European Journal of Agronomy 170 (2025) 127750

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

Enhancing cotton yield prediction with robust deep neural network-based framework

Md Abdul Quddus [a,*,1], Sudipta Chowdhury [b,1], Warren Jasper [a,2], Lokesh Das [c,1]

[a] Department of Textile Engineering, Chemistry and Science North Carolina State University, Raleigh, NC 27695, United States of America
[b] Department of Mechanical & Industrial Engineering Marshall University, Huntington, WV 25755, United States of America
[c] School of Computing Wichita State University, Wichita, KS 67260, United States of America

ARTICLE INFO

Keywords:
Deep neural network
Cotton production
Machine learning
Cotton supply chain
Textile industry

ABSTRACT

Accurate prediction of cotton yield is essential for optimizing agricultural resource allocation, mitigating risks, and informing decision-making. This study introduces a deep learning framework that combines advanced feature engineering with a Deep Neural Network (DNN) model to forecast cotton production. The model incorporates meteorological variables such as precipitation, snowfall, temperature extremes, and derived features like Growing Degree Days (GDD), extreme weather indices, and seasonal precipitation metrics. To address missing data, time-series interpolation is employed, and features are engineered to capture key growth-stage influences and extreme climatic events. The DNN with noise injection model achieved an impressive R^2 of 97.9% and a Root Mean Square Error (RMSE) of 25.3 lb/acre, significantly outperforming traditional machine learning models. This framework effectively captures the non-linear relationships between climate and crop yield, offering valuable insights for agricultural planning. Using North Carolina as a case study, the model predicts cotton yield at the county level, shedding light on regional yield variations. By incorporating diverse weather data, this study provides actionable insights for optimizing cotton production and resource allocation in the supply chain. The framework is adaptable and can serve as a benchmark for yield prediction in other crops and regions, driving advancements in precision agriculture.

1. Introduction

Cotton is one of the most important cash crops globally, playing a crucial role in the agricultural economy and textile industry. Its strategic importance is underscored by its wide geographical adaptability and the increasing demand for natural fibers. Its production significantly impacts the livelihoods of millions of farmers and contributes to the economic stability of many regions (World worldlife fund, 2024). Accurate prediction of cotton yield is essential for optimizing resource allocation, managing agricultural risks, and supporting informed decision-making processes.

Extreme weather events such as droughts, floods, and heatwaves can significantly reduce yields, degrade fiber quality, and disrupt agricultural planning (The farming insider, Climate vs. Cotton: The Battle for Yield Stability, 2024). Climatic variability, including factors such as temperature fluctuations, precipitation patterns, and extreme weather events, profoundly influences cotton yields. Research indicates that both short-term and long-term climate factors play crucial roles in determining cotton production levels across various regions. Research has also found that climate-induced shifts in phenology, such as earlier or later planting and altered flowering times, can affect the temporal alignment of cotton development with optimal environmental conditions (Wang et al., 2017; Yang et al., 2014; Ahmad et al., 2017). Farooq et al. (2023) further highlighted that the transgenerational effects of climate variability can influence the inherent stress tolerance and yield potential of cotton cultivars, making the development of high-yield, climate-resilient genotypes a priority for sustainable cotton production. One consistent finding across many studies is that rising temperature is among the most critical factors affecting cotton yield. For instance, Wang et al. (2022) demonstrated a 1 °C increase in mean temperature can alter crop growth dynamics, although appropriate irrigation strategies under plastic film mulching can partially mitigate these effects. Studies have also noted that increased temperatures may raise the overwintering potential of pests and diseases, thereby

* Corresponding author.
E-mail addresses: mquddus@msstate.edu (M.A. Quddus), chowdhurys@marshall.edu (S. Chowdhury), wjasper@ncsu.edu (W. Jasper), lokesh.das@wichita.edu (L. Das).
[1] Assistant Professor.
[2] Professor.

https://doi.org/10.1016/j.eja.2025.127750
Received 1 January 2025; Received in revised form 6 May 2025; Accepted 18 June 2025
Available online 8 July 2025

compounding the stress on cotton plants and affecting both yield and fiber quality (Li et al., 2023). Similarly, Williams et al. (2015) showed that increased temperatures due to climate change impacted overall yield outcomes, where the benefits from CO_2 fertilization can be offset by thermal stress. Adare et al. (2023) pointed out that temperature fluctuations affect cotton growth stages, with maximum temperatures impacting yield during critical phases such as flowering and boll opening. These studies underscore the importance of adapting agronomic practices to buffer the negative impacts of heat stress on the photosynthetic and reproductive phases of growth. In addition to temperature, water availability remains a decisive factor for cotton yield under changing climate conditions. Studies by Sultan et al. (2010) have linked inter-annual rainfall variability directly to yield fluctuations in West Africa, and similar trends have been observed in regions such as Pakistan's Indus River basin, where analyses revealed that increases in minimum temperatures and relative humidity tend to have a deleterious effect on cotton yield, while sunshine hours could enhance it (Naveed et al., 2021). Moreover, optimal water management, including advanced irrigation practices, has been identified as a critical adaptation strategy. For example, Jia et al. (2024) optimized irrigation regimes to counteract drought intensification due to climate change. Adequate rainfall was also found to be crucial during specific growth stages, particularly during square initiation (Cetin and Basbag, 2010; Mandal et al., 2005). Shahzadi et al. (2023) found that precipitation levels could determine water availability, which has been found to be critical for crop health. Such multi-faceted influence of water highlights that both insufficient and excessive moisture can impair growth, demanding precise water management.

Understanding and predicting the impact of these climatic variables on cotton production is vital for developing effective agricultural strategies and ensuring food security. This study aims to address this need by leveraging advanced deep learning techniques to create a robust predictive model for cotton yield, and by incorporating a wide range of meteorological data and engineered features to capture the complex interactions between climate and crop performance. Accurate predictions can help manage risks associated with cotton yield failures due to adverse weather conditions or pest infestations, leading to more stable incomes and reduced financial uncertainty. This also supports better planning for storage, transportation, and marketing, stabilizing prices and ensuring a steady cotton supply chain. Furthermore, governments and agricultural organizations can use these predictions to make informed decisions about import-export policies, subsidies, and other economic measures, ultimately benefiting the agricultural sector and contributing to economic stability.

1.1. Machine learning applications

By utilizing advanced machine learning techniques for tasks such as land-cover segmentation, farmers and policymakers can gain a clearer understanding of agricultural landscapes, enabling more efficient allocation of resources like water, fertilizers, and labor—ultimately minimizing waste and reducing production costs (Khan et al., 2025; Mahdipour et al., 2024; Marzvan et al., 2021; Felegari et al., 2023). For instance, Gupta et al. (2024), Mishra and Mishra (2023), and Balducci et al. (2018) found that machine learning algorithms enable farmers to analyze historical data, weather patterns, and market trends, facilitating optimal planting and resource allocation. Overall, these studies collectively illustrated the transformative potential of these algorithms in addressing the complex challenges posed by contemporary agricultural and environmental monitoring needs. Such methods (e.g., clustering, decision trees, and random forests), alongside relevant statistical models have also shown promise in predicting cotton yield. Several machine learning approaches have been observed to leverage climatic, biophysical, and soil parameters to model the complex interactions affecting cotton yield. Key approaches in cotton yield prediction include using machine learning methods like Random Forest, Support Vector Regression, and Light Gradient Boosting, alongside field and synthetic data, to account for climatic change, soil diversity, cultivars, and fertilizer applications (Mitra et al., 2024). For example, Balmumcu et al. (2024) studied four machine learning algorithms: multilayer perceptrons, long short term memory, quantile regression, and extreme gradient boosting (XGBoost), with XGBoost achieving the highest accuracy in predicting cotton yield based on dynamic and static parameters. Umutoni et al. (2024) discussed using Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) machine learning algorithms for cotton yield prediction, utilizing data from AquaCrop simulations and field tests to optimize yield forecasting and resource management for farmers. However, it must be noted that machine learning and statistical models can struggle with data quality issues, such as missing values or outliers, which can skew predictions and reduce reliability (Haider et al., 2024). Despite their advancements, these models may also not fully account for the dynamic and multifaceted nature of agricultural systems. In addition, while useful for their interpretability, machine learning models can be prone to overfitting, especially with complex datasets involving multiple variables like soil type and climate (Selvakumar et al., 2024). This suggests a need for hybrid approaches that integrate machine learning, deep learning, and statistical methods for improved accuracy and robustness in yield predictions.

