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A Novel Spectral–Temporal Attention-Based WaveNet Model for Corn Yield Prediction Using Multi-Source Data in the U.S. Corn Belt

Mahdiyeh Fathi [1,2], Reza Shah-Hosseini [1*], Hossein Arefi [2], Armin Moghimi [3]

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran – Tehran, Iran,
mahdiyeh.fathi@ut.ac.ir, rshahosseini@ut.ac.ir
[2] i3mainz, Institute for Spatial Information and Surveying Technology, Mainz University of Applied Sciences, Mainz, Germany,
hossein.arefi@hs-mainz.de,
[3] Department of Photogrammetry and Remote Sensing, Geomatics Engineering Faculty, K. N. Toosi University
of Technology, Tehran, Iran, moghimi.armin@kntu.ac.ir

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Abstract

Accurately predicting crop yields at a large scale is crucial for safeguarding global food security and optimizing the management of agricultural resources. Although diverse data sources, such as satellite imagery, climatic variables, and soil characteristics, have become increasingly available, traditional machine learning models still struggle to capture the complex nonlinear interactions and underlying spectral–temporal dependencies inherent in these datasets. This study proposes a novel Spectral–Temporal Attention-Based WaveNet (STAW-Net) architecture that integrates dilated causal convolutions with combined spectral and temporal attention mechanisms. The proposed model effectively learns long-range dependencies and adaptively extracts and fuses informative features from heterogeneous data sources, thereby enhancing the accuracy and robustness of crop yield predictions. The model was trained using a comprehensive dataset comprising radar imagery from Sentinel-1, multispectral optical data from Sentinel-2, daily meteorological variables from Daymet, and soil characteristics from SoilGrids. The dataset spans major U.S. corn-producing regions between 2016 and 2022; data from 2016–2020 were used for training, while 2021–2022 were reserved for independent testing to evaluate model generalization. Results that the proposed STAW-Net outperforms other models, including Random Forest, DeepRF, the standard WaveNet, Temporal-Attention WaveNet, and Spectral-Attention WaveNet models. The STAW-Net achieved R^2 values of 0.81 and 0.75, MAE of 12.80 and 15.18, and RMSE of 16.44 and 20.55 for 2021 and 2022, respectively. These findings highlight the model's strong generalization capability and its effectiveness in capturing complex spectral–temporal patterns for reliable crop yield prediction across diverse environmental and climatic conditions.

1. Introduction

The rapid growth of the global population and continuing economic changes at regional and global scales have made ensuring food security a major global challenge (Al-Shammari et al., 2025; Zhou et al., 2025). Corn, one of the world's major staple crops, plays a vital role in global food systems, ranking third after wheat and rice in importance for human consumption (Al-Shammari et al., 2025). The United States, the largest corn producer worldwide, underscores the crop's strategic significance in global agriculture (Al-Shammari et al., 2025; Fathi et al., 2024).

Corn yield is influenced by a complex interaction of environmental and management factors, including climatic conditions, soil properties, and agronomic practices (Mena et al., 2024). Conventional crop yield prediction methods, which are usually performed post-harvest, are time-consuming and often insufficient for timely and efficient agricultural resource management (Al-Shammari et al., 2025; Zhou et al., 2025). Recent advancements in remote sensing (RS) technology and the integration of satellite and ground-based observations have provided powerful tools for accurately predicting crop yields (Fathi et al., 2023, 2025). Among the most effective RS indicators are vegetation indices (VIs), which quantify key aspects of plant health during the growing season (Hatfield & Prueger, 2010). Vegetation indices derived from satellite platforms such as Landsat-8, Sentinel-2, and MODIS, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), Land Surface Temperature (LST), and radar-based indices from Sentinel-1, offer valuable insights into the physiological status of crops at various growth stages (Psomiadis et al., 2017; Sun et al., 2019). Among these indices, NDVI is the most widely used indicator for crop yield prediction (Aklilu Tesfaye & Gessesse Awoke, 2021). However, it tends to saturate in high-biomass regions, limiting its effectiveness in dense crop canopies. In contrast, red-edge-based indices, such as the Triple Red Edge Index, Chlorophyll Index Red-Edge, and Vogelmann Red Edge Index, are more sensitive to chlorophyll content, thereby improving yield prediction accuracy, particularly in dense-canopy environments (Al-Shammari et al., 2025).

