

Review

Requirements for Flood-Driven Forecasting Systems for Small and Medium-Sized Catchments in Germany

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Abstract

Unlike most other measures in flood risk management, flood forecasting stands out because it is not designed to address a pre-defined return period. In principle it is applicable to a whole range of possible events and can be operated continuously in real time. This makes flood forecasting an effective non-structural measure for saving lives and property, even in the face of increased hydro-meteorological variability and extremes. In Germany, a series of regional and transregional flood forecasting centres and services have been established that cover the entire national territory. For large basins, the existing forecasting centres are well equipped to provide accurate real-time forecasts. Nevertheless, there are remaining challenges that need to be met when the focus is on small to medium-sized catchments. This study focuses on discussing the capabilities of six state-of-the-art flood forecasting centres and derives the most important requirements for significant improvements in flood forecasting capabilities for small to medium-sized catchment areas. We emphasise that future research must focus on flood-driven predictions, including the prediction of flood inundation and consequences for buildings and infrastructure, as well as geotechnical failure mechanisms in Germany.

Keywords: flood forecasting; real-time forecasting; small and medium sized catchments; consequences



Academic Editor: Luís Filipe Sanches Fernandes

Received: 2 October 2025

Revised: 5 November 2025

Accepted: 11 November 2025

Published: 17 November 2025

Citation: Leandro, J.; Althoff, I.; Fischer, S.; Mudersbach, C.; Lesny, K. Requirements for Flood-Driven Forecasting Systems for Small and Medium-Sized Catchments in Germany. *Water* **2025**, *17*, 3283. <https://doi.org/10.3390/w17223283>

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1. Introduction

Short-term flood forecasting systems (up to 48 h) are some of the measures at our disposal to reduce the risk of flooding. Interventions for flood risk mitigation can be broadly categorised into non-structural and structural measures. Typical examples of the latter are the installation of flood defences or retention basins, while planning regulation, financial instruments, and flood forecasting are good examples of the former. Forecasting stands out from other measures because it is not designed to address a specific return period, as it is in principle applicable to a whole range of possible runoff events and can potentially be operated continuously for short- to medium-term time horizons. It can be used for issuing warnings to populations of eminent threats, but it can be also used for mobilising rescue services or initiating the installation of mobile flood defences. This study

focuses on the analysis of flood-driven forecasting systems for small and medium-sized catchments of six flood forecasting centres in Germany and suggests the requirements for significant improvement based on the current state of the art in science and likely future research developments.

In Germany, several regional and transregional services are responsible for flood forecasting. A global overview is available at <https://www.hochwasserzentralen.de/> (accessed on 29 October 2025). The website provides links to 23 flood forecast services that provide detailed forecasts to the different regions in Germany. Flood forecasting is based on a chain of models. This includes not only weather forecast models but also hydrological and hydraulic models (Luong, T.T. et al., 2021) [1], (Najafi, H. et al., 2024) [2]. Forecasts are, however, uncertain. The uncertainty inherent in forecasts is often quantified through the analysis of their performance based on past events or/and using an assemble of model runs (Leandro et al., 2019a) [3]. In either case, an uncertainty band with a given confidence interval is provided along with a deterministic forecast (López et al., 2014) [4]. The use of numerical simulations has the advantage that different sources of uncertainty can be included and propagated through a chain of interlinked numerical models, the forecast chain of models.

Accurate discharge measurements in open channels are essential for flood forecasting and water resource management. Over the decades, a wide range of measurement techniques have been developed, each with specific advantages and limitations depending on site conditions, flow regimes, and the required temporal and spatial resolution. Traditional point-based methods, such as current meters or electromagnetic sensors mounted on wading rods, remain widely used for manual flow gauging due to their simplicity and portability (Gore & Banning, 2017) [5]. In addition, permanently installed ultrasonic transit-time systems provide continuous monitoring by measuring the travel time difference of acoustic pulses along diagonal paths across a stream, offering long-term data with relatively low maintenance requirements (Rajita & Mandal) [6]. In recent years, non-intrusive, image-based techniques have gained increasing attention. Camera-based surface flow measurement methods, such as Large-Scale Particle Image Velocimetry (LSPIV) and Space–Time Image Velocimetry (STIV), enable high-resolution surface velocity estimations without contact with the water, which is especially valuable in hazardous or inaccessible environments (Tauro et al., 2017) [7], (Eltner et al., 2020) [8].

Our study starts by drafting the main requirements for flood forecasting systems in small and medium-sized catchments. After that we describe the details behind the production of forecasts together with the uncertainty assessment. In this context we discuss data and models as the main sources of uncertainty and how data can be included in forecasts. Next, a description of possible classes of flood forecasting is given; this is where we distinguish between conventional process-based and data-driven (rainfall–runoff and flood inundation) forecasting, and the ability to perform event-based and continuous forecasting. Then we present six forecasting centres in Germany, which we use to exemplify the current state of the art of forecasting in Germany. Possible improvements are highlighted in four points, which we will discuss in detail, namely, model-based and data-driven rainfall–runoff models, data-driven 2D flood inundation forecasting, measurement database and data assimilation, and communication of warnings. We see these as the most important areas where improvements are required and where research is already being conducted, or which are being investigated by researchers or/and some flood forecasting centres.

In the final section we look into flood-driven consequences for buildings and infrastructure, including geotechnical failure mechanisms (including mass movements). At present there is no known (significant) effort to address the role of mass movements in the

context of flood-driven forecasts by flood forecast centres in Germany, despite its likely increased relevance for very extreme events in the face of climatic change. Therefore, we discuss existing methods applied in risk assessment while emphasising the need to raise awareness for research on this issue. Finally, and for the sake of clarity, we would like to state that we do not address in this study any legal or administrative aspects of flood forecasting in Germany; hence, we refer the interested reader to other relevant sources on these matters (Demuth & Rademacher, 2016) [9].

2. Requirements for Flood Forecasting Systems for Small and Medium-Sized Catchments

In this study we focus on flood forecasting for small and medium-sized catchments in Germany because they have been hit the most by extreme events experienced in recent years and because these events are more difficult to predict. In this study, we defined watersheds with a catchment area between 50 km² and 300 km² as small-sized catchments and medium-sized catchments as those with an area between 300 km² and 1000 km². These catchment sizes are generally not covered by most forecasting centres due to a lack of measuring instruments in place. A system for operational flood forecasting is based on a chain of inter-linked simulation models. Such systems mimic the rainfall–runoff generation and concentration processes in natural and urban catchment areas (Byaruhanga et al., 2024) [10]. Their main aim is to simulate the consequences of precipitation events in terms of the runoff behaviour of catchment areas in channels and to forecast the runoff or water level at critical points. Traditionally, the decisive variable for decision-makers has been (mostly) limited to the water level, as this is directly comparable to the height of flood protection structures (e.g., dikes) and represents a good hazard indicator. Discharge values, estimated by hydrological models, require, on the other hand, conversion into water levels using either hydrodynamic models and/or empirical formulas (Hersch, 2008) [11], or water level–discharge relationships, which are required at specific locations. However, constant recalibration of those relationships is essential for operational flood forecasting. The maintenance of a reliable hydrometric monitoring network (precipitation and discharge monitoring stations) and the data retrieved form the basis of today’s existing flood forecasting systems (Mishra & Coulibaly, 2009) [12].

Precipitation forecasts are derived from weather models, ML approaches (Price et al., 2025) [13], or from radar and satellite images, the latter two products only being able to cover a limited forecast period of a few hours (Sokol et al., 2021) [14]. This is why the term “now-casting” is used in this case. In addition, forecasting of streams and rivers for a small or medium catchment area is more difficult. Strong rainfall events occur locally and have a strongly convective character, i.e., very high, short-term precipitation intensities (Bowden et al., 2024) [15]. In such events, the water level rises suddenly and the runoff reacts almost instantaneously to the precipitation (Meyer et al., 2022) [16]. Hence, the larger the catchment area, the more accurate the predictions tend to be, as the longer flow times enable better integration of measurement data. Incorrect assumptions about the initial conditions in a catchment (e.g., soil moisture) also have a greater impact in smaller catchments than in larger catchments (Uber et al., 2018) [17]. For example, the Simbach event in Germany in 2016 was very difficult to predict (Piper et al., 2016) [18]. The catchment area is only 50 km² in size. A Danube flood in Passau, on the other hand, affects around 50,000 km² and is therefore much more predictable.

3. Forecast Uncertainty

A perfect forecast would require exact knowledge of the processes happening in the atmosphere and in the catchment, and very precise input data. This is, however, not

possible because the processes are complex, data is limited, and nature is inherently affected by chaos. While for practical purposes often a single (deterministic) outcome of the forecast is considered, it is important to acknowledge that for the previously mentioned reasons a single forecast can never be accurate. Instead, forecasting based on a chain of models will carry a smaller or larger portion of uncertainty in each component of that chain forward up to decision-making (Figure 1). Therefore, the outcome of forecasting should ideally consist of a range of possible (probabilistic) realisations, representing the uncertainty range of the forecast (Boelee et al., 2019) [19]. This is similar to the classical confidence interval ranges that are used in standard statistics and modelling.

More generally, it is possible to distinguish between two types of uncertainty in forecasting: the errors associated with the input data, which includes the chaotic nature of atmospheric processes (aleatoric uncertainty) and data measurement errors, and the error associated with the forecasting model chain itself (epistemic uncertainty), which includes the imperfect representation of physical processes and the imperfect calibration of the models. We provide more details on both types of uncertainty in the following two subsections.

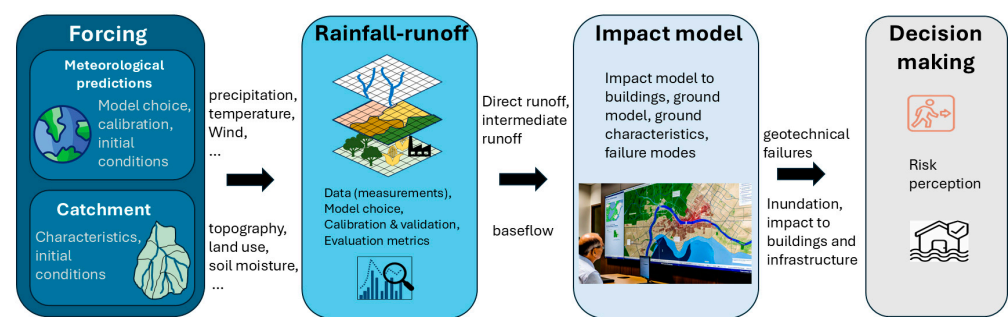


Figure 1. Propagation of uncertainty from meteorological inputs through the model chain to the final forecast and decision-making.

