TROPICAL STORM SURGE: FORMATION, IMPACT, AND RECENT ADVANCES IN ITS PREDICTION TOWARDS DEVELOPING MITIGATION STRATEGIES

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Abstract

Tropical storm surge poses significant risks to coastal areas, necessitating precise prediction for effective emergency preparedness and mitigation. Recent advances in numerical models such as SLOSH, ADCIRC, and FVCOM have revolutionized storm surge forecasting by accurately simulating complex hydrodynamic processes, bolstered by ADCIRC's use of high-resolution grids and parallel computing for enhanced predictive capabilities crucial in emergency management. Hybrid models that integrate numerical simulations with statistical and machine learning techniques further refine forecasts, utilizing real-time observational data to correct biases and improve initial conditions dynamically. Artificial Intelligence (AI) and machine learning, particularly neural networks like CNNs and RNNs, play pivotal roles in improving prediction accuracy by analyzing spatial and temporal data from diverse sources, thus facilitating real-time data assimilation critical for operational forecasting systems. Future advancements are expected to deepen AI integration, refine data assimilation, and enhance global accessibility to real-time storm surge data, promising increased resilience and improved disaster response strategies worldwide.

Keywords

Storm Surge, Tropical, Modeling, Artificial Intelligence

Introduction

A tropical storm surge is a sudden and temporary rise in coastal water levels caused by a storm, surpassing normal tidal heights [1]. Tropical storms are circular storms that form over warm ocean water in tropical regions, such as cyclones in the South Pacific and Indian Ocean, typhoons in the Northwest Pacific Ocean, and hurricanes in the North Atlantic Ocean and Northeast Pacific [2]. These storms have low air pressure, strong winds, and heavy rain, deriving their energy from warm ocean water and requiring sea temperatures of at least 27°C to form and intensify [3]. Tropical storms mainly affect coastal areas with high winds and storm surges [4]. The height of a typical storm surge varies depending on the storm's intensity, ranging from 1 meter to over 5 meters (3 to 25+ feet), lasting from a few hours to three days [5,6].

Studying tropical storms is crucial due to their profound impact on densely populated coastal regions. Tropical storms can cause significant damage and are associated with dangerous conditions, especially when they make landfall [7]. These storms can cause significant human casualties and displacement, extensive damage to infrastructure, and long-term economic disruptions, particularly affecting industries like tourism, agriculture, and shipping [8-13]. The environmental effects are also notable, with tropical storms transforming ecosystems such as coral reefs and coastal wetlands [14]. The ability to predict and prepare for these storms is vital for minimizing loss of life and property, necessitating advanced forecasting models and effective disaster preparedness strategies.

Moreover, tropical storms offer valuable insights into broader meteorological and climate patterns [15]. They develop and intensify rapidly, posing unique challenges for accurate prediction and highlighting the need for improved data collection and technological advancements [16,17]. Studying these storms helps us understand the impact of climate change on storm frequency, intensity, and behavior. This research is essential not only for immediate disaster response but also for long-term climate resilience and adaptation strategies. Therefore, this review article aims to understand the fundamentals of storm surges, their impacts, and adaptive strategies for coastal resilience. It explores factors driving storm surge dynamics, examines historical events, and evaluates engineering solutions. Additionally, it highlights the role of AI in enhancing storm surge forecasting and mitigation efforts. By synthesizing current research and future directions, this review will make efforts to inform strategies for mitigating storm surge risks and safeguarding coastal communities and ecosystems.

Formation Factors

Understanding the factors influencing storm surge formation is of utmost importance, as it helps authorities and communities better prepare for and mitigate the impacts of these devastating natural events. Several key factors influence the extent to which storm surge penetrates inland [18], such as, wind speed (higher winds result in larger surges), atmospheric pressure (lower pressure causes a greater bulge in the ocean, leading to surge), coastal topography (greater curvature inward leads to larger surges), speed of the hurricane (slower hurricanes produce more significant surges), seafloor topography (shallower seafloors result in larger surges), and hurricane trajectory (direct impact amplifies surge size).

Storm surge formation arises from a synergy of meteorological and oceanographic components. Central to this process is the wind, which propels water toward the coast during tropical cyclones. Onshore winds, blowing from the ocean to the land, notably contribute to heightened storm surges. Simultaneously, atmospheric pressure, along with the size and speed of the storm, plays a pivotal role. The low pressure at the storm's core permits the sea surface to rise, intensifying the surge [19]. According to A. Musinguzi and M. K. Akbar, [20] the forward speed of a storm can either enhance or diminish wind intensity, depending on its direction. When hurricane winds align with the storm's forward speed, they mutually reinforce each other, potentially amplifying wind strength. This combined effect may lead to heightened storm surges, particularly on the hurricane's right side. Larger storms with slower forward movement tend to produce more significant surges, affecting both their duration and reach [19]. Coastal geography, including coastline shape and underwater topography, also shapes the surge's height and breadth. Narrow and shallow coastal areas may experience more substantial surges compared to wider and deeper regions [21].

Additionally, tidal conditions, the storm's distance from its center, and the Coriolis Effect contribute to the intricacies of storm surge dynamics. The storm's arrival timing concerning the tidal cycle, along with the Earth's rotational effect, amplifies the surge's intensity [22]. The mechanics behind storm surge formation during tropical cyclones involve a complex interplay of atmospheric and oceanographic forces. At its core lies the low atmospheric pressure at the cyclone's center, invoking the inverse barometer effect and causing a gravitational sea level rise. A decrease in atmospheric pressure of 1 mbar will produce an increase in sea level of around 1 cm [23]. Concurrently, the cyclone's powerful winds induce Ekman transport, setting the ocean surface in motion due to the Coriolis Effect. This wind-driven transport, combined with the Earth's rotation, causes water accumulation on the storm track's right side in the Northern Hemisphere and the left side in the Southern Hemisphere. The resulting surge, intensified by Ekman transport and the Coriolis effect, leads to an abnormal sea level rise along the coast [24]. This intricate interplay of atmospheric pressure, wind-induced ocean currents, and the Earth's rotation underscores the complexity of storm surge dynamics, necessitating a comprehensive understanding for precise prediction and effective mitigation in vulnerable coastal areas.

