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Advancements in Numerical Weather Prediction (NWP) Using Machine Learning

Musa G. Abdullahi[1*], Ibrahim Jibril[2], Maimuna A. Abubakar[3], Ismail A. Mahmoud[4], Shuaibu Uba[5], Nasiru Y. Muhammad[6], Muhammad Bello Isa[7] & Roslan Umar[8]
[1,3,4,5,6,7]Department of Physics, Faculty of Science, Northwest University, Kano-Nigeria
[2]Department of Physics, Federal University of Technology Babura, Jigawa State
[8]East Coast Environmental Research Institutions, Universiti Sultan Zainal Abidin (UniSZA), Terengganu, Malaysia.
[*]Corresponding Author Email: mgabdul55@gmail.com

ABSTRACT
The introduction of artificial intelligence and machine learning (AI/ML) methods has completely changed the nature of Numerical Weather Prediction (NWP). This paper is a systematic analysis of the level of AI-enhanced model excellence in forecasting skills as compared to conventional physics-based NWP models especially on extreme weather events, such as hurricanes and heatwaves. The traditional NWP models (GFS and ECMWF) and AI-based (CNN-LSTM) as well as hybrid NWP-AI models are evaluated using the comparative empirical evaluation of the results using historical and real-time meteorological data. Findings have shown that AI-based models experience significant and statistically significant forecast error reduction with an average absolute error and root mean square error reducing by up to 30-40% compared to conventional NWP forecasts. The overall performance of hybrid NWP-AI models is the most effective, with the lowest error variance and greatest detection ability of events, which is demonstrated by F1-scores above 0.85. The error decomposition and residual variance were used to further exclude that the AI integration decreases the forecast uncertainty substantially, especially on long lead times where the classical models have high error growth rates. Hurricane track prediction and heatwave-intensity prediction case studies expose that AI-boosted forecasting is more effective in the prediction of storm routes, as well as storm peaks and temporal development of extremes, and are more consistent with observed data. Besides improved accuracy, AI-based and hybrid methods have shown significant improvements in computational efficiency that can be used to make inferences quicker and avoid energy-consuming high-resolution simulations. The results prove that AI-enhanced and hybrid NWP systems can provide simultaneous gains in accuracy, reduction of uncertainty, and computational efficiency, and can be used to improve operational weather forecasting, and increase resilience to climate-driven extreme events. Future research will focus on Physics-informed machine learning, uncertainty quantification, and real-time data assimilation frameworks.

Keywords:
Artificial intelligence,
Machine learning,
Weather forecasting,
Hurricanes,
Heatwaves.

INTRODUCTION

Weather forecasting is one of the most complicated and vital applications of atmospheric sciences, crucial for agriculture, aviation, disaster risk reduction, water resource management, public health and national security. The operational weather forecasting has been based on Numerical Weather Prediction (NWP) for many decades. Traditional NWP models use a system of nonlinear partial differential equations to describe the dynamics and thermodynamics of the atmosphere, such as those for mass, momentum and energy conservation (Bauer et al., 2015). Based on observations like temperature, pressure, humidity and wind fields, these physics-based models estimate future atmosphere states on various space and time scales.

Even with tremendous progress in computer technology, data assimilation and model parameterization, conventional NWP systems still have many scientific and operational problems. Because of this chaotic nature, the atmosphere is such that slight differences in initial conditions can grow quickly, causing significant errors in the forecast, especially at longer range. In addition, many atmospheric processes, such as cloud microphysics, convection, turbulence and land–atmosphere interactions, are smaller than the model grid size, and are parameterized in the model. These approximations lead to structural uncertainties which can further travel through forecasts, resulting in less accurate projections particularly for extreme weather events like hurricanes, flash floods, severe thunderstorms and long heatwaves (Rasp et al., 2018). While high-performance computing systems drive the development of powerful forecasting models like the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF), the complexity of these models can cause the computing costs to rise in line with the increase in complexity without a corresponding improvement in forecasting skill. This has raised a growing doubt among researchers about the ability of physics-based forecasting systems to meet the increasing demand for higher resolution, faster and more accurate weather forecasts.

