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Review

Nature-based solutions as buffers against coastal compound flooding: Exploring potential framework for process-based modeling of hazard mitigation

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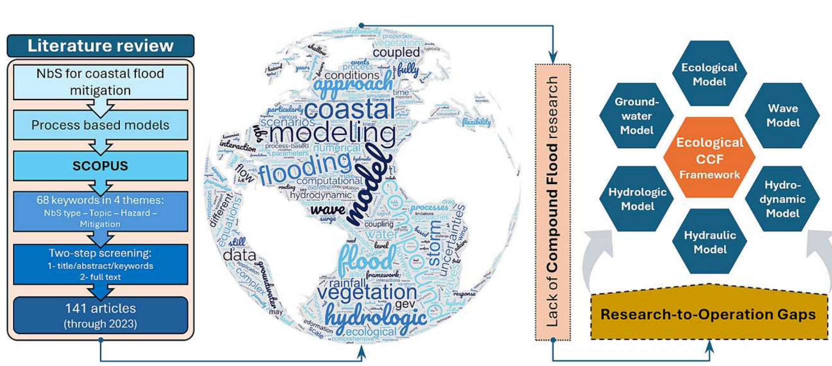
HIGHLIGHTS

- Analysis of 141 publications on NbS for coastal flood mitigation using numerical models
- 61 % of studies were at local scales, and mostly in the United States and Netherlands.
- Marsh is the most studied NbS type (43 % of the literature).
- Provides a comprehensive framework for adequate representation of NbS in compound flood models
- Addresses research-to-operations gap and provides insights into multidisciplinary collaborative research

GRAPHICAL ABSTRACT



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ABSTRACT

As coastal regions face escalating risks from flooding in a changing climate, Nature-based Solutions (NbS) have garnered attention as promising adaptation measures to mitigate the destructive impacts of coastal flooding. However, the challenge of compound flooding, which involves the combined effects of multiple flood drivers, demands a deeper understanding of the efficacy of NbS against this complex phenomenon. This manuscript reviews the literature on process-based modeling of NbS for mitigating compound coastal flooding and identifies knowledge gaps to enhance future research efforts. We used an automated search strategy within the SCOPUS database, followed by a screening process that ultimately resulted in 141 publications assessing the functionality of NbS against coastal flooding. Our review identified a dearth of research (9 %) investigating the performance of NbS against compound flooding scenarios. We examined the challenges and complexities involved in modeling

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such scenarios, including hydrologic, hydrodynamic, and ecological feedback processes by exploring the studies that used a process-based modeling framework. Key research gaps were identified, such as navigating the complex environment, managing computational costs, and addressing the shortages of experts and data. We outlined potential modeling pathways to improve NbS characterization in the compound flooding framework. Additionally, uncertainties associated with numerical modeling and steps to bridge the research-to-operation gaps were briefly discussed, highlighting the bottlenecks in operational implementation.

1. Introduction

Approximately 40 % of the global population resides within a 100-km proximity to oceanic coastlines, twice the global average population density (Maul and Duedall, 2019). With growing populations and economic expansion in coastal regions, exposure to flood risk is projected to increase (Bates, 2022; Hallegatte et al., 2013; Hauer et al., 2021; Sandifer and Scott, 2021). Coastal flooding events can be triggered by different drivers, such as high tides (Sweet et al., 2021), storm surges (Helderop and Grubesic, 2019), heavy rains (Tabari, 2020), high river flow (Bermúdez et al., 2021; Ghanbari et al., 2021), and long-term increases in sea level (Nicholls et al., 2021).

In addition, coastal flooding may result from the concurrent or successive interaction of inland factors, such as precipitation and discharge, and coastal drivers, including storm surges, waves, and tides. This combination is known as coastal compound flooding (CCF) (Feng et al., 2023; Moftakhari et al., 2017; Santiago-Collazo et al., 2019). In recent years, many coastal flooding events were counted as CCF, like flooding due to Hurricane Harvey (Van Oldenborgh et al., 2017) and Hurricane Irma in 2017; the Brisbane and Thailand Floods in 2011; Hurricane Isaac and tropical storm Debby in 2012; typhoon Haiyan in 2013; and the series of winter storms in the UK in 2013/2014 (Wahl et al., 2015). Recently, Hurricane Ian (2022), the fifth-deadliest hurricane in the United States since 1963, also caused CCF (Masters, 2022). Unlike individual drivers that do not impact coastal regions, the interactions between inland-coastal or coastal-coastal processes can lead to intricate nonlinear effects. These effects can amplify the overall impact of multiple factors (Bilskie et al., 2014; Dykstra and Dzwonkowski, 2021; Shen et al., 2019; Xu et al., 2014). As a consequence of these interactions, extreme flood hazards can arise, leading to negative socio-environmental impacts (Hinkel et al., 2014; Wahl et al., 2017). The intensified joint effects of these multivariate drivers highlight the importance of considering the intricate dynamics within inland and coastal systems when addressing coastal flooding phenomena. Notably, climate change has further altered the exposure of coastal communities to various flood drivers such as sea level rise (SLR) and precipitation (Bilskie et al., 2022; Jongman et al., 2012; Kulp and Strauss, 2019; Nicholls et al., 2021; Pfahl et al., 2017; Santiago-Collazo et al., 2021).

The increasing likelihood of floodings demands better knowledge to implement concrete strategies to reduce flood risk (Niazi et al., 2021). Achieving this goal requires a comprehensive understanding of the financial implications, benefits, and effectiveness of a series of individual actions or policies. This understanding is an essential component of a holistic strategy during the planning phase, aimed at ensuring that synergistic actions are effectively taken to mitigate flood risk across both immediate and extended planning intervals. Risk-reducing options for coastal communities may include hard or structural engineering solutions (referred to as gray infrastructure), Nature-based Solutions (NbS) (Evans et al., 2019; Ghofrani et al., 2017; Zandersen et al., 2021), or hybrid solutions involving elements of both gray and green (Cohen-Shacham et al., 2016).

Using hard-engineered structures, such as dikes, sea walls, and earthen embankments is a traditional and common mitigation and adaptation strategy. However, these fixed defenses come with ongoing and more expensive implementation and maintenance requirements compared to their competitors. The expenses are further intensified by the need to repeatedly adjust and expand these structures in response to elevated water levels (Christie et al., 2020; Le Coent et al., 2023; van Rees et al., 2023). Moreover, gray solutions typically focus on mitigating flood impacts without considering environmental aspects (Suedel et al., 2022).

NbS have emerged as alternative solutions that can provide multiple benefits for ecosystem and flood protection, including biodiversity and habitat conservation, long-term sustainability, lower maintenance costs, less raw material consumption, applicability at different spatial scales, while being more environmentally friendly and reducing greenhouse gas emissions (Mutlu et al., 2023; van der Meulen et al., 2023; Van der Nat et al., 2016). These solutions also offer aesthetic and cultural value, making them appealing options for coastal protection. NbS performance is hard to assess due to a limited knowledge of their flood protection effectiveness. A paradigm shift is necessary to recognize that NbS can be used alongside (hybrid) or as a replacement for traditional infrastructure to achieve more sustainable and efficient mitigation of flood risks and associated impacts. Tidal marshes, mangrove forests, intertidal flats, dunes, barrier islands, and maritime forests are examples of NbS that can effectively dissipate wave energy, reduce storm surge impacts that coincide with coastal flooding, and contribute to infrastructure damage and erosion. In some cases, NbS has shown superiority or comparable performance to gray solutions for wave attenuation (De Costa and Tanaka, 2021; Hynes et al., 2022; Montgomery et al., 2019). Moreover, the combination of hard and soft solutions is often proposed as a beneficial complement to traditional coastal defense and risk mitigation techniques (Carrick et al., 2019; van Wesenbeeck et al., 2014).

The efficacy of NbS in protecting against CCF depends on several factors, in particular the different types of species and their characteristics (e.g. the drag coefficient), the type of flood drivers (wave, storm surges, or river discharge), and the seasonal variability of vegetation characteristics (Ascencio et al., 2022; Garzon et al., 2019b). Evaluating NbS efficiency often requires the use of a multifaceted approach that includes laboratory and field experiments, numerical modeling, or a combination of both. In field and laboratory experiments, it is quite challenging to simulate hydrodynamic conditions with strong waves and water depths of several meters (Vuik et al., 2016). Other major drawbacks of this approach are the difficulties in adequate replicating plant properties and the costs of ongoing measurements (Garzon et al., 2019b; Hadadpour et al., 2019). Numerical models offer more flexibility and advantages in terms of feature evolution, roughness characterization, and wave attenuation. In addition, the advancement in computational resources motivates the widespread application of numerical models (Garzon et al., 2019b). Therefore, the scope of this review paper is centered on process-based models. There is a significant limitation in the current research landscape as most modeling investigations in the context of NbS implementation have focused on individual flood drivers rather than CCFs. It is noteworthy that the inclusion of inland processes, such as river discharge, precipitation, and groundwater level, has been conspicuously missing from the modeling studies carried out.

In this study, we review the studies that focus on the effects of NbS on coastal flooding, particularly compound coastal flooding. The analysis covers the geographical locations, the spatial extent evaluated, and the numerical tools used in the relevant studies. It also explores the potential integration of NbS with traditional engineering, the types of flooding events considered, and the economic dimensions associated with these strategies. Following this, we narrow our scope to CCF and numerical studies to synthesize existing knowledge and mobilize it toward bridging research gaps.