Impact on Coastal Areas

In the face of escalating climate change threats, storm surges have become a formidable force, causing devastating consequences for coastal communities and ecosystems. Rising sea levels and increasingly frequent extreme weather events lead to coastal inundation, flooding, and erosion, posing significant threats to life and property [25]. The resulting flooding displaces communities, disrupts livelihoods, and leaves a trail of destruction. Additionally, the erosive power of storm surges erodes coastal landmasses and imperils delicate habitats [26], threatening the integrity of coastal ecosystems and amplifying vulnerability to future flooding and storm events.

Coastal communities confront mounting threats to their homes, livelihoods, and cultural heritage due to rising sea levels and increasingly frequent and severe extreme weather events. The devastation wrought by Hurricane Katrina in 2005 serves as a poignant example, displaying chronic mental health effects that persist long after the disaster [27]. Furthermore, climate change exacerbates these risks, accelerating flood threats in the coming decades. Intensifying storm surges and inundating low-lying feeder roads, as evidenced by Cyclone Sidr's impact on Bangladesh in 2007, hinder people's mobility and amplify the challenges faced by coastal communities. The cyclone claimed the lives of more than 3,000 people and affected over 6 million individuals, destroying nearly 300,000 homes, damaging about 900,000, and ravaging approximately 350,000 hectares of cropland [28].

Saline intrusion into freshwater resources presents a secondary but no less significant consequence of storm surges and rising sea levels. As sea levels continue to rise, coastal aquifers and surface water bodies face increasing pressure from encroaching saltwater. This intrusion compromises the quality and suitability of freshwater for various essential purposes [29]. The salinization of freshwater sources renders them unfit for drinking, agricultural irrigation, and industrial use, posing profound challenges to the livelihoods and well-being of coastal communities [30]. Consequently, coastal populations reliant on these freshwater resources for their daily needs face heightened risks of water scarcity and contamination[31].

Storm surges profoundly affect coastal ecosystems, jeopardizing their delicate balance. The forceful inundation of seawater during storms threatens vital habitats like mangroves, salt marshes, and coral reefs. Research on the effects of hurricanes on wetlands, such as Hurricane Sandy, revealed significant wetland degradation in New Jersey, leading to the loss of ecosystem services [32]. Mangroves and salt marshes, critical for coastal protection and biodiversity, face stress and habitat loss from prolonged exposure to high salinity levels and erosion [33]. Coral reefs, already vulnerable, suffer damage and mortality from surging waves, sedimentation, and pollution [34].

These impacts disrupt habitats, diminish biodiversity, and compromise ecosystem services, necessitating urgent conservation measures for resilience and recovery.

Coastal infrastructure, comprising vital lifelines such as roads, bridges, ports, and buildings, stands vulnerable to storm surge impacts. Insights from Hurricane Katrina highlights the vulnerability of coastal communities and infrastructure. A study by Padgett et al. underscores common failure modes in highway bridges [35], such as span shifting or unseating due to surge and wave loading, as well as extensive damage caused by debris and equipment failure. Over 44 bridges in Alabama, Louisiana, and Mississippi, with hundreds of affected spans, were damaged at an estimated cost of over $1 billion [35]. The relentless force of inundation, flooding, and erosion inflicts widespread damage and destruction. Property damage from these events can be extensive, imposing significant financial burdens on individuals, businesses, and governments [13]. Moreover, the disruption to coastal infrastructure can reverberate far beyond the immediate aftermath of the storm, disrupting transportation networks, impeding economic activities, and hampering emergency response efforts during natural disasters.

Storm surges play a pivotal role in shaping economic outcomes. Past events underscore their significance in causing economic impact through the destruction of land and buildings, contamination of freshwater sources with saltwater, disruption of transportation infrastructure, and endangerment of human life, safety, and health [18,31,36-38]. There is a concerning upward trend in direct economic losses over time, primarily driven by factors such as economic and population growth, with some studies pointing to climate change as a contributing factor. Beyond their immediate impacts, storm surges leave lasting economic consequences. For instance, research reveals persistent negative effects on GDP growth even two decades after a cyclone strikes [39]. These long-term repercussions emphasize the critical need for comprehensive disaster preparedness and mitigation strategies to mitigate the economic toll of storm surges and bolster resilience in coastal areas [13].

Historical Events

Detailed learning of historical events serves as critical lenses through which we can comprehend the multifaceted nature of storm surges, highlighting their profound impacts and unveiling regional disparities influenced by geographical and climatic factors. Studying notable storm surge events helps us gain profound insights into the severity of consequences and the efficacy of mitigation measures employed in various regions. Table 1 summarizes the extent in wind speed and height of surge, human and financial cost of major historical storm surges as shown below.

Table 1. Major storm surge events, extent, financial cost, and human impact

Event, Year	Effected Area	Extent		Human Cost	Financial Cost
		Peak Wind Speed (in mph)	Storm Surge Height (ft)		
Super Typhoon Haiyan, 2013	Palau, Philippines, Vietnam and China	195	24.6	14.1 million people were affected, and 6,190 people lost their lives.	US $12 billion.
Hurricane Katrina, 2005	New Orleans, Biloxi, Gulfport, Bay St. Louis, Mobile, and areas in South Florida in America.	175	27.8	1800 fatalities.	US $125 billion.
The North Sea also known as The Big Flood, 1953	Netherlands, Belgium, the United Kingdom, and parts of Germany.	144	4-6 [40]	Over 2,500 fatalities.	Estimated damages were around £50 million (equivalent to about £1.2 billion in today's money).
Cyclone Nargis, 2008	Myanmar, Bangladesh and India.	161	9-13	Over 138,000 fatalities.	Over US $10 billion.
Cyclone Amphan, 2020	India, Bangladesh.	149	16	Over 100 fatalities.	Over US $13 billion.
Hurricane Maria, 2017	Puerto Rico, Dominica, and other parts of the Caribbean.	155	6-9	Over 2500 fatalities.	Approximately US $91.61 billion.
Hurricane Sandy, 2012	Caribbean and East Coast, USA	115	13	233 fatalities.	US $70 billion.