Deep learning applications (a subset of machine learning), particularly Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs), have shown significant advantages in capturing non-linear relationships across various fields such as agriculture, urban planning, and ocean dynamics (Akhtarmanesh et al., 2024; Sharifi and Safari, 2025; Safari et al., 2024; Esmaeili et al., 2024). For example, in the agricultural domain, Farmonov et al. (2024) developed a novel 3D-2D CNN architecture that effectively harnessed both spectral and spatial data from hyperspectral and LiDAR sources for improved crop classification, addressing sensor data variation. MirhoseiniNejad et al. (2024) investigated the power of ConvLSTM and ViT architecture in predicting agricultural yields utilizing time-series satellite data, underscoring the integration of diverse data sources for strategic agricultural management. Moreover, a super-resolution technique developed by Vafaeinejad et al. (2025) aimed at agricultural cadastral mapping illustrates how AI-enhanced methodologies can refine boundary delineation, thus improving resource management. Observing such benefits in the agricultural domain, deep learning techniques were also increasingly employed in cotton yield prediction. These models leverage complex datasets, including UAV imagery and environmental variables, to enhance prediction accuracy. Xu et al. (2021) and Feng et al. (2024) developed a cotton yield estimation model using time series UAV remote sensing data, integrating U-Net semantic segmentation and a Bayesian regularization BP neural network for accurate yield predictions. The integration of deep learning techniques allows for the effective modeling of intricate interactions between various factors affecting cotton yield. For instance, Lu et al. (2024) and Isik et al. (2023) pointed out that models like CNN-LSTM-Attention effectively process multi-source data, capturing essential spatial and temporal variations, which traditional methods often overlook. Niu et al. (2024) demonstrated that CNNs have superior performance in predicting cotton yields compared to traditional models. Modular DNN approaches further enhance predictions by considering data collected at different growth stages (Shrestha et al., 2023). While deep learning models excel in capturing non-linear relationships, they require substantial datasets for training and may face challenges in interpretability compared to simpler models like multiple linear regression (Yildirim et al., 2022; Cao et al., 2021).

Feature engineering integrated with machine learning and/or deep learning techniques also plays a pivotal role in enhancing the accuracy and interpretability of cotton yield prediction models by extracting and constructing meaningful variables from raw climatic data. Key metrics include Growing Degree Days (GDD), which quantify heat accumulation critical for plant development, especially during crucial growth stages such as flowering and boll maturation (Prasad et al., 2021; Ahmad et al., 2017). J.B. (2012) found in his study that extreme weather indices, such as frost days, heatwaves, and prolonged dry spells, capture the effects of climatic extremes on crop performance. Similarly, Arshad et al. (2021) revealed that these indices are vital for understanding the thresholds beyond which yield losses become more likely. Moreover, precipitation trends, particularly during the vegetative growth stage and seasonal rainfall variations, provide essential insights into water availability, which is crucial for crop health (Shahzadi et al., 2023).

1.2. Research gaps and contributions of this study

Despite significant advancements in cotton yield prediction, several gaps persist in the field. One major limitation is the overgeneralization of predictive models that do not account for region-specific climatic variability. Models that fail to incorporate the unique climatic conditions of specific regions, like North Carolina, often lack accuracy and relevance when applied in localized agricultural systems. For example, North Carolina's unique climate – characterized by a humid subtropical climate, variable rainfall patterns, and periodic heatwaves – requires customized feature engineering approaches. Generalized methods often overlook the specific climatic nuances that influence cotton yield in this region, highlighting the need for feature engineering strategies that account for localized weather patterns while being adaptable to broader contexts. Another significant gap is the insufficient integration of feature engineering techniques with deep learning approaches tailored to specific crops or regions. While feature engineering has been explored, its full potential when combined with deep learning techniques remains underutilized, particularly in the context of regional customization. Furthermore, there is a noticeable lack of attention to the role of extreme weather events, such as frost days or droughts, which can drastically influence cotton yields. Many studies overlook these events, yet they are critical for understanding the risks associated with unpredictable weather patterns. Additionally, issues related to data quality, such as missing values or outliers, continue to affect the reliability of predictions. While techniques like K-Nearest Neighbors (KNN) imputation are employed, more advanced methods, such as time-series interpolations or generative adversarial networks (GANs), could further enhance model robustness and reliability.

This study aims to address the aforementioned gaps by proposing a comprehensive and adaptable framework for cotton yield prediction. The primary objectives are to develop a robust deep learning model, specifically a DNN, that integrates a wide range of climatic parameters and climate-derived physiological indicators to predict cotton yield with high accuracy. The model will incorporate advanced feature engineering techniques, such as GDD, vegetative stage precipitation, and extreme weather indices, tailored to the unique climatic and agricultural conditions of North Carolina. Additionally, this study will implement techniques to handle missing data, including time-series interpolation and noise injection, to expand the dataset and ensure more reliable predictions. By utilizing publicly available datasets, the approach is made accessible and easy to implement for researchers and practitioners. Another key objective is to create a framework that is scalable to other regions and crops, balancing regional customization with the generalizability of the approach. The study will also evaluate the impact of extreme weather events, such as frost days, droughts, and heatwaves, on cotton yield and integrate these insights into the predictive model to improve risk management. Overall, this research seeks to bridge the gap between advanced feature engineering, deep learning, and region-specific agricultural practices, contributing valuable insights for farmers, policymakers, and agricultural planners.

This study makes several key contributions to the field of yield prediction and agricultural modeling:

- The study introduces a deep learning framework that integrates customized feature engineering, including metrics like GDD, vegetative precipitation, and extreme weather indices. This framework provides a robust methodology for modeling the interactions between climatic variables and crop yields, with potential for generalization beyond North Carolina.
- The research enhances the performance of the DNN model through advanced techniques such as optimizing the loss function, using dropout layers to mitigate overfitting, and implementing early stopping for improved robustness and convergence. By utilizing publicly available datasets and employing noise injection techniques to simulate climatic variability, the approach is made accessible and easy to implement for researchers and practitioners.
- The study achieves benchmark performance, with a model accuracy of 97.9% and a RMSE of 25.3 lb/acre. These results set a new standard for cotton yield prediction in North Carolina and demonstrate the scalability of the model to other regions.
- By providing practical insights, the research supports farmers, policymakers, and agricultural planners in mitigating risks, optimizing resource allocation, and promoting sustainable agricultural practices. This includes guidance on tailoring agricultural strategies to specific climatic and crop conditions.

2. Methodology

In this study, we developed and trained deep learning models, specifically DNNs, to predict cotton yield based on a range of input features. In this study, we developed and trained deep learning models, specifically DNNs, to predict cotton yield based on a range of input features. To contextualize our modeling approach, we first examine the spatial variation in cotton fiber properties across major U.S. cotton-producing regions. The U.S. Cotton Fiber Chart for the 2023/2024 season (Fig. 1) underscores regional differences in critical fiber quality metrics—Micronaire, Strength (g/tex), Length (32's), and Length Uniformity Index (LUI, %). These properties are essential for determining cotton's overall quality and its suitability for various textile applications. Such variation is largely driven by climatic conditions, reflecting how weather patterns and regional agro-climatic dynamics influence fiber development.

These observed differences reflect how regional climate dynamics shape fiber development, motivating our focus on weather-based predictors. By modeling yield as a function of climate-derived features, we aim to capture this underlying agro-climatic signal in a data-driven manner.

2.1. Data collection and preprocessing

For this study, we utilized two primary datasets: cotton yield statistics and weather data. The cotton yield data, spanning from 1954 to 2023, was sourced from the USDA site and the Agricultural Census provided by Cornell University (USDA's National Agricultural Statistics Service, 2024; USDA census of agriculture historical archive, 2024). This dataset includes detailed records of cotton yield (lb/acre) at the county level for North Carolina, offering a comprehensive historical perspective on cotton production in the state. The weather data was obtained from the National Centers for Environmental Information (NCEI) website (Natioanl centers for environmental infromation, Natioanl oceanic and atmospheric administration. Daily observational data, 2024). This dataset includes daily records of various meteorological variables such as snowfall, maximum temperature, minimum temperature, and precipitation. For the model, we used average values of these daily records: average precipitation (inches), average snowfall (inches), average maximum temperature (in degrees Fahrenheit), and average minimum temperature (in degrees Fahrenheit). These meteorological variables are critical for understanding the climatic conditions affecting cotton growth and yield.