In addition to vegetation indices, several modeling approaches have been proposed to effectively exploit RS and environmental data for accurate crop yield prediction. These models are generally categorized into three groups, data-driven, process-based, and hybrid, each with distinct strengths and limitations. (Roberts et al., 2017). Data-driven models, including machine and deep learning (ML/DL) algorithms, exploit large RS and environmental datasets to achieve high predictive accuracy (Lu et al., 2024). Process-based models simulate the physiological processes related with crop growth but are often computationally complex and data-intensive (Fathi et al., 2025;

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[*] Corresponding author

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Roberts et al., 2017). Hybrid models combine the strengths of both approaches to improve prediction accuracy (Maestrini et al., 2022). Furthermore, incorporating detailed phenological information based on actual crop growth stages, rather than fixed time intervals, can significantly enhance model performance (Pei et al., 2025).

Several ML-, DL-, and hybrid-based models have been developed for county-level corn yield prediction. In ML, algorithms such as Random Forest (RF), Artificial Neural Networks (ANN), Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and XGBoost leverage environmental features, including temperature, precipitation, soil type, moisture, vegetation indices (e.g., NDVI, EVI, LAI, NDWI), and LST, to predict crop yields (Babaie Sarijaloo et al., 2021; Ji et al., 2022; Yin et al., 2024).

In DL, architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Deep Neural Networks (DNNs) have been widely employed for yield prediction (Ji et al., 2022). More advanced frameworks, including Convolutional LSTMs (ConvLSTMs) and 3D Convolutional Neural Networks (3D-CNNs), have demonstrated a strong capacity to extract complex spatio-temporal patterns from RS data (Gavahi et al., 2021).

Hybrid approaches have recently gained attention for their ability to enhance the robustness and precision of yield forecasting. For example, combinations of CNN and RNN architectures have been used to predict corn yields using satellite time-series and soil data (Sun et al., 2020). The YPM-GAN-GAT model integrates Generative Adversarial Networks (GANs) and Graph Attention Networks (GATs) to predict yields for various corn varieties while addressing missing feature data (Yang et al., 2023). Similarly, the KSTAGE model incorporates prior knowledge with spatial and temporal attention mechanisms to model complex plant growth dynamics and achieve high prediction accuracy (Qiao et al., 2023).

Moreover, coupling the WOFOST crop simulation model with DL methods using meteorological, soil, management, and phenological data has improved yield estimation across different growth phases (Ren et al., 2023). Recent innovations such as ADANN, 3D-CNN-RNN, 3D-ResNet-BiLSTM, and MHRA-MS-3D-ResNet-BiLSTM models have further enhanced predictive performance by effectively analyzing high-dimensional, time-series data (Fathi et al., 2023, 2025; Ma et al., 2021; Oikonomidis et al., 2022).

Despite remarkable progress in DL–based yield prediction, existing architectures, such as ConvLSTM, ResNet-BiLSTM, KSTAGE, and GAN-based frameworks, still exhibit inherent limitations. ConvLSTM and ResNet-BiLSTM models suffer from high computational cost and vanishing gradients, hindering their ability to capture long-term temporal dependencies. KSTAGE, while integrating phenological knowledge, relies heavily on predefined growth stages, limiting its transferability across different regions and crops. Moreover, GAN-based models require complex training procedures and are highly sensitive to noise and data imbalance, which reduces their robustness.

To address these challenges, we propose a novel Spectral–Temporal Attention WaveNet (STAW-Net) framework for crop yield prediction that combines dilated causal convolutions with dual (temporal and spectral) attention mechanisms to enhance the extraction of long-range temporal dependencies and key spectral features from multi-source RS and environmental data. The key innovations of this study are summarized as follows:

1. **Design of a novel STAW-Net architecture:** integrates dilated causal convolutions with temporal and spectral attention mechanisms to jointly model spectral–temporal dependencies from multi-source RS and environmental data.
2. **Quantitative evaluation of attention mechanisms:** investigates the individual contribution and effectiveness of temporal and spectral attention modules in improving model performance.
3. **Comparison with RF and DeepRF models:** demonstrates the superior predictive accuracy and robustness of the proposed STAW-Net in crop yield estimation.