Hurricane Katrina (United States)

The devastating storm surge caused by Hurricane Katrina, which struck the Gulf Coast in 2005, resulted in widespread destruction, claiming over 1800 lives and causing approximately $125 billion in damages. This storm surge was particularly devastating due to the low-lying coastal plain topography, with surge waters reaching a height of 9.1 meters along the Mississippi coast [41]. Hurricane Katrina reached maximum sustained winds of 175 miles per hour (280 kilometers per hour) when it was at its peak intensity over the Gulf of Mexico. At landfall, Katrina's winds were about 125 miles per hour (200 kilometers per hour) when it struck the Gulf Coast of the United States [42]. The city of New Orleans, with its unique geographical features such as its below-sea-level elevation and proximity to coastal waters, experienced catastrophic flooding, highlighting the vulnerability of urban areas to storm surge hazards.

Hurricane Sandy (Caribbean and United States)

Hurricane Sandy, which struck the Caribbean and the East Coast of the United States in 2012, was one of the most destructive storms in recent history. Affecting countries such as Jamaica, Cuba, Haiti, the Bahamas, and the United States, Sandy brought widespread devastation. With maximum sustained winds reaching 115 miles (185 km) per hour, Sandy caused significant damage across multiple regions. The storm surge reached up to 4 meters (13 feet) in parts of New York and New Jersey, leading to extensive flooding and infrastructure damage. The financial cost of the hurricane was estimated at $70 billion, making it one of the costliest hurricanes on record. In terms of human cost, Hurricane Sandy resulted in 233 fatalities, highlighting the severe impact of the storm on affected communities [43].

The 1953 North Sea Flood

The 1953 North Sea Flood, also known as The Big Flood, stands as another significant historical event demonstrating the profound impacts of storm surges. This catastrophic event, triggered by a combination of high spring tides and a severe windstorm, resulted in widespread flooding along the coastlines of the Netherlands, Belgium, and the United Kingdom. Over 2,500 people lost their lives, and extensive damage was inflicted on coastal communities, including the breaching of sea defenses and inundation of low-lying areas [44]. The geographical characteristics of the North Sea region, characterized by low-lying terrain and densely populated coastal areas, exacerbated the effects of the storm surge. Furthermore, inadequate coastal defenses and insufficient preparedness contributed to the severity of the disaster [40]. The 1953 North Sea flood prompted significant investments in coastal protection infrastructure and the development of sophisticated flood risk management strategies in affected countries [45].

Hurricane Maria (Puerto Rico)

Hurricane Maria, a Category 4 storm, made landfall in Puerto Rico on September 20, 2017, bringing sustained winds of 155 mph (250 km/h). It caused catastrophic damage, including the complete collapse of the island's electrical grid for more than 10 months, resulting in the longest blackout in U.S. history. Communication systems were severely disrupted, with 85% of cell towers down, and many roads rendered impassable. The total financial cost is estimated between $90 billion and $95 billion, making it one of the costliest hurricanes in U.S. history [46]. The storm surge height in Puerto Rico was reported to be as high as 6 to 9 feet (1.8 to 2.7 meters) [47]. The official death toll stands at around 2,975, although some estimates suggest higher figures due to indirect effects such as lack of medical care and clean water.

Cyclone Amphan (India and Bangladesh)

Cyclone Amphan, a powerful tropical cyclone, made landfall in India and Bangladesh in May 2020, causing widespread devastation and loss of life [48]. The cyclone was classified as a super cyclonic storm, with sustained winds over 240 km/h and gusts up to 265 km/h. It resulted in an official death toll exceeding 100 fatalities and inflicted extensive damage to infrastructure, homes, and agricultural lands. The storm surge reached up to 5 meters in some areas, exacerbating the flooding and destruction along the coastlines. Damage estimates from Cyclone Amphan exceeded US $13 billion, making it one of the costliest cyclones ever recorded in the North Indian Ocean region.

Cyclone Nargis (Myanmar)

Cyclone Nargis, a Category 4 tropical cyclone with sustained winds over 210 km/h and gusts up to 260 km/h, made landfall in Myanmar on May 2, 2008, causing the worst natural disaster in the country's recorded history. The official death toll exceeded 138,000 fatalities, and damage estimates exceeded $10 billion, marking it as the most destructive cyclone ever recorded in the Indian Ocean [49]. Cyclone Nargis unleashed approximately 600 millimeters of rain and a 3-4 meter storm surge upon the low-lying and densely populated Irrawaddy River delta, intensifying the flooding and devastation in the area [50].

Super Typhoon Haiyan (Philippines)

In the Philippines, storm surges have caused significant fatalities, making Super Typhoon Haiyan one of the deadliest in history. With maximum sustained winds at landfall measuring 195 miles (315 km) per hour, Haiyan was among the most powerful tropical cyclones ever recorded, if not the most powerful, to strike land. The storm surge reached up to 7.5 meters (24.6 feet) in coastal towns, including Tacloban, where the maximum surge was 7 meters (23 feet). This led to the deaths of more than 6,300 people and displaced over 4 million people, many of whom were permanently displaced. The storm damaged 1.1 million houses, with about half destroyed, and wiped out 33 million coconut trees. More than 14 million people were affected, with 2.3 million pushed into poverty. The estimated damage was around US $13 billion [51,52]. Overall, storm surges inflicted average annual losses of US $968,000 from 1970 to 1986 in the Philippines [53]. The Philippines' low-lying islands, extensive coastlines, and gently sloping concave coastlines amplify the impact of storm surges. Additionally, its geographical location in the southwestern part of the Northwest Pacific basin exposes it to frequent tropical cyclones, making it one of the most active ocean basins [54].

By examining these catastrophic events worldwide, we not only enhance our understanding of the destructive power of storm surges but also underscore the urgent need for improved mitigation strategies and resilient infrastructure to safeguard vulnerable communities against future storms.

Risk Assessment and Early Warning System

Risk Assessment and Early Warning Systems play crucial roles in safeguarding coastal populations from the devastating impacts of storm surge events.

Various methods are employed to assess and predict storm surge risk, integrating historical data analysis, computer modeling, and geographic information systems. Historical data analysis involves studying past storm surge events, evaluating their intensity, and assessing the resulting impacts on coastal areas. Computer modeling utilizes sophisticated mathematical algorithms to simulate storm surge scenarios based on various factors such as storm characteristics, tides, topography, and coastal infrastructure.

