Recent advances and new frontiers in riverine and coastal flood modeling

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Key Points:

- Causative mechanisms of floods and underlying physical processes in both riverine and coastal floods are thoroughly discussed and reviewed
- The weak and selective validation of flood inundation models and the lack of sufficient validation data is a major challenge
- Hybrid methods linking statistical and numerical tools are recommended for efficient and more accurate coastal flood hazard analysis

Correspondence to:

H. Moradkhani,
hmoradkhani@ua.edu

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Author Contributions:

Conceptualization: Keighobad Jafarzadegan, Hamid Moradkhani
Funding acquisition: Hamid Moradkhani
Project Administration: Hamid Moradkhani
Supervision: Hamid Moradkhani
Writing – original draft: Keighobad Jafarzadegan
Writing – review & editing: Hamid Moradkhani, Florian Pappenberger, Hamed Moftakhari, Paul Bates, Peyman Abbaszadeh, Reza Marsooli, Celso Ferreira, Hannah L. Cloke, Fred Ogden, Qingyun Duan

Recent Advances and New Frontiers in Riverine and Coastal Flood Modeling

Keighobad Jafarzadegan[1,2], Hamid Moradkhani[1,2], Florian Pappenberger[3], Hamed Moftakhari[1,2], Paul Bates[4], Peyman Abbaszadeh[5], Reza Marsooli[6], Celso Ferreira[7], Hannah L. Cloke[8], Fred Ogden[9], and Qingyun Duan[10]

[1]Center for Complex Hydrosystems Research, University of Alabama, Tuscaloosa, AL, USA, [2]Department of Civil, Construction and Environmental Engineering, University of Alabama, Tuscaloosa, AL, USA, [3]European Centre for Medium-Range Weather Forecasts, Reading, UK, [4]School of Geographical Sciences, University of Bristol, Bristol, UK, [5]Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, USA, [6]Department of Civil, Environmental and Ocean Engineering, Stevens Institute of Technology, Hoboken, NJ, USA, [7]Department of Civil, Environmental and Infrastructure Engineering, George Mason University, Fairfax, VA, USA, [8]Department of Geography and Environmental Science, University of Reading, Reading, UK, [9]NOAA-NWS Office of Water Prediction, Tuscaloosa, AL, USA, [10]College of Hydrology and Water Resources, Hohai University, Nanjing, China

Abstract Over the past decades, the scientific community has made significant efforts to simulate flooding conditions using a variety of complex physically based models. Despite all advances, these models still fall short in accuracy and reliability and are often considered computationally intensive to be fully operational. This could be attributed to insufficient comprehension of the causative mechanisms of flood processes, assumptions in model development and inadequate consideration of uncertainties. We suggest adopting an approach that accounts for the influence of human activities, soil saturation, snow processes, topography, river morphology, and land-use type to enhance our understanding of flood generating mechanisms. We also recommend a transition to the development of innovative earth system modeling frameworks where the interaction among all components of the earth system are simultaneously modeled. Additionally, more nonselective and rigorous studies should be conducted to provide a detailed comparison of physical models and simplified methods for flood inundation mapping. Linking process-based models with data-driven/statistical methods offers a variety of opportunities that are yet to be explored and conveyed to researchers and emergency managers. The main contribution of this paper is to notify scientists and practitioners of the latest developments in flood characterization and modeling, identify challenges in understanding flood processes, associated uncertainties and risks in coupled hydrologic and hydrodynamic modeling for forecasting and inundation mapping, and the potential use of state-of-the-art data assimilation and machine learning to tackle the complexities involved in transitioning such developments to operation.

Plain Language Summary Every year, a large number of people are affected by flooding and suffer its costly consequences across the world. To properly manage this notorious natural disaster, the physical processes that represent riverine and coastal floods should be well understood and modeled. Over the recent decades, the scientific community has been continuously involved in characterizing the main components of floods and improving flood modeling skills using both types of physical and statistical models. Despite all these efforts, our modeling skill has major limitations which hinder an optimum performance for accurate and efficient flood forecasting. In this article, we provide a thorough review of these past efforts, highlight the main challenges, and provide potential pathways for improved flood characterization and modeling in the future. We specifically discuss the causative mechanisms of floods, physical/statistical methods used to characterize different components of flooding, coupling approaches, methods used to account for uncertainty in different layers of flood modeling, and their benefits for operational flood forecasting systems.

1. Introduction

Flooding is one of the most frequent natural disasters that endanger people's livelihoods and causes serious economic losses and damages annually. According to reports provided by the United Nations Office for Disaster Risk Reduction, flooding accounted for 43.4% of all 7,255 disaster events recorded globally between 1998 and 2017 (UNDRR, 2020). Recent studies have shown that climate change associated with global warming has increased the frequency and severity of flood hazard drivers (e.g., precipitation and sea level rise, SLR) over the past decades (Arnell & Gosling, 2016; Dangendorf et al., 2019; Davenport et al., 2021; Hay et al., 2015), while this growing trend is expected to continue and result in the extension of flood hazard areas in the future (Hirabayashi et al., 2013; Johnson et al., 2020; Winsemius et al., 2016). In addition, growing populations and socioeconomic development are leading to increased urbanization in flood-prone areas, thereby enhancing exposure to flooding, which will result in higher damage and casualties over the next decades (Jongman et al., 2012; Visser et al., 2014; W. Zhang et al., 2018).

Over the past decade, extreme floods have caused tremendous costs worldwide. In the summer of 2017, a series of disastrous floods affected more than 41 million people in South Asia (i.e. Nepal, India, and Bangladesh) and took the lives of more than a thousand people (Gettleman, 2017). In Southeast Asia, a series of devastating floods that occurred in Central and Southwest China in 2020 and 2021 disrupted the lives of millions of people and killed hundreds of them (Myers, 2020). In Europe, Germany, Belgium and Turkey experienced deadly floods in July and August 2021, where more than 250 people died and many cities were damaged (Eddy & Specia, 2021; Wong, 2021a). In 2017, the United States faced three hurricane-induced episodes of major flooding (e.g. Hurricanes Harvey, Irma, and Maria) as well as extensive floods in the Midwest and California, which caused the largest flood-related damages (>300 billion) in its history (A. Smith, 2021). In 2021, Hurricane Ida induced a strong storm surge and caused a destroying coastal flood in Louisiana (Mistich & Brumfiel, 2021). Later, it moved to the northeast of the US and caused urban and riverine flooding with a death toll of more than 40 people in New York and Philadelphia (Wong, 2021b). In the Middle East, the unusual monsoon rains and glacier melt together with poor flood management caused a series of deadly floods between June and August 2022. Summer floods in Iran damaged more than two-thirds of the country, killed dozens of people and destroyed hundreds of villages (Fassihi, 2022). The hotspot of these devastating floods was in Pakistan, where approximately 1,500 people died and more than 33 million were displaced from their homes (Goldbaum et al., 2022).

The huge losses and damages caused by past floods across the world reveal our failure in the proper management of extreme floods. One of the critical elements explaining our unsuccessful flood management strategies is the incomplete understanding of all nonlinear and complex climatic, hydrological and hydrodynamic processes involved in flooding (D. Feng, Fang, & Shen, 2020; Jafarzadegan, Abbaszadeh, & Moradkhani, 2021). This can subsequently lead to the lack of appropriate tools, methods and technologies used for flood characterization and modeling. The overarching goal of this review paper is to summarize the past advances, describe our current capacity and limitations, and recommend potential pathways to further advance our flood characterization and modeling skills.

1.1. The Merit of This Review Compared to Past Review Papers on Flood

There has been a proliferation of scientific studies that have focused on different types of floods (e.g., coastal and riverine floods), various components of flooding (i.e. hydrological and hydrodynamic processes), and different modeling approaches, that is, physically based and data-driven methods. Past review papers had typically focused on a specific flood type/component/approach and discussed their relevant literature. Considering the limited scope of those papers, it is essential to provide a more comprehensive review of coastal and riverine flooding, the causative mechanisms from both atmospheric and hydrologic perspectives, and up-to-date approaches, methods, and tools to analyze such floods, discuss challenges and provide outlooks. Particularly, considering the lack of a review paper for coastal flooding in the literature, a thorough appraisal of the state-of-the-art methods that include process-based hydrodynamic modeling, data-driven, and hybrid methods is noticeably warranted. Apart from offering one of the earliest reviews of coastal flooding, this article presents a significantly more comprehensive review of riverine floods than previous review papers. The characterization of riverine floods requires a proper analysis of both hydrological and hydrodynamic processes. For riverine floods, the focus of past review papers had narrowed down to either flood forecasting or flood inundation models. Here, on the other hand, we cover both of these topics and review both hydrologic and hydrodynamic processes involved in riverine flooding while providing the latest end-to-end approaches and technology available that have been or are yet to be employed.

To avoid confusion, it is important to distinguish between "flood forecasting" and "flood prediction" in this article. "Flood forecasting" pertains to the estimation of future floods, while "flood prediction" is typically used to describe the characterization of past flood events (hindcasting) or provid near-real-time information (nowcasting). In flood forecasting, the primary input to physical models is forecasted precipitation data, while observed

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precipitation data is used in flood prediction studies. The review of flood forecasting goes back to the study by H. L. Cloke and Pappenberger (2009) and was later updated by W. Wu et al. (2020), where they discussed the advantages of shifting toward ensemble flood forecasting, reviewed past implementations of the Ensemble Prediction System (EPS), pointed out the current weaknesses of these systems, and recommended future directions in this area. While the focus of these articles was mostly on medium-range forecasting using an ensemble of numerical weather prediction models (NWPs) and their relevant uncertainties, they rarely discussed the hydrologic and hydrodynamic modeling methods required to fully characterize the uncertainty in flooding processes. Another paper by Hapuarachchi et al. (2011) reviewed advances in flash flood forecasting and discussed both data-driven and hydrological modeling approaches.

Owing to considerable advancements made in the past decade, this article provides an update on recent flood forecasting methods such as long short-term memory (LSTM) and other machine learning (ML) methods, coupled meteorologic/hydrologic/hydrodynamic models, and uncertainty quantification techniques. In addition, we move beyond hydrological forecasts and discuss recent developments in flood inundation forecasting, a topic that needs specific attention. In a review of flood forecasting conducted by Jain et al. (2018), the authors provided a more generic outline that covered both deterministic and ensemble modeling approaches, uncertainty quantification, and remote sensing applications. However, several topics, such as pre- and postprocessing, data assimilation (DA) techniques, and flood inundation forecasting, are still lacking, which we cover here (e.g., Abbaszadeh et al., 2020; Khajehei et al., 2018; W. Li et al., 2017; Madadgar et al., 2014; Moradkhani et al., 2019). In addition, a more comprehensive review that discusses all elements involved in flood forecasting, starting from meteorological drivers to hydrologic and then hydrodynamic processes, is substantially required. This review paper provides a comprehensive flood forecasting framework that discusses the recent advances in the field, addresses the limitations at the current stage, and provides recommendations to improve flood forecasting systems in the future.

The modeling of flood inundation areas is one of the most important steps in flood risk management. Teng et al. (2017) performed a detailed review of different methods used for flood inundation mapping. They categorized these methods into three groups, empirical methods, hydrodynamic models, and simplified conceptual models while discussing the recent advances and limitations of each category. They also addressed the sources of uncertainties and briefly discussed the uncertainty quantification and communication in these methods. A recent article by Bates (2022) specifically describes the fluid mechanics of floodplain inundation and reviews some recent developments in the numerical modeling of river hydrodynamics, such as methods used for improving computational efficiency. In our proposed review paper, we take advantage of these two review papers and add our updates on recent advances in simplified methods for flood inundation mapping (e.g., S. Xie et al., 2021) and state-of-the-art techniques for improving flood inundation modeling skills (e.g., Jafarzadegan, Alipour, et al., 2021; J. Neal et al., 2021; Oruc et al., 2023). This review defines a new categorization that describes flood inundation models based on both types of floods (i.e. coastal, and riverine flood inundation models). Additionally, we create a specific section for hydrodynamic DA for flood inundation mapping (e.g., Jafarzadegan, Abbaszadeh, & Moradkhani, 2021; Muñoz, Abbaszadeh, et al., 2022), a topic that is rather new and needs further attention in the near future.

2. Causative Mechanisms of Floods

Causative mechanisms of floods refer to a series of climatic, meteorologic, hydrologic, and hydrodynamic flood-generating processes that control the time of occurrence, duration, severity, and extent of flooding. In general, the causative mechanisms of floods can be investigated from either a hydroclimatic or hydrological (watershed) perspective (Tarasova et al., 2019). While natural climatic and hydrological factors are primary drivers of flood generation, human activities can also significantly affect the frequency and extent of flooding. In the final part of this section, we will review existing literature on how human actions that can impact flood generation and explore potential pathways for further research in this area.

2.1. Hydroclimatic Perspective

From a hydroclimatic perspective, flood mechanisms (flood-generating processes) typically occur in the months and weeks preceding an event (Hofstätter et al., 2018; Schlef et al., 2019). In this approach, a large synoptic domain is set where the structure and dynamics of weather systems and lifting mechanisms (Ashley &

Ashley, 2008; Gamble & Meentemeyer, 1997), cyclone track types (Collins et al., 2014; Hofstätter et al., 2016, 2018), or atmospheric circulation patterns (Bárdossy & Filiz, 2005; Conticello et al., 2018; Jacobeit et al., 2003; Lima et al., 2017; Petrow et al., 2009; Schlef et al., 2019) are used to describe the spatiotemporal physical causes of flood events. The latter is the most common hydroclimatic approach that typically investigates a probabilistic relationship between flood characteristics and daily atmospheric circulation patterns. While early studies only related flood occurrence with atmospheric circulation patterns (Duckstein et al., 1993; Jacobeit et al., 2006), other efforts have been made to link flood frequency (Mallakpour & Villarini, 2016), flood magnitude (Bárdossy & Filiz, 2005; Petrow et al., 2009) and flood extent (Wilby & Quinn, 2013) to either atmospheric circulation patterns or climate indices (Delgado et al., 2012; J. Liu, Zhang, et al., 2018; Mallakpour & Villarini, 2016; Villarini et al., 2012; Ward et al., 2014).

Among different climate indices, the El Niño-Southern Oscillation (ENSO) has been shown to be one of the major indicators of coastal flooding (J. Liu, Zhang, et al., 2018; Marcos et al., 2015; Mawdsley & Haigh, 2016; Steptoe et al., 2018). Muis et al. (2018) investigated the influence of ENSO on extreme sea levels and its components along the entire global coastline. Their study confirmed the significant correlation between extreme sea levels and ENSO across the Pacific. Another trigger of a large number of flood events caused by extreme precipitation is the Atmospheric River (AR), which refers to a narrow elongated channel of enhanced water vapor transport in the atmosphere (Guan et al., 2013; Y. Zhu & Newell, 1994). In the US, several studies have reported that ARs are the primary cause of the majority of coastal floods in the west (Corringham et al., 2019, 2022; Dettinger et al., 2011; Guan et al., 2013; Neiman et al., 2011; Ralph & Dettinger, 2012; Ralph et al., 2006), while they can land hundreds of kilometers away from the coast and cause inland riverine flooding in the interior western or central US (Lavers & Villarini, 2013a; Mahoney et al., 2018; Moore et al., 2012; Nakamura et al., 2013; Rivera et al., 2014; Rutz & Steenburgh, 2012; Rutz et al., 2014). In Europe, ARs have also been responsible for extreme precipitation and flooding in Great Britain, Norway, the Iberian Peninsula, Poland, and France (Lavers & Villarini, 2013b, 2015; Lavers et al., 2011, 2012; A. M. Ramos et al., 2016; Schaller et al., 2020). Overall, Paltan et al. (2017) demonstrated that ARs contribute to approximately 22% of the total global runoff and explain more than 80% of floods in several regions.

Since the sample of flood events is much smaller than the total number of days, the validity of using circulation factors/climate indices for explaining underlying physical flood-generating processes is still a matter of question (Prudhomme & Genevier, 2011). In addition, the key role of soil saturation in flood-generating processes (Fundel & Zappa, 2011; Marchi et al., 2010; Norbiato et al., 2009) is commonly disregarded by linking the circulation patterns with flood characteristics. Another limitation of relying only on atmospheric circulation patterns is that they cannot properly explain snow processes, which results in a poor description of flood-generating processes in mountainous snow-dominated catchments (Parajka et al., 2010; Petrow et al., 2009).

2.2. Hydrological Perspective

The hydrological (watershed) perspective, however, focuses on a watershed and classifies flood events based on hydrometeorological variables (e.g., temperature and precipitation), pre-event watershed state (e.g., snow depth, soil moisture), and hydrological processes (e.g., infiltration or saturation excess) occurring in weeks or days preceding an event. In one of the pioneer studies conducted by R. Merz and Blöschl (2003), they introduced five flood process types, long-rain floods, short-rain floods, flash floods, rain-on-snow floods, and snowmelt floods, and assigned 11,518 Australian flood events to one of these flood types. They performed the classification by using a wide range of hydrological variables, including the timing of the floods, storm duration, rainfall depths, snowmelt, soil moisture, runoff response dynamics, and spatial coherence. The results confirmed pronounced spatial patterns and seasonality according to the flood process types. Other studies have later implemented hydrologic perspective classifications to identify flood events with similar causative mechanisms (Keller et al., 2018; Sikorska et al., 2015). Nied et al. (2014) used the same flood process types and classified a large region of European flood events according to their hydrometeorological indicators. Using 40 weather patterns clustered based on ERA-40 reanalysis data (Uppala et al., 2005) and 10 soil moisture patterns provided by Nied et al. (2013), they specifically focused on the link of flood types to these pre-event soil moisture and weather patterns and highlighted the key role of soil moisture in controlling flood generating processes (Nied et al., 2013; Schröter et al., 2015).

