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Perspective

Perspective on uncertainty quantification and reduction in compound flood modeling and forecasting

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SUMMARY

This perspective discusses the importance of characterizing, quantifying, and accounting for various sources of uncertainties involved in different layers of hydrometeorological and hydrodynamic model simulations as well as their complex interactions and cascading effects (e.g., uncertainty propagation) in forecasting compound flooding (CF). Over the past few decades, CF has come to attention across the globe as this natural hazard results from a combination of either concurrent or successive flood drivers with larger economic, societal, and environmental impacts than those from isolated drivers. A warming climate and increased urbanization in flood-prone areas are expected to contribute to an escalation in the risk of CF in the near future. Recent advances in remote sensing and data science can provide a wide range of possibilities to account for and reduce the predictive uncertainties; hence improving the predictability of CF events, enabling risk-informed decision-making, and ensuring a sustainable CF risk governance.

COMPOUND FLOODING

Compound floods (CFs) are natural hazards that originate from a coincidence/cascade of multiple oceanic, hydrological, meteorological, and anthropogenic drivers with the potential to contribute to the societal or environmental risk (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2020). Such compounding hazards might be classified into four categories of (1) preconditioned, where a pre-existing climate-driven condition amplifies the impacts (e.g., flood in Houston, US, because of preconditioned saturated soils (Valle-Levinson et al., 2020)), (2) multivariate, when multiple concurrent hazards hit the same geographical region (e.g., flood in Ravena, Italy, because of extreme rainfall and storm surge, (Bevacqua et al., 2017)), (3) temporally compounding when the succession of hazards leads to impacts greater than the sum of individual hazards (e.g., flood in Switzerland because of clusters of extreme rainfall events (Barton et al., 2016)), and (4) spatially compounding when multiple connected locations are affected by hazards within a limited time window (e.g., flood in Pakistan because of teleconnections of hydrometeorological extremes, (Lau and Kim, 2012)) (Bevacqua et al., 2021; Zscheischler et al., 2020). Because of the nature of CF events, univariate metrics and single modeling platforms would fail to appropriately characterize the risk associated with CF. Exceedance probability estimates of CF hazards, for example, require joint probability analysis based on multivariate probability distribution functions, including multivariate parametric distributions and Copulas (Hao and Singh, 2020; Salvadori et al., 2015, 2016). Joint occurrence analysis of extreme events via multivariate probabilistic methods enables researchers to conduct assessments at regional and global scale (Camus et al., 2021; Eilander et al., 2020; Nasr et al., 2021). The probabilistic approaches, though useful, require long overlapping observation records (e.g., >30 years of nearly complete data for estimating a 100-year return level) and if based on point measurements (i.e., gauges) fail to provide information regarding the spatial distribution of hazards, their dependencies and their local patterns. Physics-informed approaches are complementary to probabilistic methods and allow for simulating spatiotemporal patterns of CF over a user-defined model domain and for a given compound event (Gori et al., 2020a, 2020b, 2022; Muis et al., 2019). From a physical perspective, coupling process-based models (e.g., hydrological and hydrodynamic) are necessary for a reasonable representation of interactions between various drivers of CF. This coupling can be achieved in various modes including one-way, loosely, tightly, and fully coupled fields (Santiago-Collazo et al., 2019). Several recent studies reported challenges in developing coupled