3.1. Uncertainty Related to Data

Flood forecasting relies on a variety of different data sources. First of all, observation data from past periods is required to set-up the hydrological models included in flood forecasting, i.e., long time series of discharge and precipitation and often additional data, such as temperature or snowmelt data, is considered. This data for calibration is already affected by uncertainty. Besides the measurement errors, often only short or incomplete data records are available for a certain catchment. This leads to sampling errors. In addition, small or medium-sized catchments are often insufficiently monitored and hence require supplementary regionalised data. Regionalisation generates a large amount of uncertainty due to the assumption of transferability of rainfall–runoff processes across different catchments (Blöschl, 2013) [20]. Another issue is the observation of extreme events. Since the aim of flood forecasting is to predict extreme flood events, the models used for flood forecasting should be able to capture these. However, given that the latter have a low probability of occurrence, one cannot guarantee that they have been observed in the past. In such a case, a hydrological model needs to extrapolate beyond the observation range, which adds another source of uncertainty (Fischer et al., 2025) [21].

Finally, it must be considered that the hydrological and climate data undergo changes over time. A changing climate leads to high variability in precipitation and other atmospheric data. Discharge observations might be additionally affected by anthropogenic impacts. These (often) large variations in the input data cause uncertainty in the forecasting processes, as the target period might be related to already altered conditions.

Besides the uncertainty in data used for calibration, one also must consider the uncertainty in the input data used directly for driving the forecasting models. Flood forecasting usually considers a precipitation forecast as input, coupled with the current (or initial rainfall condition) state of the catchment. The catchment's current state is itself an uncertain observation, as point measurements are necessarily limited in space and therefore a generalisation is required over the entire catchment. However, precipitation forecasts are even more uncertain in time (Valdez et al., 2022) [22]. The longer the forecasting periods are, the larger the uncertainty of the input data used for the forecast grows. The further we move ahead from the current known state, the more uncertainty is carried forward and added in time by the above-mentioned causes.

3.2. Uncertainty Related to Hydrological and Hydraulic Models

The second main source of uncertainty in flood forecasting is related to model choice. As mentioned above, a model chain is often used, in which different models are operated sequentially; hence, uncertainty is propagated along the chain (Disse et al., 2017) [23]. The nature of the models themselves is a source of uncertainty: models can only try to mimic the complex and chaotic processes of nature and consist of a simplification of these processes in the form of mathematical equations. Or, as prominently stated: "All models are wrong but some are useful" (Box, 1979) [24]

Besides this epistemic type of uncertainty, which hypothetically would be reducible if a perfect model were to exist, further sources of uncertainty are introduced by the model choice, namely, parametrisation (structural) and generalisation. The choice of the model introduces uncertainty, as different professionals/researchers select/develop different models, e.g., statistical, deterministic, or data-driven models, with different parametrisations (i.e., considered rainfall–runoff processes). A spatial simplification or regionalisation will further generate errors and lead to further uncertainty, as local processes are scaled up to large areas. Particularly for event-based modelling approaches, this may become critical because of the significant influence of the choice of model spatial resolution in the accurate simulation of specific events. Time variation of hydrological processes (as described in the previous subsection) is usually not considered in hydrological models either, or it is extrapolated in a very general way, e.g., by assuming consistent trends (Merkuryeva et al., 2015) [25]. All these simplifications and generalisations in a model affect the flood forecast and lead to higher uncertainty.

Besides the impact of the choice of models, uncertainty is introduced during the calibration/validation phase. Calibration of the model parameters might lead to certain processes being ignored or overrepresented, leading to inaccuracies in the estimates of the probabilities of occurrences of such events. Moreover, in general, only one parameter set is considered for all kind of flood events (deterministic approach), though different parameter sets might cause very different outcomes. There are two runoff processes that contribute to the formation of floods: (i) Hortonian surface runoff (Horton, 1933) [26] and (ii) Dunneian surface runoff—i.e., the saturation excess runoff (Dunne et al., 1975) [27]. For example, high-intensity rainfall will lead to a faster reaction and probably to an infiltration excess, while long-duration rainfall will slowly saturate the soil. The resulting flood events are very different in terms of shape, peak, and volume but are still supposed to be captured by the same parameter set, which will likely lead to inaccurate forecasts.

Finally, model evaluation can be a source of uncertainty. For example, metrics that focus the evaluation on the mean behaviour of discharge instead of the extremes may provide good general model performance; however, the flood peaks might be heavily underestimated (Mizukami et al., 2019) [28]. Typical examples are the use of metrics such as NSE or the KGE when applied to continuous series of discharge.

3.3. Consideration of Uncertainty in Flood Forecasting

A typical way to consider uncertainty is through ensemble forecasting (Cloke & Pappenberger, 2009) [29]. Ensemble forecasting is a form of Monte Carlo analysis, where instead of the most probable scenario an ensemble of forecasts is generated. An ensemble can be created by different approaches: variation in initial conditions such as rainfall or the catchment state, consideration of several hydrological and hydraulic models, consideration of different parameterisations of the models, or the use of statistical approaches to account for the uncertainty (Wu et al., 2020) [30]. These approaches consider different sources of uncertainty, as discussed earlier. The resulting ensemble can account for all possible or only some pre-selected realisations, or apply some weights according to certain criteria, such as probability of occurrence or severity (Doycheva et al., 2017) [31]. Albeit in theory each member has the same probability, initial conditions or past experiences can be used to assign ensemble members with a distinct probability of occurrence. However, unlike continuous simulations, where the effects of incorrect initial conditions may only be noticeable at the beginning of the simulations, they are crucial in event-based simulations. The effects on the quality of the simulation are noticeable well into the event-based simulation. One way to reduce this influence is to incorporate a warm-up phase period before the event (or forecast) so that the model internal conditions can converge to a more realistic state at the desired start of the forecast (Beg et al., 2019) [32]. An example of a discharge forecast for the Middle Rhine is shown in Figure 2.

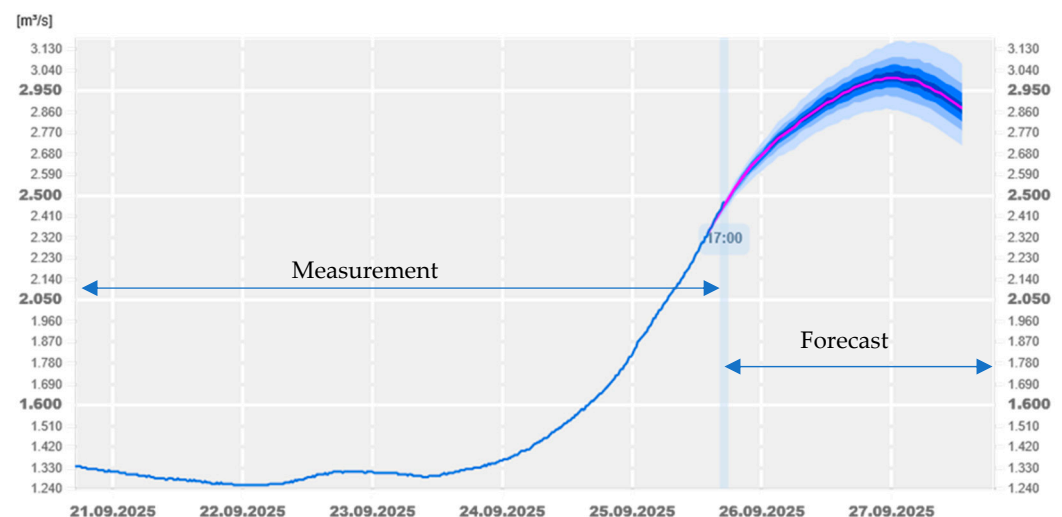


Figure 2. Discharge forecast (including associated uncertainty in blue) of the Federal Institute of Hydrology from 25 September 2025 13:00 for the gauge Cologne/Rhine [<https://www.hochwasser.rlp.de/flussgebiet/mittelrhein>, accessed on 29 October 2025].

Other approaches aim to evaluate and update flood forecasting to reduce uncertainty. In this case, precipitation and discharge are tracked and evaluated in real time to exclude unrealistic scenarios from a flood forecast (Doycheva et al., 2017) [31]. Though the forecasting could still be affected by the uncertainty of the observed data, such an approach might reduce the epistemic uncertainty. Alternatively, the output of a flood forecast can be evaluated regarding uncertainty and eventually corrected. In this case, the residuals of the model are analysed. Such post-processing methods often rely on statistical approaches, such as regression or kernel-based methods, Bayesian approaches, or distribution-based adaption (Li et al., 2017) [33].

An important role when considering uncertainty in flood forecasting is the communication with stakeholders and decision-makers (Jean et al., 2023) [34], (Fischer et al., 2025) [21]. As in practice often only one forecast value can be considered, the related uncertainty is

often ignored. Furthermore, the perceptions of risk of stakeholders and decision-makers may differ. This adds an extra source of uncertainty into the decisions being taken. Risk-averse and risk-seeking persons will likely have different perceptions of a hazard (Bhola et al., 2020) [35] and thus make different decisions regarding mitigation measures or evacuation orders. A straightforward and simplified communication of the uncertainty range would likely improve the flood awareness of stakeholders and subsequently the process of decision-making during crisis management.

4. Classes of Flood Forecasting Systems and Requirements

4.1. Model-Based Forecasting Systems

In Germany, hydrological models are used in operational flood forecasting; precipitation forecasts are based on numerical weather models. Data are provided by the German Weather Service (DWD). For flood modelling, both spatially high-resolution water balance models, such as LARSIM and PANTA RHEI, (Bremicker & Varga, 2014) [36], (Meyer et al., 2012) [37] and rainfall–runoff models, such as ArcEGMO and HydPy, (Müller et al., 2018) [38], (Tyralla, 2016) [39] are used.

Precipitation–runoff models use a deterministic relationship between precipitation and runoff to predict flooding. The predictions include discharge volumes and water levels at predefined points along major rivers, with the model parameters calibrated using measured discharge hydrographs at the location of the gauges. By varying parameters, the model output should be approximated as close as possible to a reference value. The storages arranged in the model represent a sequence of different natural processes such as interception or infiltration (Oppel, 2019) [40]. Water balance models are widely used in hydrology. They are used, for example, to simulate the impacts of climate and land use changes on the water balance (Althoff, 2025) [41] but can also be used for operational runoff forecasting (Bastian et al., 2024) [42]. Water balance models, diametrically opposed to rainfall–runoff models, take into account not only numerical weather forecasts (time series as precipitation, air temperatures, global radiation, wind speed, humidity, and air pressure) but also relevant hydrological processes, such as actual evapotranspiration; soil water saturation (soil water balance); and, if applicable, the development of snow cover, continuously (Gelleszun et al., 2020) [43], (Haag et al., 2022) [44].