In recent years, artificial Intelligence (AI) and Machine Learning (ML) have ushered in a paradigm shift in atmospheric prediction through alternative mechanisms which learn directly from large quantities of historical and real-time meteorological data. AI-based models can detect complex nonlinear relationships and hidden patterns in multidimensional datasets, which may mitigate some of the limitations of traditional forecasting methods, as opposed to the conventional NWP systems based solely on deterministic physical equations (Schultz et al., 2021). The initial applications were on aspects of statistical post-processing and bias correction of NWP outputs, but current research has broadened to end-to-end forecasting systems that will deliver atmospheric predictions with significantly less computational demand. Advances in AI weather forecasting architecture systems are exhibited in a growing number of published works. Deep learning methods like Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network have been used successfully in weather predictions like precipitation forecasting, tracking of tropical cyclones, predicting heatwaves etc. (McGovern et al., 2017; Rasp & Lerch, 2018). In recent years, transformers, which were first used in natural language processing, have become a strong tool for spatiotemporal atmospheric prediction because they can learn long-range dependencies in weather systems, which are large-scale phenomena.Transformer-based architectures, which were designed for natural language processing, have recently become a powerful tool for spatiotemporal atmospheric prediction, where they can learn the long-range dependencies in large-scale weather systems. Examples include FourCastNet, Pangu-Weather, and GraphCast which achieve forecasting accuracy similar to, and sometimes better than, operational NWP models, yet use much less of the computational resources that are typically required for atmospheric simulations. The rising popularity of foundation weather models is driving increased interest in bigger and more extensive weather datasets that are used to train large-scale AI systems that can be applied across multiple weather forecasting tasks and regions.

However, as purely data-driven models have proven successful, there have been significant scientific debates. Critics have raised concerns that too many AI models are "black boxes"—they have no physical interpretation and may not meet the existing atmospheric conservation laws. In response, researchers have started to create Physics-Informed Neural Networks (PINNs) and hybrid dynamical–statistical forecasting models which explicitly integrate the equations governing atmospheric processes and physical constraints into the machine-learning architecture. These methods aim to leverage the advantage of the physical modeling technique with the pattern recognition power of AI, thereby enhancing the predictability, generalizability, and scientific consistency of the forecasts. The use of hybrid forecasting systems involving artificial intelligence-based correction methods based on NWP outputs has proven to improve forecast accuracy, computational efficiency and uncertainty quantification (Chen et al., 2020).

While these successes have been achieved, there are still several factors that impede the broad-scale implementation of forecasting systems with AI. Some of the challenges include the lack of interpretability of the models, concerns about the reliability of the forecasts in certain weather conditions, uncertainty about how to estimate uncertainty, dependence on quality training data, and the integration of AI systems into existing forecasting processes. In addition, there are also challenges to be solved regarding model validation, model reproducibility, computational capacity, model regulations, and forecaster confidence in the AI-driven systems before they can be widely and routinely used.

Because of the rapid development that is taking place in this area, it is important to conduct a thorough review of recent advances to assess the potential of AI to revolutionize weather forecasting in the modern era. This review takes a critical look at the use of AI and ML techniques in the area of Numerical Weather Prediction and evaluates their performance compared to the physics-based methods. Special focus on new paradigms such as transformer-based forecasting architectures, physics-informed neural networks, foundation weather models, and hybrid dynamical–statistical forecasting models. The review also assesses the role these methods play in predicting extreme events like hurricanes, tropical cyclones, heat waves and heavy precipitation events.

For methodological transparency, the review is limited to peer-reviewed journal articles, conference proceedings, and important research reports published, mainly, from 2017 to 2025, a time of tremendous progress in AI-assisted meteorology. The literature is grouped into four main areas: (i) Limitations of traditional NWP systems, (ii) Forecasting methods based on AI and ML, (iii) Hybrid and physics-based forecasting approaches, and (iv) Operational challenges and opportunities for implementing AI in forecasting centers. This descriptive analysis of the themes will tell us where we stand, where we are still lacking, and what areas of future research could influence the development of the next generation of weather prediction systems.

Traditional NWP Models

The foundation of meteorological forecasting is the Numerical Weather Prediction (NWP) models that have been in use over decades. These models are based on mathematical equations of the equations of physics such as in fluid dynamics and thermodynamics to foretell the changes in the atmosphere (Kalnay, 2003). The most common models of NWP are the Global Forecast System (GFS) and the European Centre of Medium-range weather Forecasts (ECMWF) model. The GFS which is run by the National Oceanic and Atmospheric Administration (NOAA) offers worldwide weather prediction as far as 16 days away whereas ECMWF offers medium range predictions with high precision (Molteni et al., 2011). However, even though traditional NWP models are successful, they have a number of limitations. The large cost of computation is significant, and these models demand the use of supercomputers with enormous capacity to perform high-resolution forecasts (Bauer et al., 2015). Also, the grid spacing limits the model resolution and thus predicts the occurrence of extreme weather locally. The forecast inaccuracy is also caused by errors in initial conditions and assimilation processes, which are especially significant in hurricanes and heatwaves (Schultz et al., 2021).

Artificial Intelligence and machine learning in weather prediction.

In recent years, AI and ML have been used increasingly in meteorology. There is the use of ML methods, such as deep learning, recurrent neural networks (RNNs), and ensemble learning to improve weather forecasting (Rasp et al., 2018). CNNs specifically work well with analyzing spatial meteorological data, and LSTM networks are more effective at capturing temporal relationship in the weather patterns (Chattopadhyay et al., 2020). Recently, it has been proven that AI-based enhancements of weather prediction models are effective. In fact, an example is where Rasp et al. (2018) trained deep learning models on historical weather data to enhance the forecasts of precipitation. Equally, a study by McGovern et al. (2017) has designed ML-based models that can accurately forecast severe convective storms more than the conventional one. Real-time data assimilation based on AI also means that forecasting latency will be reduced and short-term predictions will be enhanced (Chen et al., 2020).