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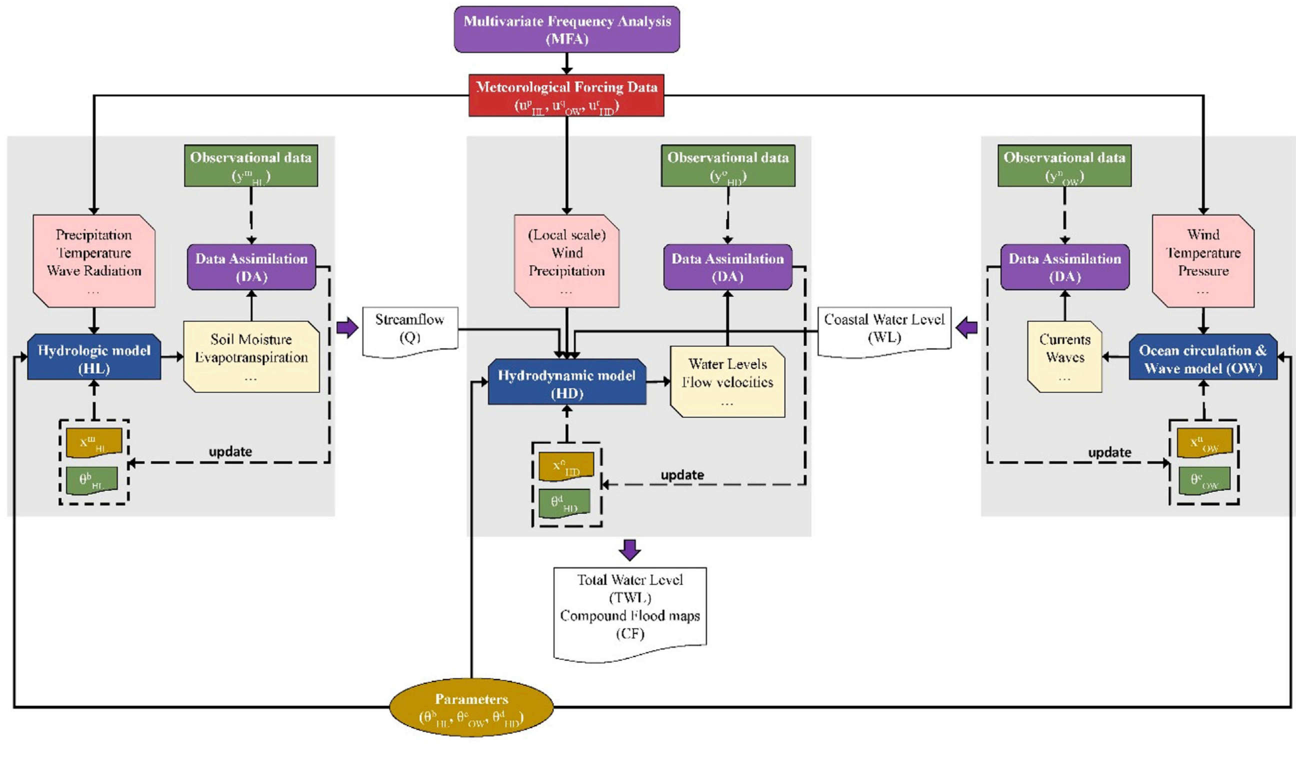

Model	State	Observation	Forcing	Parameter
Multivariate Frequency Analysis (MFA)	–	–	–	θ^a_C
Hydrological (HL)	x^m_{HL}	y^m_{HL}	u^p_{HL}	θ^b_{HL}
Ocean and Waves (OW)	x^n_{OW}	y^n_{OW}	u^q_{OW}	θ^c_{OW}
Hydrodynamic (HD)	x^o_{HD}	y^o_{HD}	u^r_{HD}	θ^d_{HD}

Figure 1. Schematic of cascading uncertainty resulting from the interplay of hydrologic, hydrodynamic, and oceanic models in compound flood modeling and forecasting

process-based models including forcing conditions and computational complexities despite the growing access to powerful and low-cost computational resources (Bilskie et al., 2021, 2022; Huang et al., 2021; Ye et al., 2020). The complementary nature of process-based and statistical approaches motivated researchers to develop 'hybrid' methods. Hybrid methods mainly focus on linking these two approaches to alleviate computational burden as they focus on the most likely pair-wise forcing conditions given the correlation structure (or statistical dependence) of flood drivers and desired return period (e.g., 50, 100, 500 years) (Moftakhari et al., 2019; Serafin et al., 2019).