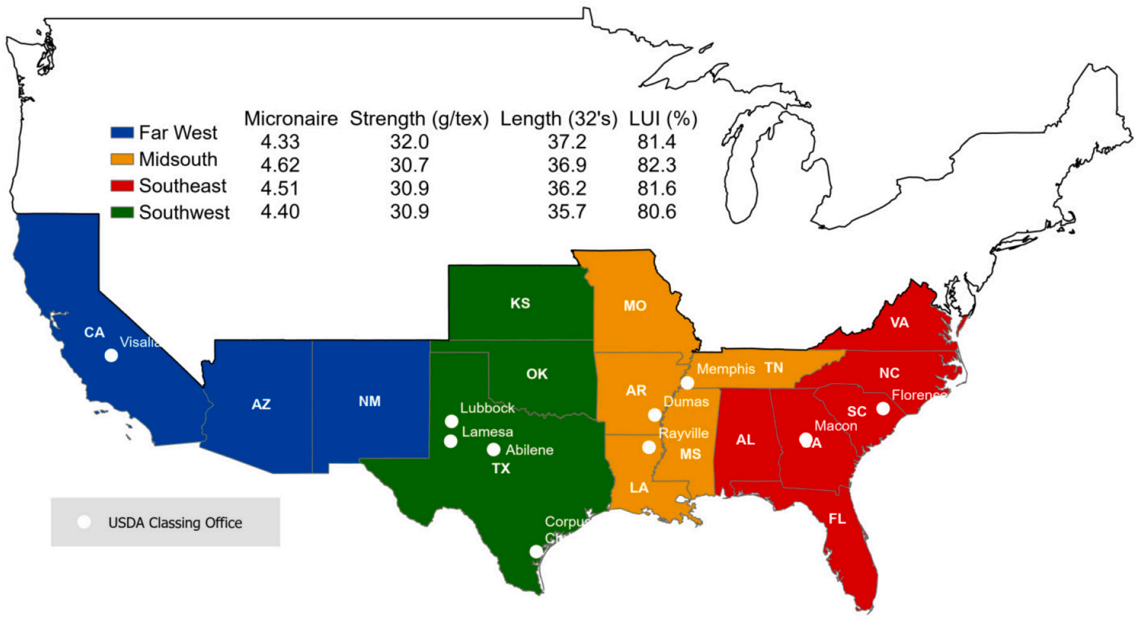

Fig. 1. U.S. cotton fiber chart 2023/2024.

The features used in our model include these four meteorological variables, along with additional features derived through feature engineering, while the target variable is cotton yield (lb/acre). To ensure the integrity and usability of the data, missing values in daily precipitation, snowfall, maximum temperature, and minimum temperature were addressed using time-series interpolation. This approach applied linear or spline techniques to estimate missing values based on temporal patterns, preserving the continuity of climatic trends. Outliers were identified using the Interquartile Range (IQR) method, which is effective in detecting extreme values in continuous data. For each feature, such as cotton yield, average precipitation, average snowfall, and average maximum temperature, the IQR method flagged data points falling outside the range defined by:

$$\left(Q_1 - 1.5 \times \mathrm{IQR}, Q_3 + 1.5 \times \mathrm{IQR}\right)$$

Where Q_1 and Q_3 represent the 25th and 75th percentiles, respectively, and IQR is the interquartile range. These outliers could signify extreme climatic events or anomalies in data recording. After identifying outliers, decisions on handling them were made based on their context:

- If an outlier reflected a genuine extreme weather event (e.g., a heatwave or heavy precipitation), it was retained in the dataset to preserve its impact on cotton yield.
- Outliers deemed as erroneous or irrelevant were removed to prevent distortion in model predictions.
- In some cases, extreme values were capped at the upper or lower bounds to minimize their influence while retaining the data.

Additionally, all features were normalized to ensure uniform contribution during modeling, which is crucial for improving the performance and convergence of the deep learning model. By integrating these datasets and preprocessing steps, we aim to develop a robust predictive model that accurately forecasts cotton yields, accounting for the complex interactions between climatic variables and crop performance. This comprehensive approach not only enhances the model's accuracy but also provides valuable insights for optimizing agricultural practices and decision-making.

2.2. Data preparation and feature engineering

The data preparation and feature engineering process for predicting cotton yield involved several critical steps. We began by loading the cotton yield and weather data. The cotton yield data was filtered to focus on Northampton County, NC ensuring that only relevant observations were considered. The weather data, which included daily records of precipitation, snowfall, maximum temperature, and minimum temperature, were then processed.

To facilitate analysis over time, we extracted the year and month from the `DATE` column. These time-based features allowed us to aggregate the weather data on both annual and monthly scales. For the annual aggregation, multiple statistics were computed for each weather variable, including the mean, minimum, maximum, sum, and median values, as shown in Appendix Table A.1. This provided a comprehensive overview of the weather conditions for each year.

To capture seasonal trends and variations, pivot tables were created for each weather variable at the monthly level. These pivot tables computed various statistics, such as the mean, minimum, maximum, sum, and median, for each month within each year. The annual and monthly weather data were then merged to create a complete dataset that captured both long-term trends and seasonal variations. Finally, the cotton yield data was merged with the weather data on the year level to create a unified dataset, which was trimmed to the first 70 observations for analysis.

Initial model runs using only raw weather variables (e.g., daily temperature and precipitation aggregates) resulted in poor predictive accuracy, highlighting the need for more informative predictors. Guided by prior studies in cotton and other field crops (J.B., 2012; Arshad et al., 2021; Ahmad et al., 2017; Prasad et al., 2021), we adopted a two-stage feature engineering strategy. First, we incorporated basic seasonal statistics. Then, we added biologically meaningful features such as Growing Degree Days (GDD), precipitation during key phenological stages, and extreme weather indices known to affect cotton yield. These variables were selected based on their established relevance to crop growth, water stress, and heat/frost sensitivity. These include:

- **GDD**: This metric was calculated to assess the cumulative temperature exposure above a base temperature (50° F), which is relevant for plant growth.
- **Vegetative Precipitation**: Total precipitation during the vegetative stage (March to May) was calculated to capture the moisture available during critical growth periods.
- **Grain Filling Temperature**: The average maximum temperature during the grain-filling stage (July to September) was computed, as temperature during this period can influence yield.
- **Extreme Weather Indices**: Several extreme weather indices were developed, including:
  - Days above 86° F, which measures the number of hot days that might stress the plants.
  - Frost days, calculated as days with a minimum temperature below freezing.
  - Longest dry spell, which identifies prolonged periods without precipitation, potentially impacting crop growth.
- **Vapor Pressure Deficit (VPD)**: This simplified index was used as a proxy for atmospheric dryness, which can affect plant transpiration and yield.

These new features were calculated on an annual basis and merged with the weather data to form a comprehensive set of climatic factors (Appendix Table A.2) that could influence cotton yield. The final dataset combined both the raw weather data and the engineered features, providing a robust foundation for modeling cotton yield prediction.

2.3. Deep learning architecture

The architecture of the DNN model consists of an input layer, multiple hidden layers, and an output layer, which together aim to predict the cotton yield as a regression problem. The model was built using the Keras library with TensorFlow backend.

- **Input Layer**: The input layer receives a comprehensive set of features derived from raw and engineered climatic variables, including temperature, precipitation, snowfall, and agro-climatic indices such as Growing Degree Days (GDD), vapor pressure deficit (VPD), and extreme weather indicators (e.g., hot days, frost days, and dry spells). These features are presented in detail in Appendix Table A.2. All input features are normalized to a 0–1 range using a `MinMaxScaler` to ensure consistent scaling and efficient training of the deep learning model. Appendix Table A.2 provides an overview of the engineered features, while Appendix Table A.3 summarizes the retained features after the multicollinearity testing process.
- **Hidden Layers**: The model contains three hidden layers, each with ReLU (Rectified Linear Unit) activation. The ReLU function is given by:

  $$f(x) = \max(0, x)$$

  This activation function is widely used due to its efficiency and simplicity in overcoming the vanishing gradient problem. The number of hidden layers (three) was selected based on empirical testing during model development. Architectures with fewer layers (e.g., one or two) underfit the training data and failed to capture complex feature interactions. Deeper networks (more than three layers) yielded diminishing performance gains and exhibited overfitting, despite using dropout and L2 regularization. Thus, a three-layer architecture provided a favorable balance between accuracy, generalization, and computational efficiency. This design choice is consistent with prior work in yield prediction using DNNs (LeCun et al., 2015; Chandraprabha and Dhanraj, 2023).
- **Output Layer**: The output layer has a single neuron with a linear activation function. The output is a continuous value representing the predicted cotton yield (in pounds per acre).
- **Activation Functions**: We used ReLU activation for the hidden layers and a linear activation for the output layer. ReLU helps the network learn non-linear relationships, while the linear activation allows the network to predict continuous values.
- **Optimizer**: The Adam optimizer is used for training the model. Adam combines the advantages of two other extensions of stochastic gradient descent (SGD), namely Adagrad and RMSprop, and computes adaptive learning rates for each parameter. The update rule for Adam is given by:

  $$\theta_t = \theta_{t-1} - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

  where $\hat{m}_t$ and $\hat{v}_t$ are the bias-corrected first and second moment estimates, η is the learning rate, and ϵ is a small constant to prevent division by zero.
- **Learning Rate**: A default learning rate of 0.001 was used for the Adam optimizer.