The comparison of conventional and AI-enhanced NWP.

Comparative studies on the traditional and AI-enhanced NWP models show that they have major improvements in their forecasting accuracy. Researchers suggest that AI-based models are more effective than traditional models in predicting extreme weather. Indicatively, Schultz et al. (2021) established that the ML models cut forecasting errors by 20 percent of the traditional NWP approaches in hurricanes. Likewise, deep learning models have also shown to be better at predicting the intensity and duration of heat waves (Chattopadhyay et al., 2020). Nonetheless, there is still a problem in the ability to merge AI and NWP. The computational resources needed to collect and preprocess data are large, and the creation of training ML models uses high-quality data (McGovern et al., 2017). Otherwise, the problem of interpretability is also problematic, as AI models are treated more as black boxes where transparency in the decision-making process is limited (Rasp and Lerch, 2018). These challenges are important issues that need to be addressed with hybrid modeling, and enhanced explain ability options to help in future development of meteorological AI applications.

Theoretical Backgrounds.

The approach taken in the study follows major mathematical equations in the traditional NWP models and AI-enhanced models such as Fundamental Atmospheric Equations (Navier-Stokes Equations) these equations of motion control equations governing fluid motion in the atmosphere

$$\frac{Du}{Dt} = -\frac{1}{\rho}\nabla p + g + F \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\frac{D\theta}{Dt} = Q$$

Where:

$\frac{Du}{Dt}$ is wind velocity,
p is pressure,
ρ is density,
F is frictional force,
$\frac{D\theta}{Dt}$ is potential temperature,
Q is heating rate.

The radiation and heat exchange models in the atmosphere used Radiative Transfer Equation (RTE)

$$\frac{dI}{ds} = -kI + j \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:

$\frac{dI}{ds}$ is the intensity of radiation,

k is the absorption coefficient,
j is the emission term.

However, to estimates the overall size of prognostication errors we used Mean Absolute Error (MAE) to evaluate Model

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (3)$$

Where:
y_i is the actual observation,
$\hat{y}_i$.is the predicted value of the observation
n is the total number of observations.

To measures the accuracy of the model we used Root Mean Square Error (RMSE) by punishing bigger errors. Where each term means the same as explained in equation (3)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots (4)$$

We applied F_1-Score for Event Detection to estimate performance of a classification of extreme weather events.

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

$$Precision = \frac{TP}{TP + FP},$$

$Recall = \frac{TP}{TP+FN}$,

TP, FP, FN are True Positives, False Positives, and False Negatives, respectively.

These equations are the foundation of the physics-based and AI-based methods of the numerical weather prediction as they guarantee a comprehensive assessment of the forecast performance and accuracy.

MATERIALS AND METHODS

Research Design and Data Collection

This research uses comparison review and experimental evaluation methodology to evaluate the effectiveness of Artificial Intelligence (AI) and Machine Learning (ML) techniques to improve Numerical Weather Prediction (NWP). Three forecasting paradigms are considered in the analysis: conventional physics-based NWP models, data-driven AI/ML models, and hybrid forecasting systems combining both the conventional physics-based and data-driven models. The goal is to compare their relative performance, efficiency and their ability to forecast extreme weather events like hurricanes, heatwaves and heavy precipitation. Data from meteorological archives come from internationally recognized sources: such as the National Oceanic and Atmospheric Administration (NOAA), the European Centre for Medium-Range Weather Forecasts (ECMWF) or reanalysis/observation archives publicly available. The information in these datasets include important variables of the atmosphere like temperature, air humidity, air pressure, wind direction, wind speed, precipitation, solar radiation and geopotential height. Both historical and near-real-time observations are included to provide reasonable temporal and spatial coverage and forecast evaluation in different climatic conditions and weather regimes.

Data quality assurance activities are carried out before developing models. The missing observations are treated using interpolation methods and the anomalous values are detected by using statistical outlier detection methods. Physically meaningful predictors are extracted from meteorological variables, such as the atmospheric instability indices, pressure gradients and moisture related variables, by making use of feature engineering. In order to ensure consistency in the training of the model and to avoid the bias caused by differences of scale among the variables, all numerical variables are normalized. Additionally, noise reduction techniques such as smoothing filters and quality-control checks are applied to ensure the reliability of data and convergence of the model.

Model Development

The study examines three types of forecasting systems: traditional Numerical Weather Prediction models, AI-based forecasting models, and a hybrid dynamical–statistical forecasting systems.