In a more comprehensive and detailed investigation, Nied et al. (2017) studied the interacting control of soil moisture as a proxy for the hydrological pre-event conditions and weather patterns as a proxy for the meteorological event conditions over a variety of flood characteristics. They utilized a regional flood model (RFM) that was fed with a large set of reshuffled hydrometeorological inputs to simulate hydrologic and hydrodynamic processes as well as losses. They demonstrated that soil moisture, weather patterns, and their combinations have different impacts on flood characteristics. For example, they found that weather patterns mostly control the flood magnitude, soil moisture affects the flood extent and their combined impacts have a negligible influence on flood severity. Berghuijs et al. (2016) demonstrated that hydrological processes play a key role in understanding the timing and variability of extreme floods. They showed that flood variability in the United States is poorly explained by precipitation variability, whereas evaporation and soil moisture-controlled precipitation excess are dominant factors in generating a majority of extreme floods in the United States. In another study, J. A. Smith et al. (2018) revealed that intense thunderstorms occurring in mountainous catchments are a major indicator of the most extreme floods in the United States.

Overall, flood magnitude and frequency are mainly controlled by large-scale synoptic climatic (e.g., circulation patterns) and hydrological variables (e.g., precipitation and soil moisture). However, to recognize the controlling processes in flood extent and inundation areas generated by flooding, a thorough understanding of the topography and morphology of rivers is required. Knowing these two key factors is crucial to properly route the flood waves downstream of the rivers. In addition, the land-use type and details of the properties that are exposed to flooding are other important factors that explain flood loss and damages.

2.3. Human Influence

Flood generation can be significantly influenced by human interventions in the environment, including land-cover change activities, global warming, and the construction of flood control structures. Among various land-cover activities, urbanization is a factor that significantly contributes to flood generation. Urbanization increases impervious areas, reduces the infiltration rate, and leads to higher flood volumes with reduced time to peak (Saghafian et al., 2008; Suriya & Mudgal, 2012; W. Zhang et al., 2018). Mazzoleni et al. (2022) recently conducted a global analysis of the relationship between annual maximum flood extent (AMFE) and impervious artificial areas as a proxy for urban areas. The study revealed that hydroclimatic variability alone cannot account for changes in AMFE, and urbanization plays a critical role in explaining flood generation in most basins. Such studies are motivated by the need to control unplanned urban development and promote resilient communities to achieve Sustainable Development Goals (Di Baldassarre et al., 2019). In addition to urbanization, Rogger et al. (2017) elaborated on other human-induced land-cover change activities that impact floods at the catchment scale. These activities include forest changes (Alila et al., 2009), soil compaction due to agricultural practices, artificial drainage, and terracing. To improve our understanding of the interactions between land-cover change and flood generation across different space and time scales, the authors proposed four pathways. These pathways involve systems thinking to link processes across time scales, controlled long-term field experiments at the plot scale, a focus on connectivity and spatial patterns, and organizing a coherent research theme within and across disciplines.

Global warming is a pressing environmental issue caused by human activities that release large amounts of greenhouse gases (GHGs) into the atmosphere. The burning of fossil fuels for energy is a major contributor to the increase in GHG concentrations, including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and water vapor. These gases trap heat in the atmosphere and cause a rise in the Earth's average surface temperature, leading to devastating consequences such as more frequent and severe storms, hurricanes and floods. For example, recent studies have demonstrated the key role of anthropogenic global warming in generating historical floods such as Hurricane Harvey (Risser & Wehner, 2017; Wehner & Sampson, 2021), the 2021 British Columbia floods (Gillett et al., 2022), and seasonal floods in Kenya (Kimutai et al., 2022). To analyze the potential impacts of global warming on flood inundation, a common approach is to set up several global climate models (GCMs) with different anthropogenic effect scenarios and couple them with hydrologic/hydrodynamic/loss models to find the inundation areas and losses corresponding to different scenarios (Bates, 2022; Dottori et al., 2018; Gillett et al., 2022; Kimutai et al., 2022; Tabari et al., 2021).

The optimum solution for coping with global warming crises and managing corresponding floods is to adopt both mitigation and adaptation policies simultaneously (Al-Ghussain, 2019). According to the Intergovernmental Panel on Climate Change (IPCC), mitigation techniques aim to reduce the sources or enhance the sinks of GHGs. This can be achieved by either reducing the GHG emissions from their sources or developing techniques to absorb the greenhouse emissions from the atmosphere (Al-Ghussain, 2019). On the other hand, adaptation policies refer to techniques that focus on reducing the impacts of global warming on society. An example of a global warming adaptation technique is the construction of flood barriers such as levees, dikes, and seawalls to protect vulnerable areas from flooding.

Flood barriers, such as levees and dams, are intended to control flooding, but they can have unintended consequences. They may negatively impact river hydrodynamics by altering channel and floodplain conveyance, resulting in extreme floods that cause additional losses (Di Baldassarre et al., 2009; Heine & Pinter, 2012). Therefore, a comprehensive cost analysis is necessary to evaluate the potential impact of flood barriers. This analysis should consider a range of scenarios, including those with and without flood barriers at various locations along the river, and estimate the corresponding losses. Remo et al. (2012) designed a similar cost analysis for the management of the Middle Mississippi River, which involved defining multiple scenarios. The study showed that agricultural levees can effectively prevent losses in medium floods, up to 50- to 100-year floods. However, during large floods such as a 500-year flood, flood-control structures may overtop or fail, and the presence of levees can exacerbate losses by reducing floodplain conveyance and storage, leading to higher flood stages.

Furthermore, if the flood event's magnitude exceeds the design return period, structural failure can occur. The failure of a dam or a levee breach can cause devastating flooding conditions that lead to significant damage (Begnudelli & Sanders, 2007; Gallegos et al., 2009). The catastrophic failure of New Orleans's levees during Hurricane Katrina is a stark example of such a devastating condition, leading to one of the nation's worst-ever disasters. While a significant portion of the damage from Hurricane Katrina resulted from the storm itself, many engineering and policy failures contributed to the destruction (Sills et al., 2008). The operation of dam reservoirs is also a critical human-induced factor that can impact downstream discharge and potentially lead to flooding (Mateo et al., 2014). To address this, an integrated framework is needed to link reservoir operation rules with hydrologic/hydrodynamic models. An optimization model can be utilized to determine the optimal reservoir outflow strategies while minimizing the risk of flooding. By employing such an approach, it is possible to effectively manage the operation of reservoirs and mitigate the potential losses for downstream flooding. Overall, it is highly recommended to use integrated frameworks that encompass all riverine and coastal structures, while simultaneously simulating human activities and physical processes. These frameworks should be designed under multiple scenarios and should estimate the total costs of flooding by being linked to loss models. The interactions between floods and society, as well as the associated feedback mechanisms, can be conceptually represented by dynamic models (Di Baldassarre et al., 2013). Employing such conceptualization in modeling is highly beneficial for comparing different scenarios and devising optimal flood management policies for coupled flood-human systems.

3. Riverine Flood

In riverine flooding (also referred to as fluvial flooding), rivers and their floodplains are the center of attention, where excessive rainfall, snowmelt, or ice jams raise the water level in rivers and result in an overflow of water onto the surrounding banks and neighboring lands. Riverine flooding, resulting from excessive rainfall or snowmelt, is the most common type of flood representing classic overbank flooding and is typically referred to as a "flood" by the public. This type of flooding comprises both hydrological and hydrodynamic processes. The former is required to determine (predict/forecast) the flow in rivers, while the latter routes the flow along the rivers and valley floors to generate the flood depth and inundation areas. Figure 1 displays a schematic of flood-generating processes and key factors that generate riverine flood inundation areas. From a watershed-scale hydrological perspective, extreme precipitation is the primary force that initiates flooding conditions. Other physical/hydrological components, such as the shape and slope of the catchment and river network, land use type (e.g., impervious areas), high evapotranspiration and saturated soil, increase the surface runoff and upstream flows in rivers (Figure 1a). The physical processes simulated through hydrodynamic analysis explain the movement of upstream flow and surface runoff along the river network and subsequently result in flood inundation. From a hydrodynamic perspective, the topography of the channel and floodplain, geometry of riverine cross-sections, roughness of the channel and floodplain and existence of riverine structures are key factors that affect the flood inundation area (Figure 1b).

3.1. Flood Forecasting

Traditional flood management systems have mostly focused on using structural protection measures (e.g., dams and levees) to moderate the flood peak and extent. The high economic and environmental costs of these structural

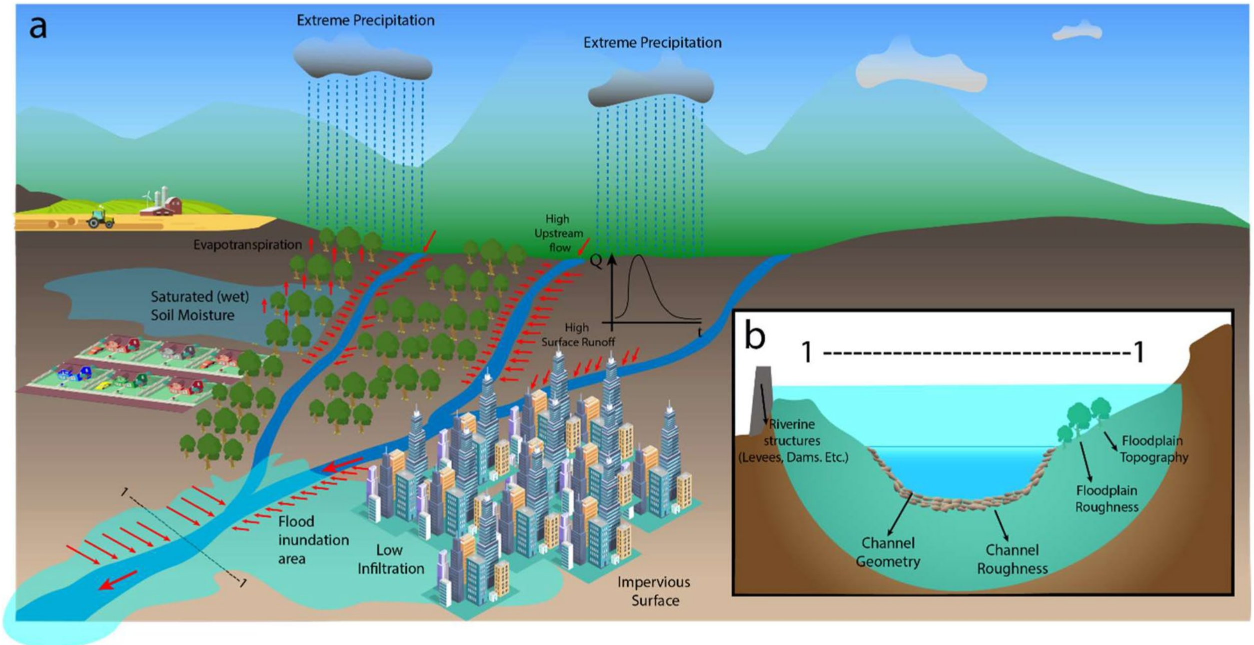

Figure 1. Schematic of flood-generating processes from a hydrological (a) and hydrodynamic (b) perspective. (a) Extreme precipitation initiates flooding conditions where hydrological factors, such as low evapotranspiration, saturated soil moisture and impervious surface area, result in high surface runoff and upstream flows (red arrows). (b) The analysis of these high flows within the rivers is conducted from a hydrodynamic perspective, where factors such as channel geometry and roughness, floodplain topography and roughness and riverine structures explain the flood inundation areas.

measures and their failure to protect several past flood events resulting from nonstationary and uncertainties in design flood estimation have led to the development of a transition plan from structural measures to soft-path solutions in recent decades (Gleick, 2003; Implementing Nature Based Flood Protection, 2017). Soft-Path-Solutions refer to a water resource management strategy that complements centralized physical infrastructure with lower-cost community-scale systems, decentralized and open decision-making, water markets and equitable pricing, application of efficient technology, and environmental protection (Brandes et al., 2011). In flood risk management, a "soft-path" approach assumes that floods will occur, all flood control infrastructures can fail, and this failure must be planned for. Unlike structural protection measures that aim to prevent flooding, soft-path solutions seek to understand, adapt and work with natural hazards. Flood forecasting and warning systems are one of the few feasible options among soft-path solutions that focus on reducing hazard exposure and provide more flexible and less expensive mechanisms compared to structural measures (Dale et al., 2014; DiFrancesco & Tullos, 2014; Pappenberger et al., 2015).

Flood forecasting and warning systems include several technical and policy steps, beginning with observations, weather forecasting, and DA through the design and communication of effective warnings and action-based protocols to save lives and property (R. Emerton et al., 2020; Q. Zhang et al., 2019). The key part of this chain focused on here is the flood forecast, in which the actual magnitudes of upcoming fluvial flooding produced by a rain or snowmelt event are estimated. The implementation and promotion of the EPS is a major milestone in flood forecasting (Duan et al., 2019). In meteorology, unlike traditional deterministic approaches that rely on a single forecast, EPS uses an ensemble of NWP models to generate a range of meteorological forecasts (Cuo et al., 2011). It complements a single deterministic forecast with probabilistic predictions while accounting for uncertainties involved in initial conditions, boundary conditions, model parameterization, and model structure (Buizza et al., 2005). EPS uses various approaches, such as ensemble averaging, ensemble-based DA, and targeted observations, to improve performance and reduce the uncertainties associated with a deterministic forecast (Du et al., 2019; Du & Li, 2014). Although EPS often operates at a larger grid scale compared to a deterministic model setup, the overall forecast skill is improved. The higher forecast skill of EPS together with its ability to communicate uncertainties have convinced meteorologists to regard EPS as an advanced method for weather forecasting. As a result, the majority of national weather services (NWSs) across the world (e.g., NOAA in the United States, ECMWF in Europe, UK Met Office, and Meteo France) operate EPS regularly on a daily scale. The high complexity and nonlinearity that exist in the atmosphere (Lorenz, 1969), together with the high sensitivity of weather forecast models to the patterns of initial conditions and subgrid parametrization (Buizza et al., 1999), justify the transition from deterministic modeling to EPS in the last two decades. This transition has been instrumental in transforming flood forecasting because the EPS outputs (e.g., an ensemble of precipitation and temperature) can be used as inputs to a hydrologic model to propagate the uncertainty and forecast an ensemble of streamflows (H. L. Cloke & Pappenberger, 2009; H. Cloke et al., 2013; Gouweleeuw et al., 2005; Pagano et al., 2013; Schaake et al., 2007; W. Wu et al., 2020). In addition, the hydrological model can be implemented together with a weather forecast model within an integrated earth system approach (Harrigan et al., 2020) The whole process of generating ensemble meteorological forecasts within an EPS and coupling them with a hydrologic model to produce probabilistic flood forecasts is implemented within an integrated system referred to as the hydrological ensemble prediction system (HEPS). In the past decade, a large number of studies have implemented HEPS in various regions using EPS inputs from several global weather services and various hydrological models (Duan et al., 2019; J. Wu et al., 2014) (e.g., Africa, Thiemig et al., 2010, 2015, Europe, Doycheva et al., 2017; Komma et al., 2007; Nester et al., 2012; M.-H. Ramos et al., 2007; Ravazzani et al., 2016, Asia, He et al., 2010; Hopson & Webster, 2010; Hsiao et al., 2013; S. Kim et al., 2009; L. Liu et al., 2017, 2019; H. Shi et al., 2015; Ushiyama et al., 2014; J. Wu et al., 2014; J. Ye et al., 2016; Yu et al., 2015, and the Americas, Bischiniotis et al., 2019; Siqueira et al., 2016).

A HEPS contains several key components, including meteorological preprocessing to generate an ensemble of meteorological forecasts, a hydrological modeling component to simulate the underlying physical processes, a hydrologic data assimilator to generate ensemble streamflow forecasts, a hydrological product generator or a hydrological postprocessor that compares ensemble streamflows with observations. The system reduces errors through bias correction, provides user-friendly outputs for stakeholders and decision-makers, and a verification system that evaluates the reliability and robustness of the final products based on different verification approaches. In the next sections, we briefly review the most recent advances related to these components and discuss the challenges for future studies accordingly.

3.1.1. Hydrological Modeling

A hydrologic model represents the pathways of water flow and storage of a real-world hydrologic system through a series of equations (Jain & Singh, 2019). They are used to understand hydrological scientific questions about water and environmental processes, provide predictions of the future and provide impact assessment (Devia et al., 2015). Hydrological models can be as simple as a conceptual storage and routing model treating a river basin as one large leaky bucket, with the bucket representing the surface and subsurface storage capacity of the catchment and the leaks representing the flowpaths to the river channel. On the other hand, they can be as complex as the hydrological land surface component of an earth system model involving hundreds of physics-based equations, and thousands of parameters, spatially discretized vertically and horizontally into many grids or tiles and coupled dynamically to the atmosphere. The boundaries between statistical models and those based on physical equations are being increasingly blurred, particularly with the incorporation of uncertainty and dynamic parameterization techniques into the core of hydrological models (Wanzala et al., 2022).

All models are simplifications of reality and thus cannot completely represent every process and aspect of a river basin, but the majority of hydrological models of all types can represent to some extent peak flow magnitude, timing and duration if the data are available to train the model, but this may not be sufficiently reliable or precise to use for flood forecasting. The choice of model for operational flood forecasting is not simple because of different representations of hydrological processes that may or may not be suitable for the location of interest (for example, adequate representation of groundwater flows or wetlands and lakes), data scarcity issues for parameterizing, calibrating and evaluating models, hydrologic uncertainty and, very importantly, the computational and human resources available for operating the flood model.