HYDROLOGICAL AND HYDRODYNAMIC SYSTEMS FOR MODELING COMPOUND FLOOD EVENTS

This section discusses the hydrometeorological and hydrodynamic forecasting systems required for CF modeling. We explain all sources of uncertainties, i.e., aleatory and epistemic, involved in different layers of hydrometeorological and hydrodynamic model simulations, and argue that a thorough analysis of their propagation, interaction, and cascading effects is needed that contribute to enhancing the modeling skills. For doing so, we provide a schematic illustration that conceptualizes different sources of uncertainties and their linkage through different layers of modeling (Figure 1).

Sources of uncertainties in hydrologic modeling

Hydrometeorological forecasts are not often accurate because models suffer from inadequate conceptualization of underlying physics, non-uniqueness of model parameters, or inaccurate initialization

(Moradkhani et al., 2018). The core of hydrologic forecasting systems is the hydrologic (HL) model. HL models represent spatially and temporally heterogeneous properties of a real hydrologic system characterized by parameters and state variables. Parameters are not often easily measurable; rather they are estimated indirectly through either prior knowledge or model calibration with the consequent introduction of errors and uncertainties (Gupta et al., 2003; Liu et al., 2005; Moradkhani and Sorooshian, 2008). Calibration is used to estimate the model parameters by matching the model output(s) at a specific location(s) where the equivalent observation is available. Because of equifinality or non-uniqueness, there may be more than one combination of parameters that are equally capable of generating similar (but not necessarily identical) model outputs (Beven and Binley, 1992). This is also known as un-identifiability. In addition to model calibration, the parameter estimation problem has been referred to by other names such as parameter optimization, parameter tuning, inverse problem, data assimilation, etc. HL model parameters have been estimated using a variety of optimization techniques, including the shuffled complex evolution (SCE) algorithm (Duan et al., 1992; Arsenault et al., 2014; Bárdossy, 2007; Immerzeel and Droogers, 2008) and dynamically dimensioned search (DDS) algorithm (Tolson and Shoemaker, 2007). These global optimization strategies are ideally suited to a class of single-criterion calibration problems. Because these methods rely on deterministic nonlinear optimization approaches and only seek to identify a single optimum parameter set, they do not account for the uncertainty associated with the model parameter(s). HL models are simplified versions of complex water cycle systems that are commonly used to forecast hydrologic conditions. These simplifications are primarily owing to our limitations to simulate real-world processes that introduce structural uncertainty. Other terms used in the literature to describe structural uncertainty include ''model inadequacy'' (Kennedy and O'Hagan, 2001) and ''model discrepancy'' (Smith et al., 2015). Measurement uncertainty is introduced by errors in the measurements of model input (e.g., rainfall) and model output (e.g., streamflow). Although some researchers (Nearing et al., 2016) suggest that measurement uncertainty is the same as structural uncertainty, we agree with others (e.g., Gupta and Govindaraju, 2019) that the two terms must be distinguished because a modeler cannot minimize measurement error whereas structural error can be reduced (Moradkhani et al., 2018). From another perspective, as model parameters can be tuned to compensate for structural errors, it is presumed that explicitly acknowledging structural error or uncertainty in a model is not necessary (Xu et al., 2017a, 2017b). Although this is true when calculating best-fitting parameters at a certain location where the observation is available, an explicit representation of structural uncertainty is indispensable for an accurate and realistic assessment of the total uncertainty (MacCallum and O'Hagan, 2015). This has been the main topic of many studies that explored the benefit of 'explicitly' accounting for model structural uncertainty in improving HL model predictions through the data assimilation (DA) (Abbaszadeh et al., 2019; Gupta and Govindaraju, 2019; Pathiraja et al., 2018a, 2018b; Xu et al., 2017a, 2017b).