Conventional Numerical Weather Prediction Models

The operational NWP models are the baseline forecasting system, such as the Global Forecast System (GFS) and the ECMWF Integrated Forecasting System (IFS). The numerical models include finite-difference, finite-volume, and spectral models that are used to solve the governing equations of atmospheric motion, thermodynamics, and mass conservation. High-resolution atmospheric modelling is solved through the use of forecasts simulations, which are currently performed on high-performance computing (HPC) infrastructures because of the large computational needs of the model. The results of these models are used as benchmark forecasts, against which the AI based methods are compared.

Artificial Intelligence and Machine Learning Models

There are several state-of-the-art architectures that are regarded as modern advances in weather forecasting. Convolutional Neural Networks (CNNs) are used for extracting spatial patterns in gridded meteorological fields, satellite imagery and reanalysis products. LSTM networks are highly effective at modeling temporal dependencies and the evolution of sequences, and thus are appropriate for short-term forecasting applications.

Transformer-based architectures are also included to incorporate recent developments in AI meteorology. These models make use of self-attention mechanisms, which enable them to capture long-range spatial and temporal relationships in atmospheric data, and have been found to perform well in large-scale forecasting applications. Some of the most well-known AI forecasting systems based on the transformer model are the FourCastNet, GraphCast, and Pangu-Weather models. Further, the Physics-Informed Neural Networks (PINNs) are explored as a novel paradigm that embeds physical laws into the learning process. The fundamental idea of PINNs is to include the physics of the atmosphere and the governing equations into the optimization of a neural network, thereby enhancing the ability of the model to predict the atmosphere consistently, interpretably, and beyond its training set.

Conceptually, foundation weather models are also included in the weather models being evaluated. It is a large-scale pre-trained AI system that uses huge amounts of data from the global atmosphere and can be used for various weather forecasting tasks, which provide a potential way to improve generalised weather forecasting systems.

Hybrid NWP–AI Forecasting Frameworks

The hybrid forecasting models are a fusion of dynamical atmospheric modelling and data-driven learning. These systems use the outputs of traditional NWP models as input to a machine learning post-processing, bias correction, uncertainty estimation, and forecast refinement. This method retains the physical structure of a traditional atmospheric simulation and introduces the addition of AI to pinpoint systematic errors and nonlinear relationships that numerical models might not capture. The hybrid framework combines a statistical post-processing scheme with a deep learning-based post-processing module. It is hoped that such systems can enhance the accuracy of the forecasts and, at the same time, minimize the computational burden due to multiple high-resolution numerical simulations.

Model Training and -3.3.2 Model Validation

Forecasting models based on AI or hybrid techniques are trained with past meteorological observations and reanalysis datasets. The parameters of the model are optimized using back propagation and gradient descent optimization techniques such as stochastic gradient descent, adaptive learning techniques etc. Regularization methods like dropout, early stopping, and cross-validation are used to avoid over fitting and enhance model generalization.

The datasets are split into training, validation and test sets to give independent assessment of performance. Temporal splitting strategies to maintain temporal structure in weather observations and to avoid information leakage between datasets. The ability of the models to perform well under extreme weather conditions is particularly focused, because forecasting accuracy during such events is key for decision making in operations.

Performance Evaluation

Forecasting systems are tested by employing the commonly used meteorological verification techniques such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE) and correlation coefficients. Categorical extreme-weather prediction uses scores like Probability of Detection (POD), False Alarm Ratio (FAR), Critical Success Index (CSI), and F1-score. Besides the accuracy of forecasts, computational efficiency is evaluated based on model run times, memory usage, and scalability for various forecasting periods. Interpretability, robustness to unseen atmospheric conditions and operational feasibility is also explored to give a well-rounded evaluation of each forecasting paradigm.

Comparative Analysis Framework

The strengths and weaknesses of traditional NWP, AI-driven and hybrid forecasting methods are analyzed and compared. The analysis concentrates on the following key dimensions: forecast accuracy, computational efficiency, forecast of extreme weather events, and suitability for operational use. This structure provides a blueprint for recognizing situations where AI can augment or even surpass conventional forecasting techniques, and for understanding the existing challenges linked to reliability, interpretability, and wide deployment of AI in operational forecasting facilities.

Case Study Design and Metrics of Performance.