2. Methodology and scope

This study uses an online database search to extract relevant literature from the SCOPUS database. The purpose of this literature review is to retrieve papers that adopt numerical modeling tools to examine the performance of NbS against coastal flooding. We aim to understand the existing knowledge and then narrow down the focus to put a spotlight on the research gaps and pathways within the framework of CCF as a growing threat to coastal communities in a warming climate. For this purpose, various keyword sets have been incorporated into the search query as outlined in Fig. 1. We selected a subset of keywords and keyword categories from the systematic mapping protocol of (Paxton et al., 2023) to compile the evidence base on the performance of NbS related to coastal protection. In our methodology, four search strings were developed to align with the key elements of our overarching goal. Within each substring, a list of keywords was employed and separated using "OR" operator to reflect that search string comprehensively. The first substring is "NbS type" and involves keywords representing common NbS types. This list can be expanded to include other types in the future studies. The next substring, i.e. "Topic", was used to ensure that the retrieved documents encompass nature-based perspectives. For this reason, some of the commonly used alternatives to the NbS keyword were included. The third search string is "Hazard" and was deployed to retrieve only flooding hazard studies. Complementary keywords such as sea level rise, water waves, wave propagation, wave transmission, storm surge condition, and storm damage help lower the chance of missing relevant documents during online database search. Finally, the search string "Mitigation" represents the scope of the relevant documents. Since our objective is only the papers investigating the functionality of NbS in mitigating coastal flooding hazard, we employed 68 keywords to effectively constrain search results to those within the study scope. Like any other online database search, this methodology results in a list of articles that should be screened. Therefore, first the titles, abstracts, keywords, and then, the full texts of the initial results were reviewed to ensure papers utilized in the review are relevant and fully aligned with the scope. After this step, we identified 141 articles for the final database. It is important to note that almost any systematic review paper cannot ensure that its final list encompasses all relevant documents. Yet, the authors have attempted to consider a large body, if not all, of research papers examining the performance of NbS against coastal flooding to avoid unnecessarily expanding of the scope of the present study.

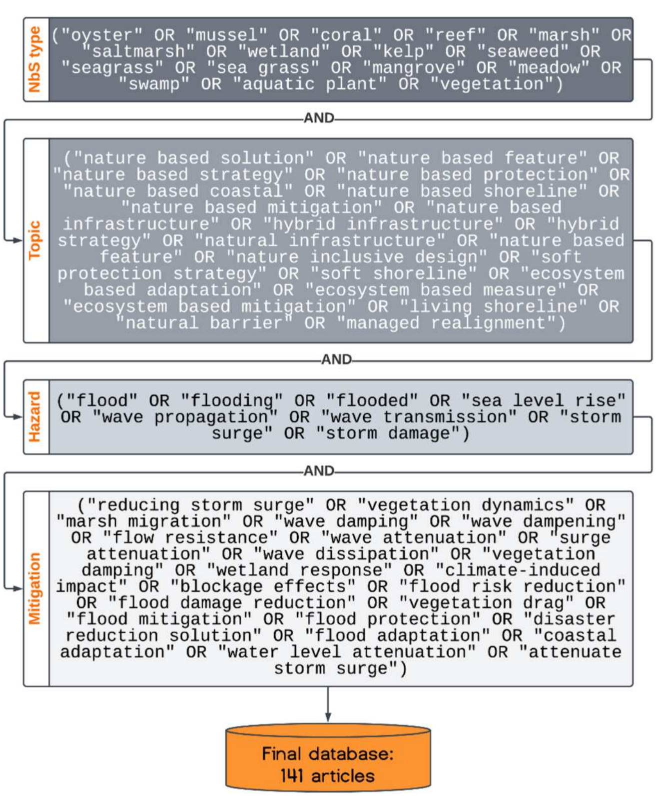

Fig. 1. Literature retrieval methodology.

The final database of 141 articles is summarized in Table S1, chronologically from oldest to newest. To organize subsequent discussions for in-depth analysis, this collection of articles has been classified into six categories. The 1st category determines the spatial scale of each article. Its associated four categories are (i) *Global*: study on a global or intercontinental scale; (ii) *Regional*: study in several provinces or states; (iii) *Local*: study along a coast, a bay, or a city; and (iv) *N/A*: for experimental or idealized studies. The 2nd category summarizes the list of countries and states in the case of the USA. The 3rd category mentions all numerical tools adopted for characterizing the performance of vegetation fields and conducting the analyses. The 4th category presents the types of examined Nature-based Solutions. Categories five and six determine whether the mentioned study addresses hybrid solutions (a combination of soft and hard solutions) or compound flooding.

3. Literature review results and analysis

This section provides a statistical overview of the existing knowledge on investigating the performance of NbS against coastal flooding from various perspectives. Fig. 2 represents the evolution of the number of publications over time. Based on the documents from the SCOPUS database, the oldest papers were published in 2009. There has been a gradual upward trend over the years. However, two notable periods of increase in 2016 and 2022 culminate in sharp peaks, each followed by a significant decline in the next year.

The relevant literature on this topic has been published in 60 academic journals. In this list, 25 journals have at least two publications and are displayed in the treemap of Fig. 3, along with their number of relevant papers. As can be seen, the journal "Coastal Engineering" is the most frequent choice of researchers in this field, with 20 articles (15 % of the documents). The next journal is "Ocean Engineering". The large body of literature published in these two journals can be attributed to the abundance of journal papers investigating the wave attenuation behavior of idealized vegetation fields.

Fig. 4 represents the distribution of the analysis scales. The results show that a large proportion of studies (61 %) are carried out at the local scale and focus on individual coasts, cities, or bays. Three studies examined the regional effects of vegetation patches, all conducted in different states in the US (see Table S1 for more details). Further, two studies considered mixed scope. Narayan et al. (Narayan et al., 2017) considered local and regional analyses, and Menendez et al. (Menéndez et al., 2020) considered local, regional, and global scales.

Fig. 5 depicts the distribution of the number of documents worldwide and the number of articles in the US and Asia, which have been provided in sub-panels of this figure for better representation. The research was conducted in 22 countries, of which 12 countries were mentioned more than once. Notably, there are no studies from Africa. As expected, the US is the most studied country, accounting for 53 % of study locations in the relevant literature. Within the US, the coastal regions of Virginia and New York were the most frequently studied for the influence of vegetation. After them, the states of Maryland and Florida (selected six times) and Louisiana and New Jersey (selected five times) were the most studied areas in previous studies. Outside the US, 12 articles focused on the sites in the Netherlands. China is the third most frequently studied country, with five articles.

The eight most common tools for numerical studies are shown in Fig. 6. Simulating WAves Nearshore (SWAN) was adopted as a

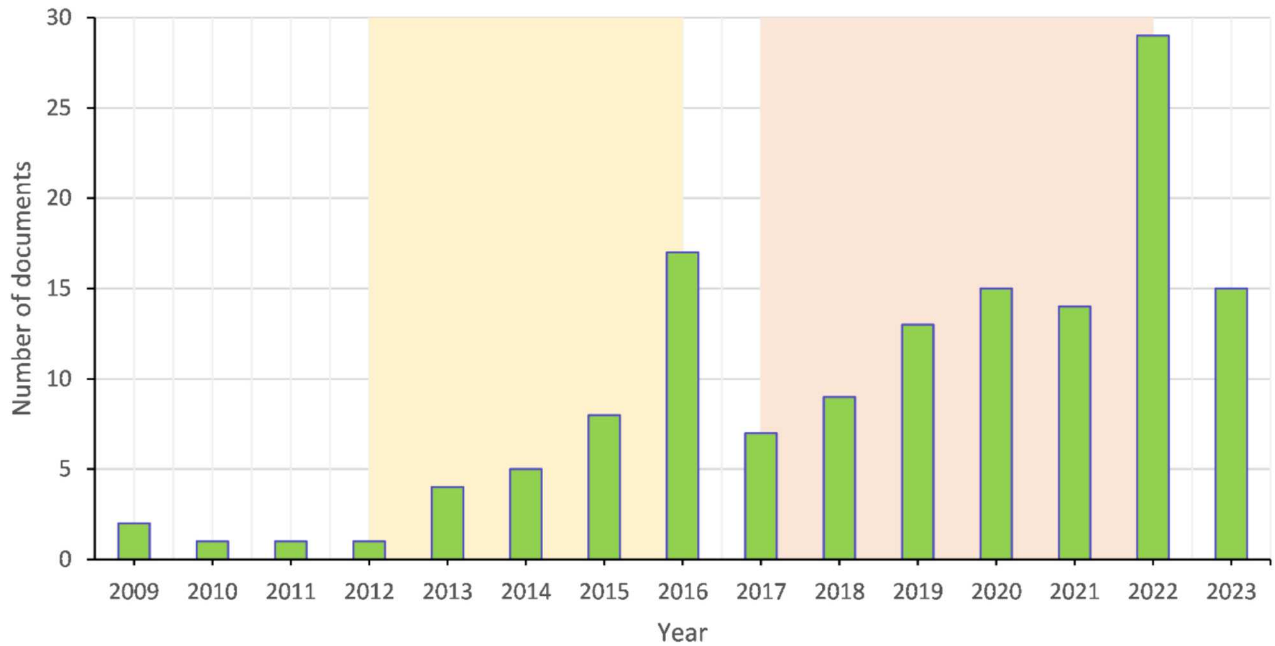

Fig. 2. Number of documents per year retrieved from the Scopus database published between 2009 and 2023.