Sources of uncertainties in hydrodynamic modeling

Flood forecasting and water level (WL) prediction using hydrodynamic (HD) models are also subject to uncertainties associated with the initial state of the system, observational and forcing data, model parameters, and model structure. These sources of uncertainty, when not accounted for, can significantly affect the accuracy of flood inundation maps, flood extent, and floodwater velocity maps (Bales and Wagner, 2009; Merwade et al., 2008; Muñoz et al., 2020; Thompson et al., 2008; Vousdoukas et al., 2018; Willis et al., 2019). The initial state of the system is affected by uncertainties stemming from topographic and bathymetric (topobathy) data including elevation errors in light detection and ranging (LiDAR) datasets and inadequate representation of flood-protection infrastructure in digital elevation models (DEMs) (e.g., levees, barriers, and seawalls) (Bates et al., 2021; Gallien et al., 2018; Holmquist and Windham-Myers, 2022). Likewise, uncertainty from bathymetric data can affect velocity and current speed magnitude estimates, and thereby complex processes such as sedimentation, backwater effect, salinization, and mixing in tidal rivers (Cea and French, 2012; Neal et al., 2021; Ye et al., 2018). Uncertainties from observational and forcing data are considered other major sources of errors that can propagate from ensemble-based meteorological predictions to boundary conditions and accordingly translate into flood inundation extent and WL errors (Flowerdew et al., 2009; Jafarzadegan et al., 2021b; Pappenberger et al., 2005; Saleh et al., 2017). CF dynamics in low-lying coastal areas are influenced by various terrestrial and coastal flood drivers and their interactions such as tides and river flow (Loganathan et al., 1987; Jay et al., 2015; Guo et al., 2015), tides and precipitation (Lian et al., 2013; Xu et al., 2014), storm surge and river flow (Klerk et al., 2015; Svensson and Jones, 2002; Gori et al., 2020a, 2020b, 2022; Moftakhari et al., 2019), storm surge and precipitation (Wahl et al., 2015; Zheng et al., 2013), river flow and sea-level rise (Moftakhari et al., 2017; Ward et al., 2018), waves and WL (Hawkes et al., 2002; Wahl et al., 2016), and even more than two flood drivers acting together

(Bevacqua et al., 2017; Olbert et al., 2017). Uncertainties underlying these forcings and their correlation structure propagate through the system (Muñoz et al., 2022). Model parameter uncertainty is another source of error that can influence WL and flood propagation over natural and urbanized areas. These include bed roughness, surface friction, and sea surface (wind) drag, among other physical coefficients that control the dynamics of terrestrial and coastal flood processes (Bates, 2022; Bhola et al., 2019; Hall et al., 2005; Lin and Chavas, 2012; Werner et al., 2005). Typical values and empirical equations for roughness values have been proposed in literature because of difficulties in direct measurement of surface friction in the field (Liu et al., 2018; Papaioannou et al., 2017). Uncertainty from model structure refers to limitations and *a priori* assumptions in the physically-based modeling (Moradkhani et al., 2018). HD models require numerical discretization and simplification of oceanic, hydrological, and meteorological processes and are therefore subject to process uncertainty. Overall, the two main components of model structural uncertainty in HD models are the formulation and numerical schemes used to route the flow throughout the domain and the spatiotemporal discretization of the domain (Willis et al., 2019). Although diverse numerical schemes (or methods) have been developed to solve the momentum and mass balance equations (e.g., Eulerian, Eulerian-Lagrangian, and diffusion-wave, among others), we argue that grid-cell size is the most influential factor in accurately simulating flood dynamics based on global-sensitivity analyses (Alipour et al., 2022). Nevertheless, there is always a trade-off between model accuracy and computation burden (or run time) that should be evaluated before any attempts of large-scale mesh refinement.

QUANTIFYING AND REDUCING UNCERTAINTIES

This section provides a review of approaches that are used for quantifying and reducing the uncertainties associated with CF modeling. These include Monte Carlo Based method, Generalized Likelihood Uncertainty Estimation, Data Assimilation (DA), and post-processing methods (e.g., Bayesian Model Combinations and Copula-based methods). Among those statistical approaches, DA has been successfully applied in many hydrological, meteorological, and oceanic studies as it helps account for the aforementioned sources of uncertainty.