2. Materials

2.1 Study area

Corn yield prediction was carried out across 18 central and northern U.S. states, which collectively account for the majority of national corn production (outlined in red in Figure 1). These geographically contiguous states provide favorable climatic and soil conditions for corn cultivation, making them an ideal study area for this research. In these regions, corn is usually planted from April to May, grows from June to August, and is harvested between September and November (https://ipad.fas.usda.gov/rssiws/al/crop_calendar/us.aspx).

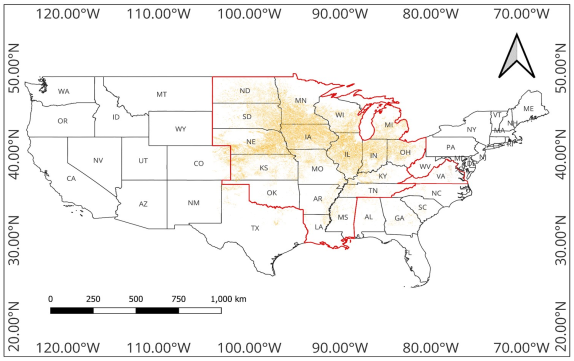

Figure 1. The study area and corn distribution derived from the Cropland Data Layer (CDL) across 18 U.S. states in 2022.

2.2 Dataset

The dataset comprises monthly time-series data collected from Sentinel-1 and Sentinel-2 sensors and the Daymet over seven years (2016–2022), along with soil information from SoilGrids, crop yield records from the USDA, and cropland and county-level boundary layers (see (Fathi et al., 2023, 2025)), for details on data collection). Figure 2 presents the spatial distribution of county-level corn yields during this period. In total, 7,238 records were available, with yield values ranging from 19.80 to 246.70 Bu/acre and an average yield of 163.52 Bu/acre. These yield data were used as ground truth for training the DL model.

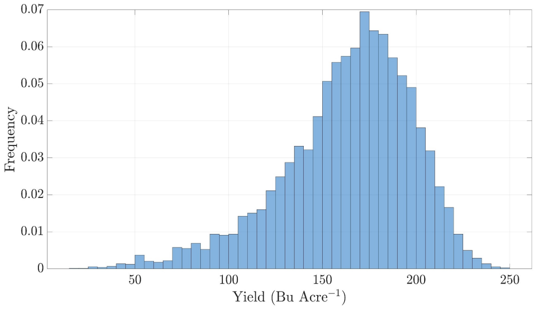

Figure 2. Distribution of yields from 2016 to 2022.

3. Method

We propose a novel framework that integrates RS data, climatic variables, and soil information to predict county-level corn yields using a Spectral–Temporal Attention-Based WaveNet model. The framework consists of two main stages: (1) data pre-processing and (2) model design and training.

In the first stage, 54 features (listed in Table 1) were extracted from multiple data sources via the Google Earth Engine platform to generate monthly composites. Cloud-contaminated and non-corn pixels were subsequently removed, and the county-level mean of each feature was computed to produce aggregated inputs for modeling.

In the second stage, the Attention-Based WaveNet model was designed and trained using data from 2016–2020, and its generalization capability was evaluated on independent test data from 2021–2022. Details of the proposed model architecture are provided in Section 3.1.

Name	Data
Blue, Green, Red, Red Edge1/2/3/4, Nir, Swir1/2	Sentinel-2
Normalized Difference Vegetation Index (NDVI)	
wide dynamic range vegetation index (WDRVI)	
Difference Vegetation Index (DVI)	
Land Surface Water Index (LSWI)	
Soil Adjusted Vegetation Index (SAVI)	
Green Normalized Difference Vegetation Index (GNDVI)	
σ_{VV}, σ_{VH}	Sentinel-1
σ_{VV}-σ_{VH}	
Radar Vegetation Index (RVI)	
T_{min}, T_{max}, Vapor Pressure, and Precipitation	Daymet
Cation Exchange Capacity, PH, Clay, Silt, Sand	Soil-Grid

Table 1. The extracted features from Sentinel 1 /2, Daymet, and Soil-Grid (Fathi et al., 2025)

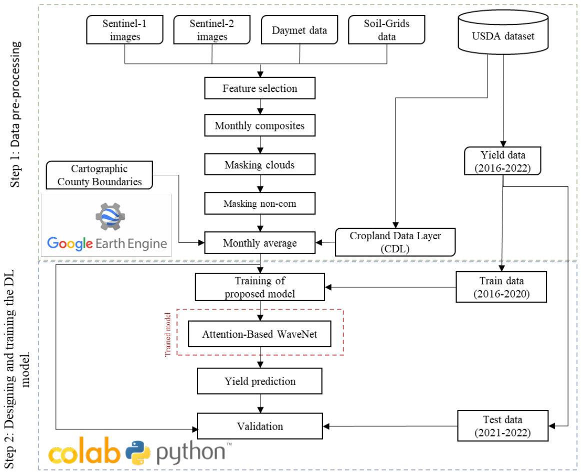

Figure 3. Workflow of the proposed Spectral–Temporal Attention-Based WaveNet model for corn yield prediction.

