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ABSTRACT

The use of deep learning methods in weather forecasting is examined in this paper, with an emphasis on forecasting coastal sea levels in areas that are susceptible. Accurate and timely forecasting has become essential for early warning systems, infrastructure development, and emergency response because to the growing threats of coastal flooding brought on by climate change, storm tides, and sea level rise.

Even while hydrodynamic and numerical weather prediction (NWP) models are accurate, they are slow and computationally demanding; they frequently require supercomputers to execute simulations over hours or days. Deep learning algorithms, on the other hand, provide quick, affordable predictions with same accuracy. The report showcases cutting-edge architectures such as Long Short-Term Memory (LSTM) networks for capturing time-based relationships and Convolutional Neural Networks (CNNs) for spatial analysis of storm systems. To produce precise, real-time multi-location forecasts, the hybrid CNN-LSTM models combine tidal inputs with atmospheric data.

The Deep Learning Weather Prediction (DLWP) model, which produces ensemble forecasts effectively on GPUs and outperforms many conventional systems in terms of speed and scalability, is also covered in the paper. These models' higher spatiotemporal accuracy, reduced computational costs, and increased adaptability for real-time forecasting are some of its main advantages.

The study comes to the conclusion that deep learning offers a revolutionary change in environmental modelling, despite several obstacles, like the underestimate of uncommon extreme occurrences, restricted interpretability, and operational trust. It provides vital resources for coastal communities' climate resilience and catastrophe preparedness, opening the door for future forecasting systems that are more inclusive, scalable, and effective.

1. INTRODUCTION

Given the growing effects of climate change and relative sea level rise, the field of deep learning for weather forecasting in coastal locations aims to meet the urgent demand for accurate and timely predictions of coastal weather, particularly water levels (Shahabi, A., & Tahvildari, N. 2024). Accurate forecasting is crucial for resilience, early warning, infrastructure development, and emergency management since low-lying coastal areas are increasingly at risk from storm tides and frequent nuisance floods.

With storm surges inflicting over $100 billion in damages and sea level rise exacerbating erosion and saltwater intrusion, climate change has exacerbated hurricanes and tropical cyclones, raising the risk of coastal flooding (Shahabi, A., & Tahvildari, N. 2024). Based on shallow water equations, traditional hydrodynamic and numerical models such as ADCIRC, SLOSH, and Delft3D have been in use for decades. However, they have significant drawbacks, including high computational costs, hours to days on high-performance systems, and a tendency to force a trade-off between resolution and scale. Combining them with wave models adds even more complexity, emphasising the need for more effective flood prediction techniques to protect areas that are already at risk.

The high computational cost of weather prediction traditional models has spurred interest in Deep learning (DL) as a faster, cost-effective alternative for coastal weather prediction (Shahabi, A., & Tahvildari, N. 2024). While ML-based surrogate models offer rapid results, they have historically faced reliability challenges in accurately capturing surge levels. Neural networks (NNs) have emerged as the leading ML approach, evolving from early Artificial Neural Networks (ANNs) which predicted water levels at single timesteps but struggled with temporal lags to more advanced Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models that better handle time-series data, though longer lead times can reduce accuracy (Shahabi, A., & Tahvildari, N. 2024). Recently, Convolutional Neural Networks (CNNs) have enabled improved processing of 2D wind fields, capturing finer spatial details than point-based methods, while hybrid CNN-LSTM architectures combine atmospheric inputs with historical water levels for more robust predictions.

Conventional NWP systems, such as ECMWFs, need a lot of supercomputing capacity to run huge ensembles with little expertise. A CNN-based system on a cubed-sphere grid, the DLWP model, provides a revolutionary alternative to deep learning. It can produce 320-member six-week forecasts in just 3 minutes on a single GPU, far surpassing the ECMWF's supercomputer-dependent 50-member ensemble (Weyn et al., 2021). Six important atmospheric variables are recursively predicted by the model, which also simulates mid-latitude systems, generates tropical cyclones on its own (like Hurricane Irma), and captures the dynamics of near-surface temperatures without the need for explicit parameterisation. Its incorporation of total column water vapour signals advances the modelling of tropical convection, indicating a leap in effective, physically realistic S2S forecasting, even though it is still in its infancy (e.g., no direct precipitation forecasts yet) (Weyn et al., 2021).

