources as diverse as reports, newspaper articles, storm spotter networks, and mission archives. This requires a table and attribute design that enables unified storage of event information while maintaining the spatial, temporal and content-related accuracy of the event information. Furthermore, the database is used to investigate frequency, temporal evolution, spatial distribution and patterns, fatalities and injuries, as well as the seasonality of heavy rain-induced floods in Germany. To support spatial analysis, the database must be able to aggregate datasets based on linking event information with geographical data, such as political boundaries or catchments. Since we process geodata like digital elevation models, the database's ability to handle large data volumes and return spatial queries quickly is a prerequisite.

The various spatiotemporal analyses require different event information and geodata sets. Information about the date of the event and the affected location is the prerequisite for the evaluation of historical events with regard to frequency, spatial distribution, hot spots, and seasonality. More detailed temporal analyses require additional information on the beginning and end of the triggering rain and the resulting flooding. Based on losses, damage descriptions and the number of injuries and fatalities, a damage analysis can be performed. To classify events in a hydrometeorological context, we need event information on the amount, duration and intensity of the triggering precipitation, and/or discharge and water level measurements or estimates. Furthermore, for spatial event aggregation in these analyses, we require data on political boundaries, convective cell extents or catchments.

3.2.2 System architecture and interfaces

The implemented system consists of a relational database management system that is accessible via various front-end software (Fig. 3.1). We made several demands on the chosen database management system (DBMS). The DBMS should (i) be able to store and process geographic data in vector and raster format, (ii) should be supported by ArcGIS Pro and QGIS, and (iii) should be free and open-source. Due to these requirements, we selected the relational DBMS *PostgreSQL* (version 12.3 64-bit) with its geospatial extension *PostGIS* (version 2.5).

The applied system architecture retains flexibility regarding data entry, manipulation, and retrieval as well as connection to other applications. Depending on the investigation objective, the HiOS database can be accessed via different front-end software. For database development and administration, for example, we use the management tool *pgAdmin 4* for PostgreSQL databases. To carry out spatial analyses or create maps, the GIS software ArcGIS Pro and QGIS are suitable. Moreover, the Python scripting language offers a variety of options for database editing and analyses. We access the HiOS database via the library *Psycopg 2* and perform spatial operations on geographic data using the library *GeoPandas*. Using the open-source web application *Jupyter Notebook*, we run analyses and create maps directly in the browser.

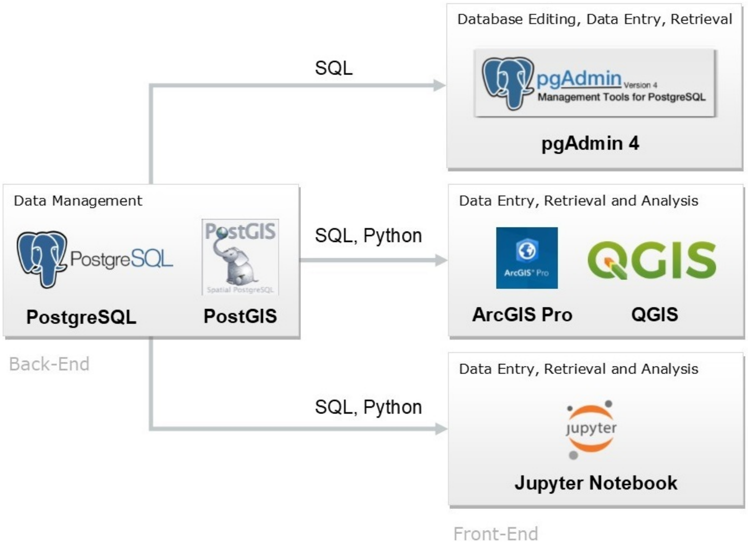

Figure 3.1: System architecture of the HiOS database system. PostgreSQL extended by PostGIS provides flexibility via interfaces to various front-end solutions such as programming languages and GIS software.

3.3 Design and implementation of the HiOS database

Our objective was to develop an effective and sustainable database system that supports systematic event collection and spatiotemporal hazard analyses. By effective, we mean a flexible database system that enables the targeted analyses. A flexible database system can answer all possible questions and is easy to expand or adapt to new datasets. To be effective, the database system needs to return query results quickly and assist in performing event analyses by providing aggregated and systematic datasets. In addition to effectiveness, the sustainability of the database design is vital. To ensure long-term use, the database structure must be easy for third parties to understand and expand. In addition, a comprehensible and detailed documentation of the database structure with its tables, attributes and relationships is essential.

3.3.1 Event definition

To obtain a consistent dataset, we have to define which flood events are considered in the database. The HiOS dataset includes flood events that have been caused by heavy precipitation, i.e. flash flood and pluvial flood events. A pluvial flood occurs when heavy precipitation triggers a flood event independent of an overflowing water body. Pluvial flooding is usually caused by infiltration excess and overwhelmed drainage systems. Flash floods are triggered by short but high-intensity rainfall, which causes a torrent of high velocity. Although flash floods and pluvial floods are both triggered by heavy precipitation, they behave differently. While flash flooding usually arises from a watercourse, pluvial flooding is caused by water flowing towards watercourses. Since flash floods and pluvial floods can occur simultaneously and the available event information usually does not allow a distinct assignment, we do not differentiate between flash floods and pluvial floods in our database. Therefore, to address both flood types, we speak of heavy rain-induced floods.

In our database, we apply the flash flood definition outlined by Kaiser et al. (2020b), which is adapted to Continental conditions. Since most of our event data containing precipitation information originates from the ESWD, we have adopted the ESWD precipitation threshold to obtain an overall dataset that is as uniform as possible. Therefore, according to our definition, a flash flood event is triggered by a heavy rainfall event that lasts between 30 min and 24 hours and exceeds a given minimum rain amount. According to ESSL (2014), we define as the threshold for a heavy precipitation event:

$$P \geq 2\sqrt{5 \cdot d} \tag{3.1}$$

where P is the precipitation amount in mm and d is the duration in min. Regarding spatiotemporal occurrence, Kaiser et al. (2020b) limit flash flood occurrence to catchments of up to 500 km^2 in size and to the period between April and October. In case the precipitation amount is unknown, a short flooding rise time and/or little to no warning time as well as a small catchment size are used as proxy indicators (Kaiser et al., 2020b). We apply the same thresholds for the identification of pluvial floods. With the difference that if no precipitation measurement is available, the heavy precipitation event must have caused flooding and an extreme impact to be documented. According to ESSL (2014), extreme impacts are characterized by several firefighting operations, cascade effects such as landslides, flooded basements, disruption of public transport, or closed roads.

For the database, the way a flash flood or pluvial flood event is uniquely stored also needs to be defined. According to Kaiser et al. (2020b), an event can be uniquely identified by the affected city and the occurrence date. In this context, the term city stands for any settlement size ranging from a village to a city that can still be uniquely identified. Since we consider it highly unlikely that two heavy rain-induced flood events will occur on the same day at the same location, we consider our definition valid. According to this definition, the relationship between the *cities* and *events* tables is a one-to-many relationship:

a flash flood or pluvial flood event occurs in one city, and a city has experienced zero, one or more flash flood / pluvial flood events.

3.3.2 Database tables

For comprehensive analyses, the HiOS database combines information on flash flood and pluvial flood events with relevant geographic data. Geographic information relevant for flood investigations includes catchment information and measurements, information on administrative structures, geodata such as maps, and digital elevation models. In total, the HiOS database consists of 34 tables, four of which are pure geodata tables. The database tables can be grouped into the following categories: event description, event documentation, administration structure, catchment information, measurements, claims, geodata and metainformation (Table 3.1).
The database tables are either reference or data tables. Reference tables contain general, steady information related to an object. The federal states table, for example, holds information on each federal state including name, official code, population and size. Data tables, in contrast, contain the collected measurements and event information that may change with each entry. As an example, each flood event is documented as a new event entry in the events table, including occurrence date, city name and official municipality code. In the following, we explain the database tables of each category in detail. For reasons of clarity, we write table names in italics and enclose attributes in quotation marks below.

Table 3.1: List and description of the HiOS database tables. Database tables containing vector or raster data are asterisked.

Category	Table name	Description	Data source
Event description	events	List of flood events caused by heavy rainfall in Germany	THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018
	space_time, meteorology, hydrology, damage	Description of spatiotemporal extent, hydrological effects, damages of the flood event and the triggering heavy rain	
	entries	Description of the event entry regarding source type, quality level, editor, entry date and last review	
	sources	Description of the event information sources regarding right of use and citation	
Event documentation	documents, videos, photos, websites	Metainformation on descriptive documents, videos, photos and websites	
Administrative structure	federal_states*, government_districts*, rural_districts*, municipalities*, cities*	Information on the administrative structure of Germany from federal state over government and rural district, to municipality and city	BKG, 2015; BKG, 2017
	zip_codes*	ZIP code areas of Germany	OpenStreetMap contributors, 2018
	water_authorities*	Information on Bavaria's water authorities including contact details and area of responsibility	LfU, 2017a
Catchment information	lakes*	Description of the characteristics of the German lakes	
	watercourses*	Description of the characteristics of the German watercourses	
	gauges*	List of the German gauging stations	
	catchments*	List of the official catchments of Germany with indication of catchment characteristics	
	gauge_catchments*	Table of the gauge catchments of Bavaria	self-derived
Measurements	discharge_measurements	Measurement time series of the Bavarian discharge gauges in hourly resolution	LfU, 2018
	discharge_investigation	List of measured flash flood events with derived discharge parameters	Kaiser et al., 2020a
	heavy_rain_hours	Indication of heavy rain hours since 2001 per ZIP code area, considering rainfall events that exceeded $25\,\mathrm{l/m^2}$ in $1\,\mathrm{h}$ or $35\,\mathrm{l/m^2}$ in $6\,\mathrm{h}$	GDV and DWD, 2018
Claims	claims_frequency	Description of the damage frequency due to heavy precipitation in Germany for the years 2002–2017, aggregated at the rural district level	GDV and DWD, 2019
Geodata	elevation_model*	Digital Elevation Model of Germany in 25 m resolution	EEA, 2016
	landcover*	CORINE Land Cover of Germany in 10 ha resolution	BKG, 2016
	soil*	Topsoil map of Germany (1:1,000,000)	BGR, 2008
	natural_region*	Natural classification of Germany	BfN, 2020
Metainformation	geodata_descriptions, table_descriptions, attribute_descriptions	Description of the stored geodatasets, database tables, and table attributes including unit, basic dataset and source, if applicable	

The central component of the HiOS database is the collection of event information in the tables of the event description. A flood event is described via entries in the *events*, *space_time*, *meteorology*, *hydrology*, *damage*, *entries*, and *sources* tables. In the *events* table, we list all events by date and location. In the *space_time* table, we describe the event's spatiotemporal extent and evaluate the temporal and spatial accuracy of the event information. We document the event's meteorological conditions in the *meteorology* table. Not only is information on the heavy rain event recorded (e.g., duration, amount, intensity, start, end), but also the information on the accompanying phenomena of thunderstorms such as hail, lightning and storms. Documenting the meteorological conditions helps to better assess the occurred damage and its cause. In the *hydrology* table, we specify the hydrological effects of the heavy rain event. In addition to information on flooding and discharge (e.g., highest affected floor, water level, discharge), we document the occurrence of cascade effects such as flotsam, landslides or dike breaches. All losses and damages are recorded in the *damage* table. We document financial losses and describe the occurred damages separated for buildings, businesses, infrastructure, forestry and agriculture. Furthermore, we record the number of injuries and fatalities. Documenting early warnings, disaster alerts or evacuations helps to better assess the event magnitude and the occurred damage. In addition, we specify the accuracy of measurements and estimates in the comment attributes of the *meteorology*, *hydrology*, and *damage* tables.

The *sources* and *entries* tables store important metainformation. We store information about the used sources regarding usage rights, citations, as well as a dataset description, in the reference sources table. Metainformation about the event entry is recorded in the *entries* table. In addition to the editor, we store the source type, the entry date and the last review date for each event entry. Furthermore, we evaluate the quality of the event information.

In addition to event information, we also archive information on the source documents in our database. For event documentation, the *documents*, *videos*, *websites*, and *photos* tables are available. In these tables, we archive important metainformation about the source documents and the accompanying material of the event. The tables not only indicate the usage rights, citation, author and quality of the source document, but also describe the source file and the storage location. Videos and photos of flash flood and pluvial flood events are important because they provide much better insight into the event's course and severity than a purely textual event description. For later analyses, it is essential to document the original sources adequately.

We use the *federal_states*, *government_districts*, *rural_districts*, *municipalities*, *cities*, and *zip_codes* tables to classify the events into the German administrative structure. Since Germany is a federal republic, it is divided into 16 federal states. The four federal states of Baden-Wuerttemberg, Bavaria, Hesse, and North Rhine-Westphalia are further subdivided into government districts, which serve as mid-level local government units. The next subdivision level of the federal states or government districts is the rural district. Rural districts, in turn, are composed of municipalities, which can include several villages, towns, and cities. Major cities in Germany usually form their own rural district. The table *rural_districts* thus contains both rural districts, which are composed of municipalities, and major cities with district status. For reasons of simplicity, we call the table *cities*, although it includes settlements of any size. The administrative structure tables contain the official names, abbreviations, and identification numbers as well as the bounding shapefiles and population numbers. The geographical dimension of cities/towns/villages is specified by official bounding boxes. Regarding geographic information, we indicate the center and average altitude of each city. ZIP codes and associated shapefiles are stored in the *zip_codes* table. In the *water_authorities* table, we reference information on the Bavarian water authorities, whose areas of responsibility are based on the government districts. Due to the federal system, the water management administration is organized differently in the 16 federal states. Within the scope of the project, we only had access to official, detailed information about the Bavarian water management administration.

The *catchments*, *watercourses*, *lakes*, *gauges*, and *gauge_catchments* tables enable the hydrological classification of flood events. In the *lakes* and *watercourses* table, we store official information on the German lakes and watercourses along with their delimiting polygons and polylines. The information available in the *lakes* table includes, e.g., the number of inflows, the maximum depth and the residence time. For watercourses, we hold information on, e.g., the river order, length, and width in the database. In the *catchments* table, we describe the characteristics of the German catchments using parameters such as mean slope, form factor, and relief. In addition, the *catchments* table holds the official catchment polygons, which were provided by the respective federal states. In the *gauge_catchments* table, we store the catchments of the gauging stations. In addition to the gauge location, we store information such as catchment area, gauge type, gauge quality or gauge zero in the *gauges* table.

The category measurements include the *discharge_measurements*, *discharge_investigation*, and *heavy_rain_hours* tables. Since we could only obtain the discharge measurements for Bavaria, the *discharge_measurements* and *discharge_investigation* tables only contain information about the state of Bavaria. The *heavy_rain_hours table*, on the other hand, reflects all of Germany. For 486 Bavarian gauges, we save the discharge time series in hourly resolution for their entire measurement periods in the *discharge_measurements* table. The *discharge_investigation* table contains the results of a discharge study. The study by Kaiser et al. (2020a) investigated the discharge time series of 342 gauging stations regarding flash floods. The flash flood determination was based on the discharge characteristics defined by a specific peak discharge $\geq 0.3\,\mathrm{m}^3\,\mathrm{s}^{-1}\,\mathrm{km}^{-2}$, a time-to-peak $\leq 20\,\mathrm{h}$, and a period of occurrence from April to October (Kaiser et al., 2020a). In the *discharge_investigation* table, we save each identified flash flood hydrograph of this study along with the identified event begin, peak and end, as well as the discharge values of begin, peak and end. Furthermore, we indicate the hydrograph-describing parameters, which are percent increase, time-to-peak, specific peak discharge, gradient, volume, peak-to-volume, return period, and corresponding flood discharge. In addition, we store the results of a freely available dataset from the GDV and the DWD in the *heavy_rain_hours* table. This dataset sums up all periods of heavy rain in Germany based on the weather radar records from 2001 to 2016.

The *claims_frequency* table contains information on insurance claims due to heavy rain in Germany for the years 2002–2017. The insurance claims are aggregated at the rural district level. This dataset by the GDV and DWD specifies the number of heavy rain events, the damages per building, the average damage, as well as the number of affected buildings per 1,000 buildings.

Geodatasets for spatial analyses are in separate tables in the HiOS database. The geodata group includes the *elevation_model*, *natural_region*, *landcover*, and *soil* tables. We store both vector and raster datasets. Since the table attributes are dataset-specific, they are not described further here.

Information about the database design is stored in the *table_descriptions*, *attribute_descriptions* and *geodata_descriptions* tables. These tables support the sustainability of the database, as they contain important metainformation for understanding the database structure. In *table_descriptions*, we indicate the content of each database table. Similarly, the *attribute_descriptions* table describes each table attribute regarding content, unit and, if applicable, the underlying dataset and source. Accordingly, the *geodata_descriptions* table contains the official names and abbreviations as well as a brief description of the datasets.

3.3.3 Table attributes and attribute domains

The table attributes significantly influence the later analysis options. The choice of the non-key attributes is essential since the descriptive attributes determine which questions can be answered. When choosing the non-key attributes, it is of fundamental importance to anticipate potential questions and to know the information and datasets to be stored. To answer future questions, attributes must provide flexibility. Attributes that are too general entail the risk of losing information and restricting analyses, whereas attributes that are too specific complicate analyses. Therefore, ensuring flexibility often implies an increased complexity and number of attributes.

We chose the table attributes based on the used datasets and collected information, as well as on potential questions. Table A.1 in the Appendix lists the table attributes together with their data type, constraints and keys. However, we do not list the attributes of the geodata tables in Table A.1, as their attributes are dataset-specific and therefore not of general interest. We adopted nationwide reference systems such as state codes, names, and abbreviations. Information from various datasets was standardized and summarized in attributes. Due to German federalism, each state provided differently organized hydrological information. To obtain a German dataset, we therefore had to summarize the information for the *catchments*, *watercourses*, and *lakes* tables. The challenge of homogenization is to define attributes that summarize the information without overly generalizing it.

To facilitate the automated evaluation of stored information, we defined attribute domains for most non-key attributes. This domain specification is particularly important for the attributes of the event description tables, since this information forms the basis of the analyses. Free text is generally hard to evaluate, as it is unstructured. Therefore, Kaiser et al. (2020b) suggest using fixed categories besides free text for attribute description. They propose three types of attribute domains: (i) yes/no/null, (ii) given attribute values, and (iii) text blocks. The “yes”, “no”, and “null” attribute values document, for example, the occurrence or non-occurrence of sedimentation, landslides or dike failures. Kaiser et al. (2020b) further suggest attribute-specific domains, such as basement, first floor, second floor, third floor for the “highest affected floor” attribute or oil, sewage, chemicals, other to describe the type of contamination. For damage description, Kaiser et al. (2020b) use text blocks consisting of an adjective and a noun, where the adjective describes the extent of the damage and the noun specifies the affected object. Possible attribute values are, for example, “destroyed houses”, “flooded streets”, or “eroded agricultural land". The attribute domains proposed in Kaiser et al. (2020b) were applied to the attributes of the *space_time*, *hydrology*, *meteorology*, and *damage* tables.

3.3.4 Table relationships and keys

Most entities in the HiOS database are connected by a one-to-many relationship. A one-to-one relationship exists only between the *claims_frequency* and *rural_districts*, *heavy_rain_hours* and *zip_codes*, *gauges* and *gauge_catchments* entities. Due to high maintenance efforts, we largely avoided the use of many-to-many associations. However, a few many-to-many relationships exist, such as between the event documentation entities (e.g., *documents*, *videos*) and the *events* entity. Fig. 3.2 shows the Entity-Relationship (ER) diagram, which represents the associations between the entities of the HiOS database. Thematically related entities are grouped and marked with the same color (cf. Table 3.1). For reasons of clarity, we only listed the key attributes of the entities.

Regarding manageability and consistency, we implemented only the necessary relationships between the database entities, and not all the possible ones. Therefore, for some queries, detours via other entities have to be accepted when no direct association is implemented. However, entities holding geographic data can also be linked via spatial relationships. For example, the lakes and catchments entities can be connected using the PostGIS function ST_Within. The only entities without association are the metainformation entities, since the *table_descriptions*, *geodata_descriptions*, and *attribute_descriptions* entities serve as pure information tables.

To increase the usability of the HiOS database, we employed simple, intuitive, and non-composed primary keys wherever possible. To this end, we inherited natural keys that were already contained in the datasets, such as the 12-digit municipality keys or the state names. Adopting natural keys has the advantage that the key also has a meaning outside the database and is therefore often easier for the user to remember and interpret. We only introduced surrogate, sequential primary keys when merging different datasets in one table, as in the catchment information tables, or when creating an own, new dataset. The *table_descriptions*, *geodata_descriptions*, and *attribute_descriptions* entities are an exception to this rule since these entities have the entity and attribute names they describe as primary keys. Table A.1 and Fig. 3.2 indicate the primary and foreign keys of the database tables.

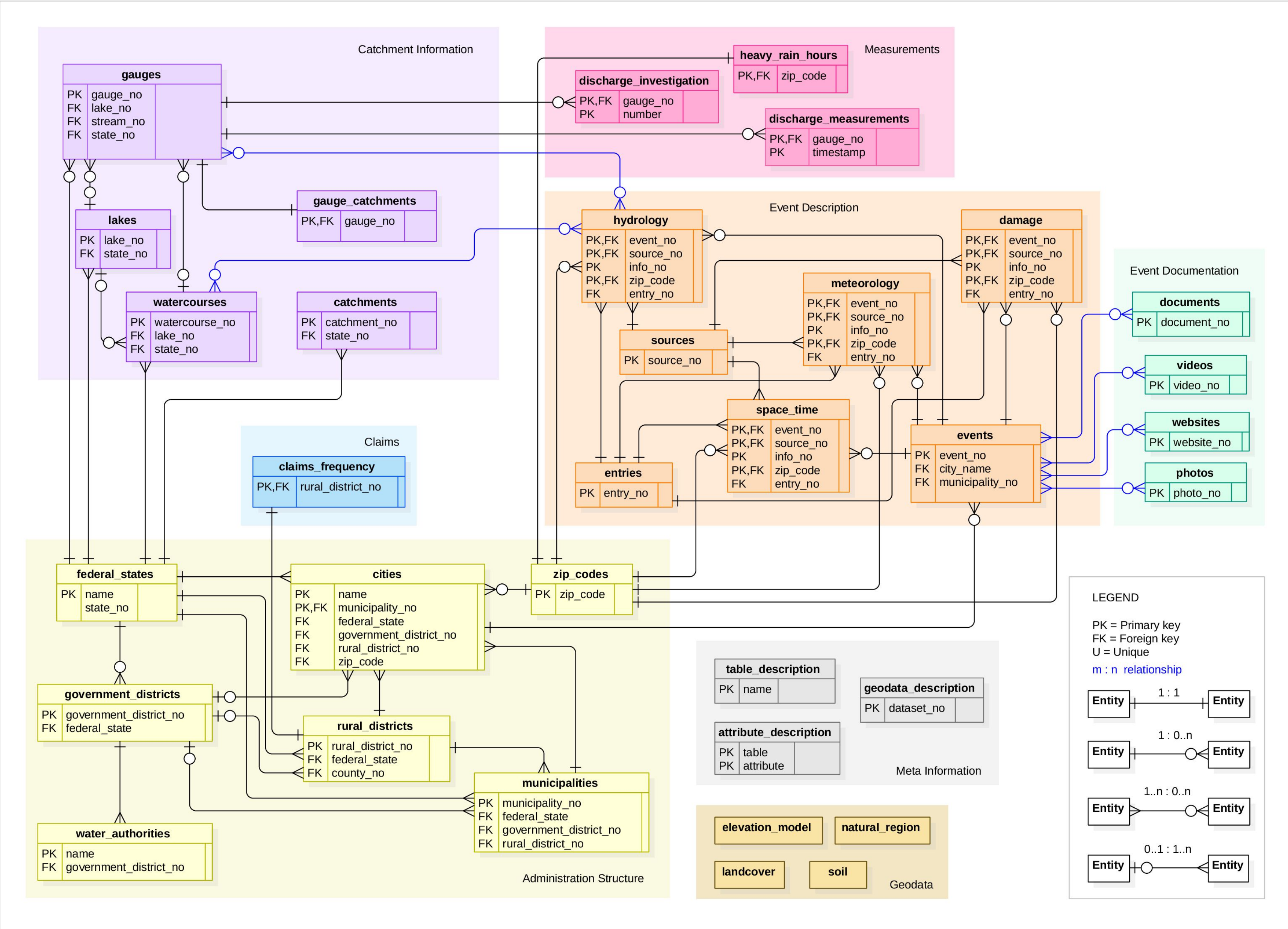

Figure 3.2: Entity-relationship diagram of the HiOS database.

In eight tables, we use composite primary keys consisting of two or four attributes. For example, the primary key of the *cities* entity is composed of the “name” and the 12-digit “municipality_no”. In the *attribute_descriptions* table, “table” and “attribute” together form the primary key, since some attribute names occur in several tables. The *discharge_measurements* entity contains the discharge time series of the Bavarian gauging stations. To uniquely identify a measured discharge value, we query the “gauge_no” and the “timestamp”. The *discharge_investigation* table holds discharge parameters on identified flash flood events from Kaiser et al. (2020a). By using the “gauge_no” and “number” attributes, we retrieve discharge information on a specific flash flood hydrograph. The *space_time*, *meteorology*, *hydrology*, and *damage* tables use the same compound key. The compound key consists of the four attributes “event_no”, “source_no”, “info_no”, and “zip_code”. We will clarify the use and advantages of this composite key in Section 3.3.5.

3.3.5 Documentation of event information

To guarantee sustainability, it is important to ensure traceability, comprehensibility and editability of the generated event dataset. For this reason, we document metainformation about the event information and sources, and store source documents, if available. Although this metainformation may seem unnecessary for the event investigation, it contributes to an understandable and editable event dataset. Most importantly, this metainformation allows users to get the most out of the dataset for their purposes.
The sources table contains information about the sources used, their usage rights and citation, and gives a dataset description. To comply with formalities, we document specifications on data sharing and publication in the “usage_rights” attribute. In addition, we use the "dataset_description" attribute to describe the dataset creation and the changes we have made to it. By not allowing null entries in the *sources* table, we force editors to think about the underlying publication rights and restrictions of the datasets used. Overall, the sources table supports compliance with good scientific practice, which in turn contributes to a responsible and sustainable dataset generation and use.
Like the sources table, we store metainformation about each event entry in the entries table, where we specify the “source_type” as literature, report, website, newspaper article, damage report, photo/video, TV/radio. With the “quality_level” attribute, we assess the quality of the event information using the four categories QC0, QC0+, QC1, QC2, as proposed by Dotzek et al. (2009). QC0 stands for event information that is adopted “as received”, QC0+ describes events that are “plausibility checked”, QC1 stands for

"event confirmed" and QC2 means "event fully verified" (Dotzek et al., 2009).
Considering the source type and quality assessment, we can better estimate the reliability of the event information. Furthermore, we note the "editor" of each event entry together with the "entry_date" and the "last_review" date. Specifying the editor maintains the flexibility to alter event entries if, for example, an editor applied a different flood definition or made a systematic mistake in event documentation. The indication of the last review date further allows retracing when the event information was last changed. The *documents*, *videos*, *websites*, and *photos* tables serve a purpose similar to the sources table. In these tables, metainformation about the original documents regarding "author", "usage_rights", "citation", "quality", and "storage_location" is stored. We also note a "description" and "comment" about the source documents.
Since event documentation for scientific investigations is a central task of the database, we attached particular importance to the flexible design of the involved tables. We use a primary key composed of four attributes for the *space_time*, *hydrology*, *meteorology*, and *damage* tables. The compound key uses the "event_no", source_no", "info_no", and "zip_code" attributes and allows for different aggregation levels of the event dataset. The "event_no" uniquely identifies each event in the *events* table. To query all available information about one specific event, regardless of the source, we search for the event number. Using the event number, we can aggregate all event information stored in the database on a specific event. For each event entry, we indicate the source using the "source_no" attribute. Specifying the source enables to hide sensitive information such as insurance data, or to exclude sources from analyses considered less reliable (Kaiser et al., 2020b). We further indicate the "zip_code" of the affected city. For large cities, we can differentiate damages by ZIP code areas and thus maintain spatial accuracy. For towns with only one ZIP code, we specify the district in which flooding occurred in the "districts" attribute. To avoid information loss, we introduced the "info_no" attribute, which is a continuous integer. We use the "info_no" attribute to record several items of information on the same event. This is, for example, the case when we document several starts of the triggering precipitation event with different precipitation amounts and durations. To summarize, only the composition of the "event_no", source_no", "info_no", and "zip_code" attributes enables the unique identification of an event in the event information tables. Using parts of this composed key enables different aggregation levels of the event information providing the greatest possible query flexibility.