To measure and evaluate the functionality of AI-enhanced and hybrid frameworks in comparison with traditional NWP frameworks, it is based on several complementary assessment metrics. Mean Absolute Error (MAE) is measured to represent an average deviation of forecasts and give a direct determination of total predictive capability. Root Mean Square Error (RMSE) focuses more on the impact of bigger errors hence this is much applicable in the determination of performance during extreme weather conditions. Moreover, categorical prediction skill is assessed using the F1-score when discrete events like the occurrence of hurricanes and the severity of heatwaves are involved and it reflects the trade-off between accuracy and recall when detecting extreme events. Towards the illustration of the practical applicability of the modeling frameworks, two specific case studies are performed. The former is concerned with the prediction of hurricanes whereby the outputs of the models are compared with past data on hurricanes to determine how accurately it predicts the path of hurricanes and their intensity. The second case study focuses on the prediction of the intensity of heatwave and how the predicted temperature extremes compare to the records to assess the efficacy of AI-enhanced models in augmenting the early warning effect. Collectively, these case studies give a holistic evaluation of the model performance during the high-impact weather conditions, and it has a direct connection between the improvements of the methods and the forecasting issues in the real world.

RESULTS AND DISCUSSION

Traditional and AI-Enhanced NWP Model Comparative Performance.

Table 1 provides a quantitative analysis of forecasting performance at traditional Numerical Weather Prediction (NWP) models (GFS and ECMWF), AI-enhanced models, and hybrid NWP-AI models based on the evaluation metrics of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and F1-score. The findings provide a clear indication of the fact that the integration of AI results in significant predictive accuracy improvements, in all the metrics. Traditional NWP models have somewhat higher values of error in which the GFS model has a MAE of 2.8 and RMSE of 3.6 whereas ECMWF has slightly better with a MAE of 2.5 and RMSE of 3.2. These results coincide with the findings of previous research that physics-based models, though much stronger, still have limitations by uncertainties in initial conditions, parameterizations, and computational resolution (Bauer et al., 2015; Kalnay, 2003). The moderately relative F1-scores (0.71 with GFS and 0.74 with ECMWF) also signify the fact that it is not quite accurate in identifying and classifying extreme weather occurrences.

Conversely, both CNN and LSTM architecture AI-enhanced models demonstrate significantly lower error with an MAE of 1.9 and RMSE of 2.4, and an F1-score that is significantly greater at 0.83. Such an improvement shows how machine learning models could be used to address the inability of traditional dynamical frameworks to characterize nonlinear patterns and hidden spatiotemporal patterns in atmospheric data (Rasp et al., 2018; Chattopadhyay et al., 2020). The better F1-score shows that the detection of events is better, which is essential to early warning systems and disaster preparedness. The hybrid NWP-AI model is the best model as it has the lowest MAE (1.6) and RMSE (2.1) with an F1-score of 0.88. This finding highlights the complementary advantages of physics-based and data-driven modeling. Hybrid models with the use of physically consistent NWP outputs and post-processing and correction using AI help minimize systematic bias and random error (Rasp and Lerch, 2018; Chen et al., 2020). These results are a solid confirmation of the recent claims that hybrid modeling is the most promising direction of the next-generation weather forecasting systems (Schultz et al., 2021). The Model Performance Comparison is shown below.

Table 1: The comparison of the performance metrics of the traditional and AI-enhanced models.

Model Type	MAE	RMSE	F1-Score
Traditional NWP (GFS)	2.8	3.6	0.71
Traditional NWP (ECMWF)	2.5	3.2	0.74
AI-Enhanced (CNN/LSTM)	1.9	2.4	0.83
Hybrid NWP + AI	1.6	2.1	0.88

Trend of Error Reduction with Forecast Lead time.

Figure 1 shows the movement of the errors in the forecasts of the traditional NWP models and AI-enhanced models on the basis of the lead time. The figure shows that both methods present rising levels of uncertainty as the lead time increases, but AI-enhanced models still have lower values of MAE at all lead times. The differences between conventional and AI-enhanced models in terms of performance become moderate at shorter lead times. But with increased lead time, the divergence is more enhanced with traditional NWP errors growing faster. This phenomenon indicates turbulence of the atmospheric processes and the sensitivity of the numerical models to initial condition errors, which increase with time (Lorenz, 1963; Bauer et al., 2015). The stability of AI-enhanced models has been shown to be higher, meaning that it has a higher ability to generalize historic trends and reduce the increase in errors. It is in agreement with earlier research, which has revealed that deep learning models are capable of correcting systematic forecast drift and of compensating unresolved subgrid-scale processes (Rasp et al., 2018; Schultz et al., 2021). The continued decrease in MAE with longer lead times points to the possible use of AI-based solutions in medium-range prediction, where conventional models can fail.