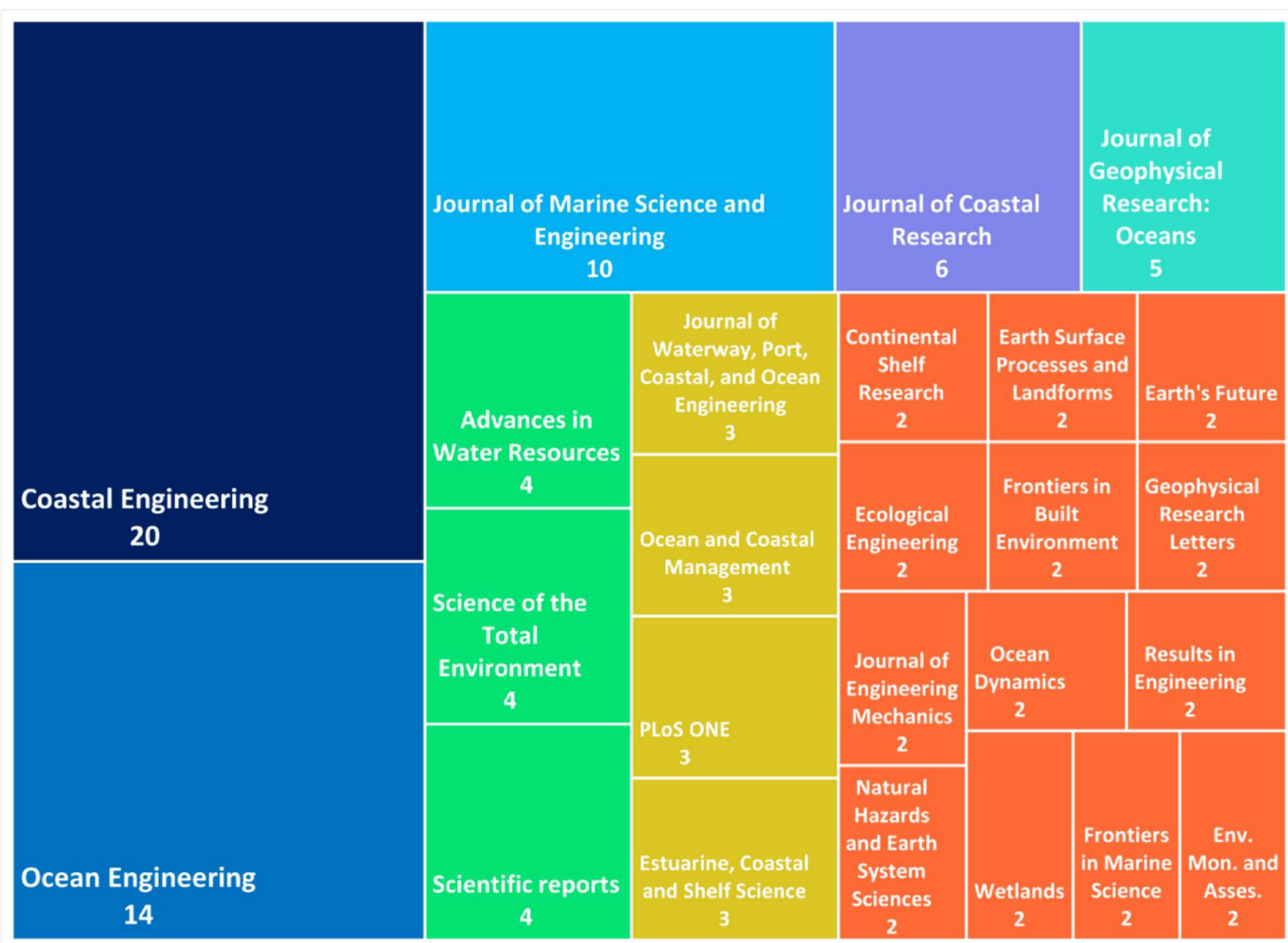

Fig. 3. Most frequent journals, along with their number of relevant published papers.

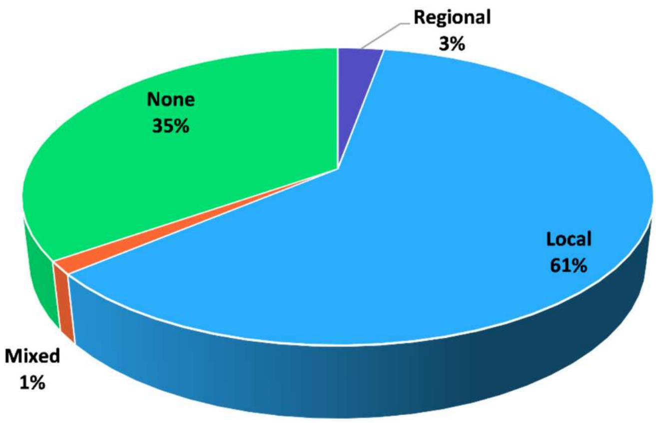

Fig. 4. Spatial scale of relevant studies. "None" in this plot refers to studies that modeled an idealized or prototype vegetation, not a geographical study domain in nature.

numerical tool in 36 articles. After that, computational models such as finite volume and finite difference were frequent with 24 articles. Advanced CIRCulation (ADCIRC) was the third choice with 23 studies. Notably, in this context, the coupling of ADCIRC and SWAN was also widely used with 16 studies. Furthermore, the results support the notion that ArcGIS, XBeach, and Delft3D have received considerable attention in the literature.

Since our ultimate goal is to discuss the research directions toward understanding the performance of NbS against compound flooding, a closer look at the numerical tools used is helpful. Our analysis (see Fig. 7) showed that TELEMAC and SWAN (4 articles) were the most common numerical tools in such studies. In addition, in the presence of hybrid solutions (a combination of NbS and a hard coastal-defense structure), it was more common to use SWAN (9 articles), TELEMAC (7 articles), and Delft3D (5 articles) for numerical analysis.

Different NbS types in previous studies have been classified into seven categories, as presented in Fig. 8. Based on these results, marshes are the most frequent NbS type, responsible for 43 % of case studies. In addition, 22 % and 11 % of the literature selected swamps and barrier islands as their NbS model, respectively. Besides, 8 % of studies reported seagrass as their NbS ecosystem. Another 23 % mentioned only wetlands or used idealized vegetation models as a general class (not a specific type). Further, 8 % and 5 % of publications focused on reef and dune models, respectively, in their analyses.

The key finding of the literature review is that only 9 % have numerically investigated the performance of NbS against compound flooding in terms of attenuation or mitigation functions. This motivates the need for further investigation to gain a more consistent and comprehensive understanding of NbS functionality. Therefore, in the following section, various components of a comprehensive numerical modeling framework for NbS efficacy in face of compound flooding are discussed, and remarks are presented on the challenges and possible future research directions.

4. Discussion: process-based modeling framework for evaluating NbS efficacy in mitigating CCF

Adequate representation of nature-based features in a numerical model is challenging due to the difficulties in linking multiple process-based models, considering various hydrometeorological scenarios, geomorphological parameters, vegetation characteristics, and gray structures (see Fig. 9). This challenge can be further exacerbated when considering the evaluation of NbS against CCFs, making it a multidimensional modeling challenge. CCF is a complex coastal hazard that includes multiple oceanic, hydrological, meteorological, and anthropogenic drivers. This multi-dimensional event can be characterized and described through various process-based, data-driven, machine learning-based, and statistical approaches (Jafarzadegan et al., 2023; Santiago-Collazo et al., 2019). Generally, full representation of CCFs (see Fig. 9) requires a model that accounts for (a) wave generation,

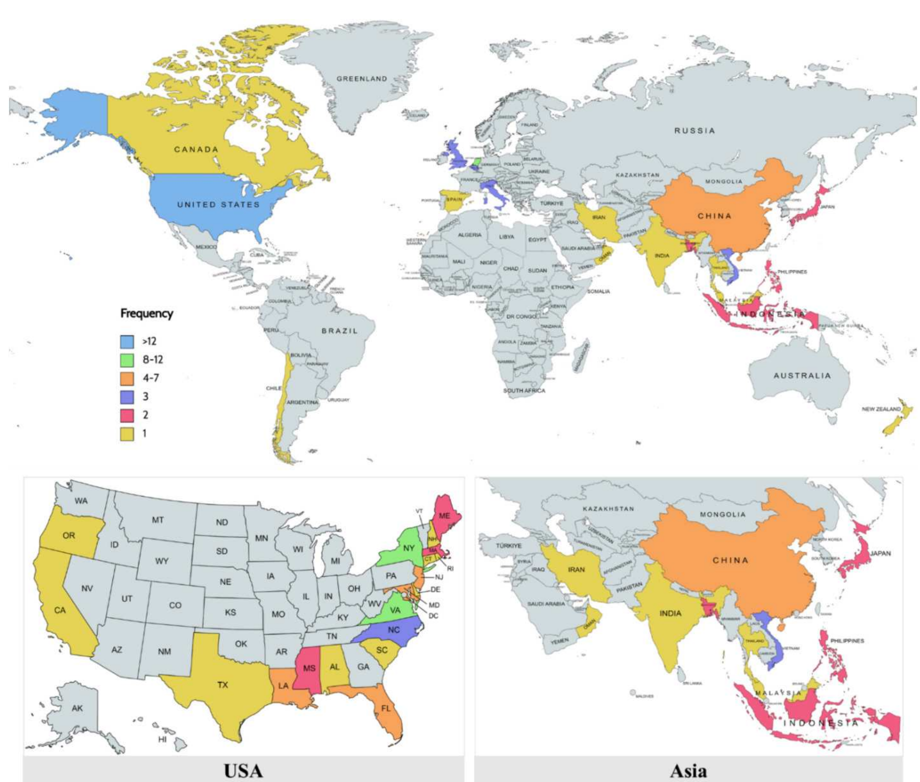

Fig. 5. World map of study locations and their number of mentions in the relevant literature.

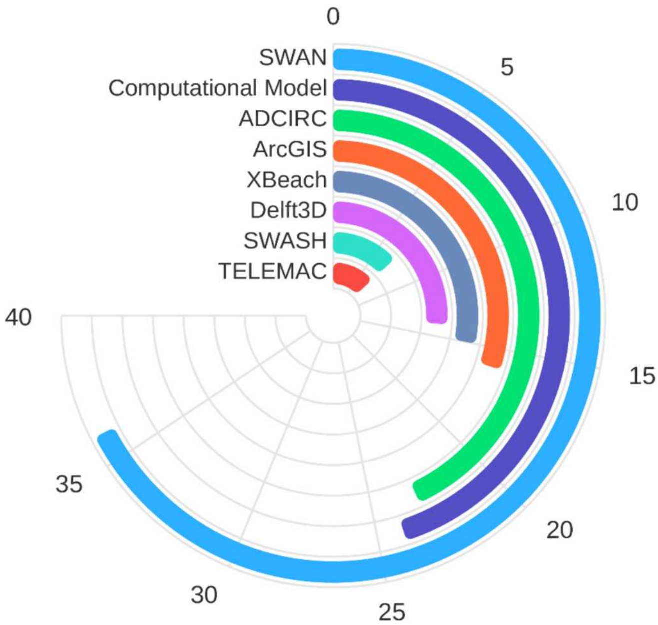

Fig. 6. Most frequent numerical models in the relevant studies.

storm surge, and tide processes in the offshore boundary; (b) short and long waves and shoaling (namely, shoaling zone processes), breaking and wave setup/set down (namely, surf zone processes), swash, runup and overtopping (namely, swash zone processes) in the nearshore; (c) flow over land, sudden transitions, and obstacle interaction (namely, flow-related processes); (d) other processes like infiltration, precipitation, wind setup, and river discharge (Leijnse, 2018). These complexities have hindered a widespread evaluation of the functionality of NbS in mitigating the risks of CCFs. In this area, numerical models hold promise because they provide high-resolution predictions of flooding extent, land change, and ecological conditions and can be further adapted for analysis of infrastructure exposure and vulnerability.