3.3.6 Data sources

Our database contains 23,752 flash flood and pluvial flood events that were triggered by heavy rainfall in Germany. We composed the event dataset from a variety of sources. The event information originates from insurance companies, mission archives, scientific projects, agencies, and media. Our flood record starts in 346 and ends in 2017. However, most events are available from 2000 onwards. It should be mentioned that events in the federal states of Thuringia, Baden-Wuerttemberg, Hesse, and Rhineland-Palatinate are potentially overrepresented since an insurance dataset with 16,900 events was obtained for these federal states (Kaiser et al., 2020b). Kaiser et al. (2020b) present the HiOS event dataset in detail, together with a description of the temporal and spatial resolution and the number of extracted events from the various sources used.
For spatial analyses, we store various geodatasets covering Germany in the database. In addition to a digital elevation model, we archive a topsoil map, a land cover map and the natural regions of Germany (Table 3.1). The environment ministries of the respective federal states provided official information on lakes, watercourses, gauges and catchments, including point, line and polygon shapefiles. The database also contains the German administrative structure. In addition to the official reference data, the bounding polygons and centers of the various administrative levels are stored.
The HiOS database also contains measurements. Regarding discharge, we store the discharge time series of 486 Bavarian gauges in hourly resolution for the respective total measurement period. From the study by Kaiser et al. (2020a), we have the identified discharge time series of several thousand flash floods together with parameters describing the discharge event, such as specific peak discharge, time-to-peak or percent rise. We further use two datasets published by the German Weather Service and the German Insurance Association. One dataset indicates the sum of heavy rain hours in Germany since 2001 per ZIP code area. Heavy rain considered in this study had to exceed $25\,\mathrm{l/m^2}$ in $1\,\mathrm{h}$ or $35\,\mathrm{l/m^2}$ in $6\,\mathrm{h}$, which corresponds to the warning level 3 of 4 of the German Weather Service. The second dataset describes the damage frequency due to heavy rain in Germany for the years 2002-2017, aggregated at the rural district level.

3.4 Methods

3.4.1 Event rate

To ensure the comparability of the number of events between cities, we have normalized the number of events. The number of inhabitants correlates moderately with the number of flash flood and pluvial flood events, meaning that larger cities tend to experience more heavy rain-induced floods (cf. Section 3.5.3). To find out which cities are most frequently affected, regardless of their size, we used a normalized variable that eliminates the population bias in the number of events. For reasons of comparability, we introduced the dimensionless event rate, which is defined as the quotient of the number of events and the logarithm of the population to the basis 10:

$$Event\,rate = \frac{Number\ of\ events}{\log_{10} Population} \tag{3.2}$$

The population distribution of Germany has a strong right-skewed distribution. Therefore, to resolve skewness and obtain a small divisor, we applied a log transformation to the population data. The only disadvantage of the event rate compared to the number of events is the loss of intuitive comprehensibility.

3.4.2 Hot spot analysis

We investigated the hot and cold spots of heavy rain-induced floods in Germany using the Global Moran's I and Getis-Ord-Gi* statistics. Both approaches are implemented in the Spatial Statistics toolbox of the GIS software ArcGIS Pro. The "Spatial Autocorrelation (Global Moran's I)" tool measures spatial autocorrelation for a given set of weighted spatial features using the Global Moran's I statistic. The Moran's I Index evaluates whether the data shows a dispersed, random or clustered pattern. A positive Moran's Index value implies a tendency toward clustering, while a negative index value suggests dispersion. The global Moran's I Index is defined as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{j=1}^{n} (x_j - \overline{x})^2} \tag{3.3}$$

where $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total feature number, and S_0 is the aggregate of the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{3.4}$$

The z-score is computed as:

$$z = \frac{I - E[I]}{\sqrt{Var[I]}} \tag{3.5}$$

where $E[I]$ and $Var[I]$ are given as:

$$E[I] = -1/(n-1) \tag{3.6}$$

$$Var[I] = -E[I^2] - E[I]^2 \tag{3.7}$$

For each feature, the Gi* statistic is calculated, and a z-score and p-value are returned. A statistically significant z-score is obtained when the local sum differs greatly from the expected local sum and the difference is too large to be the result of randomness. A statistically significant hot spot is a feature with a high value that is surrounded by other features with high values. A significant cold spot is in contrast described by a low negative z-score and a small p-value. In geosciences, the Moran's I and Getis-Ord-Gi* statistics have been widely applied, e.g., to assess heavy-metal concentrations (S.-M. Kim and Choi, 2017), to detect landslides (Lu et al., 2019), or to improve forest management (Rossi and Becker, 2019). Khajehei et al. (2020) recently applied hot spot analysis to cluster gauging stations in the U.S. regarding the magnitude, duration, frequency and severity of measured flash floods.

3.4.3 Event binning

To better explore the event dataset, we used feature binning using ArcGIS Pro. Feature binning is a method to aggregate and visually represent point data. By grouping the event points into bins, the dense information is summarized. A bin represents all events within its boundaries and is displayed wherever there is at least one event in it. We chose bins with a size of $100\,\mathrm{km}^2$ as a compromise between resolution and graphic representability. Using bins rather than political boundaries for event aggregation is preferable. By using bins of equal size, we avoid visually emphasizing areas, as would be the case, for example, with unevenly sized rural districts.

3.5 Investigations on heavy rain-induced floods in Germany

Due to its good spatial and temporal coverage, the HiOS dataset enables the holistic investigation of heavy rain-induced floods in Germany. We used the database's functionalities to manipulate the collected data for our flood analyses. Using SQL queries, we generated the datasets required for our investigations from the HiOS dataset. To illustrate how a database supports spatiotemporal investigations, we provide the SQL queries applied in the Appendix. These SQL statements can serve as examples and inspiration for others who wish to conduct similar investigations.

3.5.1 Spatial distribution and frequency

Many fundamental questions regarding the spatial occurrence of floods caused by heavy rain in Germany are still unanswered, such as: Where did flash floods and pluvial floods occur in Germany? Do they occur everywhere in Germany? Which cities had the most events in the past? We can now address these questions, thanks to the availability of the HiOS dataset.

For our investigations, we created a table view of the events table entitled *events_analysis* containing only the events relevant to our analyses (B.1). To ensure valid investigations, we excluded possibly irrelevant events that did not occur between April and October, which is considered the season of heavy rain-induced floods for Germany (see Section 3.5.5). Overall, the flood events investigated below comply with the event definition given in Section 3.3.1. However, we would like to point out that the flood events are not, due to missing information, differentiated according to their magnitude or flood type. Therefore, minor and severe flood events, as well as flash floods and pluvial floods, are treated equally. To avoid distortions of the investigation, we further excluded the events from the insurance dataset, since it only covers 4 of the 16 federal states. Without the insurance dataset, we obtain a roughly representative dataset of heavy rain-induced floods for Germany with 8,718 events. Unless otherwise stated in the following sections, we used the *events_analysis* table view as a data basis.

To investigate the spatial distribution of heavy rain-induced flood events in Germany, we created a dataset that summarizes the number of flood events for each affected city (B.2). For this purpose, we joined the *events_analysis* table view on the cities table. Using the SQL statement in Appendix B.2, we also queried the city centers from the HiOS database for mapping.

Fig. 3.3 shows the number of documented flash flood and pluvial flood events per city in Germany. We find that floods caused by heavy rain occurred all over Germany, although not all regions were affected equally often in the past. In total, the HiOS dataset documents events for 4,875 cities. Of these cities, 70 % were affected once, 17 % twice, 6 % three times, and 7 % more than three times. On the median, the affected cities were hit once, with the 95 % quantile being 5 events and the 99 % quantile 11 events. Regarding the distribution of the more frequently affected cities, there appears to be a slight north-south gradient with less heavy rain-induced flood events in the Northern

German Plain (Fig. 3.4). This decrease of events from south to north seems plausible given the flat orography of the Northern German Plain.

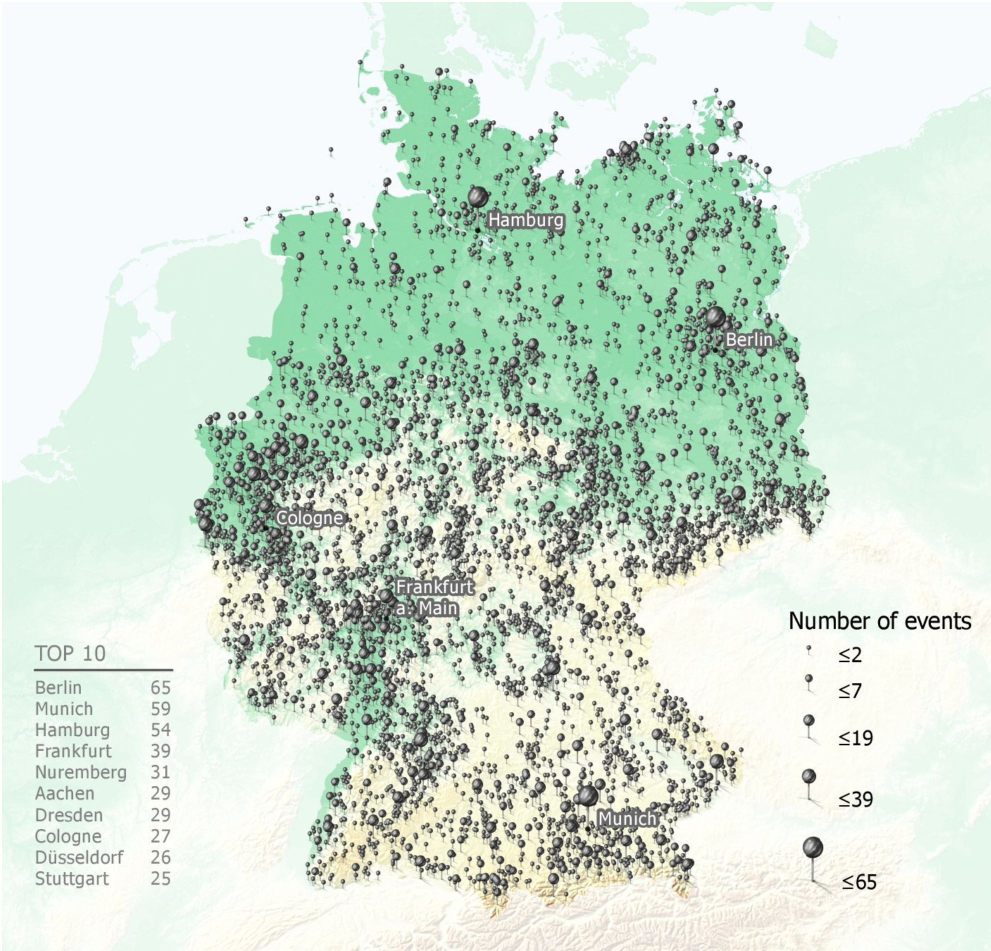

Figure 3.3: Number of flood events caused by heavy rain in Germany until 2017, collected in the HiOS project (data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

Many events particularly occurred in metropolitan areas such as the Rhine-Ruhr area or the Rhine-Main area with 11 and 6 million inhabitants, respectively. Most events were reported for the metropolises of Berlin (65), Munich (59), and Hamburg (54) (Fig. 3.3). With regard to the event rate, the top 10 are: Berlin (13), Munich (12), Hamburg (11), Frankfurt (8), Aachen (7), Nuremberg (7), Cologne (6), Dresden (6), Düsseldorf (6), Dortmund (6). Overall, the top 10 most frequently affected cities are only those with more than 250,000 inhabitants, both in terms of event numbers and normalized event rates. However, not all highly urbanized regions stand out with a particularly large number of events, as can be seen from the metropolitan areas of Northwest (Bremen-Oldenburg and surroundings, 3 million inhabitants) and Hanover-Brunswick-Göttingen (4 million inhabitants).

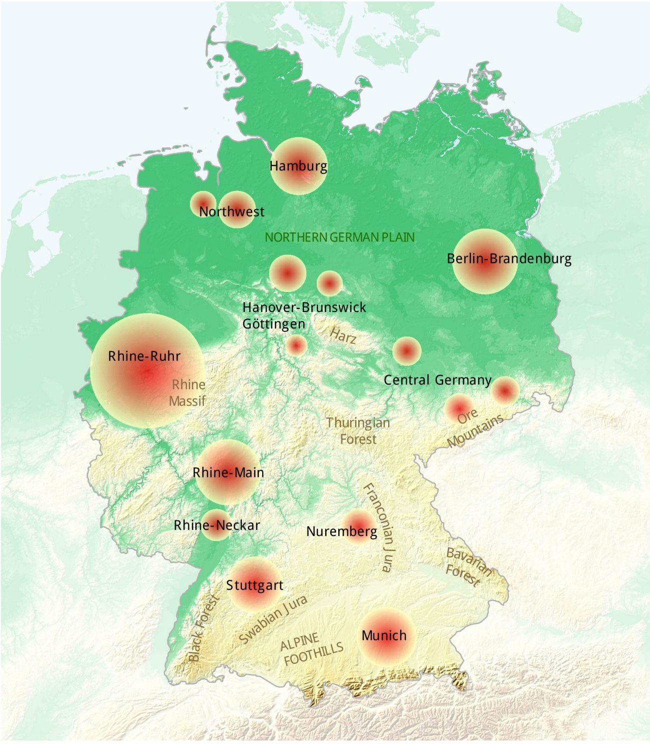

Figure 3.4: Metropolitan areas in Germany and topographic details.

3.5.2 Temporal analysis

Fig. 3.5 shows the annual frequency of floods caused by heavy rain as well as the number of people injured and killed by flash floods and pluvial floods in Germany in the period 1990–2017. We summarized the number of events, injuries, and fatalities per year since 1990 using the SQL statement from B.3. For these 28 years, we collected 8,256 events in which 583 people were injured and 89 died. Statistically, people were injured in 7 % and killed in 1 % of the flood events. The most documented events so far occurred in the year 2011 (1,065 events) and 2016 (1,025 events). Although most events were documented for 2011, this year did not cause the most deaths and injuries. In the period considered, the events of 2016 and 2006 caused 24 % and 23 % of the documented injured people, respectively. Most deaths were reported for the years 1990 (24) and 2016 (17). However, relative to the number of events, 1990 was more extreme with seven events claiming 50 injuries and 24 deaths. Regarding the number of events, the years 1990, 1991, and 1996 had the highest death rates with 3.43, 0.13, and 0.10 deaths per event. The highest rates of injuries were documented for the years 1990 (7.14), 1994 (0.20), and 2006 (0.25).

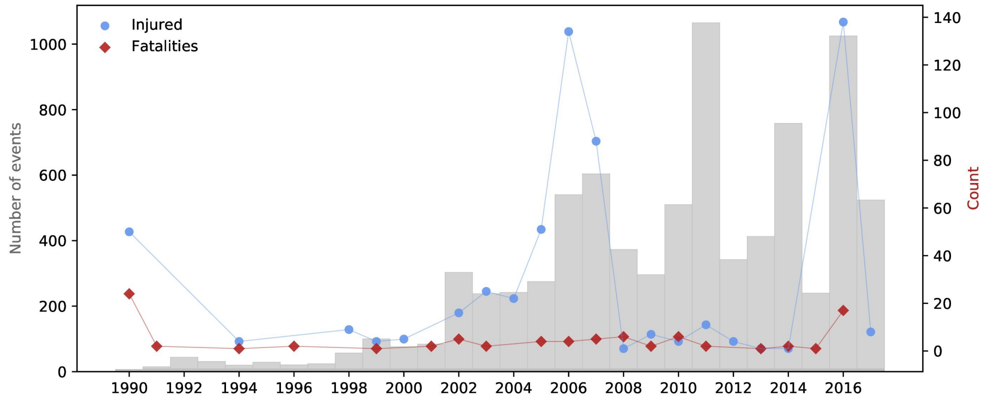

Figure 3.5: Time series of heavy rain-induced floods, injuries and fatalities in Germany in the period 1990–2017 (number of events: $n = 8,256$, fatalities: $n = 89$, injuries: $n = 583$, data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

To better understand the temporal occurrence of heavy rain-induced floods, we analyzed the documented floods regarding their onset. Using the extract function of PostgreSQL, we grouped the events by the hour of occurrence and counted the number of events, fatalities, and injuries (B.4). The start time of 8,150 events is known. This refers to the flooding onset and not to the beginning of the triggering precipitation. The first inundations outside creeks and river banks mark the beginning of the flood event. It should be noted, however, that in most cases the flooding onset cannot be reliably measured or determined. Therefore, the start time is usually an estimate with high uncertainties.

Fig. 3.6 shows the frequency of the flood onset for each hour of the day using one-hour bins. The local times given hereinafter refer to Central European Summer Time, which is valid in Germany from March to October and corresponds to UTC+2. Most of the documented heavy rain-induced flood events occurred at 15:00 local time. Almost half of all events began between 14:00 and 18:00 local time. During the night and in the early morning, floods triggered by heavy rain rarely occurred.

Investigating the onset of the events, in which people were injured or killed, provided us with insights into the influence of flood timing on human losses. Fig. 3.6 indicates that most people were killed in floods starting around 12:00 (93 deaths) and 21:00 local time

(67 deaths), whereas people were mostly injured between 18:00 and 19:00 local time (20 and 22 injuries). Overall, the frequency of injuries and fatalities increases roughly with the frequency of the events.

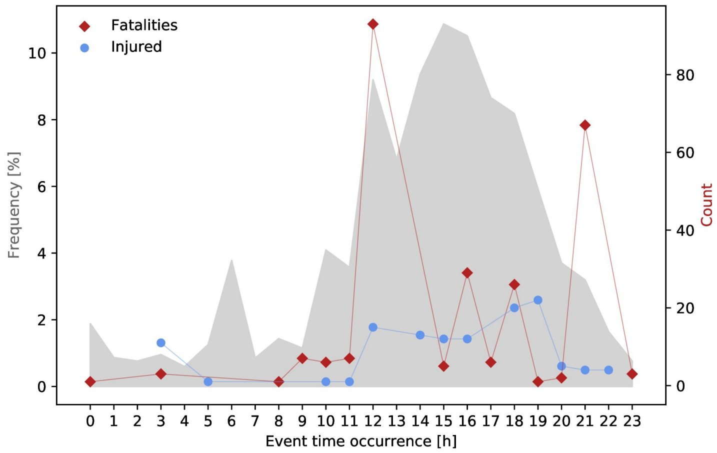

Figure 3.6: Diurnal distribution of flood onset and the number of people injured or killed during heavy rain-induced flood events (number of events: $n = 8,150$, fatalities: $n = 257$, injuries: $n = 121$, data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

3.5.3 Influence of population

Fig. 3.3 raises the question to what extent population influences heavy rain-induced flood occurrences. Since flash floods and pluvial floods often cannot be recorded automatically, e.g., at gauging stations, their flood reporting generally relies on human observation (Marjerison et al., 2016). Therefore, one may hypothesize that the number of reported heavy rain-induced flood events is higher for larger cities where more people can report them. In addition, population may influence heavy rain-induced flood occurrence, as the proportion of impervious area generally increases with population, which is known to facilitate surface runoff. Thus, we are interested to know whether the event frequency correlates with the population and whether regions with a high proportion of built-up area report more events.

To answer these questions, we investigated the relationship between event frequency and population as well as event frequency and sealing percentage. Due to the resolution of the population data, we aggregated the events at the rural district level. For this analysis, we used the information on population density, rural district area and sealing percentage contained in the *rural_districts* table. We joined the *events_analysis* table view on the *rural_districts* table and grouped the events by the 401 German rural districts. From this intermediate table, we queried the necessary district information, including the shapefiles (B.5).

Fig. 3.7 shows the population density of the rural districts, superimposed over the associated number of events. We observe tendencies that higher population densities are associated with more reported events. Especially in the densely populated metropolitan regions of Rhine-Ruhr, Rhine-Main, Stuttgart and Munich, we notice a high number of flood events caused by heavy rain. However, contrary trends are also evident when looking at the area of the Ore Mountains, the Alpine Foothills and the Northeastern German Plain. In these regions, we have comparatively high event frequencies but rather low population densities.

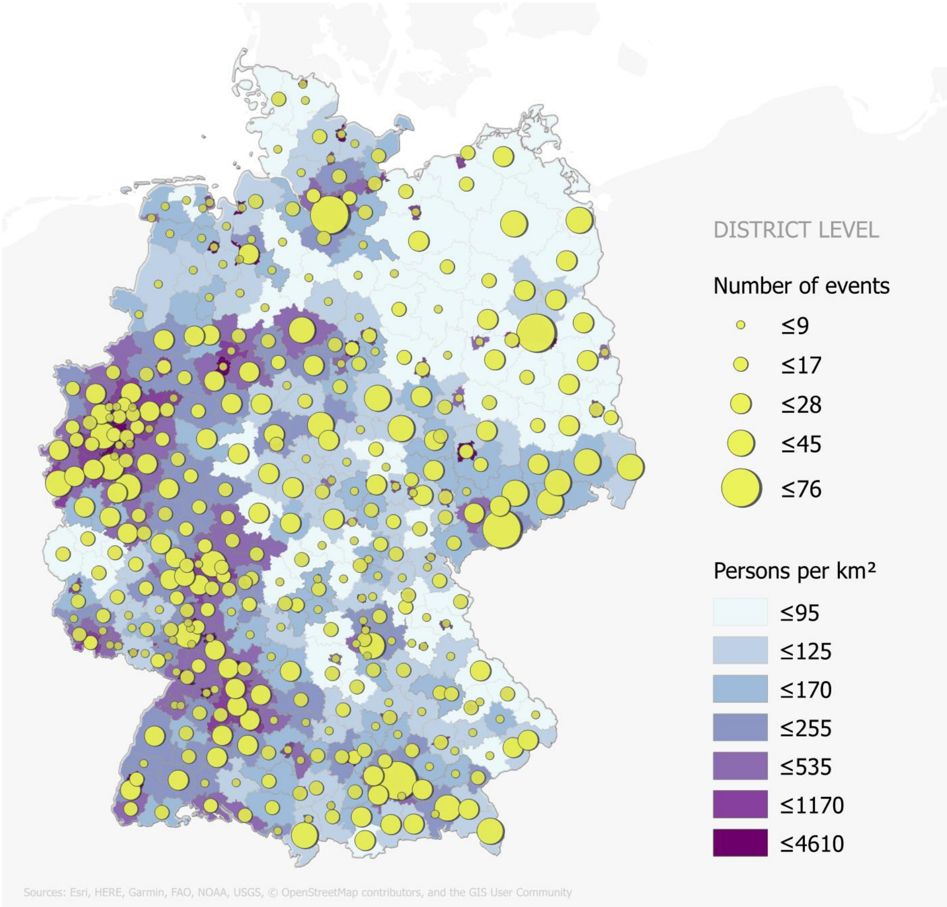

Figure 3.7: Correlation between population density and heavy rain-induced flood events aggregated at rural district level (data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

To assess the correlation, we plotted the number of flood events against the number of inhabitants (Fig. 3.8). For better representation, we transformed the number of inhabitants with the logarithm of the basis 10. According to the Pearson correlation coefficient, a moderate positive correlation ($r = 0.62$, $p = 3.33 \cdot 10^{-44}$) exists between the number of heavy rain-induced flood events and the number of inhabitants, which is also apparent in Fig. 3.7. Therefore, a population increase often leads to a higher frequency of flash flood and pluvial flood events. Contrary to expectations, our event dataset indicates no correlation between the number of heavy rain-induced flood events and the degree of sealing ($r = 0.07$, $p = 9.07 \cdot 10^{-11}$). However, the number of heavy rain-induced flood events correlates weakly with the district area ($r = 0.32$, $p = 1.63 \cdot 10^{-1}$). We would expect a strong correlation between the district area and the number of floods, if heavy rain-induced flood occurrence were a random process, meaning that the number of flood events would increase as the district area increases as well. However, the districts seem to be spatially too homogeneous and furthermore do not take hydrological relationships into account. Given a weak correlation with the district area, we can assume that the aggregation level of the events does not distort the correlation between heavy rain-induced flood events and population.

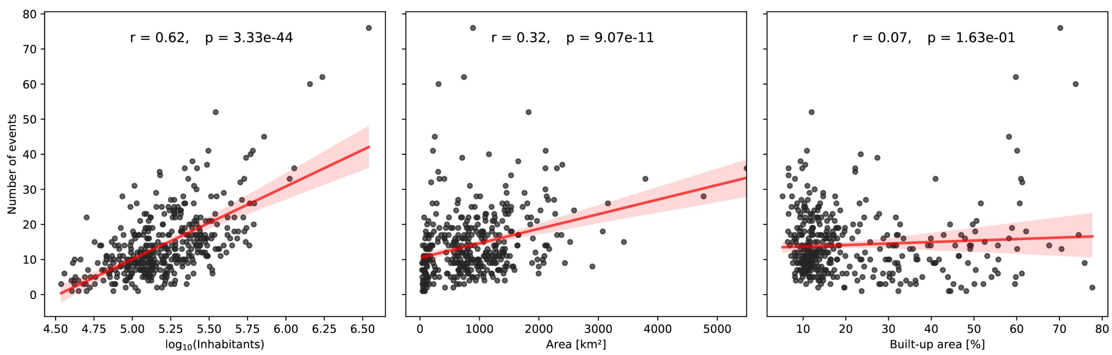

Figure 3.8: Correlation between number of heavy rain-induced flood events and number of inhabitants, area and share of built-up area at the rural district level, with the 95 % confidence interval for the regression estimate ($n = 401$, data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

3.5.4 Hot spots and cold spots

To better cope with the flood hazards from heavy rain, we need to identify particularly endangered regions. The first step is thus to analyze the spatial pattern of heavy rain-induced flood occurrences in Germany. Regarding prevention, it is essential to discover the regions that experience particularly numerous or few flood events and to localize these hot and cold spots. Since we are interested in finding significant hot and cold spots independently of city size, we use the event rate instead of the number of events. We calculated the event rate for each city in Germany using the SQL statement in B.6 of the Appendix. By joining the *cities* table on the *events_analysis* view, we linked the information on the number of events and the city population required for this analysis. If a city has not yet been affected, we set the event rate to 0. Taking advantage of the SQL CASE expression, we computed the event rate for all German cities (B.6). To reduce the bias in our event dataset towards positive cases, we considered all German cities regardless of whether an event was documented for the city. As the HiOS dataset lacks confirmed not yet affected cities, we assumed in a simplified approach that the non-listed cities have not been so far affected by a flash flood or pluvial flood event.

As the flood events are linked to the city they affected, we need to analyze whether the spatial distribution of the cities influences that of the flood events. If the spatial pattern of the cities affects the heavy rain-induced flood distribution, the hot spot analysis will reveal the pattern of the cities, not of the events. Therefore, we investigated the spatial pattern of the German cities using the "Average Nearest Neighbor" tool. The tool calculates the nearest neighbor index that is given as the ratio of the observed mean distance of each city to its nearest neighboring city to the expected mean distance in case of random distribution of the cities. The nearest neighbor index of the German cities is 1.2, which indicates that the observed average distance between the cities is greater than a hypothetical random distribution (Table 3.2). German cities thus show a dispersed pattern. Calculating the nearest neighbor ratio only for the affected cities yields 1.0, indicating that affected cities are randomly distributed over Germany (Table 3.2). As German cities show a dispersed pattern but affected cities are randomly distributed, we can conclude that the location of the cities does not distort the spatial distribution of the flash flood and pluvial flood events. Using the Global Moran's I statistic, we further investigated the spatial patterns of the German cities regarding population, number of events and event rate. We found that population, number of events and event rates show a statistically significant clustered pattern over Germany (Table 3.3).

Table 3.2: Investigation of the spatial patterns of the German cities and the cities affected by heavy rain-induced floods using the average nearest neighbor index.

Feature	Observed mean distance	Expected mean distance	Nearest Neighbor Index	z-score	p-value	Distance method	Null hypothesis	Interpretation
German cities	1,695.22 m	1,398.96 m	1.212	86.693	0.000	Euclidean	rejected	dispersed pattern
Affected cities	4,316.57 m	4,297.93 m	1.004	0.578	0.563	Euclidean	not rejected	random pattern

Table 3.3: Investigation of the spatial patterns of the German cities considering population, number of heavy rain-induced flood events and event rates (number of events divided by log10 of population) using the Global Moran's I statistic.

Feature	Attribute	Moran's Index	Expected Index	Variance	z-score	p-value	Conceptualization	Null hypothesis	Interpretation
German Cities	Population	0.060	-0.00002	0.000	252.581	0.000	Fixed distance	rejected	clustered pattern
German Cities	Number of events	0.008	-0.00002	0.000	34.386	0.000	Fixed distance	rejected	clustered pattern
German Cities	Event rate	0.010	-0.00002	0.000	40.323	0.000	Fixed distance	rejected	clustered pattern

Fig. 3.9 shows the identified hot and cold spots of heavy rain-induced floods for Germany. In sum, we localized seven hot spots and two cold spots. Some hot spots are found in more urbanized regions, such as around Berlin, in the Rhine-Ruhr metropolitan region, and in the conurbations of Rhine-Main, Rhine-Neckar and Stuttgart. However, other hot spots are located in the less populated but hilly terrain of the Bavarian Alpine foothills, in the Ore Mountains, and in the region between the Thuringian Forest and the Harz Mountains. Two statistically significant cold spots are found in the Northwestern German Plain (except Hamburg) and in North-Central Bavaria north of the Danube. We further note that not all metropolitan areas are hot spots. Hamburg and Hanover-Brunswick-Göttingen, for example, do not have statistically significant event rates, and the metropolitan regions Northwest and Nuremberg lie in a cold spot.