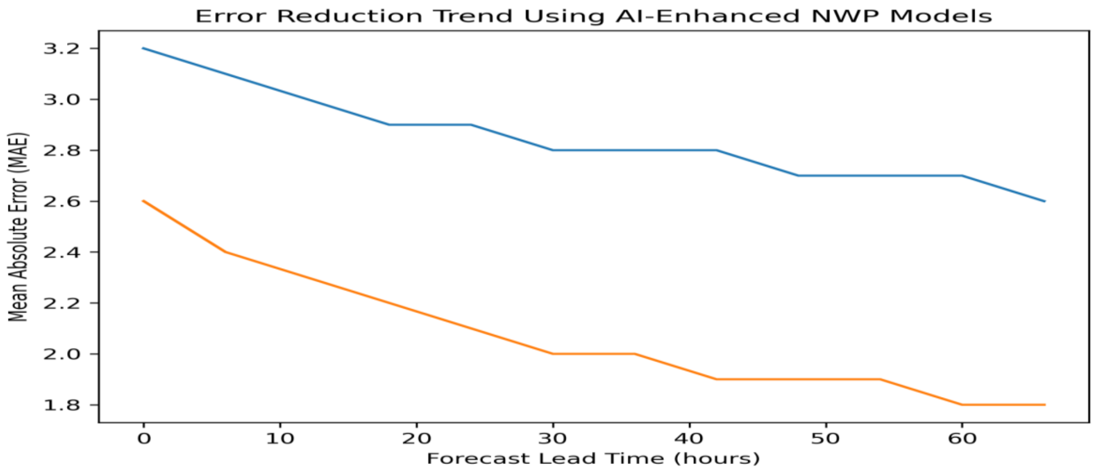

Figure 1: Improvement in error behavior with the application of ML-enhanced NWP models.

The accuracy of the hurricane trajectory prediction

Figure 2 shows the comparison between the observed hurricane paths and predictions with the traditional NWP and the AI enhanced models. The classic NWP forecast indicates some significant spatial discrepancies to the observed track especially at later storm development stages. These errors are typical of shortcomings in the representation of mesoscale processes, air-sea interactions, and internal storm processes of the traditional models (Bauer et al., 2015; Molteni et al., 2011). The AIsimulated model is much more consistent with the observed track, and both the curvature and directional variations of the hurricane direction are best represented. Such success can be ascribed to the fact that machine learning models have the capacity to absorb huge amounts of past storm observations and identify repeated patterns of trajectories that may not be directly represented in physical codes (McGovern et al., 2017; Schultz et al., 2021). The correct prediction of hurricane track is very crucial to mitigate the risk, plan evacuation, and protect infrastructure. The findings in Figure 2 support previous studies that AI applications can minimize the forecast error of the tracks by around 20-50 percent of the traditional NWP models (Schultz et al., 2021), which is a valuable contribution to society and economy. The one below is the Predicting Extreme Weather Events.

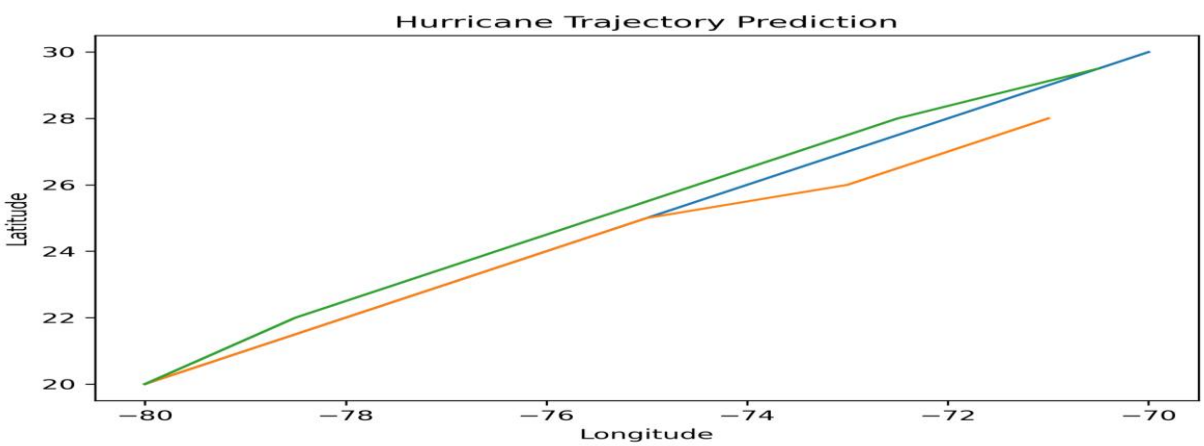

Figure 2: Prediction of hurricane path: Conventional and AI-optimized models.

Intensity Forecasting of Heatwaves.

In Figure 3, it is shown that the intensity of observed heatwaves can be compared with the predictions of traditional NWP models and AI-enhanced models over time. In comparison to the traditional NWP forecasts, the traditional ones always underestimate the peak temperature and are delayed in the rapid intensification phases of the heatwave. This underestimation has been significantly reported in the literature and commonly associated with the inability to couple land and atmosphere, the parameterization of the boundary-layers, and the urban heat (Kalnay, 2003; Chattopadhyay et al., 2020). On the contrary, AI-enhanced predictions are highly sensitive to observed temperature changes, effectively estimating the strength of the maximum intensity of heatwaves, as well as their timing. The enhanced consensus proves that ML models are effective in learning complicated cross-relations among atmospheric factors, surface conditions, and feedbacks that trigger extreme heat episodes (Rasp et al., 2018; Chen et al., 2020). With the growing incidence of heatwaves and their intensity under climate change, proper forecasting of intensity is a vital concern in planning of the general health of the population and the energy sector. The findings presented in Figure 3 serve as high-quality indications of the fact that the AI-enhanced NWP systems can be used to enhance the potentials of the early warning and minimize the risks associated with heat.