Coastal populations, especially those in low-lying areas, are increasingly at risk from storm tides and frequent nuisance floods, which are made worse by climate change-driven increases in the frequency and intensity of tropical cyclones. Rising sea levels increase the effects of flooding, speeding up shoreline erosion, saltwater intrusion, and infrastructure vulnerability, and extreme storm surges already cause over $100 billion in damages (Shahabi, A., & Tahvildari, N. 2024). For these increasingly vulnerable areas, accurate and fast water-level forecasts are essential for enhancing resilience, facilitating efficient early warning systems, flexible infrastructure design, and life-saving emergency readiness.

Over many years coastal weather prediction especially floods has relies on physics models like Delft3D which make them inefficient since they use days to bring the result. The computational burden of traditional physics-based models has accelerated adoption of machine learning (ML) as a faster, cost-effective alternative for coastal flood prediction. While early ML approaches struggled with reliability in capturing surge levels, advances in deep learning now offer compelling solutions.

Modern architectures leverage CNNs to process high resolution 2D wind fields capturing complex storm dynamics (cyclones, Nor'easters) while LSTMs model temporal dependencies in water levels. Hybrid CNN-LSTM frameworks merge these strengths, integrating gridded atmospheric data with tidal inputs to produce accurate, multi-hazard water level predictions (Shahabi, A., & Tahvildari, N. 2024). These innovations mark a paradigm shift toward scalable, real-time flood forecasting without sacrificing physical fidelity.

The primary objectives of this topic are:

- To provide timely and reliable predictions of coastal water levels for vulnerable coastal communities. This is critical for building resilience in these areas, which face growing risks from recurrent nuisance flooding and storm tides due to climate change and accelerating global sea level rise. Such predictions are essential for early warning systems, infrastructure planning, and emergency management.
- To explicitly maintain temporal consistency and exploit physical relationships in the model design. This objective addresses a gap where many prior ML studies did not fully exploit the physical correlation between input and output data. The aim is to ensure that inputs (like atmospheric and tidal data) and outputs (sea state) pertain to the same time window, enhancing accuracy and predictability
- To overcome the computational burden and speed limitations of traditional hydrodynamic models. Physics-based numerical models, while widely used for coastal flood modeling, are computationally demanding, requiring significant time (hours to days) and high-performance computing resources to calculate water levels across regional scales. Deep learning aims to develop "fast yet inexpensive data-driven or surrogate models" for coastal flooding to alleviate this burden. For example, a deep learning weather prediction (DLWP) model can produce a large ensemble of forecasts in minutes on a single GPU, significantly reducing computational cost compared to traditional supercomputer-reliant numerical weather prediction (NWP) systems.

The remainder of the paper is organized as follows: Section 2 describes the methodology, Section 3 Current state of the topic, Section 4 present challenges and limitations, and Sections 5 present opportunities and future direction and 6 give the conclusion.

2. METHODOLOGY

Sources were identified through a systematic literature search using academic databases such as Google Scholar. The search strategy involved using specific keywords and phrases including *"deep learning for weather forecasting," "coastal flood prediction,".* Boolean operators (e.g., AND, OR) were used to refine results. Filters were applied to select peer-reviewed articles**,** recent publications (within the last 10 years), and studies written in English. References within selected papers were also reviewed to identify additional relevant sources (backward snowballing).

The collected information was first organized by grouping sources based on themes, such as machine learning approaches and deep learning innovations. An excel sheet was created to compare each study objectives, methods, data sources, model used and findings. This thematic organization helped to identify common trends, research gaps and advancements of those over time.

For analysis, a qualitative content analysis approaches was used to examine how deep learning techniques are being applied in coastal weather predictions especially for flood. Particular attention was paid to model architectures (e.g., CNN, LSTM), performance outcomes, and how each study addressed limitations of traditional models. This process enaled a critical evaluation of how deep learning improves forecasting accuracy, speed, and scalability in comparison to traditional models.

3. CURRENT STATE OF THE TOPIC

Deep learning is revolutionizing coastal water level predictions through advanced architectures like CNN-LSTM models. These models combine Convolutional Neural Networks (CNNs) to analyze 2D wind fields capturing detailed storm patterns and LSTM networks to integrate atmospheric data with tidal levels, producing accurate time-series forecasts. Unlike traditional methods, this approach provides spatiotemporal predictions (simultaneous forecasts across multiple locations) rather than single-point outputs, making it highly versatile for storms like hurricanes and Nor'easters. The model excels in predicting both extreme flooding and minor water level changes, offering real time flood risk assessments. Additionally, it maintains physical consistency between inputs and outputs, ensuring reliable forecasts. Meanwhile, global weather prediction is also benefiting from deep learning, with DLWP (Deep Learning Weather Prediction) models using CNNs on a cubed-sphere grid to forecast atmospheric variables at high resolution (~1.4°). The U-Net architecture helps retain fine-scale weather patterns, while ensemble forecasting (using hundreds of randomized model variants) improves probabilistic predictions. These models can even spontaneously simulate tropical cyclones and perform well in subseasonal to seasonal (S2S) forecasting (2–6 weeks ahead).

