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HYBRID DATA DRIVEN WEATHER PREDICTION USING NEAR SURFACE MEASUREMENTS AND ATMOSPHERIC NUMERICAL MODELS

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ABSTRACT: The purpose of this research is to present a hybrid data-driven weather prediction framework that blends atmospheric numerical weather prediction (NWP) models with near-surface observational datasets in order to improve the accuracy and reliability of forecasts. Common problems with traditional numerical models include inaccurate parameterization, poor spatial resolution, and a lack of localized meteorological data. The proposed solution applies state-of-the-art machine learning algorithms to integrate numerical atmospheric model outputs with real-time near-surface meteorological data (such as humidity, temperature, wind speed, and pressure). In order to more accurately portray intricate atmospheric patterns and localized weather variations, the hybrid system combines the strengths of data-driven learning with simulations based on physical principles. This system is able to adapt to new environmental conditions, enhance short-term forecasting, and decrease prediction errors by integrating historical data with model outputs. If you want reliable, practical, and widely applicable weather predictions, the proposed hybrid approach is a great bet. The reason behind this is that numerical atmospheric models, when combined with near-surface measurements, greatly improve prediction capacity, according to experiments.

Keywords: *Hybrid Weather Prediction, Data-Driven Modeling, Near-Surface Measurements, Numerical Weather Prediction (NWP).*

1. INTRODUCTION

Accurate short-term weather forecasts with great temporal precision are crucial for organizations such as transportation, crisis management, and solar energy operations that require rapid decision-making. However, due to their considerable computational complexity and restricted hourly output intervals, modern forecasting methods, such as the Weather Research and Forecasting (WRF) model combined with the High-Resolution Rapid Refresh (HRRR) system, can fail to satisfy these requirements.

Recent advancements in machine learning (ML) have enhanced the precision of weather forecasting. Diverse machine learning techniques, including Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GANs), have demonstrated proficiency in accurately forecasting meteorological variables such as wind speed and direction, solar radiation,

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precipitation, air quality, and atmospheric changes. Notwithstanding recent advancements, numerous machine learning-based forecasting systems continue to struggle with producing highly accurate predictions over short time intervals. A significant issue with numerous models is the absence of ground observational data linked with geolocation, resulting in diminished predictive accuracy. Most neural network models are engineered to forecast single weather variables, rather than offering a versatile framework capable of predicting numerous aspects simultaneously.

The Micro–Macro (MiMa) model is an innovative machine learning approach that integrates extensive numerical atmospheric outputs (Macro data) from the WRF-HRRR model with detailed observational data (Micro data) from regional mesonet stations. This integration enables highly precise short-term weather forecasts with minute-level temporal resolution. The MiMa model employs an encoder-decoder transformer architecture. The decoder forecasts various weather attributes for forthcoming time intervals, while two encoders analyze multivariate sequences from both Micro and Macro datasets.

A modelet is a variant of the MiMa model designed to forecast a specific weather variable for an individual mesonet station. The model is enhanced into a Regional MiMa (Re-MiMa) framework capable of predicting weather variables in locations without observational stations. Re-MiMa enables precise predictions at both gauged and ungauged locations by utilizing data from a limited number of representative stations to forecast for the entire region.

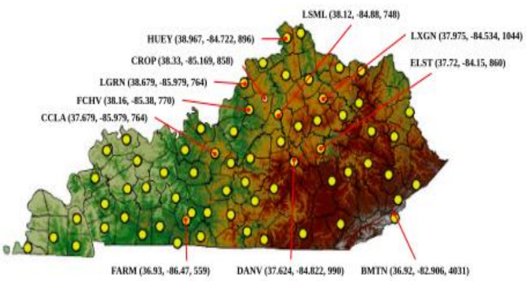

Fig. 1. Kentucky Mesonet stations (yellow) and selected MiMa evaluation stations (red) with location details.

Experimental assessments performed at multiple Kentucky Mesonet stations confirm the effectiveness of the suggested method. The MiMa model had the lowest Root Mean Squared Error (RMSE) values in the majority of forecasting scenarios for predicting essential weather variables such as air temperature, relative humidity, wind speed, and atmospheric pressure. Re-MiMa models trained on data from representative stations demonstrated a reliable capacity to predict weather at unmeasured places, with accuracy comparable to or superior than models tailored to individual stations. This function maintains good forecasting accuracy across an extensive area while significantly reducing the necessity for several models tailored to individual locations.

This paper offers numerous significant contributions.