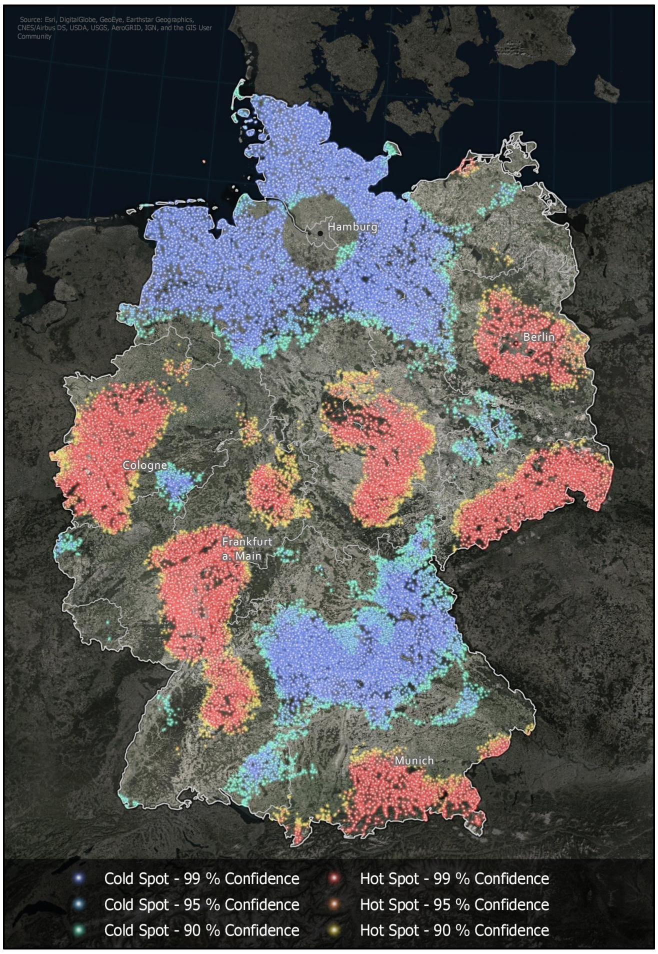

Figure 3.9: Statistically significant hot and cold spots of heavy rain-induced flood events in Germany (data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

It is further of interest whether injuries and fatalities occur more frequently in hot rather than in cold spots. Therefore, we superimposed the hot and cold spots over the number of injuries and fatalities (Fig. 3.10). Using the SQL statement of B.7, we summarized the number of injured and killed people per city. During the period 1900–2017, flash and pluvial floods killed 499 and injured 583 people. In general, we find that few injurious and fatal events have occurred in the Northern German Plain compared to the rest of Germany. Central Bavaria, where a cold spot has been identified, also appears to be less affected. In particular, many deadly events happened in the Ore Mountains hot spot, mostly due to two major events in 1927 and 2010 that affected several cities. The injuries within the Ore Mountains hot spot, in contrast, are due to recent flood events caused by heavy rain in 2003, 2006 and 2012. Also in the Rhine-Ruhr and Rhine-Main to Stuttgart hot spots, many people have been injured and killed by heavy rain-induced floods in the past. The four cities with the most reported injuries were all caused by one flood event that was caused by heavy rain: Neuhausen ob Eck (BW) 82 injuries on 24.06.2016, Balingen (BW) 41 injuries on 24.06.2005, Wenden (NW) 37 injuries on 09.06.2007, and Kaiserslautern (RP) 35 injuries on 27.05.2016.

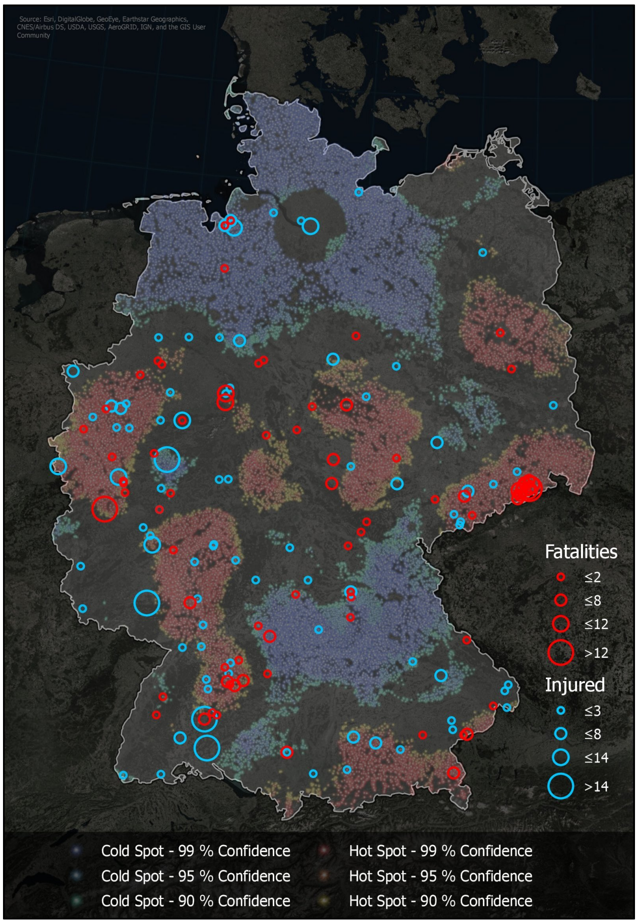

Figure 3.10: The identified hot and cold spots of heavy rain-induced flood events superimposed over the number of flood-related injuries and fatalities (1900–2017: fatalities: $n = 499$, injuries: $n = 583$, data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

3.5.5 Seasonality

We are further interested to know when floods triggered by heavy rain mostly occur in Germany. Is there a season for heavy rain-induced floods? Which months have the most flood events caused by heavy rain? And does the seasonality differ for different regions in Germany? To investigate the seasonality, we summarized the seasonal heavy rain-induced flood occurrence for the individual federal states (B.8) and for the whole of Germany (B.9).
Germany has a pronounced summer season with regard to floods caused by heavy rain (Fig. 3.11). Most documented flash flood and pluvial flood events occurred in the

summer months of June, July and August, followed by events in spring (March to May). In contrast, flood events triggered by heavy rain rarely occurred in autumn (September to November) or winter (December to February). With 68.5 % of the documented events, summer is the predominant flood season in Germany. Overall, 90 % of the documented events took place in summer or spring, which indicates that autumn (6.9 %) and winter events (3.1 %) play a negligible role in Germany.

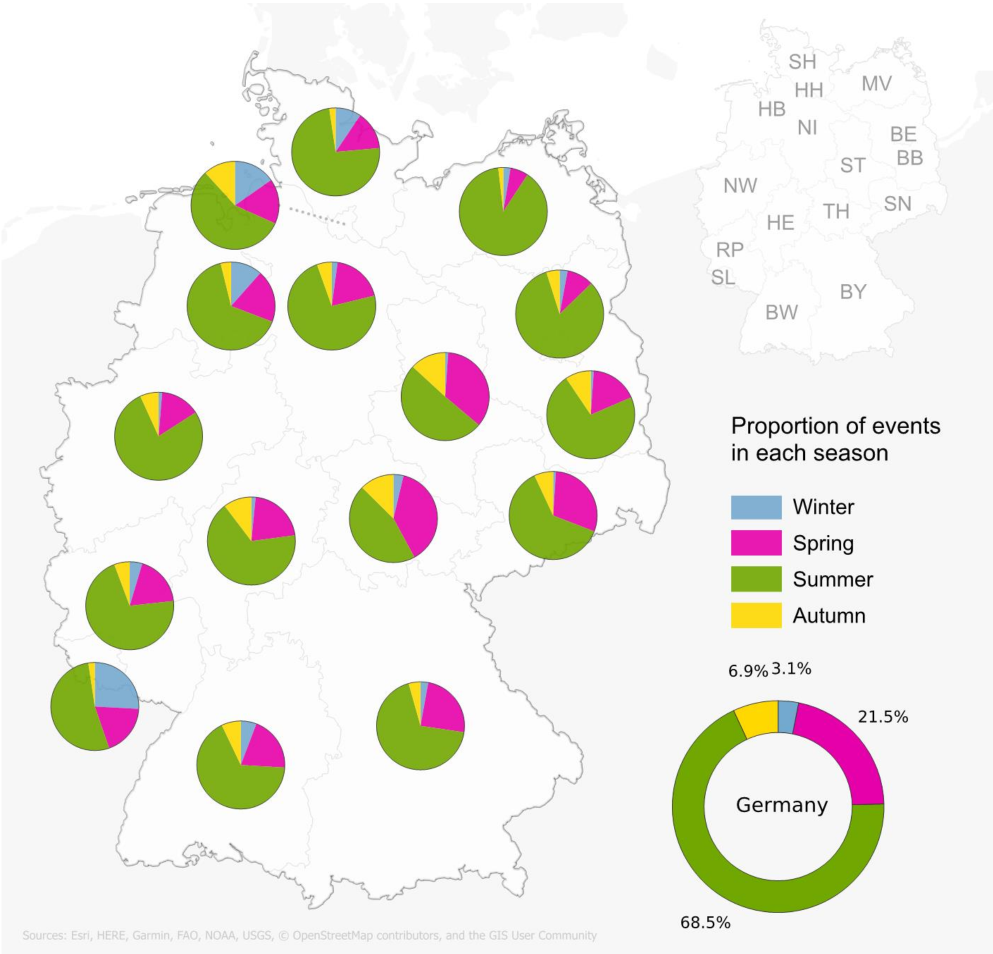

Figure 3.11: Proportion of heavy rain-induced flood events per season for the federal states of Germany (BW: $n = 902$, BY: $n = 1,768$, BE: $n = 102$, BB: $n = 540$, HB: $n = 26$, HH: $n = 85$, HE: $n = 763$, MV: $n = 378$, NI: $n = 661$, NW: $n = 1,289$, RP: $n = 649$, SL: $n = 85$, SN: $n = 690$, ST: $n = 448$, SH: $n = 212$, TH: $n = 461$; Germany: n= $9,059$; data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

Although summer is the predominant season of flash and pluvial floods throughout Germany, the proportion of events in the individual seasons varies considerably between the federal states (Fig. 3.11). We note that the proportion of spring events in the eastern central German states are well above the average of 20 %, with 30 % in Saxony (SN), 35 % in Saxony-Anhalt (ST), and 38 % in Thuringia (TH). While the share of spring events is larger in southern and central states, spring events occur less frequently in northern Germany. Mecklenburg-Western Pomerania (MV) and Berlin (BE) had particularly few events in spring (7 and 10 %, respectively). Regarding summer events, there is a slight trend towards more summer events in a northerly direction. On average, almost 7 % of the documented German events occurred in autumn, with a tendency towards slightly more autumn events in central Germany. Heavy rain-induced floods in winter are rare in Germany. In most federal states, winter events do not account for a significant share. Exceptions to this are the state of Saarland (26 %, SL), and the northern city-states of Hamburg (15 %, HH) and Bremen (12 %, HB), whose sample sizes, however, are too small to ensure statistical significance.

Furthermore, we investigated the regional seasonal patterns of heavy-rain induced floods in Germany (Fig. 3.12). To study the monthly patterns throughout Germany, we first counted the number of heavy rain-induced flood events per month for each city using the SQL statement in B.10. We then grouped the events into bins and determined for each bin the month with the most events. For the investigation of the monthly patterns, we focused on the events that occurred during the main season from April to October. Fig. 3.12 shows the regional seasonality patterns in Germany by displaying the month with the most documented flash flood and pluvial flood events. Overall, July and June are the months most often affected. The main season runs from late spring to early autumn, with April and October marking the beginning and end of the heavy rain-induced flood season.

Throughout Germany, the summer events in June and July dominate. However, May events are particularly frequent in eastern Germany (Ore Mountains, Thuringian Forest, Harz) and the Rhine-Neckar metropolitan region. The state of Bavaria (BY) has also experienced some spring events in the past. Autumn events rarely dominate but occurred in central Germany along a single strip and sporadically in southwest Germany. In the state of North Rhine-Westphalia (NW), we find an accumulation of events in late summer. Overall, we observe slight differences in the regional patterns of flood seasonality in Germany.

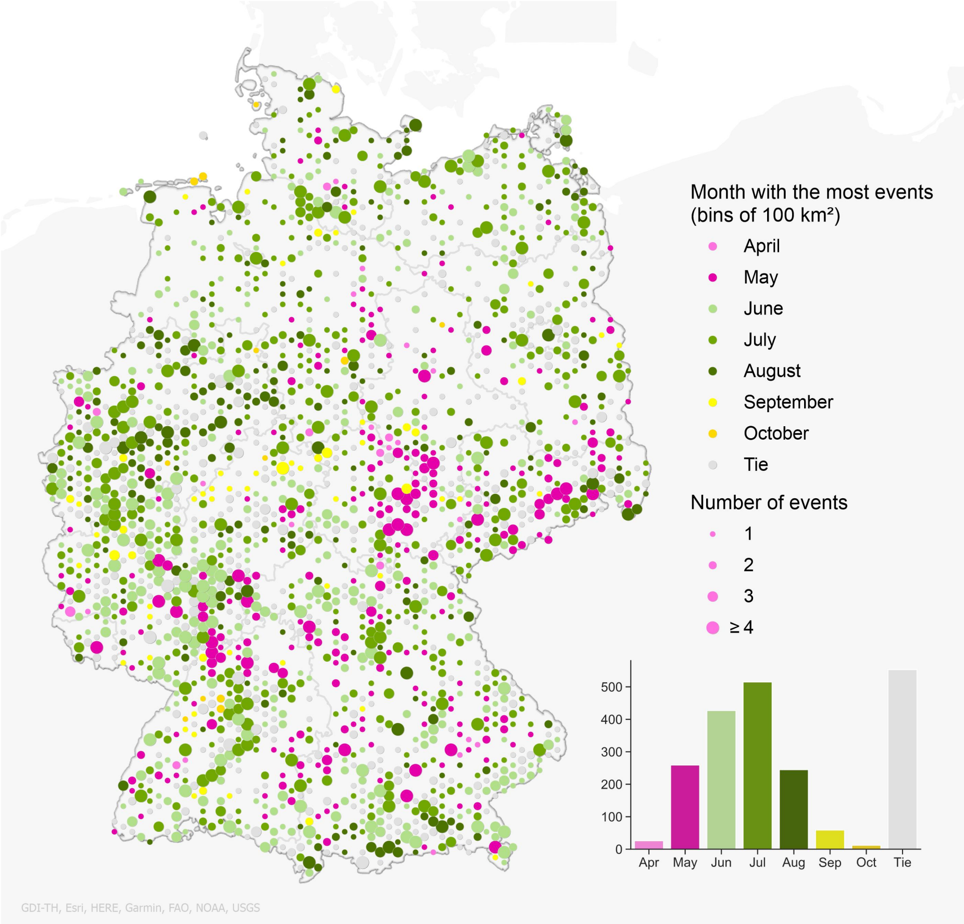

Figure 3.12: Seasonality of heavy rain-induced flood events over Germany. Indication of the month with the most events aggregated in bins of 100 km^2 (data sources: THW, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; ESWD, 2017; HANG, 2018; LfU, 2017b; URBAS, 2018).

3.6 Discussion

3.6.1 Insights from event database setup

Most articles about flood and flash flood databases omit the technical details of the underlying database. Therefore, information on the database management software used, the event definition or the database design itself is rare. The lack of technical details hampers the comparison of the HiOS database with other event databases, but underlines the importance of the article.

To fully profit from setting up a database for floods caused by heavy rain, a spatial database should be chosen. Using a spatial database, such as PostgreSQL, enables merging and maintaining all required information in one place: geographical data, event data, and metadata. Nevertheless, it is also possible to separate event information and geodata. Barnolas and Llasat (2007) and Papagiannaki et al. (2013), for example, used MS Access for their event databases and stored the geoinformation in a GIS software. However, a GIS software is no longer necessary when using a spatial database. We used PostGIS functions, for example, to derive the mean slope and elevation of the catchments using the stored catchment shapefiles and the DEM. Therefore, separating event and geographic data unnecessarily complicates analyses, as spatial databases can hold spatial and non-spatial data and provide spatial functions.

Furthermore, it is important to choose a spatial database that provides interfaces to several front-end solutions. Effective flood investigations require interfaces to common GIS software (e.g., ArcGIS Pro, QGIS), programming languages (e.g., Python, R), and database management software. With this variety of front-end software, researchers can select the system best suited for a given task. In some cases, for example, spatial queries in PostgreSQL were faster than calculations in ArcGIS Pro. Furthermore, we generated datasets that required programming within Jupyter Notebook and the python libraries Psycopg 2 and GeoPandas. These datasets could not have been created within the database environment since databases are not created to support complex programming tasks. In addition, Python offers a variety of easy-to-use libraries and functions for scientists that facilitate data analysis. However, dataset processing outside the database requires knowledge of another programming language and maintenance of an additional system.

To uniquely define a flood event, a space and time reference is required. While the occurrence date is clear as a temporal reference, the spatial reference of a flood event is controversial. For the HiOS database, we chose a damage-based definition, which uses the affected city as the spatial reference and the time of occurrence in the city as the event date. However, other researchers use meteorological or hydrological event definitions in their flood databases. Barnolas and Llasat (2007), for example, group flood events under the same event ID if they were triggered by the same meteorological event. Thus, the size of the rain cell defines the spatial event extent. Consequently, the initial and final date of the triggering rainfall marks the beginning and end of the event (Barnolas and Llasat, 2007). Adhikari et al. (2010), in contrast, apply a hydrological event definition to their Global Flood Inventory. Therefore, affected cities in the same catchment obtain the same event ID and the event start corresponds to the start date of the flood event.

Hydrometeorological event definitions are impractical since documenting flash flood and pluvial flood events in a hydrometeorological context requires prior analyses of convective cells and catchments. It is also not possible to add new flood events without first finding out whether the event already exists in the database and what the event ID is. However, when applying a damage-based definition, we can still aggregate the events hydrometeorologically. By using the stored catchment shapefiles or radar images and the event date, we can group flood events according to the meteorological or hydrological context.

The design of the database tables influences the later event analyses. To avoid restricting subsequent analyses, the database design should maintain the spatial accuracy of the event information. As soon as the event information is entered into the database in aggregated form, e.g., summarized for the municipality or rural district, distinct damage analyses for individual cities or catchments become impossible. We therefore advocate documenting event information at the city level with the possibility to further differentiate the affected districts by specifying the postcodes (for major cities) or the affected urban areas (for cities). In addition, inundated areas or affected houses can be specified by polygons and points (e.g., Gourley et al., 2017; Diakakis, 2014). However, preserving the spatial accuracy of event information requires a more complex database design as well as more effort for data preparation.

A complex event database, like the HiOS database, may not be required for every study. It is therefore advisable to weigh the effort for database creation against the study objectives. Setting up an event database for a few simple analyses is probably not worthwhile. However, an event database offers further advantages that should be considered, besides data management. For example, the database could be integrated into a website where researchers or interested parties can view and/or download event data (e.g., ESWD, Storm Events Database). Furthermore, people could report events via an online form, which are entered directly into the event database. To maintain quality standards, public reports would have to be reviewed and verified by trained personnel or experts. In this way, the ESWD, for example, enlarges its event dataset (Dotzek et al., 2009). In the future, methods of machine learning can help increase flood datasets. One possibility to do so is, for example, automatically extracting flood event information from online newspaper articles (cf. Yzaguirre et al., 2015; Zarei and Nik-Bakht, 2019) and subsequently updating the event database. However, a final quality control of the extracted event information by an expert would remain necessary.

3.6.2 Findings from spatiotemporal investigations

Our investigations show that heavy rain-induced flood occurrences are randomly distributed over Germany, which the recent findings of the German Weather Service (Lengfeld et al., 2019) on short-term heavy precipitation also show. The analysis of radar data from 16 years (2001–2016) revealed that short heavy precipitation events occur with a similar frequency and intensity throughout Germany (Lengfeld et al., 2019). Lengfeld et al. (2019) have proven that hourly precipitation is equally likely in both flat and mountainous areas, as short precipitation events appear to be hardly controlled by orography. Consequently, every German region can be affected by pluvial floods and flash floods triggered by heavy rain.

We cannot make statements about trends regarding the number of heavy rain-induced flood events in Germany. This is because we estimate the time series to be too short for a reliable trend analysis, as the HiOS dataset can only be considered comprehensive from 2000 onwards (Kaiser et al., 2020b). Nonetheless, the 10-year moving average of documented heavy rain-induced flood events per year has increased from 42 in 2000 to 555 in 2017. This increase in flood events may be attributed to increased press coverage of natural hazards (Llasat et al., 2009) as well as to the advent of the Internet (Wirtz et al., 2014), which facilitated the search for events and thus made more event information available. Furthermore, climate change could lead to an increase in heavy rain-induced floods, as a significant increase in heavy precipitation events is projected for Europe (Kovats et al., 2014). Concerning the development of deaths and injuries related to floods caused by heavy rain, our time series suggests neither a decrease nor an increase.

Floods triggered by heavy rain in Germany seem to occur more likely between noon and late afternoon, with a peak at 15:00 local time. For western U.S., Ahmadalipour and Moradkhani (2019) found a similar diurnal distribution with more flash flood events starting between 15:00 and 20:00 local time. With regard to the atmospheric processes, this diurnal distribution of heavy rain-induced flood events appears plausible, since convective precipitation in summer is often associated with thunderstorms. Thunderstorms usually form in the late afternoon or early evening, when warm, humid air near the ground has heated up due to strong solar radiation and is forced to rise into colder layers of air.

The most injurious and deadly flood events caused by heavy rain in Germany started around noon and late in the evening. Previous studies by Špitalar et al. (2014) and Terti et al. (2017) have proven an accumulation of injurious and fatal events in the evening.

Špitalar et al. (2014) examined 21,546 flash flood events in the U.S. from 2006 to 2012 and discovered that flash floods claimed most injuries and fatalities when they occurred in the late evening. Špitalar et al. (2014) observed that the most fatal events occurred at 21:00 local time. Terti et al. (2017) investigated 1,075 flash flood deaths in the U.S. from 1996 to 2014 and showed that 63 % of the deaths were related to vehicles. Their analysis revealed a peak in vehicle-related fatalities between 19:00 and 21:00 local time. Terti et al. (2017) assumed that people are often unwilling to leave their cars, e.g., when commuting to/from work, even when the streets are flooded. This assumption is supported by the fact that many of the victims in the study died trying to drive through the floodwaters (Terti et al., 2017). Špitalar et al. (2014) hypothesized that poor visibility in the twilight hours leads to more motorists driving into flooded roadways by accident. The unwillingness to leave the car and poor visibility seem to be plausible reasons for the high number of victims in the evening hours, also for Germany. However, it is unclear why there were also many victims in the midday hours in Germany. This could possibly have to do with the fact that at lunchtime many people are outdoors (e.g. end of shift, lunch break, end of school) and are thus outside of protective buildings. However, this remains speculation, as the circumstances of death are not recorded in our database. In addition, the beginning of the event and the time of death are not necessarily the same and can therefore be far apart.

Our investigation indicates a moderate correlation between the number of inhabitants and the number of flash floods and pluvial floods. This correlation is probably the reason why several studies use the population as one of several predictors to explain the spatial distribution of flash floods (Marjerison et al., 2016; Liu et al., 2018; Ma et al., 2019). Further studies have investigated the correlation between population density and flash flood impacts (Calianno et al., 2013) or have predicted flash flood human impacts using population density as one of the explanatory variables (Terti et al., 2019). Although we showed a relationship between heavy rain-induced flood events and population, we cannot say what constitutes this relationship. At the rural district level, we could not find a correlation between the number of heavy rain-induced floods and the sealing degree. In the study by Marjerison et al. (2016), however, the share of the impervious area was positively correlated with the number of flash flood reports in Binghamton, New York. Still, Marjerison et al. (2016) conclude that the relationship between population and soil sealing is not straightforward and that the sealing degree thus only partially explains the correlation with the population. As the relationship between flash floods and human activities is complex (Liu et al., 2018), further detailed analyses are needed to understand its nature.

Although short heavy precipitation events occur with a similar frequency and intensity in Germany (Lengfeld et al., 2019), we detected that some regions are more frequently affected than others. Therefore, the occurrence of hot and cold spots of heavy rain-induced floods evidences that catchments are susceptible to flash and pluvial flooding in different ways. If the catchment characteristics had no influence on the occurrence and magnitude of a flash flood, the regions would be affected about equally often. This seems plausible, since other studies have been able to predict the occurrence of flash floods using catchment properties (e.g., Bui et al., 2019a; Costache, 2019b; Marjerison et al., 2016; Ma et al., 2019; Janizadeh et al., 2019).
We identified a relatively good spatial correspondence between identified hot spots and human-impacting events. Still, injurious and fatal events also occurred in cold spots or statistically non-significant areas. In this regard, we must keep in mind that every injury and death is the result of unique circumstances and thus cannot be directly attributed to the location. Yet in regions with frequent heavy rain-induced flood occurrences, the probability of people being injured or killed increases. When investigating more than 20,000 flash flood events in the U.S., Špitalar et al. (2014) found that fatalities – and especially injuries – were more frequent in rural than urban areas. However, when human-impacting events occurred in urban regions, they caused more injuries and fatalities per event than in rural areas (Špitalar et al., 2014). To confirm these observations for Germany, more detailed analyses would have to be carried out.
Our study showed that there is a summer seasonality of floods caused by heavy rain for Germany, confirmed by the seasonality patterns evidenced in previous studies (Gaume et al., 2009; Kaiser et al., 2020a). Various studies confirm that the flash flood seasonality of Mediterranean and Inland Continental countries in Europe differ from each other. While the main flash flood season is autumn for Mediterranean countries (Gaume et al., 2009; Llasat et al., 2014; Tarolli et al., 2012; Papagiannaki et al., 2015), Inland Continental countries experience most flash flood events in the summer (Gaume et al., 2009; Kaiser et al., 2020a). England also has a pronounced summer seasonality (Archer et al., 2019) and is thus comparable with the seasonality of Central European countries such as Germany, Austria, Slovakia and Romania.
When interpreting the results of our investigations, we have to consider potential inherent biases in the HiOS dataset. One shortcoming of our event database might be a temporal bias, which leads to an increase in natural hazard events over time (Gall et al., 2009). According to Gall et al. (2009), this temporal upward trend can be attributed to the increase in population and prosperity, especially in high-risk areas, as well as progress in hazard monitoring and reporting. Kron et al. (2012) assume, however, that the tem-

poral bias of hazard reporting for Western Europe has not been too pronounced over the past 30 to 40 years. In addition, flood events that happened in densely populated areas might be overrepresented in the HiOS dataset (geography bias) (Gall et al., 2009). Finally, we must also bear in mind that in our analyses pluvial floods and flash floods, as well as different event magnitudes are considered together. This is largely because the event type or magnitude of most documented events, apart from well-documented catastrophic events, cannot be reliably determined by the given event information.

3.7 Conclusion

This paper illustrates how to design an effective event database suitable for flash flood research. Using the HiOS database, we exemplified the considerations and assumptions required to set up a relational database for investigations on heavy rain-induced floods in Germany. After defining the database's purpose and requirements, we described the system architecture with its front-end solutions. We further explained in detail the table design, attributes, and relationships of the HiOS database. We investigated the spatiotemporal occurrence of heavy rain-induced floods in Germany by creating necessary datasets using the database.
By providing details on the database design, we provided a starting point for those who wish to set up a similar event database. For scientific investigations, we need a flexible database structure supporting all targeted analyses. Reviewing our experiences, we can make the following recommendations for designing an effective flash flood event database:

(1) Choose a database management system that offers interfaces to a GIS software (e.g., ArcGIS Pro, QGIS), a programming language (e.g., Python, R), and a database management tool (e.g., pgAdmin). A system architecture with multiple front-end solutions offers the flexibility to use the software best suited for the investigation.

(2) Use a spatial database system to bundle all required information and data in one place: event information, geodata (e.g., DEM, soil, land use), measurements (e.g., discharge, precipitation), reference data (e.g., administration structure), hydrological information (e.g., catchments, rivers), metainformation (e.g., sources, quality estimation).

(3) Implement an event definition that allows the documentation of flood events without the need for prior hydrometeorological analyses. Avoid storing events aggregated by catchment or triggering precipitation event.

(4) Design database attributes in such a way that they enable differentiated event documentation. Implement attributes to allow for differentiation of flash flood impacts within cities, e.g., by specification of ZIP codes and city districts.

Furthermore, we investigated the documented flash flood and pluvial flood events using the HiOS database. We examined the occurrence of heavy rain-induced floods in Germany regarding spatial distribution and patterns, temporal evolution and seasonality. The main findings from the study are summarized as follows:

- Floods caused by heavy rain occur throughout Germany, both in flat and in mountainous terrain. However, there is a slight tendency toward the Northern German Plain experiencing less flash flood and pluvial flood events.

- Heavy rain-induced flood events occurred most frequently at 15:00 local time. Overall, the occurrence of heavy rain-induced floods is more likely between noon and late afternoon (14:00–18:00 local time) than at night or in the early morning. Most people died in heavy rain-induced floods that started around noon or 21:00 local time. Injuries were most common during floods with onsets between 18:00 and 19:00 local time. Commute and bad visibility during twilight are suspected to increase the injury and death rates in the late evening.

- There is a moderate positive correlation ($r = 0.62$) between the number of heavy rain-induced flood events and the number of inhabitants. In our study, the share of impervious area did not explain the correlation between heavy rain-induced flood events and population. Therefore, further analyses investigating the complex relationship between heavy rain-induced floods and human activity should consider other factors, such as the number of culverts, the degree of river obstruction, land use and topographic features.

- The flash flood frequency shows a clustered pattern over Germany. We identified seven hot spots, four attributed to mostly metropolitan areas and three to the less populated, mountainous regions. The Northwestern German Plain and North-Central Bavaria are cold spots with particularly few flash flood and pluvial flood events.