3.1 Spectral–Temporal Attention-Based WaveNet architecture

In this study, we developed a Spectral–Temporal Attention-Based WaveNet (STAW-Net) architecture for crop yield prediction (Figure 4). This architecture leverages WaveNet's capability to model complex temporal dependencies in sequential data. WaveNet is a deep convolutional neural network that employs dilated causal convolutions to capture long-range temporal relationships without relying on recurrent structures (Oord et al., 2016a). This capability is particularly valuable for agricultural prediction tasks, as time-series inputs such as weather variables and vegetation indices influence crop growth through delayed and seasonal patterns.

The WaveNet model comprises a series of residual blocks, each containing two parallel convolutional layers with gated activation units utilizing tanh and sigmoid functions (Oord et al., 2016b). These units enable selective extraction of informative features from time-series data. The outputs of the gated units are combined through element-wise operations to enhance the model's capacity to emphasize meaningful temporal patterns. Residual and skip connections are incorporated to improve gradient propagation during backpropagation, which facilitates faster convergence and enables deeper network configurations (Devi et al., 2024).

To further enhance the baseline WaveNet's ability to extract temporal and spectral information from multi-source datasets (e.g., RS, climatic, and soil data), we integrated a dual-attention module consisting of spectral and temporal attention mechanisms. The spectral attention component captures interdependencies among input feature channels (e.g., different vegetation or spectral indices), allowing the model to adaptively prioritize the most informative variables (Zhan et al., 2022). The temporal attention component identifies key time steps within the input sequence that exert a significant influence on crop yield (Zhang et al., 2020). By embedding this dual-attention block into each residual unit, the model dynamically emphasizes critical spectral features and temporal periods, thereby enhancing representational efficiency and predictive accuracy.

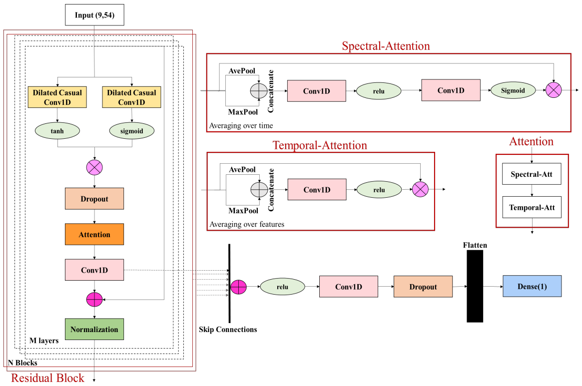

Figure 4. Spectral–Temporal Attention-Based WaveNet model.

3.2 Model Training and Experimental Setup

The The proposed method extracts 54 input features from a combination of Sentinel-1 and Sentinel-2 satellite imagery, Daymet climatic data, and SoilGrids soil information, aggregated over nine temporal steps. The dataset was divided into 4,568 training samples, 507 validation samples, and 2,163 test samples.

The model architecture comprises two residual blocks, each consisting of three convolutional layers, where each layer employs a one-dimensional convolution (Conv1D) with 24 filters. To mitigate overfitting and enhance generalization, a dropout rate of 0.2 and a patch size of 5 were applied. The model was trained for 100 epochs using the Adam optimizer with a learning rate of 0.001 and an L^2 regularization coefficient of 0.001. The Mean Absolute Percentage Error (MAPE) was adopted as the loss function. This configuration enabled a robust evaluation of the Spectral–Temporal Attention-Based WaveNet's capability to model spatio-temporal dependencies in multi-source RS data.

3.3 Assessment Metrics

The performance of the proposed deep learning (DL) model and comparative approaches was evaluated using multiple statistical metrics, including the RMSE, MAE, MAPE, coefficient of determination (R^2), and Index of Agreement (D) (Fathi et al., 2025).