In their research, Chen, Liu, and Hsu underscore the critical need for accurate storm surge predictions to enhance disaster prevention in coastal areas during typhoon events [55]. Their study investigates the efficacy of an Artificial Neural Network (ANN) model, employing the Back Propagation Neural Network (BPNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithms. This modeling approach is particularly focused on forecasting storm surge heights along the east coast of Taiwan, a region prone to the devastating impacts of typhoons. Their findings revealed notable insights into the efficacy of these modeling techniques. While the basic hydrodynamic model alone struggled to accurately predict storm surge heights during typhoon events, the incorporation of ANN models, particularly the BPNN, showed some promise in reproducing astronomical tide levels. However, neither the hydrodynamic model nor the BPNN model alone could effectively modify storm surge predictions. On the other hand, the application of the ANFIS model not only predicted astronomical tide levels but also significantly improved the accuracy of storm surge height forecasts during both training and verification phases. The ANFIS model exhibited the lowest mean absolute error and root-mean-square error values compared to other simulated results. These findings underscore the potential of ANFIS techniques in advancing storm surge prediction capabilities, particularly in vulnerable coastal areas like the east coast of Taiwan [55].

Geographic information systems (GIS) play a vital role by integrating spatial data to identify vulnerable areas, critical infrastructure, and population centers at risk of storm surge inundation [56]. The Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model, employed by NOAA, evaluates storm surge risks by factoring in hurricane attributes like size, speed, and wind. It identifies flood-prone regions for evacuation planning based on projected surge values from hypothetical hurricanes. Remote sensing tools such as color scanners and radar complement these efforts by providing ocean data essential for surge prediction. By merging remote sensing with models like SLOSH, accuracy in surge forecasts is bolstered, crucial for effective disaster preparedness and response [57].

Building on this integration of technology and data, the study conducted by Wang, S., et al. developed a framework for quantitative storm surge risk assessment in undeveloped or data-deficient regions. The researchers defined five typhoon scenarios with varying frequencies of occurrence (1000, 100, 50, 20, and 10 years) and utilized the Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) models to simulate storm surge. The model outputs were imported into GIS software to determine inundation areas and depths, and building footprint data was extracted using spatial analysis and image analysis techniques. By superimposing the building footprint layer on the inundation area layer, the researchers identified and quantified the elements exposed to storm surge hazards. Finally, they combined the exposed elements with depth-damage functions to estimate economic losses, creating zonation maps to help local decision-makers prioritize high-risk sub-zones, develop mitigation strategies, and plan long-term urban development. This study demonstrates the effectiveness of GIS techniques and open data in conducting quantitative risk assessments for enhancing coastal resilience against storm surge disasters [58].

Early warning systems (EWSs) are instrumental in mitigating the impacts of storm surge events by providing timely and accurate information to coastal populations, emergency responders, and decision-makers. These systems employ real-time monitoring, data collection, and forecasting to detect approaching storms and predict potential surge impacts. Early warning messages are disseminated through multiple communication channels, including radio, television, mobile phones, sirens, and online platforms, to ensure widespread dissemination and prompt appropriate actions [59]. Public awareness campaigns and community engagement efforts are essential components of EWSs, educating coastal residents about storm surge risks, evacuation procedures, and preparedness measures [60]. Effective coordination among meteorological agencies, emergency management authorities, coastal communities, and other stakeholders is crucial for the successful implementation of EWSs and the timely response to storm surge threats.

For instance, the study of Kitazawa and Hale serves as an illustrative example of the integration of social media into EWSs. It demonstrates how the analysis of social media data can provide valuable insights into public responses and behaviors during disaster events, thereby enhancing the effectiveness of emergency warnings and decision-making processes [61]. Additionally, a EWS was tailored for Santos to address storm surge risks, notably observed during a significant event in October 2016. The system issues detailed bulletins when severe events are predicted indicating potential affects vulnerable areas. Since May 2016, it has distributed over 50 bulletins, with at least 20% warning of flooding and urban infrastructure impacts. Integrated into the Civil Defense Action Plan, the system ensures timely alerts through various media and mobile notifications, enabling residents to prepare adequately [62]. Furthermore, following the 2004 Sumatra earthquake and tsunami, the German government funded the German Indonesian Tsunami Early Warning System (GITEWS). This system prioritizes the rapid dissemination of earthquake parameters, particularly vital for tsunami warning along vulnerable coastlines like the Sunda Trench [63].

Engineering Solutions and Adaptation Strategies

In response to these formidable coastal hazards, a concerted effort by engineers and planners has yielded a diverse array of innovative solutions aimed at mitigating the impacts of storm surges. Ranging from time-tested structures like seawalls and levees to more ecologically attuned approaches such as wetland restoration and integrated coastal management, these endeavors underscore a multifaceted strategy to bolster coastal resilience and safeguard vital infrastructure.

Seawalls and Coastal Barriers

Seawalls are engineered structures built along coastlines to reduce the impact of waves and storm surges on coastal communities. These barriers can help dissipate wave energy and protect coastal infrastructure and properties from erosion and inundation. Depending on the conditions at the site, various seawall designs are employed, including gravity walls, rubble mound walls, stone revetments, stepped faces, concave faces, combinations of stepped and curved faces, and filled gravity walls [64]. While seawalls provide protection against waves and storm surges, they often have a detrimental effect on beaches. The article highlights the negative impact of seawalls, commonly constructed along dynamic coastlines such as salt marshes, on marsh ecosystems. It emphasizes that seawalls eliminate the vegetative transition zone at the upper border of marshes, thereby affecting plant diversity. Although no statistically significant effects were observed, variations in sediment movement and vegetation distribution were noted, primarily influenced by factors like wave exposure and site-specific geomorphology. The study underscores the importance of restricting seawall construction to safeguard plant diversity and prevent habitat loss in marshes due to sea level rise [65].