Methods to quantify and reduce uncertainties in hydrologic modeling

DA is a state-of-the-art approach that helps account for model structural uncertainty with model parameter and input uncertainties by probabilistically conditioning the states and parameters of the model on observations (Abbaszadeh et al., 2018; Clark et al., 2008; Moradkhani et al., 2005, 2018; Parrish et al., 2012). Pathiraja et al. (2018b) presented a data-driven approach to model uncertainty characterization for the system where the states are partially observed and minimal prior knowledge of the model error processes is available. This approach can estimate the uncertainty in hidden model states while improving predictions of observed variables. More recently, Abbaszadeh et al. (2019) proposed a hybrid ensemble and variational data assimilation method that effectively combines sequential and variational assimilation approaches to account for all sources of uncertainties involved in hydrologic predictions. The presented approach operates simultaneously in batch processing and sequential manners, leading to a more complete estimation of prognostic variables' posteriors. It also explicitly quantifies model structural uncertainty by incorporating the model error covariance matrix in the variational data assimilation cost function. Another approach to account for model uncertainty is a multi-model ensemble (Bohn et al., 2010; Madadgar and Moradkhani, 2014; Regonda et al., 2006). A forecast based on a diverse range of models implicitly compensates for the errors associated with each model. Multi-modeling via Bayesian Model Averaging (BMA) has become an increasingly popular procedure in hydrologic forecasting applications (Duan et al., 2007; Madadgar and Moradkhani, 2014; Najafi and Moradkhani, 2016). Sequential Bayesian Combination (SBC) is a variation of this method that estimates the posterior model probability progressively over time (Hsu et al., 2009). These two techniques (BMA and SBC) have been proven to work effectively with the ensemble DA (DeChant and Moradkhani, 2014; Parrish et al., 2012). These advancements have led to moving toward a more complete accounting of uncertainty in the hydrologic forecasting (Liu et al., 2012). Several studies have shown that combining multi-modeling and DA produces more reliable probabilistic hydrometeorological forecasts than other traditional approaches (Bourgin et al., 2014; Liu et al., 2012; Moradkhani et al., 2006)(Liu et al., 2012; Bourgin et al., 2014; Moradkhani et al., 2006). DeChant and Moradkhani (2011), used an Ensemble Streamflow Prediction (ESP) in conjunction with a DA technique to quantify initial condition uncertainty and SBC to quantify model errors. They concluded that their method provides a more complete description of seasonal hydrologic forecasting uncertainty.

Methods to quantify and reduce uncertainties in hydrodynamic modeling

The accuracy of HD model simulations is affected by topobathy errors and uncertainties associated with LiDAR-derived DEMs. Recent advances in remote sensing and machine learning (ML) techniques have shown the benefits of using satellite, radar, and unmanned aerial imagery to correct elevations errors associated with building artifacts, flood defense structures, forests, and wetlands (Cooper et al., 2019; Hawker et al., 2022; Liu et al., 2021; Zhao et al., 2022). In addition, these techniques have been used to estimate bathymetry in rivers, near shore, and intertidal zones for ungauged sites with satisfactory results (Kasvi et al., 2019; Legleiter and Harrison, 2019; Ma et al., 2020; Moramarco et al., 2019; Neal et al., 2021). HD models are also subject to model parameter uncertainties such as channel bed and floodplain friction that are often represented via Manning's roughness (n) coefficients. Roughness coefficients vary in space according to land cover type distributions, and therefore they require a comprehensive spatially-varying calibration to estimate the most suitable n-coefficients that minimize simulation errors and ensure the highest model's performance in urban, riverine, and estuarine systems (Attari and Hosseini, 2019; Bakhtyar et al., 2020). Uncertainties from forcing data can be estimated *a priori* by introducing a random (or stochastic) error distribution according to the observational and forcing type, hence improving flood forecast and WL prediction (Moradkhani et al., 2018; Saleh et al., 2017). In CF, multivariate frequency analysis, either parametric distributions or copula-based methods, pose uncertainties associated with multivariate sampling, dependence modeling, selection and parametrization of marginals, and hazard scenario generation. This source of uncertainty can be treated by advanced statistical methods (Sadegh et al., 2018; Jane et al., 2022).