These models can provide indications of possible flooding several days in advance. The simulation results serve for flood early warning and represent an essential complement to flood forecasts during an ongoing flood. The simulations not only enable a 7-day forecast for low, mean, and floodwater situations, but also a daily and, in the event of flooding, an hourly forecast. Usually, these models are calibrated to all discharge ranges (Bremicker & Varga, 2014) [36]. Regardless of the model chosen, the difference between the measured and simulated discharge should be as small as possible, usually $\pm$ a few centimetres in terms of water elevation.

In general, flood warnings of up to 7 days serve the advance planning of flood protection measures. In operational forecasting, predictions are compiled with models and published for the corresponding discharge gauges. If model results deviate too much on average from measured data, an automatic adjustment of the appropriate model parameters is made in the simulation period, so that the models represent the water balance or the rainfall–runoff process as well as possible at the prediction time, and thus an optimal initial condition is available for the prediction simulation (Bremicker & Varga, 2014) [36], (Müller et al., 2018) [38].

At the European level, EFAS (European Flood Awareness System) shows current and forecast floods up to ten days in advance. EFAS uses spatially distributed, area-wide hydrological modelling (using the LISFLOOD model system) primarily for gauge-

related discharge predictions. EFAS products consist of maps and graphics that illustrate possible future flood risks from EFAS forecast simulations. They are created by comparing the forecasts with reference flood thresholds and categorised according to different lead times: (i) flash flood indicators, which provide information on the risk of flash floods for up to five days; (ii) medium-term flood forecasts, which provide an overview of upcoming flood events for the next ten days; (iii) seasonal and sub-seasonal hydrological prospects, which summarise the hydrological situation for the next eight weeks; and (iv) flood impact forecasts, which show regions with expected impacts in the next ten days [www.copernicus.eu/en/european-flood-awareness-system, accessed on 29 October 2025]. The products are for overview purposes only and are too uncertain for small and medium catchment areas.

4.2. Rainfall–Runoff Data-Driven Models

Data-driven models are adaptable and effective methods for hydrological forecasting because they do not necessarily require a physical description of the catchment. Thanks to novel machine learning (ML) techniques and increasing computing power, data-driven models have evolved to the point where they are capable of modelling highly non-linear and complex relationships between inputs and outputs.

The most common examples of data-driven models for hydrology are the unit hydrograph, linear regression, and the auto-regressive integrated moving average (ARIMA) (Ivo et al., 2021) [45]. Recent developments in computational intelligence and ML have significantly expanded the possibilities of data-driven methods with tools such as Support Vector Machines (SVMs) (Han et al., 2007) [46], Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Inference Systems (ANFISs), Genetic Algorithms (GAs), Evolutionary Programming, and Chaos Theory (Mosavi et al., 2018) [47].

Although runoff prediction has traditionally been performed using hydrodynamic and conceptual models (Leandro et al., 2019b) [3], data-driven models are particularly useful options in areas where the collection of geophysical and topographical information about a catchment is difficult. On the other hand, advanced artificial intelligence models generally require more readily available observations (time data series) to model the complex phenomena in catchments (Piadeh et al., 2022) [48].

It is known that data-driven models need to be trained outside the range of historical records for the purpose of forecasting. This can be achieved by training the models with data sets from physically based models that are based on synthetic or historical events (Crotti et al., 2020) [49]. The prerequisite, however, is that the physically based models can calculate extreme situations reliably. In this way, a data-driven model is also able to make predictions outside the range of known extreme events. Therefore, even extreme events, such as the one that occurred in the Eifel, in Germany, in July 2021, could in principle still be predicted reliably.

4.3. Event-Based and Continuous Forecasting Systems

Since different organisations and stakeholders, such as the public, should be able to contribute to the components of flood protection and act accordingly (Perera et al. 2019) [50], early warnings are also important in small, medium, and fast-reacting catchments. The regional flood early warning for small catchment areas (<200 km²) is based on a forecast period of a maximum of 48 h, although early warning maps are updated as often as hourly. Warnings are derived based on spatially distributed, operational hydrological models that cover an entire federal state (e.g., Baden-Württemberg, Hesse). Precipitation forecasts are based on numerical weather models based on data from DWD. The generated runoff forecasts, which refer to model nodes (administrative boundaries such as rural districts),

are compared with regionalised peak discharges or peak discharge per unit area. The model nodes of a warning region, where the forecast discharge reaches or exceeds a specified statistical value (annuality), are weighted and areal warning information is derived (Philipp & Kerl, 2017) [51]. In principle, the same system is used for the operational creation of gauge-related predictions (Haag et al., 2022) [44]. Furthermore, early warning systems for catchment areas smaller than 500 km² exist (e.g., in Rhineland-Palatinate), which differ from the previously mentioned system in that the early warning is catchment-based and probabilistic precipitation (LFU, 2016) [52] is used instead of a deterministic quantitative precipitation forecast. On the one hand, it can be seen that the small-scale meteorological events causing floods are predictable by numerical weather models to a limited extent in terms of their spatial–temporal occurrence [<https://www.hydro-meteo.de/index.php/niederschlag/niederschlagsvorhersage/>, accessed on 29 October 2025], and thus no reliable gauge-related predictions are possible. On the other hand, the current status of the map marking discharge gauges in Germany [<https://umwelt.info/de/artikel/flussmessstelle-n-deutschland>, accessed on 29 October 2025] shows that these normally are inexistent for small water bodies, and therefore model nodes are used instead in forecasting.

To improve the above-mentioned existing methods for flood forecasting and early warning in small and medium-sized catchment areas, research has been carried out in recent years, but so far this has been limited to pilot catchment areas. Examples include the research by (Luong et al. (2021)) [1] and (Haag et al. (2022)) [44], or the research projects HoWa-PRO in Saxony [<https://www.wasser.sachsen.de/howa-pro.html>, accessed on 29 October 2025] and “Flood Protection System 4.0” in the Bergisches Land [<https://nrwinnovativ.de/ki-gestuetztes-hochwasserwarnsystem-in-nrw/>, accessed on 29 October 2025].

4.4. Two-Dimensional Flood Inundation Forecasting

Existing forecasting systems are limited to hydrological discharge hydrographs and/or water levels for 12–48 h, and do not enable the simulation of flood inundation via two-dimensional (2D) models. Unfortunately, flood inundation forms the basis for decision-making in flood risk management. Flood risk management requires information on flood hazards based on water depth, the extent of flooded areas, and flow velocity (Bhola et al., 2020) [35]. The dynamic prediction of the inundation extent of a flood is difficult, as the creation of flood maps for this purpose in real time is very computationally intensive (Bhola et al., 2018a) [53].

The introduction of multi-core central processing unit (CPU)- and graphical processing unit (GPU)-based hardware architectures has significantly improved the computing power of numerical models in recent years (Caviedes-Voullieme et al., 2023) [54]. However, the resource consumption and regular maintenance required for such an infrastructure represent major challenges for operational use. Therefore, such developments have not yet become established in operational use, even though they facilitate real-time modelling. In addition, it is important to develop methods to equip forecasting centres with cost-effective and resource-efficient methods. Such methods should not require computationally intensive and time-consuming calculations of 2D inundation models in real time to enable them to create and analyse inundation patterns well in advance of emergencies.

5. Flood Forecasting Systems in Germany

Flood forecasting centres in Germany apply hydrological models that calculate discharges for gauging stations or nodes for the coming hours or days based on hydro-meteorological data like precipitation and current water levels at upstream gauging stations, using forecast hydro-meteorological data from DWD. Depending on the quality of the

model's input data and the forecast period, forecasts are characterised by smaller or larger uncertainties (see Section 3). As discussed before, hydrological models calculate discharges where gauges are located or where nodes are defined. The discharge information must be transformed into water levels for relevant gauge location. This is often carried out using water level–discharge relationships (or rating curves). Rating curves can be derived by either machine learning or statistical methods (Rozos et al., 2022) [55], or by means of 2D model simulations. Warnings about expected water levels can then be issued on this basis.

A flood warning is to be distinguished from a flood forecast. A flood warning occurs only when one or more previously defined warning levels (water levels) are reached or expected to be exceeded. A flood warning is therefore triggered by a flood forecast, although a flood warning service can also be operated without a numerical flood forecast by only issuing warnings based on current water level measurements at the gauges. In the latter case, it is generally less often possible to act with foresight, and the response times for corresponding flood protection measures are severely limited, especially in small-sized catchments (Leandro et al., 2024) [56].

The next six subsections summarise the information available online provided by six forecast centres in Germany from a total of twenty-three, which can be accessed via <https://www.hochwasserzentralen.de/> (accessed on 29 October 2025). Even though each individual centre is solely responsible for the forecasts provided, it can be stated that the selected examples are representative of the main forecast methods and assumptions applied in Germany by forecast centres and thus provide a good overview of the current state of the art in the country. A summary of the six centres is presented in Table 1.

Table 1. Summary of the six forecast centres in Germany analysed in this study.

State	Size (km ²)	Forecast Model Used	Number of Stations with Forecast (*)	Forecasting Period (Hours)
Bavaria	70.550	LARSIM	243	12
Baden Württemberg	35.751	LARSIM	165	24 and 48
Hesse	21.115	LARSIM	131	24
Northrhine-Westphalia	34.098	LARSIM	117	24 and 48
Rhineland Palatinate	19.858	LARSIM	142	24 and 48
Saxony	18.416	ScoHM/DeHM	104	48

Note: Sources: (*) <https://www.hochwasserzentralen.de/> (accessed on 29 October 2025).

5.1. Bavaria

The Flood Information Service (HND) of the Bavarian State Office for the Environment (LFU) in Augsburg is responsible for warning the population of floods in Bavaria. There are five regional flood forecasting centres that are responsible for calculating flood forecasts. They are organised according to the catchment areas of the Main, Danube, Isar, Iller/Lech, and Inn rivers. The service considers a total of 600 water levels at various locations across the Bavarian watercourses. Of the 600, 570 water levels are automatically read out at 15 min intervals and included in the HND.

The HND makes it possible to retrieve this information online in the form of warnings, tables, and maps. If certain threshold values are reached, the HND informs the responsible water management authorities. From there, the information is forwarded to the towns and municipalities via the district offices' reporting centres. The towns and municipalities are of particular importance as they are the last link in the reporting chain. Their reporting plans specify who is to be warned when and how and which measures are to be taken at which water levels. For this purpose, the municipalities keep site plans of endangered areas or objects as well as organisational plans that are necessary for flood protection.