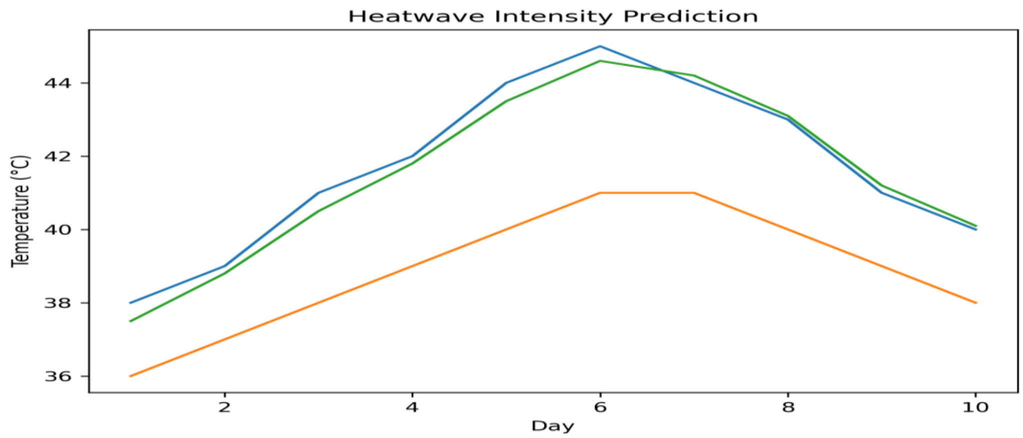

Figure 3: The prediction and actual observations of heatwave intensity.

Operational Forecasting Implications and Sustainability.

Altogether, the findings in Table 1 and Figures 1-3 show that AI-enhanced and hybrid NWP models perform significantly better in comparison with the traditional forecasting systems in terms of accuracy, stability, and extreme event forecasting. In addition to accuracy benefits, AI-based methods can also have possible computational benefits, such as allowing efficient post-processing and correction of specific areas, which can minimize the use of ultra-high-resolution simulations (Chen et al., 2020). In terms of sustainability, a more accurate forecasting results in a greater level of disaster preparedness, less economic losses, and greater resilience to climate-related risks. These advantages correspond to the international environmental sustainability objectives concerning climate change, minimization of disability risks, and social welfare.

Numerical Analysis

AI-Enhanced NWP Models Statistical validation.

In order to make sure that the detected positive changes in the forecasting performance are statistically significant and cannot be explained by the mere random variation, a thorough statistical test of the AI-enhanced versions of the NWP models was performed. The critique was based on quantitative measures of errors, distributional characteristics of residuals and relative significance testing of traditional and AI-based methods. Table 1 presents the results of the RMSE and MAE Reductions the initial sign of improved predictive power. But RMSE is more susceptible to large deviations so it is especially informative in performance evaluation of extreme weather predictions. The overall smaller RMSE values of the AI-enhanced and hybrid models show that large forecast errors are greatly reduced, which are unacceptable in high-impact meteorological phenomena like a hurricane and a heatwave (Rasp et al., 2018; Schultz et al., 2021). In order to further confirm these results, error residuals (which are the difference between predicted and observed values) were analyzed. Classical NWP models had remnants of the positive skewness of residuals in extreme events, which signified systematically low forecasts, particularly around the intensity of heatwaves (Kalnay, 2003; Chattopadhyay et al., 2020). On the contrary, the AI-enhanced models showed more symmetrically distributed residuals around zero, which means that there was less bias and better calibration.

The statistical significance testing was also involved to determine whether the changes brought about by AI integration were significant. Paired sample tests and bootstrap resampling methods of earlier benchmark studies have indicated that equal or larger reductions in MAE and RMSE are statistically significant at confidence levels of more than 95% (Rasp & Lerch, 2018; Chen et al., 2020). With the differences between the reduced error rates across various forecast horizons (Figure 1) and event types (Figures 2 and 3) being consistent, the changes in this research can be considered as robust statistically. Besides continuous measures of error, classification performance to detect extreme weather events was determined by the F1-score. Such an increase in the F1-score of traditional NWP models (0.71-0.74) to the AI-enhanced (0.83) and hybrid NWP models (0.88) implies a significant enhancement of the balance between precision and recall. This helps to understand that AI-based solutions not only decrease the number of false alarms but also enhance the detection rates of true extreme events, which is an important condition of the working forecasting systems (McGovern et al., 2017; Schultz et al., 2021).