A holistic process-based modeling framework demands the integration of various numerical models, including ecological, hydrologic, hydraulic, ocean circulation (hydrodynamic), nearshore, and deepwater wave models. Fig. 10 shows schematically the scope of each modeling component. In the following sections, we provide an overview of the various components of a comprehensive numerical model, excluding the deepwater wave models. Additionally, we briefly overview alternatives for pure numerical models (i.e. hybrid models) and their inherent uncertainties.

Eliminating any of the CCF sources can result in substantial prediction errors; therefore, the use of coupling techniques is inevitable to address the complex interplay of various drivers of compound flooding events in the coastal regions. The computational burden often rises when there is a need to capture the impacts of hydrodynamic and hydrologic components via coupling process-based models. This coupling can be achieved in a variety of ways, including one-way (a.k.a. linking technique), loosely (a.k.a. two-way), tightly, and fully coupled schemes (Santiago-Collazo et al., 2019). Referring to Table S1 and Fig. 7, it is evident that most coupling efforts to address the interaction between ecological feedback and coastal flood response have focused on the development of tightly coupled wave and ocean circulation models (mainly ADCIRC and SWAN models). In tightly coupled modeling, the source codes of independent models are integrated, and some kind of information exchange occurs at each computational time step.

Fully coupled modeling is the most comprehensive and sophisticated approach for compound flood modeling. In this method, the hydrologic, hydraulic and hydrodynamic models are fully integrated and solved simultaneously, taking into account the mutual feedback and interaction between the models at each time step. This approach captures the dynamic coupling of rainfall-runoff and flooding processes by solving the governing equations for all physical processes simultaneously, thereby enabling a comprehensive representation of the compound flooding phenomena. The single modeling technique can be described as 'full-coupling' when all relevant equations from hydrology, hydraulic and hydrodynamic are solved simultaneously (Santiago-Collazo et al., 2019). Fully coupled models require significant computational resources due to the complex interactions taken into account but provide the most accurate representation of compound flood events. Basically, in an ideal fully or two-way coupled model, upstream flood water, tributary runoffs, main water body or river system, ecological feedback, and storm surge contribution should be characterized accurately and efficiently.

The nonlinear relationship between multiple flood drivers is also crucial, as evidenced by various studies examining the impacts of compound flooding resulting from hurricanes (Stephens et al., 2022). Discrepancies and shortcomings in the outcomes of various numerical models due to their unique frameworks and capabilities underscore the need to develop a fully coupled CCF modeling framework capable of simulating complex flooding drivers and their nonlinear interactions. Current state-of-the-art modeling efforts still lacks a holistic framework

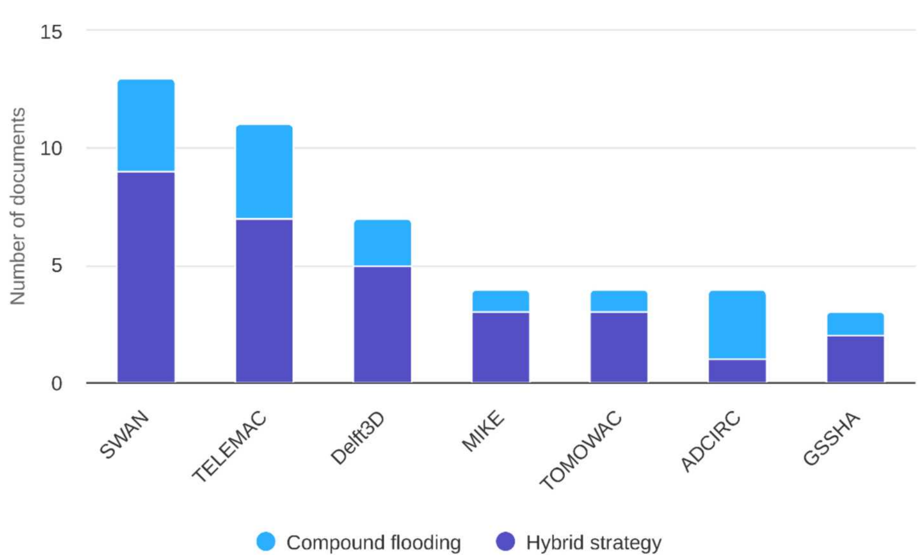

Fig. 7. Most frequent numerical tools in the studies considering compound flooding and hybrid structures.

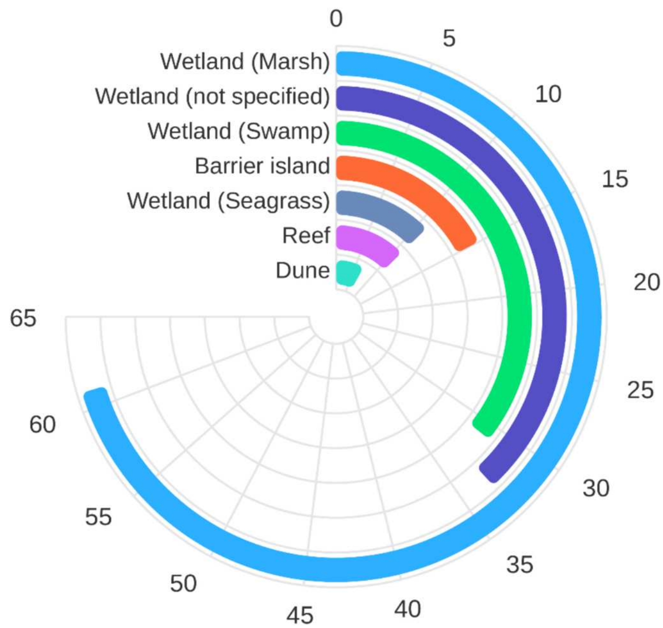

Fig. 8. Different types of NbS in the relevant literature.

that accounts for the multidimensional dynamics and interactions. Moving toward a full coupling model requires overcoming challenges related to the complex mathematical representation of their physical processes, the computational power required, and the temporal and spatial resolution (different time and length scales) of the numerical models (Tanim et al., 2022). Furthermore, the limited research on coupled CCF-ecological models highlights the pressing requirement to develop more extensive coupling frameworks for CCF modeling in the presence of ecological feedback.

4.1. Ecological model

Evaluating the performance of NbS hinges on their comprehensive and accurate representation in various environmental scenarios. Over the last decade, there have been an increasing number of studies exploring numerical schemes to adequately represent nature-based features. Despite all these developments, numerical studies have their own challenges and a unified and universal approach for vegetation simulation is still missing. (Wamsley et al., 2010) listed six challenges in numerical models that account for wetland characterization: (1) considering storm-induced changes in wetland structure; (2) enhancing frictional formulations by explicitly accounting for bottom (bathymetric) friction and form (frictional) drag; (3) a method for capturing the wave setup when vegetation is present; (4) modeling of the three-dimensional vegetation; (5) considering sub-grid channels through vegetated fields; (6) identifying changes in hurricane structure. (Van Rooijen et al., 2016) also emphasized that a suitable numerical model for NbS simulation in the nearshore zone should account for three items: attenuation of wind sea and swell waves (e.g., (Mendez and Losada, 2004)); wave setup/set-down reduction due to emergent vegetation or nonlinear waves (e.g., (Guannel et al., 2015; Ma et al., 2013)); and the presence of infragravity waves as a major driver of wave runup (e.g., (Ruggiero et al., 2001; Stockdon et al., 2006)).

The relevant literature from Section 3 shows that a proper simulation of wave-vegetation interaction (i.e. wave propagation and attenuation) should entail several components. As shown in Fig. 11, the components include: (a) hydrodynamic conditions; (b) storm characteristics (intensity, track, duration, and forward speed); (c) geomorphological factors (land/water configuration, surrounding bathymetry and topography); (d) vegetation characteristics (height, thickness, density, buoyancy, stiffness, distribution of roots, stems and canopies, and seasonal effects); and (e) presence of human interventions, such as channels, dikes and levees (Ascencio et al., 2022; Augustin et al., 2009; Baaij et al., 2021; Highfield et al., 2018; Hu et al., 2015; Kiesel et al., 2022; Phan et al., 2019; Smolders et al., 2015; Vuik et al., 2016; Wamsley et al., 2010).

Various approaches have been used to simulate wave energy dissipation through vegetation, including: (1) a bottom friction or bed roughness approach (Hasselmann and Collins, 1968); (2) modeling vegetation as structural elements like cylinders (Dalrymple et al., 1984; Mendez and Losada, 2004); (3) treating vegetation as a porous medium (Hoffmann, 2004; Zinke, 2012). The bottom friction approach is the most used approach in the literature, especially for marshes. It is implemented in numerical models through Manning's n formulation, Darcy-Weisbach friction factor or Chézy coefficient (Familkhalili and Tahvildari, 2022). The bottom friction approach does not take into account the emergence and submergence levels (depth-dependent or height characteristics) of vegetation fields (Hewageegana et al., 2022;

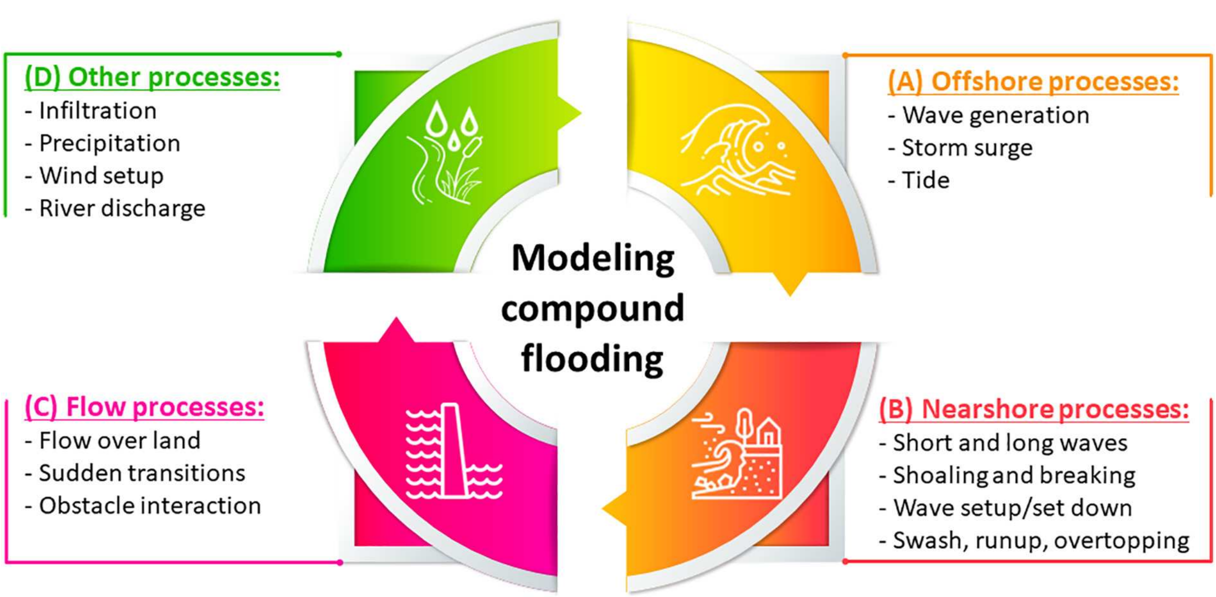

Fig. 9. Different components of a full compound flood model.