- There is an increased incidence of injuries and fatalities in identified hot spots. Injurious and fatal flash flood and pluvial flood events were less frequent in the Northern German Plain and Central Bavaria, where cold spots were identified.
- Flash floods and pluvial floods occur in Germany mainly between April and October, with summer being the predominant season. Autumn and winter events hardly occur. There is a tendency towards more summer events in Northeastern Germany, while Central-Germany has a more pronounced spring season.

We benefit from our findings with regard to flood risk management and public relations. Now that flood hot spots have been identified, we can prioritize detailed investigations and adapt local flood risk management. Knowledge of the diurnal and seasonal occurrence of heavy rain-induced floods and high-risk areas is valuable information to improve risk assessment and decision-making. In addition, the knowledge gained about heavy rain-induced flood occurrences in Germany helps to describe the characteristics of the natural hazard to the public.

This paper demonstrates that event databases are essential scientific tools that help to advance our understanding of flood hazards from heavy precipitation. By ensuring the usability and quality of event data, databases are valuable instruments for various applications in flash flood research, such as damage modeling, risk assessment, socio-economic analyses, or climate change studies. Due to climate change and the associated need to better understand flash flood hazards, the importance of event databases will continue to increase.

To enable concrete prevention measures derived with the help of the event database, we have to carry out site-specific analyses of factors promoting and triggering flash floods and pluvial floods. These analyses must link catchment characteristics, topography, soil properties, and land use with the occurrence of flash and pluvial floods to evaluate the influence of the area properties. The result of this regional risk assessment could be presented in a map indicating the flood hazards from heavy precipitation, as planned for the state of Bavaria within the HiOS project.

4 Predicting pluvial and flash flood susceptible areas in the state of Bavaria (Germany) using tree-based classifiers

This chapter is submitted as:

Kaiser, M., Günnemann, S., Disse, M., 2021. Predicting pluvial and flash flood susceptible areas in the state of Bavaria (Germany) using tree-based classifiers. Submitted to *Journal of Hydrology* (under review).

Abstract Flood events triggered by heavy rain, such as pluvial and flash floods, are a common threat in the state of Bavaria (Germany). However, it is unknown which areas and cities in Bavaria are particularly vulnerable to flooding caused by heavy rain. To improve flood risk management, we aimed at identifying susceptible areas within the state territory (70,500 km^2) using machine learning models. To this end, we trained a Random Forest (RF), a Gradient Boosting Decision Tree (GBDT), and a CatBoost model (CB) using 1,864 flood and non-flood locations and 11 spatially distributed and six catchment-related influencing factors. Regarding performance metrics, all three models performed equally well (CB: AUC = 0.819, RF: AUC = 0.816, GBDT: AUC = 0.813), with the CatBoost model performing best. Although we had only three sample points per 100 km^2, we achieved good model performance. This is because we have ensured homogeneous spatial coverage of Bavaria and representation of the four major landscapes in the training and testing set. We found that the particularly vulnerable regions are located in southeastern Bavaria (Alpine foothills, Munich and its surroundings, the southern part of the eastern low mountain range) and northern Bavaria (metropolitan area of Nuremberg, Würzburg and its surroundings, along the Main River). Based on the pluvial and flash flood susceptibility assessment, we calculated an overall susceptibil-

ity score for the Bavarian cities, which evidences that 16 % of the Bavarian cities are at high risk. Those responsible for spatial planning and flood risk management can use the susceptibility map generated to identify pluvial and flash flood-prone areas in Bavaria.

4.1 Introduction

Since flash floods pose a deadly threat to humans, researchers are looking for ways to improve flash flood forecasting and warning. Yet protecting against the natural hazard is challenging as flash floods are difficult to predict and can occur anywhere. Nonetheless, researchers have succeeded in establishing early warning systems using weather radar, hydrologic and hydrodynamic models, and drainage network monitoring (e.g., J. A. Smith et al., 2007; Javelle et al., 2010; Looper and Vieux, 2012; Bartos et al., 2018; Hofmann and Schüttrumpf, 2020). For warning purposes, researchers identify flash flood-prone areas using various modeling techniques, such as GIS, hydrodynamic models, or data-driven models (e.g., Iosub et al., 2020; Nguyen et al., 2020; Li et al., 2019)

For several years, researchers have increasingly used machine learning (ML) models instead of hydrodynamic or physical models in flood modeling. According to Mosavi et al. (2018), the increasing popularity is because ML models can describe the flood events' nonlinearity based on historical data alone, without having to consider physical processes. In addition, ML models are less costly and faster to set up than hydrodynamic models. Meanwhile, researchers have successfully derived flood and flash flood susceptibility maps using ML models (e.g., Bui et al., 2019a; Chen et al., 2019; Tien Bui et al., 2020). The ML algorithms applied in (flash) flood susceptibility modeling are diverse: logistic regression (e.g., Costache, 2019a), decision trees (e.g., Costache and Tien Bui, 2019), support vector machines (e.g., Tehrany et al., 2014), Naïve Bayes (e.g., Khosravi et al., 2019), ensemble methods (e.g., Bui et al., 2019b), artificial neural networks (e.g., Ngo et al., 2018). To further improve prediction performance, researchers have hybridized ML algorithms with bivariate models (e.g., Frequency Ratio, Weights-of-Evidence, Shannon's Entropy), multi-criteria decision methods, or GIS techniques (e.g., Wang et al., 2019; Khosravi et al., 2016; Costache et al., 2020c)

The state of Bavaria (Germany) has been affected by heavy rain-induced floods in the past, yet it is not known which areas are prone to pluvial and flash flooding. In the recent past, the year 2016 stands out with 410 documented pluvial and flash flood events (Kaiser et al., 2020b). Most of these heavy rain-induced flood events occurred in May and June, claiming seven lives and causing €1.25 billion in damage in the most affected

district (LfU, 2017e). To better assess pluvial and flash flood hazards, it is necessary to generate a susceptibility map for Bavaria, which provides information on areas at risk.
To identify endangered regions in Bavaria, we need to derive a susceptibility map for pluvial and flash floods using a modeling technique that is affordable, quick, and can process a large study area. In this paper, we illustrate how to generate a pluvial and flash flood susceptibility map for the state of Bavaria using tree-based ensemble models and appropriate explanatory factors. First, we review the influencing factors applied in flash flood susceptibility studies (Section 4.2). This is followed by a description of the study area (Section 4.3). We then introduce the datasets and methods used (Section 4.4) and present the study results (Section 4.5). Finally, we discuss our findings from susceptibility map generation for a state using tree-based algorithms (Section 4.6) and provide concluding remarks (Section 4.7).

4.2 Influencing factors on flash flood occurrence

To set up a good predictive model, it is crucial to choose robust explanatory features. Several studies have proven that it is possible to predict whether a location was affected by a flash flood in the past based on area characteristics (Bui et al., 2019a; Nguyen et al., 2020; Pham et al., 2020a). To find out the most frequently applied explanatory features, we compared 23 recent studies on flash flood modeling that applied machine learning algorithms. For direct comparison, we listed the explanatory features used in each of these studies in Table 4.1. We summarized the influencing factors in the categories of topography, soil and geology, land cover, river network, precipitation characteristics, and anthropogenic factors.
In the studies examined, the number and type of influencing factors applied varied. We identified a total of 37 different influencing factors, 12 of which were topography-related. The explanatory factors applied cover a broad spectrum and range from elevation and soil type through the fraction of vegetation cover and river density to the sealing degree. The studies reviewed used between 6 and 15 influencing factors for flash flood modeling, with 10 factors representing the median.
Topographic parameters were the most frequently used explanatory factors in these studies (Table 4.1). The studies examined applied between 2 and 7 topographic parameters (5 parameters on average). The slope, as the only explanatory factor, was used by each of the 23 studies reviewed. Other frequently considered topographic parameters were aspect, elevation, and the Topographic Wetness Index (TWI), which were applied in 16, 15, and 14 studies, respectively.

We attributed five explanatory factors to the category land cover, namely Normalized Difference Vegetation Index (NDVI), fraction of vegetation cover, land use, curve number (a combination of soil type and land use), and surface roughness. Usually, one of these five land cover parameters was used to explain the flash flood occurrence. In 61 % of the studies, the explanatory factor land use was chosen, which makes it the fifth most frequently used parameter besides TWI.
In the studies investigated, six parameters were used to describe the characteristics of the river network. Most often the parameter river density was applied, followed by the distance to the river and the convergence index. The flow direction, in contrast, was only considered in the study by Pham et al. (2020b). In three studies, a maximum of three river network parameters was considered simultaneously, while the study by Tang et al. (2019) completely disregarded parameters of the river network in its modeling.
Precipitation characteristics and anthropogenic factors were used far less often as explanatory factors compared to the other categories. Only 61 % of the studies used precipitation information to explain flash flood occurrence, and only three studies considered anthropogenic factors. We counted population, sealing degree, gross domestic product, and flash flood prevention investments among the anthropogenic factors. The studies, in which precipitation was considered, generally used information on the mean annual precipitation for different durations and the rainfall amount of a defined interval, in most cases the event.
According to our literature review, it is at least necessary to describe an area's topography, lithology, land use, and river network to explain the occurrence of flash flooding with an ML model. Since topography has a significant influence on the occurrence of a flash flood, the topography of an area must be comprehensively described by several parameters (e.g., slope, aspect, elevation, TWI) in the ML model. The comparison of the studies also suggests that lithology is an essential parameter in explaining flash flooding, often used in combination with soil type or hydrological soil group. The characteristics of the river network should also be considered in the ML model (e.g., via river density, distance to the river, convergence index), although no river network parameter, such as slope or lithology, has prevailed in previous studies. However, how well the chosen parameters can explain flash flood occurrence depends not least on the combination of parameters, the quality of the underlying datasets, and the characteristics of the study area.
The investigated studies were carried out in six different countries: Vietnam (Bui et al., 2019b; Ngo et al., 2018; Nguyen et al., 2020; Pham et al., 2020b; Tien Bui et al., 2019; Tien Bui et al., 2020), Romania (Costache and Tien Bui, 2020; Costache,

2019a; Costache, 2019b; Costache and Zaharia, 2017; Costache et al., 2019; Costache et al., 2020a; Costache et al., 2020b; Costache et al., 2020c), Iran (Hosseini et al., 2020; Janizadeh et al., 2019; Khosravi et al., 2016; Chapi et al., 2017; Pham et al., 2020a; Khosravi et al., 2018), China (Tang et al., 2019; Ma et al., 2019; Chen et al., 2019), Saudi Arabia (Youssef et al., 2016), and Greece (Diakakis et al., 2016). Of the 23 studies, 9 studies were performed in Europe and 14 at study sites in Asia. Although the studies cover different climate zones, there is no discernible difference in the choice of the influencing factors based on the site location. However, the influencing factors may have had different feature importances in the models of the different regions, which we have not examined.

Table 4.1: Influencing factors used in various studies on flash flood susceptibility.

	Bui et al., 2019a	Costache and Tien Bui, 2020	Costache and Zaharia, 2017	Costache et al., 2019	Costache et al., 2020a	Costache et al., 2020b	Costache et al., 2020c	Costache, 2019a	Costache, 2019b	Diakakis et al., 2016	Hosseini et al., 2020	Janizadeh et al., 2019	Khosravi et al., 2016	Khosravi et al., 2018	Ma et al., 2019	Ngo et al., 2018	Nguyen et al., 2020	Pham et al., 2020a	Pham et al., 2020b	Tang et al., 2019	Tien Bui et al., 2019	Tien Bui et al., 2020	Youssef et al., 2016
Topography																							
Aspect	x	x	x	x		x	x	x	x		x	x				x	x	x	x		x	x	
Circularity ratio									x														
Curvature	x													x		x	x		x		x	x	x
Elevation	x									x	x	x	x	x	x	x	x	x	x	x	x	x	x
L-S factor			x		x											x							
Plan curvature		x		x		x	x	x	x				x			x							
Profile curvature		x	x	x	x	x	x	x	x														
Slope	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Topographic Position Index		x		x	x	x	x	x	x		x												
Topographic Roughness Index											x												
Topographic Wetness Index	x			x	x	x	x	x	x		x		x	x	x	x	x				x		
Toposhade	x															x					x		
Soil & geology																							
Hydrological soil group		x	x	x	x	x		x															
Lithology	x		x	x	x	x	x	x	x		x	x	x	x		x	x	x	x		x	x	x
Soil depth											x												
Soil moisture															x								
Soil type	x										x	x				x	x	x	x		x	x	x
Soil water capacity/retention																				x			
Land cover																							
Curve number	x						x		x						x								
Fraction of vegetation cover															x					x			

Table 4.1: *Continued.*

	Bui et al., 2019a	Costache and Tien Bui, 2020	Costache and Zaharia, 2017	Costache et al., 2019	Costache et al., 2020a	Costache et al., 2020b	Costache et al., 2020c	Costache, 2019a	Costache, 2019b	Diakakis et al., 2016	Hosseini et al., 2020	Janizadeh et al., 2019	Khosravi et al., 2016	Khosravi et al., 2018	Ma et al., 2019	Ngo et al., 2018	Nguyen et al., 2020	Pham et al., 2020a	Pham et al., 2020b	Tang et al., 2019	Tien Bui et al., 2019	Tien Bui et al., 2020	Youssef et al., 2016
Land use		x	x	x	x	x		x			x	x	x	x			x	x	x				x
Normalized Difference Vegetation Index	x										x		x	x		x					x	x	
Surface roughness																				x			
River network																							
Convergence index		x	x	x	x	x	x	x	x														
Distance to river										x	x	x	x	x				x	x				x
Flow accumulation/contributing area									x	x	x												
Flow direction																			x				
River density	x		x								x			x	x	x	x		x		x	x	
Stream power index	x				x								x	x		x					x		
Precipitation characteristics																							
Max. precipitation intensity of diff. durations										x					x								
Mean annual precipitation of diff. durations												x	x	x	x		x	x					
Modified Fournier index							x		x														
Precipitation amount (of event)	x									x	x					x					x	x	
Anthropogenic factors																							
Gross domestic product															x								
Population															x								
Prevention investments															x								
Sealing degree										x										x			
Number of influencing factors	12	8	9	10	10	10	10	10	12	7	15	8	10	11	12	12	10	8	10	6	12	9	7

4.3 Description of the study area

The state of Bavaria is located in southern Germany. With an area of 70,542 km^2, Bavaria is the largest state among the 16 German states. Bavaria has the second most inhabitants of all the federal states with 13.12 million inhabitants (Destatis, 2020a). The capital Munich is the largest metropolitan area in the Bavarian state. Another metropolitan region is found around the city of Nuremberg in Northern Bavaria. Bavaria has 2,056 municipalities, including 317 cities (Destatis, 2020b).

Bavaria can be divided into four major landscapes: the Alps, the Alpine foothills, the eastern and south-western low mountain range (Fig. 4.2). The Alps in southern Bavaria are the smallest major landscape regarding area. The Bavarian Alps are characterized by high mountains with heights between 1,500 and almost 3,000 m. The Alpine foothills (elevation range 300–800 m) describe the region north of the Alps and south of the Danube, which is characterized by glacial deposits. South of the Danube, there is fertile hilly country to which an area with numerous lakes connects further in the south. The eastern low mountain range is located in the northeast of Bavaria and the south-western low mountain range is found in north-west Bavaria. The low mountain ranges are mountainous areas with rounded, wooded ridges and elongated valleys.

Bavaria is characterized by a warm-moderate climate, as it is located in the transition zone between the maritime climate of Western Europe and the continental climate of Eastern Europe. Bavaria's climate is influenced by the different altitudes and the structure of the low mountain ranges, the Alpine foothills, and the Bavarian Alps (StMUV, 2015). The altitudes range from 100 m, in the northwestern part of Bavaria, to nearly 3,000 m in the Alps.

Differences between the seasons are clear but not extreme in Bavaria. In the period 1971–2000, the annual average temperature in Bavaria was 7.8 °C. The average summer temperature in Bavaria was 16.2 °C, the average winter temperature 0.5 °C. In the reference period 1971–2000, July was the warmest month, and January the coldest. Due to the altitude dependence, however, the annual average temperatures vary greatly over Bavaria (StMUV, 2015).

The average annual precipitation amount in Bavaria is 945 mm, but regional differences are large. The highest average annual precipitation amount with 1,800 mm are recorded in the Alpine region. With an average of 600 to 700 mm per year, it rains the least in central and northwest Bavaria. High rainfall amounts are common for the low mountain ranges, the Alpine foothills, and the Alps. With 111 mm on average, July is the month with the most precipitation, whereas February is the month with the fewest precipitation (56 mm) (StMUV, 2015). Overall, the warmer, dry Northwest contrasts the precipitation-rich regions of the south and east of Bavaria. The pluvial and flash flood season in Germany is summer, with July being the month with the most events. The state of Bavaria also experiences heavy rain-induced flood events in spring. With 59 recorded events until 2017, Munich was the second most affected city after Berlin (65) (Kaiser et al., 2021).

Bavaria is a water-rich state with about 100,000 km of flowing waters. Large waters of national importance account for 4,200 km, another 4,800 km are waters of regional importance (LfU, 2017d). About 91,000 km are small waters that considerably influence the formation of flash floods. A main European water divide runs through Bavaria, separating the Danube, Rhine, and Elbe River basins. The Danube is Bavaria's largest river, which is characterized by its water-rich tributaries originating from the Alps and the Bavarian Forest in the eastern low mountain range (StMUV, 2012). The Danube drains most of Bavaria from the south, while the Main drains the north-west of Bavaria.

Agriculture and forestry are an important economic sector in Bavaria. More than half of the state area (53.4 %) is used for agriculture, 65 % of which is arable land and 35 % is grassland (BBV, 2020). Forests and near-natural areas account for 37.9 % and are mainly found in the alpine region and the low mountain ranges in east and south-western Bavaria. Wetland and water bodies sum up to 1.2 % of the area. The built-up area makes up 7.5 % of the state territory. In 2015, the degree of soil sealing in Bavarian municipalities was between 27 and 75 %. In relation to Bavaria's total settlement and traffic area, the proportion of sealed surfaces amounts to 50.9 % (Üreyen and Thiel, 2017).

Based on their runoff potential, the Bavarian soils can be divided into the four hydrological soil groups A, B, C, and D. The hydrological soil group A, which corresponds to sand, loamy sand, or sandy loam types of soils, occurs on 13 % of the Bavarian area. The hydrological soil groups B (silt loam or loam) and C (sandy clay loam) have an area share of 14 and 49 %, respectively. The hydrological soil group D, which are soils of clay loam, silty clay loam, sandy clay, silty clay or clay, covers 24 % of Bavaria. The soils of group D are characterized by very low infiltration rates and thus favor the generation of surface runoff. These soils with high runoff potential are mainly found in the alpine region and the south-western low mountain ranges. Overall, the soils with low and very low infiltration rates (C and D) account for 73 % of the total area.

To sum up, the study area has a large extent and includes a variety of different natural landscapes. Bavaria combines a great diversity regarding land use, soil, vegetation, morphometry, and climatic conditions. Therefore, low mountain ranges and cultural

landscapes stand for Bavaria as much as large forests, a multitude of rivers and lakes, and the Alpine region.
However, the large natural heterogeneity of Bavaria poses a challenge for the ML model. To achieve high model performance, the selected explanatory factors must comprehensively describe the different characteristics of the four major landscapes. In addition, a sufficient amount of training data in the different major landscapes is necessary to learn the relationships in a sound way.

4.4 Data and methods

4.4.1 Methodical approach

For the generation of the pluvial and flash flood susceptibility map of Bavaria, we followed the steps shown in Fig. 4.1. The overall workflow consists of the following steps: (i) feature selection based on literature review, multicollinearity analysis, and feature importance, (ii) feature preparation including handling of missing data, standardization, and Weight-of-Evidence encoding, (iii) construction of the training and test datasets, (iv) model training and validation using performance statistics, (v) final model selection, and (vi) generation of the pluvial and flash flood susceptibility map. In the following sections we describe each step in detail.

4.4.2 Flood inventory, training and test dataset

The derivation of the flash flood susceptibility for a given area using machine learning models requires the knowledge of formerly affected and unaffected locations. Based on the affected and unaffected locations, the model learns which area characteristics and conditions favor the occurrence of flash floods. In this study, we use the pluvial and flash flood dataset generated within the framework of the HiOS project. Kaiser et al. (2020b) created a dataset of past German pluvial and flash flood events triggered by heavy rain using a variety of sources ranging from agencies over mission archives and insurance companies to media reports. According to this dataset, 932 Bavarian settlements and cities were affected by one or more pluvial and flash flood events by 2017.
To prevent introducing bias into the model, we chose the same number of unaffected locations as affected locations. We randomly selected 932 locations from the remaining Bavarian towns, assuming that we know all affected locations and that the remaining locations have therefore not been affected. To ensure the representativeness of the major

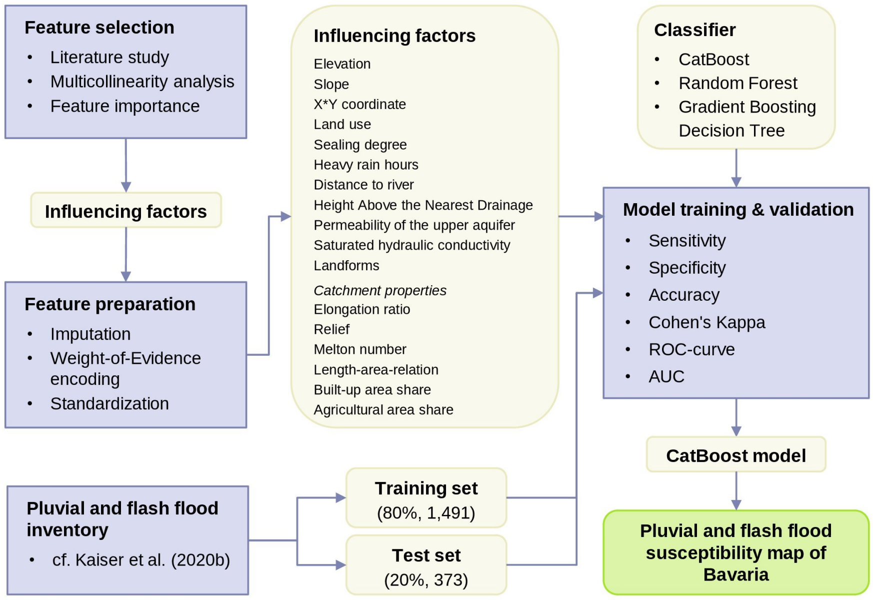

Figure 4.1: Flow chart of the methodical approach.

landscapes, we selected as many unaffected locations in each major landscape as affected locations were known.

Subsequently, we split the generated pluvial and flash flood dataset of 1,864 samples into a training and test dataset. For the training dataset, we randomly selected 80 % of the dataset. The remaining 20 % of the dataset was used as a test dataset (Fig. 4.2). Since this is a binary classification problem, the values "1" and "0" were assigned to the flood and non-flood samples, respectively. At each sample point, we also extracted the values of the influencing factors. We calculated the catchment-related factors for 12,964 catchments whose average size was 5 km^2 and their median size was 2 km^2. Since flash floods mainly occur in small catchments, we chose a catchment scale that can finely represent the catchment characteristics of Bavaria.

4.4.3 Chosen influencing factors

Based on the literature study and data availability, we preselected possible influencing factors. We then used multicollinearity analysis and the classifiers' feature importance to gradually reduce the over 30 influencing factors to 17. Although tree-based models are insensitive to collinear predictors, we reduced the number of influencing factors as

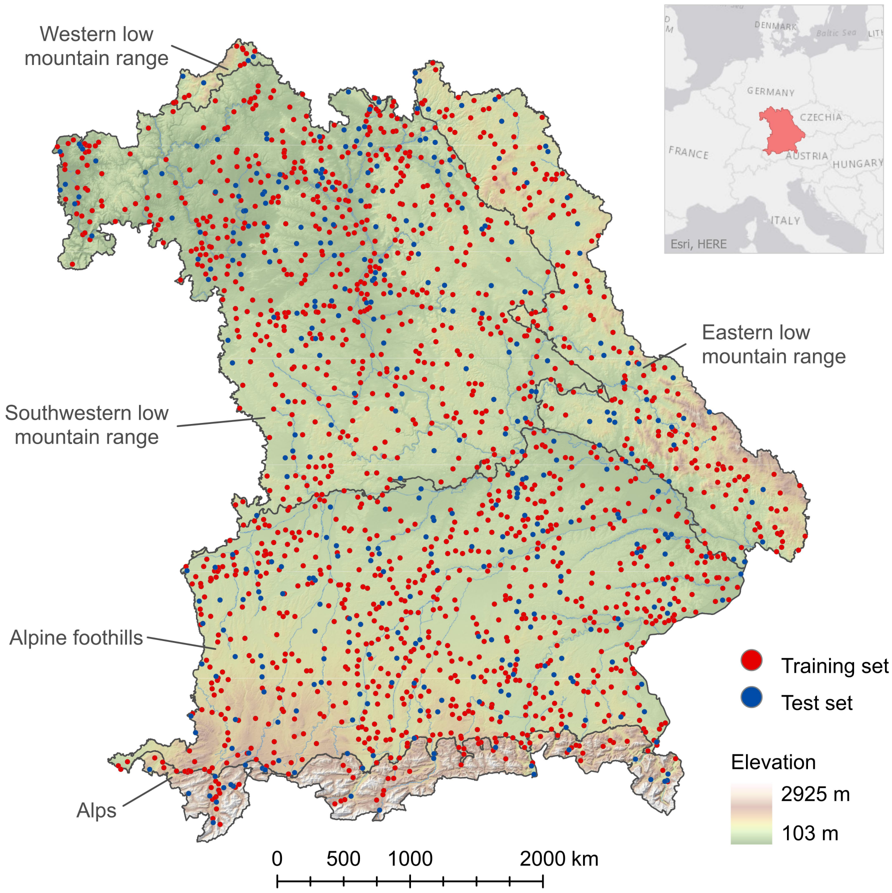

Figure 4.2: The study area, the state of Bavaria (Germany), with the training and test locations.

much as possible. We aimed at reducing the model complexity to make them easier to understand. To ensure the acceptance of the flash flood susceptibility map, it is important to use models that are as simple and comprehensible as possible.

We applied the indicators variance inflation factor (VIF) and tolerance (TOL) to evaluate collinearity among the predictors. In the literature, VIF > 10 and TOL < 0.1 are often considered as thresholds for the presence of multicollinearity (Dormann et al., 2013). Table 4.2 shows that all 17 selected influencing factors except the product of the X- and Y-coordinate meet these thresholds. However, we do not consider this to be a problem, since on the one hand tree-based classifiers are tolerant of multicollinearity and on the other hand the high VIF was caused by the inclusion of products of two

Table 4.2: Multicollinearity analysis of the flash flood influencing factors. The (c) indicates catchment-related influencing factors.

Factor	Variance inflation factor	Tolerance
X*Y coordinate	12.170	0.082
Relief (c)	4.229	0.236
Melton number (c)	3.759	0.266
Heavy rain hours	2.034	0.492
Length-area-relation (c)	1.990	0.503
Elevation	1.806	0.554
Distance to river	1.756	0.569
Height above the nearest drainage	1.686	0.593
Built-up area share (c)	1.661	0.602
Agricultural area share (c)	1.500	0.667
Sealing degree	1.292	0.774
Slope	1.215	0.823
Land use	1.212	0.825
Permeability of upper aquifer	1.157	0.864
Landforms	1.053	0.950
Saturated hydraulic conductivity	1.023	0.978
Elongation ratio (c)	0.872	1.147

variables. Furthermore, the predictor X*Y coordinate is a combined predictor that implicitly considers two predictors simultaneously and thus adding value to the model. Using multicollinearity analysis and feature importance, we gradually reduced the number of influencing factors to 17. While reducing the input features, we took care to retain explanatory variables from all domains that can explain the occurrence of pluvial and flash floods. Thus, we retained features describing topography, land use, soil and geology, river network, heavy precipitation, and catchment properties. Overall, we selected the following influencing factors: elevation, slope, landforms, land use, sealing degree, distance to river, height above the nearest drainage, the permeability of the upper aquifer, saturated hydraulic conductivity, the product of X- and Y-coordinates, heavy rain hours, and the catchment-related variables relief, Melton number, elongation ratio, length-area-relation, built-up area share, and agricultural area share. Table 4.3 lists the sources, resolution and original format of the datasets used to derive the influencing factors. For the study, we converted the influencing factors into raster of 25 m.

Table 4.3: Sources and resolutions of the datasets used.