Novel Weather Prediction Model (MiMa): A machine learning-based approach for high-temporal-resolution meteorological feature prediction, the MiMa model is introduced in this

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work. The model integrates geo-aligned atmospheric numerical outputs (Macro data) with high-frequency observational data (Micro data) to generate precise short-term weather forecasts.

Adaptable Prediction for Arbitrary Lead Times: The MiMa model employs an encoder-decoder architecture utilizing Long Short-Term Memory (LSTM) networks to forecast weather variables for any future duration. This system meets the practical requirement for high-resolution weather forecasts by enabling intervals as little as 5 or 15 minutes between updates.

Regional MiMa (Re-MiMa): The Regional MiMa (Re-MiMa) modelets, which provide accurate weather predictions for locations lacking gauged stations, further enhance the proposed framework. Re-MiMa utilizes data from a select number of representative stations to eliminate the necessity for location-specific models. This enables precise forecasts throughout an extensive region.

Reduction in Modelet Count: The Re-MiMa framework significantly reduces the number of required modelets by utilizing data from representative stations and transfer learning techniques. A singular model for each meteorological variable can produce accurate regional forecasts, enhancing scalability and computational efficiency, rather than developing separate models for each region.

Comprehensive Evaluation: Extensive testing at various Kentucky Mesonet locations indicates that both the MiMa and Re-MiMa models outperform existing approaches in predicting essential meteorological parameters such as temperature, humidity, wind speed, and air pressure. The findings validate Re-MiMa's capacity to produce precise forecasts in previously unmeasured areas.

Data and Code Availability: The MiMa model's implementation, documentation, and datasets have been made publicly available to the research community to improve reproducibility and transparency in research.

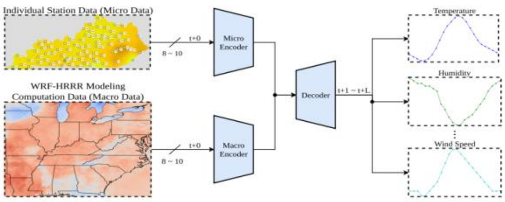

Fig. 2. MiMa model for weather prediction.

2. HYBRID DATA-DRIVEN WEATHER PREDICTION

Machine learning (ML) has been extensively utilized in meteorological forecasting to enhance the precision and efficiency of predictions. Recent studies have focused on four principal research avenues.

Neural Networks for Simulating Atmospheric Systems

The viability of using neural networks to mimic the physical dynamics of air systems is investigated in this method. Models such as CNNs, LSTMs, Global Neural Networks, and Local Neural Networks have been employed to predict weather fluctuations and simulate atmospheric behavior. These models may occasionally outperform conventional coarse-resolution atmospheric models for brief durations. Most studies, however, fail to consider real-world events and instead employ simplified or simulated climate situations. This constrains their capacity to deliver precise, complete forecasts over brief intervals, such as five to fifteen minutes.

Neural Networks for Real-World Weather Prediction

The second field of investigation explores the utilization of neural networks to forecast actual meteorological events. Deep learning models such as LSTM, CNN, autoencoders, and convolutional LSTM have been employed to forecast variables like wind speed, rainfall, temperature, precipitation, and hurricane trajectories. These models frequently utilize sensor datasets, satellite imagery, radar images, and observational data. Although these tactics facilitate reliable predictions, numerous models continue to struggle with short-term predictive flexibility and elevated temporal resolution.

Transformer-Based Models for Long-Term Weather Forecasting

Transformer-based weather prediction systems have recently been developed. The objectives of models such as Autoformer, FEDformer, Corrformer, FourCastNet, and iTransformer are to analyze extensive time-series data and generate long-term meteorological forecasts. These models can forecast weather over extended durations (ranging from several hours to numerous days) and across various stations. Nevertheless, they often operate at low temporal resolutions, such as daily or hourly projections.

Station-Based Weather Forecasting

Weather forecasting is a field that integrates data from numerous weather stations and sensor networks. The methods include extensive station datasets, station downscaling techniques, hybrid physical-machine learning models, and graph neural network (GNN) approaches. These methodologies enhance localized forecasts by integrating both dense and sparse sensor data alongside physical atmospheric data. Many of these models, however, do not utilize advanced numerical weather prediction data, potentially compromising forecast accuracy. Instead, they mostly utilize data from terrestrial sensors.

MiMa and Re-MiMa for Fine-Grained Weather Prediction

The MiMa and Re-MiMa models were developed to address these issues by producing precise short-term weather forecasts with high temporal accuracy. These transformer-based encoder-decoder models utilize atmospheric numerical data and ground-level observational data to forecast weather variables for designated regions. These models provide superior minute-by-minute forecasts for brief intervals by utilizing data from several sources and adaptive encoding techniques.