2.4. Model training

To enhance model performance and reduce overfitting, we employed several techniques:

- The model utilizes the Mean Squared Error (MSE) loss function, which is appropriate for regression tasks. The formula for MSE is:

  $$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

  where y_i is the actual value and $\hat{y}_i$ is the predicted value for the ith observation.
- We applied *Time Series Split* cross-validation to evaluate model performance. This method ensures that the data is split in a way that respects the temporal order of the observations, which is crucial in time series forecasting.
- The dataset was split into five folds for training and validation using time series split. This cross-validation method ensures that the model is trained on different subsets of the data and evaluated on unseen data to get an unbiased performance estimate.
- We used early stopping to prevent overfitting. The model's training is stopped when the validation loss does not improve for a predefined number of epochs, ensuring that the model does not continue to learn noise from the data.
- Dropout layers were added to the model to reduce overfitting by randomly setting a fraction of input units to 0 during training. L2 regularization (also known as weight decay) was applied to the layers to penalize large weights, thus helping prevent overfitting.
- To further enhance the model's ability to generalize, Gaussian noise was added to the features and target variable. By creating synthetic data, we augment the existing dataset, making the model more robust to variations and noise in real-world data.

The original dataset consisted of 100 counties observed over a 70-year period, resulting in 7000 unique county-year samples. Each observation was represented by approximately 246 engineered features. The final training dataset included 42,000 samples comprising 7000 original observations and 35,000 generated via Gaussian noise augmentation.

2.5. Check for multicollinearity

To ensure that the input features were not highly correlated, we performed a multicollinearity test using the Variance Inflation Factor (VIF). Initially, the dataset included 246 engineered features derived

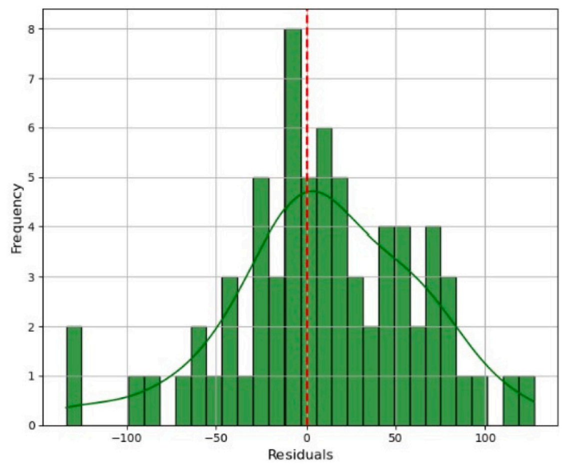

Fig. 2. Histogram of residuals for DNN model (Training set).

from climatic variables such as monthly weather statistics, extreme weather indices, and derived agronomic metrics. We systematically eliminated features with a VIF score greater than 10, which indicates high collinearity, through iterative removal and transformation. This process reduced the feature set to 50 independent and informative variables, improving both the robustness and interpretability of the DNN model. Appendix Table A.2 presents the full list of engineered features prior to multicollinearity filtering, while Appendix Table A.3 details the retained features after the filtering process.

2.6. Evaluation metrics

To assess the performance of the model, we selected the following metrics:

- RMSE is used to measure the difference between predicted and actual values. It is given by:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE is preferred in this study because it penalizes large errors more heavily.
- The R-squared R^2 score is a statistical measure of how well the regression model fits the data. It is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where $\bar{y}$ is the mean of the actual values. A higher R^2 value indicates a better fit of the model to the data.
- The Mean Absolute Error (MAE) is another metric used to evaluate the performance of the model. It is given by:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAE provides a linear score and is more interpretable than MSE.

The evaluation metrics were calculated for each fold in the cross-validation process, and the average values were used to report the overall model performance. The DNN terminates training when any of the following conditions are satisfied:

- Performance Metrics: Validation loss does not improve for 10 consecutive epochs.
- Maximum Iterations: Total epochs exceed 300.
- Tolerance Gap: RMSE and MAE between predicted and actual values falls below a predefined threshold ϵ.

A pseudo-code of the DNN with Noise Injection provided in **Algorithm 1**.

Algorithm 1: DNN with Noise Injection

Initialize:
Load input data $\boldsymbol{X}$ (features) and target $\boldsymbol{y}$.
Scale features with *StandardScaler* and target with *MinMaxScaler*.
Set noise factor η, number of synthetic copies C, number of folds for *TimeSeriesSplit* K.
Step 0: Check for Multicollinearity
Compute VIF for all features in $\boldsymbol{X}$.
While any feature has VIF > 10 **do**
Remove or transform the feature with the highest VIF.
Recompute VIF for the remaining features.
end while
Step 1: Data Augmentation with Noise Injection
for $c = 1$ to C **do**
Generate Gaussian noise: $\epsilon_X \sim \mathcal{N}(0, \eta^2), \epsilon_y \sim \mathcal{N}(0, \eta^2)$.
Create synthetic dataset: $\boldsymbol{X}_{\text{synthetic}} = \boldsymbol{X} + \epsilon_X$, $\boldsymbol{y}_{\text{synthetic}} = \boldsymbol{y} + \epsilon_y$.
Append synthetic dataset to original.
end for
Combine original and synthetic datasets: $\boldsymbol{X}_{\text{combined}}$, $\boldsymbol{y}_{\text{combined}}$.
Step 2: Model Development
Define DNN architecture:
Input layer: size equals number of features.
Hidden layers: ReLU activation, L2 regularization, and dropout for generalization.
Output layer: Linear activation for regression.
Compile with Adam optimizer, loss as MSE, and metrics including MAE.
Step 3: Cross-Validation and Training
Initialize *TimeSeriesSplit* with K folds.
for $k = 1$ to K **do**
Split data into train and test sets.
Train DNN on training set with early stopping and learning rate reduction.
Evaluate on test set: Calculate R^2, RMSE, and MAE.
end for
Compute average metrics over all folds.
Step 4: Final Model Training and Evaluation
Train DNN on entire dataset with increased epochs.
Predict target values for combined dataset.
Calculate final RMSE, R^2, and MAE for the entire dataset.

3. Results and discussion

This section presents the results and discussion for the cotton yield prediction study, focusing on Northampton County, NC. The dataset includes detailed records of cotton yield (lb/acre) at the county level for North Carolina, offering a comprehensive historical perspective on cotton production in the state. While Northampton County is used as a case study, the framework provides a robust methodology for modeling the interactions between climatic variables and crop yields, with potential for generalization beyond North Carolina.

3.1. Performance analysis with DNN model

This subsection evaluates the performance of the DNN model in predicting cotton yield, focusing on its predictive accuracy and potential areas for improvement. Various plots illustrate the residuals, actual versus predicted values, and scatter distributions, offering a comprehensive assessment of the model's performance.

Fig. 2 presents the residual plot for the DNN model on the training dataset. Residuals, calculated as the difference between actual and

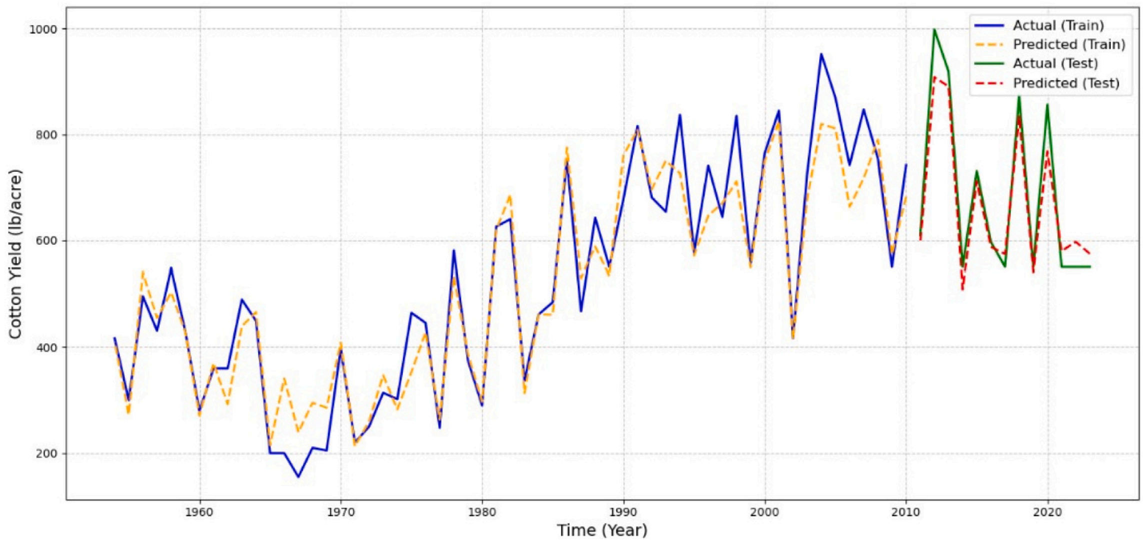

Fig. 3. Model performance: Actual vs. Predicted cotton yield over time for DNN model.

predicted values, provide insights into model accuracy and bias. The distribution of residuals around zero suggests that the DNN model does not exhibit systematic over- or under-prediction. However, the spread of residuals widens for higher and lower yield values, indicating that the model struggles with edge cases influenced by extreme weather events. This highlights the importance of targeted feature engineering to better capture the effects of outliers or rare climatic conditions. Fig. 3 illustrates the comparison of actual and predicted values for the DNN model across the train and test datasets. The lines for actual (train), predicted (train), actual (test), and predicted (test) are closely aligned, confirming the model's strong performance in capturing yield trends across typical ranges. This close alignment highlights the model's effectiveness in generalizing patterns. However, slight deviations at the extremes of the yield range suggest opportunities for further refinement to improve the model's handling of outlier scenarios. Lastly, Fig. 4 presents a scatter plot of predicted versus actual cotton yields for both training and testing datasets. The red dashed line representing a perfect fit, where predictions match actual values exactly. The tight clustering of points around the perfect fit line underscores the DNN model's predictive reliability. Yet, the few deviations at yield extremes indicate challenges in capturing highly variable or rare climatic interactions. These insights emphasize the need for additional data or advanced modeling techniques to handle such edge cases effectively.