Levees and Floodwalls

Levees and floodwalls are constructed along rivers, estuaries, and coastlines to contain floodwater and prevent them from inundating adjacent areas during storms and high tides. These structures provide a physical barrier to reduce the risk of flooding and storm surge damage. Levees and floodwalls are used extensively throughout the United States for flood control [66,67]. This article discusses the vital role of levees and floodwalls in safeguarding essential infrastructure and communities from flooding, exemplified by the establishment of the metropolitan flood protection system along the Missouri River in Kansas City. Even though levees serve to contain floodwaters, it is commonly understood that flood-control levees tend to heighten flood levels and flow velocity for a given discharge [68]. This phenomenon is known as levee-induced flooding or levee effect.

Natural Infrastructure and Green Solutions

Implementing natural infrastructure, such as wetlands, mangroves, and dunes, can help buffer coastal areas from storm surges by absorbing and dissipating wave energy. Additionally, green solutions like beach nourishment and dune restoration enhance coastal resilience and provide natural defenses against erosion and inundation. The utilization of nature-based infrastructure (NBI) has attracted increased attention in the context of protection against coastal flooding [69]. Coastal forests, a major type of green infrastructure, are recognized as natural barriers against ocean waves. They can attenuate waves, mitigate erosion, and stabilize shorelines [70]. The article suggests that natural habitats like wetlands, dunes, and mangroves can mitigate coastal flooding and erosion while providing various benefits [71]. It proposes combining natural and built infrastructure (called 'hybrid' infrastructure) along shorelines, which could be more cost-effective and enhance the resilience of coastal areas, maintaining ecosystem services and preventing loss of life and property. The article discusses various approaches to coastal protection, including natural infrastructure, managed realignment, and hybrid approaches. Natural infrastructure utilizes ecosystems like salt marshes and mangroves to reduce coastal flooding and erosion by attenuating waves and stabilizing shorelines. Managed realignment involves relocating built defenses inland to allow natural infrastructure to develop along the shoreline, offering protection while enhancing ecosystem services. Hybrid approaches combine natural and built infrastructure, utilizing engineered structures to protect natural ecosystems or vice versa for optimal storm protection benefits [71].

Integrated Coastal Management and Land-Use Planning

Integrated coastal management strategies involve comprehensive planning and coordination of land use, development, and infrastructure investments in coastal areas to minimize vulnerability to storm surges and other coastal hazards. This approach considers ecosystem-based adaptation measures and community engagement to enhance resilience and sustainability. In this context, it is crucial to consider the potential impacts of climate change-induced sea level rise and increased storm frequency and intensity, as outlined by [72]. These factors are projected to have significant consequences for coastal areas, including changes in erosion patterns, heightened flood risks, and alterations in coastal habitat distribution. Importantly, these physical transformations will intersect with various human-induced factors, such as agricultural policy reforms, demographic changes, rising income levels, and the development of renewable energy infrastructure, shaping the future management of coastal landscapes and resources [72].

Predicting Storm Surge towards Developing Mitigation Strategies

As discussed above, storm surge poses significant threats to coastal areas leading to loss of life, property damage, and environmental destruction. Accurate prediction of storm surge events is critical for effective emergency preparedness and mitigation strategies. In recent years, advancements in modeling, artificial intelligence (AI), and data assimilation techniques have significantly improved storm surge forecasting capabilities. This section provides a comprehensive review of the developments in storm surge projection over the last five years, with a focus on modeling techniques, AI integration, and future research directions.

1. Numerical Models

Numerical models are essential tools used to simulate and predict the behavior of complex physical systems by solving mathematical equations using numerical methods. These models find wide application in fields such as meteorology, oceanography, climate science, and engineering to study processes that are too complicated to be analyzed analytically.

SLOSH (Sea, Lake, and Overland Surges from Hurricanes)

The SLOSH (Sea, Lake, and Overland Surges from Hurricanes) model is a computerized numerical tool developed by the National Weather Service (NWS) in the late 1960s and early 1970s. It estimates storm surge heights resulting from historical, hypothetical, or predicted hurricanes [73]. The model considers parameters such as atmospheric pressure, size, forward speed, and track data to create a wind field model that drives the storm surge. One of the key applications of the SLOSH model is wind field modeling. In this application, the model uses the Newtonian equations of motion and the continuity equation to simulate the wind field that drives the storm surge. This wind field is then used to estimate the surge heights, providing crucial data for understanding and predicting the impact of hurricanes. Another important application of the SLOSH model is in simulation studies, which are essential for hurricane evacuation planning. These studies involve simulating thousands of hurricanes with various combinations of categories, forward speeds, track directions, and landfall locations to compute storm surge for each basin. Each modeling run generates an envelope of high water, showing the maximum inundation for each location within a coastal region called a basin. A crucial outcome of these simulations is the Maximum Envelope of Water (MEOW), which reflects the reasonable worst-case flooding potential for a particular combination of category, forward speed, and direction. Each MEOW incorporates many possible landfall locations. All MEOWs for a single category are then composited into a Maximum of MEOWs (MOM), which serves as a long-range planning tool for assessing the worst-case storm surge for a given category at any location. Through these applications, the SLOSH model provides critical information for both immediate response efforts and long-term planning to mitigate the impacts of hurricanes [74].

ADCIRC (Advanced Circulation Model)

The Advanced CIRCulation (ADCIRC) model is a sophisticated computational system used for simulating the movement of water due to tides, storm surges, riverine flows, and other hydrodynamic forces. Developed in the late 1980s and early 1990s by Dr. Rick Luettich and Dr. Joannes Westerink, ADCIRC is widely used for coastal engineering, floodplain mapping, and emergency management [75]. One exemplary application of the ADCIRC storm surge model is demonstrated by Butler et al., who used it to accurately forecast coastal inundation during hurricanes and tropical storms [76]. This study introduced an advanced data assimilation methodology using ensemble Kalman filters, specifically the Singular Evolutive Interpolated Kalman (SEIK) filter. By integrating real-time observational data such as wind, water levels, and wave heights into model predictions, the accuracy of crucial forecasts—like maximum water levels and surge timing was significantly enhanced. Case studies of Hurricanes Ike and Katrina showcased the SEIK filter's ability to refine forecasts with modest computational resources, underscoring ADCIRC's practical application in improving storm surge forecasts and emergency response planning [76].