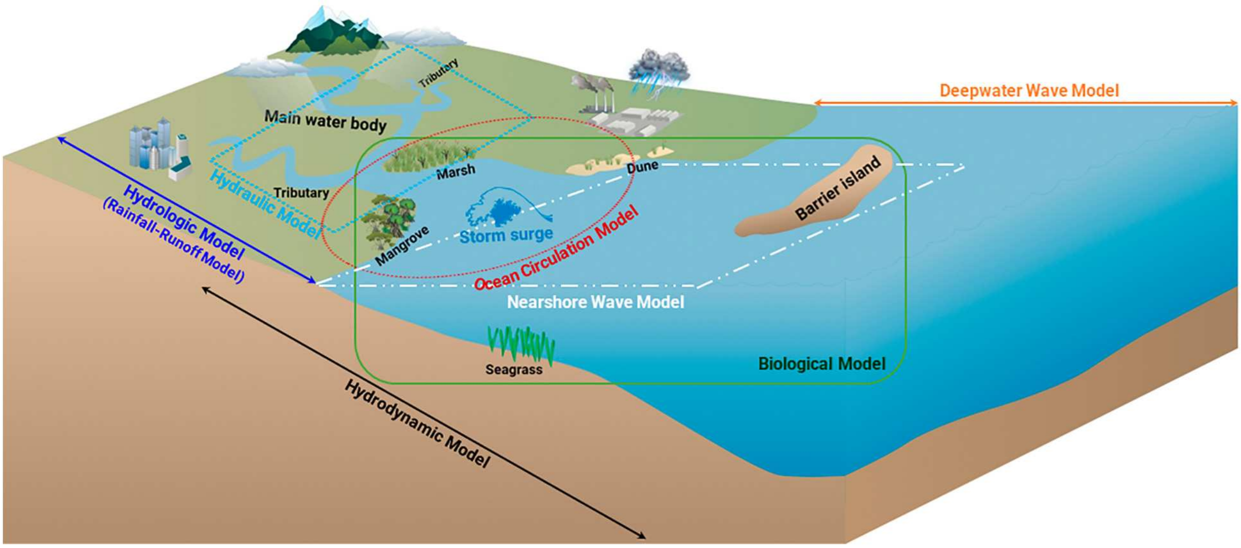

Fig. 10. Conceptual diagram of CCF modeling components in the coastal environment.

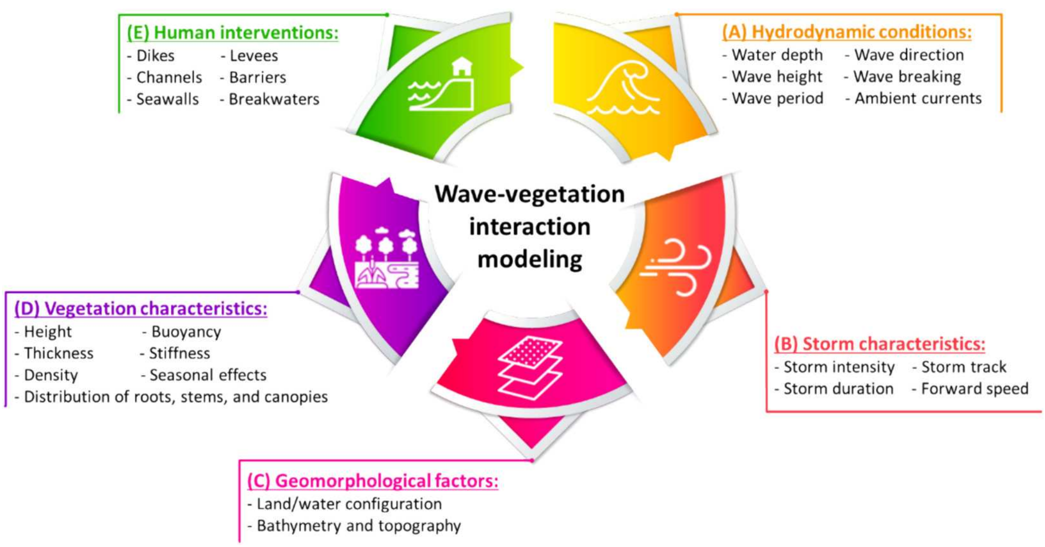

Fig. 11. Different types of factors affecting the wave-vegetation interaction.

Stark et al., 2016). Among them, determining Manning's n coefficient through a 2D parameterization using landcover types or vegetation characteristics (e.g. stem diameter, height and density) is common (Cao et al., 2021). In addition, this approach is uncertain for vegetations with time-varying roughness, such as seagrasses and kelps (Holzenthal et al., 2022). The 2D parameterization is inadequate when the relative vegetation height (stem height to water depth) is not negligible (Cao et al., 2021). To overcome some of these limitations, 3D parameterization can be used to resolve flow through vegetation (Lapetina and Sheng, 2014; Zhang et al., 2020).

The second approach (modeling as structural elements) relies on a pre-defined bulk drag coefficient, C_D, which is subsequently calibrated or obtained from similar studies and direct measurements (Garzon et al., 2019b; Wang et al., 2019). Several influential parameters and many uncertainties involved in the process of selecting the prior drag coefficient exert challenges in the modeling process (Ascencio et al., 2022). It should be noted that incorporating prior knowledge might introduce more uncertainty into the modeling process. However, the use of C_D has the advantage of addressing unresolved factors like the swaying motion of plants (flexibility), spatial variations, the attenuation of orbital motion, array blockage, wake interaction in dense vegetation, and sheltering effects, especially in mangroves (Figueroa-Alfaro et al., 2022; Vuik et al., 2016). An alternative approach to determining C_D that eliminates the need for calibration is to use drag formulations based on Reynolds number (Re) or Keulegan–Carpenter number (KC) (Garzon et al., 2019b). (Vuik et al., 2016) and (Henry et al., 2015) reviewed some of the most common drag coefficient formula in the literature based on Re and KC. Ignoring blade flexural rigidity (Zhu et al., 2020), and absence of wave frequency (Marsooli et al., 2017) in most formulations impedes this alternative approach from becoming common practice. Furthermore, the lack of a universal formulation for different vegetation types and wave conditions further hinders widespread application (Chen and Zou, 2019; Figueroa-Alfaro et al., 2022).

The third approach, treating vegetation as a porous medium, uses a porosity term in Volume Averaged Navier–Stokes (VRANS) equations (Hadadpour et al., 2019) or in the shallow water equations to reduce the computational cost with Boussinesq-type equation and RANS model (Magdalena et al., 2021). The use of a porosity term is particularly recommended for highly complex 3D structured marine ecosystems such as coral reefs (Lowe et al., 2008; van Rooijen et al., 2022).

Besides, the inertia force is often ignored in wave-vegetation interaction models based on the Morrison equation. In shallow intertidal areas with nonlinear waves, this assumption is not valid. In particular, considering the inertia force is more important when the vegetation is dense and has low porosity (Suzuki et al., 2019). In dense vegetation fields such as dense forests, in addition to inertial forces, porosity is also of great importance (Zhu et al., 2020), as the wave attenuation capacity is reduced by inertial forces, whereas it is enhanced by porosity due to the reflective effects of vegetations (Arnaud et al., 2017). It is noteworthy that for dense vegetation such as mangrove roots or horizontal brushwood, the ability to capture the drag force induced by horizontal cylinders contributes to better simulation of such NbS (Suzuki et al., 2019).

From the aspects presented in Fig. 11, many of the relevant methods in this area still deal with issues related to flexibility and seasonality effects. Most existing numerical models and tools are based on a rigid schematization of vegetation and avoid modeling flexible plants. Therefore, considering flexibility has been one of the most challenging aspects of wetland characterization over the past decade. Flexibility plays a pivotal role in modeling of marsh ecosystems as it controls wave damping and velocity structure (van Veelen et al., 2020). In efforts to address this research need, several methodologies have been proposed to improve numerical models by increasing bottom friction (Möller et al., 1999; Smith et al., 2016); reducing drag coefficient (Jadhav et al., 2013; Losada et al., 2016; Marsooli et al., 2017; van Veelen et al., 2020); using the concept of effective blade length (Beudin et al., 2017; Lei and Nepf, 2019; Luhar et al., 2017; Luhar and Nepf, 2011); implementing cantilever beam theory (Chen and Zou, 2019; Hu et al., 2021; Mattis et al., 2019; Zhu et al., 2020); or utilizing damped oscillatory dynamic equation (Ikeda et al., 2001; Maza et al., 2013; Zhu and Chen, 2015). Addressing spatial and temporal variability of vegetations is also crucial for a realistic representation of wetlands. While the spatial variability of vegetation properties is well known in the literature, the temporal variability is not well documented and is often overlooked in numerical modeling studies. The temporal variability of vegetation properties can be attributed to seasonal growth and decay (Garzon et al., 2019a; Möller et al., 2003; Silinski et al., 2016). CCF models need to account for the actual vegetation cover, which can be low and high at low and peak biomass, respectively. Using a piecewise linear relationship or coupling vegetation characteristics with storm characteristics could be informative in this regard (van Loon-Steensma et al., 2016).