4. Results and Dissection

The performance of the proposed STAW-Net was compared with several ML and DL models, including Random Forest (RF), Deep-RF, and three WaveNet variants: baseline WaveNet, Temporal Attention–WaveNet, and Spectral Attention–WaveNet (Oord et al., 2016a; Shah et al., 2022). Hyperparameters of the RF and Deep-RF models were optimized using the Optuna algorithm, which employs distributed search and a tree-structured Parzen estimator (TPE) to identify optimal parameters such as n_estimators, max_depth, and max_features (Ekundayo, 2020). The optimized parameters are summarized in Table 2, and performance metrics for the comparative models are presented in Table 3.

Model		N_estimators	Max_depth	Max_features
RF	RF1	98	30	None
Deep-RF	RF1	92	25	Log2
	RF2	99	9	Log2
	RF3	89	19	None

Table 2. Optimized hyperparameters for RF and Deep-RF models using Optuna.

Year	Model	RMSE	MAE	MAPE	R^2	D
2021	RF	18.16	14.68	10.04	0.77	0.92
	Deep-RF	20.20	16.40	11.38	0.72	0.90
	WaveNet	17.64	14.01	8.96	0.79	0.94
	Temporal Attention-WaveNet	16.84	13.22	8.79	0.80	0.94
	Spectral Attetion-WaveNet	16.81	13.27	8.80	0.80	0.94
	Spectral-Temporal Attention-WaveNet	16.44	12.80	8.57	0.81	0.95
2022	RF	23.00	17.41	14.18	0.68	0.88
	Deep-RF	25.00	18.81	16.30	0.62	0.84
	WaveNet	21.27	15.80	13.12	0.73	0.91
	Temporal Attention-WaveNet	21.16	16.09	12.76	0.73	0.91
	Spectral Attetion-WaveNet	21.07	15.75	12.81	0.73	0.91
	Spectral-Temporal Attention-WaveNet	20.55	15.18	12.66	0.75	0.92

Table 3. Performance comparison of Spectral–Temporal Attention-Based WaveNet and other models.

The STAW-Net consistently achieved the best performance in 2021 and 2022, exceeding all baseline and single-attention variants. It produced the lowest RMSE, MAE, and MAPE, and the highest R^2 and D values among all models. In 2021, STAW-Net achieved an RMSE of 16.44, MAE of 12.80, and MAPE of 8.57, corresponding to respective improvements of 6.8%, 8.6%, and 4.3% over the standard WaveNet. In 2022, its RMSE decreased from 21.27 (WaveNet) to 20.55, while MAE and MAPE decreased by 4% and 3.5%, and R^2 improved from 0.73 to 0.75. These findings indicate that integrating dual spectral–temporal attention mechanisms enables the model to more effectively capture cross-dimensional dependencies in multi-source data, leading to higher accuracy and robustness in yield prediction.

When the attention mechanisms were applied individually, Temporal Attention–WaveNet and Spectral Attention–WaveNet improved performance relative to the baseline WaveNet, although their improvements were less pronounced than those achieved by the STAW-Net. For example, in 2021, single-attention models achieved RMSE values around 16.8 and R^2 = 0.80, compared with RMSE = 17.64 and R^2 = 0.79 for the baseline. This confirms that while each attention mechanism enhances feature extraction in its respective domain (temporal or spectral), their combined effect provides the most robust and accurate predictions.

In contrast, the Deep-RF model showed the weakest performance among all tested methods, with higher error rates and lower R^2 values than RF and DL-based models. Although RF achieved moderate accuracy, its lack of temporal learning limited performance compared with WaveNet-based models. The attention-augmented STAW-Net demonstrated the most stable and accurate results across years, underscoring the benefit of integrating dual attention mechanisms for effective spectral–temporal modeling in crop yield prediction.

A paired t-test conducted on the absolute errors of the baseline WaveNet and the proposed STAW-Net confirmed that the improvement in performance is statistically significant ($t = 6.03$, $p < 0.001$).