The flood situation is indicated by four reporting levels:

- Level 1: Minor flooding in places.
- Level 2: Agricultural and forestry areas flooded, or minor traffic obstructions on main roads and local roads.
- Level 3: Individual built-up properties or cellars flooded, or closure of local traffic routes or isolated use of water or dam defences necessary.
- Level 4: Built-up areas flooded on a large scale, or large-scale deployment of water or mobile/temporary flood defences required.

The warnings are also divided into four categories:

- Warning of flood risk (light orange);
- Warning of overtopping and flooding (orange);
- Warning of flooding for built-up areas (red);
- All-clear (green).

Warnings of flooding are issued for rivers and streams. Dangers from strong rainfall or thunderstorms are excluded. Each HND warning contains a reference to the impossibility of forecasting localised flooding due to heavy rain. ('Note: No warnings or forecasts can be issued for localised flooding, such as that caused by localised heavy rainfall (thunderstorms).')

A forecast of water levels or discharge can be visualised for the next 12 h. The expected water levels are predicted with the help of water balance models, in this case, LARSIM models, which are adapted to the catchment area. Depending on the weather forecast and the size and nature of the catchment area, these forecasts can be subject to uncertainties. To provide an indication of the possible range of fluctuation of the forecasts, additional uncertainty ranges are estimated together with the observed data. The uncertainty ranges are determined by statistically analysing past observations. The deviations of past forecast results are compared with the measured values. The quantiles of the deviations are derived based on a statistical analysis using distribution functions. The HND applies the 10% and 90% percentiles to the forecasts to be displayed online.

5.2. Baden-Württemberg

In Baden-Württemberg, flood forecasting essentially relies on two instruments. The Flood Notification Regulation (HMO) is a legal instrument designed to ensure that the responsible authorities and departments are informed of emerging hazards and can initiate any necessary measures. The Flood Forecasting Centre (HVZ-BW) of the Baden-Württemberg State Institute for the Environment (LUBW) serves as an information technology instrument and is responsible for the provision and forecasting of hydrological data.

The HVZ-BW publishes associated water level and discharge data for 165 gauging stations. They are assigned to the catchment areas of Lake Constance, the High Rhine, the Upper Rhine, the Danube, and the Neckar and its important tributaries, as well as the Main and Tauber rivers. For low and mean water, these values are updated hourly and include a forecast of up to 10 days, which is updated daily. To counter the underlying uncertainties, a best-possible estimate is calculated from a selected combination of weather forecasts.

During the formation of supra-regional flood events, the measured values are updated up to every 15 min and the forecasts every hour for the next 24 and/or 48 h. For small catchment areas (less than 150 km²), it is not possible to forecast water levels accurately due to the lack of correctness in the meteorological precipitation forecasts. In this case, a regional flood early warning system is used. This employs a combined application of meteorological and hydrological models to classify the flood risk in the urban and rural districts according to the various warning levels: Low, Moderate, Medium, and High.

The map calculated in this way is updated every three hours according to the short-term forecast of DWD.

In addition to the level-related forecasts and regional warning levels, the HVZ-BW regularly publishes up-to-date reports in the event of flooding, which provide an overview of the flood situation and the course of the event. All data is bundled and made available to the responsible administrative bodies, the population, and the media and is published via the internet, teletext, radio, and an automatic telephone announcement. In addition, the web-based specialised system FLIWAS 3 is used at all levels of public administration and by the water boards to provide information and communication, thereby automating notifications.

No forecasts are issued for localised flooding or flooding due to strong rainfall. This can be seen from a note on the HVZ-BW website: Note: 'Forecasts cannot be issued for localised flooding, such as that caused by localised strong rainfall or thunderstorms.'

To calculate the discharge and water level forecasts, measured and forecasted weather data and water levels at the gauging stations are required up to the time of the forecast. This input data is retrieved at least hourly at the water level measuring points, as well as the meteorological data at the various measuring points of the LUBW and the weather service. Based on all measurement and forecast data, the LARSIM model calculates the snow cover, evapotranspiration, soil moisture, water release from the catchment areas, and water transport in rivers in a 1×1 km grid.

In addition to the HVZ-BW, the HMO is the second instrument and regulates flood warning/alerting and responsibilities. According to these regulations, threshold values in the form of water levels are defined for all water levels. If the observed water level is above this threshold, a flood alarm is triggered. The alarm is divided into three phases:

- Monitoring phase: Observation and expert advice on further weather and flood developments.
- Pre-alarm: All offices, agencies, aid organisations, and especially the persons responsible for properties at risk of flooding are informed if the observation of the weather situation and the relevant water levels indicates an increased risk of flooding.
- Flood alert: The threshold value from the HMO is exceeded.

5.3. Hesse

Flood warning and reporting in the state of Hesse is the responsibility of the Hessian State Agency for Nature Conservation, Environment and Geology (HLNUG). Water level and discharge values for the 95 gauging stations in Hesse and the 44 flood retention basins and reservoirs are updated at least every hour for flood forecasting purposes. According to flood service regulations (HWDOs), the local water authorities are responsible for warning residents at risk of imminent flooding. There are five HWDOs in Hesse for the five main river basin districts (Rhine, Main, Lahn, Kinzig, Hessian part of the Weser (Diemel)). The HWDOs specify warning levels for selected gauges. If the water levels are exceeded, the corresponding warning levels are activated. There are also defined reporting limits for selected precipitation measuring stations. Decentralised HWDOs (DHWDOs) apply to 25 other water bodies in small catchment areas. The threshold values for warnings are determined individually for each gauge or each watercourse. There are currently three levels of warning in Hesse:

- Reporting level 1: Small flooding in places.
- Reporting level 2: Extensive flooding of properties close to banks, slight traffic obstructions on municipal and main roads, danger to individual buildings, flooding of cellars.
- Reporting level 3: Built-up areas largely flooded, closure of supra-local transport links.

The forecasting for runoff and water levels in Hesse is also based on the LARSIM model. By continuously updating the model, the forecast calculation is always based on the current hydrological and land-use-specific conditions of the river basin districts. Currently LARSIM is used in the river basins of the Lahn, Werre, the Hessian part of the Weser, and the Rhine and Main tributaries, as well as the non-Hessian parts of the Lahn, Eder, Diemel, and Werra river basin districts. Hesse is divided into approx. 5000 sub-areas, each with a size of 4–5 km². Input variables for the simulation of forecasts for medium and large catchment areas are water level hydrographs and weather data from weather prediction forecast models from DWD.

Smaller bodies of water and sections of waters are currently not included due to very short lead times and the current resolution of weather models. With LARSIM, at least an early flood warning can also be provided for non-gauged watercourses in small catchment areas (up to approx. 200 km²) through the constant simulation of (soil) pre-moisture and with precipitation forecasts. In this way, the soil water balance and runoff can be simulated outside of flood periods. These warnings are valid for 24 h and are displayed in a warning map for each district.

The results of the forecasts are made available internally to the Ministry of the Environment, the regional council, and the lower water authorities as soon as the threshold values defined in each DHWDO are exceeded. The public is informed via the Internet (flood portal for Hesse/the federal states, HLNUG website), radio, press, and television. The results are also made available to other federal states and federal authorities.

5.4. North Rhine-Westphalia

The state of North Rhine-Westphalia (NRW) currently operates a comprehensive flood warning service (FWS) based on measured data of flood warning gauges. The FWS covers the areas shown in Figure 3. The flood warning gauges are generally only available for medium-sized and larger water bodies. Flood warning gauges for small bodies of water are rather rare. The Environmental Agency LANUK website provides current water levels at water bodies in NRW as well as flood reports relating to flood warning gauges in accordance with the flood reporting regulations. In the event of flooding, “hydrological reports” are also produced and published. In addition, weather information is available, which is produced by DWD.

In 2023, a flood forecasting system based on the LARSIM model was set up for the state of NRW. The LARSIM model simulates flow rates based on the hydrological processes of interception and evapotranspiration, snow accumulation and ablation, soil water storage and runoff formation, and lateral water movement in the area, as well as translation and retention in channels and lakes in the sub-catchment areas.

The model covers the entire state of NRW and is divided into ten model areas. A particular challenge in the development of the model lay in the large number of different types of watercourses, the inclusion of transboundary watercourses, and a strongly changing topography, as well as many dams, open-cast lignite mining, and a network of shipping canals. The Interface Delft-FEWS software is used to control and manage the inputs/outputs of LARSIM and to generate the corresponding reports. The aim is to produce water level-related flood forecasts for the flood warning gauges. The flood forecasting model is intended for catchment areas larger than 300 km². Flood forecasting for smaller catchment areas has not yet been implemented.

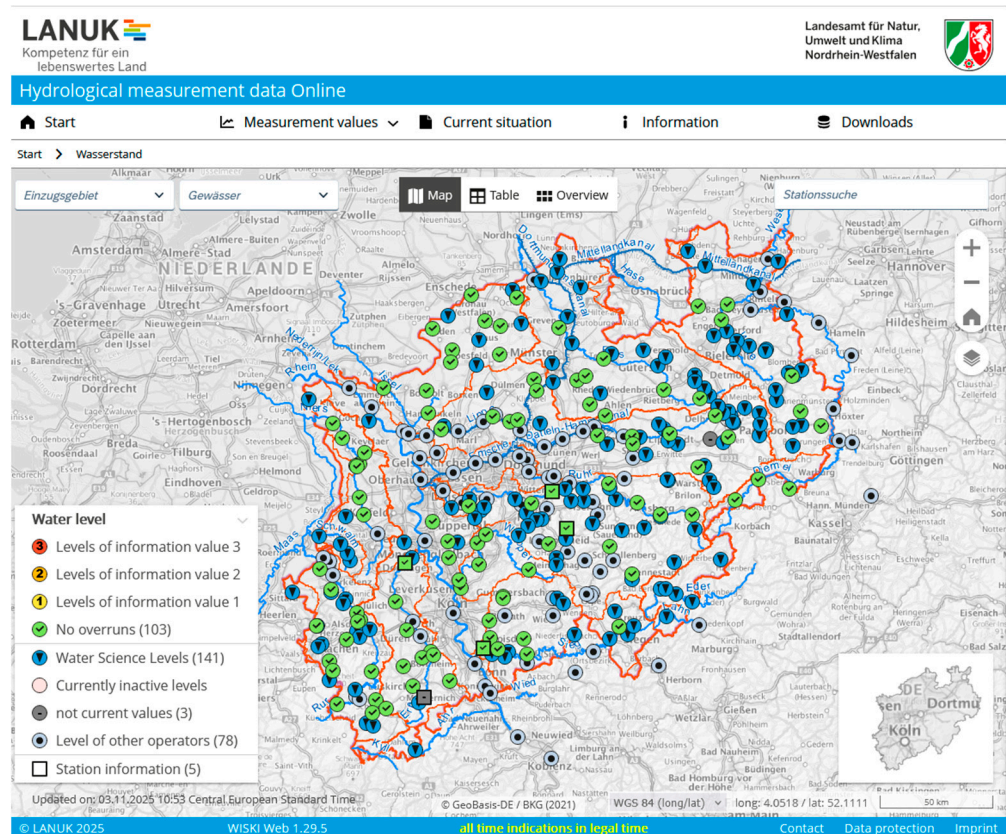


Figure 3. Flood warning levels shown on the LANUK website for North Rhine-Westphalia (www.hochwasserportal.nrw, accessed on 29 October 2025, provided by the LANUK).