In the last two decades, sensitivity analysis (Alipour et al., 2022; Hall et al., 2005; Pappenberger et al., 2008; Thomas Steven Savage et al., 2016), Monte Carlo Based methods (Apel et al., 2004; Domeneghetti et al., 2013), Generalized Likelihood Uncertainty Estimation (Aronica et al., 2002; Domeneghetti et al., 2013; Romanowicz and Beven, 2003), and Data Assimilation (Brêda et al., 2019; Durand et al., 2008; Xu et al., 2017a, 2017b) have been commonly applied for uncertainty quantification and reduction in HD models and flood inundation mapping. Compared to DA in HL modeling, the integration of DA in HD modeling has received much less attention in scientific literature. This is mainly because of limited access to high spatiotemporal resolution remote sensing data needed for assimilation in HD modeling. As an alternative to remote sensing data, recent studies demonstrated that point-source observations can be assimilated and provide a robust characterization of uncertainty in HD models (Annis et al., 2022; Jafarzadegan et al., 2021a; Muñoz et al., 2022). Xu et al. (2017a, 2017b) used a Particle Filter technique to assimilate several point-source WL observations into two-dimensional (2D) HD models. Jafarzadegan et al. (2021a) introduced a DA framework that assimilates both discharge and WL while considering correlations among point-source observations. This framework can generate probabilistic flood inundation maps while accounting for all sources of uncertainties in model parameters, state variables, and boundary conditions.

Furthermore, DA has been used to improve storm surge prediction in coastal areas. Peng and Xie (2006) developed a four-dimensional variational DA (4D-Var) to determine initial conditions by assimilating WL and surface currents. Mayo et al. (2014) used a singular evolutive interpolated Kalman filter to assimilate WL and estimate n-coefficients. Similarly, Siripatana et al. (2017) quantified uncertainties from n-coefficients in HD modeling using an ensemble Kalman filter (EnKF) method with appropriate ensemble size and inflation ratio. Zheng et al. (2018) used an adjoint-free 4D-Var method to estimate wind drag coefficient and improve storm surge forecasts. Regarding model structural uncertainty, Asher et al. (2019) developed an optimal interpolation-based DA scheme to correct WL residuals arising from physical processes that are not fully resolved in HD models (e.g., steric variations, baroclinicity, and major ocean currents). More recent studies have accounted for all sources of uncertainty in HD modeling using a pre-established EnKF method for model state-variable and parameter estimation (Moradkhani et al., 2005). This method has been applied for the probabilistic flood inundation mapping (Jafarzadegan et al., 2021a) and further adapted to WL prediction and CF hazard assessment in near-real time (Muñoz et al., 2022).

HYBRID MODELING PLATFORMS FOR EFFICIENT COMPOUND FLOOD PREDICTION

Our previous studies and experiences all indicate that conventional methods based on univariate statistics and/or single physical driver modeling fall short in the appropriate representation of CF dynamics (Moftakhari et al., 2017,2019; Muñoz et al., 2021). When multivariate statistical methods or coupled process-based modeling are implemented, a new set of challenges arise. Each statistical and process-based modeling approach comes with benefits that can be combined in a hybrid model and provide a complimentary benefit to the other method. For example, to cover the wide range of impacts from CF scenarios, one might need computationally expensive numerical models under hundreds or even thousands of synthetic scenarios with the same return period. This, even with the help of supercomputers, is not quite feasible. Recent efforts to link statistical and process-based dynamical modeling approaches propose hybrid schemes that help reduce the number of scenarios needed for a comprehensive CF analysis, with the help of a dependence-informed sampling (Anderson et al., 2021; Moftakhari et al., 2019).