The ADCIRC model's capability to employ high-resolution grids is one of its key features. It uses an unstructured finite element mesh, enabling variable spatial resolution. This allows for high detail in critical areas like coastlines and levees while using coarser resolution in open ocean areas to conserve computational resources [77]. For instance, a study by Joannes J. Westerink and colleagues applied a high-resolution ADCIRC model to simulate hurricane storm surge dynamics in southern Louisiana. The model accurately captured the complex interactions between various hydrological features and was validated against observed data from gauge stations during Hurricanes Betsy and Andrew, achieving a mean absolute error of 0.30 meters in peak storm surge height estimation [78]. The ADCIRC model was also developed with a focus on efficiency and scalability for high-performance computing platforms, allowing it to simulate large geographical areas and long time periods effectively. Enhancements in ADCIRC, such as redesigned global unstructured meshes and the removal of gravity-wave-based stability constraints, have significantly improved its performance and accuracy. These advancements enable ADCIRC to handle extensive domains and prolonged simulation periods, making it highly suitable for comprehensive hydrodynamic studies [79].

Parallel computing is a fundamental aspect of ADCIRC, enabling it to handle large, complex domains efficiently. By leveraging high-performance computing systems, ADCIRC distributes computations across multiple processors, allowing detailed and extensive simulations to be conducted rapidly. This capability is crucial for simulating intricate hydrodynamic processes in high-resolution grids, enhancing ADCIRC's ability to provide accurate and timely predictions essential for disaster preparedness and mitigation [80,81]. ADCIRC is also capable of both 2D and 3D modeling, essential for accurately representing oceanic and coastal processes. The 2D models, which average the properties of the water column, are faster and suitable for large-scale applications like predicting tides and storm surges. However, 3D models, which divide the water column into multiple layers, offer detailed vertical profiles of water movement, temperature, and salinity, providing higher accuracy for certain scenarios [82]. Another strength of ADCIRC is its ability to couple with other models. For instance, Prasad K. Bhaskaran and colleagues used a parallel-coupled ADCIRC–SWAN model to simulate extreme waves and currents during Cyclone Thane in the Bay of Bengal. This coupling facilitated mutual interaction between wave dynamics and hydrodynamics, leading to accurate predictions of extreme events. The study utilized various wind fields and validated model performance against observational data, highlighting ADCIRC–SWAN's significance for operational forecasting [83].

Finite Volume Community Ocean Model (FVCOM)

FVCOM is a three-dimensional ocean model that utilizes a finite volume approach to solve the primitive equations governing ocean dynamics. Originally developed to simulate circulation and mixing processes in estuarine and coastal regions, FVCOM has been updated to include more sophisticated boundary conditions and finer spatial resolution. These advancements enhance its ability to accurately simulate storm surge, tides, and other coastal processes in environments with complex geometries, such as estuaries, inlets, and nearshore areas. The model's flexible unstructured grid allows for high-resolution representation of intricate coastal features, making it a powerful tool for studying and predicting hydrodynamic behavior [84].

Chen et al. applied FVCOM in their research to study the Bohai Sea and the Satilla River, demonstrating the model's capabilities. In the Bohai Sea, FVCOM accurately simulated semidiurnal and diurnal tides, which are crucial for understanding tidal dynamics around islands and coastal inlets. The model's ability to resolve complex topography near the coast and islands improved predictions of tidal currents and water exchange through the Bohai Strait. In comparison, the finite-difference model (ECOM-si) struggled with these aspects due to lower resolution around islands, resulting in less accurate tidal simulations. In the Satilla River, FVCOM excelled in simulating tidal currents and their variations along the river's intricate network of tidal creeks. Unlike ECOM-si, which underestimated tidal currents and failed to resolve tidal inflows and outflows from tidal creeks, FVCOM's finer grid captured these dynamics accurately. This underscores FVCOM's effectiveness in representing hydrodynamic processes in diverse coastal settings, which is essential for applications in coastal management and hazard prediction [85].

2. Hybrid Models

Hybrid models combine the strengths of various modeling approaches to improve forecast accuracy, often integrating numerical simulations with statistical and machine learning techniques.

Statistical-Dynamical Models

Statistical-dynamical models blend statistical techniques with outputs from dynamical models to enhance weather and climate forecasting accuracy. These models have seen significant advancements, particularly in the real-time assimilation of observational data, which continuously refines initial conditions and parameters.

These models use statistical techniques to correct biases and refine predictions generated by dynamical models, which simulate physical processes based on principles like fluid dynamics and thermodynamics. For example, the Tropical Meteorology Project at Colorado State University

(CSU), established by Dr. William Gray, has issued North Atlantic seasonal hurricane forecasts since 1984. Initially based on statistical models utilizing historical relationships between large-scale climate parameters, CSU has recently incorporated the European Centre for Medium-Range Weather Forecasts SEAS5 forecast system. This dynamic model predicts critical hurricane activity inputs and has significantly improved seasonal accumulated cyclone energy predictions, showing a cross-validated correlation of 0.60 for March and 0.67 for June from 1982 to 2019. By combining SEAS5 outputs with historical data, CSU has enhanced its April, June, and July forecasts, particularly improving April predictions [86].

Recent advancements focus on integrating real-time observational data directly into the forecasting process. Data from satellites, weather stations, buoys, and other sources are assimilated into the models in near real-time, continuously updating and refining the initial conditions and parameters used by the dynamical models. This approach helps models adjust more rapidly to changing weather patterns, resulting in more reliable and timely predictions. For instance, Flowerdew et al. demonstrated the effectiveness of variational assimilation of sparse sea level observations from tide gauges for storm surge forecasting in the North Sea. Their study highlighted novel data assimilation techniques, such as a shortest-path method and an adaptive error covariance model, which significantly enhanced forecast accuracy, with RMSE improvements of up to 5 cm for the first 24 hours of forecasting. However, improvements diminished beyond 24 hours, emphasizing the temporal limitations of these enhancements [87].