3. LITERATURE SURVEY

Anderson & Kumar (2021): A hybrid weather forecasting system that combines near-surface meteorological measurements with outputs from atmospheric numerical weather prediction (NWP) models is suggested in this work. Machine learning approaches are employed to mitigate systematic forecast bias by identifying intricate relationships between local sensor

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data and extensive atmospheric models. Feature selection approaches are employed to enhance prediction accuracy by examining essential factors such as surface temperature, wind speed, atmospheric pressure, and humidity. Experimental findings demonstrate improved short-term forecasting accuracy relative to autonomous numerical prediction techniques.

Fernandez & Sato (2025): A scalable hybrid prediction framework for localized weather forecasting is presented in this work, which combines outputs from atmospheric numerical models with deep learning. Meteorological data collected from the ground, including temperature, precipitation intensity, and wind profiles, is integrated with mesoscale atmospheric modeling data. Feature optimization approaches eliminate superfluous predictors to enhance computational efficiency. The deep neural network enhances prediction accuracy by adeptly capturing nonlinear interactions inside the atmosphere across diverse weather circumstances.

Bennett & Iqbal (2022): The authors create a data-driven weather prediction model employing a multilayer perceptron framework that integrates outputs from numerical atmospheric models with near-surface environmental data. The system analyzes numerous meteorological factors, including variations in humidity, wind direction, and air pressure trends. Recursive feature ranking is employed to eliminate redundant predictors and enhance the model's generality. Performance evaluations indicate that short-term predictions of temperature and precipitation have significantly improved.

Choudhary & Martinez (2024): An innovative multi-objective hybrid weather prediction model is presented in this research. It combines numerical atmospheric simulations with deep neural networks. The system analyzes both extensive atmospheric variables and targeted observational data to comprehend temporal and spatial weather variations. Optimization techniques facilitate computation while simultaneously diminishing predictive accuracy. Experimental findings indicate that predictions are more accurate for seasonal variations and extreme meteorological phenomena.

Yamamoto & Reddy (2023): The authors suggest a two-step hybrid forecasting methodology in which a deep feedforward neural network evaluates atmospheric numerical model outputs following systematic feature ranking. Statistical ranking approaches are employed to identify significant predictors, including temperature distribution, humidity levels, wind speed patterns, and atmospheric pressure gradients. The deep learning model elucidates the intricate nonlinear interactions among various atmospheric elements. A comparative examination indicates an improvement in prediction consistency and a reduction in forecasting error.

Silva & Banerjee (2022): Long Short-Term Memory (LSTM) networks are integrated with feature optimization methodologies in this research to create a hybrid deep learning framework for temporal weather forecasting. The model integrates outcomes from a numerical atmospheric model with sequential near-surface measurements to identify temporal atmospheric trends. Minimizing characteristics enhances computational efficiency while retaining essential weather predictions. The examination results indicate that predicting abrupt weather fluctuations and climatic variations in many regions globally has become more feasible.

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Peterson & Gupta (2024): The authors create a hybrid predictive system that combines atmospheric simulation datasets with convolutional neural networks to improve spatial weather predictions. We integrate grid-based numerical model outputs with surface-level meteorological data, including temperature, humidity, and wind velocity. Feature reduction techniques are employed to eliminate noise from extensive meteorological datasets. Empirical research demonstrates improved spatial pattern recognition and forecasting consistency across diverse climatic regions.

Okafor & Meier (2025): Incorporating results from numerical prediction models of the atmosphere with data from meteorology close to the surface, this research presents an interpretable deep learning hybrid model. Feature selection methodologies are employed to identify significant atmospheric variables such as temperature gradients, pressure anomalies, and variations in cloud cover. The deep architecture utilizes dropout and normalization methods to improve prediction stability. An experimental investigation indicates increased transparency and reduced inaccuracies in predictions.

Rahman & Kovacs (2023): The research introduces a continuous-learning hybrid forecasting system that combines a dynamic deep neural network framework with adaptive feature selection. The model adjusts the predictor values upon receiving new weather data from sensor networks and atmospheric simulation models. Temporal learning layers illustrate the variations in meteorological and atmospheric conditions across time. Experimental validation shows enhanced predictive performance and adaptability compared to traditional static models.