3.1.2. Preprocessing and Postprocessing for HEPS

Both observations and forecasts contain uncertainties and systematic errors. To improve forecasts by reducing uncertainties and errors, statistical or ML-type methods can be applied to both the incoming meteorological variables, such as temperature, evaporation, or precipitation and the forecast outputs of hydrological variables, such as river discharge/streamflow, flood depth or extent (Khajehei & Moradkhani, 2017; Madadgar et al., 2014; Matthews et al., 2022; Wetterhall & Smith, 2019). These errors are considered in terms of different attributes of "forecast quality."

Pre- and postprocessing methods aim to improve forecast quality in terms of skill, accuracy and value. It is therefore not surprising that post- and preprocessing is part of every hydrological forecasting system (Gneiting & Katzfuss, 2014; Schaake et al., 2006). Preprocessing directly addresses the fact that meteorological forecasts are rarely reliable and that such reliability depends not only on the forecast model quality in use but also on lead time. For example, many systems are underdispersive (too narrow a range of possibilities given the observations) at the beginning of the forecasts at shorter lead times and overdispersive (too wide a range of possibilities).

Preprocessing and postprocessing methods do not differ fundamentally, meaning that many methods which are used for pre-processing can also be applied for post-processing and vice versa, however, methods maybe more or less suitable given the statistical properties of the variable which is corrected. For example, river discharge and 2 m temperature are both variables with a high temporal autocorrelation, with temperature often having a clear diurnal cycle and both variables having seasonal cycles in most parts of the world. Any method that works well within the context of such properties can be applied to both variables. It would not be appropriate to apply the same approaches to variables with vastly differing statistical properties; for example, convective precipitation (low spatial and temporal autocorrelation) and inundation extent (extremely high spatial and temporal correlation) require very different approaches. The forecast horizon (for example, seasonal or short range 48 hr ahead) will also determine what processing is applied.

It is important that processing is not just about improving statistical properties but also about improving communication with those using the forecasts and taking decisions and actions and considering what it is about the forecast that is most important to them. Different types of deficiencies can be improved through processing, including forecast sharpness, spread, timing, and peak (Abaza et al., 2017). In correcting for one of these, it may be that another property deteriorates, and thus, any processing method will have to trade-off between these different properties and can be directly guided and impacted by decision-making or planning. Many flood forecasting systems build a type of postprocessing into their decision rules on when to issue a warning regarding warning triggers, forecast consistency and forecast uncertainty (J. Xu et al., 2022).

Several recent publications reviewed processing methods starting from Duan et al. (2019) to updated references such as W. Li et al. (2017) and Vannitsem et al. (2018). There are also more targeted reviews within the context of HEPS systems; for example, Troin et al. (2021) reviewed methods and approaches for generating ensemble streamflow forecasts over the last 40 years. W. Li et al. (2017) looked specifically at hydrology and meteorology and provided a useful general classification of methods into quantile methods, analog methods, conditional distribution-based methods, regression-based methods, ensemble dressing methods and "others." In general, most scientific publications report a positive impact on the forecast quality of postprocessing. Notably, the results are more mixed for the report on preprocessing techniques. Although most publications report positive impacts, some publications also clearly state that preprocessing can even lose any impact on discharge when fed through the nonlinear system. It also must be emphasized that a comprehensive comparison to simpler approaches is rarely shown despite the need for simplistic methodologies in an operational forecasting chain. Indeed, Hegdahl et al. (2021) find that in an analysis of the benefits of pre- and postprocessing, the answer depends on "region, catchment and season", which inherently controls the nonlinear processes that dominate flood generation.

Although methods and results are often compared, there is a lack of evidence regarding whether such findings can be generalized or are more likely to be specific to the particular forecast system, catchment, time period, and forecast system purpose. This also applies to multimodel processing methods when forecasts from different forecasting systems are combined. The jury on whether such multimodel ensemble forecasting approaches offer a valuable and strategic way forward out is still open and is posed by Troin et al. (2021) as one of the key future challenges that need to be scientifically addressed—although operational systems such as the European Flood Awareness System already practice such an approach.

As pre- and postprocessing methods are trained on recent data, they are often unable to support seasonal or climate-related changes in the system. The issue of climate change and nonstationarity is less relevant as post and preprocessing methods are trained on recent data. Relevant for longer ranges that is, correction of seasonal forecasts as there may not be enough data to train the correction method that is, seasonal systems are only issued often once per month, they have a 20–30 year "hindcast," that hindcast influences by climate change and drifts—of course in becomes relevant for decadal or longer-term predictions.

3.1.3. Data-Driven Methods (Statistical and ML-Based)

Over the past decades, data-driven methods have been continuously considered as an alternative to hydrological models for streamflow forecasting. These methods refer to all statistical and ML-based techniques that only rely on historical data and do not consider the underlying physical processes in the catchment. To properly set up a data-driven streamflow forecasting model, the required predictors, the type of model (method) and the lead time of forecasting should be well defined. The majority of studies have either used a time series of gauged streamflow in preceding time steps as the only predictor (S. Huang et al., 2014; Hussain et al., 2020; Kasiviswanathan et al., 2016; Kisi et al., 2012; Ravansalar et al., 2017) or considered both precipitation and streamflow time series data (Adnan et al., 2019; Ding et al., 2020; Nourani, 2017; Rezaeianzadeh et al., 2014; Z. X. Xu & Li, 2002; S. Zhu et al., 2016). While point-source gauged precipitation data have been dominantly used as the main input to ML models for streamflow forecasting, several recent studies have investigated the use of satellite-based gridded precipitation data as predictors (Nanda et al., 2016; Santos et al., 2019; Sulugodu & Deka, 2019; Wang et al., 2021). Nanda et al. (2016) showed that although the accuracy of satellite-based rainfall products is less than that of gauge-based rainfall data, the real-time TRMM-RT satellite product can be properly fed into data-driven models and provide satisfactory results for real-time flood forecasting. In another study, Kumar et al. (2021) demonstrated that adding gridded soil moisture data as a new predictor along with satellite-based precipitation data can improve the performance of ML-based streamflow forecast models. This opens a new avenue for using satellite-based hydrological variables as predictors of ML models, which is significantly advantageous for flood forecasting in data-scarce regions.

The choice of data-driven methods and the use of innovative techniques to improve the reliability and robustness of flood forecasting skills have been the main areas of research in recent decades. One of the early attempts to improve the streamflow forecasting skill was the development of linear stochastic models, such as autoregressive moving average (ARMA) and its nonstationary version, autoregressive integrated moving average (ARIMA) (Abrahart & See, 2000; Montanari et al., 2000; Rezaeianzadeh et al., 2014; Toth et al., 2000; Valipour et al., 2013). The former is defined with two hyperparameters showing the lag order and order of the moving average, while the latter includes the order of the differencing operator to account for nonstationarity in the time series. Despite their popularity, the highly nonlinear nature of underlying processes in streamflow forecasting has suggested ML models as a better alternative for flood forecasting in recent decades (Brath et al., 2002; Valipour et al., 2013). In recent years, advances in computer technology using graphic processing units (GPUs) and access to big data (Schmidhuber, 2015) have facilitated the use of deep learning techniques, especially the LSTM for streamflow forecasting (e.g., Afan et al., 2022; Bai et al., 2019; G.-L. Feng, Yang, et al., 2020; Frame et al., 2022; Khosravi et al., 2022; Kratzert et al., 2018; Y. Liu et al., 2022; Ni et al., 2020; Zhou et al., 2021). LSTM is a special type of recurrent neural network (RNN) that receives time series of data as input and considers the time dependence among data. Unlike RNNs that only memorize a short sequence of data (limited to the last 10 instances (Bengio et al., 1994)). LSTM has the ability to memorize long sequences of data (more than years), which is significantly important for hydrological predictions (Kratzert et al., 2018). Considering the success of LSTM deep learning-based models in the accurate forecasting of streamflow and their high efficiency for rapid flood forecasting after training, the potential for replacing physically-based hydrological models with these data-driven techniques in operational flood forecasting systems is a matter of debate among hydrologists.

Depending on the application and type of problem, streamflow forecasting can be implemented for 1 day, multiple days ahead, or monthly forecasting. M. Cheng et al. (2020) investigated the potential of using both LSTM and conventional artificial neural network (ANN) models for long lead time streamflow forecasting at both daily and monthly scales. They found that LSTM outperforms ANN for long lead daily forecasts, while ANN is superior at the monthly scale. In another study conducted over two stations in China, ANNs showed better performance than all hybrid data-driven models used for monthly streamflow forecasting (X. Zhang et al., 2015). Convolutional neural networks (CNNs) are another set of advanced ML techniques that have been recently used for flood forecasting and have demonstrated acceptable performance for monthly streamflow forecasting (C. Chen et al., 2021; Shu et al., 2021). Overall, past studies show that, depending on the scale of forecasting, lead time, and case study, the type of data-driven techniques should be changed. There are many open areas of research to improve the performance of these models, especially for the long-lead time and monthly flood forecasting using advanced ML techniques. In addition, including new remote sensing predictors, such as gridded soil moisture (e.g., Abbaszadeh et al., 2019), and evapotranspiration data, as inputs to CNNs can capture the spatial correlation, provide richer inputs for training and improve the performance of these models for future flood forecast studies.

3.1.4. Hydrological Data Assimilation for Flood Forecasting

Hydrological models most often do not provide accurate and reliable estimates of prognostic variables (e.g., soil moisture and streamflow) due to multiple sources of uncertainties, including hydrometeorological forcings, model parameters, boundary or initial conditions, and model structure (Abbaszadeh et al., 2019; Bi et al., 2015; Leach

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et al., 2018; Moradkhani et al., 2019). These uncertainties are usually accounted for when the hydrologic predictions are produced within a probabilistic framework (Kuczera & Parent, 1998; Marshall et al., 2004; T. J. Smith & Marshall, 2008). This is typically performed through Bayesian inference. DA is formulated in a Bayesian context. DA has gained increasing attention among researchers and practitioners as an effective and reliable tool for incorporating hydrometeorological observations from in situ and remotely sensed measurements into hydrological models to improve forecasting skills while accounting for associated uncertainties (Moradkhani, Hsu, et al., 2005; Moradkhani et al., 2006). DA allows for updating state variables in a hydrologic model to represent the initial condition of a watershed more accurately than the standard spin-up approach (Boucher et al., 2020). DA is often a prerequisite for hydrological forecasting (Gavahi et al., 2022; Moradkhani et al., 2019). The main DA techniques used in the hydrological forecasting context include the ensemble Kalman filter (EnKF) and particle filter (PF). The most widely used DA technique in the hydrologic community is the EnKF (Crow & Wood, 2003; De Lannoy et al., 2007; Reichle et al., 2002). Although the successful application of this DA technique and its variants has been reported in numerous hydrological studies, EnKF has some inherent features that result in suboptimal performance (Abbaszadeh et al., 2018; Moradkhani et al., 2019). These include the Gaussian assumption of errors, linear updating rule within the EnKF, and violation of water balance (DeChant & Moradkhani, 2012; Gavahi et al., 2020; Moradkhani, Hsu, et al., 2005; Noh et al., 2011; Plaza et al., 2012; L. Xu et al., 2020). Given these concerns, PF DA has garnered increasing attention in the hydrologic community as a viable alternative to the EnKF (Dong et al., 2015; Montzka et al., 2013; Moradkhani et al., 2012; Noh et al., 2011; H. Yan et al., 2017). This approach can relax the Gaussian assumption of error distributions by potentially characterizing multimodal or skewed distributions in state variables and parameters. Therefore, it can provide a thorough representation of the posterior distribution for a given nonlinear and non-Gaussian system. Evolutionary particle filter and Markov chain Monte Carlo (EPFM), developed by Abbaszadeh et al. (2018), is a successor version of PF-MCMC (Moradkhani et al., 2012) to improve both the state and parameter estimation of a high-dimensional system. We refer the readers to (Moradkhani et al., 2019) for a comprehensive description of different DA approaches that are commonly used in hydrological forecasting studies.

Streamflow is one of the most commonly observed hydrologic variables and is used as an input to hydrodynamic models for flood inundation forecasting and mapping. The assimilation of streamflow observations into hydrological models is known as an effective method to improve the streamflow forecasting skill of hydrological models and contribute to enhancing flood forecasting and early warning systems (Clark et al., 2008; DeChant and Moradkhani, 2011a, 2011b, 2012; Ercolani & Castelli, 2017; H. K. McMillan et al., 2013; Noh et al., 2013; Rafieeinasab et al., 2014; D.-J. Seo et al., 2009; L. Sun et al., 2015; Weerts & El Serafy, 2006). Streamflow DA is mainly used to account for the error in the initial condition and improve short-term flood forecasting in operational settings (El Gharamti et al., 2021; Samuel et al., 2014). In the United States, the National Water Model (NWM) is operated by the NWS for flood forecasting in more than 2 million river reaches. To account for the uncertainties involved in the hydrologic model and improve NWM flood forecasting skills, streamflow observations are operationally assimilated into the WRF-Hydro hydrological model. Streamflow DA in the NWM improves model simulation and forecasting of initial conditions by correcting modeled streamflow using observations at gauging stations (B.-C. Seo et al., 2021). While past efforts have proven that streamflow DA and multivariate assimilation of streamflow and other hydrological fluxes are significantly useful, operational flood forecasting systems do not often use DA (R. E. Emerton et al., 2016) due to their sophistication and implementation process. The barriers between hydrological forecasting research and operations have been described in depth by Y. Liu et al. (2012).

Accurate estimation of soil moisture conditions can significantly improve streamflow prediction and short-term flood forecasting (Berthet et al., 2009; Brocca et al., 2012; Crow et al., 2005), as it dominates infiltration and runoff processes. Assimilating soil moisture from in situ measurements or satellite retrievals can compensate for the deficiency of the antecedent conditions (Meng et al., 2017) and therefore result in better flood forecasting. Many studies have shown the usefulness of near-surface soil moisture assimilation to adjust prestorm soil moisture conditions and improve storm rainfall-runoff modeling (Abbaszadeh et al., 2020; Alvarez-Garreton et al., 2016; F. Chen et al., 2014; Crow & Ryu, 2009; Massari et al., 2014). In addition, multivariate assimilation of soil moisture and streamflow has been known as an efficient approach for improving flood forecasting. However, it is often not easy to simultaneously assimilate two different types of observations into a hydrologic model due to a time lag between soil moisture and streamflow owing to the runoff routing process (Meng et al., 2017). H. K. McMillan et al. (2013) found that the retrospective ensemble Kalman filter (REnKF) can overcome the time lag between upstream watershed wetness and flow at gauging locations. Another alternative to address this problem is to use the ensemble Kalman smoother (EnKS), which is able to improve hydrologic model states and streamflow prediction by considering time lag in the routing process (Y. Li et al., 2013; H. K. McMillan et al., 2013).

3.1.5. Challenges

Challenge 1: Quality: Understanding whether a forecast is good enough is critical for forecast users to have confidence in a forecast system, but "good enough" should be considered in light of the decisions that need to be made, such as issuing a flood warning, shutting flood defense structures, and issuing evacuation orders. Many already existing forecast verification scores measure different aspects of system performance, but the key challenge is condensing this into something meaningful for the decision-makers. The development of traffic light systems that indicate how good the forecast is for the decision entails green (high confidence in the forecast), yellow (some confidence in the forecast—proceed with caution); red (low confidence in the forecast—do not use). The challenge is thus to condense and weigh all information on reliability, sharpness, and other system qualities in such a simplified and yet meaningful metric. Some attempts have been made in seasonal climate forecasts, and the challenge is to extend such concepts to HEPS. In addition, a set of standardized scores that are widely used for operational quality assessment of forecasts would make objective comparisons easier to achieve.

Challenge 2: Verification: The verification of extremes is not robust enough (extremes in terms of extreme events but also extremes/tails of the probability distribution). Average performance does not necessarily reflect extreme performance, which is why we need score metrics and methods that accurately express the performance for the tails of the distribution. Although some progress has been made in this area, the problem has yet to be fully resolved. Furthermore, these metrics should provide relevant information for end-users and assess the quality of flood simulations, including the ability to predict peak flow, timing, magnitude, duration, flood depth, and extent. For flood forecasting, these metrics should be expressed as a function of "lead time."

Challenge 3: Processing: Fully coherent spatial and temporal processing methods are needed. Most preprocessing methods focus on improving a singular variable or driver such as improving a precipitation data set. In hydrological forecasting, it is important to obtain the correct spatial correlation of hydrological variables (i.e. precipitation is often topography driven) as well as the correct temporal evolution. In particular, all spatial and temporal corrections must be physically "correct." This is also important when other variables are corrected (i.e. correction for precipitation types such as snow are closely linked to temperature). Evaporation is also not independent of temperature. Correcting a single variable alone may severely impact the overall water balance. The challenge is to develop spatially, temporally and intervariably coherent correction methods that may well require additional developments in artificial intelligence. Interestingly, this is one of the reasons why physically based models are deployed, as they already provide such coherence, and an optimal fusion between coherent processing and physically based model output has to be developed.