Some water boards in NRW also have flood information services (HOWISs) that are used for flood forecasting. The water boards Emscher-Genossenschaft/Lippeverband (EG/LV), Ruhrverband (RV), Wupperverband (WV), and Wasserverband Eifel-Rur (WVER) have been cooperating with other associations and the DWD for several years to share water management and meteorological data. The five water boards mentioned above also operate a forecasting platform based on Delft-FEWS for further processing of the data provided.

5.5. Rhineland-Palatinate

In Rhineland-Palatinate, the state's Flood Forecast Center (HVZ-RLP) is responsible for early warnings on the rivers of the Upper Rhine, Middle Rhine, Lower Rhine, Moselle, Nahe, Lahn, Sieg, Ahr, Glan, and Wied. Information on current flood risk is available for 46 warning regions. The flood warnings are regionwide and based on the high-resolution water balance model LARSIM (see Sections 4.1 and 4.2). The modelling considers different possible weather developments based on the forecasts of the DWD as well as precipitation and water level measurements. In Rhineland-Palatinate, 246 discharge gauges of the HVZ-RLP and 42 discharge gauges of the municipalities or districts are available. The warnings on the flood warning map (Figure 4) and the 48 h forecasts for country gauges are thus also based on flood forecasts (prediction computations) for the very small rivers. If the predicted discharges exceed certain warning stages in several waters' segments within a warning area, then this warning area receives a warning colour divergent from green on the warning map. The warning map shows the flood risk for small and medium-sized catchment areas based on six warning classes, from a low up to an extreme hazard. The warning classes contain information on the probability of the expected flood peaks as well as other general information on the flood hazard. The warning map warns of river floods and not of small-scale flooding. The warning map for Rhineland-Palatinate is updated

twice a day at approximately 9:30 a.m. and 3:30 p.m. and refers to the possible flood risk for the next 24 h. Furthermore, if a major flood is expected in the next 48 h and possibly in the subsequent period, an early warning will be issued for the corresponding region. The flood alert service is opened by the HVZ-RLP for a river basin when the measured water levels exceed a certain water level (reporting height) at a reporting gauge. From the opening of the flood alert service, the measured water levels for a river basin affected by flooding will be provided hourly via the information channels. In addition, water level forecasts and, where possible, estimates for longer periods are provided several times a day at 3 h intervals.

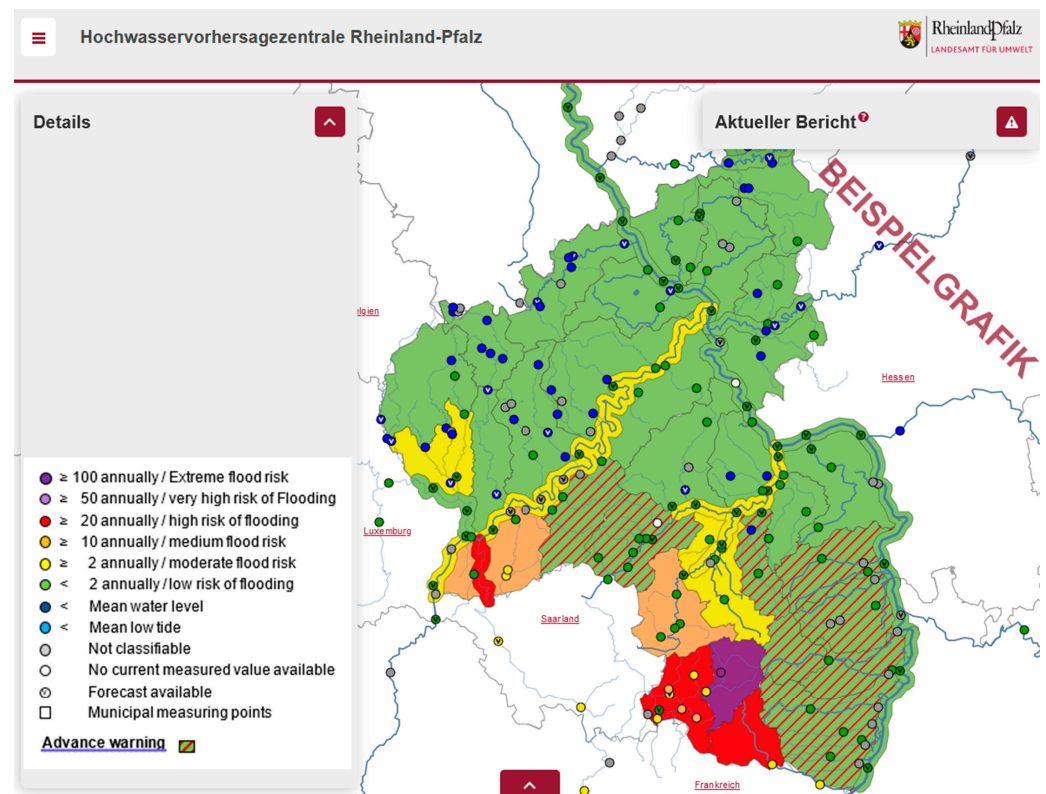


Figure 4. Flood early warning map—current measured value at the gauge, 24 h forecast for warning region (<https://www.hochwasser.rlp.de/>, accessed on 29 October 2025, provided by the HVZ-RLP).

5.6. Saxony

In Saxony, the State Flood Center (LHWZ) is responsible for early warning in the main river basins (White Elster, Mulde, the Elbe and tributaries, Black Elster, Spree, and Lusatian Neisse). Altogether, information on the current flood risk is available for 16 warning regions. For the main river basins in Saxony, deterministic hydrological forecasts based on rainfall–runoff models and flood-routing models are available, which are prepared by the State Flood Center (LHWZ) and forwarded on an event-related basis. For catchment areas larger than 1000 km², forecasts with a prediction period of up to two days can be realised; for the Elbe River, reliable forecasts with a prediction period of up to three days are possible (Philipp et al., 2017) [51].

For small catchments (up to 200 km²), ScoHM (Metzkes, 2016) [57] is used as a scoring model, and thus a classifying assessment method, for flood vulnerability to derive forecasts (Philipp et al., 2017) [51]. Moreover, in research in small pilot areas, the event-based, conceptual, hydrological model DeHM (Schwarze et al., 2015) [58] is used to improve the forecasts (Grundmann, 2022) [59]. The modelling considers different possible weather developments based on the forecasts of the DWD as well as precipitation and discharge

measurements. In Saxony, over one hundred discharge gauges have been designed as so-called flood warning gauges; in addition to these, there are others that also deliver data to the LHWZ via remote transmission in quasi-real time. In total, the measuring network consists of approximately 300 measuring points (Philipp et al., 2017) [51]; data for 192 gauges are available on the LHWZ website. The flood early warning map is updated hourly and provides an assessment of the flood risk for up to 24 h ahead. It should be noted that the predicted hazard situations shown on the early warning map apply to small catchment areas but are only valid regionally for the 16 sub-regions of Saxony, without specifying a specific location. Flood risk is divided into five categories, ranging from “low risk” to “very high risk” (Figure 5). The regional colouring of the warning map results from the outcome evaluation of the early warning system over the entire forecast period. To assess the reliability of the flood early warning, a so-called ongoing verification is implemented. This involves calculating daily how often the early warning is “wrong” or “right”. Four alert levels are defined for each flood warning gauge. The proclamation of the alert level for each river section is made by the responsible lower water authority and not by the LHWZ; however, special consideration is given to the data provided on the LHWZ information platform. The flood news and alert service is initiated by a so-called urgent flood notification. This is rendered by the LHWZ and distributed to the flood news and alert service participants when the water level at a flood warning gauge reaches or exceeds the reference value for alert level 1. The flood news and alert service are oriented on river basins, which in turn are subdivided into warning areas.

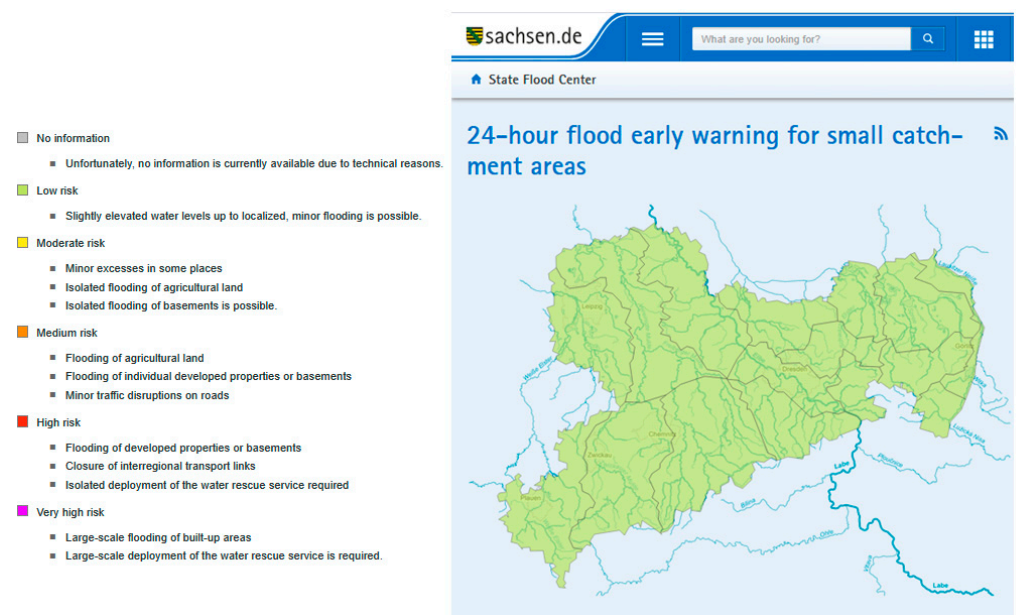


Figure 5. Twenty-four-hour flood early warning for small catchment areas [<https://www.umwelt.sachsen.de/umwelt/infosysteme/hwims/portal/web/fruehwarnung>, accessed on 29 October 2025]. Note: There was no risk on the day of access, therefore the map does not display a warning.

6. Potential for Improving Forecasting for Small and Medium-Sized Catchments

The previous sections presented the state of the art of flood forecasting in Germany, which is applicable also to many other countries in Europe. The operational implementation of flood forecasting is manifold. It leaves room for improvement, for which we highlight the main directions in this section.