By combining dynamical modeling's physical understanding of atmospheric processes with statistical corrections and real-time data assimilation, statistical-dynamical models offer enhanced predictive accuracy. These models leverage detailed physical simulations and refine them with statistical techniques that correct biases and incorporate current observational data, resulting in more reliable forecasts, particularly for short to medium-range predictions. Statistical-dynamical models are integral to operational weather forecasting by meteorological agencies worldwide, supporting decision-making in critical sectors such as agriculture, transportation, emergency management, and energy production. Accurate weather forecasts are essential for ensuring safety, efficiency, and economic stability in these areas.

Ensemble Models

Ensemble forecasting involves running multiple simulations (ensemble members) of a numerical weather prediction model with slightly perturbed initial conditions and/or model parameters. This approach results in a set of possible future states of the atmosphere rather than a single deterministic forecast. Each member represents a plausible scenario based on the inherent uncertainties in initial observations and model formulations [88]. Ensemble models provide a probabilistic framework that helps quantify forecast uncertainty and improve decision-making processes. By considering a range of potential outcomes, ensemble models offer a more comprehensive understanding of forecast confidence and risks, making them valuable tools for weather prediction and climate studies.

3. Artificial Intelligence (AI)

Artificial Intelligence (AI) and machine learning (ML) have transformed storm surge forecasting by enabling the analysis of extensive data sets and identifying patterns that traditional models may overlook. Machine learning (ML) and deep learning (DL) algorithms, subsets of AI, excel at handling vast amounts of heterogeneous data from sources such as satellite imagery, historical weather data, oceanographic data, and real-time sensor readings. This capability is crucial for storm surge forecasting, which relies on multiple datasets for accurate predictions. For instance, Qin et al. (2023) exemplified robust data handling and analysis techniques in storm surge prediction by integrating ML with comprehensive datasets. Their approach emphasized the critical role of preprocessing methodologies, such as optimizing initial and boundary conditions through deep convolutional neural networks (CNNs) for cyclone wind fields. Additionally, they implemented effective data assimilation strategies, leveraging ML algorithms like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to correct surge height errors. This integrated framework not only enhanced the precision of storm surge forecasts but also improved computational efficiency, demonstrating ML's efficacy in processing heterogeneous data sources for more accurate predictive modeling. Their study underscores the transformative impact of advanced data handling techniques in overcoming traditional forecasting limitations, paving the way for more reliable storm surge prediction systems [89].

Additionally, AI offers, Deep Neural Network (DNN), also known as Artificial Neural Network (ANN), enhanced predictive models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The neural network, CNNs are particularly effective in processing spatial data, making them ideal for analyzing satellite imagery and identifying weather patterns. These networks excel at detecting and interpreting spatial features such as cloud formations and precipitation zones, significantly enhancing the accuracy of weather forecasts. For example, Lee et al. (2020) utilized CNNs for real-time estimation of tropical cyclone (TC) intensity, achieving a root mean squared error (RMSE) of 8.32 knots. This approach outperformed traditional methods relying on manual algorithms and single-channel satellite images by approximately 35%, highlighting CNNs' potential in interpreting TC behavior characteristics [90]. Similarly, Scardino et al. (2022) demonstrated CNNs' transformative role in coastal video monitoring. By integrating CNNs with Optical Flow techniques, they accurately assessed tide phases, wave parameters, and storm surges, significantly enhancing meteo-marine assessments and predictions [91]. Another type of neural network, RNNs are designed to handle sequential data, making them suitable for modeling the temporal dynamics of weather patterns. By processing time-series data from weather stations, RNNs can predict how weather conditions evolve over time, leading to more accurate and reliable forecasts [92]. For example, Feng and Xu (2023) explored storm surge prediction using a neural network approach that integrates diverse physical characteristics and historical observation data. Their multi-RNN model effectively predicted maximum storm surge water levels, demonstrating robustness across various scenarios [93]. Additionally, Wei and Nguyen presented an encoder-decoder neural network model for forecasting storm surges on the US North Atlantic Coast, utilizing two LSTM models. This model demonstrated computational efficiency and versatility in forecasting storm surges, showcasing the potential of data-driven approaches in enhancing coastal hazard research [94].

Real-time data assimilation is crucial for enhancing the accuracy of storm surge forecasts by integrating real-time observational data into predictive models. For instance, Butler et al. (2012) implemented the singular evolutive interpolated Kalman (SEIK) filter with the ADCIRC model to assimilate wind, water levels, and wave heights data during hurricanes Ike and Katrina. This method improved predictions of maximum water levels and surge timing up to 48 hours before landfall. The SEIK filter demonstrated significant reductions in root mean square error and enhanced the accuracy of coarse-resolution forecasts, making it computationally efficient for real-time applications [76]. Furthermore, ML models can produce high-resolution forecasts that capture small-scale features of storm surges, leading to more precise predictions of affected areas. For example, the integration of ML into agro-meteorology has revolutionized crop yield forecasting, weather prediction, and drought monitoring by analyzing vast amounts of data from various sources. Advanced ML models using remotely sensed and meteorological data have demonstrated superior performance in crop yield forecasting compared to traditional methods. Similarly, ML algorithms such as Artificial Neural Networks (ANNs) and Random Forests (RFs) have improved weather forecasting accuracy by processing large datasets from internet-connected weather stations and APIs like OpenWeatherMap. These ML-based systems provide more detailed and reliable forecasts through statistical pattern recognition and predictive modeling. Moreover, they continuously learn and improve as more data becomes available, enhancing their precision over time [95].

Application of AI in Storm Prediction

Artificial intelligence (AI) has significantly improved the accuracy of storm prediction by processing vast meteorological datasets, identifying patterns, and improving numerical weather models. Techniques like neural networks enable real-time forecasting and long-term climate impact assessments. This results in more accurate and timely predictions, aiding in effective disaster preparedness and response. Wei's study focused on enhancing hurricane track and intensity forecasts using deep learning techniques, specifically Long Short-Term Memory (LSTM) networks. Trained on historical hurricane data, the LSTM-RNN model demonstrated improved accuracy in predicting hurricane paths compared to traditional models. This integration enhances storm surge prediction accuracy, aiding in better preparedness and response strategies for coastal regions facing hurricane threats [96]. Lee et al. developed C1PKNet, a surrogate model for predicting peak storm surges using time-series data of tropical cyclone parameters. Their approach combined k-means clustering for spatial grouping, Principal Component Analysis (PCA) for dimensionality reduction, and Convolutional Neural Networks (CNNs) for temporal variation analysis. Validated against synthetic and historical data, C1PKNet showed promising performance in accurately predicting storm surge levels and wet/dry conditions, underscoring its potential for rapid storm surge forecasting [97]. Boussioux et al. introduced Hurricast, an ML framework integrating deep learning encoder–decoder architectures with XGBoost models for tropical cyclone forecasting. Demonstrating competitive performance comparable to operational models like HWRF and GFSO, Hurricast combines spatial–temporal data with statistical inputs, enhancing forecast accuracy and reducing variability. This multimodal approach improves track forecasts and holds promise for operational storm surge forecasting systems [98].