Challenge 4: Modeling framework: Most operational forecast chains are still organized in a traditional modeling framework where the individual components are treated and modeled separately. The hydrological model is loosely attached to the meteorological forcing, and the decision-making framework is another add-on. This separation of concern is scientifically and socially convenient, as every scientist and developer can specialize in a part of the system and keep improving the particular element. It ignores the fact that the earth's system is connected and interacts with complex feedback loops, which leads to "double" developments and compensating errors, for example, every meteorological and climate forecasting system has a land surface scheme duplicating functions of hydrological processes. This challenge requires a more radical way of working together and exchanging ideas and solutions across disciplines and is as much about reframing social-scientific interactions. The NOAA Next Generation Global Prediction System (NGGPS) is an excellent example of an integrated, fully coupled innovative earth system model. Its purpose is to enhance flexibility and capability for implementing model component improvements within a unified system, allowing for the expansion and acceleration of critical weather forecasting research into operation (https://vlab.noaa.gov/web/osti-modeling/nggps1).

3.2. Flood Inundation and Extent Mapping

A flood inundation map indicates the water depth at different locations and is typically time-varying, showing the evolution of inundated areas over the flooding period. The common approach for producing flood inundation maps is to set up a hydrodynamic model to simulate the river physics during flooding and route the streamflow downstream along the river network. These models estimate the spatiotemporal distribution of water depth along rivers and floodplains. When the simulated flow exceeds the bankfull capacity, the floodplains adjacent to the channel are inundated, and damage can begin to occur. The flood inundation maps provided by hydrodynamic models are the primary resource for flood risk mapping (Apel et al., 2006; De Risi et al., 2013; Lu et al., 2018; Oubennaceur et al., 2019). Flood extent maps, however, are binary data sets that only distinguish flooded from non-flooded areas and provide less information compared to inundation maps.

According to Bates (2022), flood inundation and extent mapping activities can be categorized into three broad classes of problems. The first class of problems seeks to estimate hazard areas exposed to a flood event of a given probability (Dottori et al., 2016). Here, the main forcing data used as boundary conditions for hydrodynamic models are synthetic hydrographs corresponding to a given return period. A common approach to estimating the peak of these flow hydrographs is to use extreme value frequency analysis of long time series of measured discharge (Bobée & Rasmussen, 1995; Ramachandra Rao & Khaled, 2019; Stedinger & Griffis, 2008) or regionalized flood frequency analysis at ungauged sites (Drissia et al., 2022; Han et al., 2020; Ouarda, 2016). Flood risk assessment is typically an ultimate goal of this class of problems where the probability of flooding (i.e. hazard) estimated by flood frequency analysis is integrated with flood consequences (Apel et al., 2004; de Moel et al., 2015; B. Merz et al., 2014). The spatial distribution of flood depth provided by flood inundation models is commonly overlain with monetary losses (e.g., using flood stage-damage function curves) to estimate the flood consequences caused by a flood event of a given probability (B. Merz et al., 2010; Olesen et al., 2017; Romali et al., 2015).

The second and third classes of problems aim to predict flood inundation and extent areas corresponding to actual flood events. In the second class, the focus is on near-real-time inundation forecasts (Krajewski et al., 2017; G. J.-P. Schumann et al., 2013). For this class of application, the goal is to predict inundation patterns that are likely to occur in the immediate future as a result of forecasted weather, river flow, or coastal high-water-level events. Thus, the main forcing data used as boundary conditions of hydrodynamic models are either forecasted flows (or water levels) provided by hydrologic models or flow observations if the data are available with low latency. Flood inundation forecasting should be classified as a key component of operational flood forecasting systems. Due to the critical role of this class of problems in reducing the potential loss from upcoming flood events, we provide a separate section that specifically discusses the challenges and provides a more detailed literature review on this topic.

The third class of problems seeks to simulate flood inundation areas corresponding to past flood events, a flood inundation hindcast. The main advantage of this class of problems compared to the other two classes is the availability of data for past flood events. The streamflow/water level data at gauge stations (or hydrologic model outputs provided from observed rainfall data) as well as satellite remote sensing data provide extremely beneficial pieces of information for calibrating, assimilating and validating flood inundation models. The goal of this class of problems is to answer scientific flood-relevant questions to further improve flood inundation modeling skills.

In addition to hydrodynamic models, a large number of simplified methods (low-fidelity, topography-based, and data-driven models) have emerged as alternatives for both flood extent and inundation mapping in the last decade. These techniques are computationally efficient for the rapid estimation of flood inundation and extent but have not yet been subject to sufficiently rigorous testing for out-of-sample flood events that are unlike those on which they have been trained. In the following sections, we first review the most recent advances in hydrodynamic modeling and highlight the main challenges that need further attention. Then, we explain simplified methods while summarizing their weaknesses and strengths for flood inundation and extent mapping. The next section will review the hydrodynamic DA literature, explain the concept of inundation forecasting, including major sources of uncertainty, and highlight potential challenges for real-time probabilistic flood inundation mapping. Finally, we summarize the main challenges in flood inundation and extent mapping.

3.2.1. Hydrodynamic Models

The central premise of hydrodynamic models (also referred to as hydraulic and routing models) is to numerically solve derivations of the Navier-Stokes (NS) equations and estimate the spatiotemporal distribution of water depth in the riverine system. These equations are the mathematical expression of two principal laws in physics, conservation of mass and conservation of momentum, which simulate the water motion in channels. Flood inundation mapping is typically performed by one-dimensional (1D), two-dimensional (2D), or coupled 1D/2D models. These approaches vary in terms of how the channel and floodplain are discretized and are already comprehensively reviewed in a number of existing publications, including Teng et al. (2017) and Bates (2022) such that only the most recent developments are discussed here.

In 1D hydrodynamic modeling, a series of cross-sections are defined along the river, while each cross-section represents both channel and floodplains with a single average velocity in the downstream direction. On the other hand, 2D models generate a mesh of polygonal cells (usually regular grids or irregular triangles, but sometimes regular hexagons or a mix of geometric or hierarchical shapes) that represent the topography of channels and floodplains in a more realistic way (Pinos & Timbe, 2019). As a result of these differences, large-scale empirical studies conducted in the last few years (e.g., Apel et al., 2009; Hocini et al., 2020) have demonstrated the clear superiority of 2D over 1D methods in most circumstances, but 2D models can be computationally expensive.

Given this, the most important recent numerical developments have focused on improving the computational efficiency of numerical 2D simulations rather than on incremental improvements to solution quality. Approaches here have included solving reduced forms of the shallow water equations (principally diffusion and local inertial waves; Bates & De Roo, 2000; Bates et al., 2010; Bradbrook et al., 2004) optimizing model structure for fluvial applications through the adoption of hybrid 1D/2D schemes (J. Neal et al., 2012), code optimization and parallelization (J. C. Neal et al., 2010, J. Neal et al., 2018; Sanders & Schubert, 2019) and harnessing of high-performance computing (HPC) and GPU architectures for code speed-up (Kalyanapu et al., 2011; Liang et al., 2016; Shaw et al., 2021).

The rationale for 1D/2D hybrid approaches is that for efficient computation, structured grids are often preferred, but a small cell size is required to represent the channel geometry, which is often an over-specification in floodplain areas. Unstructured grids can resolve this issue but are more complex to code and slower to execute. Hybrid approaches attempt to resolve this issue by using a 1D model for the channel and a structured 2D model for the floodplain, thereby decoupling channel and floodplain representations. The 1D model simulates in-channel flow as described above, thereby avoiding the limitations of this approach for representing floodplains, with water transferred to the overlying 2D model only once backflow is exceeded. This can be the most efficient representation of fluvial floods in many circumstances (Apel et al., 2009).

Reduced forms of shallow water equations save computational cost as fewer calculations are needed and, often, very simple and efficient numerical methods can be adopted. Over time, the local inertial approximation to the shallow water equations (Bates et al., 2010), where only the convection term is omitted, has come to be seen as the best solution if the full equations are not required. The local inertial form of the shallow water equations has been shown to give near-identical results to the full equations at Froude (Fr) numbers less than 0.5, with divergence increasing thereafter up $Fr = 1.0$ but almost always less than errors in typical input data for real-world applications (Almeida & Bates, 2013). For $Fr > 1.0$, the flow becomes supercritical, and the convection term that is missing from the local inertia form becomes increasingly dominant such that for these supercritical flows, the simpler models are contra-indicated (J. Neal et al., 2011). Nevertheless, if areas of subcritical flow are limited in spatial extent, then local inertia models can sometimes do a useful job (Luke et al., 2015).

In general, hydrodynamic models are set up with (a) terrain data such as a digital elevation model (DEM) or other topographic data sets (e.g., TIN) that are necessary for routing surface flow on the ground; (b) channel/floodplain roughness coefficients (parameters) characterizing the flow resistance during floods; (c) upstream/downstream river boundary conditions (forcings) typically defined by a time series of flow or water stage hydrographs; and (d) the initial condition of the system defining water level/flow along channels (initial conditions). Of these, most recent efforts have focused on improving terrain data inputs, as new remote sensing techniques have allowed significant advances to be made. The breakthrough here came with the development of airborne LiDAR as a technique for operational terrain mapping of river reaches around the start of the present century (Gomes Pereira & Wicherson, 1999; Marks & Bates, 2000) but has since expanded to global terrain data collection efforts using a variety of radar and optical interferometric techniques (Baugh et al., 2013; Farr et al., 2007; Hawker et al., 2019, 2022; Yamazaki et al., 2017). Among the different topographic data sources used for flood inundation mapping, LiDAR provides the most accurate flood inundation maps (Casas et al., 2006) due to its great vertical accuracy of 0.05–0.1 m and fine horizontal resolution of 0.5–3 m (Aguilar et al., 2010). However, two main limitations of LiDAR are its limited availability for most regions of the world (according to Hawker et al. (2018), it covers just 0.005% of the Earth's land area) and the huge computational cost of running hydrodynamic models with this data set. To improve the performance of 1D hydrodynamic models in areas where only coarse-resolution DEMs are available, Saksena and Merwade (2015) proposed a methodology that relates the water surface elevation (WSE) to DEM resolutions. They extrapolated the developed regression equations to estimate WSE for fine-resolution DEMs. Omer et al. (2003) applied different levels of data filtering to LiDAR and demonstrated that filtering to four degrees can significantly reduce the computational cost of LiDAR-based 1D hydrodynamic modeling without losing accuracy. Another potential solution is to run hydrodynamic models with coarse DEMs and then downscale the results to a finer resolution (G. J.-P. Schumann et al., 2014).

Remote sensing has also been used in a limited number of studies to improve the parameterization of friction coefficients in hydrodynamic models (Cobby et al., 2003; Mason et al., 2003; Straatsma & Baptist, 2008), but improvements to the boundary and initial condition data have proven much more elusive. In one of the recent efforts, Jafarzadegan, Alipour, et al. (2021) demonstrated that including lateral flows and vertical fluxes as additional boundary conditions in 2D hydrodynamic models provides a more physics-informed simulation and improves the accuracy of 2D flood inundation models. While we can measure water level with high precision and accuracy, perhaps to ∼1 cm on the ground and to a few 10s of cm using spaceborne radar altimeters (Birkett et al., 2002; Jarihani et al., 2013; Schneider, Tarpanelli, et al., 2018), our ability to measure river flow at gauging stations has remained stubbornly unchanged over many decades, and there is no immediate prospect of any improvement. Errors are 20% for average flow conditions, and perhaps as much as 40% or more for flood flows are not atypical (H. McMillan et al., 2012). Gauged flow data are also used to calibrate and validate the hydrologic models that are used in inundation forecasting so that whether inflow discharge for an inundation simulation comes from observations or a hydrology model, it is still affected (perhaps significantly so) by these errors. In fact, for a hydrodynamic model built using LiDAR, it is likely that the forcing data used to drive the simulation currently constitutes the greatest source of uncertainty.

3.2.2. Simplified Methods

The high computational cost required to numerically solve derivations of the NS equations is a major limitation of hydrodynamic models. Depending on the scale of the problem (e.g., the total length of the simulated rivers) and the total number of grid cells (mesh size) used in 2D/3D hydrodynamic models, the computational time for a core i7 computer desktop can vary from a few hours to several days. Floods can, however, occur in a short time, endanger human lives, and cause damage promptly. Thus, the running time of models used for flood simulation is a critical factor for emergency responders and flood managers. This has led to the development of a series of simplified methods for rapid flood inundation and flood extent mapping in the last decade (Hamidi et al., 2023). Although less accurate compared to hydrodynamic models, they are more parsimonious models with less computational demand, which makes them appealing solutions for rapid, real-time, and ensemble-based flood inundation and extent mapping.

One of the most common types of simplified methods is topography-based techniques, where a DEM is used as the main input to map flood-prone areas. The main philosophy of using these techniques lies in the distinguishable geomorphologic and hydrological properties of floodplains compared to their adjacent neighbors. During floods, the water that exceeds the river banks moves onto the floodplains and fills the low-elevation areas first. Since the early 20th century, several studies have used this simple concept to identify floodplains. These include the Rapid Flood Spreading Model (RFSM), which divides floodplains into smaller areas and uses a filling/spilling process to fill in these areas according to topographic characteristics (Lhomme et al., 2008), planner methods that intersect surface water planes with a DEM (Teng et al., 2015; W. A. Williams et al., 2000) and regression-based relationships that estimate floodplain areas based on hydraulic geometry information at a large scale (Dodov & Foufoula-Georgiou, 2006; McGlynn & Seibert, 2003). Later, hydrogeomorphic approaches that take advantage of both DEM and stream characteristics were introduced as a modified version of DEM-based techniques for floodplain mapping (e.g., Nardi et al., 2006). Among the different hydrogeomorphic features calculated from the DEM, the height above nearest drainage (HAND), first introduced by Rennó et al. (2008), has received a great deal of attention for flood inundation and extent mapping. HAND can be used for the identification of flood-prone areas corresponding to a given flood frequency (Jafarzadegan & Merwade, 2019) or for real-time flood inundation mapping (Johnson et al., 2019; Y. Y. Liu, Maidment, et al., 2018).

HAND-based methods used for the identification of flood-prone areas rely on binary classifiers where a threshold is set on a hydrogeomorphic feature (e.g., HAND) to distinguish flooded cells from non-flooded ones (Degiorgis et al., 2012; Manfreda et al., 2014). In these methods, the binary classifier is trained on a reference floodplain map that is typically generated via a well-calibrated hydrodynamic model. In addition to HAND, the Geomorphic Flood Index (GFI) introduced by Samela et al. (2017) has shown to be a great indicator of floodplains in binary classifications. Using a ML algorithm, such as random forest, the hydrogeomorphic features have been recently coupled with climate, land use, and soil characteristics of catchments to provide continental-scale 100-year floodplain maps for the United States (Jafarzadegan et al., 2018; Woznicki et al., 2019) and Europe (Tavares da Costa et al., 2020). HAND-based real-time flood inundation mapping can be carried out by inserting forecasted discharges (produced by a hydrologic model) and HAND features into Manning's equation, which results in generating a library of synthetic rating curves (X. Zheng et al., 2018). Due to the high computational efficiency of this method for large-scale flood mapping, the National Weather Center in the United States has devoted significant effort to linking this method to the NWM for real-time flood inundation mapping across the CONUS. The high level of simplifications made in this method, such as replacing time-variant Saint-Venant equations with steady-state Manning's equation and assuming a single discharge and water depth for each stream reach, has led to its poor performance compared to hydrodynamic models (Afshari et al., 2018; Hocini et al., 2020). Overall, HAND methods do not conserve mass or momentum and tend only to work in confined floodplains. Thus, although they can still be more accurate than other topography-based approaches, such as planar methods (McGrath et al., 2018), they should be replaced with physically based hydrodynamic models if high accuracy is of high priority.

Other types of simplified methods used for flood extent and inundation mapping include response surface surrogates or meta-models (Razavi et al., 2012). In these techniques, ML models are trained on the results of a high-fidelity hydrodynamic model to emulate its response more efficiently. A properly trained surrogate model is a non-physics-based model that can emulate non-linear and highly complex physical processes involved in flooding. Typically, domain boundary conditions, including upstream and downstream flows and precipitation data, are used as the main inputs to ML models, where the outputs are inundation depth values at each grid cell. The most common approach is to develop a large number of trained ML models, such as support vector machines (SVMs) (Bermúdez et al., 2019), random forests (Kabir et al., 2021; H. I. Kim & Han, 2020), and ANNs (Chu et al., 2020; Q. Lin et al., 2020; S. Xie et al., 2021; Zhou et al., 2021), where each model is set up for a specific grid cell. Some of these studies can only predict the maximum flood extent (Bermúdez et al., 2019; H. I. Kim & Han, 2020; Q. Lin et al., 2020) and cannot simulate the temporal behavior of floods. On the other hand, ANN models are able to receive the time series of input boundary conditions and consider the temporal correlation of inputs (Chu et al., 2020; S. Xie et al., 2021; Zhou et al., 2021).

Using hundreds (or thousands) of single ML models where each one is trained on a single grid cell is impractical, especially in large study areas. To train these ML models, a large number of high-fidelity hydrodynamic model simulations are required. Additionally, single-grid training does not account for the spatial correlation among nearby cells. A potential solution for improving the efficiency of response surface models and accounting for spatial correlation in the domain is to divide the study area into homogenous regions using clustering methods (Chu et al., 2020). In these methods, a proper selection of physical/climatic characteristics and similarity metrics that reflect hydraulic processes is crucial. Jafarzadegan et al. (2020) introduced a cross-modeling behavioral similarity metric that considers the similarity between physical processes. They incorporated this similarity metric into the hierarchical clustering algorithm and tested its performance for detecting homogenous regions with similar rating curves (Jafarzadegan & Moradkhani, 2020). After dividing the domain into homogenous regions, two sets of ML models are set up. The first set of models predicts the inundation depth at those reference points that represent the clusters, while the second set of ML models expands the reference point results within each cluster (Chang et al., 2010; Jhong et al., 2017; G.-F. Lin et al., 2013). It is worth mentioning that although the clustering approach accounts for spatial correlation among nearby cells, it may cause discontinuities in simulated water levels between nearby regions (Chu et al., 2020). Thus, it is still necessary to consider the connection between water levels in different homogenous regions. S. Xie et al. (2021) introduced a hybrid modeling approach that clustered the study area into data-rich and data-sparse regions. The data-rich regions included the main rivers with high-quality water level information, while data-sparse regions were composed of floodplains with less access to training data. They considered the connection between these two regions by adding a rectified linear unit (ReLU) relationship to their ANN model structure and demonstrated the efficacy of their proposed hybrid ANN approach for efficient flood inundation mapping in data-sparse regions.