6.1. Model-Based and Data-Driven Rainfall–Runoff Models

The currently available approaches to process-based modelling in coupled meteorological–hydrological–hydraulic model systems are adequate tools for flood simulation. However, their results are often limited by data availability and simplification of the complex non-linear processes in runoff generation (Bronstert et al., 2023) [60]. The authors of (Thieken et al., 2023) [61] highlighted the need to improve the communication of warnings issued by hydrologically based forecast models. Recent research projects have attempted to improve hydrological models used for operational flood forecasting, but this has remained limited to pilot areas (Stahl & Caspar, 2017) [62], (Najafi et al., 2024) [2], (Luong et al., 2021) [1], Haag et al., 2022) [35]. Others are focusing on improving precipitation forecasts, including DWD projects such as SINFONY (Development of DWD’s Seamless Integrated Forecasting System) or IVS Severe Weather Research.

Data-driven approaches, on the other hand, such as Artificial Neural Networks (ANNs) are known for their ability to describe highly non-linear phenomena. While the first applications of the method for rainfall–runoff modelling date back to the 1990s, the use of various ANNs for flood forecasting was only extensively researched a decade later. Their application for flood forecasting is still quite young and at an early stage of development. The state of the art in neural networks lies in areas such as image and object recognition and classification, or natural language processing and speech recognition. Advanced and complex architectures are used in these areas. The need for accuracy and efficiency in applications has motivated researchers to develop a wide range of advanced optimisation and fine-tuning solutions (Dtissibe et al., 2020) [63].

Research in the field of deep learning has evolved to utilise physical information to solve numerical process equations or to improve computational methods for solving process equations. The authors of (Raissi et al., 2019) [64] presented the Physics-Informed Neural Network (PINN). A PINN is able to approximate any physical process description underlying a quantity of data. PINNs are deep learning methods that are used to solve mathematical process equations by approximating the actual process solution. The hypothesis for PINNs is to bridge the gap between classical methods and data-driven neural networks by utilising available physical information. A PINN was recently developed and applied for spatial and temporal prediction of flooding on a 1D channel. It consists of a neural network architecture encoded with physical or a priori information, in this case physical–hydrodynamic process equations (Mahesh et al., 2022) [65]. This is an elegant solution for runoff and water level forecasting that, unlike pure conceptual hydrological models, has the potential to preserve both continuity and dynamics in forecasts.

Both model-based and data-driven models require large amounts of data. The former require it for the calibration and validation process, the latter for the training phase. The former benefit from lower computational costs and scalability for complex or even unknown domains. Transferability for unknown domains poses a challenge for data-driven models, especially for 2D flood forecasts, as detailed in the next subsection.

6.2. Data-Driven 2D Flood Inundation Forecasting

To the authors’ knowledge there is currently no flood forecasting system operating in Germany that can predict flood inundation for small and medium-sized catchment areas. Furthermore, existing systems are limited to forecasting runoff (discharge) and/or water depths. While forecasting of water levels or discharges along a stream is important, prediction of flood inundation enables forecasts to include the outreach and the impact (see also Section 7.1) on floodplains. Predicting the inundation extent of a flood, especially in real time, is still considered an open challenge. However, there are promising avenues that could be explored to improve existing forecasting systems. The improvement can be

sought both for existing systems based on hydrological modelling and for new systems based solely on artificial intelligence. In either case, the ability to generate two-dimensional (2D) flood forecasts is the major contribution. This is of the utmost importance, as it is the only way for the operator of a flood forecasting centre to accurately reconstruct the flood risk. Only with this type of forecast is it possible to know exactly which areas will be affected and to what extent.

In general, the 2D hydrodynamic wave propagation models required for flood mapping are computationally intensive and therefore not suitable for real-time flood forecasting. Recently, scientific research has focussed on the development of new methods to counteract this limitation. One method is the creation of pre-run scenarios and database queries to select suitable flood maps in real time. In this method a set of pre-calculated flood maps is stored in a database. Specific knowledge-based procedures are then applied to retrieve the most likely maps and scenarios in real time. For example, the method can use the real-time discharge forecast at upstream gauging stations (using conventional R-R models) as input and match it with the pre-recorded scenarios. The advantage of this method is that it provides an efficient early warning system with a clear visualisation of the flood extent, as the offline selection of flood maps is performed in a short time (Bhola et al., 2018) [53]. The FloodEvac tool developed specifically for this purpose takes the approach of carrying out the 2D hydrodynamic calculations for many flood scenarios in advance (Figure 6) and saving them every hour. In the event of a flood, these maps are then displayed. If required, they can also be interpolated depending on the previously calculated (scenario) hydrographs. In this way, hourly 2D flood forecast maps can also be created using a standard PC.

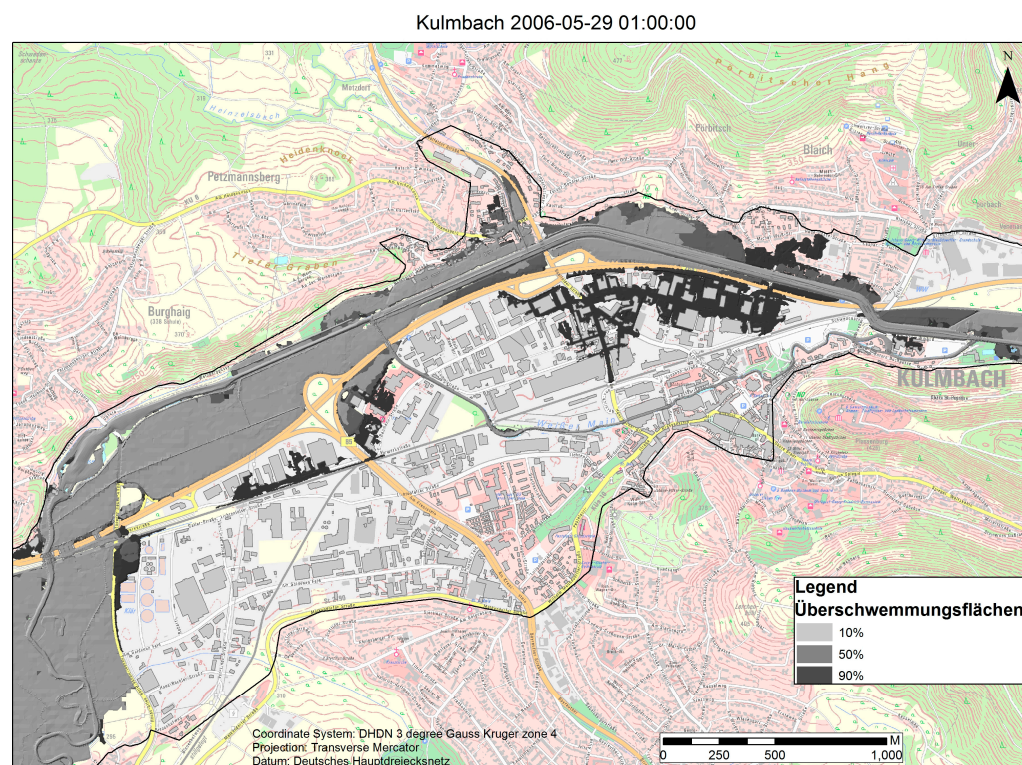


Figure 6. FloodEvac flood inundation forecast using 2D flood maps (Disse et al., 2018) [66].

Another alternative is to use ANNs or Convolution Neural Networks (CNNs) to generate flood forecasts in real time. The concept is that an ANN (or CNN) can be trained to emulate a 2D hydrodynamic model to be used later in the prediction phase. The authors of (Berkhahn et al., 2019) [67] applied a CNN for two-dimensional (2D) prediction of the

extent of urban flooding. The authors of (Lin et al., 2020) [68] later used a backward-propagating network to predict the maximum extent of flooding with an accuracy on a par with a physical–hydrodynamic model. The ANN model was able to perform 2D flood predictions with a very fine resolution of 4×4 m in real time. Recently, a CNN has been developed for multi-level predictions (Schmid & Leandro, 2023) [69] and is therefore suitable for planning time sequences for the implementation of flood protection measures.

The FloodEvac tool and data-driven models can produce real-time flood inundation predictions, but due to their domain-specific training, they are only applicable to the specific study site. Löwe et al. (2021) [70] and Schmid et al. (2025) [71] recently proposed promising approaches to making data-driven models domain-independent. These advances could lead to universal systems that can be deployed worldwide.

6.3. Improving the Measurement Database and Data Assimilation

The essential basis for all flood forecasts is reliable data on precipitation, flow rates, and water levels. This data is required to calibrate/validate and operate the models. The less data is available, the greater the uncertainties in the modelling results. Therefore, in addition to improving the modelling approaches and infrastructure, there is also an urgent need to improve the hydro-meteorological monitoring networks. While the covering of the monitoring network of precipitation stations in Germany is quite well developed, this database can also be improved and be given a higher spatial resolution using radar data from the DWD. The coverage of the water level monitoring network on watercourses is in any case much coarser.

For example, according to the monitoring network concept of the LANUV NRW, the gauging stations are categorised into the basic monitoring network, the condensed monitoring network, and the special monitoring network. The current raw hydrological data from 175 gauging stations can be visualised at www.hochwasserportal.nrw (accessed on 29 October 2025). During the flood event in July 2021, the water levels measured at 40 of 175 gauging stations on NRW watercourses were very high. During and after the event, it became apparent that certain gauges were damaged or destroyed by the flood itself. Additionally, it was found that the installed measurement technology was in some cases not suitable for recording the extreme flood discharges. As a result, valuable information was lost. In September 2021, the LANUV NRW commissioned an initial report to analyse the effects of the flood event of 12–19 July 2021 on the water level system in North Rhine-Westphalia. Here it became clear once again that the design of a climate-resilient water level measurement network is of particular importance. The improvement of the existing water level network therefore essentially consists of two main acts: on the one hand, the construction of new gauging stations at suitable locations, and, on the other, the upgrading or optimisation of existing gauging stations so that they meet the requirements for climate-resilient gauging stations.

This also applies to the flow rates determined from the discharge curves. A climate-resilient design means capturing both flood and low water conditions, in a failure-safe manner, and at the same time providing meaningful and realisable solutions for the operators. Redundant–diverse water level recording, i.e., the use of two or more independent measuring methods, ensures that the data can be transmitted even if one transmitter fails. Data is also transmitted via two independent paths. This reduces the risk of data gaps occurring when recording the water level. Systematic deviations in the various measuring systems can also be recognised.