A major advantage of deep learning in weather and flood forecasting is its unmatched computational speed. While traditional hydrodynamic models take hours to days on supercomputers, trained deep learning models generate coastal water predictions in seconds on a laptop. Similarly, DLWP models produce 320 ensemble forecasts for six weeks in just three minutes on a single GPU, far outpacing conventional Numerical Weather Prediction (NWP) systems. Despite their speed, these models remain highly accurate, rivaling physics based models like ADCIRC+STWAVE for flood prediction and performing comparably to ECMWF's S2S ensemble at long lead times (4–6 weeks). To enhance accuracy, bias correction techniques are applied, reducing systematic errors, especially over land. Another benefit is the differentiability of CNNs, which simplifies the creation of adjoint models for studying forecast errors a complex task with traditional NWP. While deep learning models are still slightly less precise than high-fidelity simulations, their speed, scalability, and adaptability make them invaluable for real-time disaster preparedness and long-term climate forecasting.

In writing this report there are some key contributors that do there home works very well in the field of deep learning for weather forecasting Include:

1. Dr. Shahabi and Dr. Tahvildari**:** Researchers known for developing advanced deep learning models that improve the accuracy of coastal flood predictions by addressing limitations in earlier machine learning models.
2. Weyn et al**:** Notable for their work on the Deep Learning Weather Prediction (DLWP) model, which applies CNNs on cubed sphere grids for efficient subseasonal-to-seasonal weather forecasting.
3. National Oceanic and Atmospheric Administration (NOAA) A major U.S. government agency that provides critical data, supports coastal flood modeling research, and promotes integration of AI in weather prediction.
4. European Centre for Medium-Range Weather Forecasts (ECMWF): Known for high-quality numerical weather prediction models and for supporting research in machine learning applications for weather and climate.
5. Google DeepMind and NVIDIA: Tech companies that have explored the use of AI and deep learning in weather forecasting, offering high-performance computing resources and advanced models.
6. Academic Institutions: Universities such as Stanford, MIT, and the University of Virginia have published influential studies on ML and DL in environmental and geophysical modeling.

Emerging trends and innovations in the field include:

- Hybrid Deep Learning Models: Integration of Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to capture both spatial and temporal patterns in coastal flood prediction. These models improve the accuracy of water level forecasts over multiple locations and time steps.

- Spatiotemporal Forecasting of models that can predict water levels at multiple tide gauge locations simultaneously**,** rather than being trained for a single site, increasing efficiency and scalability.
- Efficient Weather Forecasting with Deep Learning Models like DLWP (Deep Learning Weather Prediction) demonstrate how large-scale weather forecasts (e.g., 6-week forecasts) can be generated within minutes using a single GPU, offering a low-cost alternative to traditional supercomputer-driven models.
- Use of Gridded Atmospheric Data – Instead of relying solely on point data or storm tracks, newer models use 2D gridded wind and pressure fields, allowing better representation of storm structure and interactions with coastal geography.

4. CHALLENGES AND LIMITATIONS

The reviewed literature identifies several common problems and obstacles in both traditional numerical weather prediction (NWP) and hydrodynamic models, as well as in the development and application of deep learning (DL) models for weather and coastal forecasting some of those include:

- ✓ Computational Burden of Traditional Models: Traditional systems and global weather forecasting institutions heavily rely on computationally demanding hydrodynamic models and NWP models that require massive supercomputers. This leads to these physics-based models being run either at small scales with high resolution or at large scales with low resolution to manage the computational burden.