Together, these analyses validate the DNN model's ability to capture complex non-linear relationships between climatic features and cotton yield, while also identifying opportunities for further improvement to enhance robustness and precision.

3.2. Improved performance with noise injection

This subsection highlights the significant performance gains achieved by applying noise injection to the DNN model, emphasizing its impact on generalization and predictive accuracy. The scatter plot (Fig. 5) reveals a tighter clustering of points around the perfect fit line for both the training and testing datasets compared to the baseline DNN model. This demonstrates the model's enhanced ability to generalize, particularly for unseen test data. Similarly, the residual plot (Fig. 6) illustrates a dramatic reduction in prediction errors, with residuals concentrated near zero across the entire yield range. This consistency in residuals indicates the model's capability to predict both typical and extreme yield values with high accuracy. The improved performance can be attributed to the introduction of stochastic variations during training via noise injection. By simulating uncertainties and variability in climatic data, this technique enhances the model's robustness, reduces overfitting, and equips it to handle diverse and unseen conditions effectively. These results underscore the value of noise injection as a powerful regularization technique in building reliable and accurate crop yield prediction models.

3.3. Model performance and comparative analysis

This section evaluates the performance of six models used for cotton yield prediction, emphasizing their ability to capture non-linear relationships and handle diverse climatic influences. The models include Multiple Linear Regression (MLR) both with and without multicollinearity adjustment, XGBoost, a baseline Deep Neural Network (DNN), a tuned DNN, and a DNN enhanced with Noise Injection.

As summarized in Table 1, the MLR model trained on the full set of features without multicollinearity correction (denoted as[a]MLR in the table) performs poorly, with a test R^2 of 60.3%, RMSE of 176.5 lb/acre, and MAE of 188.4 lb/acre. This demonstrates the detrimental effect of multicollinearity on model reliability. After addressing multicollinearity using VIF-based feature selection, the feature set was reduced from 246 to 50, and all subsequent models – including the corrected MLR, XGBoost, and the three DNN variants – were trained using this refined and independent feature set. The adjusted MLR model, now using the reduced feature set, improves significantly to a test R^2 of 84.4%, RMSE of 65.1 lb/acre, and MAE of 50.4 lb/acre. XGBoost, a tree-based ensemble method, further enhances predictive accuracy with R^2 values of 90.3% on training and 89.9% on testing, although slight overfitting is observed.

The baseline DNN model leverages non-linear relationships effectively, achieving R^2 values of 92.2% and 91.4% for the train and test datasets, respectively. While RMSE and MAE are improved compared to MLR and XGBoost, prediction errors for extreme yield values persist. The tuned DNN model achieves substantial improvements through hyperparameter optimization, with R^2 on the test set increasing to 94.8% and RMSE dropping to 45.3 lb/acre. The MAE is also reduced to 29.6 lb/acre, reflecting enhanced predictive accuracy.

Finally, the DNN with Noise Injection emerges as the best-performing model, achieving R^2 values of 98.1% and 97.9% for the training and testing datasets, respectively. Its RMSE (24.1 lb/acre for training, 25.3 lb/acre for testing) and MAE (19.6 lb/acre for training, 18.9 lb/acre for testing) are substantially lower, showcasing the benefits of noise injection in enhancing generalization and minimizing overfitting. These results collectively highlight the superior performance of DNN-based models, particularly when augmented with advanced techniques like tuning and noise injection.

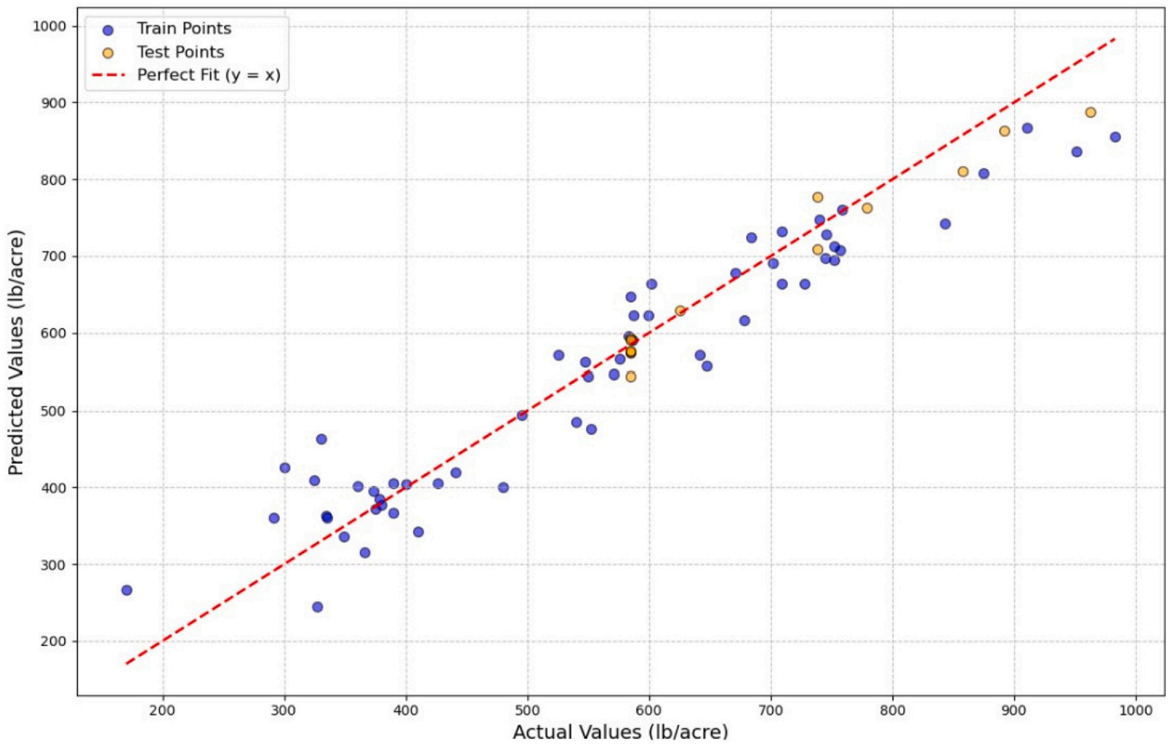

Fig. 4. Scatter plot: Actual vs. Predicted cotton yield for DNN model.

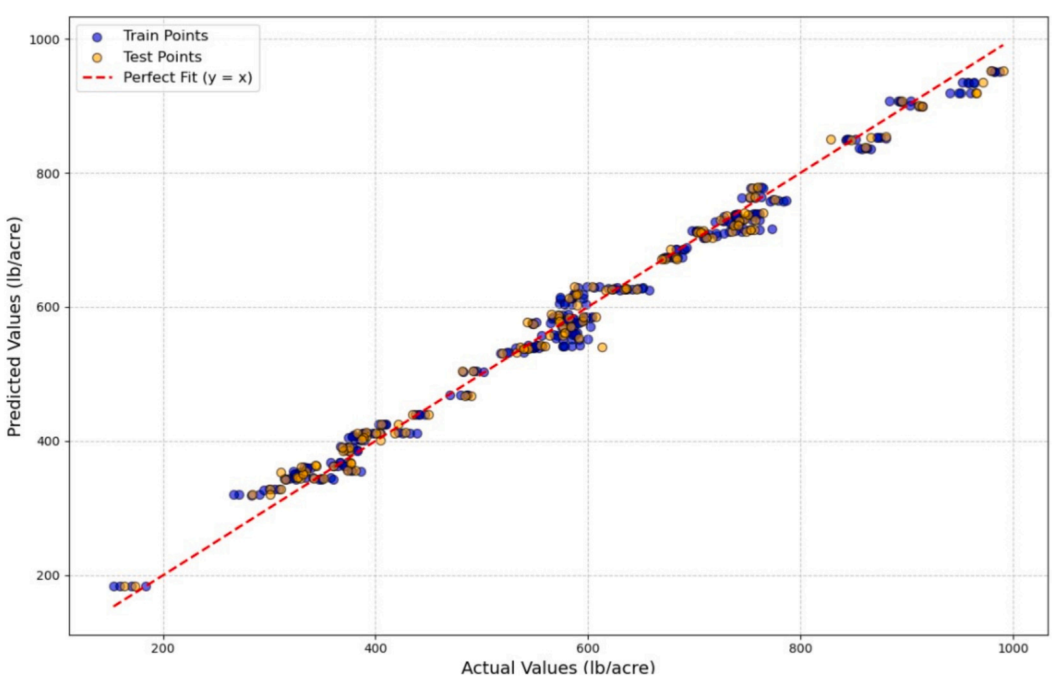

Fig. 5. Scatter Plot: Actual vs. Predicted cotton yield for DNN noise injection model.