Flood events do not only affect large rivers and urban areas. There are serious consequences for missing smaller bodies of water and rural areas. In this respect, the network of water level gauges should be consolidated or extended into the smaller catchment areas.

The development of new approaches to improve data assimilation could be crucial in these cases. This could include new methods or algorithms for implementing real-time data updates or refining spatial and temporal resolution. Since such scales may require a larger number of sensors, efforts should be made to develop novel, lower-cost sensors, where redundancy should again play an important role. Improving data assimilation methods would reduce uncertainties in flow measurements—especially during high and low water—and thus gradually improve data quality. Here, a strategy to diversify the measured parameters (e.g., temperature, soil moisture, or humidity) and the inclusion of innovative methods (e.g., crowdsourcing, citizen science, or satellite remote sensing) and sensors (e.g., cosmic-ray neutron sensors) to obtain potentially correlated data could help reduce some of the uncertainty.

6.4. Communication of System Warnings to Decision-Makers

A central challenge in an operational flood forecasting system is the timely and immediately understandable transmission of an alarm signal to institutional decision-makers so that they are supported in initiating appropriate measures that are sufficient for civil security. Forecast uncertainty also plays an important role here. Since a model forecast is inherently uncertain for reasons explained in Section 3, it is necessary to prepare and support the decision-maker who is confronted with the responsibility of an evacuation order or the implementation of a protective measure so that they are not left alone with the decision. This aspect seems to have played a decisive role in the case of the Ahr flood disaster in 2021. To counteract this, regular training is required to enable people to interpret a warning signal in the operational forecast in a specific spatial and temporal context. The type of catchment area (large/small, steep/flat, urban/rural) and precipitation event (large/small cells) plays a decisive role here. While, for example, the dynamics of a flood wave on a large river such as the Rhine can be predicted very precisely in terms of time and space, flood events in smaller catchment areas occur suddenly and are completely unexpected in their extent. The events are characterised by considerable and often completely underestimated forecasting uncertainties, which must be dealt with pragmatically in the interests of safety in the event of an extreme situation. A prerequisite for this is a standardised and transparent level of communication, both at a technical and institutional level. It is also advisable to compare flood forecasts with other available systems (e.g., the European Flood Awareness System (EFAS)) to be able to assess and interpret the uncertainties deriving from different forecast systems.

7. Flood-Driven Consequences for Buildings and Infrastructure and Geotechnical Failure Mechanisms

While existing forecasts focus mostly on water levels or discharges, little effort has been put into forecasting consequences and/or failure mechanisms. We will therefore refrain from discussing the how and instead focus on the why, and on what consequences and error mechanisms could be included in the forecast. Hence, we focus the next subsections on highlighting the challenges of assessing such consequences in current flood risk assessment frameworks. The incorporation of any of the methods described below in flood forecasting system in Germany is per se novel.

7.1. Flood-Driven Consequences and Safety Analysis

For effective disaster control planning and the development of suitable flood mitigation measures, the consequences for buildings and infrastructure need to be evaluated within a risk assessment (see, e.g., damage analysis for buildings in Maiwald and Schwarz's (2012)

study [72]. Such damage can be the result of the exposure of these structural systems to surface water inundation during extreme events, e.g.,:

- Excessive external water pressure on structural elements of buildings or bridge piers and abutments. In the case of bridges, potential clogging may amplify these processes (Schüttrumpf, 2023) [73].
- Overtopping, flow around and underneath structures (e.g., dikes).
- Impact loads caused by floating objects.
- Ingress of water into buildings through the sewerage system in the absence of a backflow flap, through openings (unsealed or open windows, doors, shafts, leaking house connections, etc.) or through walls or the base slab.

In addition, processes related to the ground may lead to geotechnical failure of ground-embedded structures or of the ground itself. Among these are, e.g., (see Figure 7):

- Undermining due to flow of water in the ground and uplift caused by rising ground water level in the base of foundations or other infrastructure objects (i.e., pipelines, sewers, and tunnels).
- Material transport, which may lead to hydraulic failure, such as subsurface erosion due to surface water runoff, internal erosion (e.g., piping), or hydraulic heave around a structure caused by flow of water in the ground induced by hydraulic gradients.
- Slope failure or landslides due to the loss of shear strength of the ground triggered by infiltration of water or a rise in groundwater level.

The design and assessment of civil engineering structures in Europe is based on the rules defined in the Eurocode series (e.g., Eurocode 7-EN 1997 [74] for geotechnical design). The main goal is to ensure the sufficient reliability of a structure, which includes verifying that defined (ultimate and serviceability) limit states are not reached. This is the case if the resistance of the structure against a specific limit state is greater than the loading on the structure. This task involves the determination of the design loading and resistance as accurately as possible. For example, representative values of groundwater and external water levels for the most unfavourable scenarios need to be derived. Here, climate conditions and possible climate change effects shall explicitly be addressed according to the second-generation Eurocode 7, with the uncertainties described in the previous sections. Therefore, establishing representative loading scenarios requires close cooperation between hydraulic engineering experts and geotechnical designers.

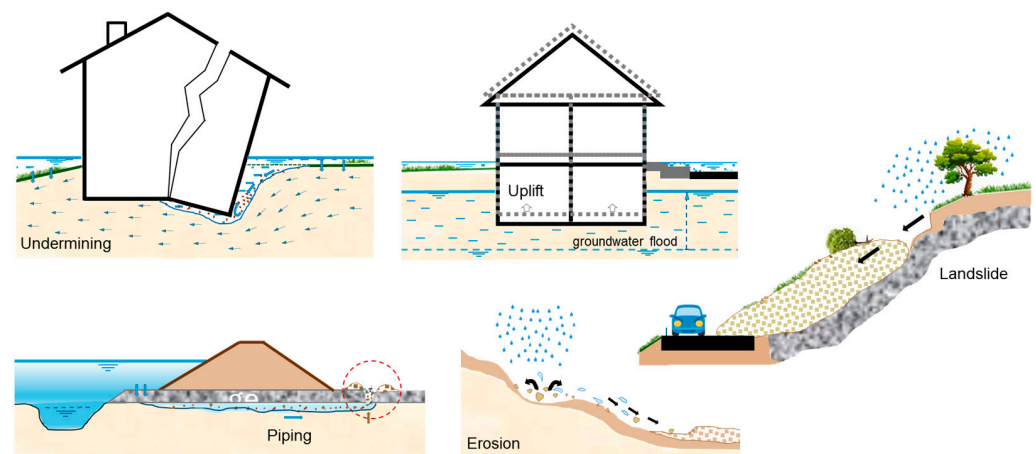


Figure 7. Ground-related failure scenarios.

However, due to the complex nature of the ground as a multiphase system, not only the uncertainties on the loading side but also the uncertainties related to the ground are

relevant, which makes the possible forecasting of ground-related failure scenarios difficult. These aspects will be discussed in the next subsection.

7.2. Uncertainties in the Ground Model

The highly uncertain ground characteristics primarily result from the heterogeneity of the ground because of its formation history. Further, limitations in determining the relevant ground properties as well as in modelling the true ground behaviour contribute to uncertainties in the ground model. Usually, in geotechnical engineering the following sources of uncertainties related to ground properties are distinguished, e.g., (Phoon & Kulhawy, 1999) [75]; (Phoon et al., 2022) [76]; (van Den Eijnden, 2024) [77]:

- Inherent variability describes the natural variability of a quantity, e.g., of the soil strength within a certain soil unit.
- Measurement errors are caused by imperfect measurements (e.g., insufficient, poorly calibrated measurement equipment).
- Transformation uncertainties describe uncertainties involved when deriving ground properties indirectly from field measurements by using empirical correlations between a ground property and a measured quantity, e.g., derivation of the angle of internal friction from the tip resistance measured in a cone penetration test.
- Finally, statistical uncertainty refers to limited information about the ground conditions, such as a limited number of boreholes or soundings and laboratory test results. Also, statistical model uncertainty is introduced when selecting a certain probability distribution.

The basis for geotechnical design and assessment according to Eurocode 7 is the ground model (GM), which is a 2D or (ideally) 3D visualisation of an area of ground derived from the results of ground investigations (usually borehole measurements, soundings, laboratory tests, groundwater measurements, and sometimes geophysical measurements). It involves the identification of different geotechnical units and stratification and layer boundaries, including the groundwater surface. With this, further (geometrical) uncertainties are introduced besides those related to the ground properties of the different units. This is especially relevant in the case of rock, which, like soil, is a highly discontinuous material, where rock masses are separated by, e.g., joints or faults.

The fact, that borehole measurements and soundings are usually conducted at pre-defined distances and thus only represent the ground at single locations is a major problem in deriving a GM. This lack of information requires interpretation by a geotechnical expert with sufficient knowledge and experience to avoid misleading results. For example, errors may occur if layer boundaries are simply interpolated between the locations without considering specific geological anomalies such as inclusions. Expertise is also necessary for interpreting the results from soundings, as well as other indirect exploration methods, such as areal geophysical measurements, as they do not provide the required results directly.

There are geostatistical methods available to derive a spatial GM from single locations, e.g., (Chiles & Delfiner, 2012) [78], (Atkinson & Lloyd, 2021) [79], but these require in-depth knowledge of the formation history of the ground to avoid misinterpretation of such results. Hence, they are rarely used in geotechnical design practice.

Nowadays, construction projects are increasingly developed using Building Information Modelling (BIM). In infrastructure projects under the responsibility of the Federal Ministry of Digital and Transportation, for example, the use of BIM is mandatory (for more information, see <https://www.bmdv.bund.de/bim>, accessed on 29 October 2025) [80]. In this context, the ground model is one of several other models which is composed of different sub-models (Beck & Henke, 2021) [81]; (Satyanaga et al., 2023) [82] (see Figure 8).

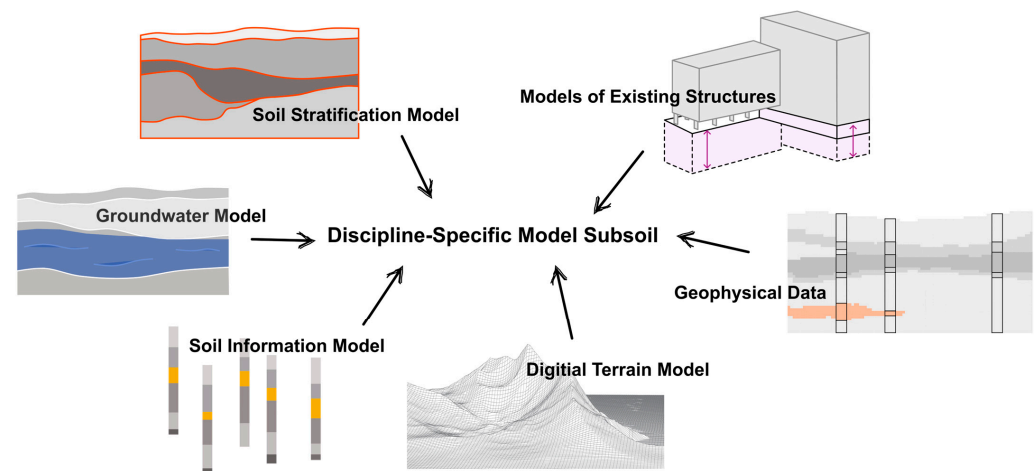


Figure 8. Components of the ground model in BIM.