- ✓ While machine learning (ML) models for coastal water levels offer speed, they struggle with reliability, especially for extreme surges, due to limited training data on rare events. Earlier models, like basic ANNs, failed to capture temporal lags between weather and sea states, and increasing lead times reduced accuracy. Many past studies ignored physical correlations in input-output data and provided only single-point outputs, requiring separate training per location. Additionally, models often underestimate extreme surges because loss functions balancing accuracy and extremes remain challenging. Performance also declines in inner bays where complex hydrodynamics (tidal reflections, river inflows) aren't fully resolved, and reliance on atmospheric forecast inputs adds uncertainty

The reviewed literature identifies several significant gaps in research and technological adoption within weather and coastal forecasting, spanning both traditional and deep learning approaches:

- ✓ A primary obstacle is the heavy reliance of current flood advisory systems and global weather forecasting institutions on computationally demanding hydrodynamic and numerical weather prediction (NWP) models. These models necessitate the use of massive supercomputers and are typically run either at small scales with high resolution or at large scales with low resolution to manage their computational burden.

- ✓ For subseasonal-to-seasonal (S2S) forecasting, achieving predictive skill requires large ensembles of these computationally expensive NWP models, which rapidly approach modern-day computing limits.

- ✓ A significant obstacle for current DLWP models is the lack of coupling with other Earth system components, such as the ocean. This results in sub-optimal temperature forecasts over oceans and the inability to capture phenomena strongly influenced by ocean dynamics, such as El Niño events.
- ✓ DLWP models can exhibit systematic drift (bias) in long-term forecasts, similar to traditional NWP models. While bias correction strategies are used, it highlights an inherent issue with long-term stability without explicit physical constraints.

Based on the reviewed literature, several socio-technical, ethical, and practical challenges and obstacles are identified in both traditional and deep learning approaches to weather and coastal forecasting:

Socio-technical Challenge:

- Reliability and Trust for Operational Adoption: A major socio-technical hurdle is that while machine learning (ML) models are fast, they still face challenges in ensuring reliability and their ability to capture all surge levels, particularly extreme events. This directly impacts their widespread adoption, as flood advisory systems continue to rely on computationally demanding hydrodynamic models, signifying a gap in fully integrating these new, faster ML models into established operational workflows.

Ethical Challenge:

- Underestimation of Extreme Events and Public Safety: Although not explicitly stated as "ethical," the critical practical challenge of larger prediction errors for the most extreme storm tides due to their scarcity in training data has clear ethical implications. If these models are used for critical decision-making processes like early warning, infrastructure planning, and emergency management, an underestimation of severe storm surges could lead to inadequate warnings, insufficient protective measures, and potentially increased risk to life and property. The difficulty in minimizing this underestimation through loss functions without diminishing overall model performance highlights this ethical tightrope.

Practical Challenges:

- Traditional flood advisory systems and global weather forecasting heavily rely on computationally demanding hydrodynamic models and Numerical Weather Prediction (NWP) models that require massive supercomputers. This computational burden forces these physics-based models to be run either at small scales with high resolution or at large scales with low resolution.

- Generating data for regional risk analysis usually requires simulating thousands of scenarios, which is hard to achieve with physics-based numerical models.

- The error in prediction is larger for the most extreme storm tides due to their scarcity in the training data record. This also leads to a situation where the model's strong performance during general testing doesn't necessarily guarantee its ability to predict storm tides, as training sets are majority normal sea state data.

5. OPPORTUNITIES AND FUTURE DIRECTIONS

The latest developments in deep learning for weather and coastal forecasting offer several significant applications and benefits, addressing key limitations of traditional models here are some those many:

- Substantial Reduction in Computational Time: Deep learning (DL) models can dramatically reduce the time required for predictions compared to traditional hydrodynamic or numerical weather prediction (NWP) models. While physics-based models may take hours to days to calculate water levels across regional scales on supercomputers, a trained machine learning (ML) model can produce water levels in a few seconds on a personal laptop. Similarly, a Deep Learning Weather Prediction (DLWP) model can produce a 320-member set of six-week global forecasts in just three minutes on a single GPU, whereas state of the art NWP models like ECMWF's require massive supercomputers for a 50-member ensemble. A one-week DLWP forecast, with a 12-hour time step and 6-hour resolution, can be performed in approximately 0.1 seconds on a GPU.
- Improved Lead Times for Coastal Predictions: While increasing lead time previously diminished accuracy for water level time series predictions, the novel CNN-LSTM architecture aims to maintain high analogy to hydrodynamic modeling, suggesting better performance over relevant temporal spans by correlating input and output data based on physical reality.
- Learning Physics-Based Phenomena: Despite being data-driven, the DLWP model demonstrates a remarkable capability to learn physics-based phenomena, including the complex evolution of near-surface temperatures and long-term patterns in the tropics, which are convection-dominated. It can capture processes that require complex physical parameterizations in conventional NWP models with minimal information like land-sea mask and terrain elevation.