There is also an ongoing debate about the application of implicit (bottom friction) or explicit (stem drag) dissipation models. Recently, (Ascencio et al., 2022) showed that for vegetations with small stem-submergence ratio, h_v/h (i.e., vegetation height/water depth), an implicit model using enhanced bottom roughness is appropriate, whereas an explicit model based on bulk vegetation properties is preferred for vegetations with a high h_v/h. The level of uncertainty could be exacerbated due to seasonal differences in vegetation if stem drag is different between winter senescence and summer peak biomass seasons. The frequency-dependent explicit model proposed by (Jacobsen and McFall, 2019) in SWAN acts as a bridge between these two extreme conditions, reducing the need to make a single selection between them to characterize vegetation canopies. However, their model has a significant computation burden for dense vegetations (more than twice that of the simpler implicit or explicit models when vegetation cover is at least 40 %). Another potential improvement could be adding more layers in numerical models, especially in the case of mangroves since sufficient mimic requires layering different characteristics of vegetation elements in the water column (Ostrow et al., 2022). As a concluding remark, it should be noted that while the response of NbS is unpredictable due to the breadth of influential factors and increased uncertainties in the future climate conditions, current efforts are primarily focused on validating numerical models under specific storm and field conditions (Ostrow et al., 2022). To tackle this challenge, it would be informative to evaluate NbS models using synthetic scenarios that include different ecosystem conditions and vegetation morphologies, storm characteristics, water level scenarios, and potential intervention strategies.

4.2. Wave model

The mathematical models used for wave modeling can be either phase-averaged or phase-resolving. Phase-averaged models deal with waves stochastically rather than individually, often using linear wave theory in conjunction with empirical formulations derived from field or laboratory experiments (Buckley et al., 2014). Such models offer benefits in terms of computational efficiency, making them more applicable to large scale and long duration studies (Ma et al., 2013; Van Rooijen et al., 2016). Nevertheless, their approach to physically represent vegetation fields through enhanced bottom friction or a vegetation term based on local hydrodynamic conditions, vegetation characteristics and drag coefficients may appear unrealistic (Garzon et al., 2019b; Marsooli et al., 2017). Examples of these models are SWAN (Suzuki et al., 2011), WAVEWATCH-III (WW3) (Roland, 2008), and Steady State Spectral Wave (STWAVE) (Anderson and Smith, 2015). The predominant choice for the wave model in the literature is SWAN model (see Table S1 and Fig. 6). A common approach to simulating the wave-induced surge is to incorporate the effects of wind waves on storm surges by coupling an ocean circulation model (see Section 4.3) with a phase-averaged wave model. SWAN and STWAVE models are primarily designed for nearshore (shallow water) waves. Typically, they can be coupled with a deep-water wind wave model such as WAM (The Wamdi Group, 1988) or a regional scale wave model such as WW3 to generate open-water boundary conditions by extracting the wave energy spectra.

On the other hand, phase-resolving (or wave-resolving) models use conservation of mass or momentum to explicitly reproduce wave processes and can also be supplemented by empirical formulations calibrated to experimental data (Buckley et al., 2014). A key advantage of these models is that they provide velocity structures with intra-wave resolutions and can be used to directly assess the attenuation effects of vegetations. In this way, they properly model nearshore wave transformations, including wave breaking, as well as accounting for low-frequency infragravity waves (Torres-Freyermuth et al., 2012). This makes them numerically more expensive than phase-averaged models. Nonlinear shallow water (NLSW) models and full Navier Stokes (NS) equations models are two categories of phase-resolving modes (Jafarzadegan et al., 2023). NLSW models, which solve a simplified form of the NS equations, are popular for studying wave runup and overtopping due to their computational efficiency (Briganti and Dodd, 2009; Hu et al., 2000). Full NS models or their Reynolds-averaged Navier–Stokes equations, which serve as their approximate time-averaged solutions, provide a more detailed flow description. They utilize Eulerian-based techniques such as the Volume-Of-Fluid method to trace fluid-air interfaces or employ Lagrangian-based approaches such as Smoothed Particle Hydrodynamics to simulate particle interactions. However, it is essential to note that these methods are computationally intensive (Jafarzadegan et al., 2023; Rosenberger and Marsooli, 2022). As computational resources and efficiency increase, large-scale simulations of coastal wetland can benefit from these models (van Rooijen et al., 2022).

Reviewing of the literature reveals that there have been attempts to integrate an ecological model into a CCF modeling framework, such as coupled ADCIRC + SWAN + SLAMM in (Rezaie et al., 2020) or CH3D + SWAN in (Dietrich et al., 2012; Peter Sheng et al., 2022a). Relying on widely-applicable model of ADCIRC, Refs. (Alizad et al., 2018; Alizad et al., 2016; Bilskie et al., 2016) employed a coupled hydrodynamic-marsh model called Hydro-MEM. This integrated two-dimensional model projects marsh productivity, vegetation, and migration in response to sea-level rise. Additionally, the Wetland Accretion Rate Model for Ecosystem Resilience (WARMER (Swanson et al., 2014)) is a 1-D model of elevation that incorporates both ecological and physical processes of vertical marsh accretion. Buffington et al. (2021) presented an application of this modeling framework to assess elevation changes in three tidal wetlands in the San Francisco Bay estuary.

4.3. Hydrodynamic model

Hydrodynamic models are essential tools for characterizing water level fluctuations in the coastal environment. A comprehensive hydrodynamic modeling approach can be achieved by integrating ocean circulation, wave, atmospheric, and sediment transport models (Roland et al., 2012; Warner et al., 2010; Warner et al., 2008). Table S2 provides an overview of some of the widely used numerical models applicable to CCF simulation. The use of a 2D depth-averaged model is a common practice to reduce the computational burden of CCF simulations due to their applicability to large-scale circulation. However, it is important to note that a depth-averaged model is at risk of misinterpretation because it overlooks strong vertical gradients in wave velocity. This increases local turbulence induced by coastal canopy structures (van Rooijen et al., 2022; van Rooijen et al., 2020).

Typically, ocean circulation models replicate astronomical tides as well as wind- and pressure-induced water level surges (i.e., storm surge events) (Santiago-Collazo et al., 2019). The most common ocean circulation model in previous studies is ADCIRC. The robustness of this model has been successfully tested in several coastal regions (please refer to (Abdolali et al., 2022; Bilskie et al., 2022; Deb and Ferreira, 2017; Holzenthal et al., 2022) among others). ADCIRC can be coupled with WW3 or SWAN to account for the effects of short-range waves (Loveland et al., 2021). The Semi-implicit Cross-scale Hydroscience Integrated System Model (SCHISM) model (Zhang et al., 2016) is another flexible and increasingly uses hydrodynamic model. The SCHISM model is an open source modeling framework based on Navier-Stokes equations and unstructured grids. On a smaller scale, wave-resolving nearshore models that solve non-hydrostatic equations (e.g. Xbeach-NH (Roelvink et al., 2009)) or the ones that implement Boussinesq approximations (e.g., FUNWAVE (Bruno et al., 2009)) are applicable. It should be noted that the inclusion of the non-hydrostatic term in the pressure correction significantly improves the ability to properly model incident waves, run-up and overtopping (Roelvink et al., 2018). This improvement is particularly important at shallower depths where the assumption of hydrostatic pressure distribution may not be valid due to shorter wave periods (Leijnse et al., 2021). SFINCS (Leijnse et al., 2021) is another hydrodynamic model that incorporates simplified shallow water equations to simulate CCFs relatively fast and with sufficient accuracy (Leijnse et al., 2020; Röbke et al., 2021). Other alternatives include CH3D-SSMS (Peter Sheng et al., 2022b) and Delft3D (Muñoz et al., 2020; Muñoz et al., 2022), which have been used to explore the vegetation effects on CCF using spatially varying Manning's *n*.

4.4. Hydrologic model

In the hydrological cycle, runoff is an important component that regulates the flow of water into streams and redirects excess water to the oceans (Jehanzaib et al., 2022). Rainfall, temperature, watershed topography, vegetation, and hydrogeology are essential elements of a rainfall-runoff model to simulate runoff (Devia et al., 2015). Developing a reliable and efficient rainfall-runoff model can be considered as the primary challenge in CCF simulation. The complexity arises from the interplay of various physical processes such as 1D channel flow, 2D overland flow, infiltration and groundwater flow, precipitation interception, snow melting, and evapotranspiration. There is still a lack of tools and software that enable seamless integration of hydrology and storm surge models, further exacerbating the challenges.

Based on the routing calculation scheme, hydrological models can be classified into empirical, conceptual, or physics-based (i.e., process-based) models (please refer to (Devia et al., 2015) and (Li et al., 2021c) for more detail). Further, these models can be categorized into four classes according to their spatial discretization and routing scheme: lumped, semi-distributed, distributed, and fully distributed (Shen and Jiang, 2023). Lumped hydrologic models represent the entire watershed as a single unit, disregarding spatial variations in hydrological processes. One of the best models of this type is the Sacramento Soil Moisture Accounting (SAC-SMA) model, which has been used by the National Weather Service since 1973 and it is still one of the best lumped hydrologic models. Although lumped models are relatively simple and require fewer inputs, they typically underestimate the actual response of a rainfall–runoff system. Semi-distributed hydrologic models divide the watershed into multiple sub-catchments, considering spatial variations in land characteristics and runoff generation processes. This class of hydrologic models uses a 1D routing scheme, which is a highly simplified routing representation and poses a significant limitation in flood forecasts. Distributed hydrologic models further refine the representation by dividing sub-basins into computational units, so-called hydrologic response units (a.k.a. HRUs), while accounting for variations in topography, land use and soil properties. However, the use of a 1D routing scheme is their main drawback. Due to the underestimation of lumped models, the use of a distributed or semi-distributed model improves accuracy because they take into account the interconnected nature of hydrological processes, including runoff generation, snow formation and melting, groundwater recharge, evapotranspiration, soil moisture dynamics, and routing in lakes and rivers (El-Nasr et al., 2005). Finally, fully distributed hydrologic models enable spatial representation at the finest scale by dividing the entire watershed into numerous HRUs or grids, allowing for a comprehensive and detailed representation of hydrological processes across the landscape. This class incorporates a 2D routing scheme to capture runoff transport more realistically as it is more consistent with the runoff routing. This feature and requirement of reach dataset incurs a much higher computational cost compared to the lumped, semi-distributed or distributed models.