3.4. Spatial visualization of predicted cotton yield across North Carolina

To further assess the practical utility of the best-performing model (DNN with Noise Injection), we generated a spatial prediction map of cotton yield across North Carolina for the 2023 growing season. This choropleth map, shown in Fig. 7, reveals a gradient of predicted yields across the cotton-producing counties. Only counties known for cotton production are included in the prediction layer; the remaining counties are shown in a lighter blue shade to provide geographic context. These non-producing counties – primarily located in the Mountain and Piedmont regions, such as Cherokee, Graham, and Clay – were assigned a yield value of zero (lbs/acre), represented by the lightest color on the map.

Mid-range yield values, represented by medium blue shades (approximately 614 to 930 lbs/acre), are observed in counties such as Robeson, Columbus, and Sampson, located in the Coastal Plain region. The darkest blue regions indicate the highest predicted yields, notably in counties like Northampton, Bertie, and Gates are also located in

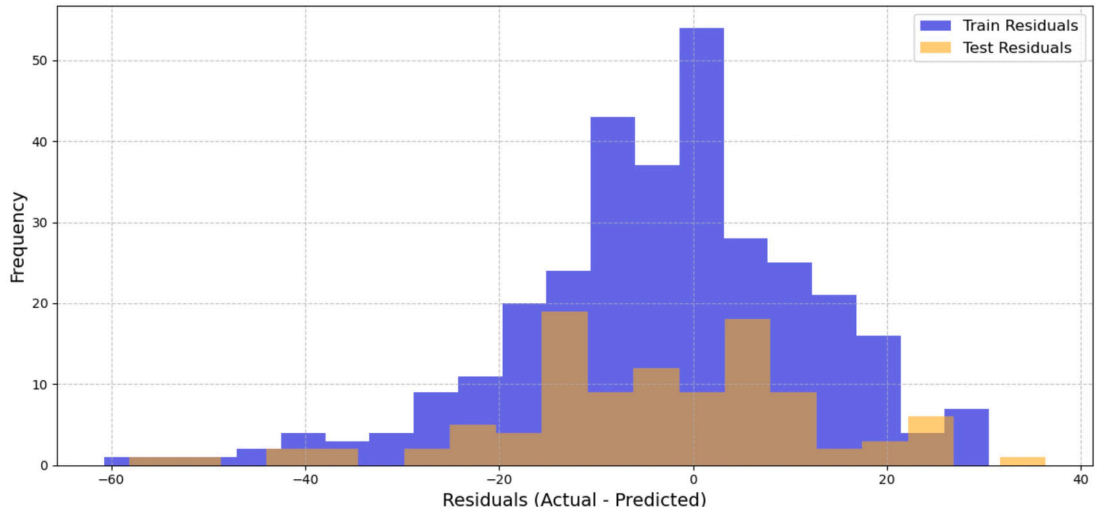

Fig. 6. Histogram of residuals for DNN noise injection model.

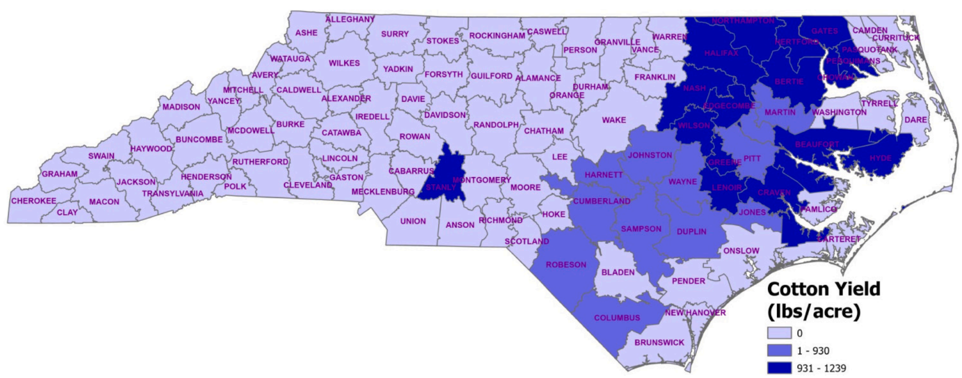

Fig. 7. Predicted cotton yield (lbs/acre) for cotton-producing counties in North Carolina for 2023.

Table 1
Comparison of results by region.

Model	Train			Test		
	R^2	RMSE	MAE	R^2	RMSE	MAE
[a]MLR (w/o Multicollinearity)	65.4	171.6	192.5	60.3	176.5	188.4
MLR	87.5	51.4	45.7	84.4	65.1	50.4
XGBoost	90.3	54.3	49.7	89.9	60.1	55.4
DNN	92.2	55.8	43.5	91.4	65.7	52.9
DNN Tuned	95.8	43.4	38.2	94.8	45.3	29.6
DNN with Noise Injection	**98.1**	**24.1**	**19.6**	**97.9**	**25.3**	**18.9**

[a] Multiple Linear Regression.

Table A.1
Raw data: Summary of feature types and missing data for climate variables.

No.	Feature	Type	Missing
1	Year	Categorical	0
2	Yield	Numerical	0
3	Avg snowfall	Numerical	0
4	Avg precipitation	Numerical	0
5	Avg max temp	Numerical	0
6	Avg min temp	Numerical	0

the Coastal Plain with the exception of Stanly County, situated in the Piedmont region. These spatial patterns align well with established cotton production trends in North Carolina and highlight the model's ability to generalize across different geographic and climatic contexts. By visually communicating spatial variability in cotton yield, this figure enhances the interpretability of the model's outputs and supports the development of region-specific agricultural planning strategies. It serves as a valuable complement to the quantitative performance metrics presented earlier.

4. Significance of findings and implications

The findings of this study highlight the transformative potential of integrating advanced machine learning techniques with domain-specific feature engineering to address critical challenges in agricultural yield prediction. By leveraging deep neural networks (DNNs) and novel regularization methods such as noise injection, the research demonstrates significant improvements in predictive accuracy and model robustness, even in the face of complex even when dealing with complex, non-linear relationships between climatic variables and crop yield.

Our DNN with Noise Injection model performed exceptionally well, achieving an R^2 of 97.9% and an RMSE of 25.3 lb/acre. These results have several important implications:

- The predictive insights from this framework can help farmers make better decisions about resource allocation, irrigation

Table A.2
Processed data: Feature details with missing information and types after feature engineering.

No.	Feature	Type	Missing	No.	Feature	Type	Missing
1	Year	Cat	0	26	Max max temp	Num	0
2	Yield	Num	0	27	Sum max temp	Num	0
3	Avg snow	Num	0	28	Avg max temp_4–12	Num	varies
4	Med snow	Num	0	29	Med max temp_4–12	Num	varies
5	Min snow	Num	0	30	Min max temp_4–12	Num	varies
6	Max snow	Num	0	31	Max max temp_4–12	Num	varies
7	Sum snow	Num	0	32	Sum max temp_4–12	Num	varies
8	Avg snow_4–12	Num	varies	33	Avg min temp	Num	0
9	Med snow_4–12	Num	varies	34	Med min temp	Num	0
10	Min snow_4–12	Num	varies	35	Min min temp	Num	0
11	Max snow_4–12	Num	varies	36	Max min temp	Num	0
12	Sum snow_4–12	Num	varies	37	Sum min temp	Num	0
13	Avg prcp	Num	0	38	Avg min temp_4–12	Num	varies
14	Med prcp	Num	0	39	Med min temp_4–12	Num	varies
15	Min prcp	Num	0	40	Min min temp_4–12	Num	varies
16	Max prcp	Num	0	41	Max min temp_4–12	Num	varies
17	Sum prcp	Num	0	42	Sum min temp_4–12	Num	varies
18	Avg prcp_4–12	Num	0	43	GDD annual	Num	0
19	Med prcp_4–12	Num	0	44	Total prcp vegetative	Num	0
20	Min prcp_4–12	Num	0	45	Avg grain filling temp	Num	0
21	Max prcp_4–12	Num	0	46	Hot days	Num	0
22	Sum prcp_4–12	Num	varies	47	Frost days	Num	0
23	Avg max temp	Num	0	48	Longest dry spell Days	Num	0
24	Med max temp	Num	0	49	VPD annual	Num	0
25	Min max temp	Num	0				

Table A.3
Processed data: Final feature details with missing information and types after feature engineering and multicollinearity test.