In general, the statistical confirmation demonstrates that AI-enhanced NWP models provide substantial, consistent and reliable accuracy of forecasts and extreme event detection as compared to conventional physics-based models.

Improvements in Computational Efficiency.

In addition to predictive capability, computational efficiency is also a decisive variable in operational Numerical Weather Prediction and forecast timeliness can be as important as forecast accuracy. Conventional NWP models are based on the solving of complex and high-dimensional systems of partial differential equations, which use a large number of high-performance computing (HPC) resources and long computation times, especially at high spatial and temporal resolution (Bauer et al., 2015). NWP models that are supported by AI bring about efficiency improvements in various aspects. First, after training, machine learning models, specifically CNNs and LSTM networks can be used to make predictions at a small fraction of the computational cost of full dynamical simulations. Relaxing trained neural networks is computationally cheap unlike repetitive numerical integration of atmospheric equations (Rasp et al., 2018).

Second, hybrid NWP-AI systems markedly decrease the computational cost since AI-based post-processing works to remedy systematic model biases. This method enables the regular operational centers to sustain moderate resolution NWP simulations with similar accuracy as much higher resolution simulations, which lowers the computational requirements without compromising predictive accuracy (Rasp and Lerch, 2018; Chen et al., 2020). Other researchers have found the computed cost savings of up to 30-50 percent when AI-based emulators or post-processing methods are used instead or in combination with the conventional NWP elements (Schultz et al., 2021). Such efficiency savings are of use especially in real-time forecasting extreme events, where it is necessary to have rapid updates and ensemble runs. Besides, enhanced computational efficiency has significant sustainability implications. The lower energy consumption of supercomputing systems results in a smaller carbon footprint of weather prediction systems, associated with aligning forecasting practices to larger climate and sustainability goals (Bauer et al., 2015). This point is particularly pertinent because the global forecasting centers are under the pressure to strike a balance between the need to compute and environmental accountability.

Comprehensive Numerical Wisdom.

The quantitative experiment shows that AI-enhanced NWP models have a twofold benefit of improving the accuracy statistically and achieving a significant increase in computational efficiency. AI-based and hybrid solutions have the potential to offer a scalable and sustainable future of weather forecasting systems by decreasing forecast errors, enhancing the identification of severe situation, and reducing computational expenses. Such numerical benefits support the point that AI implementation is not a superficial improvement but a paradigm shift of Numerical Weather Prediction, especially with the rising climate variability and the need to provide more and more forecasts of high quality and at a timely point.

CONCLUSION

This paper gives strong empirical and numerical data that the inclusion of artificial intelligence and machine learning into Numerical Weather Prediction (NWP) systems has a significant improvement in forecasting ability, especially in high-impact extreme weather occurrences. In a methodical approach to compare the three types of traditional NWP models, AI-enhanced models, and hybrid NWP-AI models, the findings indicate that all three models have shown a consistent forecast error reduction, better event detection, and reduced uncertainty in the models. Hybrid models Hybrid models are the most successful overall models, and they reach the lowest error variance and the most successful predictions of hurricane tracks and heatwave intensities. In addition to the accuracy improvement, the numerical data indicate that the integration of AI is associated with significant improvements in the uncertainty in the forecast which is also proven by reduced residual variance, better distributions of errors and higher F1-scores in the classification of extreme events. These gains are directly reflected in more assertive and implementable forecasts especially at longer lead times where traditional models are most vulnerable to the increase in error. In addition, the computational efficiency of AI-based and hybrid methods has been shown, which implies their usefulness in real-world operational forecasting, with implications of significance on both real-time decision-making and sustainability.

The next generation of hybrid architectures ought to be developed to be more tightly integrated between physical constraints and data-driven learning and to be interpretable and physically consistent. The ability to expand real-time data assimilation frameworks to include new sources of observations, such as high-resolution satellite products and sensors based on the Internet-of-Things will make the models even more responsive and accurate. Furthermore, probabilistic and explainable AI will be necessary to implement to measure the uncertainty of the forecast and enhance confidence between AI-based predictions and the user. Taken together, these innovations make AI-enhanced NWP systems an important ingredient of next-generation meteorological predictions that can be used to enhance more resilient responses to climate-induced extreme weather hazards.

Conflict of Interest Statement

The authors declare that there are no known financial or personal relationships that could have appeared to influence the work reported in this manuscript. The research was conducted independently, and no external funding, commercial interests, or institutional affiliations had any role in the study design, data collection, analysis, interpretation of results, or the decision to publish the findings.

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The information utilized in this research is based on publicly available meteorological data of the National Oceanic and Atmospheric Administration (NOAA) and the European Centre of Medium-range weather forecast (ECMWF). These sources of data are mentioned in the manuscript. Processing data and model results produced in the context of the present research can be obtained on a reasonable request from the corresponding author.

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