Integrating physics-informed and ML approaches has also been gaining attention in the scientific community as it allows for alleviating the computational burden and efficiency required in complex large-scale HD modeling. Typically, ML approaches are developed to provide time series of predictive WL and streamflow at specific gauge stations of a given study region (Mosavi et al., 2018). Nevertheless, we believe that hybrid frameworks that integrate ML and HD models have the potential to recognize spatiotemporal features from historic flood events and so help predict spatially distributed water depth and flood inundation extent from fluvial and coastal drivers (Hosseiny et al., 2020; Hu et al., 2019; Kabir et al., 2020). To incorporate physics-informed data into ML models, one might conduct geospatial analyses and feature engineering to derive spatiotemporal features from available satellite, radar, and DEM datasets. This information, in addition to input forcing data associated with historic flood events, could be then used to train specialized ML models. One of the main limitations of developing advanced ML models for CF simulations is the lack of access to large and reliable training data. Therefore, an essential line of research is to utilize advanced remote sensing technologies, and statistical techniques to develop a reliable archive of historical CF events that include forcing data and affected inundated areas corresponding to those events. Access to such a valuable dataset at a large scale paves the way to test past CF events, learn from them and forecast CFs more accurately. Moreover, this dataset together with appropriate ML models can be adapted to conduct regional CF mapping using local-scale HD models and leveraging transfer learning techniques in data-scarce regions or ungauged locations, i.e., extracting gained knowledge from a specific location/flood event and applying it to new locations, to recognize hidden patterns from available satellite, radar data, and elevation data (Muñoz et al., 2021).

Summary and conclusion

CFs are natural hazards characterized by the interplay of multiple complex drivers in space and time. Such drivers are not necessarily extreme in nature, but their compounding effects are often responsible for the largest impacts and escalated risks that society and the environment have experienced in recent years. To properly characterize the impacts and risks associated with compound flooding, researchers rely on either data-driven or physically-based approaches that account for multiple concurrent or cascading drivers (e.g., multivariate statistical methods and coupling process-based models). Likewise, linking both approaches in the so-called 'hybrid' method has gained attention in the research community as it alleviates computational burden when simulating CF hazards at a large scale. In that regard, CF can efficiently be characterized in space and time by (1) focusing on the most likely pair-wise forcing conditions via statistical analysis, and (2) generating the corresponding physics-informed flood hazard map for a given return period. Nevertheless, uncertainties stemming from observational and forcing data, model parameters, the initial state of the system, and model structure can affect the accuracy of CF modeling and forecasting. Among the statistical approaches developed for uncertainty quantification and reduction, data assimilation (DA) has been successfully applied in many hydrological, meteorological, and oceanic studies as it helps account for the aforementioned sources of uncertainty. DA approaches in the field of CF are, however, in an infant stage and only a few studies have recently reported the benefits of DA for CF modeling and forecasting at a local and regional scale. The physical models, typically used to simulate CF impacts are computationally expensive. Given the key role of time management during CF hazards in a real-time scenario, the use of ensemble-based techniques, such as DA, has gained less attention in practice. However, the recent advances in the parallel computation of physical models using supercomputers have overcome this limitation and opened a new avenue to efficiently combine DA with hydrodynamic models for CF inundation forecasting in operational systems. These studies mainly focused on sequential DA using the EnKF technique, and so future work is recommended using more advanced techniques such as Particle Filtering (PF) and evolutionary PF. Although Kalman filtering-based data assimilation techniques have been widely and successfully used in hydrologic studies, this technique has some inherent features that limit its superiority. These include the Gaussian assumption of errors, linear updating rule within the EnKF, and violation of water balance. Furthermore, machine learning (ML) and transfer learning techniques integrated with the hybrid method can aid in the model calibration of process-based models as well as CF mapping at the regional scale by leveraging local scale hydrologic and/or hydrodynamic models. ML can benefit from multisource satellite and radar imagery via specialized deep learning algorithms that can also be trained to replicate process-based models. Therefore, future work is advised in this line of research to benefit from physics-informed ML models. Although utilizing the physics-informed ML models is gaining popularity in recent years as an efficient tool for real-time flood modeling and forecasting, designing such emulators and their configurations are still challenging as they keep all the uncertainties involved in the physical models and just represent them with different language within the ML models. Coupling ML with physical models although theoretically seems promising, there have not been sufficient studies yet to rely on and confidently demonstrate its usefulness and effectiveness in solving the unknown questions and challenges in the hydroclimate community.

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AUTHOR CONTRIBUTIONS

P.A. wrote the first draft of the manuscript. D.F.M., H.M., and K.J. equally contributed to editing and writing the manuscript. H.M. edited the manuscript and supervised the entire study.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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