- Critical for Resilience and Emergency Management: Timely and reliable predictions of coastal water levels are critical for resilience in vulnerable coastal areas facing increasing risks from nuisance flooding and storm tides due to climate change and sea level rise.

- Unprecedented Use of Reforecasts: The computational efficiency of DLWP models allows researchers to make unprecedented use of large numbers of reforecasts for past weather events (e.g., 85,800 reforecasts in hours on a single GPU). These can be used for calibrating ensemble probability distributions, analyzing model errors, or investigating predictability sources.

The latest developments in deep learning for weather and coastal forecasting open up several promising avenues for further research and innovation those are as follows:

- Improving Skill for Extreme Events in Coastal Forecasting: While the developed deep learning model for coastal water levels is effective in capturing nearly all water levels, from regular sea states to major flooding, the error is larger for the most extreme storm tides due to their scarcity in the training record. Future works can combine synthetic storm simulations with real gauge data to improve the model's skill for unseen extreme storms.

- Creating Adjoint Models for Predictability Studies: Unlike complex operational NWP models, for which adjoint models are difficult to create, a Convolutional Neural Network (CNN) is fully differentiable. This inherent property makes it easy to produce the corresponding adjoint model for DLWP systems, which can enable new research avenues into error growth and atmospheric predictability, such as examining how model errors depend on initial condition uncertainties.

- Improving Performance in Specific Atmospheric Dynamics: The DLWP model's performance relative to ECMWF models is worse during boreal winter in the northern hemisphere extra-tropics, suggesting that it performs less effectively when synoptic-scale dynamics exert more influence on the weather. This indicates a potential area for targeted research to improve the model's handling of complex synoptic-scale processes.

The latest developments in deep learning for weather and coastal forecasting offer significant applications and benefits that, while not always explicitly detailed for sectors like agriculture or education in the provided sources, broadly contribute to societal resilience and decision-making by improving forecast accuracy and efficiency.

- ✓ Enhanced Resilience and Early Warning The model provides timely and reliable predictions of coastal water levels. This is crucial for enhancing resilience in vulnerable coastal areas that face increasing risks from recurrent nuisance flooding and storm tides due to climate change and relative sea level rise. Such rapid water level predictions can be directly used for early warning systems, enabling local and regional authorities to implement timely precautions and warnings.
- ✓ Improved Accuracy Across Flood Levels The developed deep learning model is effective in capturing nearly all water levels, from regular sea states to major flooding, representing a significant improvement over previous machine learning studies that rarely trained models for such a wide range. This broad applicability makes it a potential tool for various practical applications, including assessing normal-day sea levels, recurrent nuisance flooding, and extreme storm surges.
- ✓ Support for Infrastructure Planning and Emergency Management The rapid water level prediction model can be leveraged for infrastructure planning and emergency management. The data from NOAA tide gauges, used to train these models, is already widely utilized by local and regional authorities for flood warning and emergency management purposes. The development of such a robust and rapid model is beneficial for addressing the intensifying flooding issues in regions like the Chesapeake Bay and other coastal communities facing similar challenges.

6.CONCLUSION

In conclusion, this paper has examined how deep learning can revolutionise coastal weather forecasting, namely in the area of flood prediction. Even if they are realistic, traditional physics-based models have limited scalability and large computational requirements. Deep learning models provide a scalable, affordable substitute that can generate precise, timely predictions with less resources, particularly hybrid architectures like CNN-LSTM. These models are ideal for multi-hazard and real-time forecasting because they are excellent at capturing both temporal and geographical dynamics.

Even though there are issues with model interpretability, trust in operational parameters, and the lack of training data for extreme occurrences, the advantages greatly exceed the drawbacks. Traditional forecasting systems can be replaced or improved by innovations like DLWP and spatiotemporal forecasting systems, which provide projections in minutes as opposed to hours or days. Additionally, the combination of physically consistent learning, differentiable adjoint models, and reforecasting offers fresh avenues for future study and real-world application.

In the end, deep learning has enormous potential for improving coastal resilience, assisting early warning systems, and directing infrastructure planning and disaster response. Adopting AI-driven weather prediction techniques becomes not only advantageous but also necessary as climate change continues to increase the threats that coastal residents confront.

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