No.	Feature	Type	Missing	No.	Feature	Type	Missing
1	Year	Cat	0	27	Max max temp	Num	0
2	Yield	Num	0	28	Sum max temp	Num	0
3	Avg prcp_4	Num	0	29	Min min temp_4	Num	0
4	Avg prcp_7	Num	0	30	Min min temp_6	Num	0
5	Avg prcp_10	Num	0	31	Min min temp_7	Num	0
6	Max prcp_1	Num	0	32	Min min temp_8	Num	0
7	Max prcp_5	Num	0	33	Min min temp_9	Num	0
8	Max prcp_10	Num	0	34	Min min temp_10	Num	0
9	Max prcp_12	Num	0	35	Min min temp_11	Num	0
10	Sum prcp_2	Num	0	36	Min min temp_12	Num	0
11	Sum prcp_7	Num	0	37	Max min temp_1	Num	0
12	Sum prcp_10	Num	0	38	Max min temp_3	Num	0
13	Avg max temp_12	Num	0	39	Max min temp_4	Num	0
14	Min max temp_4	Num	0	40	Max min temp_11	Num	0
15	Min max temp_5	Num	0	41	Max min temp_12	Num	0
16	Min max temp_11	Num	0	42	Sum min temp_6	Num	0
17	Max max temp_1	Num	0	43	Sum min temp_10	Num	0
18	Max max temp_5	Num	0	44	Sum min temp	Num	0
19	Max max temp_12	Num	0	45	GDD annual	Num	0
20	Sum max temp_2	Num	0	46	Total prcp vegetative	Num	0
21	Sum max temp_4	Num	0	47	Avg grain filling temp	Num	0
22	Avg min temp_6	Num	0	48	Hot days	Num	0
23	Avg min temp_12	Num	0	49	Frost days	Num	0
24	Med min temp_2	Num	0	50	Longest dry spell Days	Num	0
25	Med min temp_6	Num	0	51	VPD annual	Num	0
26	Min min temp_2	Num	0				

schedules, and planting strategies. By understanding how specific climatic factors affect cotton yields, farmers can adopt practices to mitigate risks from extreme weather or unfavorable growing conditions.
- Policymakers can use these findings to design targeted interventions that enhance agricultural resilience. For instance, identifying key features like GDD and extreme weather indices provides actionable data for developing climate adaptation strategies, ensuring sustainable cotton production under changing environmental conditions.
- The integration of advanced feature engineering, such as seasonal precipitation metrics and vegetative stage analysis, offers a template for precision agriculture applications. This level of detail enables optimization at the field level, reducing waste and improving yield efficiency.
- The framework outlined in this study can be extended to other crops and regions, making it a valuable tool for global agricultural stakeholders. Using publicly available datasets, combined with robust preprocessing and modeling techniques, ensures accessibility for researchers and practitioners worldwide.
- The findings highlight the need for proactive measures to mitigate the impacts of climate variability on crop production. The ability to predict yields under extreme conditions provides a basis for developing adaptive farming practices, enhancing food security, and reducing the economic vulnerabilities of farming communities.

By bridging the gap between machine learning advancements and practical agricultural applications, this study represents a significant step forward in addressing the dual challenges of food security and climate resilience. The implications extend beyond cotton yield prediction, laying the groundwork for broader impacts across the agricultural sector.

5. Conclusions and future research

This study confirms that a deep learning framework, especially a DNN model with noise injection and hyperparameter tuning, can deliver highly accurate cotton yield predictions when informed by carefully engineered climatic features. Achieving an R^2 of 97.9% and an RMSE of 25.3 lb/acre on the test set, the model demonstrates the potential of combining domain-informed feature engineering with regularization strategies to improve predictive robustness. Key predictive contributors such as growing degree days (GDD), extreme weather indices, and seasonal precipitation metrics underscore the non-linear and temporally dynamic nature of climate–yield relationships. These insights offer valuable guidance for farmers, agricultural planners, and policymakers seeking to manage production risks, allocate resources effectively, and adapt to climate variability. The general framework—grounded in publicly available data and replicable methods can serve as a basis for extending yield modeling to other crops and regions.

Despite the strong predictive performance of the proposed deep learning framework, several limitations must be acknowledged to contextualize the findings. First, the model focuses exclusively on climatic variables, omitting potentially influential factors such as soil properties, crop management practices, and pest dynamics. This narrows the scope of the modeled relationships and may limit applicability in more complex agronomic settings. Second, the spatial generalizability of the model is constrained by its reliance on U.S.-specific data, and its performance in other geographic regions with distinct agro-climatic conditions would require retraining or adaptation. Third, the model's temporal stability under future climate scenarios is uncertain, as shifting weather patterns and evolving farming practices may impact its long-term reliability. Additionally, the approach depends heavily on the quality and completeness of publicly available datasets, which may introduce inconsistencies or biases into the training process. Finally, while we employed feature importance analysis, the inherent complexity of deep neural networks presents challenges for interpretability, limiting transparency in how specific inputs influence yield predictions. Addressing these limitations presents clear opportunities for future research and model refinement.

Future work can focus on incorporating soil data, such as nutrient levels and pH, to enhance the model's predictive power. Exploring advanced architectures like Transformers or Convolutional Neural Networks (CNNs) could capture additional complexities in temporal and spatial data. Expanding the framework to multi-crop and multi-regional analyses will test its adaptability and reveal broader agricultural patterns. Lastly, integrating economic factors and developing real-time prediction tools can further support decision-making for farmers and policymakers. While our model is designed for planning-level predictions at the county scale to support agricultural decision-making, integrating soil properties and pH data could improve operational-level forecasts at finer spatial resolutions, such as the field or farm level.

CRediT authorship contribution statement

Md Abdul Quddus: Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization, Investigation, Project administration, Writing – review & editing. **Sudipta Chowdhury:** Writing – review & editing, Validation. **Warren Jasper:** Writing – review & editing, Methodology. **Lokesh Das:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables A.1–A.3.

Data availability

Data will be made available on request.

References

Adare, Z.M., Adare, S.A., Velchala, P.R., Tata, R.P., Thatikunta, R.T., 2023. Meteorological variables of crop phenophases impact on yield and yield components of cotton (G. hirsutum L. Authorea Prepr..

Ahmad, S., Abbas, Q., Abbas, G., Fatima, Z., Naz, S., Younis, H., Khan, R.J., Nasim, W., Habib ur Rehman, M., Ahmad, A., Rasul, G., 2017. Quantification of climate warming and crop management impacts on cotton phenology. Plants 6 (1), 7.

Akhtarmanesh, A., Abbasi-Moghadam, D., Sharifi, A., Yadkouri, M.H., Tariq, A., Lu, L., 2024. Road extraction from satellite images using attention-assisted unet. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 1126–1136.

Arshad, A., Raza, M.A., Zhang, Y., Zhang, L., Wang, X., Ahmed, M., Habib-ur Rehman, M., 2021. Impact of climate warming on cotton growth and yields in China and Pakistan: A regional perspective. Agriculture 11 (2), 797.

Balducci, Fabri., Impedovo, D., Pirlo, G., 2018. Machine learning applications on agricultural datasets for smart farm enhancement. Machines 6 (3), 38.

Balmumcu, A., Kayabol, K., Erten, E., 2024. Machine learning-based crop yield prediction by data augmentation. 2024 32nd Signal Process. Commun. Appl. Conf. (SIU) 1–4.

Cao, J., Zhang, Z., Luo, Y., Zhang, L., Zhang, J., Li, Z., Tao, F., 2021. Wheat yield predictions at a county and field scale with deep learning, machine learning, and google earth engine. Eur. J. Agron. 123, 126204.

Cetin, O., Basbag, S., 2010. Effects of climatic factors on cotton production in semi-arid regions-a review. Res. Crop. 11 (3), 785–791.

Chandraprabha, M., Dhanraj, R.K., 2023. Ensemble deep learning algorithm for forecasting of rice crop yield based on soil nutrition levels. EAI Endorsed Trans. Scalable Inf. Syst. 10 (4).

Esmaeili, M., Abbasi-Moghadam, D., Sharifi, A., Tariq, A., Li, Q., 2024. ResMorCNN model: Hyperspectral images classification using residual-injection morphological features and 3Dcnn layers. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 219–243.