An alternative to developing numerous ML models using a single grid training approach is to develop a single complex ANN model for the whole domain using a CNN model (Kabir et al., 2020). This approach solves the spatial correlation issue between nearby cells, but it has a large number of parameters (order of millions), which makes model development difficult. The large number of parameters and the complex structure of CNN models limit the application of these models to reach-scale flood inundation mapping problems. Zhou et al. (2021) introduced a dimensionality reduction technique that identifies key locations along the main channel and floodplains for training. This significantly reduces the number of ML models required for training. They trained deep-learning LSTM models in those key locations and then used interpolation techniques to map the flood inundation area over the whole domain. Another novel technique is to develop hybrid methods that combine low-fidelity physical models with ANN surrogate models (Carreau & Guinot, 2021). These hybrid methods take advantage of both types of simplified models, as they still consider river physics while using ML models for efficient flood inundation mapping. In these methods, first, a low-resolution physical model generates flood inundation areas at a coarse resolution. Then, a well-trained ANN is used to downscale the low-resolution flood maps into a fine-scale product. The ANN algorithm maps the relationship between high-resolution and low-resolution flood inundation maps.

3.2.3. Flood Inundation Forecasting

Operational forecast systems utilize EPS and hydrological models to provide ensembles of short,-medium-, and long-term streamflow forecasts. The outcome of most operational flood forecast systems is often limited to these streamflow forecast hydrographs without the simulation of a physical model to convert streamflow forecasts to flood inundation areas. To provide a more comprehensive forecast system, these streamflow hydrographs should be converted to flood inundation maps. Compared to point-source flood hydrographs, forecasted flood inundation maps are much more informative for emergency responders and decision-makers. A common approach for forecasting flood inundation areas is to feed a hydrodynamic model with the aforementioned streamflow data produced within operational forecast systems (De Roo et al., 2003; Gomez et al., 2019). Hydrodynamic modeling requires extensive resources for the proper simulation of flood waves along rivers. The setup, calibration, and computational time required to simulate flooding via these models are also significantly high. Because flood waves propagate rapidly over a short period and can spread to large regions, utilizing these localized computationally expensive hydrodynamic models in operational forecast systems is challenging. One solution is to couple hydrologic models with a simplified hydrodynamic model (low fidelity models) with coarse resolution grids. In one of the early attempts at flood inundation forecasting at a large scale, G. J.-P. Schumann et al. (2013) coupled the VIC hydrologic model and European Center for Medium-Range Weather Forecast (ECMWF) ensemble (ENS) weather forecasts and then fed an ensemble of streamflow forecasts into a low fidelity (very coarse resolution with 1 km grid size) hydrodynamic model to forecast inundation areas. They used a subgrid structure within the LISFLOOD-FP hydrodynamic model that allows simulating flow in channels that are much smaller than the actual grid size.

Another approach to practical flood inundation forecasting is to develop a library of prerecorded flood inundation maps based on simulating a multitude of streamflow forecast scenarios (Bhola et al., 2018; Leedal et al., 2010). During the flood, the forecasted streamflow hydrographs are compared with the list of hydrographs used in different scenarios to find the closest flood inundation map from the library. The main limitation of this offline flood forecast framework is the dependence of the results on prerecorded scenarios. The number of these potential scenarios will exponentially increase in larger study areas with more upstream boundary conditions. This provides a large number of scenarios with various combinations of upstream flows, which limits the application of this approach to reach-scale problems. The concept of using a library of prerecorded data and offline flood inundation mapping has already been used by defining a library of rating curves for river cross-sections (Buahin et al., 2017). Using rating curve libraries for offline flood inundation forecasting is the foundation of the HAND methods currently used by the NWS for real-time flood inundation mapping across the United States (Z. Li et al., 2022; Y. Y. Liu, Maidment, et al., 2018; X. Zheng et al., 2018). In this approach, a library of synthetic rating curves is provided for all stream reaches across the United States. During the flood, the forecasted streamflow and these rating curves are used together to estimate the water depth in channels and generate flood inundation maps accordingly. Surrogate surface models can also be used as an alternative to hydrodynamic models for more efficient flood inundation forecasting (Chang et al., 2010, 2018; Kao et al., 2021; G.-F. Lin et al., 2013). A review of these ML models and their advances was discussed in Section 4.1. To use these models in forecast mode, the input streamflow data should be forecasted hydrographs provided by operational hydrologic forecast systems. It is also possible to replace both hydrological and hydrodynamic models with surrogate surface models where meteorological drivers, such as precipitation, are directly used to forecast water levels and inundation areas (Nevo et al., 2022).

In addition to improving the computational efficiency of flood inundation forecasting methods, it is crucial to improve the accuracy of forecasted inundation maps while accounting for all sources of uncertainties involved in different layers of modeling. This can be accomplished by coupling DA techniques with hydrodynamic models. In operational forecasting systems, DA is a key component for updating the initial state and parameters of environmental and earth systems models. Considering riverine floods as complex phenomena that include combined interactions of meteorological, hydrological, and hydrodynamic processes, DA has only been coupled with meteorological and hydrological models in practice. However, coupling DA with hydrodynamic models is essential for operational flood forecasting systems because it provides a more comprehensive uncertainty quantification of flooding that includes additional sources of uncertainties involved in hydrodynamic processes. Furthermore, it helps to forecast more accurate flood inundation maps resulting from updating the hydrodynamic model's initial state and parameters with new observations. Given the essential need for including a DA-hydrodynamic modeling framework in operational forecast systems, we review past studies that utilized DA-hydrodynamic modeling, highlight recent advances and discuss future directions in the next section.

3.2.4. Hydrodynamic Data Assimilation for Inundation Mapping

The assimilation of observations into hydrodynamic models has received little attention in both science and practice. The main reason is the lack of access to reliable satellite remote sensing data that meets the spatiotemporal requirements for the proper assimilation of hydrodynamic models. Due to the local nature of flooding and the fine scale of hydrodynamic processes, the spatial resolution of observational data should be on the order of meters (∼DEM resolution and river width). The rapid changes in the dynamics of flooding at sub-daily scales also require access to observations at daily/sub-daily temporal resolution. Thus, an ideal observation for DA-hydrodynamic modeling is fine-grided water level data (grid size ∼ DEM resolution) at high temporal resolution (daily/sub-daily scale). Regardless of advances and developments in remote sensing technologies over the past decade, access to such a product seems almost impossible in the near future. The gridded observations (e.g., water level and flood extent maps) currently provided by satellite imagery technologies are usually available for a given instance (due to their long revisit cycle) and cannot track the flood wave dynamics over time. On the other hand, point source observations (e.g., sensors and gauges) reflect the temporal changes at single points, while they cannot properly represent the spatial behavior of flooding over a domain.

Despite all these limitations, a wide range of observations has been assimilated into 2D hydrodynamic models to update inundation forecasts. This includes spatially distributed gridded data such as water level (Cooper et al., 2018; García-Pintado et al., 2013; Giustarini et al., 2011; Hostache et al., 2010; Lai & Monnier, 2009; Matgen et al., 2010), binary flood extent maps (Hostache et al., 2018; Lai et al., 2014; Revilla-Romero et al., 2016), point-source time series data, such as channel water level and discharge hydrographs at gauge stations (Jafarzadegan, Abbaszadeh, & Moradkhani, 2021; X. Xu et al., 2017), and in situ floodplain/channel water level sensors (J. C. Neal et al., 2007; Van Wesemael et al., 2019). To account for both the spatial and temporal behavior of flood waves, a combination of spatially distributed remote sensing data and point-source data can be assimilated into a hydrodynamic model (Annis et al., 2022). The need for joint assimilation of hydrodynamic models with both ground data and remote sensing observations has been highly emphasized in the past (Matgen et al., 2010; G. Schumann et al., 2009). Using this approach provides an optimum range of observations that capture both the spatial and temporal behavior of flooding while opening new research opportunities for improving DA-hydrodynamic modeling performance in the future.

Satellite radar altimeters (e.g., ENVISAT, ICESAT, and JASON 2) have been specifically designed to measure water levels in large water bodies (e.g., lakes and oceans). The coarse resolution of these satellites (orders of kilometers) limits their application for water level measurements in rivers. However, some studies have shown the effectiveness of satellite altimetry for the validation and assimilation of large rivers (e.g., the Amazon river) (Brêda et al., 2019; de Paiva et al., 2013; Michailovsky et al., 2013; Schneider, Ridler, et al., 2018). The forthcoming Surface Water and Ocean Topography (SWOT) due to launch in December 2022 will be the first satellite altimeter that records water levels at a fine spatial scale (∼100 m). This provides a useful resource for assimilating spatially distributed gridded water level observations into hydrodynamic models and for real-time flood inundation forecasting in operational systems. Due to the high impact of these remote sensing data on improving flood forecasting skills, several studies have generated synthetic SWOT data and investigated the assimilation of this data set into hydrological and hydrodynamic models (Durand et al., 2008; Munier et al., 2015; Pedinotti et al., 2014; Yoon et al., 2012).

Among various satellite imagery products, active microwave technology using synthetic aperture radar (SAR) has been shown to be the best source of remotely sensed flood extent and water level data for the assimilation of hydrodynamic models (Grimaldi et al., 2016; Hamidi et al., 2023; G. Schumann et al., 2009; K. Yan et al., 2015). Unlike available satellite altimeters, SAR data provide high-resolution images on the order of meters. In addition, the ability of microwaves to penetrate cloud cover during floods, the relatively low cost of SAR imagery, and the ability to acquire SAR data at night are three main reasons for making SAR data an attractive tool for real-time flood inundation forecasting. A common assimilation approach is to estimate a grid of water levels from SAR and assimilate it into a hydrodynamic model. Unlike radar altimeters that directly measure water level, deriving SAR-derived water level maps is not straightforward. Using a variety of image processing techniques (Manavalan, 2017), SAR data can be converted to flood extent maps. To provide a grid of SAR-derived water levels, various statistical/geospatial methods can be used to overlay the flood extent map with a high-resolution DEM (Hostache et al., 2010; Martinis et al., 2015; Matgen et al., 2007, 2010; Raclot, 2006; G. Schumann et al., 2007).

The indirect generation of SAR-derived water level maps and their assimilation into hydrodynamic models has been investigated in several studies (García-Pintado et al., 2015; Giustarini et al., 2011; Hostache et al., 2010; Mason et al., 2012; Matgen et al., 2007). However, applying indirect methods to convert SAR images into water level maps is difficult, time-consuming, and poses additional uncertainty. This limits the application of indirect methods for real-time flood inundation forecasting, where high efficiency and automatic assimilation of observations into hydrodynamic models are the main priorities. In addition, these methods can only provide water levels at the flood extent shorelines, and they need high-resolution DEMs (e.g., LiDAR) that are not globally available (Hostache et al., 2018). A more efficient alternative approach is to assimilate the flood extent maps into hydrodynamic models (Di Mauro et al., 2021; Hostache et al., 2018; Lai et al., 2014). Dasgupta et al. (2021) recently investigated the impact of the location, timing, and frequency of SAR-derived flood extent observations on DA-hydrodynamic modeling performance. They demonstrated that the river morphology can highly affect the optimum number of images required to maximize the forecast improvements. In another promising study, Cooper et al. (2019) proposed a novel observation operator that directly uses backscatter values from SAR instruments as observations. They compared this operator with two conventional SAR-derived water level operators and demonstrated that this operator can be a valuable alternative in operational forecasting systems where efficient and rapid assimilation of observations is crucial.

The crowdsource data referred to as Volunteered Geographic Information (VGI) (Goodchild, 2007) is another potential source of observation that can be assimilated into hydrodynamic models. This data set is often obtained by citizens who are prone to flooding using their smartphones, cameras, or other devices to share georeferenced data that provide information about the location of a flood, flood extent, or water level (Assumpção et al., 2018). The potential advantages of assimilating this data set into 1D and 2D hydrodynamic models have been investigated in two recent studies (Annis & Nardi, 2019; Mazzoleni et al., 2018). While the assimilation of crowdsourced data as a new source of observation into hydrodynamic models is an interesting topic of research, two main research questions should be addressed. First, the current application of crowdsourced data is for post-processing where a historical flood is analyzed. It is crucial to provide an automatic and standardized platform for real-time flood inundation mapping. Using this platform, citizens can share flood-related data where a set of preprocessors remove trivial information and capture flood location, extent, and water level rapidly. Second, the high uncertainty that exists in these data sets can hinder robust and reliable DA-hydrodynamic modeling in real-time. Thus, more advanced techniques are required to properly account for the uncertainty of observed crowdsource data in the assimilation framework.

The four-dimensional variational (4DVAR) method is a commonly used DA technique in meteorology that has been coupled with hydrodynamic models in only a few studies (Hostache et al., 2010; Lai et al., 2014; Lai & Monnier, 2009). Similar to the field of hydrology, sequential DA techniques, namely, EnKF and PF, have received more attention for updating hydrodynamic model results and flood inundation forecasting. García-Pintado et al. (2015) used an extension of the EnKF, the local ensemble transform Kalman filter (LETKF), and introduced a novel along-network filter localization to moderate the development of the forecast error covariance matrix and improve the flood forecasting skill. Using the LETKF method, Waller et al. (2018) specifically focused on water level satellite-derived observations and introduced a novel technique to properly account for the spatial correlation in observation error. In another study of ETKF-based DA-hydrodynamic modeling frameworks, Cooper et al. (2018) demonstrated that joint assimilation of hydrodynamic models by including channel roughness parameters highly improves flood forecasting results. They also reinitialized the water velocity at each grid cell and showed that this novel method can eliminate the initialization shock that typically happens if only water levels are updated at each time step. To account for the correlation between in situ observations, Jafarzadegan, Abbaszadeh, and Moradkhani (2021) modified the observation covariance matrix of EnKF and proposed a dual state-parameter DA-hydrodynamic modeling framework for operational flood inundation forecasting.

The Gaussianity assumption of observational errors used as the base of EnKF techniques can pose spurious results (Moradkhani, Sorooshian, et al., 2005, 2019) due to the non-Gaussian nature of SAR-derived flood observations. To address this problem, PF techniques have been used as an alternative technique for DA-hydrodynamic flood forecasting in the past decade (Giustarini et al., 2011; Hostache et al., 2018; Matgen et al., 2010; X. Xu et al., 2017). One of the main challenges of using PF techniques is the proper selection of likelihood functions used to estimate the particle weights. The typical approach is to use local-wise probability density functions at the location of observations and then estimate the global joint likelihood as the product of all local-wise functions assuming that the spatial correlation between observations is negligible. To cope with this limitation, Dasgupta et al. (2021) proposed the use of mutual information (MI) for the estimation of particle weights. They tested the PF-MI technique for synthetic SAR-derived flood extent assimilation of hydrodynamic models and demonstrated that their approach can significantly improve flood forecasting skill.

3.2.5. Challenges

Challenge 1: The proper selection of models used for flood inundation and extent mapping is still a critical debate in hydrodynamic modeling. In particular, we do not yet have enough studies that examine whether simplified techniques, such as topographic-based methods and ML models used to accelerate flood simulation, can actually work properly or whether we instead always need the physics of shallow water equations. In a recent study, Hocini et al. (2020) compared the performance of 1D and 2D hydrodynamic models against a topographic HAND-based approach. This was a large-scale, nonselective and robust study that used high-quality observed validation data, including a large number of HWMs and detailed flood extent maps provided by local authorities through field surveys. They demonstrated that the HAND method fails to properly capture the flood extent in many cases and that hydrodynamic models outperform in the majority of rivers. They also showed that 2D hydrodynamic models have higher accuracy than 1D models. Such kinds of detailed comparisons are rare but need to be extended to other case studies in the future where novel ML learning techniques (Ivanov et al., 2021) can also be compared with physics-informed models. At this stage, we broadly know the physics of flood flows and have good numerical solutions for this, but we could still use more computational power. Given the recent progress in using supercomputers and HPC, we believe that the traditional obstacles to the efficient simulation of floods with physical models have been partially overcome and will not be a main matter of concern in the near future. However, while physical models are the main priority for flood inundation mapping, simplified topographic-based or ML models are still advantageous in emergency conditions when a rapid preliminary estimation of inundation area is of the main priority, for example, where time is limited as in a flash flood and where there is limited access to HPC facilities.

Challenge 2: The lack of access to detailed information on channel bathymetry and flood defenses globally (location, fragility curves) decreases the accuracy of our flood inundation model results when applied over large domain areas. Channel bathymetry information is critical to properly route flood waves along rivers. The access to samples of field surveys of measured bathymetry data along some channels has provided an opportunity to combine statistical techniques, remote sensing data, and expert knowledge to extrapolate these bathymetry data to more rivers across the globe. Another approach is to consider channel bathymetry as a parameter of physical models and estimate it through comprehensive calibration and assimilation techniques (Brêda et al., 2019; Legleiter, 2015; Legleiter & Overstreet, 2012; Schaperow et al., 2019; Wood et al., 2016). In addition, access to a global data set that shows the geographical location of river structures (e.g., levees, dams) and other information, such as reservoir performance curves, can be highly valuable for improving our hydrodynamic modeling skills (Belletti et al., 2020; Mulligan et al., 2020; Whittemore et al., 2020; X. Yang et al., 2022).