The Hydrologic Engineering Center- Hydrologic Modeling System (HEC-HMS) model (Scharffenberg and Fleming, 2006) and the Storm Water Management Model (SWMM) (Rossman, 2010) are the two widely-used conceptual-based lumped-parameter hydrologic models. For long-term modeling, a physics-based, semi-distributed, continuous simulation model, the Soil and Water Assessment Tool (SWAT; (Arnold et al., 1998)), can be used to predict the impacts of land management practices on water, sediment, and agricultural chemicals in large complex watersheds on a daily basis. Because SWAT is typically executed in a daily or sub-daily time steps, the model can be run on a decadal scale (Johnson et al., 2023). In addition, this model has been used to quantify rainfall-runoff flooding events when linked to other hydraulic models such as HEC-RAS and LISFLOOD-FP, and also to determine river discharges when used independently (Santiago-Collazo et al., 2019). In the category of physically-based, distributed-parameter hydrologic models, one of the prominent models is the Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model (Downer et al., 2003). The fully distributed GSSHA model is intuitively more realistic compared to a lumped HEC-HMS model in terms of land use change (Sith and Nadaoka, 2017). Additionally, GSSHA has been successfully applied to small to medium-sized watersheds (e.g. acres to a 1000 mile^2) and/or for seasons and design years (e.g. annual record periods of high, medium, and low rainfall intensity) (Johnson et al., 2023; Pradhan et al., 2014; Sharif et al., 2010). Likewise, the MIKE-SHE (Danish Hydraulic Institute, 2014) and the Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM) (Colorado Basin River Forecast Center, 2008) are other fully distributed alternatives. On the other hand, Interconnected Channel and Pond Routing (ICPR) is a physically-based distributed model that can provide a computationally efficient approach for large-scale flood modeling (Joyce et al., 2018; Saksena and Merwade, 2022; Saksena et al., 2021).

4.5. Hydraulic model

The resulted runoff from the hydrological model can be fed into either the hydraulic model or the ocean circulation model, allowing simulation of water level or inundation extent (Dresback et al., 2013). Thus, it is imperative to first estimate rainfall-runoff in the hydrologic domain and then, transport it using a routing scheme. Nonetheless, flood modeling has limitations because the hydrologic models fail to consider the actual physical properties of the rivers in the routing scheme. Therefore, hydraulic models such as HEC-RAS (Warner and Brunner, 2001), MIKE 11 (Havnø et al., 1995), FLO-2D (O'Brien et al., 1993) and LISFLOOD-FP (Bates et al., 2005) have been used to simulate floods together with hydrologic models due to their reliance on the channel and floodplain topography, aligning with principles of continuity and momentum while requiring minimal parameters (Nguyen et al., 2016). Using a 2D version of these tools with rain-on-grid options could also be an interesting alternative. However, extensive application of these models is hampered by the fact that they do not incorporate hydrologic fluxes and the full range of physical processes in CCF (Tanim et al., 2022). Using the discontinuous Galerkin shallow water equations model (DG-SWEM) (Dawson et al., 2011), the discontinuous Galerkin Section-Averaged Kinematic wave Eq. (DG-SAKE) (West et al., 2017), deep neural networks (e.g., using long-short-term-memory (LSTM) (Lee et al., 2023a; Li et al., 2021a; Li et al., 2021b), or HRU-based LSTM (Abbas et al., 2020)) are other alternatives for the runoff transport model.

4.6. Groundwater model

In addition to fluvial (river) flooding, pluvial (surface) flooding, and coastal flooding, the interaction of groundwater flooding can also increase the likelihood of CCFs (Peña et al., 2022). This phenomenon causes the water table in permeable rocks to rise to reach cellars or over the surface and can last for weeks or even months. The contribution of surface-subsurface interactions from permeable soil strata is often neglected in CCF models. Regions that lie on permeable rocks are particularly affected by groundwater flooding. Although these events are rare, the significant consequences arising from these events and their potential complex interactions with other flood drivers emphasize the importance of incorporating groundwater flooding into CCF models. This is particularly crucial for areas prone to groundwater leaks. Failure to do so may result in substantial uncertainty in estimating flood risk in terms of magnitude, timing and overall assessment. ModelMuse (Winston, 2009) and MODFLOW (McDonald and Harbaugh, 1988) can be used to incorporate groundwater flooding. The detailed description of groundwater models is beyond the scope of this review.

4.7. Hybrid CCF model

Another challenge associated with coupling process-based models is their numerical cost. Although substantial headway has been achieved, process-based models face limitations due to the requirements for accurate geographic data, proficient users capable of creating the computational mesh and input files, and performing computationally demanding calibration and inference processes (Li, 2021). This computational complexity stems from the multitude of parameters, forcing conditions and uncertainties involved, process-based models can be numerically expensive (Bilskie et al., 2022; Bilskie et al., 2021; Huang et al., 2021; Ye et al., 2020). These costs depend heavily on the grid size as the most influential parameter in accurately simulating flood dynamics (Alipour et al., 2022). Therefore, in many cases a trade-off between model accuracy and computational effort is unavoidable. In response to the limitations associated with process-driven models, there have been several attempts in recent years to leverage machine learning, data-driven and statistical methods in establishing a hybrid compound flood model. This hybrid modeling framework consist of a coupling between a hydrodynamic model and a data-driven model, a statistical model or a physics-informed machine learning model (Jafarzadegan et al., 2023). Recent efforts in this category of hybrid models have been based primarily on random forest algorithm (Zahura and Goodall, 2022; Zahura et al., 2020), support vector machines (Bermúdez et al., 2019), convolutional neural network (Lee et al., 2021; Muñoz et al., 2021), and also, data assimilation schemes, e.g., using combination of the ensemble Kalman filter (EnKF) technique (Jafarzadegan et al., 2021a) and the Delft3D hydrodynamic modeling in (Muñoz et al., 2022). Also, Ref. (Li, 2021) proposed a two-way coupling scheme of RNN runoff model and ADCIRC.

Combining statistical approaches with process-based models to develop hybrid models is also strongly recommended (Moftakhari et al., 2019; Serafin et al., 2019). Using copulas in this approach facilitates flexibility in selecting marginal distributions and modeling nonlinear dependencies (Hao and Singh, 2016). Such features favor the wide application of copulas in exploring the of coastal ocean water level and freshwater discharge, coastal water level and waves, storm surge and river flow, storm surge and river flow with precipitation, storm surge and precipitation, wave/surge parameters, and storm surge, wave, river flow and precipitation ((Jafarzadegan et al., 2023) discussed further details). Despite all benefits of joint density approaches, the sufficient number of realizations that adequately cover the wide range of compound hazard scenarios remains a major obstacle in these models. To tackle this challenge, using reduced physics surrogate modeling (Anderson et al., 2021; Bass and Bedient, 2018), utilizing HPC systems to generate numerous scenarios based on Monte Carlo simulation (Yang et al., 2020), merging joint cumulative distribution functions and joint probability density functions to implement informed sampling (Moftakhari et al., 2019; Muñoz et al., 2020; Sadegh et al., 2018) may be of interest (Jafarzadegan et al., 2023).

Non-stationarity also plays a critical role in linking statistical and hydrodynamic models. Warming climate may undermine stationarity assumption of extremes, making it invalid (Barbier et al., 2013; Cheng et al., 2014; Tan and Gan, 2017). This problem will be more acute, particularly for compound flooding, as multiple components interact and neglecting non-stationarity, if present, could result in significant over- or underestimation of flood risk. Table 1 summarizes the relevant literature dealing with the impacts of non-stationarity in compound flood modeling. The results are based on a recent review paper by (Radfar et al., 2023) and have been extended to the end of 2022. At first glance, it can be seen that incorporating non-stationary extreme value analysis (hereafter, NEVA) into the CCF framework has attracted considerable attention in recent years. However, the number of publications to date is very limited and this is an area that requires further research. One of the major limitations in advancing this topic is the paucity of long overlapping data records. This motivates to use process-based models, hindcast or reanalysis data to achieve a long and homogenous observation record. As a rule of thumb, at least 25 to 30 years of continuous data is required for 100-year multivariate estimates (Radfar et al., 2021; Vanem, 2015), but for reliable capturing of long-term trends and variations, availability of 60–70 years of data is a prerequisite (Calafat et al., 2022; Obeysekera and Park, 2013).

It is noteworthy that the tendency to consider the non-stationarity of rainfall is consistent with the findings that the uncertainty in a non-stationary framework is determined primarily by rainfall and not by sea level and its dependence (Naseri and Hummel, 2022). Also, it can be observed that the consideration of non-stationarity in the parameters of the GEV model is extremely common in the CCF modeling framework, and deploying other types of extreme value models is almost unaddressed in the relevant literature. Further investigations is needed to test the applicability of other extreme value models, such as GP (with time-varying scale and shape parameters), mixture models (e.g., GP-Poisson, GP-Normal, GP-Gamma) or 4-parameter kappa distribution (Radfar et al., 2023). Moreover, integration of non-stationarity was mainly done through the location parameter of the GEV distribution. This approach only addresses the variations in the mean values of the variables. Therefore, performing NEVA based on a single time-varying parameter may not adequately capture the trends and variations and requires further improvements to overcome the challenges and uncertainties

Table 1
Categorization of the studies that implemented NEVA within compound flood modeling framework.

Reference	Estimated variable	Covariate(s)	Model	Nonstationary parameter	Using simulation data	Bayesian approach
(Chapon and Hamdi, 2022)	Surge, Wave height	SLP, SST, Wind speed	PP	μ, σ, ξ	–	Yes
(Xu et al., 2022)	Rainfall, Storm tide	Time (linear)	GEV	μ	–	–
(Naseri and Hummel, 2022)	TWL, Rainfall	Time (linear)	GEV	μ	–	Yes
(Razmi et al., 2022)	ESL, Rainfall	Temperature, Time (logarithmic)	GEV	μ, σ, ξ	–	–
(Karamouz and Mahani, 2021)	TWL, Rainfall	Time (linear)	GEV	μ	Yes	–
(Ghanbari et al., 2021)	ESL, River flow	SLR, Time (linear)	GP	u	–	–
(Karamouz and Mohammadi, 2020)	Rainfall, Surge	SOI, SST, Time (linear, polynomial)	GEV	μ, σ	–	–
(Karamouz et al., 2020)	Rainfall, Surge	Time (linear)	GEV	μ	–	Yes
(Binh et al., 2019)	TWL, Rainfall	ENSO, PDO, SLR, Global warming, LMT	GEV	μ, σ	–	–
(Karamouz et al., 2017)	TWL, Rainfall	Time (linear)	GEV	μ	–	–

* **ENSO**: El Niño Southern Oscillation index; **ESL**: extreme sea level; **GEV**: generalized extreme value distribution; **GP**: generalized Pareto distribution; **LMT**: local mean temperature; **PDO**: Pacific Decadal Oscillation; **PP**: point process approach; **SLP**: sea level pressure; **SLR**: sea level rise; **SOI**: Southern Oscillation index; **SST**: sea surface temperature; **TWL**: total water level.