Derived factor	Name of input data and official abbreviation	Scale / resolution	Original format	Data source / reference
Built-up share	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Agricultural share	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Melton number	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Relief	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Elongation ratio	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Length-area-relation	Catchments (EZG25)	1:25,000	Vector	LfU, 2014a
Landforms	Digital Elevation Model (DEM)	25 m	Raster	BVV, 2017
Slope	Digital Elevation Model (DEM)	25 m	Raster	BVV, 2017
Elevation	Digital Elevation Model (DEM)	25 m	Raster	BVV, 2017
X*Y coordinate	Digital Elevation Model (DEM)	25 m	Raster	BVV, 2017
Land use	CORINE Land Cover 5 ha (CLC5)	5 ha	Vector	BKG, 2020
Sealing degree	Imperviousness density 2015 (IMD)	100 m	Raster	Copernicus, 2018
Saturated hydraulic conductivity	Soil map (ÜBK25)	1:25,000	Vector	LfU, 2017c
Permeability of the upper aquifer	Hydrogeological Map (HÜK 200)	1:200,000	Vector	BGR and SGD, 2016
Distance to river	River network (FGN25)	1:25,000	Vector	LfU, 2014b
Height above the nearest drainage	River network (FGN25)	1:25,000	Vector	LfU, 2014b
Heavy rain hours	Heavy rain hours since 2001 per zip code area	Zip code area	Vector	GDV and DWD, 2018
Pluvial and flash flood inventory	Settlements and cities affected by pluvial and flash floods in Germany until 2017		Point	LfU, 2017b; HANG, 2018; ESWD, 2017; Deutsche Rück, 2018a; Deutsche Rück, 2018b; DWD, 2018; THW, 2017; URBAS, 2018

Topography controls the hydrological processes of an area to a large extent. Researchers consider the slope to be the most important factor influencing the occurrence of flash floods (Tehrany et al., 2013; Vaezi et al., 2017; Diakakis et al., 2016). The higher the slope, the less the soil infiltration and the higher the surface runoff. While high slopes promote runoff concentration, flat areas favor flooding. In addition to slope, elevation is a good explanatory factor for flash flooding. Since water follows the gradient, the lower-lying areas of a catchment tend to be more often affected by flooding than the higher-lying areas (Tehrany et al., 2015; Chapi et al., 2017). For our study, we derived the slope and elevation using the 25 m digital elevation model (DEM) using ArcGIS Pro (Fig. 4.3).

To assess inundation areas, evaluating the overall topographic setting is crucial since the surface shape influences the flow accumulation (MacMillan and Shary, 2009). The division into landforms offers the possibility of a quantitative classification into different landscapes. Landform types can be determined by the characteristic terrain pattern, which manifests through variation of the geomorphic features in shape, size, and scale (MacMillan and Shary, 2009). We applied the approach by Weiss (2001), in which landforms are differentiated based on discrete slope position classes using the standard deviation of the Topographic Position Index (TPI). To determine the TPI, the elevation of each cell of a DEM is compared to the mean elevations in the predefined vicinity of the cell (Weiss, 2001). Weiss (2001) distinguishes 10 landform types: canyons, midslope drainages, upland drainages, u-shape valleys, plains, open slopes, upper slopes, local ridges, midslope ridges, and mountain tops. We derived the landforms using the ArcGIS topography toolbox by Dilts (2015) (Fig. 4.4).

Land use influences the formation of runoff. Depending on the type of land use, the nature of the topsoil changes and with it the infiltration capacity and surface roughness (e.g., Chandler et al., 2018; Sofia et al., 2019). Studies have shown that forests reduce the runoff volume and lower the peak discharge (e.g., Hundecha and Bárdossy, 2004; Hümann et al., 2011), while urbanization leads to an increase in peak flows (e.g., Miller and Hess, 2017; Pumo et al., 2017). Niehoff et al. (2002) have further proven that the impact of land use on the runoff generation depends on the precipitation characteristics. Accordingly, the influence of land use on storm runoff generation is greater for convective storm events than for advective ones (Niehoff et al., 2002; Bronstert et al., 2002). For the influencing factor land use, the CORINE Land Cover dataset served as the data basis, which was aggregated to the following classes: built-up area, agricultural area, forests and near-natural areas, wetlands, water surfaces (Fig. 4.3).

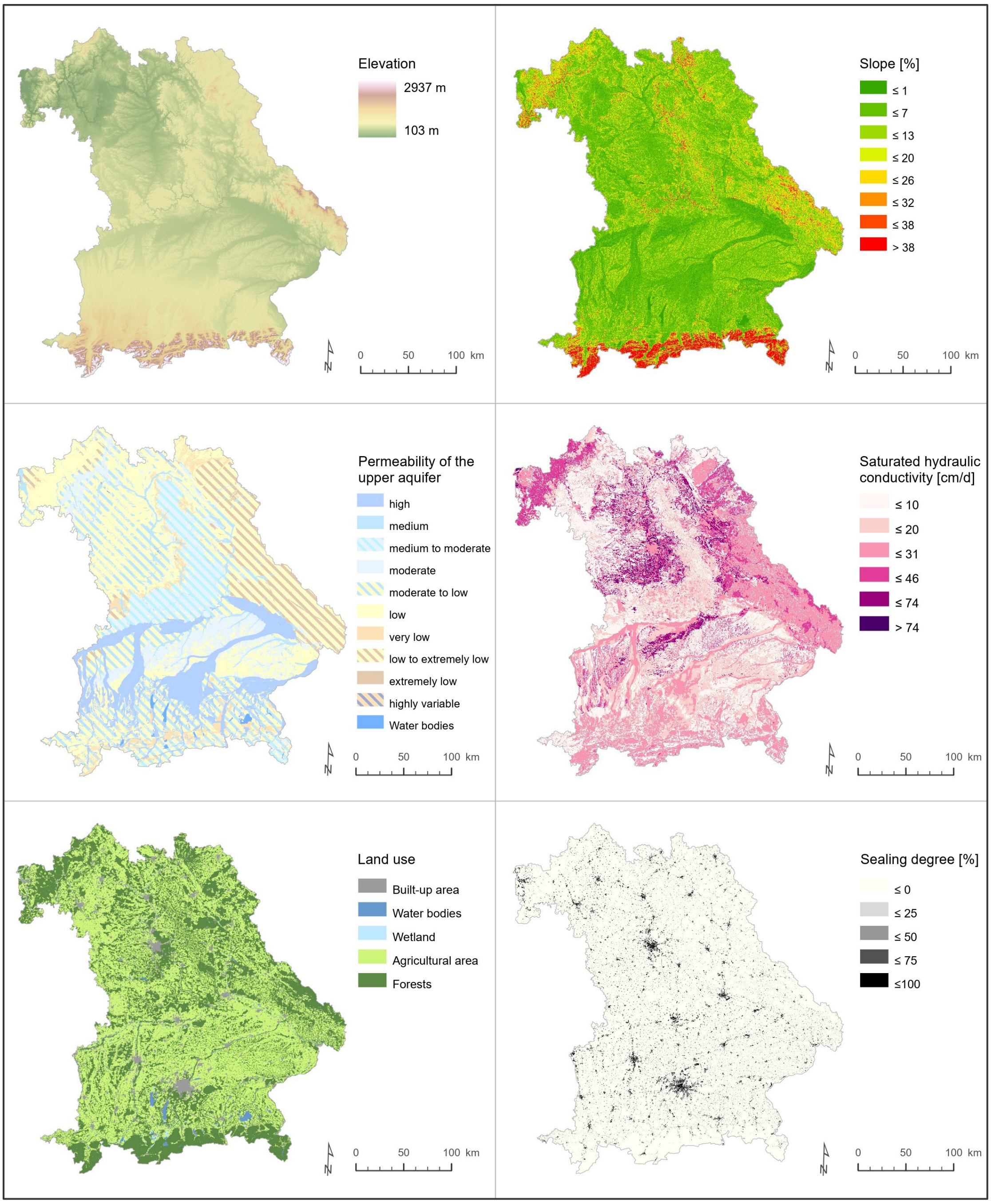

Figure 4.3: Pluvial and flash flood influencing factors: elevation, slope, permeability of the upper aquifer, saturated hydraulic conductivity of the topsoil, land use, sealing degree.

As a supplement to land use, we also considered the sealing degree in our models. Because the higher the degree of sealing, the less water can infiltrate and the more surface runoff forms. Diakakis et al. (2016) found that the sealing degree and the slope were the most important factors in explaining flash flooding in Athens (Greece). For our models, we used the dataset of imperviousness density from Copernicus (2018), which gives the percentage of soil sealing for each pixel (Fig. 4.3).
The porosity and permeability of the soils and rocks are decisive for the infiltration performance, since the soil texture influences the hydraulic conductivity. To account for the influence of the soil, we incorporated the saturated hydraulic conductivity of the topsoil in the models. In Bavaria, the saturated hydraulic conductivity varies between 0 and 156 cm/d and averages 20 cm/d (Fig. 4.3). Regarding lithology, we considered the permeability of the upper aquifer in our models. The hydrogeological map by BGR and SGD (2016) divides the upper aquifers of Bavaria into 10 permeability classes ranging from high (10^{-2} – 10^{-3} m/s) to extremely low ($< 10^{-9}$ m/s)(Fig. 4.3).
The distance to a river is a good proxy of the probability of being affected by a flash flood and is thus a frequently chosen explanatory factor (Janizadeh et al., 2019; Hosseini et al., 2020; Khosravi et al., 2018). Because regions near streams are more likely affected by flooding than regions far away from any river. However, regions remote from streams can also be flooded by concentrated surface runoff. We calculated the distance to the nearest stream using the “Euclidean Distance” tool of ArcGIS Pro and the official river network of Bavaria (Fig. 4.4).
In addition to the distance to a river, we considered the metric Height Above the Nearest Drainage (HAND). The HAND value returns the “hydrologic” height by calculating the height of each catchment cell above the nearest river into which it flows (Nobre et al., 2011). In summary, the HAND value normalizes the terrain heights with regard to the river network. The HAND value is often used to map susceptibility to flooding and gully erosion (Arabameri et al., 2020; Carvalho et al., 2020; Olorunfemi et al., 2020; Garousi–Nejad et al., 2019). All in all, the HAND value is a valuable predictor for susceptibility to flash flooding that supplements the feature distance to a river. We derived the HAND metric using the ArcGIS toolbox by Dilts (2015), the DEM and the official river network of Bavaria (Fig. 4.4).
Heavy rain is the trigger of a flash flood and is therefore an important influencing factor (Hapuarachchi et al., 2011). Generally, short and high-intensity rains are associated with the occurrence of flash floods (Gaume et al., 2009; Borga et al., 2011). Lengfeld et al. (2019) have shown based on radar measurements of 16 years that hourly precipitation events in Germany are significantly less influenced by the orography than daily precip-

itation events. To incorporate the rainfall in our models, we used the dataset heavy rain hours from GDV and DWD (2018) (Fig. 4.4). This dataset sums up all hours of heavy rain that occurred in Germany since 2001 per zip code area. To qualify as heavy rain, the rain event had to exceed 25 l/m^2 in 1 h or 35 l/m^2 in 6 h (GDV and DWD, 2018).

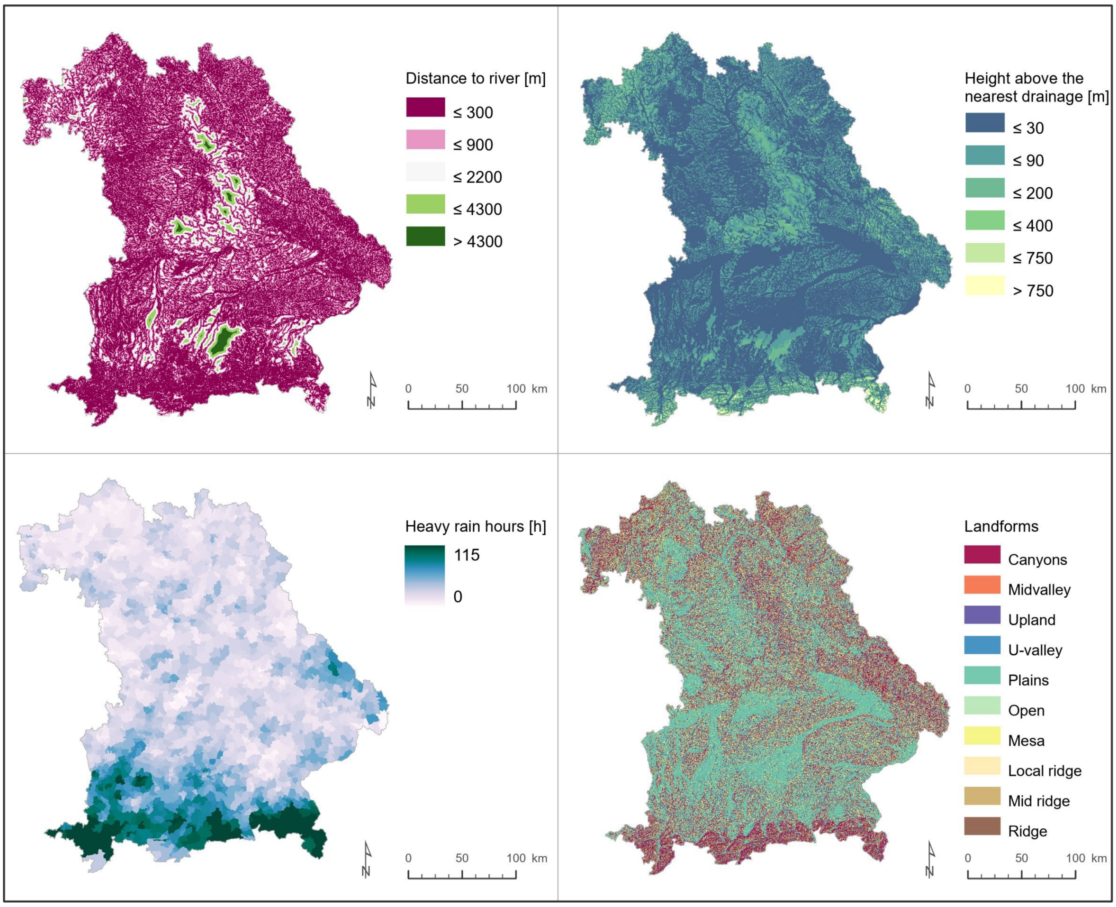

Figure 4.4: Pluvial and flash flood influencing factors: distance to river, height above the nearest drainage, heavy rain hours, landforms.

Since there is a relationship between the catchment geomorphology and its hydrologic response (Costa, 1987; Harlin, 1984; Patnaik et al., 2015), it is crucial to consider catchment properties as influencing factors. We thus incorporated the catchment characteristics regarding shape, topography, and land use in our models. It is known that the catchment shape affects the time of runoff concentration (Costache, 2019b). A rounded catchment will have a shorter concentration time than an elongated catchment (Schumm, 1956). Due to the shorter concentration time and the simultaneous drainage to the catchment center, round catchments represent the greater risk for high peak discharges. For each catchment, we determined the elongation ratio, which is a dimensionless parameter that quantifies the basin shape (Fig. 4.5). According to Schumm (1956), the elongation ratio E of a catchment is defined as follows:

$$E = \frac{2 * \sqrt{A/\pi}}{L_b} \tag{4.1}$$

where A is the catchment area in km^2 and L_b is the basin length in km. The elongation ratio of a catchment can be classified as follows: more elongated (< 0.5), elongated (0.5–0.7), less elongated (0.7–0.8), oval (0.8–0.9), circular (> 0.9) (Schumm, 1956).
For further description of the catchment properties, we applied Hack's Law, which is an empirical scaling law for river networks (Sassolas-Serrayet et al., 2018) (Fig. 4.5). Based on fractal mathematics, Hack (1957) described the relationship between catchment size and mainstream length as a power function, assuming that the mainstream length scales with the catchment size. Hack's Law has been intensively studied and applied since its publication (e.g., Maritan et al., 1996; Reis, 2006; Sassolas-Serrayet et al., 2018). Hack's Law is defined as follows:

$$L = 1.4 * A^{0.6} \tag{4.2}$$

where A is the catchment area in km^2 and L is the mainstream length in km.
In addition to the shape, the topography of the catchment also plays a role in the runoff formation. The basin relief allows conclusions about the geomorphological and hydrological characteristics of a catchment. We used the relief to describe the terrain of the catchments (Fig. 4.5). The catchment relief R is computed as the difference of the maximum catchment height H_{max} and the minimum catchment height H_{min} (Schumm, 1956):

$$R = H_{max} - H_{min} \tag{4.3}$$

As another topography indicator, we applied the Melton ruggedness number (Fig. 4.5). The Melton ruggedness number is a slope index describing the relief conditions of a catchment. In geomorphology, the Melton ruggedness number is mostly used to assess sediment transport processes within basins (e.g., Scally and Owens, 2004; Marchi and Dalla Fontana, 2005). To quantify the ruggedness of a basin, Melton (1965) proposed the following dimensionless ratio:

$$M = R/\sqrt{A} \tag{4.4}$$

where A is the catchment area in km^2 and R is the basin relief in km. The Melton number can vary from zero to some large number, although it rarely exceeds one. Melton numbers between 2 and 3 indicate a very rugged area for a first-order catchment (Melton, 1965). To further describe the catchment response to heavy rain, we considered the land use distribution within the catchments. To do so, we included the percentage of built-up area and agricultural area of a catchment derived from the CORINE Land Cover dataset (Fig. 4.5).

The spatial relationship between the sample points plays an important role. Because as we know from Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). To account for the spatial dimension in the model, we included the X- and Y-coordinate as explanatory features. However, to reduce the number of features and minimize collinearity, as well as to increase the informative value of the predictor, we used the product of the X- and Y-coordinates.

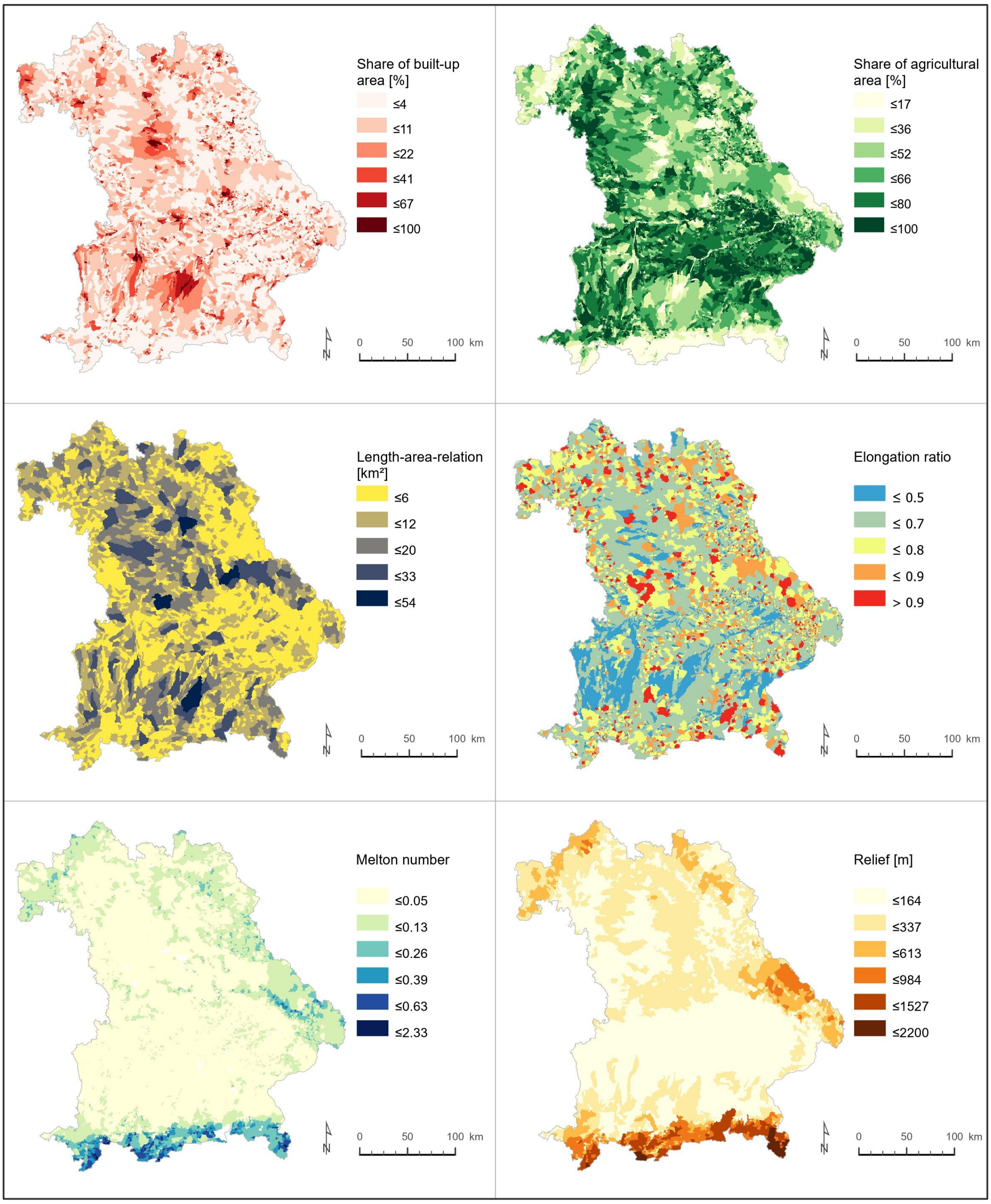

Figure 4.5: Pluvial and flash flood influencing factors related to the catchment: share of built-up area, share of agricultural area, length-area-relation, elongation ratio, Melton number, relief.

4.4.4 Feature preparation

We prepared the influencing factors with the GIS software ArcGIS Pro 2.6. For further feature processing, we used the Python library *scikit-learn* (Pedregosa et al., 2011). To avoid losing valuable samples, we replaced missing values in the dataset. For categorical features, we used the function *SimpleImputer* to replace missing values with the most frequent feature value. Missing numerical values were replaced using the mean value from the five nearest neighbors in the dataset (*KNNImputer*), where two samples are close if the features that are not missing in both samples are close.
We transformed the three categorical features (i.e., landforms, land use, permeability of the upper aquifer) into numbers using Weight-of-Evidence (WoE) encoding (Table 4.4). The WoE method is a bivariate Bayesian statistical approach that has been widely used in flood susceptibility studies (e.g., Tehrany et al., 2014; Hong et al., 2018; Costache, 2019b). Using the WoE method, we can measure the predictive power of an independent variable (an influencing factor) regarding the dependent variable (pluvial and flash flood occurrence). In the case of flood modeling, the WoE coefficient is computed based on the relationship between the non-occurrence and occurrence of pluvial and flash floods within each class of the categorical feature. The WoE coefficient for each categorical class is calculated as follows:

$$WoE = \ln \frac{B/A}{\bar{B}/\bar{A}} \tag{4.5}$$

where B indicates the number of flood pixels in the given class and A the total number of flood pixels of all classes. Accordingly, the number of non-flood pixels within the investigated class is given by $\bar{B}$, and the number of non-flood pixels of all classes is represented by $\bar{A}$.
We scaled all features using standardization (*StandardScaler*), which is less affected by outliers than min-max scaling. In some flood susceptibility studies, the numerical features are discretized using the natural breaks or quantile method (e.g., Costache, 2019b; Tien Bui et al., 2019; Tang et al., 2020). However, we did not group the continuous features, as tree-based classifiers are good at determining complex relationships between the independent and dependent variables.

Table 4.4: Weights-of-Evidence coefficients of categorical influencing factors.

Explanatory factor	Class	WOE coefficient	WOE standardized coefficient
Land use	Built-up area	0.30	1.41
	Forests and near-natural areas	−1.39	−0.67
	Agricultural areas	−1.44	−0.74
Landforms	Canyons, deeply incised streams	−0.04	0.76
	Midslope drainages, shallow valleys	−0.41	−1.22
	Upland drainages, headwaters	−0.41	−1.22
	U-shape valleys	−0.13	0.27
	Plains	0.21	2.09
	Open slopes	−0.19	−0.06
	Upper slopes, mesas	−0.09	0.51
	Local ridges, hills in valleys	−0.11	0.40
	Midslope ridges, small hills in plains	−0.41	−1.22
	Mountain tops, high ridges	−0.24	−0.31
Permeability of the upper aquifer	High (10^{-2} – 10^{-3} m/s)	0.00	−0.71
	Medium (10^{-3} – 10^{-4} m/s)	1.22	1.38
	Medium to moderate (10^{-3} – 10^{-5} m/s)	−0.41	−1.41
	Moderate (10^{-4} – 10^{-5} m/s)	0.33	−0.14
	Moderate to low (10^{-4} – 10^{-6} m/s)	0.29	−0.22
	Low (10^{-5} – 10^{-7} m/s)	0.39	−0.04
	Very low (10^{-7} – 10^{-9} m/s)	0.06	−0.61
	Low to extremely low ($<10^{-5}$ m/s)	0.46	0.07
	Extremely low ($<10^{-9}$ m/s)	0.42	0.01
	Highly variable	1.81	2.38
	Waters	0.00	−0.71

4.4.5 Classifiers applied

In this study, we compare the ensemble methods Random Forest, Gradient Boosting Decision Tree, and CatBoost. Before choosing these three classifiers, we tried several different machine learning algorithms (e.g., Naïve Bayes, support vector machines, neural networks, AdaBoost Decision Tree) without optimizing their hyperparameters. Based on the first classification results, we selected the three most promising of all classifiers. In the following subsections, we briefly describe the three classifiers used in this study. A comprehensive description of the underlying principles can be found in the literature (e.g., Kuhn and Johnson, 2016; Bentéjac et al., 2020; Bonaccorso, 2020).

4.4.5.1 Random Forest

In 2001, Leo Breiman first introduced the Random Forest (RF) model (Breiman, 2001). A Random Forest model consists of a large number of decision trees that are as uncorrelated as possible. To generate an uncorrelated forest of trees, the Random Forest uses bagging and feature randomness in the formation of the decision trees. This means that each tree receives a random sample that is drawn from the training set with replacement (bootstrapping). Each tree also only receives a random subset of the features. Due to this implemented randomness, the prediction of the Random Forest model is often more accurate than the predictions of any individual decision tree (Breiman, 2001).
The Random Forest classifier is one of the most frequently used classification algorithms. This is probably because Random Forest models are powerful ensemble methods that are not sensitive to multicollinearity and can handle missing and unbalanced data. Random Forests have been applied in many studies of flood susceptibility mapping and achieved high predictive accuracies (Chen et al., 2020; Costache et al., 2020a; Hosseini et al., 2020; Hong et al., 2018; Tang et al., 2020).
In this study, we used the *RandomForestClassifier* from the machine learning library scikit-learn (Pedregosa et al., 2011) for the Python programming language. Unlike the original publication by Breiman (2001), the scikit-learn implementation averages the probabilistic prediction of the decision trees (soft voting) rather than using the majority decision of the classifier votes (hard voting) (Pedregosa et al., 2011). Compared to hard voting, soft voting often achieves higher performance because it accounts for the uncertainty of each classifier in the final decision (Géron, 2017).

4.4.5.2 Gradient Boosting Decision Tree

Boosting is a method to create ensemble models. Under boosting we understand the training of several weak learners in a sequential and adaptive manner to obtain a stronger learner (Kuhn and Johnson, 2016). At first, one initial model is fitted to the data. Then, a second model is trained concentrating on improving the shortcomings of the previous model, and so on. The underlying assumption is that the combination of the models is better than one model alone, since each subsequent model tries to improve the shortcomings of the combined ensemble model. Many boosting algorithms exist, however, AdaBoost and Gradient Boosting are among the most popular (Géron, 2017). The Gradient Boosting algorithm was first presented by Breiman (1997) and further developed by Friedman (2001). Gradient Boosting fits the new learner to the residual errors of its predecessor. The predecessor's shortcomings are identified by the gradient (e.g., residual) of an exponential loss function. After the current model is added to the previous model, a new model is fit to the residuals to minimize the loss function, and so on (Kuhn and Johnson, 2016).

In our study, we applied the class *GradientBoostingClassifier* of scikit-learn (Pedregosa et al., 2011) that uses decision trees as base estimators by default. The Gradient Boosting algorithm has not yet been used in a flood susceptibility study. However, Bui et al. (2019b) already applied the boosting algorithms AdaBoost and LogitBoost for flash flood susceptibility modeling.

4.4.5.3 CatBoost

The third classifier applied in this study also uses gradient boosting on decision trees and is called CatBoost for "Categorical Boosting" (Prokhorenkova et al., 2018). The CatBoost classifier is available as an open-source library for Python provided by the technology and Internet services company Yandex. The CatBoost algorithm differs from classical gradient boosting in two ways. First, CatBoost applies ordered boosting, which is a permutation-driven alternative to the standard gradient boosting algorithm (Prokhorenkova et al., 2018). At each training step, CatBoost uses the independent permuted historical samples and thus achieves unbiased boosting. Second, CatBoost uses ordered target statistics to encode categorical features (Hancock and Khoshgoftaar, 2020). Both techniques were implemented to combat target leakage, a specific type of overfitting that occurs in all classical gradient boosting algorithms (Dorogush et al., 2018; Prokhorenkova et al., 2018).

Due to the two algorithmic advances, CatBoost has advantages over other implementa-

tions of gradient boosted decision trees. Dorogush et al. (2018) proved that CatBoost outperforms other gradient boosting algorithms such as XGBoost, LightGBM, or H2O on popular datasets. Besides, CatBoost handles heterogeneous datasets with categorical features well and is easy to use (Hancock and Khoshgoftaar, 2020).
In geosciences, the CatBoost algorithm has recently been used to classify formation lithology (Dev and Eden, 2019) and to estimate reference evapotranspiration (G. Huang et al., 2019; Y. Zhang et al., 2020). Kang et al. (2020) also applied CatBoost to calculate an hourly wildfire risk index. In a comparative study of four gradient boosting algorithms for landslide susceptibility mapping, CatBoost achieved the highest predictive ability (Sahin, 2020). Recently, Hancock and Khoshgoftaar (2020) reviewed studies from various disciplines that employed the CatBoost algorithm to analyze its effectiveness and shortcomings.