Figure 5 presents a detailed comparison of model performance in predicting corn yields for 2021 and 2022 using scatter plots with a 1:1 reference line ($y = x$). The plots illustrate that the Deep-RF model exhibits substantial dispersion, with predictions deviating considerably from the ideal line. The RF model

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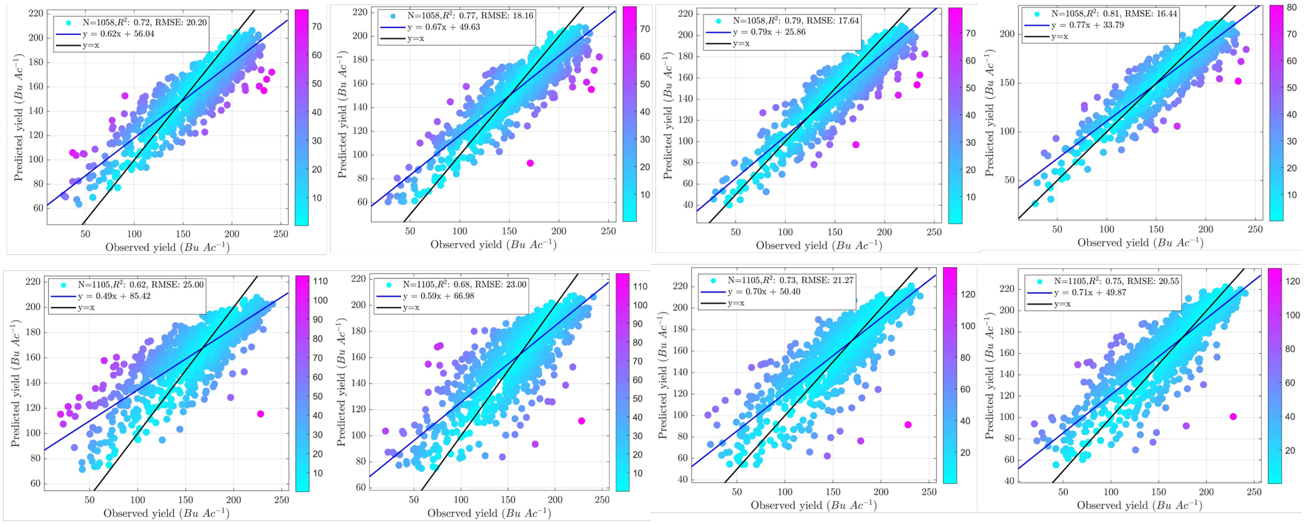
performs moderately better but still shows noticeable variability. The WaveNet model yields predictions that lie closer to the reference line, indicating improved accuracy. In contrast, the STAW-Net demonstrates the highest concentration of points around the ideal line and the least scatter, signifying superior predictive precision and stronger agreement between observed and predicted yields.

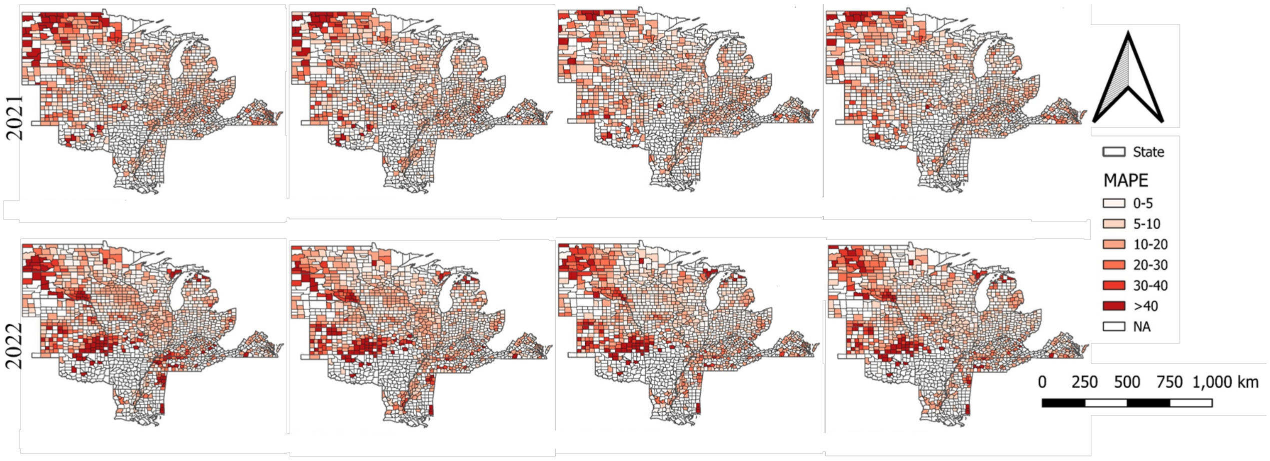
Figure 6 presents the county-level MAPE maps generated by different models for corn yield prediction. Brighter areas on the maps indicate lower prediction errors and, consequently, better model performance. The STAW-Net map shows extensive bright regions, suggesting low MAPE values across most counties. In contrast, the Deep-RF map contains numerous darker regions, reflecting higher prediction errors and weaker predictive accuracy. Most of the larger errors are concentrated in regions that experienced drought conditions during the growing season, where yield variability was high and prediction uncertainty increased (https://droughtmonitor.unl.edu/Maps/MapArchive.aspx).