** μ, σ, ξ: location, scale, and shape parameters in the PP and GEV extreme value model; u: threshold parameter in the GP model.

around detecting a non-stationary behavior (Naseri and Hummel, 2022; Wong et al., 2022). Improper model selection and parameters' estimation as well as the relatively short records can majorly contribute to the uncertainty of the NEVA estimates (Liu et al., 2018; Serinaldi, 2013). To circumvent this problem, the Bayesian approach was applied in the NEVA framework of three studies (see Table 1) to reduce the uncertainty resulting from the extreme value models. Finally, it can be seen that the most common assumption for covariates is that parameters of extreme value distributions change linearly over time. Nevertheless, it is known that time covariates are poorly suited to capture trends and variations in hydrological and oceanic parameters and only maintain constant patterns (Du et al., 2015). Therefore, it is imperative to include physically-based covariates in the NEVA models to gain insights into the physical driving mechanisms that generate the observed sequence or signal (Agilan and Umamahesh, 2017; Bayazit, 2015). To resolve this issue, several studies incorporated temperature, SLR or climatic indices, such as SOI, PDO and ENSO in their models. Despite this, investigating the impacts of this type of covariates, particularly climatic variables, in the CCF modeling framework is a research gap and it would be an active field of research over the coming years.

4.8. Uncertainties involved in CCF modeling

Despite the significant advantages of CCF modeling, the existence and cascade of uncertainties in hydrologic and hydrodynamic modeling should be taken seriously. Parameter estimation problems due to non-uniqueness of model parameters resulted from calibration (referred to as un-identifiability) (Moradkhani et al., 2018), structural uncertainty, including model inadequacy (Abbaszadeh et al., 2019; Kennedy and O'Hagan, 2001; Pathiraja et al., 2018) and model discrepancy (Smith et al., 2015)), and measurement uncertainty (Gupta and Govindaraju, 2019; Moradkhani et al., 2018) are important elements of hydrologic uncertainties. Besides hydrodynamic uncertainties may originate from initial state of the system (i.e., topobathy data errors and inadequacies) (Bates, 2022; Gallien et al., 2018; Holmquist and Windham-Myers, 2022), observational, forcing data and boundary condition (Flowerdew et al., 2009; Jafarzadegan et al., 2021b; Oruc Baci et al., 2024; Pappenberger et al., 2005; Saleh et al., 2017), model parameters (e.g., bed roughness, surface friction, and sea surface (wind) drag), and model structure (due to limitations and simplifications in the physically-based modeling) (Moradkhani et al., 2018). Among these parameters, input data is recognized as a major source of uncertainty and error in the CCF modeling process. The accuracy of the input data has a great impact on the modeling process. For example, (Eilander et al., 2022) listed bathymetry in data-scarce areas as an important source of uncertainty in their SFINCS model. They suggested using bathymetry estimation approaches such as gradually varying flow theory-based method (Garambois and Monnier, 2015; Neal et al., 2021) instead of approximation methods in areas with no or insufficient local measurements. Also, a subgrid schematization improves model performance in streams smaller than the model resolution (Neal et al., 2012; Volp et al., 2013). Lack of information about the locations and specifications of flood protection structures can significantly affect the accuracy of the flood model (Scussolini et al., 2015; Wing et al., 2019). Further, forcing data into ungauged areas should be carefully considered to reduce uncertainty in modeling (Hoch and Trigg, 2019; Wing et al., 2020). Different methods can be incorporated to deal with uncertainties, including Monte Carlo method (e.g., traditional Monte Carlo, Latin hypercube sampling and Multi-level Monte Carlo in (Aitken et al., 2022)), Generalized Likelihood Uncertainty Estimation (e.g., generalized extreme value and generalized logistic in (Ellis et al., 2021)), Data Assimilation (Abbaszadeh et al., 2020; Abbaszadeh et al., 2018)), and post-processing methods like Bayesian Model Averaging(Liu and Merwade, 2019; Madadgar and Moradkhani, 2014; Madadgar et al., 2014), or Sequential Bayesian Combination in (DeChant and Moradkhani, 2014; Hsu et al., 2009)' and multivariate copulas in (Tanim and Goharian, 2021)). With regard to ecological feedback, parametrization of vegetations (i.e. the definition of roughness coefficients) and time-dependent updating of vegetation characteristics represent a significant uncertainty. All in all, uncertainty quantification is still an area of active research in the field of CF modeling and still requires much more research efforts.

4.9. Research-to-operation gap

Despite the recent advances reviewed here, significant challenges still need to be faced to comprehensively and efficiently model CCF. The challenges include navigating the complex environment, managing computational costs, and addressing a shortage of experts and sufficient data. The individual models to understand overland flooding, coastal water levels, and storm surges are at an operational capacity for near-term forecasting and for assessing the performance of hazard mitigation approaches. Unfortunately, the coupling of these approaches to provide estimates of the compound flood risk is not operational. There is substantial support through funding agencies (e.g. federal and state resources in the US) being applied toward advancing compound flood models capable of evaluating policy decisions and restoration activities that include nature-based flood mitigation approaches. However, most efforts are local and in a research phase. The modeling community has yet to reach a point where they have consistent approaches to inform CCF decision-making.

In addition to the models' advancement as recommended above, there remains a need to develop the models with those that will be users of the information. We still lack the foundational literature and evaluation of what coupled models are most effective at informing decisions. It is not enough to advance modeling in an academic space, they need to be codeveloped with stakeholders to ensure the outputs are actionable, consider the scenarios relevant to decisions, and are trusted. Preliminary studies that have involved end user feedback, highlighted a need for common language and understanding between researchers and stakeholders on the importance of compound flood modeling and what coastal water level and precipitation scenarios are most useful to different types of decisions. An example of such approaches is underway in coastal Alabama, where together modelers and stakeholders identified four general compound flood scenarios to be studied that balance computational rigor with utility of the information (Lee et al., 2023b; Moftakhari et al., 2024). This included a moderate probability storm surge with a moderate probability precipitation event, both opposite low probability and high probability combinations of surge and precipitation, and low probability extreme water level and precipitation combinations. This provided end users with additional information for short-term and long-term hazard mitigation with each scenario providing different perspectives. For example, in the case of the low-probability extreme compound flood events, there is limited opportunity to avoid the damage predicted; however, it can inform conversations around land acquisition, policy decisions on zoning or buy outs, or protection of critical facilities.

Beyond the specific flood scenarios, there are other critical aspects co-development can provide to enhance the usability of CCF outputs. For example, working toward faster assessments of flood mitigation strategies will enhance the use of these models in planning and decision-making. Additionally, more work is done to understand how best to integrate CCFs into forecasting and public warnings. The process of collaborating with end-users as the foundation of CCF modeling is built, will speed up adoption of these models when they have reached an operational readiness stage.

5. Conclusions

This study reviews the existing numerical modeling studies for simulating NbS against CCF. To expand our knowledge of NbS performance against CCF hazard, we recommend more efforts toward coupling various components affecting CCF while considering and simulating NbS. Major challenges in assessing the NbS impacts on the CCF mitigation in a numerical model are (a) sufficient mimic of vegetation dynamic, accounting for plant characteristics (including its dimension, motion, flexibility, and seasonality) as well as hydrodynamic and storm conditions (Section 4.1), (b) selection of a tool with adequate representation of underlying physics, vegetation characteristics, morphology and hydrology (Sections 4.2 and 4.3), (c) coupling of different model with effective information exchange during model execution process (Sections 4.4 to 4.6).

Various approaches to mimic NbS including bottom friction techniques, modeling vegetation as structural elements, and considering vegetation as a porous medium, have limitations, such as uncertainties with time-varying roughness and computational effort (Section 4.1). Strategies such as 3D parameterization, sensitivity analysis, and development of universal formulations could improve predictability and effectiveness. Modeling wave-vegetation interactions is also challenging because it oversimplifies the flexibility and variability of plants over time. Potential solutions include improving the representation of bottom friction, adjusting drag coefficients, applying the effective blade length concept, and using cantilever beam theory and piece-wise linear relationships.

Aside from the challenges of ecological modeling, CCF modeling per se requires meticulous setup and calibration to fully integrate ecological, hydrological, hydraulic and hydrodynamic processes (Sections 4.2 to 4.5). Hybrid approaches can help with high computational costs and difficulties in harmonizing dynamic interactions in purely process-based models, but they have limitations in data availability, non-stationarity, and nonlinear interactions (Section 4.7). Dealing with structural, model and measurement uncertainties, particularly due to the time-varying properties of vegetations should be given serious consideration (Section 4.8).

From a broader perspective, there is an important research-to-operation gap that the modeling community not yet reached the point of having consistent approaches to inform CCF decision making (Section 4.9). To address this challenge, it is crucial to develop models collaboratively with end-users and ensure actionable results that consider relevant scenarios and are trustworthy. Through collaborative development efforts specific CCF scenarios can be identified that balance computational power with practical utility. Additionally, co-development can improve the usability of CCF outputs by accelerating the assessment of flood mitigation strategy and improving integration into forecasts and public warnings. It is expected that collaborating with end-users lays the foundation for CCF modeling adoption, speeding up the transition to operational readiness.

CRediT authorship contribution statement

Soheil Radfar: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Sadaf Mahmoudi:** Validation, Writing – original draft. **Hamed Moftakhari:** Conceptualization, Methodology, Resources, Writing - Review & Editing, Supervision, Funding acquisition. **Trevor Meckley:** Methodology, Writing – review & editing. **Matthew V. Bilskie:** Methodology, Writing – review & editing. **Renee Collini:** Writing – review & editing. **Karim Alizad:** Writing – review & editing. **Julia A. Cherry:** Writing – review & editing. **Hamid Moradkhani:** Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Hamed Moftakhari reports financial support was provided by The University of Alabama. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary data

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