4.4.6 Performance measures

We assessed the predictive ability of the selected classifiers using various performance metrics. The Receiver Operating Characteristic (ROC) curve is used to assess binary classifiers (Altman and Bland, 1994; Brown and Davis, 2006; Fawcett, 2006). The ROC curve plots the false positive rate (FPR) on the x-axis against the true positive rate (TPR) on the y-axis. The true positive rate, also called recall or sensitivity, is the ratio of positive samples correctly identified by the classifier:

$$TPR = \frac{TP}{TP + FN} \tag{4.6}$$

where TP is the number of true positive samples, and FN is the number of false negative samples. Conversely, the false positive rate describes the ratio of negative samples that are incorrectly identified as positive:

$$FPR = \frac{FP}{FP + TN} = 1 - TNR \tag{4.7}$$

where TN is the number of true negative samples, and FP is the number of false positive samples. The FPR is equal to one minus the true negative rate (TNR), which is also called specificity. The TNR is the proportion of negative samples correctly classified as negative:

$$TNR = \frac{TN}{TN + FP} \tag{4.8}$$

The ROC curve displays the classifier's ability to discriminate between a flood and a non-flood event. The diagonal of the ROC curve represents a random classifier. The aim is to obtain a classifier that is as far away from the diagonal as possible. However, there is a trade-off as higher true positive rates come along with more false positive predictions. For visual comparison, the classifiers' ROC curves are superimposed graphically. To compare the classifiers' ROC curves quantitatively, we used the area under the ROC curve (AUC) (see Fig. 4.6). The AUC value measures the two-dimensional area underneath the ROC curve and thus aggregates the classifier's performance for all possible candidate thresholds. Possible AUC values range from 0 to 1. The higher the AUC value, the better the predictive power of the classifier, while an AUC value of 1 represents the perfect classifier. When comparing the models, the most effective model is the one with the largest area under the ROC curve. We further evaluated the classifiers' performances using the metrics accuracy and Cohen's Kappa, also called Kappa statistic. The accuracy measures the correctly identified samples and is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4.9}$$

However, the disadvantage of the accuracy metric is that it does not differentiate between the types of error being made. Cohen's Kappa, in contrast, considers the class distributions of the training set (Kuhn and Johnson, 2016). Cohen's Kappa measures the agreement between two raters on a classification problem, taking into account the accuracy that would result from chance alone (Cohen, 1960). The Kappa statistic can be computed as:

$$\kappa = \frac{O - E}{1 - E} \tag{4.10}$$

where O is the observed accuracy, and E is the expected accuracy by chance. Cohen's Kappa can take values between -1 and 1; while 1 means perfect agreement and 0 means no agreement between the observations and predictions. If the Kappa statistic is less than 0, than the classifier is worse than agreement by chance. Landis and Koch (1977) proposed the following classification of the Kappa statistic: < 0 no agreement, 0–0.20 slight, 0.21–0.40 fair, 0.41–0.60 moderate, 0.61–0.80 substantial, and 0.81–1 almost perfect agreement.

4.4.7 Model-specific and model-agnostic interpretation methods

In this paper, we applied model-specific and model-agnostic methods to interpret the trained classification model. As model-specific methods, we used feature importance

and pairwise feature importance, also called feature interaction. The feature importance describes the strength of the relationship between the predictor and the outcome. In most tree-based models, feature importance is an intrinsic measure that monitors the performance as each feature is added to the model (Kuhn and Johnson, 2016). The feature importance ranges between 0 and 1, and the sum of the importance of all features is 1. In addition to feature importance, we computed feature interaction, which is a two-way interaction measure indicating the interaction strength for each pair of features. The feature interaction is a dimensionless statistic based on Friedman's H-statistic and describes the proportion of the variance explained by the interaction (Friedman and Popescu, 2008).
As a model-agnostic method, we applied SHapley Additive exPlanations (SHAP) by Lundberg and Lee (2017). SHAP is a unified framework for interpreting individual predictions by assigning an importance value to each feature (Lundberg and Lee, 2017). SHAP computes Shapley values (Shapley, 1953) from coalitional game theory, which describe how much each "player" (= feature) contributed to the "game" (= prediction) (Molnar, 2019). To understand how much the classification model relies on each influencing factor for making predictions, we used the training data to calculate feature importance, feature interaction, and SHAP.

4.5 Results

4.5.1 Model validation and comparison

We validated the three ensemble models using the 373 flood and non-flood locations of the test set. All three models performed equally well on the test set and achieved similar performance statistics (Table 4.5). The CatBoost model correctly detected the most flood and non-flood locations of the three models (281). The Gradient Boosting Decision Tree model achieved the highest sensitivity with 76.9 %, followed by the CatBoost and Random Forest model with 75.3 % each. Regarding predictive accuracy, the CatBoost model performed best (75.3 %), followed by the Random Forest model (75.1 %) and the Gradient Boosting Decision Tree model (74.8 %). According to the Kappa classification by Landis and Koch (1977), all three models achieved a moderate agreement, with the CatBoost model having the highest Kappa value (0.51).

Table 4.5: Performance of the proposed tree-based ensemble models on the test set.

Statistical measure	CatBoost	Random Forest	Gradient Boosting Decision Tree
True positive	140	140	143
True negative	141	140	136
False positive	46	47	51
False negative	46	46	43
Positive predictive rate [%]	75.27	74.87	73.71
Negative predictive rate [%]	75.40	75.27	75.98
Sensitivity [%]	75.27	75.27	76.88
Specificity [%]	75.40	74.87	72.73
Accuracy	75.34	75.07	74.80
Cohen's Kappa	0.51	0.50	0.50

We evaluated the global performance of the ensemble methods using the AU-ROC method. Fig. 4.6 compares the three classifiers' ROC curves and indicates their AUC values. The CatBoost, Random Forest, and Gradient Boosting Decision Tree models all achieved high AUC values for the test set. However, the CatBoost model has the highest predictive power (AUC = 81.9 %), followed by the Random Forest (AUC = 81.6 %) and the Gradient Boosting Decision Tree model (AUC = 81.3 %).
Overall, we find that all three models proved to be powerful in identifying the general pattern of pluvial and flash flood susceptibility in the state of Bavaria. The predictive power of the classifiers is comparably good, and thus no classifier significantly outperforms the others. Regarding accuracy, AUC, and Kappa statistic, the CatBoost model is the best performing. Regarding the statistical measures, we therefore rank the CatBoost model first, the Random Forest model second, and the Gradient Boosting Decision Tree model third. Since the CatBoost model has the highest predictive power, we used it to derive Bavaria's pluvial and flash flood susceptibility.

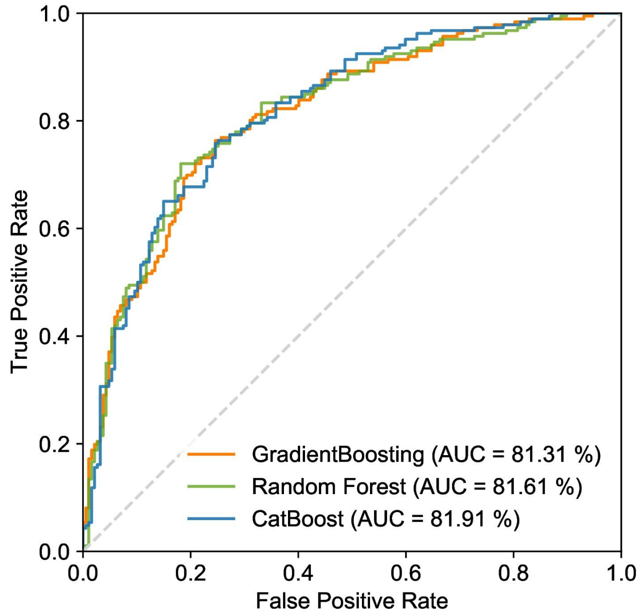

Figure 4.6: ROC curves with associated AUC values for three tree-based models computed from the test set.

4.5.2 Model interpretation

Based on the feature importance, we rank the 17 influencing factors (Fig. 4.7). By far, the highest predictive power is attributed to the sealing degree (16.8 %) and the built-up area share of a catchment (11.7 %). The importance of the 15 remaining influencing factors ranges between 7 and 2 %. The Melton number of a catchment (7.2 %) and the hours of heavy rain (7.1 %) are equally important, followed by X*Y coordinate (6.4 %), HAND (6.0 %), and the proportion of the agricultural area of a catchment (5.9 %). Contrary to our expectations, the slope is not among the most predictive explanatory factors. On the contrary, the slope ranges in the lower third with 4.1 %. According to the feature importance, the catchment-related influencing factors are as important for model prediction as the spatially distributed ones. Among the three most influential explanatory factors, two are catchment-related (built-up area share, Melton number). However, catchment-related variables describing land use distribution and relief conditions in the catchment are more important than variables describing the catchment shape. The distance to the river is the least contributing influencing factor with 2.4 %.

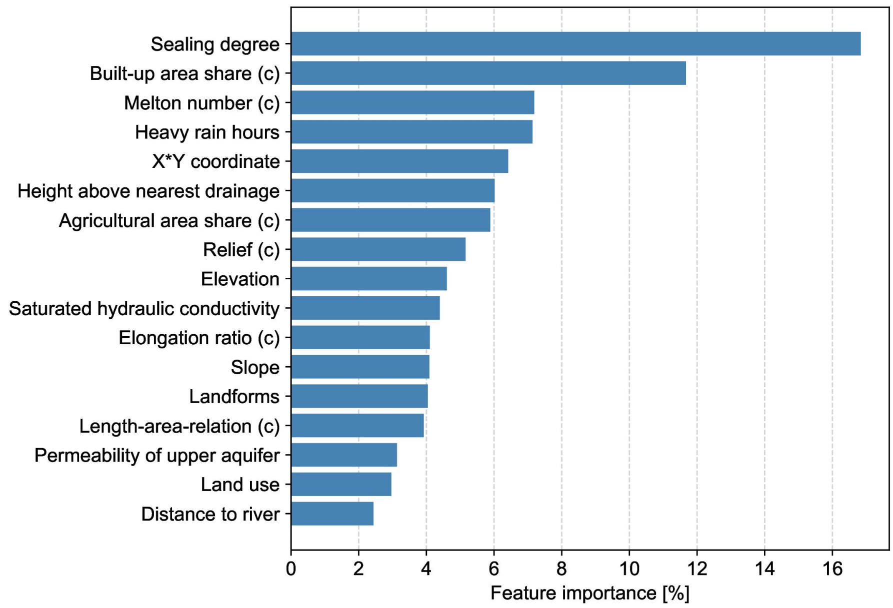

Figure 4.7: Feature importance of the influencing factors in the CatBoost model. The (c) indicates catchment-related influencing factors.

For model interpretation, we also investigated pairwise feature importance. Of the 136 possible pairs of influencing factors, we plotted the top 15 interaction pairs in Fig. 4.8. These 15 pairs contain 11 different influencing factors, four of which are catchment-related. The sealing degree and the built-up area share, which had the highest feature importance, occur in 9 and 6 of the 15 interaction pairs, respectively. Interestingly, the factor agricultural area share appears in the second and third strongest pair with the sealing degree and the proportion of the built-up area, although its feature importance was not so high. However, the agricultural area share probably complements the sealing degree and the proportion of the built-up area. Although the slope's single feature importance was only ranked 12th, the slope forms strong pairs with the built-up area share, the sealing degree, and the heavy rain hours. Similarly, the saturated hydraulic conductivity, which was only ranked 10th regarding feature importance, forms a strong pair with the sealing degree (ranked 5th).

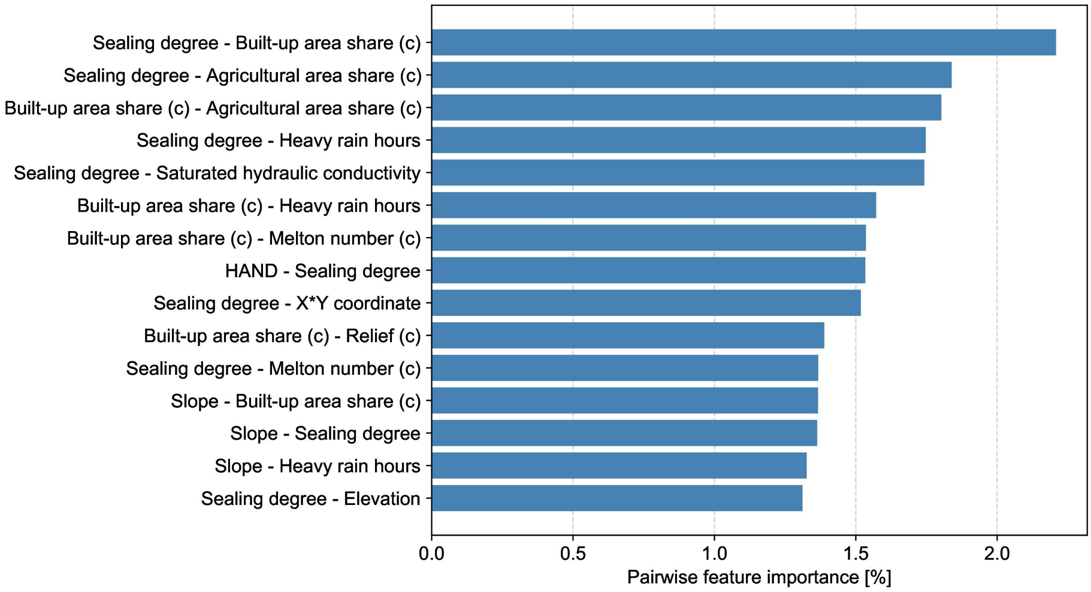

Figure 4.8: Pairwise feature importance of the first 15 interaction pairs of the CatBoost model. The (c) indicates catchment-related influencing factors.

To investigate the relationship between the influencing factors and the prediction, we used a SHAP summary plot. The summary plot in Fig. 4.9 orders the features on the y-axis according to their importance. Each point represents a SHAP value for a feature value and a prediction instance. The continuous color scale indicates low to high feature values. In the case of overlapping points, the points were jittered in the direction of the y-axis.

Sealing degree and built-up area share are the only factors that reach absolute SHAP values above 1, and thus can strongly influence the prediction result in one direction or the other. A high sealing degree significantly increases the risk of flooding, while medium to low sealing degrees reduce flood risk. A high percentage of built-up area in a catchment generally increases flood risk. In addition to the sealing degree and the built-up area share, six other influencing factors can significantly affect the prediction (absolute SHAP values above 0.5): heavy rain hours, X*Y coordinate, Melton number, agricultural area share, elevation, and saturated hydraulic conductivity. It is plausible that a high number of heavy rain hours increases the risk of flooding. The less rugged a catchment is (low Melton number), the lower the risk of being affected by flash flooding. Interestingly, a high percentage of agricultural land in a catchment leads to a decrease in flood risk and, conversely, a low percentage of agricultural area to an increase. This can probably be attributed to the fact that the proportion of agricultural land is related to the proportion of built-up land, and thus a low proportion of agricultural land could mean a high proportion of built-up area. The summary plot also reveals that low-lying areas are more susceptible and high values of saturated hydraulic conductivity reduce flood hazard.

Overall, the classification model seems to confirm relationships between influencing factors and flash flood occurrence that are known or suspected among hydrologists. According to the summary plot, elongated catchments with little ruggedness, low relief, and a low proportion of built-up areas should be less susceptible to flash flooding. In addition, highly permeable topsoils and upper aquifers can reduce the risk of flooding.

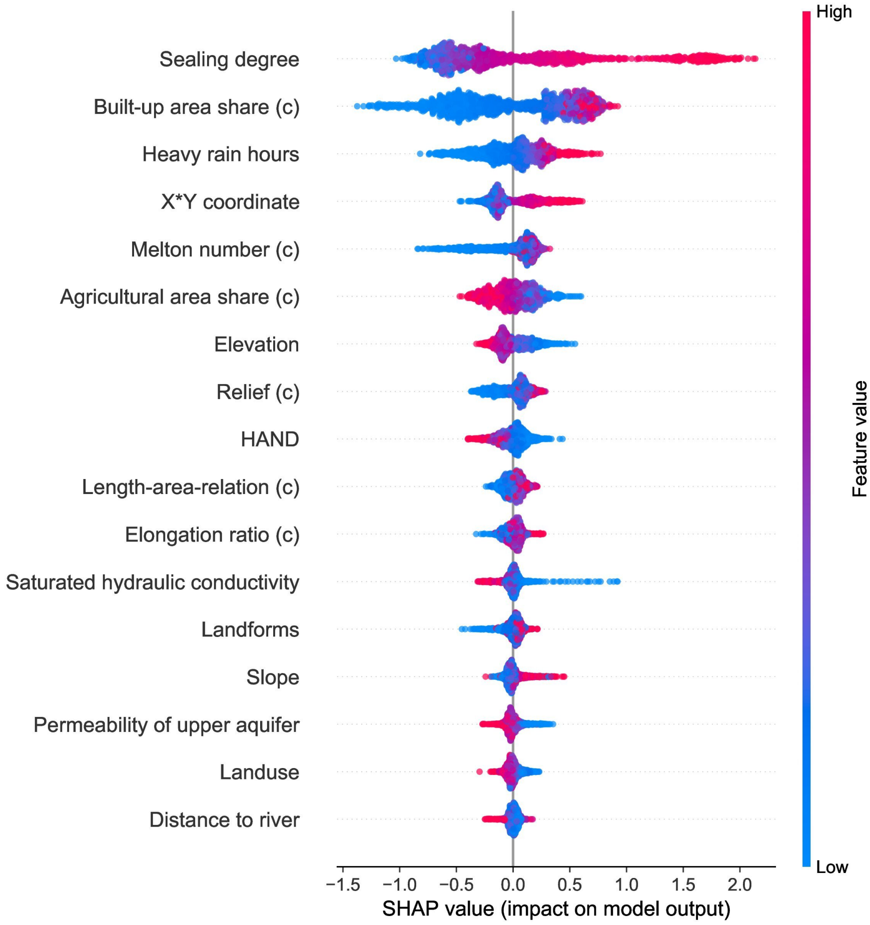

Figure 4.9: SHAP summary plot indicating the effects of the influencing factors on the prediction outcome. Each point represents a SHAP value for a feature value and a prediction instance. The (c) indicates catchment-related influencing factors.

Although we can now better understand the relationship between the influencing factors and the prediction result, we should be cautious about deriving general rules from the summary plot. Since the influencing factors affect each other, each prediction instance is the result of all feature values. Therefore, a low proportion of built-up area in a catchment does not necessarily reduce flood risk (Fig. 4.9). As shown in Fig. 4.8, the built-up area share interacts strongly with the sealing degree, the agricultural area share, the heavy rain hours, the Melton number, the relief, and the slope. The same is true for slope, for example. There is a tendency for high slope values to increase the risk of flooding (Fig. 4.9). However, there are also cases where the flood risk was reduced despite high slope values, probably due to the strong interaction of the slope with the built-up area share, the sealing degree, and the heavy rain hours (Fig. 4.8).

4.5.3 Susceptibility map

Using the CatBoost model, we determined the susceptibility of all raster pixels of Bavaria. As an indication of susceptibility, we used the predicted probability of each raster pixel to be assigned to class 1 (affected) returned by the CatBoost model. The predicted probability is the result of weighting each tree in the ensemble, which in turn calculate a probability of class 1 for each of their leaves. The susceptibility values ranged from 0.20 to 0.99. The methods quantile or natural breaks are usually chosen for classifying flash flood susceptibility maps (e.g., Costache, 2019a; Khosravi et al., 2018; Ngo et al., 2018; Youssef et al., 2016). With the natural breaks classification method, classes are based on natural groupings within the dataset. Class boundaries are set in such a way that similar values are summarized and differences between the classes are maximized. Since our susceptibility values have a skewed distribution, the natural breaks classification is more appropriate than the quantile classification. Using the natural breaks method, we divided the prediction dataset into four susceptibility classes, labeled low (≤ 0.20), moderate (> 0.20–0.35), high (> 0.35–0.53), and very high (> 0.53–0.99). The susceptibility classes low and moderate cover 37 % and 33 % of the Bavarian state, respectively. According to our model, 21 % of Bavaria is considered highly susceptible. The highest susceptibility class makes up 8 % of the state territory. Overall, 30 % of the state of Bavaria is at high or very high risk of pluvial and flash flooding (Fig. 4.10). Regions with high and very high risk occur throughout Bavaria. The most flood-prone areas are identified in the Alpine region, in the south of the Alpine foothills, and in the border region of southeast Bavaria. Furthermore, we find highly susceptible areas in northern Bavaria, especially along the Main River and toward the state of Hesse in northwestern Bavaria. Less susceptible areas are identified in central Bavaria.

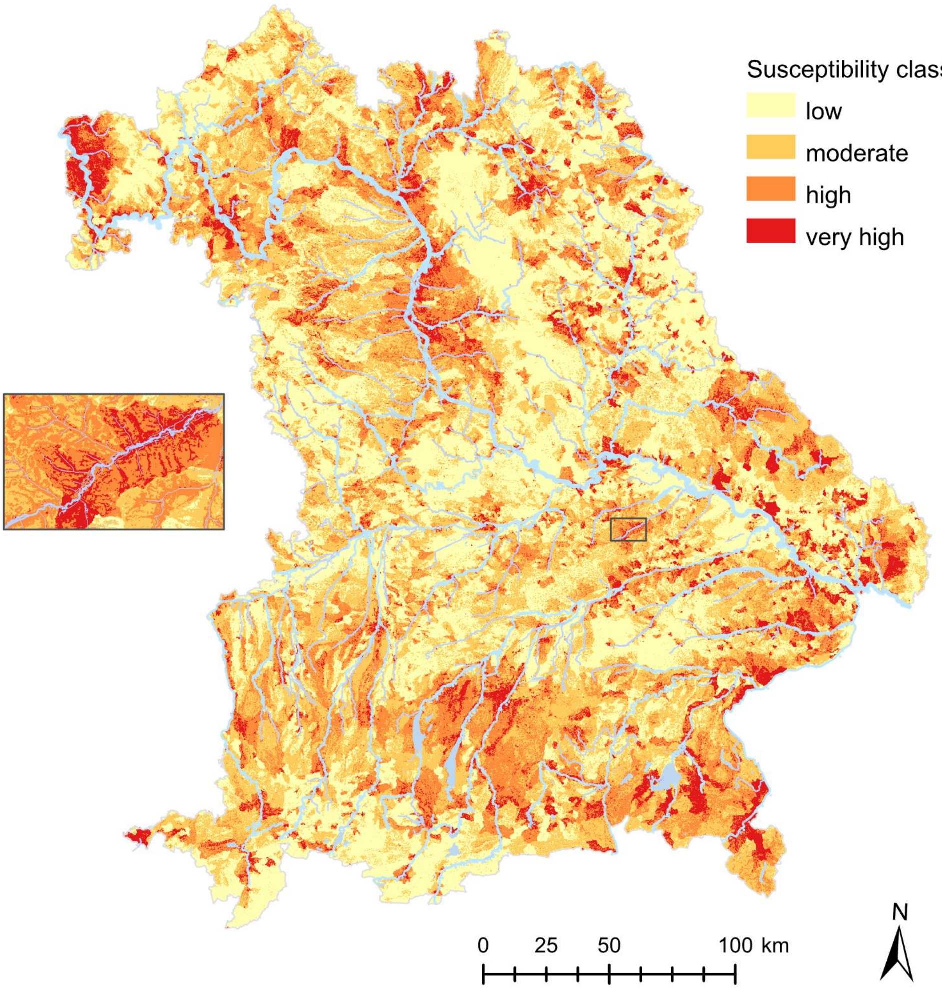

Figure 4.10: Map showing the susceptibility for pluvial and flash flooding for the state of Bavaria (Germany) with superimposed river network.

4.5.4 Endangered cities

To compare the hazard situation among cities, we calculated an overall susceptibility score for all Bavarian cities. The susceptibility score of the cities may help decision-makers on regional or state level to prioritize cities for detailed investigations. We calculated the overall susceptibility of a city using the smallest circumscribing rectangles—so-called bounding boxes—of the cities. The dataset by BKG (2015) provides the bounding boxes for all German cities, which we used as an approximation of the city area. Within each bounding box, we determined the area-weighted average of the four susceptibility classes, which was used as the city's overall susceptibility. When calculating the overall susceptibility of a city, we assume that the proportions of the susceptibility classes within the bounding box approximate the city's hazard situation. Consequently, a city with a large number of high to very high-classified raster pixels is more at risk than a city with a large number of low to moderate classified pixels.

We determined the overall susceptibility of all Bavarian cities (Fig. 4.11). Similar to the pluvial and flash flood susceptibility map, we classified the city scores into four susceptibility classes (low, moderate, high, very high) using the natural breaks method. According to this classification, 28 % and 32 % of the cities are considered to be at low and moderate risk, respectively. Classified as highly susceptible are 24 % of the cities. In the highest susceptibility class are 16 % of the Bavarian cities.

The cities at particularly high risk are distributed across Bavaria, but cluster in specific regions (Fig. 4.11). Especially in the southern part of the natural region eastern low mountain range, many cities are classified as very endangered. The border region with neighboring Austria in southeastern Bavaria also has many cities colored red. Furthermore, the southern part of the Alpine foothills, as well as Munich and its surrounding area, are endangered. In the north of Bavaria, the Nuremberg metropolitan region stands out with the major cities of Nuremberg, Fürth, and Erlangen. In addition, Würzburg and the region toward the state of Hesse along the Main River are classified as highly endangered. However, not all major cities are automatically classified as being at highest risk, as the regions around Augsburg and Ingolstadt show.

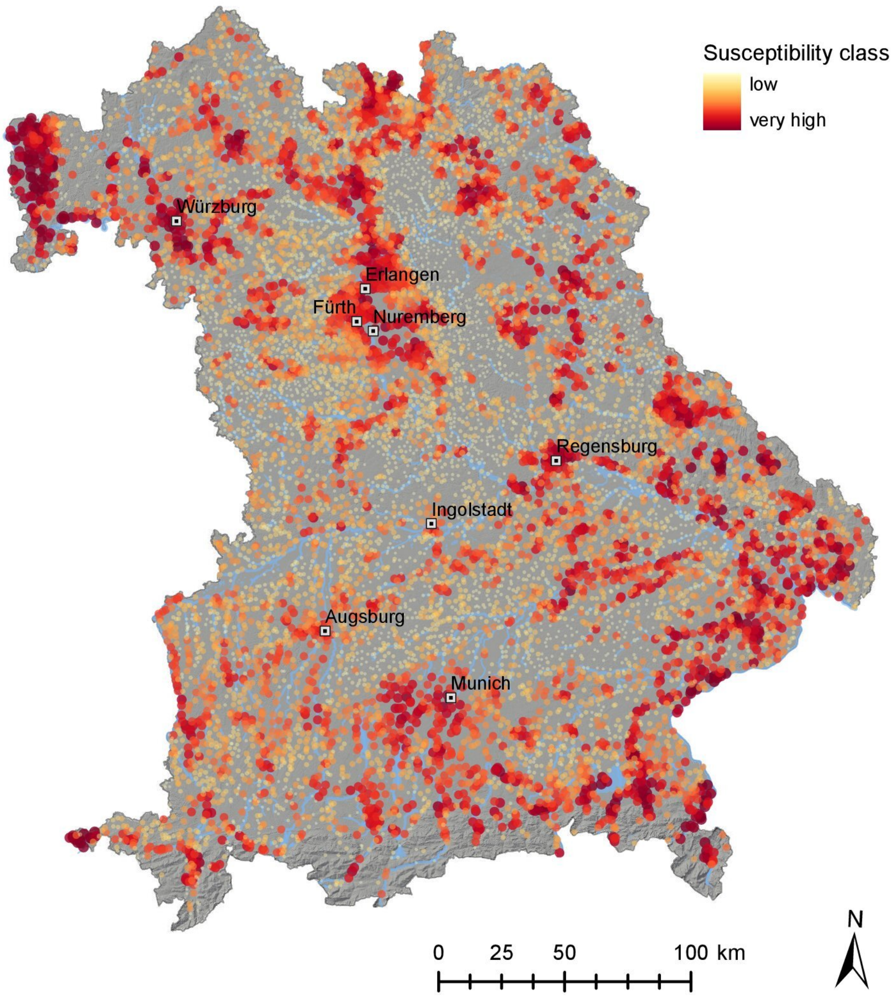

Figure 4.11: Pluvial and flash flood susceptibility classification of the Bavarian cities and towns, indicating the cities with more than 100,000 inhabitants.

In histograms, we compare the distribution of the susceptibility scores of the Bavarian cities in the training and test set (Fig. 4.12). In both the training and the test set, the distribution of the susceptibility scores is roughly balanced. However, when differentiating the cities according to their affectedness, it becomes apparent that affected cities tend to be assigned a higher and unaffected cities a lower susceptibility score. This tendency is evident in both the training and test set, although it is more pronounced in the training set. The histograms suggest that the overall classification of the cities can be considered plausible.