Farmonov, N., Esmaeili, M., Abbasi-Moghadam, D., Sharifi, A., Amankulova, K., Mucsi, L., 2024. HypsLiDNet: 3-D–2-D CNN model and spatial–spectral morphological attention for crop classification with DESIS and LiDAR data. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 11969–11996.

Farooq, M.A., Chattha, W.S., Shafique, M.S., Karamat, U., Tabusam, J., Zulfiqar, S., Shakeel, A., 2023. Transgenerational impact of climatic changes on cotton production. Front. Plant Sci. 14, 987514.

Felegari, S., Sharifi, A., Khosravi, M., Sabanov, S., 2023. Using experimental models and multitemporal landsat-9 images for cadmium concentration mapping. IEEE Geosci. Remote. Sens. Lett. 20, 1–4.

Feng, A., Zhou, J., Vories, E., Sudduth, K.A., 2024. Prediction of cotton yield based on soil texture, weather conditions and UAV imagery using deep learning. Precis. Agric. 25 (1), 303–326.

Gupta, R., Padmawar, T.S., Kumar, D., Ray, D., Kadam, P., 2024. Significance of machine learning in crop yield prediction. 2024 2nd World Conf. Commun. Comput. (WCONF) 1–7.

Haider, S.T., Ge, W., Li, J., Rehman, S.U., Imran, A., M., Sharaf, Haider, S.M., 2024. An ensemble machine learning framework for cotton crop yield prediction using weather parameters: A case study of Pakistan. IEEE Access.

Isik, M.S., Celik, M.F., Erten, E., 2023. Interpretable cotton yield prediction model using earth observation time series. IGARSS 2023- 2023 IEEE Int. Geosci. Remote. Sens. Symp. 3442–3445.

J.B., Phillips, 2012. Cotton Response to High Temperature Stress During Reproductive Development. University of Arkansas.

Jia, Y., Yang, B., Han, Y., Wang, G., Su, T., Li, X., Lei, Y., Zhi, X., Xiong, S., Xin, M., Li, Y., 2024. Enhanced cotton yield and fiber quality by optimizing irrigation amount and frequency in arid areas of northwest China. Agronomy 14 (2), 266.

Khan, S.N., Iqbal, J., Khan, M.R., Malik, N.A., Khan, F.A., Khan, K., Khan, A.N., Wahab, A., 2025. Using remotely sensed vegetation indices and multi-stream deep learning improves county-level corn yield predictions. Eur. J. Agron. 164, 127496.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Natures 521 (7553), 436–444.
Li, N., Liang, J., Yang, Q., Du, T., 2023. International literature characteristics and hotspots evolution of the impact of climate change on cotton: A bibliographic study. J. Water Clim. Chang. 14 (4), 1285–1299.
Lu, J., Li, J., Fu, H., Tang, X., Liu, Z., Chen, H., Sun, Y., Ning, X., 2024. Deep learning for multi-source data-driven crop yield prediction in northeast China. Agriculture 14 (6), 794.
Mahdipour, H., Sharifi, A., Sookhak, M., Medrano, C.R., 2024. Ultrafusion: Optimal fuzzy fusion in land-cover segmentation using multiple panchromatic satellite images. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 5721–5733.
Mandal, D.K., Mandal, C., Venugopalan, M.V., 2005. Suitability of cotton cultivation in shrink–swell soils in central India. Agricult. Sys. 84 (1), 55–75.
Marzvan, S., Moravej, K., Felegari, S., Sharifi, A., Askari, M.S., 2021. Risk assessment of alien azolla filiculoides lam in anzali lagoon using remote sensing imagery. J. the Indian Soc. Remote. Sens..
MirhoseiniNejad, S.M., Abbasi-Moghadam, D., Sharifi, A., 2024. ConvLSTM–Vit: A deep neural network for crop yield prediction using earth observations and remotely sensed data. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 17489–17502.
Mishra, H., Mishra, D., 2023. Artificial intelligence and machine learning in agriculture: Transforming farming systems. Res. Trends Agric. Sci 1, 1–16.
Mitra, A., Beegum, S., Fleisher, D., Reddy, V.R., Sun, W., Ray, C., Timlin, D., Malakar, A., 2024. Cotton yield prediction: a machine learning approach with field and synthetic data. IEEE Access.
Natioanl centers for environmental infromation, Natioanl oceanic and atmospheric administration. Daily observational data, 2024. Available from: . https://www.ncei.noaa.gov/maps/daily/.
Naveed, M., He, H.S., Yasir, Q.M., 2021. Analyzing the impact of climate change on cotton yield using spatial analysis and statistical modeling in the Indus River Basin, Pakistan. Ann. Agric. Crop. Sci 6, 1089.
Niu, H., Peddagudreddygari, J.R., Bhandari, M., Landivar, J.A., Bednarz, C.W., Duffield, N., 2024. In-season cotton yield prediction with scale-aware convolutional neural network models and unmanned aerial vehicle RGB imagery. Sensors 24 (8), 2432.
Prasad, N.R., Patel, N.R., Danodia, A., 2021. Crop yield prediction in cotton for regional level using random forest approach. Spat. Inf. Res. 29, 195–206.
Safari, M.M., Sharifi, A., Mahmood, J., Abbasi-Moghadam, D., 2024. Mesoscale eddy detection and classification from sea surface temperature maps with deep neural networks. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 17, 10279–10290.
Selvakumar, R.K., Tanoj, S.S., Goud, T.H., 2024. A review and comprehensive analysis of recent research in crop yield prediction using machine learning algorithms. 2024 IEEE Recent. Adv. Intell. Comput. Systems (RAICS) 1–6.
Shahzadi, I., Mazhar, N., Abbas, S., 2023. An assessment of changes and variability of climate impact on cotton production yield over southern punjab, Pakistan. Environ. Dev. Sustain. 1–17.
Sharifi, A., Safari, M.M., 2025. Enhancing the spatial resolution of sentinel-2 images through super-resolution using transformer-based deep-learning models. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 18, 4805–4820.
Shrestha, A., Swaminathan, V., Thomasson, J.A., Rajan, N., Poudyal, C., Miyanaka, N., Siegfried, J.A., 2023. A modular artificial neural network technique for early estimation of cotton yield using unmanned aerial system. Auton. Air Ground Sens. Syst. Agric. Optim. Phenotyping VIII 12539, 25–33.
Sultan, B., Bella-Medjo, M., Berg, A., Quirion, P., Janicot, S., 2010. Multi-scales and multi-sites analyses of the role of rainfall in cotton yields in west africa. HAL.
The farming insider, Climate vs. Cotton: The Battle for Yield Stability, 2024. Available from: . https://thefarminginsider.com/climate-vs-cotton-for-yield-stability/.
Umutoni, L., Samadi, V., Payero, J., Koc, B., Privette, C., 2024. Application of machine learning approaches for cotton seasonal yield estimation. Copernic. Meet..
USDA census of agriculture historical archive, 2024. Available from: . https://agcensus.library.cornell.edu/census_parts/{1940}-special-cotton-report/.
USDA's National Agricultural Statistics Service, 2024. Available from: . https://www.nass.usda.gov/{Statistics_by_State}/{North_Carolina}/publications/{Annual_Statistical_Bulletin}/index.php.
Vafaeinejad, A., Alimohammadi, N., Sharifi, A., Safari, M.M., 2025. Super-resolution AI-based approach for extracting agricultural cadastral maps: Form and content validation. IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens. 18, 5204–5216.
Wang, Z., Chen, J., Xing, F., Han, Y., Chen, F., Zhang, L., Li, Y., Li, C., 2017. Response of cotton phenology to climate change on the North China plain from 1981 to 2012. Sci. Rep. 7 (1), 6628.
Wang, H., Yin, Z., Zhang, L., Zhao, F., Huang, W., Wang, X., Gao, Y., 2022. Irrigation modulates the effect of increasing temperatures under climate change on cotton production of drip irrigation under plastic film mulching in southern Xinjiang. Front. Plant Sci. 13, 1069190.
Williams, A., White, N., Mushtaq, S., Cockfield, G., Power, B., Kouadio, L., 2015. Quantifying the response of cotton production in eastern Australia to climate change. Clim. Change 129, 183–196.
World worldlife fund, 2024. Available from: . https://www.worldwildlife.org/industries/cotton.
Xu, W., Chen, P., Zhan, Y., Chen, S., Zhang, L., Lan, Y., 2021. Cotton yield estimation model based on machine learning using time series UAV remote sensing data. Int. J. Appl. Earth Obs. Geoinf. 104, 102511.
Yang, Y., Yang, Y., Han, S., Macadam, I., Li Liu, D., 2014. Prediction of cotton yield and water demand under climate change and future adaptation measures. Agricult. Water. Manag. 144, 42–53.
Yildirim, T., Moriasi, D.N., Starks, P.J., Chakraborty, D., 2022. Using artificial neural network (ANN) for short-range prediction of cotton yield in data-scarce regions. Agronomy 12 (4), 828.