Different software packages are available for establishing a 3D ground model in BIM. In these, the modelling of the layer boundaries is carried out using different algorithms, which automatically create and interpolate the individual surfaces. However, uncertainties involved in this procedure or in the attributed ground properties are not considered, and thus the results, though very helpful, especially for larger and complex projects, must be used with care.

Obviously, the uncertainties described before could be reduced by performing more ground investigations at closer distances and more lab tests, but in practice there are often time and cost limitations. However, investments in more ground investigations conducted by geotechnical experts will clearly be beneficial in reducing ground-related uncertainties.

Besides the design of new structures, evaluating the consequences of floods often means assessing the performance of existing buildings and structures. This is difficult, as there is often a lack of available data about the ground conditions and the layout of the structures encountered. The geological services of the federal states in Germany provide archives of databases with results from drillings and other information such as geological and hydrogeological maps. They are continuously being updated, as data from public construction projects must be communicated to the service. However, information on the necessary ground properties needed for geotechnical design and assessment are usually not available and must be established based on engineering judgement if no new ground investigation campaigns are initiated. On the other hand, data such as geotechnical reports from private projects usually includes such information but is not publicly available, and it may be difficult to get access to. Another problem in this context is the use of different data formats, which causes problems in a thorough data analysis where different parties are involved. Hence, for risk management and assessment, a comprehensive and open-access data collection and storage system is desirable. The new database, GeoVal API, established by the Federal Waterways Engineering and Research Institute (Kunz et al., 2024) [83], is oriented towards this purpose.

7.3. Evaluating and Modelling Geotechnical Failure Scenarios

Besides damage to buildings and structures, mass movements are typical flood-driven failure scenarios (see, e.g., (Wehinger, 2023) [84]). They occur, e.g., as landslides on defined translational or rotational sliding surfaces, or as mud or debris flow without a defined sliding surface if the material is fully water-saturated and behaves as a viscous fluid. Mass movements are a problem worldwide (see, e.g., (Highland, 2008) [85]; (Haque et al., 2016) [86]; (Lombardo et al., 2020) [87]).

In Germany, the federal states and their geological services are responsible for risk assessment of such scenarios. Efforts in this regard concentrated first on the southern mountainous regions, where the states of Bavaria, Baden-Wuerttemberg, and Saxony provide publicly available landslide hazard information maps based on GIS-based, remote sensing, and geological evaluation of possibly hazardous slopes.

However, hazards due to landslides, mud, or debris flow appear to be increasingly problematic in other areas of Germany, such as in the low mountain regions of North-Rhine Westphalia and Rhineland Palatinate. Recent incidences and studies have shown that small and mid-size catchments with notch valleys are possibly endangered by these failure scenarios (see, e.g., (Balzer et al., 2020) [88]; (Wang et al., 2023) [89]; (Banaszak et al., 2024) [90]). So far, as a result of the MABEIS project (Werner et al., 2021) [91], Rhineland-Palatinate established a GIS-based online database for mass movements. Also, Lower Saxony published an online hazard map (see Klose et al., 2014 [92] and <https://numis.niedersachsen.de/trefferanzeige?docuuiid=3258e370-c48e-42d4-a087-06cb75c34ec6>, accessed on 29 October 2025 [93]), whereas the geological service of Hesse provides a report on the results of remote sensing mapping of suspected areas, which is available on its website (HLNUG, 2024 [94]).

Additionally, the Federal Ministry of Digital and Transportation, in a national research program, conducted a climate impact analysis to increase the resilience of the transport infrastructure for which they are responsible (for example, federal highways and railway tracks). Results on mass movements are presented in (Lohrengel, 2020) [95].

As already indicated, the hazard information maps currently used in practice have been established predominantly by an evaluation of available information via a set of pre-defined criteria and/or by remote sensing. They are easy to implement in practice, but they do not model the process of mass movement itself. For stability assessment or for the assessment of the movement of the ground material in a forecast, the failure process must be described mathematically. An overview of various calculation models is provided in (Li, 2022) [96]; (Lei et al., 2023) [97]), where two groups of models can be distinguished:

- Physically based models;
- Models based on artificial intelligence.

Physically based models describe the mechanics of a system. There are models that address only ground stability based on the shear strength of the ground and those that can simulate the movement of soil mass. For stability evaluation, Limit Equilibrium (LE) methods are frequently used, where the equilibrium of driving and resisting forces is evaluated for pre-defined failure surfaces in the ground (e.g., plane or circular). There are also models available with a focus on the effect of infiltrating water. However, these are often associated with simplistic mechanical failure models such as the infinite slope model (see, e.g., (Rossi et al., 2013) [98]; (Montrasio & Valentino, 2008) [99]); hence, they are able to handle mass stability analysis for larger computational domains but with limited accuracy due to model simplifications.

In numerical methods such as the Finite Element Method (FEM), on the other hand, the failure surface is a result of the calculation, and the ground behaviour can be considered by advanced constitutive models. However, mass movements are large deformations which cannot be modelled satisfactorily using conventional mesh-based FEM simulation techniques and thus require specific procedures to overcome the associated problems (see, e.g., (Wang et al., 2015) [100]). Further, direct coupling of ground-water flow calculations and the analysis of the mechanical behaviour in three-dimensional space is computationally demanding and hence limited to small system dimensions. As an alternative, particle-based methods such as the Material Point Method (MPM) or mesh-free Smoothed Particle Hydrodynamics (SPH) can be used, especially for modelling fluid–solid interaction as well

as large deformations (see, e.g., (Augarde et al., 2021) [101]; (Onyelowe et al., 2023) [102]), but the computational effortfulness remains and the model validation may be challenging.

However, physically based methods, regardless of simple LE or more advanced FE, SPH, or MPM models, are all based on the simplification of a real-world scenario into a system which can be modelled. This also holds for the representation of ground models and the ground properties in these models. Due to this, and in view of the computational limitations of such models for flood-driven forecasting, machine learning approaches have been recently applied also to the problem of mass movements (see, e.g., (Ma et al., 2021) [103]; (Wang et al., 2021) [104]). However, this raises the issue of access to local training data sets from comparable case histories, which are often limited, and the question of the transferability of the results to other sites arises. Their combination with physically based machine learning approaches which are trained by fulfilling physical constitutive relationships (see, e.g., (Pei et al., 2023) [105]) may be a solution.

In the end, mass movement prediction remains a challenging task and is associated with significant uncertainties within risk assessments. Particularly in flood-driven forecasting, this remains an open challenge. An integrative approach of multiple methodologies such as data mining and data fusion and innovative modelling techniques together with real-time monitoring (for the latter, see, e.g., Bell et al., 2008 [106] or <https://aimon-project.de/about-news>, accessed on 29 October 2025 [107]) can be a suitable solution.

8. Conclusions

Flood risk management strategies focusing on flood forecasting can be very effective in saving lives and property during extreme hydro-meteorological events. Such strategies are applicable to the whole range of possible events, as they are not designed for a specific return period. In this study we have discussed six of the several regional and transregional services responsible for flood forecasting in Germany. We have discussed the main features they address, as well as their suitability for forecasting flows in large catchments. However, there are remaining challenges which need to be addressed when the focus is on small to medium-sized systems. Our study has shown that in some federal states, flood forecasts for areas of less than 150 km², 200 km², or 300 km² are not considered for Baden-Württemberg, Hesse, or North Rhine-Westphalia, respectively.

Regarding potential improvements, we highlight five points that need to be addressed. These points are not prioritised; a decision must be based on the specific circumstances of each centre, which cannot be fully covered here. Examples include budget constraints, time-frames, and even a nationwide strategy that may need to be developed or reviewed before prioritisation can take place. These are, in any case, the most important areas for improvement, requiring further research or targeted transfers from science to practical application:

1. Model-based forecasting systems—Meteorological forecasts remain the largest source of uncertainty throughout the flood forecasting process. Adaptation of models for high computational performance is imperative for near-real-time forecasts; improving data assimilation is required for model updating.
2. Data-driven R-R models—The application of data-driven models for flood forecasting is still quite young and at an early development stage. ANNs and, in particular, further research into PINNs is required for the development of robust R-R models that are able to preserve continuity and the dynamics of floods.
3. Data-driven 2D flood inundation forecasting—ANNs and CNNs, among other deep learning methods, have shown an excellent ability to perform 2D flood predictions. This is a fast-growing field; hence, it is likely that new methods will emerge. However, existing ones are already suitable for this purpose. The introduction of 2D flood

inundation forecasts is required for flood forecasting centres to improve and extend their existing services beyond water level of discharge-driven predictions.

4. The measurement database—While the covering of the monitoring network of precipitation stations in Germany is quite well developed, this database should still be improved to reduce meteorological uncertainty. The coverage of the water level monitoring network on watercourses is too coarse. The improvement of the latter would have a beneficial impact on the calibration and validation of R-R models. Lastly, the inclusion of diversified measurement parameters or innovative measuring methods was mentioned as having the potential to further reduce uncertainties in the data.
5. Communication of system warnings to decision-makers—Regular training is required to enable people to interpret warning signals in operational forecasts. Raising awareness of the benefits of extending accurate 2D spatial and temporal modelling to forecasts by the flood forecasting centres is needed to facilitate the uptake of recent and future advances.

Finally, we uncovered the need for research into flood-driven forecasting of consequences for buildings and infrastructure, especially those due to geotechnical failure mechanisms. We concluded that, currently, this topic is not addressed in forecasts in an integrated and systematic way. However, one main challenge associated with this task is the scarcity of ground data and their variability in space and time. In this regard, the benefits of comprehensive ground investigations and open-source databases for the reduction of predictive uncertainty should be recognised. Another challenge is the computational time required by physically based numerical ground models. Hence it is likely that data-driven models, i.e., machine learning, together with real-time monitoring could become a very attractive solution for enabling real-time forecasting of consequences and mechanisms of failure.

Author Contributions: Conceptualization, J.L., I.A., S.F., C.M. and K.L.; Investigation, J.L., I.A., S.F., C.M. and K.L.; Writing—original draft, J.L., I.A., S.F., C.M. and K.L.; Writing—review & editing, J.L., I.A., S.F., C.M. and K.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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