Challenge 3: Flood inundation models are often not properly validated; specifically, many model testing studies are weak, selective, and not comprehensive. The main limitation of current validation methods is the lack of access to high-quality flood extent observations. Recent advances in remote sensing technology have increased the chance of recording historical flood extents. However, first, these observed flood extent maps are subject to high uncertainties that stem from imperfect methods used to convert satellite images to a flood extent map (quality issue). Second, the spatiotemporal coverage of satellites used to extract flooded areas does not meet our expectations for detailed flood inundation model validation. In general, we are interested in simulating flood

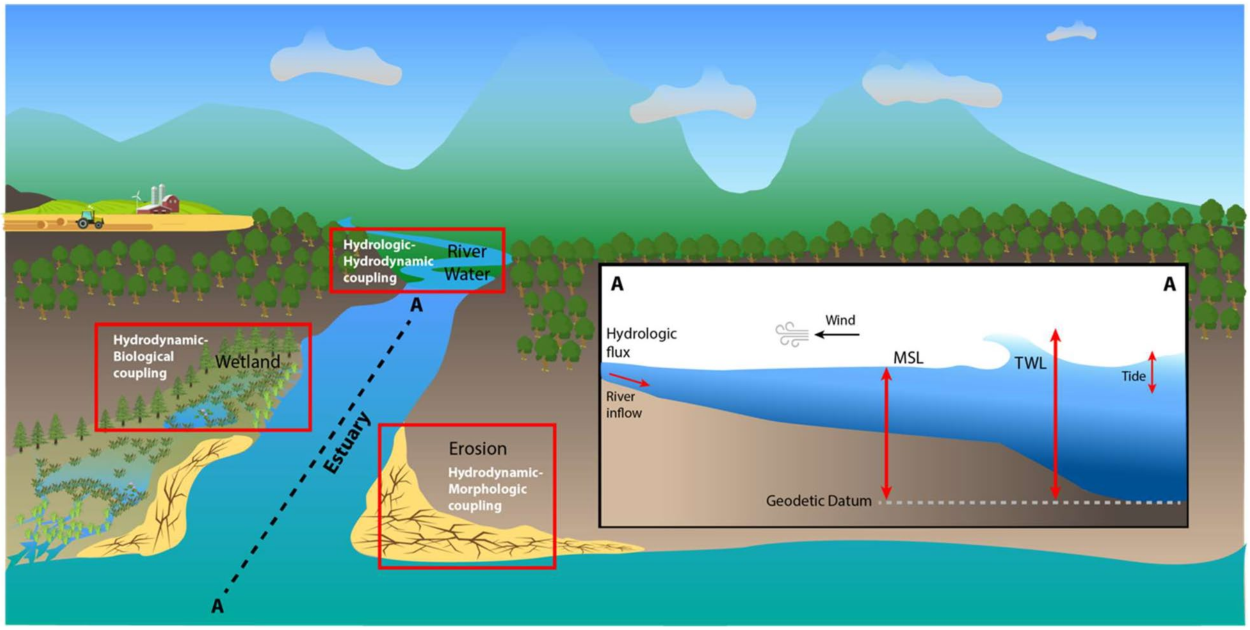

Figure 2. Physical, biological and morphological processes impacting coastal water levels.

waves propagating hourly/daily at fine spatial resolutions (e.g., <30 m). However, available satellites used for flood extent extraction either provide fine-scale spatial resolution with a long revisit time (e.g., SAR satellites are available every 10–14 days, but their spatial resolution ranges are 10–30 m) or give coarse resolution maps (>500 m) at the daily scale (e.g., MODIS). A potential line of research is to use advanced data fusion, ML techniques, and downscaling methods to improve the quality and quantity of available remote sensing flood extent maps. This can result in creating an archive of historical flood events that include their type, timing, and location together with their corresponding flood extents, which would be highly beneficial for improving our validating data. Other information, such as survey results provided aftermath of those flood events (e.g., HWMs), can also be attached to this validation archive.

4. Coastal Flood

4.1. Drivers of Coastal Flooding

One billion of the world's population currently dwells on land less than 10 m above the high tide line (Kulp & Strauss, 2019). Nearly 40% of the United States (U.S.) population lives in counties directly connected to a shoreline, and nearly half of the U.S. economic output is increasingly threatened by coastal flooding (NOAA, 2013, 2017; NOAA NCEI, 2020). To help these vulnerable communities prepare against escalating flood hazards driven by oceanic (e.g., tides) and atmospheric processes (i.e. wind and pressure gradient) at the coast, a thorough analysis of extreme water level dynamics under various forcing scenarios is essential. It is expected that a majority of coastal communities around the globe will experience the present-day 100-yr extreme sea level at least once a year by the end of this century, even under 1.5 °C of warming (Tebaldi et al., 2021).

Extreme coastal water level (ECWL) dynamics are governed by multiple processes at various spatiotemporal scales and can be broken down to mean sea level (MSL), astronomical tides (AT), nontidal residuals (NTR), and wave setup and runup (Gregory et al., 2019; Serafin et al., 2017). While the observed water level at conventional tide gauges, known as the still water level, is useful to document fluctuations at tidal and subtidal frequencies, surface gravity waves need additional instrumentation to characterize water level fluctuations at very high frequencies (i.e. order of seconds). Furthermore, water levels in coastal waters are impacted by a complex interaction between physical, biological and geomorphological processes (Figure 2).

4.1.1. Sea Level Rise

MSL refers to the time-mean of sea level over a period long enough to eliminate fluctuations in meteorological/tidal frequency (Gregory et al., 2019). An elevated MSL, called SLR, has been reported in the majority of gauges around the globe over the past decades, and it is projected to continue in the following decades (Church & White, 2011; IPCC, 2019). While the rate of SLR depends on various anthropogenic factors, its major contributors are known to be the thermal expansion of sea water, altered ocean dynamics, and mass loss from glaciers, ice caps, and ice sheets in a warmer climate (Kopp et al., 2014, 2017). A global SLR rate of ~3 mm/yr has been reported that is subject to acceleration in a warming climate (Dangendorf et al., 2017, 2019; IPCC, 2019; Palmer et al., 2020). Spatial variability exists in the reported rates of relative SLR due to local factors, that is, land subsidence and crustal uplift (Gregory et al., 2019).

SLR reduces the freeboard between high tidal datums and flood stages and introduces uncertainties in required flood risk allowances (Arns et al., 2017; Buchanan et al., 2016; Hunter, 2012). SLR not only shifts the distribution of ECWL to higher elevations but also modulates the ECWL regime through nonlinear processes. In fact, AT and NTR are shallow-water waves and react to changes in MSL through barotropic effects (e.g., frictional effects and altered tidal resonance, Talke & Jay, 2020). Therefore, MSL and its spatiotemporal variation play a crucial role in coastal flood risk assessment and need to be considered in coastal risk and adaptation assessments (Kopp et al., 2019; Nicholls et al., 2021). Probabilistic projections of SLR are available at the majority of global tide gauges (Kopp et al., 2014, 2017; Sweet et al., 2022) and can be useful for managing coastal flood risk (Kopp et al., 2019).

4.1.2. Astronomic Tides

ATs are periodic fluctuations in sea level due to the gravitational forces of the moon and the sun. These components of ECWL are mainly predictable in the open ocean (Pugh & Woodworth, 2014; Schwiderski, 1980). However, tides are long waves, and once they propagate toward the coast and within bays/estuaries, their characteristics adjust to bathymetric and atmospheric modulators (Devlin et al., 2017, 2019; Hoitink & Jay, 2016; Jay, 1991, 2009). Recently, a number of tools have been developed for tidal analysis with the help of signal processing techniques (i.e. based on Harmonics, Leffler & Jay, 2009; Matte et al., 2013; Pawlowicz et al., 2002, or wavelets, Flinchem & Jay, 2000). For Harmonics analysis, for example, ATs are assumed to be the sum of various constituents at different frequencies:

$$\mathrm{AT} = \sum_{i=1}^{n} A_i \cos(\omega_i t + \varphi_i)$$

where n is the number of constituents being considered for the harmonics analysis and A_i, ω_i and φ_i are, respectively, the amplitude, frequency and phase of the ith tidal constituent. Such tools and advancements have enabled the development of models such as TPXO with global coverage and reliable estimates of tidal elevation (Egbert & Erofeeva, 2002). Such tidal estimates help characterize the ocean boundary condition for coastal flood inundation models (Pelling et al., 2013; D. Xie et al., 2019).

4.1.3. Storm Surge

The deviation of the total water level from the predicted tides is called the NTR. NTR can be decomposed into intra-annual/inter-annual anomalies and high-frequency residuals referred to as storm surges. The latter component is mainly driven by atmospheric pressure variability and wind, including tropical cyclones. Tropical cyclones are one of the most threatening natural hazards impacting many regions throughout the world, with devastating economic consequences and loss of life. In the US, Superstorm Sandy in 2012 caused an estimated $50 billion in damage, and Hurricane Katrina was responsible for damage of over $100 billion (Lott & Ross, 2006). Recent events such as Hurricanes Ian and Fiona left a path of devastation to many coastal communities in 2022. At a global level, several countries are also regularly impacted by extreme weather events; for example, in Bangladesh, cyclone-generated storm surges have resulted in the deaths of over 700,000 people since 1960 (IPCC, 2007).

Storm surges impacting coastlines are the result of the balance between forcing mechanisms (e.g., wind stresses, barometric pressure, and wave stresses) and dissipation mechanisms (e.g., bottom friction, geometry). The magnitude of the storm surge at different parts of the coastline is affected by the storm intensity, size, track, and forward speed. For example, Irish et al. (2008) demonstrated that wind speed alone cannot reliably describe surge and that storm size played an important role in surge generation during Hurricane Katrina. Storm surges are also affected by the geometry of the continental shelf, floodplains, inlets, and coastal topography, with shelves with wide shallow-water areas (e.g., Gulf of Mexico) promoting larger surges than areas with deep offshore bathymetry (e.g., US West Coast) (Resio & Westerink, 2008). While coastal surges are mainly the result of wind and barometric pressure, momentum transmitted to the water column by breaking waves (so-called wave radiation stress) also contributes to surge levels along the coastline (Garzon & Ferreira, 2016). Bottom friction can also play an

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important role in the total water level in floodplains and coastlines by attenuating storm surges influencing the vertical and lateral structures of currents and attenuating wave energy (Ferreira et al., 2014). It is well understood that coastal marshes and submerged aquatic vegetation reduce storm surge and coastal flooding at the site and regional levels and can potentially have a mitigating effect on local SLR (Kirwan et al., 2016; Mitchell et al., 2017; Wamsley et al., 2010). Several studies have demonstrated that coastal wetland vegetation plays a major role in decreasing current velocity, wave height, erosion of marshes, and sediment transport (Glass et al., 2017; Mendez & Losada, 1999; Wamsley et al., 2010). Factors that impact these wave and erosion risk reduction benefits include meteorological conditions, local bathymetry, surface roughness provided by vegetation characteristics, the presence of streams, and other local characteristics (Resio & Westerink, 2008). While there is low confidence in observed historic trends in the surge contribution to the rising ECWL (IPCC, 2019), several valuable data sets with regional to global coverage have been developed based on numerical models (Marsooli et al., 2019; Muis et al., 2016, 2017, 2020) and data-driven methods (Tadesse et al., 2021) that help analyze historic changes and estimate the contribution of storm tide (AT + surge) in ECWL projections under climate change.

4.1.4. Wind Waves

Wind-generated waves, simply wind waves, are surface gravity waves that result in water surface oscillations at frequencies (between 0.033 and 1 Hz) much higher than ATs and storm surges. In contrast to the storm surge and ATs, which are long-period waves (with a period greater than 30 s), wind waves are short-period waves with a period between 1 and 30 s. Wind waves contribute to ECWL directly through infragravity waves and wave setup at the coast and wave runup and overtopping over coastal structures and indirectly through wave-current interactions and impacts on the wind momentum transfer from the atmosphere to the ocean (Dodet et al., 2019; Leijala et al., 2018; Lyddon et al., 2019; D. Xie et al., 2019; H. Zhang et al., 2004). Waves influence the water surface roughness and consequently, the wind shear stress, which transfers momentum downward across the air-sea interface and drives the storm surge. The role of waves in air-sea interactions has been widely recognized through laboratory measurements (Makin et al., 2007; Uz et al., 2003), field observations (Donelan et al., 1997; Högström et al., 2015), and numerical models (Babanin et al., 2018; Jiang et al., 2016). Waves also influence the boundary layer near the seafloor (Trowbridge & Lentz, 2018) and consequently the bottom shear stress, the mean flow, and the storm surge. Other important effects of wave-current interactions on the storm surge are the refraction of waves by currents and the generation of alongshore currents.

Infragravity waves are the result of nonlinear interactions of wind waves mainly close to the coast (Herbers & Burton, 1997; W. H. Wunk, 1949). It is well understood that infragravity waves have a considerable contribution to nearshore hydrodynamics (Elgar et al., 1992; Guedes et al., 2013). Wave setup is an increase in the still water level due to the transfer of momentum from breaking waves into the water column. Depending on the surf zone characteristics and storm conditions, wave setup can be an important component of the storm surge height. For example, Marsooli and Lin (2018) found that wave setup contributed up to 17% to the peak water levels induced by historical tropical cyclones at the U.S. East and Gulf Coasts.

Wave runup is another direct impact of wind waves on coastal flooding. Wave runup is the maximum vertical distance of wave uprush above the still water level, describing the time-varying elevation of the boundary that separates the land from the ocean. Wave overtopping occurs when the wave runup elevation exceeds the crest elevation of coastal structures such as seawalls and dunes (Koosheh et al., 2021). In the case of extreme waves during storms, infrastructure located above the still water level is subject to increased flood risk due to high-velocity wave runup and overtopping. Wave runup elevation depends on the incident wave characteristics, local water level, and the characteristics of the beach or protection structure encountered (Gomes da Silva et al., 2020). Since the mid-20th century, wave runup on beaches and coastal structures has been extensively studied using laboratory experiments (Granthem, 1953; Mase, 1989), field data (Guza & Thornton, 1982; Stockdon et al., 2006), and numerical methods (de Beer et al., 2021; Lynett et al., 2002), which have led to empirical parameterization methods and numerical models for estimating wave runup and overtopping. Compared to empirical methods, numerical models, once validated, are less restrictive and can provide detailed information.

4.2. Process-Based Hydrodynamics and Wave Modeling

4.2.1. Hydrodynamic Models

Process-based hydrodynamic models help numerically solve Navier Stokes equations under simplifying assumptions (i.e. Boussinesque and hydrostatic pressure approximation). The depth-averaged version of these equations, known

Table 1
Specifications of Commonly Used Hydrodynamic Models

Hydrodynamic models	2D/3D	Numerical scheme	Discretization of time	Discretization of space	Reference
DFLOW-FM	2D/3D	Finite difference (FD)	Implicit	Flexible mesh	Deltares (2021)
MIKE 21/3	2D/3D	Finite volume (FV)	Explicit	Flexible mesh	DHI (2022)
ADCIRC	2D/3D	Finite element (FE) in space/ FD in time	Implicit/explicit	Unstructured	Luettich and Westerink (2004)
TELEMAC	2D/3D	FE/FV	Implicit/explicit	Unstructured	Galland et al. (1991)
ROMS	3D	FD	Explicit	Unstructured	Warner et al. (2013)
FVCOM	2D/3D	FV	Semi-implicit	Unstructured	C. Chen et al. (2003)
SCHISM	2D/3D	FE/FV	Semi-implicit	Unstructured	Y. J. Zhang et al. (2016)
HECRAS	2D	FV	Implicit	Unstructured	USACE (2022)
LISFLOOD-FP	2D	FV	Implicit/explicit	Structured	Shaw et al. (2021)

as shallow water equations, help provide crucial information about the timing and magnitude (i.e. elevation and velocity) of flooding in coastal regions. While simplifying assumptions to reduce model complexity with the aim of improving its efficiency in flood modeling is inevitable (Gallien et al., 2018), these models are extremely helpful for flood inundation mapping under synthetic hydroclimate extreme scenarios and the characterization of risk under climate variability and anthropogenic activities (Marsooli et al., 2019; Muñoz et al., 2020). These models based on their formulation and the implemented numerical schemes can be grouped dimensionally (i.e. 1D, 2D, or 3D), based on the variable of interest (i.e. water level, flood extent, wave characteristics, or erosion), discretization scheme in time (explicit vs. implicit) or space (structured, unstructured, or flexible mesh), or numerical scheme implemented (e.g., finite difference, finite element, or boundary element) (Bates, 2022; Gallien et al., 2018; Sanders, 2017; Teng et al., 2017). Table 1 lists a number of commonly-used hydrodynamic models in coastal flood studies.

4.2.2. Wind Wave Models

While empirical relationships have been developed to estimate wind wave characteristics such as significant wave height (e.g., USACE, 1984), given the substantial assumptions made behind those methods, the resulting estimates are subject to considerable uncertainty. Spectral ("phase-averaged" or wave-averaged) wave models have been developed to overcome the limitations of empirical methods. The most advanced spectral wave models are the third-generation models (Table 1) that solve the wave energy or action balance equation to describe the evolution of the wave energy spectrum and the statistical parameters of the water surface. These models are being used for operational wave forecasting, for example, using the WAVEWATCH III wave model in the NOAA Global Forecast System (Chawla et al., 2013; Tolman, 2009) and the SWAN wave model (Booij et al., 1997) in the NOAA Nearshore Wave Prediction System for the U.S. coastal regions (https://polar.ncep.noaa.gov/nwps/). The spectral wave models are also extended from wind waves to infragravity waves (Ardhuin et al., 2014).