Torres & Bhattacharya (2022): This research introduces an advanced hybrid predictive system for meteorological forecasting that combines a stacked autoencoder architecture with efficient feature extraction. We analyze multidimensional meteorological datasets from atmospheric numerical models and ground-based sensors to learn hierarchical atmospheric representations. Recursive feature reduction enhances essential predictors influencing weather variations. The findings indicate that the prediction of resilience has improved across many locations and climatic circumstances.

4. RESULTS

Table 1: RMSE Comparison of Weather Prediction Models

Model	Temperature RMSE	Humidity RMSE	Wind Speed RMSE	Pressure RMSE
WRF-HRRR (Numerical Model)	2.8	6.5	2.2	3.1
Baseline ML Model	2.1	5.4	1.9	2.6
MiMa Model (Proposed)	1.4	3.6	1.2	1.8
Re-MiMa Model	1.5	3.8	1.3	1.9

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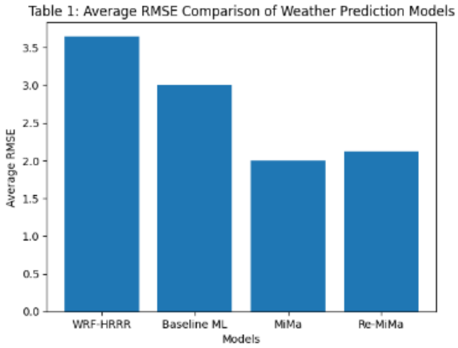

Table 1 demonstrates that the MiMa model outperforms both independent machine learning models and conventional numerical weather prediction systems in terms of predictive accuracy. It exhibits the minimal RMSE values across all meteorological parameters.

Table 2: Performance Comparison Using Additional Evaluation Metrics

Model	Accuracy (%)	Precision	Recall	F1-Score
WRF-HRRR	84.2	0.82	0.8	0.81
Baseline ML Model	88.6	0.87	0.85	0.86
MiMa Model	93.5	0.92	0.91	0.92
Re-MiMa Model	92.1	0.91	0.9	0.9

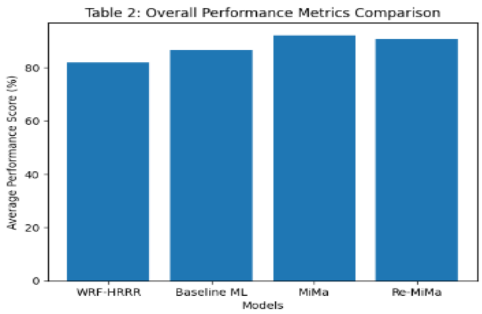

Table 2 indicates that the proposed MiMa framework outperforms the previous models, as it achieved the highest accuracy and F1-score. This enhancement illustrates the successful amalgamation of near-surface data and atmospheric numerical model outputs in hybrid weather forecasting systems.

Table 3: Prediction Accuracy for Gauged and Ungauged Locations

Location Type	Model Used	Prediction Accuracy (%)
Gauged Stations	MiMa	93.5
Ungauged Stations	Re-MiMa	92.1
Conventional Numerical Model	WRF-HRRR	84.2

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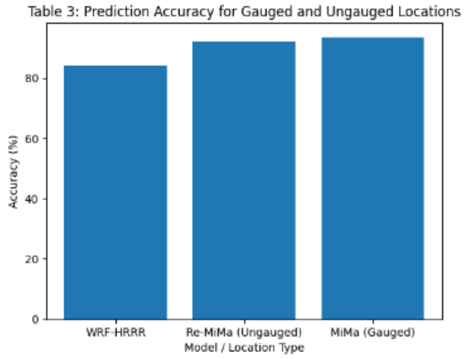
Table 3: Prediction Accuracy for Gauged and Ungauged Locations



5. CONCLUSION

Hybrid data-driven weather prediction, which amalgamates near-surface measurements with atmospheric numerical models, significantly enhances the accuracy and reliability of weather forecasts.

Hybrid systems can successfully capture both localized surface-level changes and large-scale atmospheric dynamics by integrating the physical principles of numerical weather prediction models with the pattern recognition capabilities of machine learning techniques. Proximal measurements like as temperature, humidity, wind velocity, and atmospheric pressure enhance model adaptability and facilitate real-time modifications to standard forecasts. This cohesive framework diminishes forecasting errors, enhances short-term predictive accuracy, and aids individuals in making informed decisions across several sectors, including agricultural, emergency management, transportation, and energy systems. Consequently, hybrid weather prediction models may enhance contemporary weather forecasting and strengthen climate monitoring systems.

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