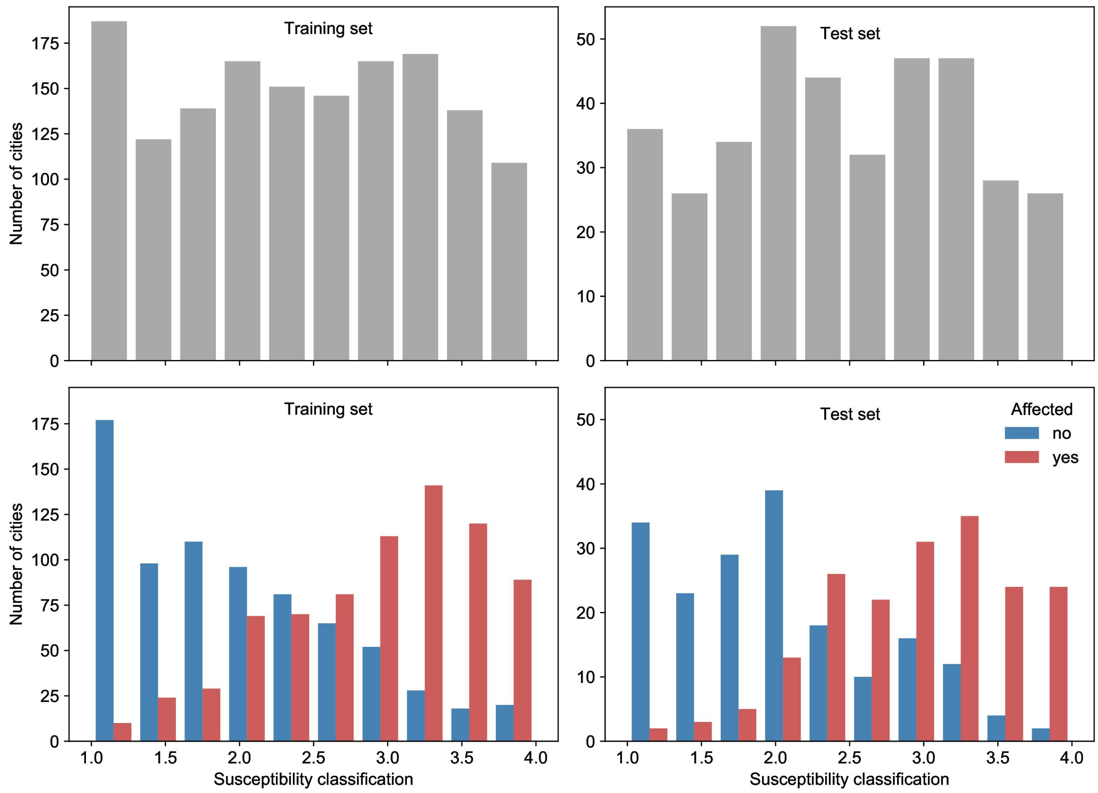

Figure 4.12: Susceptibility classification of the cities of the training and test set differentiated by affectedness.

4.6 Discussion

To the best of our knowledge, only one study exists to date in which a flash flood susceptibility map was derived for an area larger than Bavaria (70,500 km^2). Ma et al. (2019) generated a susceptibility map for Yunnan Province (China) that covers an area of 380,000 km^2. In recent flash flood susceptibility studies (cf. Table 4.1), investigation areas generally range from 200 to 4,000 km^2 and focus on watersheds rather than political entities. An exception is the study by Hosseini et al. (2020), which investigates the flash flood hazard in the Gorganroud River Basin (Iran), covering an area of 11,300 km^2. Compared to the other studies listed in Table 1, the density of our sample points was lower. The reviewed studies used between 7 and 213 sample points per 100 km^2, with a median of 42 points per 100 km^2. In our study, we had only 3 points per 100 km^2 available. Consequently, the investigation sites in comparable studies are usually not only smaller, but there are also more data points available for training and testing.

The comparatively low point density of our sample data certainly reduces the performance of our model. This is because our model has to learn the complex relationships within four different major landscapes covering low mountain ranges, cultural landscapes, and the Alps with only a few data. Therefore, compared to other flash flood susceptibility studies, differences in performance are apparent. Some ML models achieved AUC values above 0.85 and even above 0.95 (cf. Janizadeh et al., 2019; Bui et al., 2019a; Khosravi et al., 2018; Tien Bui et al., 2020). However, our performance metrics are in similar ranges as in the study by Ma et al. (2019), whose winning model achieved a Kappa value of 0.59, an AUC value of 0.81, and an accuracy of 0.79. Nevertheless, due to the spatially homogeneous distribution of the sample data and attention to the representativeness of major landscapes, our model achieved good performance even at low sample point density. An increase in model performance would only be conceivable with more training and test data so that the heterogeneity of the study area could be better learned and reproduced.

Compared to similar flash flood studies, we included more influencing factors in our model. The studies we examined used between 7 and 12 influencing factors (Table 4.1), while we used 17 influencing factors. A further reduction in the number of influencing factors led to a performance decrease so that 17 influencing factors were necessary to achieve the best possible model performance. We assume that the large heterogeneity in the study area and the small amount of learning data necessitated a higher number of different influencing factors.

In contrast to comparable studies, we included catchment-related influencing factors in addition to spatially distributed ones. The studies listed in Table 4.1 do not use catchment- related factors, with exception of the study by Costache (2019b). Costache (2019b) used the catchment's circularity ratio among other spatially distributed influencing factors. Yet, there are also studies that derived flash flood susceptibility maps based only on catchment-related influencing factors, but these use GIS techniques and not machine learning (e.g., Abdelkareem, 2017; Abdo, 2020; Adnan et al., 2019). In our model, the catchment-related influencing factors are crucial for prediction performance. According to the feature importance, the built-up area share and the Melton number, both catchment-related factors, are the second and third most contributing influencing factors.

Due to the use of catchment-specific influencing factors, entire catchments are sometimes assigned to the same susceptibility class. This is the case when important catchment-specific influencing factors, such as the built-up area share or the Melton number, assume critical values. Furthermore, the representation of the map in four susceptibility classes makes minor differences disappear. Since our susceptibility map is intended to provide initial indications and is not a substitute for a detailed site investigation, we decided to retain the catchment-related influencing factors. In the end, we prioritized a higher degree of accuracy over representation.

Due to the high complexity of the model relative to the small amount of training data, there is a risk of overfitting. To reduce the risk of overfitting, we constrained the models. Therefore, we reduced the number of explanatory factors in the model to a minimum. We also simplified the models by limiting the size of the decision trees (e.g., maximum depth, number of features, the minimum number of samples required to be at a leaf node). Using 5-fold cross-validation, the values of the regularization parameters were found.

4.7 Conclusion

In this study, we assessed the pluvial and flash flood susceptibility of the state of Bavaria (Germany) using a CatBoost model and 17 influencing factors. For this purpose, we first compared the model performance of three state-of-the-art machine learning models: Random Forest, Gradient Boosting Decision Tree, and CatBoost. We trained the models using 11 spatially distributed and six catchment-related influencing factors. All three models performed well with AUC values above 0.8. Comparing the performance measures, however, the CatBoost model achieved the best performance and was therefore used to derive the pluvial and flash flood susceptibility map.

We aimed at generating a susceptibility map to identify pluvial and flash flood-susceptible areas within the state territory. For this, we investigated how to generate a susceptibility map for a vast state territory, which is covering four major landscapes, using a machine learning model. Our findings from the susceptibility study can be summarized as follows:

- We achieved good model performance despite low sample point density (3 points per 100 km^2) by ensuring a homogeneous spatial coverage of Bavaria and the representation of the four major landscapes in the training and test set.
- To capture the natural heterogeneity of Bavaria, we required a larger number of spatially distributed and catchment-related influencing factors than otherwise applied in previous studies.
- There are area characteristics that can reduce susceptibility to flash flooding. Elongated catchments with low ruggedness and relief, a low proportion of built-up areas,

and highly permeable topsoils and upper aquifers are likely to be less susceptible to flash flooding.

- By averaging the susceptibility classes within a city area on an area-weighted basis, an overall susceptibility classification for a city can be provided. This overall susceptibility score allows for comparison between cities, e.g., for prioritization purposes.

- We found that the following regions of Bavaria are particularly vulnerable to pluvial and flash flooding: the southeast of Bavaria with the Alpine foothills, Munich and its surrounding area, and the southern part of the eastern low mountain range. In northern Bavaria, the metropolitan region of Nuremberg, Würzburg and its surroundings, and the region toward the state of Hesse along the Main River are highly endangered.

Nevertheless, the validity of our susceptibility assessment is affected by the small amount of training data and the non-consideration of time-variable influences. In our model, we neglected time-variant influencing factors such as triggering precipitation, antecedent soil moisture, or phenology of crops, which can severely impact event magnitude. In addition, the susceptibility map only indicates the actual state, since influencing factors such as the sealing degree and the proportion of built-up area in the catchment can change over the years.

With the help of the susceptibility map, those responsible for spatial planning and flood risk management in the Bavarian administrative authorities and water management offices can identify pluvial and flash flood-prone areas. Furthermore, in-depth investigations can be prioritized and initiated based on the overall susceptibility classification of the Bavarian cities. In addition, we have proven that machine learning models can handle naturally heterogeneous, large study areas even with a small amount of training data.

Further work should elaborate whether these new machine learning-derived maps are understood and applied by the public and those in charge. Since distrust of machine learning is still high among the public, researchers should also improve on the interpretability of the underlying models and the traceability of the derived flash flood susceptibility maps. To increase trust, it is necessary to communicate the strengths and weaknesses of the machine learning model and explain the model decisions with examples.

5 Concluding remarks

5.1 Findings & main contributions

The overall objective of this thesis was to develop a data-driven approach to identify pluvial and flash flood susceptible areas in the state of Bavaria. To this end, a developed four-step documentation procedure was applied to generate a dataset of flood events caused by heavy rain in Germany. To manage and link the event dataset with the required geodata, an event database was set up. The analysis of the generated event dataset provided new insights into the spatiotemporal characteristics of heavy rain-induced floods in Germany. Based on the event dataset and selected influencing factors, a machine learning (ML) model was developed and applied to map pluvial and flash flood-prone areas in Bavaria.
In the following, the five hypotheses of the doctoral thesis are addressed. It is presented how the hypotheses were confirmed, what insights were gained, and what contributions were made.

Hypothesis 1: A standardized documentation procedure is required to generate an event dataset suitable for hazard evaluation and susceptibility modeling.
In this thesis, it was shown that a unified and structured event dataset is required for the hazard evaluation of past heavy rain-induced flood events and susceptibility modeling. To be able to create a suitable event dataset, a standardized documentation procedure is needed that covers the entire documentation cycle from data collection to data preparation. For both hazard evaluation and susceptibility modeling, the documented events must be equivalent in that they satisfy a given event definition. In addition, event information, which comes from a variety of sources, must be evaluated regarding its information quality to support differentiated hazard investigations and the selection of reliable events for susceptibility modeling. For hazard evaluation, it proved necessary to process event information on meteorology, hydrology, damages, and spatiotemporal characteristics in a uniform manner using fixed categories for attribute description. Furthermore,

susceptibility modeling requires a distinct and consistent spatial definition of the heavy rain-induced flood events to ensure uniformity of the training and test dataset. To be able to link the flood events to the influencing area and catchment properties, the documentation scheme must specify the smallest, unambiguous spatial delineation possibility (the city) along with a classification of the spatial accuracy of the event information.
A new standardized procedure for the documentation of pluvial and flash flood events has been proposed that can serve several potential applications and users. Based on the documentation scheme environmental authorities, for example, can establish a central event documentation. Less experienced users or laypersons, e.g., at the municipality level, can also document events using the details provided regarding possible sources, required event information, and attribute categories. Scientists can employ this documentation procedure to create an event dataset suitable for, e.g., damage assessments, spatiotemporal analyses, or hydrological modeling of historical events. The proposed documentation procedure is suitable for different types of information and reports despite the attribute specifications.

Hypothesis 2: The design of a database for heavy rain-induced floods must consider the spatiotemporal and content-related accuracy of the event information.
It proved necessary to reflect the spatiotemporal and content-related accuracy of event information in the database design to prevent information aggregation. Failure to consider the resolution of event information in the database design results in a loss of accuracy and information, limiting subsequent analyses and uses of the event dataset. Therefore, to maintain unrestricted use of the event dataset, unnecessary spatiotemporal and content aggregation of event information must be prevented by the table, attribute, and key design. Regarding content, it is necessary to allow separation of event information by source and to specify categories and text blocks for attribute description, supplemented by a comment option. Regarding spatial resolution, the database design must allow events to be documented using the smallest administrative unit (the city) and allow further specification using the postal code (for major cities) and affected urban areas (for small cities). Regarding temporal resolution, it must be possible to specify multiple start times, durations, and intensities of heavy rain events per flood event. Of particular importance is the implementation of a damage-based event definition in the database, which, unlike a hydrological or meteorological event definition, does not aggregate event information based on catchments or thunderstorm cells.
This thesis provides detailed guidance on setting up a database for pluvial and flash

flood events, from database requirements and system architecture through table and attribute design to key and relationship definition. The developed database design supports damage assessments, spatiotemporal analyses, and susceptibility modeling, among others. However, the database is not only suitable for scientists, but also for environmental agencies or municipal administrations seeking event documentation for different uses.

Hypothesis 3: Heavy rain-induced floods in Germany show distinct spatiotemporal characteristics.
We investigated the characteristics of heavy rain-induced floods in Germany based on the created event dataset regarding seasonality, temporal occurrence, and spatial distribution. The collected pluvial and flash flood events were analyzed using spatial queries in the database and geostatistical analyses in the GIS software ArcGIS Pro.
The evaluations of the event dataset proved that heavy rain-induced floods in Germany have characteristic spatiotemporal properties. The main period for the occurrence of pluvial and flash floods in Germany is between April and October, with summer being the predominant season. In contrast to Mediterranean countries, autumn and winter events are rare in Germany. Within Germany, there are slight shifts in seasonality, with Northeastern Germany tending to experience more summer events and Central-Germany more spring events. Regarding temporal occurrence, it was found that heavy rain-induced floods most often start in the afternoon between 2 and 6 pm, with a peak at 3 pm. Heavy rain-induced floods occur throughout Germany, with slightly fewer events occurring in the Northern German Plain. There are regions in Germany where pluvial and flash floods occur particularly frequently and rarely, respectively. Of the seven localized hot spots, four are in mostly metropolitan areas (surroundings of Berlin, Rhine-Ruhr metropolitan region, conurbations of Rhine-Main, Rhine-Neckar and Stuttgart) and three are in rural, mountainous areas (Bavarian Alpine foothills, Ore Mountains, between the Thuringian Forest and the Harz Mountains). The Northwestern German Plain and North-Central Bavaria are particularly rarely affected in a Germany-wide comparison, and thus form cold spots.
The analysis of thousands of pluvial and flash flood events at the national level has improved our hazard understanding. The spatiotemporal delineation of heavy rain-induced floods in Germany also allows a better differentiation of river floods on small streams. Knowledge of the regions at risk and the diurnal and seasonal occurrence of pluvial and flash floods is relevant not only for flood risk management but also for communication with the public.

Hypothesis 4: Machine learning algorithms can be used to identify pluvial and flash flood susceptible areas in Bavaria.
In this thesis, it was proven that machine learning algorithms can be used to identify pluvial and flash flood susceptible areas in Bavaria. The methodological approach to delineate the areas at risk consisted of six steps. First, appropriate influencing factors were selected based on literature review, multicollinearity analysis, and feature importance. Eleven spatially distributed and six catchment-related influencing factors were needed to holistically cover Bavaria's natural heterogeneity. Second, the features were prepared, including the imputation of missing data, standardization, and Weight-of-Evidence encoding of categorical features. Third, the training and test locations were chosen so that good spatial coverage of Bavaria and the representation of the four major landscapes were ensured. Fourth, a Random Forest, a Gradient Boosting Decision Tree, and a CatBoost model were trained and validated using performance statistics. Fifth, the CatBoost model was selected as the model with the best performance regarding the accuracy (75.3 %), AUC (81.9 %), and Kappa statistic (0.51). Sixth, the pluvial and flash flood susceptible areas in Bavaria were mapped using the CatBoost model.
A new methodology has been developed to identify pluvial and flash flood-prone areas in Bavaria using machine learning. This ML-based method provides an estimate of an area's susceptibility based on spatially distributed and catchment-related influencing factors without consideration of event precipitation or preconditions. It was proven that machine learning models can be applied in flash flood susceptibility studies in addition to hydrological and hydrodynamic models. The identified areas at risk can inform spatial planning and flood risk management in Bavaria. Based on the identified pluvial and flash flood-prone areas, a prioritization of detailed investigations can be made.

Hypothesis 5: Area and catchment characteristics influence the occurrence of heavy rain-induced floods in Bavaria.
It was proven that the occurrence of pluvial and flash floods in Bavaria can be predicted based on area and catchment properties alone using a CatBoost model. Conversely, this means that area and catchment characteristics influence the occurrence of heavy rain-induced floods in Bavaria. The influence of individual properties and their interaction was investigated based on the trained machine learning model and model-specific and model-agnostic methods.
The influence and interaction of spatially distributed properties and catchment characteristics that promote the occurrence of heavy rain-induced floods is complex. To determine the susceptibility of an area in Bavaria, a comprehensive description of the

topography, soil and geology, land use, water bodies, catchment and precipitation characteristics is necessary. Eleven spatially distributed and six catchment-related influencing factors are required to capture the natural heterogeneity of Bavaria: elevation, slope, landforms, land use, sealing degree, distance to river, height above the nearest drainage, the permeability of the upper aquifer, saturated hydraulic conductivity, spatial location (expressed by the product of X- and Y-coordinate), heavy rain hours, and the catchment-related variables relief, Melton number, elongation ratio, length-area-relation, built-up area share, and agricultural area share. Among the influencing factors, the sealing degree and the built-up area share of a catchment have the highest predictive power, followed by the Melton number (a basin ruggedness index expressed by the quotient of the relief and the square root of the basin area), the heavy rain hours, the spatial location, and the height above the nearest drainage. The relief conditions and land use distribution of a catchment have a greater influence on the occurrence of pluvial and flash floods than the shape of a catchment. The investigations indicate that elongated watersheds with low relief and ruggedness, a low percentage of built-up areas, and highly permeable topsoils and upper aquifers are less susceptible to pluvial and flash flooding. The investigations also proved that the area and catchment characteristics influence each other. For example, the slope interacts strongly with the sealing degree, the built-up area share of a catchment, and the heavy rain hours. Due to these interactions, it is crucial to evaluate the characteristics of all influencing factors jointly to be able to make a reliable statement about the susceptibility of an area.
The investigation of the influence of spatially distributed properties and catchment characteristics on the occurrence of heavy rain-induced floods brought new insights. Furthermore, some correlations between area characteristics and susceptibility to pluvial and flash floods, which are suspected or known among hydrologists, could be confirmed. These study findings not only improve our hazard understanding but underline the suitability of machine learning for basic hydrological research.

5.2 Discussion

In the following, the potentials and limitations of the proposed data-driven approach are discussed in a broader context. In addition, unresolved questions are presented that can be addressed in future research. The following discussion follows the thesis structure, starting with the documentation procedure, followed by the event database and event analyses, and concluding with the model application.
The developed documentation scheme needs to be applied and further improved to in-

crease its general applicability in pluvial and flash flood research. Other research focuses may require the collection of more information and/or a higher level of detail than provided in the proposed documentation scheme. For example, an extension of the documentation scheme is necessary to capture the circumstances of flood fatalities. Data relevant to fatality studies could include, for example, the age and sex of the victim, time of death, and a description of the situational circumstances (see Terti et al., 2017; Terti et al., 2019). Studies on the relationship of preparedness, response, and recovery from heavy rain-induced floods may require additional information on, e.g., flood experiences, socio-economic variables, preventive and protective measures implemented (see Rözer et al., 2016; Spekkers et al., 2017).

For a holistic risk management approach, a next step could be to include other natural hazards such as debris flows, droughts, or forest fires in the event database. Not least due to climate change, the need to investigate interactions between natural hazards is gaining in importance. We are already experiencing that droughts can be followed by floods (e.g., Ward et al., 2020) or that burned landscapes promote the occurrence of flash floods (e.g., Kean et al., 2012). Murphy et al. (2018) have shown that droughts, fires, and floods can change flow paths and water quality, highlighting the need for multi-hazard assessments (e.g., Pourghasemi et al., 2020). A spatial database links not only different datasets and types but also different natural hazards, making it an interdisciplinary tool. So far, we are still in the early stages of exploiting the evaluation capabilities of an event database in geoscience.

The generated dataset of past pluvial and flash flood events in Germany could be refined and extended. To enable more differentiated analyses, the collected events must be classified according to their severity and intensity. Event severity could be estimated using event information stored in the database on monetary losses, type of flotsam, highest affected floor, and damages. Similarly, the event intensity may be classified using information on precipitation, discharge (e.g., return period, precipitation intensity), and cascade effects (e.g., clogging, landslide, dike break). Schroeder et al. (2016) and Diakakis et al. (2020), for example, propose a flash flood severity index based on damage. For events with discharge and precipitation measurements, an event classification based on derived discharge and precipitation parameters would be possible (e.g., Bhaskar et al., 2000; B.-S. Kim and H.-S. Kim, 2014; Saharia et al., 2017). However, the event dataset should not only be refined but also extended to increase the amount of training data for data-driven approaches and thus model performance. To this end, methods of natural language processing could be applied to automatically extract information on past pluvial and flash flood events from online newspaper articles (cf. Yzaguirre et al.,

2015; Zarei and Nik-Bakht, 2019).
The collected damage information of the event dataset has not been evaluated yet. Comprehensive information is available on the damage that occurred to buildings, agriculture, forestry, infrastructure, and businesses in the event database. Based on the descriptive text blocks, consisting of an adjective and a noun, an automated evaluation of the frequency and type of damage caused by heavy rain-induced floods is possible. Of particular interest is the relationship between event characteristics and the occurred damage. To investigate these complex interactions, detailed information on the triggering precipitation (e.g., amount, duration, intensity, spatial distribution) is needed from radar and ground measurements. Information from discharge measurement (e.g., time to peak, specific peak discharge, return period) can also help to establish a relationship between event magnitude and damage pattern. In addition, the influence of area characteristics on the type and severity of damage could be investigated (e.g., rugged vs. flat watersheds). Furthermore, machine learning approaches can be applied in flash flood damage analysis. Alipour et al. (2020), for example, demonstrate how flash flood damage in the southeastern U.S. can be predicted using a Random Forest model and features explaining exposure, vulnerability, and hazard.
Our analyses have proven that anthropogenic factors significantly influence the occurrence of heavy rain-induced floods. Aggregated at the rural district level, we found a positive moderate correlation between the number of inhabitants and the number of flood events triggered by heavy rain. However, there was no correlation between the sealing degree of a rural district and its reported events. Among the 17 chosen influencing factors of the ML model, the sealing degree and the built-up area share of a catchment were the two most influential factors. On average, the sealing degree and the built-up area share contributed nearly 17 and 12 % to the final decision of the decision tree. It can be assumed that the rural districts were spatially too homogeneous to prove a correlation between the sealing degree of a rural district and the number of its events. This is also shown by the fact that the share of built-up land related to the catchment area is an influential factor in the ML model.
The developed classification model disregards event-specific influencing factors and thus neglects an essential component in the analysis of factors influencing the occurrence of pluvial and flash floods. To close this gap, further analyses must consider event-specific factors such as triggering precipitation, antecedent soil moisture, and crop phenology. A major challenge here is to obtain this measurement data for a sufficiently large number of events to be able to evaluate them statistically. Another question that needs to be addressed is how to incorporate these event-specific influencing factors into the classifi-

cation model. For example, do different susceptibility maps have to be created for the different event preconditions, or can event-specific influencing factors be taken into account using statistical frequencies? Once these issues are resolved, we can investigate to what extent the event-specific influencing factors contribute to the occurrence of heavy rain-induced floods, as opposed to the susceptibility imposed by area characteristics.

Methodological and data uncertainties must be considered when interpreting the generated susceptibility map. The derivation of the pluvial and flash flood susceptibility map of Bavaria is based solely on spatially distributed and catchment-related influencing factors and does not consider event-specific influencing factors. Therefore, it cannot be ruled out that areas classified as having low susceptibility to heavy rain-induced floods may experience a devastating flash flood under unfavorable conditions, such as high antecedent soil moisture and extreme precipitation amounts. Furthermore, the derived susceptibility map is a representation of the current state. A significant change in time-variant influencing factors, such as the sealing degree, could lead to a higher or lower susceptibility in the future. The training and test locations of the unaffected locations also contain uncertainties. In the case of the unaffected locations, it cannot be excluded that they do not include affected locations, since the absence of an event report in the database does not necessarily mean that there was no event in the past. In this respect, when evaluating model performance, attention must be paid to the statistical measures describing the correct identification of affected locations (e.g., sensitivity, false-negative count).

Further insights can be expected from scenario modeling using the developed classification model (e.g., Avand et al., 2020). In our analysis, we found that the sealing degree and the proportion of built-up area in a catchment have a significant influence on the occurrence of heavy rain-induced floods. Looking ahead to future changes, it is important to understand how the susceptibility of an area changes when area characteristics such as the sealing degree, the share of built-up area in a catchment, or the land use change over time. Regarding mitigation measures, scenario modeling could help quantify the influence of these time-variant influencing factors.

Finally, we need to explore the strengths and weaknesses, possibilities and limits of data-driven models for flash flood susceptibility modeling, just as we do with hydrodynamic and hydrological models. This requires sensitivity analyses and plausibility checks of the relationships found by the machine learning model. Regarding model sensitivity, the influence of the predictor's spatial resolution (e.g., sealing degree, slope, elevation) on the model performance should be investigated (e.g., Knegt et al., 2010; Bradter et al., 2013). Also, the placement and size of the flood training and test locations could be varied, e.g., by choosing buffer areas around the city center instead of individual raster cells. In addition, we need to investigate the internal logic of the black-box models developed and examine why predicted flash flood susceptibility is high or low for a specific area. For this purpose, an increasing number of model-agnostic and model-specific interpretation methods are available, e.g., Partial Dependence Plots, Counterfactual Explanations, Local Surrogate Models, Influence Functions (Carvalho et al., 2020; Molnar, 2019). To further improve the prediction accuracy of data-driven models in hydrology, integrating spatial awareness and physical approaches into traditional machine learning techniques becomes inevitable (Jiang et al., 2020; Nearing et al., 2020; Talebi et al., 2020). Also, incorporating expert knowledge into ML models using fuzzy logic can help to improve flash flood susceptibility modeling (e.g., Hong et al., 2018; Bui et al., 2019b).

5.3 Outlook & practical recommendations

Due to the increasing availability of data in geosciences, event databases and machine learning models will continue to grow in importance. Increasingly large and complex data, also from new data sources, are available for evaluating past pluvial and flash flood events. These include for example satellite imagery, photos and videos from social media, newspaper articles, crowd-sourced stream level observations, radar images, and simulation results. To take full advantage of these datasets, we need event databases on the one hand that manage, structure, and link these different types of data. On the other hand, we need machine learning models to, e.g., extract inundation areas and water depths from satellite imagery (e.g., Ngo et al., 2018; Geyman and Maloof, 2019), assess flood severity from social media photos (e.g., Pereira et al., 2020), or estimate discharges (e.g., Petty and Dhingra, 2018). Machine learning will help us improve our predictive understanding of the complex relationships in geosystems (Bergen et al., 2019).

Event databases are not only of great benefit to research but also to society. Integrated into a website, flash flood event databases can serve as an information platform for interested parties, support science communication, and raise awareness of the danger posed by heavy rain-induced floods. In addition, citizens can get actively involved by, e.g., reporting events via an online form or investigating events in a map viewer. Especially to promote private precaution and hazard awareness, it is important to make the threat of pluvial and flash flooding tangible to citizens.

Due to their importance for science and society, event databases should be hosted sustainably. Databases of heavy rain or flash flood events are repeatedly created in scientific projects in Germany. The first German flash flood database was the URBAS database that was created in 2008 (BMBF, 2008). In addition to the HiOS database, a "Climate Event Portal" is set up in the project BAYSICS since 2018, holding event information on forest fires, flash floods, and landslides in Bavaria (bayklif, 2018). Also, the project CARLOFF, which started in 2019, aims at developing a database on convective precipitation events in Germany (climXtreme, 2020). However, linking the event databases to the projects is not sustainable because the databases are usually not maintained after the project ends and thus access is no longer possible. It is therefore recommended to host event databases at a national or international institution—such as the German Climate Computing Center, the International Centre for Water Resources and Global Change, or the Global Runoff Data Center operating under the auspices of the World Meteorological Organization—where long-term use is guaranteed, and other projects and international scientists can also gain access.

To advance the collection of flash flood event information, we need to make event documentation a community task. To this end, event databases should be publicly accessible to both the scientific community and society. Since collecting event information is time-consuming, it is important to distribute this task among as many stakeholders as possible. In the context of data collection, not only researchers but especially agencies and municipalities play an important role. Since agencies and municipalities usually have information on local events within their jurisdiction, it is important to encourage them to contribute to data collection. Agencies such as water management offices could submit their event information via an online form and upload photos, videos, and reports. After quality control by experts, the submitted event information could be added to the database. In return for their contribution to the data collection, agencies and municipalities could use the event database for their research and analysis.

Machine learning approaches have been widely applied in flood research for years (see Mosavi et al., 2018), but have yet to prove themselves in practice. This also holds true for flash flood susceptibility maps that are derived using classification algorithms. Currently, there is still a lack of experience from the application of flash flood susceptibility maps in flood risk management. This includes feedback from water management agencies, municipalities, and citizens on the comprehensibility, usefulness, and accuracy of the maps, which in turn can be used to improve the maps. Regarding the flash flood susceptibility maps, the knowledge transfer from science to practice and back still needs to take place. However, compared to flood hazard maps derived using computationally expensive hydrodynamic models, flash flood susceptibility maps have the advantage that they can be generated in a short time for a large study area using machine learning. Thus, flash flood susceptibility maps are an urgently needed complement to flood hazard maps by enabling a holistic hazard assessment of entire countries. Due to the rapid advancement of ML approaches, increasing availability of event information, and short computation time, flash flood susceptibility modeling using machine learning will become an integral part of flood risk management in the near future.