"Phase-resolving" (or wave-resolving) numerical wave models are state-of-the-art tools for quantifying wave runup and overtopping. In contrast to a spectral wave model, which treats the wave field as a stochastic phenomenon, a phase-resolving wave model treats the wave field deterministically and traces the water surface oscillations, allowing it to resolve each monochromatic wave in a group of irregular waves. Phase-resolving wave models may be categorized into two classes: nonlinear shallow water (NLSW) models and full NS equations models.

The NLSW models solve a simplified form of the NS equations, making them simpler and computationally cheaper than NS models and, thus, a popular computational tool for numerical studies of wave runup and overtopping (Briganti & Dodd, 2009; Hu et al., 2000). NS models, on the other hand, numerically solve the full NS equations, which present the most complete flow description, using either an Eulerian or Lagrangian approach. Eulerian-based NS models consider the fluid as a continuum and discretize the flow domain using control volumes while using a special technique, for example, the Volume-Of-Fluid method (Hirt & Nichols, 1981), to track the interface between fluid and gas. Lagrangian-based NS models, commonly known as Smoothed Particle Hydrodynamics (SPH) models, discretize the flow domain to a cloud of particles and track the kinematics and interactions of the particles. NS models are applicable to a wide range of conditions, including structures with complex geometries, and can fully resolve wave nonlinearity. However, NS models are computationally

Table 2
Examples of Open-Source Numerical Wave Models for Coastal Flood Studies

Model	Model type	Dimension	Best application
SWAN (Booij et al., 1997)	Spectral model	Five-dimensions: time, 2D in geographical space (horizontal), 2D in spectrum space (frequency and direction)	Modeling offshore wave characteristics at regional and global scales
WAM (Group, 1988)			
WAVEWATCH III (Tolman, 2009)			
OpenFOAM-IHFOAM (Higuera et al., 2013)	Eulerian NS model	Four-dimensions: time, 3D in geographical space (horizontal and vertical)	Modeling wave runup and overtopping at an asset scale
REEF3D (Kamath et al., 2015)			
DualSPHysics (Domínguez et al., 2022)	Lagrangian NS model	Four-dimensional: time, 3D in geographical space (horizontal and vertical)	Modeling wave runup and overtopping at an asset scale
GPUSPH (Hérault et al., 2010)			
FUNWAVE-TVD (F. Shi et al., 2012)	NLSW model	Three-dimensions: time, 2D in geographical space (horizontal)	Modeling wave runup and overtopping at asset and local scales
XBeach-nonhydrostatic (P. B. Smith et al., 2010)			

very demanding, currently limiting their applications to academic research (e.g., Alagan Chella et al., 2020; Rosenberger & Marsooli, 2022). Faster and more powerful computers and computationally faster numerical methods could result in more applications of NS models to wave runup and overtopping studies. Table 2 shows several examples of open-source numerical wave models for coastal flood studies.

4.3. Coupled Modeling

4.3.1. Hydrological-Hydrodynamic Coupled Modeling

Appropriate characterization of both upstream and downstream boundary conditions for flood modeling in the transition zone of freshwater-influenced coastal systems is important, as water level dynamics in these systems are under the influence of both inland hydrologic and ocean boundary conditioning (Bilskie & Hagen, 2018; Cai et al., 2015; Hoitink & Jay, 2016; Jay, 1991; Jay et al., 2016; van Rijn, 2011). To allow flux transfer at the interface of a hydrologic and hydrodynamics model (i.e. upstream boundary condition of an estuary) coupled modeling is inevitable. Depending on the joining technique to be implemented, coupling falls under one of the following categories: (a) one-way coupling: flux transfer allowed from one model to another, (b) loosely coupled: two-way coupling with information exchange allowed between separately running models in an iterative way, (c) tightly coupled: at which source code of independent models are integrated under a single modeling framework, (d) fully coupled: under which governing equations are solved simultaneously within the same modeling framework (Santiago-Collazo et al., 2019). While the majority of the existing literature is based on a one-way coupling approach (Bakhtyar et al., 2020; Gutenson et al., 2021, 2022; W. Huang et al., 2021; Santiago-Collazo et al., 2019; F. Ye et al., 2020), only a few studies have implemented loosely coupled (H. P. Cheng et al., 2010; Gori, Lin, & Smith, 2020), tightly coupled (Bilskie et al., 2021; Eilander et al., 2020) or fully coupled (Leijnse et al., 2021) modeling frameworks for coastal flood inundation mapping.

4.3.2. Hydrodynamic-Wave Coupled Modeling

Coupled hydrodynamic-wave models have been developed to account for the effects of wave-current interactions on water levels at the coast. Examples of commonly used coupled hydrodynamic-wave models are ADCIRC-SWAN, ADCIRC-WAVEWATCH III, and Delft3D-SWAN. To account for the contribution of wave setup to the total water level along coastlines, theories that express the momentum flux from breaking waves to the water column using radiation stress (Dietrich et al., 2011; Marsooli, Orton, & Mellor, 2017) or vortex force representations are implemented in tightly coupled models. These models also account for the effects of waves on the bottom shear stress and the wind shear stress using parameterization methods (e.g., Donelan & Hui, 1990; Powell et al., 2003; Signell et al., 1990). Recent advances in computational modeling have allowed for the two-way coupling of hydrodynamic models with phase-average wave models focused on coastal flooding applications. For example, Dietrich et al., 2011 developed the tightly coupled version of the SWAN model with ADCIRC, allowing for the two-way exchange of information with the models running on the same unstructured computational mesh. The framework allowed for wind speeds, water levels, currents and radiation stresses to be passed through memory during model run time. More recent studies have demonstrated the importance of accounting for and adopting coupled wave-hydrodynamic models for coastal flooding, and this modeling framework is currently standard practice in industry and scientific studies (Bilskie, Angel, et al., 2022; Bilskie, Asher, et al., 2022).

4.3.3. Hydrodynamic-Morphodynamic Coupled Modeling

Short-term morphological changes such as erosion and breaching of levees and barrier islands during extreme events very often exacerbate hazards associated with flooding. For example, several levees in New Orleans, Louisiana, were eroded and breached during Hurricane Katrina in 2012 (Knabb et al., 2005) and resulted in catastrophic flooding in the New Orleans metropolitan area. During Hurricane Sandy in 2012, coastal erosion and breaching of beaches and dunes took place on many barrier islands in the U.S. northeast and Mid-Atlantic regions (Sopkin et al., 2014). Waves and storm surges breached heavily populated and developed barrier islands in New Jersey, causing damage to roads and homes. High water levels during Typhoon Hagibis in 2019 resulted in levee breaches along rivers in the Kanto region in Japan, which caused extensive flooding and damage to infrastructure (Enomoto et al., 2021). To accurately predict the extent, intensity, and duration of coastal flooding, hydrodynamic modeling under extreme events should account for coastal morphological changes. This can be achieved by coupled hydrodynamic-morphodynamic numerical models. Cañizares and Irish (2008) introduced a modeling strategy to account for the interactions between barrier island morphodynamics and nearshore and bay storm hydrodynamics for coastal flood modeling. Their method employed coupled hydrodynamic and morphodynamic models, in which the stormwater levels and barrier island morphodynamics were simulated with the Delft3D model. The storm profile model SBEACH was used to precondition the barrier island topography used in Delft3D. Many other studies have used the XBeach model (Roelvink et al., 2009), which simulates the coastal responses during intense storms and hurricane events, including modeling wave propagation, erosion, and breaching, and accounts for wave dissipation (both short and long waves) and flow interactions due to the presence of several types of vegetation along the shore (Garzon et al., 2019). For example, the impact of extreme coastal erosion and flooding on barrier islands (e.g., Lindemer et al., 2010; Smallegan et al., 2016), coupling storm hydrodynamics with gravel beach morphodynamics (McCall et al., 2014), responses of high-energy coastlines (J. J. Williams et al., 2015), beach erosion and sediment transport (e.g., Elsayed & Oumeraci, 2017; Suzuki & Cox, 2021) and dune overwashes (McCall et al., 2014).

Coupling hydrodynamic and morphodynamic processes is also necessary to evaluate the effects of future geomorphological changes on coastal hazards. Bilskie et al. (2014) demonstrated the importance of incorporating the effects of a changing landscape to evaluate future coastal hazards. Ferreira et al. (2014) quantified the effects of future land cover changes and sea-level rise on coastal flooding from hurricanes along the Texas coast. Irish et al. (2010) showed the effects of integrating barrier island degradation to quantify coastal flooding impacts on infrastructure and population. Morphological changes will also impact tidal hydrodynamics in the future (Passeri et al., 2016), and Alizad, Hagen, Morris, Bacopoulos, et al. (2016) showed the importance of coupling two-dimensional hydrodynamic models with marsh models with biological feedback. While several studies have evaluated and demonstrated the importance of integrating hydrodynamic models with morphological changes, historical morphological changes also play a role when hindcasting past events (Passeri et al., 2015).

4.4. Data-Driven Methods

Where sufficient good-quality data are available, data-driven or data analytic methods would be able to provide information about coastal flood hazards or hazard risk awareness at a relatively low computational cost (Hamdi et al., 2014; Karimiziarani et al., 2022, 2023; Pollar et al., 2018). While the majority of statistical methods for coastal flood assessment are based on the extreme value theorem (Caruso & Marani, 2022; Hamdi et al., 2014), some recent studies have proposed mixed distribution or meta-statistical approaches (Ghanbari et al., 2019; Miniussi et al., 2020). These frequency analysis methods help analyze the recurrence intervals of events with significant magnitudes and thus provide information to design infrastructures that are expected to serve communities over an extended period of time.

Complementary to these frequentist methods, there has been growing interest in ML approaches that help estimate flood intensity at various spatiotemporal scales based on underlying variables (a.k.a. features). In fact, ML-based approaches that analyze the record of flooding aim to find a relationship between flood drivers and flood depth/velocity without the need to solve computationally expensive partial differential equations of fluid mechanics (Bermúdez et al., 2019). However, physics-informed ML approaches are growing to address the limitations of black-box-type ML methods and ensure the basic laws of fluid mechanics (i.e. conservation of mass) are not lost (Razavi, 2021; Razavi et al., 2012).

4.5. Hybrid Methods for Compound Flooding

Due to the complicated nature of compound floods, with multiple underlying drivers that nonlinearly interact, both conventional process-based numerical and data-driven methods face challenges in the accurate estimation of flood characteristics.

Process-based numerical models are useful tools to understand the physics of compound flooding in ungauged areas where in situ measurements are missing and provide helpful insights for resilience assessment and planning (Abbaszadeh et al., 2022; Muñoz, Moftakhari, et al., 2022). These methods, however, suffer from various limitations. The underlying assumptions in formulation and parametrization can yield uncertainty and thus affect the accuracy/precision of estimates (Abbaszadeh et al., 2022). Process-based models, when applied on large domains at a fine resolution sufficient for flood inundation mapping, are computationally expensive, and without access to supercomputers, only a handful of scenarios are manageable (Schwanenberg et al., 2018). The lack of a comprehensive record for the validation of numerical models also poses a great challenge that affects the reliability of this approach. Additionally, to ensure a comprehensive representation of natural processes underlying compound floods, in many cases, the model coupling is necessary, which itself adds another layer of complexity (Santiago-Collazo et al., 2019).

A major challenge with data-driven methods is the lack of spatiotemporal coverage of overlapping records. To detect and characterize the interdependencies of compound flood drivers, a sufficient length (usually decades) of overlapping (both in time and space) records of contributing variables is crucial. For example, Ward et al. (2018), who analyzed the statistical dependence between observed sea levels and river discharge over the globe, only found four sites in the entire African continent and three sites in South America with sufficient overlapping records to enable dependence assessment and compound flood analysis. At the local scale, too, we rarely find multiple gauges with a long observational record that capture and reflect on the variability of interdependence dynamics between flood drivers. In addition to spatiotemporal gaps, even if long records are available, pure data-driven methods, given their significant underlying assumptions (i.e. stationarity), offer limited opportunities to capture anthropogenic effects (i.e. climate change or land cover change). In fact, data-driven methods in their black-box application are incapable of extrapolating the nonlinear interactions beyond the range of observations. A recent growing interest in developing theory-infused data methods, called hybrid models, aims to provide interpretable products and address the gap of potential physical inconsistency (A. Y. Sun & Scanlon, 2019).

4.5.1. Linking Statistical and Hydrodynamic Modeling

To delineate the spatial field of flooding exposure under various design scenarios, we need statistical and hydrodynamic models to be linked for a set of exceedance probabilities. The conventional approach for flood modeling that analyzes various flooding mechanisms in isolation is straightforward, as it is based on univariate metrics. Following this approach for riverine flood inundation mapping, Q_T is the peak volumetric flow rate at return period T that follows a log-Person type III distribution and characterizes the upstream boundary condition of a given hydrodynamic model (England et al., 2019). Where coastal oceanic processes are the sole flooding mechanism governing flooding dynamics, an ECWL at return period T that follows a generalized extreme value distribution would dominate the flood wave propagation dynamics (FEMA, 2016, 2018). However, flood hazard assessment in freshwater-influenced low-lying coastal areas must account for the coincidence or close succession of coastal, pluvial and fluvial flooding mechanisms. Such compounding poses a level of threat much greater than what each in isolation is capable of it (Bevacqua et al., 2021; Zscheischler et al., 2020). In such settings, univariate methods that ignore the joint probability of flooding mechanisms fall short of providing reliable information for flood risk assessment (H. Moftakhari et al., 2019).

Multivariate flood risk analysis approaches presented in the literature include structure variable approaches (a.k.a. continuous simulations), impact-based approach (a.k.a. bottom-up approach), and joint density approaches (a.k.a. design variable method) (F. Zheng et al., 2015). In structure variable approaches, the multivariate input data are transformed to equivalent structure variable values, the distribution of which is then extrapolated to extreme values (Hawkes, 2006). For this purpose, at any particular time t, structure variable Y_t will be related to forcing vector X_t via structure/response function Δ: $Y_t = \Delta(X_t) = \Delta(X_{1,t}, X_{2,t\ldots}, X_{n,t})$. The use of a structure function reduces a joint probability problem to a single-variable problem but with some limitations/drawbacks. In this approach, the results do not retain enough information for the estimation of other types of structure functions and need a long period of input data; thus, a limited number of designs may be tested (Hawkes, 2008). For example, J. Neal et al. (2013) used Monte-Carlo simulations of all the "events" above a given magnitude over a period of time to combine flows from the tributaries and then conducted hydraulic mapping of each of these events to calculate the frequency of inundation. They highlighted two major difficulties for the approach they implemented: (a) ensuring the correct dependence structure and (b) the computational effort required to run a hydraulic model a sufficient number of times to obtain the Monte Carlo sampling uncertainty in the T-year event. In fact, the computation problem is more severe in the urban environment due to the complex topography and topology that requires modeling of flows in two dimensions at resolutions fine enough (e.g., ≤10 m) to resolve the street pattern (J. Neal et al., 2013). Such high computational expenses in generating the entire time series of the response variable might force the modelers to use very simple models with a lack of accuracy in the modeled dynamics.

The impact-based approach takes Identically and Independently Distributed (IID) extreme events from the response variable (i.e. flood level) and identifies coincident (or near-coincident) values of the flooding drivers. The idea is to start from a threshold level (defined, for instance, by stakeholders) to finally obtain the return period of this threshold. Such an "inverse" approach would allow the identification of all the forcing conditions (and their occurrence probability) inducing a threat to critical assets of the territory. Idier et al. (2013) developed an inverse flood modeling method for estimating offshore conditions leading to a given acceptable hazard level. The method helps to estimate the return period of the associated combinations and thus the maximum acceptable hazard level.

Joint density approaches use multivariate distributions and information on the dependence between them to extrapolate the input data to extreme values. Multivariate parametric distributions and copulas are the most common tools used to characterize the correlation structure between variables and joint density analysis. Multivariate parametric distributions (i.e. Gaussian, *t*, gamma, extreme value) are mainly the extensions of univariate distributions to higher dimensions. However, these models have known limitations, including inflexibility in marginal distribution selection and parameterization and the inability of these models to capture nonlinear dependence structures (e.g., nonlinear dependence) (Hao & Singh, 2016). Copulas overcome the limitation of these conventional multivariate frequency analysis methods (Durante & Sempi, 2016; Salvadori & De Michele, 2004, 2007).

Previous studies have explored the compounding effects of coastal ocean water level and freshwater discharge (Bevacqua et al., 2017; Gori, Lin, & Smith, 2020; Gori, Lin, & Xi, 2020; Lamb et al., 2010; H. R. Moftakhari, Salvadori, et al., 2017), coastal water level and waves (Serafin et al., 2017; Wahl et al., 2016), storm surge and river flow (Bass & Bedient, 2018; Bilskie et al., 2019, Bilskie, Angel, et al., 2022; Bilskie, Asher, et al., 2022; Kew et al., 2013; Klerk et al., 2015), storm surge and river flow with precipitation (Svensson & Jones, 2004), storm surge and precipitation (van den Hurk et al., 2015; Wahl et al., 2015; F. Zheng et al., 2013, 2014), wave/surge parameters (Corbella & Stretch, 2012, 2013; Salvadori et al., 2014, 2015; Shope et al., 2022), and storm surge, wave, river flow and precipitation (Camus et al., 2021; Nasr et al., 2021).