Figure 7 illustrates the predicted county-level corn yields for 2021 and 2022 generated by the most effective model, the STAW-Net, alongside the observed yield maps obtained from the USDA. The strong spatial correlation between the predicted and observed yield distributions demonstrates the model's high predictive accuracy and reliability.



(a) (b) (c) (d)

Figure 5. Scatter plot comparison of corn yield predictions for 2021–2022 generated using: (a) Deep-RF, (b) RF, (c) WaveNet, and (d) STAW-Net.



(a) (c) (b) (d)

Figure 6. MAPE maps of county-level corn yields in the U.S. for 2021–2022, generated using (a) Deep-RF, (b) RF, (c) WaveNet, and (d) STAW-Net.

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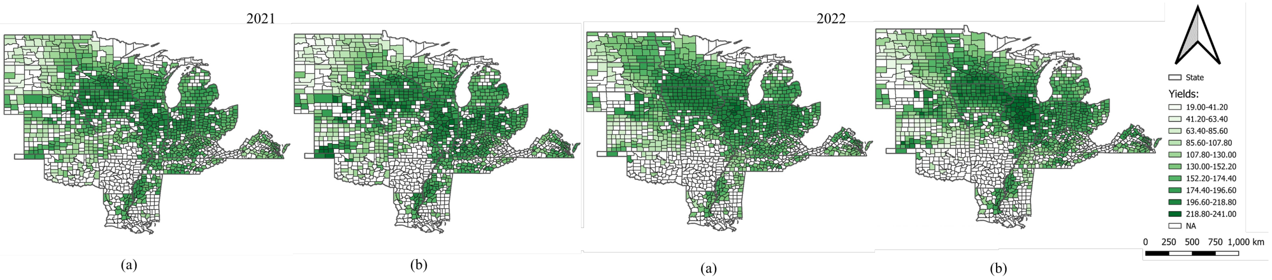

(a) (b) (a) (b)

Figure 7. Comparison of observed and predicted county-level corn yields in the U.S. for 2021–2022, generated by (a) STAW-Net and (b) USDA.

5. Conclusions

In this study, we developed and validated a Spectral–Temporal Attention-Based WaveNet (STAW-Net) to enhance county-level corn yield prediction across major U.S. corn-producing regions. The proposed model effectively integrates multi-source remote sensing and environmental data, including Sentinel-1 radar, Sentinel-2 multispectral imagery, Daymet climate variables, and SoilGrid soil properties. The STAW-Net, trained on historical data (2016–2020) and evaluated on independent test years (2021–2022), consistently demonstrated superior predictive performance and robustness compared with benchmark models such as WaveNet, Spectral Attetion-WaveNet, Temporal Attention-WaveNet, RF, and Deep-RF. The proposed model achieved R^2 values of 0.81 and 0.75 for 2021 and 2022, respectively, confirming its strong predictive accuracy and stability across different growing seasons.

By leveraging dual spectral–temporal attention mechanisms, STAW-Net efficiently captures complex dependencies among multi-source features, leading to more accurate and interpretable yield predictions. These improvements enable better data-driven decision-making and support sustainable management practices in precision agriculture.

Future work could focus on improving the model's adaptability to different agroecological zones and crop types through transfer learning, fine-tuning, and few-shot learning strategies. These approaches would enable rapid model adaptation using limited regional datasets, facilitating broader application under diverse climatic and management conditions. Additionally, the integration of satellite-based observational datasets and seasonal climate data could further enhance STAW-Net's capacity for early yield prediction, drought detection, and agricultural risk assessment under varying environmental conditions.

Disclosure instructions

During the preparation of this work, the authors used ChatGPT OpenAI in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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