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A Database tables

Table A.1: List of the table attributes of the HiOS database including data types, data lengths, constraints, and keys.

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Administrative structure	cities	municipality__no	character varying	12	no	foreign key	primary key
Administrative structure	cities	federal__state	character varying		no		
Administrative structure	cities	government__district__no	character varying	3	yes	foreign key	
Administrative structure	cities	rural__district__no	character varying	5	yes	foreign key	
Administrative structure	cities	name	character varying		no	foreign key	primary key
Administrative structure	cities	bounding__box	geometry		yes		
Administrative structure	cities	zip__code	character varying	5	yes	foreign key	
Administrative structure	cities	height	integer		yes		
Administrative structure	cities	name2	character varying		yes		
Administrative structure	cities	population	integer		yes		
Administrative structure	cities	point	geometry		yes		
Administrative structure	federal__states	name	character varying		no	foreign key	primary key
Administrative structure	federal__states	state__no	character varying	2	no	unique	
Administrative structure	federal__states	population	integer		yes		
Administrative structure	federal__states	shapefile	geometry		no		
Administrative structure	federal__states	abbreviation	character varying	2	yes		
Administrative structure	government__districts	government__district__no	character varying	3	no	foreign key	primary key
Administrative structure	government__districts	federal__state	character varying		no		
Administrative structure	government__districts	name	character varying		no	foreign key	
Administrative structure	government__districts	shapefile	geometry		no		
Administrative structure	municipalities	municipality__no	character varying	12	no	foreign key	primary key
Administrative structure	municipalities	federal__state	character varying		no		
Administrative structure	municipalities	government__district__no	character varying	3	yes	foreign key	
Administrative structure	municipalities	rural__district__no	character varying	5	no	foreign key	
Administrative structure	municipalities	name	character varying		no	foreign key	
Administrative structure	municipalities	shapefile	geometry		yes		
Administrative structure	municipalities	name2	character varying		yes		
Administrative structure	municipalities	zip__code	character varying	5	yes	foreign key	
Administrative structure	municipalities	population	integer		yes		
Administrative structure	rural__districts	rural__district__no	character varying	5	no	foreign key	primary key
Administrative structure	rural__districts	government__district__no	character varying	3	yes	foreign key	
Administrative structure	rural__districts	federal__state	character varying		no		
Administrative structure	rural__districts	name	character varying		no	foreign key	
Administrative structure	rural__districts	shapefile	geometry		no		
Administrative structure	rural__districts	population	integer		yes		
Administrative structure	rural__districts	sealing__share	real		yes		
Administrative structure	water__authorities	name	character varying		no		primary key
Administrative structure	water__authorities	government__district__no	character varying	3	yes	foreign key	
Administrative structure	water__authorities	address	character varying		yes		
Administrative structure	water__authorities	telephone__number	character varying		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Administrative structure	water__authorities	fax__number	character varying		yes		
Administrative structure	water__authorities	email__address	character varying		yes		
Administrative structure	water__authorities	website	character varying		yes		
Administrative structure	water__authorities	shapefile	geometry		no		
Administrative structure	zip__codes	zip__code	character varying	5	no	foreign key	primary key
Administrative structure	zip__codes	shapefile	geometry		yes		
Catchment information	catchments	state__no	character varying		no	foreign key	
Catchment information	catchments	area__code	character varying		yes		
Catchment information	catchments	name	character varying		yes		
Catchment information	catchments	name2	character varying		yes		
Catchment information	catchments	catchment__type	character varying		yes		
Catchment information	catchments	in__state	character varying		yes		
Catchment information	catchments	from	character varying		yes		
Catchment information	catchments	to	character varying		yes		
Catchment information	catchments	river__name	character varying		yes		
Catchment information	catchments	river__order	character varying		yes		
Catchment information	catchments	comment	text		yes		
Catchment information	catchments	shapefile	geometry		yes		
Catchment information	catchments	max__height	real		yes		
Catchment information	catchments	avg__height	real		yes		
Catchment information	catchments	std__height	real		yes		
Catchment information	catchments	river__density	real		yes		
Catchment information	catchments	catchment__no	integer		no		primary key
Catchment information	catchments	area	double precision		yes		
Catchment information	catchments	perimeter	double precision		yes		
Catchment information	catchments	relative__perimeter	double precision		yes		
Catchment information	catchments	length__area__relation	double precision		yes		
Catchment information	catchments	compactness	double precision		yes		
Catchment information	catchments	circularity__ratio	double precision		yes		
Catchment information	catchments	relief	double precision		yes		
Catchment information	catchments	relief__ratio	double precision		yes		
Catchment information	catchments	melton__number	double precision		yes		
Catchment information	catchments	avg__slope	double precision		yes		
Catchment information	catchments	max__slope	double precision		yes		
Catchment information	catchments	std__slope	double precision		yes		
Catchment information	catchments	builtup__areas	real		yes		
Catchment information	catchments	agricultural__areas	real		yes		
Catchment information	catchments	forest__near__natural__areas	real		yes		
Catchment information	catchments	wetland__area	real		yes		
Catchment information	catchments	water__area	real		yes		
Catchment information	catchments	terrain__undulation__index	real		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Catchment information	catchments	melton_ruggedness	real		yes		
Catchment information	catchments	length	real		yes		
Catchment information	catchments	form_factor	real		yes		
Catchment information	catchments	elongation_ratio	real		yes		
Catchment information	catchments	catchment_center	geometry		yes		
Catchment information	gauges	lake_code	character varying		yes		
Catchment information	gauges	station_name	character varying		yes		
Catchment information	gauges	measurement_start	date		yes		
Catchment information	gauges	operator	character varying		yes		
Catchment information	gauges	catchment_area	real		yes		
Catchment information	gauges	river_kilometer	real		yes		
Catchment information	gauges	river_side	character varying		yes		
Catchment information	gauges	gauge_type	character varying		yes		
Catchment information	gauges	gauge_quality	character varying		yes		
Catchment information	gauges	gauge_zero	real		yes		
Catchment information	gauges	remark	text		yes		
Catchment information	gauges	website	character varying		yes		
Catchment information	gauges	low_water_level	real		yes		
Catchment information	gauges	high_water_level	real		yes		
Catchment information	gauges	comment	text		yes		
Catchment information	gauges	gauge_no	integer		no	foreign key	primary key
Catchment information	gauges	owner	character varying		yes		
Catchment information	gauges	data_maintenance	character varying		yes		
Catchment information	gauges	remote_data_transmission	character varying		yes		
Catchment information	gauges	name_river	character varying		yes		
Catchment information	gauges	river_code	character varying		yes		
Catchment information	gauges	location_river_course	character varying		yes		
Catchment information	gauges	area_code	character varying		yes		
Catchment information	gauges	avg_water_level	real		yes		
Catchment information	gauges	hq1	real		yes		
Catchment information	gauges	hq2	real		yes		
Catchment information	gauges	hq5	real		yes		
Catchment information	gauges	hq10	real		yes		
Catchment information	gauges	hq20	real		yes		
Catchment information	gauges	hq50	real		yes		
Catchment information	gauges	hq100	real		yes		
Catchment information	gauges	mq	real		yes		
Catchment information	gauges	state_no	character varying		yes	foreign key	
Catchment information	gauges	point	geometry		yes		
Catchment information	gauges	hq1000	real		yes		
Catchment information	gauge_catchments	shapefile	geometry		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Catchment information	gauge_catchments	area	double precision		yes		
Catchment information	gauge_catchments	lake_area	double precision		yes		
Catchment information	gauge_catchments	gauge_no	integer		no		primary key
Catchment information	lakes	lake_code	character varying		yes		
Catchment information	lakes	state_no	character varying		no	foreign key	
Catchment information	lakes	name	character varying		yes		
Catchment information	lakes	area_ha	real		yes		
Catchment information	lakes	island_area_ha	real		yes		
Catchment information	lakes	catchment_area	real		yes		
Catchment information	lakes	drainage_influenced	character varying		yes		
Catchment information	lakes	origin	character varying		yes		
Catchment information	lakes	main_inflow	character varying		yes		
Catchment information	lakes	outflow	character varying		yes		
Catchment information	lakes	number_inflows	smallint		yes		
Catchment information	lakes	shoreline_km	real		yes		
Catchment information	lakes	volume_hm3	real		yes		
Catchment information	lakes	max_depth_m	real		yes		
Catchment information	lakes	residence_time_d	real		yes		
Catchment information	lakes	height_asl_m	real		yes		
Catchment information	lakes	volume_bankful	real		yes		
Catchment information	lakes	inland_catchment_area	real		yes		
Catchment information	lakes	catchment_area_main_inflow	real		yes		
Catchment information	lakes	area_code	character varying		yes		
Catchment information	lakes	main_use	character varying		yes		
Catchment information	lakes	shapefile	geometry		yes		
Catchment information	lakes	comment	text		yes		
Catchment information	lakes	main_inflow_code	bigint		yes		
Catchment information	lakes	lake_no	integer		no		primary key
Catchment information	watercourses	watercourse_no	integer		no		primary key
Catchment information	watercourses	state_no	character varying		yes	foreign key	
Catchment information	watercourses	river_code	character varying		yes		
Catchment information	watercourses	lake_code	character varying		yes		
Catchment information	watercourses	area_code	character varying		yes		
Catchment information	watercourses	name	character varying		yes	foreign key	
Catchment information	watercourses	name2	character varying		yes		
Catchment information	watercourses	river_order	character varying		yes		
Catchment information	watercourses	location_info	character varying		yes		
Catchment information	watercourses	length_km	real		yes		
Catchment information	watercourses	river_width	character varying		yes		
Catchment information	watercourses	slope	real		yes		
Catchment information	watercourses	catchment_area	real		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Catchment information	watercourses	river__type	character varying		yes		
Catchment information	watercourses	affected	character varying		yes		
Catchment information	watercourses	use	character varying		yes		
Catchment information	watercourses	location__source__and__estaury	character varying		yes		
Catchment information	watercourses	comment	text		yes		
Catchment information	watercourses	shapefile	geometry		yes		
Catchment information	watercourses	length	double precision		yes		
Event description	damage	event__no	integer		no	foreign key	primary key
Event description	damage	source__no	integer		no	foreign key	primary key
Event description	damage	entry__no	integer		yes	foreign key	
Event description	damage	description__damage	text		yes		
Event description	damage	comment__damage	text		yes		
Event description	damage	total__damage	real		yes		
Event description	damage	fatalities	integer		yes		
Event description	damage	injured	integer		yes		
Event description	damage	evacuation	character varying		yes		
Event description	damage	advance__warning	real		yes		
Event description	damage	disaster__alert	character varying		yes		
Event description	damage	building__damages	real		yes		
Event description	damage	number__claims	integer		yes		
Event description	damage	description__building__damages	character varying		yes		
Event description	damage	comment__building__damages	character varying		yes		
Event description	damage	forestry__agricultural__damages	real		yes		
Event description	damage	description__forestry__agricultural__damages	character varying		yes		
Event description	damage	comment__forestry__agricultural__damages	character varying		yes		
Event description	damage	infrastructural__damages	real		yes		
Event description	damage	description__infrastructural__damages	character varying		yes		
Event description	damage	comment__infrastructural__damages	character varying		yes		
Event description	damage	business__damages	real		yes		
Event description	damage	description__business__damages	character varying		yes		
Event description	damage	comment__business__damages	character varying		yes		
Event description	damage	other__damages	real		yes		
Event description	damage	description__other	character varying		yes		
Event description	damage	comment__other	character varying		yes		
Event description	damage	zip__code	character varying	5	no	foreign key	primary key
Event description	damage	info__no	integer		no		primary key
Event description	entries	entry__no	integer		no		primary key
Event description	entries	source__type	character varying		yes		
Event description	entries	quality__level	character varying		no		
Event description	entries	editor	character varying		no		
Event description	entries	entry__date	date		no		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Event description	entries	last__review	date		yes		
Event description	events	event__no	integer		no		primary key
Event description	events	municipality__no	character varying	12	no	unique, foreign key	
Event description	events	date	date		no	unique	
Event description	events	city__name	character varying		no	unique	
Event description	hydrology	event__no	integer		no	foreign key	primary key
Event description	hydrology	source__no	integer		no	foreign key	primary key
Event description	hydrology	entry__no	integer		yes	foreign key	
Event description	hydrology	flooding	character varying		yes		
Event description	hydrology	return__period	character varying		yes		
Event description	hydrology	river	character varying		yes		
Event description	hydrology	gauging__station	character varying		yes		
Event description	hydrology	comment__flooding	character varying		yes		
Event description	hydrology	cause	character varying		yes		
Event description	hydrology	debris__flow	character varying		yes		
Event description	hydrology	landslide	character varying		yes		
Event description	hydrology	sedimentation	character varying		yes		
Event description	hydrology	contamination__type	character varying		yes		
Event description	hydrology	flotsam	character varying		yes		
Event description	hydrology	flotsam__type	character varying		yes		
Event description	hydrology	log__jam	character varying		yes		
Event description	hydrology	comment__log__jam	character varying		yes		
Event description	hydrology	dike__failure	character varying		yes		
Event description	hydrology	traffic__congestion	character varying		yes		
Event description	hydrology	sewerage__system__overload	character varying		yes		
Event description	hydrology	initial__condition__catchment	character varying		yes		
Event description	hydrology	heighest__affected__floor	character varying		yes		
Event description	hydrology	zip__code	character varying	5	no	foreign key	primary key
Event description	hydrology	info__no	integer		no		primary key
Event description	meteorology	event__no	integer		no	foreign key	primary key
Event description	meteorology	source__no	integer		no	foreign key	primary key
Event description	meteorology	entry__no	integer		yes	foreign key	
Event description	meteorology	storm	character varying		yes		
Event description	meteorology	lightning	character varying		yes		
Event description	meteorology	rain__on__snow	character varying		yes		
Event description	meteorology	hail	character varying		yes		
Event description	meteorology	max__diameter__hail	real		yes		
Event description	meteorology	avg__diameter__hail	real		yes		
Event description	meteorology	layer__thickness__hail	real		yes		
Event description	meteorology	comment__meteorology	text		yes		
Event description	meteorology	date__precipitation	date		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Event description	meteorology	start_precipitation	time without time zone		yes		
Event description	meteorology	end_precipitation	time without time zone		yes		
Event description	meteorology	return_period	character varying		yes		
Event description	meteorology	comment_precipitation	text		yes		
Event description	meteorology	duration	real		yes		
Event description	meteorology	amount	real		yes		
Event description	meteorology	convection	text		yes		
Event description	meteorology	precipitation_measurement	character varying		yes		
Event description	meteorology	measuring_station	character varying		yes		
Event description	meteorology	max_30min_precipitation	real		yes		
Event description	meteorology	max_1h_precipitation	real		yes		
Event description	meteorology	max_3h_precipitation	real		yes		
Event description	meteorology	max_6h_precipitation	real		yes		
Event description	meteorology	max_12h_niederschlag	real		yes		
Event description	meteorology	max_24h_niederschlag	real		yes		
Event description	meteorology	amount_precipitation_peak	real		yes		
Event description	meteorology	duration_precipitation_peak	real		yes		
Event description	meteorology	weather_condition	text		yes		
Event description	meteorology	zip_code	character varying	5	no	foreign key	primary key
Event description	meteorology	info_no	integer		no		primary key
Event description	sources	source_no	integer		no	foreign key	primary key
Event description	sources	source_name	character varying		no		
Event description	sources	usage_rights	text		no		
Event description	sources	dataset_description	text		no		
Event description	sources	citation	character varying		no		
Event description	space_time	event_no	integer		no	foreign key	primary key
Event description	space_time	source_no	integer		no	foreign key	primary key
Event description	space_time	entry_no	integer		yes	foreign key	
Event description	space_time	zip_code	character varying	5	no	foreign key	primary key
Event description	space_time	info_no	integer		no		primary key
Event description	space_time	start_flooding	time without time zone		yes		
Event description	space_time	end_flooding	time without time zone		yes		
Event description	space_time	duration_flooding	real		yes		
Event description	space_time	temporal_accuracy	character varying		yes		
Event description	space_time	urban_district	character varying		yes		
Event description	space_time	spatial_accuracy	character varying		yes		
Event description	space_time	event_extent	character varying		yes		
Event description	space_time	comment	text		yes		
Event documentation	documents	document_no	integer		no		primary key
Event documentation	documents	author	character varying		no		
Event documentation	documents	usage_rights	text		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Event documentation	documents	comment	text		yes		
Event documentation	documents	citation	text		yes		
Event documentation	documents	quality	character varying		yes		
Event documentation	documents	description	text		yes		
Event documentation	documents	storage_location	character varying		no		
Event documentation	photos	photo_no	integer		no		primary key
Event documentation	photos	author	character varying		no		
Event documentation	photos	usage_rights	text		yes		
Event documentation	photos	comment	text		yes		
Event documentation	photos	citation	text		yes		
Event documentation	photos	quality	character varying		yes		
Event documentation	photos	description	text		yes		
Event documentation	photos	storage_location	character varying		no		
Event documentation	websites	url_no	integer		no		primary key
Event documentation	websites	author	character varying		no		
Event documentation	websites	usage_rights	text		yes		
Event documentation	websites	comment	text		yes		
Event documentation	websites	citation	text		yes		
Event documentation	websites	quality	character varying		yes		
Event documentation	websites	description	text		yes		
Event documentation	websites	storage_location	character varying		no		
Event documentation	websites	url	character varying		yes		
Event documentation	websites	accessed_on	date		no		
Event documentation	videos	video_no	integer		no		primary key
Event documentation	videos	author	character varying		no		
Event documentation	videos	usage_rights	text		yes		
Event documentation	videos	comment	text		yes		
Event documentation	videos	citation	text		yes		
Event documentation	videos	quality	character varying		yes		
Event documentation	videos	description	text		yes		
Event documentation	videos	storage_location	character varying		no		
Measurements	discharge_investigation	gauge_no	integer		no	foreign key	primary key
Measurements	discharge_investigation	number	integer		no		primary key
Measurements	discharge_investigation	event_begin	timestamp without time zone		yes		
Measurements	discharge_investigation	event_peak	timestamp without time zone		yes		
Measurements	discharge_investigation	event_end	timestamp without time zone		yes		
Measurements	discharge_investigation	discharge_begin	double precision		yes		
Measurements	discharge_investigation	discharge_peak	double precision		yes		
Measurements	discharge_investigation	discharge_end	double precision		yes		
Measurements	discharge_investigation	percent_increase	double precision		yes		
Measurements	discharge_investigation	time_to_peak	double precision		yes		

Table A.1: *Continued.*

Category	Table name	Attribute	Data type	Length	Nullable	Constraints	Keys
Measurements	discharge__investigation	specific__discharge	double precision		yes		
Measurements	discharge__investigation	gradient	double precision		yes		
Measurements	discharge__investigation	volume	double precision		yes		
Measurements	discharge__investigation	peak__to__volume	double precision		yes		
Measurements	discharge__investigation	catchment__area	double precision		yes		
Measurements	discharge__investigation	return__period	character varying		yes		
Measurements	discharge__investigation	flood__discharge	real		yes		
Measurements	discharge__investigation	comment	character varying		yes		
Measurements	discharge__measurements	timestamp	timestamp without time zone		no		primary key
Measurements	discharge__measurements	discharge	real		yes		
Measurements	discharge__measurements	gauge__no	integer		no	foreign key	primary key
Measurements	heavy__rain__hours	zip__code	character varying	5	no	foreign key	primary key
Measurements	heavy__rain__hours	heavy__rain__hours	real		yes		
Metainformation	attribute__descriptions	table	character varying		no		primary key
Metainformation	attribute__descriptions	attribute	character varying		no		primary key
Metainformation	attribute__descriptions	attribute__description	text		yes		
Metainformation	attribute__descriptions	unit	character varying		yes		
Metainformation	attribute__descriptions	name__dataset	text		yes		
Metainformation	attribute__descriptions	dataset__description	text		yes		
Metainformation	attribute__descriptions	source	character varying		yes		
Metainformation	attribute__descriptions	comment	text		yes		
Metainformation	geodata__descriptions	dataset__no	integer		no	primary key	
Metainformation	geodata__descriptions	name__dataset	character varying		no		
Metainformation	geodata__descriptions	abbreviation__dataset	character varying		yes		
Metainformation	geodata__descriptions	description	text		yes		
Metainformation	geodata__descriptions	storage__location	character varying		yes		
Metainformation	table__descriptions	name	character varying		no	foreign key	primary key
Metainformation	table__descriptions	description	text		no		

B SQL queries

B.1 View of event list

To exclude noise from possibly irrelevant events, we only considered flash flood and pluvial flood events in our analyses that occurred between April and October. Furthermore, we excluded the events from the insurance dataset (with source number 5), as this dataset does not cover Germany uniformly and thus would distort the results. For reasons of manageability, we created a table view of the events table containing only those events relevant to our analyses.

```sql
CREATE VIEW events_analysis
AS
  SELECT DISTINCT e.event_no,
                  e.municipality_no,
                  e.date,
                  e.city_name
  FROM   events e
         JOIN space_time s
           ON e.event_no = s.event_no
  WHERE  Date_part('month', date) > 3
         AND Date_part('month', date) < 11
         AND s.source_no <> 5
  ORDER  BY event_no ASC
```

B.2 Number of events per affected city

The following SQL statement summarizes the number of events per affected city, as shown in Fig. 3.3.

```
SELECT e.city_name,
       e.municipality_no,
       Count(*) AS event_number,
       c.point
FROM   events_analysis e
       JOIN cities c
         ON c.municipality_no = e.municipality_no
            AND c.name = e.city_name
GROUP  BY e.city_name,
          e.municipality_no,
          c.point
ORDER  BY ( Count(*) ) DESC;
```

B.3 Time series of heavy rain-induced floods, injuries, and fatalities

This SQL statement summarizes the number of events, injuries, and fatalities per year since 1990, as shown in Fig. 3.5.

```
SELECT Date_part('year', date) AS year,
       Count(*)                AS events,
       Sum(fatalities)         AS fatalities,
       Sum(injured)            AS injured
FROM   events e
       JOIN damage d
         ON d.event_no = e.event_no
WHERE  e.event_no IN(SELECT DISTINCT event_no
                     FROM   space_time
                     WHERE  source_no <> 5)
       AND Date_part('year', date) >= 1990
GROUP  BY year
ORDER  BY year ASC
```

B.4 Time of event occurrence and number of injuries and fatalities

This SQL statement groups the heavy rain-induced flood events, injuries and fatalities by event onset, as shown in Fig. 3.6.

```sql
SELECT Extract('hour' FROM start_flooding) AS hour,
       Count(*)                            AS events,
       Sum(fatalities)                     AS fatalities,
       Sum(injured)                        AS injured
FROM   (SELECT DISTINCT event_no,
                        start_flooding
        FROM   space_time) m
       JOIN damage d
         ON d.event_no = m.event_no
WHERE  start_flooding IS NOT NULL
GROUP  BY hour
ORDER  BY hour ASC
```

B.5 Population density and events aggregated at the rural district level

The following SQL statement queries the number of events, population density, population, sealing proportion, area and shapefiles of the rural districts (see Fig. 3.7 and Fig. 3.8).

```
SELECT r.name,
       r.rural_district_no,
       Count(*) AS events,
       Cast(r.population / (St_Area(r.shapefile)/1000000) AS INTEGER) AS
            population_density,
       Log(10, r.population) AS log10_population,
       St_Area(r.shapefile)/1000000 AS area_km2,
       r.sealing_share,
       r.shapefile
FROM   (SELECT DISTINCT date,
                        LEFT(municipality_no, 5) AS rural_district_no
        FROM   events_analysis
        ORDER  BY rural_district_no ASC) m
       JOIN rural_districts r
         ON r.rural_district_no = m.rural_district_no
GROUP  BY r.name,
          r.rural_district_no,
          population_density,
          r.population,
          area_km2,
          r.sealing_share
```

B.6 Event rate of the German cities

For each German city, we calculated the event rate as the quotient of the number of events and the logarithm of the population to base 10. Cities without events were assigned an event rate of 0. This dataset was the basis for Fig. 3.9.

```
SELECT l.name,
       l.municipality_no,
       ( CASE
           WHEN m.events IS NULL THEN 0
           ELSE m.events / Log(10, l.population)
         END ) AS event_rate,
       l.point
FROM   (SELECT e.city_name,
               e.municipality_no,
               Count(*) AS events
        FROM   events_analysis e
               JOIN cities c
                 ON c.municipality_no = e.municipality_no
                    AND c.name = e.city_name
        GROUP  BY e.city_name,
                  e.municipality_no
        ORDER  BY ( Count(*) ) DESC) m
       RIGHT JOIN cities l
               ON l.name = m.city_name
                  AND l.municipality_no = m.municipality_no
ORDER  BY event_rate DESC
```

B.7 Flood-related injuries and fatalities per city

This SQL statement summarizes the number of injuries and fatalities by city (see Fig. 3.10).

```sql
SELECT c.name,
       c.zip_code,
       Sum(fatalities) AS fatalities,
       Sum(injured)    AS injured,
       point
FROM   damage d
       JOIN events e
         ON e.event_no = d.event_no
       JOIN cities c
         ON c.name = e.city_name
            AND c.municipality_no = e.municipality_no
WHERE  fatalities > 0
        OR injured > 0
GROUP  BY c.name,
          c.zip_code,
          point
```

B.8 Events per season and federal state

The following SQL query summarizes the number of events per season for each federal state, as shown in Fig. 3.11.

```sql
SELECT f.name,
       Sum(CASE
             WHEN Date_part('month', e.date) = 12
                   OR Date_part('month', e.date) = 1
                   OR Date_part('month', e.date) = 2 THEN 1
             ELSE 0
           end) winter,
       Sum(CASE
             WHEN Date_part('month', e.date) = 3
                   OR Date_part('month', e.date) = 4
                   OR Date_part('month', e.date) = 5 THEN 1
             ELSE 0
           end) spring,
       Sum(CASE
             WHEN Date_part('month', e.date) = 6
                   OR Date_part('month', e.date) = 7
                   OR Date_part('month', e.date) = 8 THEN 1
             ELSE 0
           end) summer,
       Sum(CASE
             WHEN Date_part('month', e.date) = 9
                   OR Date_part('month', e.date) = 10
                   OR Date_part('month', e.date) = 11 THEN 1
             ELSE 0
           end) autumn,
       f.shapefile
FROM   events e
       JOIN federal_states f
         ON LEFT(municipality_no, 2) = f.state_no
WHERE  event_no IN(SELECT DISTINCT event_no
                   FROM   space_time
                   WHERE  source_no <> 5)
GROUP  BY f.name
ORDER  BY f.name ASC;
```

B.9 Events per season in Germany

This SQL queries the number of events in Germany for each season (see Fig. 3.11).

```
SELECT Sum(CASE
             WHEN Date_part('month', e.date) = 12
                  OR Date_part('month', e.date) = 1
                  OR Date_part('month', e.date) = 2 THEN 1
             ELSE 0
           end) winter,
       Sum(CASE
             WHEN Date_part('month', e.date) = 3
                  OR Date_part('month', e.date) = 4
                  OR Date_part('month', e.date) = 5 THEN 1
             ELSE 0
           end) spring,
       Sum(CASE
             WHEN Date_part('month', e.date) = 6
                  OR Date_part('month', e.date) = 7
                  OR Date_part('month', e.date) = 8 THEN 1
             ELSE 0
           end) summer,
       Sum(CASE
             WHEN Date_part('month', e.date) = 9
                  OR Date_part('month', e.date) = 10
                  OR Date_part('month', e.date) = 11 THEN 1
             ELSE 0
           end) autumn
FROM   events e
WHERE  event_no IN(SELECT DISTINCT event_no
                  FROM   space_time
                  WHERE  source_no <> 5)
```

B.10 Seasonality of heavy rain-induced flood events

The following SQL query summarizes the number of events per month for each affected city. This dataset was the basis for Fig. 3.12. We aggregated the cities into bins of 100 km^2 using ArcGIS Pro and determined the month with the most events for each bin using Python's Pandas library.

```
SELECT e.city_name,
       e.municipality_no,
       Sum(CASE
             WHEN Date_part('month', e.date) = 4 THEN 1
             ELSE 0
           END) april,
       Sum(CASE
             WHEN Date_part('month', e.date) = 5 THEN 1
             ELSE 0
           END) may,
       Sum(CASE
             WHEN Date_part('month', e.date) = 6 THEN 1
             ELSE 0
           END) june,
       Sum(CASE
             WHEN Date_part('month', e.date) = 7 THEN 1
             ELSE 0
           END) july,
       Sum(CASE
             WHEN Date_part('month', e.date) = 8 THEN 1
             ELSE 0
           END) august,
       Sum(CASE
             WHEN Date_part('month', e.date) = 9 THEN 1
             ELSE 0
           END) september,
       Sum(CASE
             WHEN Date_part('month', e.date) = 10 THEN 1
             ELSE 0
           END) october,
       c.point
FROM   events_analysis e
       JOIN cities c
         ON c.municipality_no = e.municipality_no
            AND c.name = e.city_name
GROUP  BY e.city_name,
          e.municipality_no,
```

```
            c.point
ORDER  BY e.city_name,
            e.municipality_no ASC;
```