Joint density approaches, while providing crucial information for hydrodynamic boundary conditioning, pose a serious challenge to the sufficient number of realizations that adequately cover the wide range of compound flood impact possibilities. Theoretically, there exists an infinite combination of flooding drivers involved in compound flood analysis that share the same joint exceedance probability (Salvadori et al., 2016). This means that a large population of compound hazard scenarios should be considered for a thorough compound flood risk assessment. This challenge, which is a byproduct of linking multivariate statistical and hydrodynamic modeling, can be partly overcome with the help of either reduced physics surrogate modeling (i.e., Anderson et al., 2021; Bass & Bedient, 2018) or utilizing HPC systems that map flood hazards through Monte Carlo simulation and enable thousands of scenarios based on different combinations of flood forcings involved (K. Yang et al., 2020).

Another alternative is to merge joint cumulative distribution functions and joint probability density functions to implement informed sampling. This approach has been successfully implemented in compound flood assessment and inundation analysis, and it has been concluded that a handful of wisely selected compound scenarios can cover the range of possibilities that might require thousands of simulations (H. Moftakhari et al., 2019; Muñoz et al., 2020; Sadegh et al., 2018). A potential direction is to propose a novel statistical approach that helps select tropical cyclone storm tracks with a higher cumulative likelihood of impact (CLI). This approach, based on the concept of "cumulative hazards" first proposed by (H. R. Moftakhari, AghaKouchak, et al., 2017), to make a fair comparison between hazard scenarios continuously monitoring TCs and their evolution over time and/or space, ranks them based on regional dependencies between forcing (e.g., wind and rainfall) and compound coastal flood drivers (storm surge and river flow). In fact, fluvial, pluvial, and coastal floods are all products of TCs, and different TC paths could have different flooding impacts at a given location of interest (Bloemendaal et al., 2022; Kyprioti et al., 2021a, 2021b; Marsooli et al., 2019). Thus, a probabilistic scheme that accumulates the potential hazardousness of TCs according to their intensity at a given point along their paths will be helpful for improving the efficiency of flood forecasting systems.

4.5.2. Physics-Informed ML

To overcome the limitations of black-box-type data methods and leverage their skills in the efficient estimation of flooding characteristics, recent efforts have focused on the development of physics-informed ML (Razavi, 2021). Anderson et al. (2021) developed a modeling framework of waves, winds, and tides to efficiently predict spatially varying nearshore and estuarine water levels conditioned on possible combinations of offshore forcing. The random forest algorithm has been trained to emulate hydrodynamic models in estimating flood extent and depth and to delineate between flooding locations dominated by pluvial or coastal flooding or both (Zahura et al., 2020; Zahura & Goodall, 2022). Bermúdez et al. (2019) used a SVM to generate flood inundation maps under the combined effects of terrestrial and coastal flooding drivers. Lee et al. (2021) developed a computationally efficient CNN model combined with principal component analysis and k-means clustering to predict peak storm surges across a coastal region from a time series of tropical cyclone conditions. Muñoz, Muñoz, Moftakhari, and Moradkhani (2021) proposed a CNN and data fusion framework for generating compound flood maps at moderate (30 m) spatial resolution. The framework fuses multispectral imagery, dual-polarized SAR data, and coastal DEMs to produce hurricane flood maps at the regional scale for rapid exposure assessment.

DA that combines information from model states with in situ and/or remotely sensed observations has recently been used to improve coastal flood forecasting. Muñoz, Abbaszadeh, et al. (2022) presented a DA scheme consisting of the EnKF technique and hydrodynamic modeling to provide WL predictions and near real-time compound flood hazard maps. They first developed a pair of high-resolution hydrodynamic models in Delft3D-FM using topographic data corrected for wetland elevation bias and implemented a robust model calibration with the Latin hypercube sampling technique. Then, a DA scheme was developed for accurate near real-time flood hazard mapping. Their implemented ensemble-based formulation is suitable for systems with strongly nonlinear dynamics, including those under the complex interactions of pluvial, fluvial, and oceanic drivers.

4.6. Challenges

4.6.1. Sea Level Rise

Recent estimates suggest a global SLR rate of 3.1 ± 1.4 mm yr^{-1} over the 1993–2012 period, compared to the pre-1990 rate of 1.1 ± 0.3 mm yr^{-1} (Dangendorf et al., 2017), an acceleration in SLR that far exceeds the previously reported rate of 0.009 ± 0.003 mm·year^{-2} since 1880 (Church & White, 2011). Along the coasts of the U.S. 0.25–0.30 m of SLR is expected by 2050, with higher expected rates of SLR (0.35–0.45 m) along the Gulf coast (Sweet et al., 2022). This rise alters the wave and tide characteristics (Arns et al., 2020; Haigh et al., 2019). The increased likelihood of ECWLs combined with the expected increase in the severity of fluvial and pluvial flooding (Alfieri et al., 2016; Winsemius et al., 2016) poses further uncertainties in required flood risk allowances (Arns et al., 2017; Buchanan et al., 2016; Hunter, 2012). Common statistical analyses are based on the significant assumption of stationarity. This is despite the fact that the intensity and/or frequency of these costly extremes have been rising over the past few decades, a signal to which is the fact that the top seven costliest hydroclimate extremes in the U.S., namely, Katrina (2005), Harvey (2017), Maria (2017), Sandy (2012), Irma (2017), Ida (2021), and Ian (2022), have happened over the past 16 years (NHC, 2022). The frequency and severity of compound extremes are expected to continue to increase in the future (Field et al., 2014). In a warmer climate, in addition to rising MSL, a significant increase in tropical cyclone intensity and its associated flooding is anticipated (Bender et al., 2010; Emanuel, 2013; Knutson et al., 2020). Hurricane Harvey could not have produced as much rain as registered in gauge stations without human-induced climate change (Trenberth et al., 2018), and a storm such as Hurricane Ike in the future would produce 34% more precipitation and 13% stronger winds than Ike in 2008 (Gutmann et al., 2018). Nonstationarity of individual flooding drivers and their compounding effects that are evolving, if ignored, lead to underestimation of flooding probability estimates (Hao & Singh, 2020; H. R. Moftakhari, Salvadori, et al., 2017; Naseri & Hummel, 2022; Tebaldi et al., 2021).

4.6.2. Hydrodynamic-Biologic Coupled Modeling

Wetlands are critical components of coastal systems that provide valuable ecosystem services, including flood attenuation, water and carbon storage, nutrient cycling, commercial/recreational fisheries, and shoreline stabilization that protect coastal communities and their economies (Mitsch & Gosselink, 2015). Coastal wetlands can effectively attenuate storm surges (Leonardi et al., 2018), reduce property damage with average estimates of \$1.8 million per km^2-year (F. Sun & Carson, 2020) and further enhance coastal resilience against rising seas (Rezaie et al., 2020). The sustainability of these ecosystem services depends on multiple climatic, hydrological, and oceanic conditions that can produce favorable conditions or pose additional stresses. In fact, wetlands are frequently threatened by anthropogenic activities, including water abstraction and pollution, deforestation, intensive agriculture, aquaculture, and urban development (An and Verhoeven, 2019; W. Wu et al., 2017). SLR should contribute to the loss of coastal wetlands (Kirwan & Megonigal, 2013; Rogers et al., 2019; Schuerch et al., 2018). For example, Muñoz, Muñoz, Alipour, et al. (2021) developed a CNN and data fusion framework to analyze the variability of wetland dynamics over time associated with urbanization, SLR, and hurricane impacts. Analyzing remotely sensed data since 1984, they concluded that ∼1,100 m^2 of wetlands are lost annually in Mobile Bay, AL. Coupled biologic-hydrodynamic modeling frameworks are necessary to represent the complex interactions of biological and hydrodynamic systems. Hydro-MEM is a good example of such coupling practices that couples a hydrodynamic and biological model to simulate the effects of SLR and wetland system dynamics and their interconnections in a feedback process (Alizad, Hagen, Morris, Bacopoulos, et al., 2016). This model has successfully been applied to various wetland systems along the coast of the United States and provides important insights into the sustainability of these systems in the face of anthropogenic effects, that is, SLR (Alizad, Hagen, Morris, Medeiros, et al., 2016; Alizad et al., 2018, 2022). Recent studies have also demonstrated the ability of coastal models to incorporate the effects of vegetation on surge attenuation by accounting for additional bottom friction from vegetation and its effects on the transmission of momentum from the wind to the water surface (Bigalbal et al., 2018; Cassalho et al., 2021; Rezaie et al., 2021), providing insights into the benefits of these coastal ecosystems in protecting coastal communities and infrastructure. Vegetation can also play a major role in wave attenuation (Garzon et al., 2019), including during extreme events impacting coastal areas. Recent studies have also demonstrated the evolving capability of several wave models, such as SWAN, WWIII, and XBeach, to incorporate the effects of wave attenuation in coastal applications, including implicit methods that account for modified bottom friction or explicit methods that account for vegetation characteristics such as stem height, density and diameter (Garzon et al., 2019; Marsooli, Orton, Mellor, Georgas, & Blumberg, 2017). However, limitations still remain with respect to large-scale descriptions of coastal vegetation and submerged aquatic vegetation characteristics due to its inadequate representation in numerical models and spatial and temporal predictions of future marsh migration under climate change. Future research is also under development to further improve the parametrization of biological ecosystems affecting storm surges and waves in coastal areas.

4.6.3. Wave Modeling

While third-generation spectral wave models have advanced our capabilities to predict wind waves both in the deep open ocean and coastal and marginal seas, modeling the wave spectrum, especially at regional and global scales, still encounters a series of challenges due to the limited range of data and environmental conditions considered for the parameterization of the wave energy generation, propagation, and dissipation mechanisms. As identified by Cavaleri et al. (2018), wave modeling research areas that still need improvement include wave dissipation due to white-capping, wave-wave nonlinear interactions, wave nonlinearity in shallow waters, swell propagation, wave generation and dissipation under extreme conditions, among others. Further research is also needed to advance the understanding of wave-current interactions under extreme wave conditions, given that existing methods are mainly developed under "normal" conditions (Cavaleri et al., 2018).

A main challenge in the numerical modeling of wave runup and overtopping is the high computational cost of phase-resolving wave models. Special skills are also needed for setting up and running these models and interpreting the model outputs. On the other hand, parameterization methods and particularly empirical formulae are simple and fast to use. The empirical formulae simply relate the wave runup (usually $R_{2\%}$, which is runup exceeded by two percent of the runup values from a group of waves) and overtopping (usually mean overtopping discharge) to the wave and beach/structure parameters. However, they have been developed based on data collected from laboratory or field studies under a specific range of environmental conditions (e.g., EurOtop, 2018; Hunt, 1959; Stockdon et al., 2006; USACE, 2022; Van Der Meer, 1995), limiting their applications to the tested ranges of input parameters. These formulae are primarily based on data collected under mild or moderate wave conditions and thus may be unreliable under extreme wave conditions (Elko et al., 2015). Future research should advance the parametrizations of wave runup and overtopping under extreme events. An example of ongoing efforts is the recent DUNEX field experiment started in 2019, which studies nearshore processes on the Outer Banks of North Carolina during coastal storms (https://uscoastalresearch.org/dunex).

5. Summary and Conclusion

This article provides a comprehensive overview of the key concepts and challenges in flood modeling, with a focus on riverine and coastal floods. To enhance our understanding of flood generating mechanisms, we suggest a more holistic approach that considers human influence, hydroclimatic, hydrologic, and hydrodynamic drivers. Table 3 summarizes the main challenges and pathways for an improved understanding of flood generating mechanisms.

To improve flood risk management, it is crucial to establish a robust and reliable flood forecasting system. We recommend transitioning to an innovative earth system modeling approach that connects meteorological, hydrologic, hydrodynamic, and decision-making components and allows for feedback exchange. Table 4 highlights the main challenges and pathways in flood forecasting.

Identifying flood extent and inundation areas is another critical step in flood hazard and risk management. With advances in numerical analysis and the availability of high-resolution topography data, physical models have the capability to accurately simulate flooding rivers and estimate spatiotemporal water depth distributions these days. Given the recent advances in HPC, parallel simulation of hydrodynamic models opens a future pathway for efficient simulation of flooding conditions. Although this progress has limited the application of simplified methods, they are still useful in remote regions where access to HPC is limited or during flash floods when the required time for simulation is too short. Table 5 outlines the key challenges and corresponding pathways in flood inundation modeling.

Finally, for coastal flood modeling, we recommend integrating different models within a coupled modeling system. Hybrid methods that link advanced statistical and numerical tools can facilitate efficient compound flood analysis. However, it is essential to better assess and account for the nonstationarity underlying drivers due to anthropogenic effects in future projections. A set of main challenges and pathways in coastal flood modeling are provided in Table 6.

Table 3
List of Main Challenges and Potential Pathways for Understanding Causative Mechanisms of Floods

Challenge	Pathway
Investigating the flood-generating processes through a hydroclimatic perspective disregards the key role of soil saturation and snow processes	A more comprehensive investigation of flood mechanisms is required where flood-generating processes are examined through both hydroclimatic and hydrological perspectives
Hydroclimatic and hydrologic perspectives cannot explain the controlling processes in flood extent and inundation areas properly	Details of topography, the morphology of rivers, land-use types, and properties that are exposed to flooding should be included in analyses
The human interventions in the environment are not properly modeled	It is recommended to control unplanned urban development, use systems thinking to link processes across time scales, control long-term field experiments at the plot scale, focus on connectivity and spatial patterns, and organize a coherent research theme within and across disciplines. Additionally, the development of conceptual models that simulate dominant dynamics in floodplains is beneficial. These models contain several scenarios where each focuses on specific human actions and corresponding impacts on floodplains

Table 4
List of Main Challenges and Pathways for Improved Flood Forecasting

Challenge	Pathway
The quality and degree of confidence in flood forecasts delivered to decision-makers are not clear	Condense and weigh all information about the reliability, sharpness and other system qualities with a simplified metric that shows the degree of confidence in the forecast
The verification of extremes is not robust enough. Most methods and metrics have been provided for normal climatic conditions	Develop scores and methods that express the performance for tails of the probability distribution rather than average performance
The processing method mainly focuses on improving a singular hydrologic variable and do not account for their spatiotemporal correlations	Develop spatially, temporally, and intervariably coherent correction methods. Physical models provide such coherence, thus an optimal fusion between coherent processing and physically-based model output has to be developed
Most operational forecast chains are still organized in a traditional model where the individual components are treated and modeled separately	Develop forecasting systems that use earth system modeling frameworks. This enables interactions between the atmosphere, oceans, land, biosphere, and human activities, resulting in enhanced and consistent predictions across all variables. This interdisciplinary approach spans multiple scientific fields and necessitates greater collaboration

Table 5
List of Main Challenges and Potential Pathways for Improved Inundation Modeling

Challenge	Pathway
The proper selection of models used for flood inundation and extent mapping is still a critical debate in hydrodynamic modeling	Conduct large-scale, nonselective, and rigorous studies that offer detailed comparisons between flood inundation models using ML techniques, topography-based approaches, and physical models. These studies should incorporate high-quality observed validation data and encompass diverse regions with varying topographic and climatic features
The lack of access to detailed information on channel bathymetry and flood defenses globally (location, fragility curves) decreases the accuracy of our flood inundation model results when applied over large domain areas	The availability of field survey samples containing measured bathymetry data along certain channels presents an opportunity to utilize statistical techniques, remote sensing data, and expert knowledge to extrapolate and apply these bathymetry data to rivers worldwide. In addition, we need to allocate additional resources and investments to develop a comprehensive global data set that accurately displays the geographical locations of river structures (e.g., levees, dams) and other critical information, such as reservoir performance curves
The lack of access to high-quality flood extent observation has impeded the accurate validation of our flood inundation models. As a result, many model testing studies are weak, selective, and lack comprehensiveness	Use advanced data fusion, ML techniques, and downscaling methods to improve the quality and quantity of available remote sensing-based flood extent maps. This can result in creating an archive of historical flood events that include their type, timing, and location together with their corresponding flood extents, which would be highly beneficial for improving our validating data

Table 6
List of Main Challenges and Potential Pathways for Improved Coastal Flood Modeling

Challenge	Pathway
The lack of spatio-temporal coverage of overlapping records to detect and characterize the interdependencies of compound flood drivers using data driven methods. And, significant underlying assumptions in formulation and parametrization, besides their relatively high computational demand and lack of comprehensive record for validation are challenges for process-based modeling approaches	Hybrid methods, via systematic links between advanced data-driven methods and process-based coupled models help address these issues. In such settings, multivariate statistical models generate relevant boundary forcings for the process-based models and the physics-informed machine learning algorithms help overcome the limitations of black-box-type data methods and leverage their skills in the efficient estimation of physically-relevant flooding characteristics
Nonstationarity of coastal flooding dynamics due to sea level rise	Forcing process-based models with climate-forcing projections helps characterize the dynamic interactions between processes at different spatio-temporal scales. To generate reasonable coastal ocean boundary forcing semi-stationary methods (i.e. shifting current storm tide regime up at the rate of SLR) or fully nonstationary methods that let the probability distribution parameters vary over time or co-vary with SLR are useful
Accounting for the biological response of living coastal systems to the altered dynamics of flooding due to anthropogenic effects and climate variability	Coupling hydrodynamic and biological models to simulate the effects of various coastal flooding regimes on wetland system dynamics and their interconnections in a feedback process helps systematically address this challenge
Modeling wave spectrum at regional and global scales suffers from the limited range of data and environmental conditions considered for the parameterization of the wave energy generation, propagation, and dissipation mechanisms	Further research to advance the understanding of wave-current interactions under extreme wave conditions, as opposed to normal wave condition

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data were not used, nor created for this research.

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