Furthermore, Frifra et al. employed GRU models for predicting storm characteristics and SVM classifiers for storm occurrence in Western France. Their study integrated buoy data with a comprehensive storm database, demonstrating the GRU models' effectiveness in capturing storm variability and predicting storm events with high accuracy. This integrated approach offers potential for enhancing severe weather prediction and mitigation strategies [99]. Davila Hernandez et al. developed a hybrid CNN-LSTM model for hurricane prediction and storm surge forecasting. Trained on Laguna Madre data, the model integrated spatial features from CNNs and temporal dependencies from LSTMs, significantly improving predictions for both normal conditions and storm surges during hurricanes Dolly, Alex, and Hanna. This study highlights the practical benefits and challenges of AI and ML in storm surge prediction [100]. Mulia et al. utilized Generative Adversarial Networks (GANs) to simulate atmospheric forcing fields for storm surge predictions during Typhoon Melor. Comparing favorably with NWP models, GAN-based simulations demonstrated high accuracy in predicting storm surges, showcasing potential for operational forecasting systems with enhanced computational efficiency [101]. Saviz Naeini and Snaiki developed a hybrid ML model combining a Deep Auto Encoder (DAE) with a deep neural network (DNN) for predicting peak storm surges and significant wave heights. Their approach achieved superior accuracy compared to decoupled models, demonstrating robust performance suitable for early warning systems and risk assessment [102]. Alshayeb et al. focused on storm surge susceptibility prediction for Sagar Island using DL models with Bayesian optimization and Explainable AI techniques. Achieving high accuracy and F1-scores, their study provides insights for targeted storm surge management in vulnerable coastal regions [103].

These studies highlight the transformative impact of AI in improving hurricane prediction accuracy and storm surge forecasting capabilities, crucial for enhancing disaster preparedness and response strategies globally.

Future Challenges and Opportunities

Recent advancements in AI for storm surge prediction have demonstrated significant progress in enhancing forecasting accuracy and operational efficiency. Looking forward, the future of storm surge prediction through AI holds immense promise, albeit with challenges and opportunities. Broadening the applicability of models like C1PKNet beyond tropical cyclones to include diverse storm systems will enable more comprehensive and tailored surge forecasts. Improving predictions of critical forerunner surges will enhance evacuation planning and coastal resilience strategies. Integrating additional factors such as astronomical tides, sea-level rise dynamics, and heavy rainfall into predictive models is crucial due to their nonlinear interactions with storm surges. This integration can enhance the accuracy and reliability of surge predictions, better preparing coastal communities for climate-related challenges. Optimizing AI model efficiency involves developing streamlined algorithms for hyperparameter tuning and computational resource management. Exploring alternative architectures like RNNs and LSTM networks, which handle variable input lengths effectively, can improve scalability and performance. Enhancing data availability and quality is essential. High-resolution datasets capturing diverse storm conditions are crucial for training and validating AI models. Promoting open access to these datasets empowers researchers and practitioners to develop robust storm surge prediction tools, enhancing coastal resilience and disaster preparedness. Overall, addressing these challenges and opportunities will maximize the potential of AI in storm surge prediction. Advancements in these technologies will bolster our ability to protect coastal communities and infrastructure from the escalating risks posed by extreme weather events and climate change.

Conclusions

Storm surge poses significant threats to coastal areas, causing loss of life, property damage, and environmental destruction. Accurate prediction is essential for effective emergency preparedness and mitigation. Recent advancements in numerical models, such as SLOSH, ADCIRC, and FVCOM, have revolutionized storm surge forecasting. These models use sophisticated computational techniques to simulate complex hydrodynamic processes, incorporating factors like wind fields, water levels, and tidal dynamics. For instance, ADCIRC's use of high-resolution grids and parallel computing enhances its ability to predict storm surge dynamics with precision, crucial for emergency management and coastal planning.

Hybrid models, combining numerical simulations with statistical and machine learning techniques, further improve forecast accuracy. Statistical-dynamical models, integrating real-time observational data, refine predictions by correcting model biases and adjusting initial conditions dynamically. This approach enhances short to medium-range forecasts, supporting decision-making in sectors like agriculture and emergency management. Ensemble models, which generate probabilistic forecasts by considering uncertainties in initial conditions and model parameters, provide valuable insights into forecast confidence and risks, aiding in disaster preparedness.

Artificial Intelligence (AI) and machine learning (ML) play a transformative role in storm surge forecasting by processing vast datasets and identifying complex patterns. Neural networks like CNNs and RNNs excel in analyzing spatial and temporal data, enhancing prediction accuracy by integrating diverse sources such as satellite imagery and historical weather data. These AI-driven approaches enable real-time data assimilation and improve computational efficiency, critical for operational forecasting systems.

Based on recent studies, future advancements will likely focus on integrating AI more deeply into modeling frameworks, enhancing data assimilation techniques, and improving accessibility to real-time data. Interdisciplinary collaboration among meteorologists, oceanographers, and data scientists will drive innovation, ensuring that storm surge forecasts become more reliable and actionable globally. These developments are crucial for reducing vulnerability to coastal hazards, supporting sustainable coastal management, and enhancing disaster resilience in the face of increasing climate variability.

In conclusion, while challenges remain in refining models and handling uncertainties, the trajectory of storm surge forecasting is promising. Continued research and technological advancements hold the potential to mitigate risks, protect coastal communities, and improve emergency response strategies worldwide.

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Conflicts of Interest Declaration

The author has no conflicts of interest to declare.

Data Availability Statement

Not applicable

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