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RESEARCH ARTICLE

Cotton Yield Prediction: A Machine Learning Approach With Field and Synthetic Data

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ABSTRACT The United States cotton industry is devoted to sustainable production strategies that reduce water, land, and energy consumption while enhancing soil health and cotton yield. Climate-smart agricultural solutions are being developed to increase yields and reduce operational costs. However, crop yield prediction is challenging because of the complex and nonlinear interactive effects of cultivar, soil type, management, pests and diseases, climate, and weather patterns on crops. To address this challenge, the machine learning (ML) method was used to predict yield, considering climatic change, soil diversity, cultivars, and fertilizer applications. Field data were collected over the southern US cotton belt in the 1980s and the 1990s. A second data source was generated from the process-based cotton model GOSSYM to reflect the most recent effects of climate change over the last six years (2017–2022). We focused on nine locations in three southern states: Texas, Mississippi, and Georgia. The accumulated heat for each set of experimental data was used as an analogue for the time-series weather data to reduce the number of computations. The Random Forest (RF) regressor, Support Vector Regression (SVR), Light Gradient Boosting Machine (LightGBM) regressor, Multiple Linear Regression (MLR), and neural networks were evaluated. Cross-validation was performed to obtain an improved model that did not suffer from overfitting. The RF regressor achieved an accuracy of 97.75%, with an R^2 of roughly 0.98 and a root mean square error of 55.05 kg/ha. The results demonstrate how a simple and robust model can be developed and utilized to help cotton climate-smart efforts.

INDEX TERMS Cotton yield prediction, climate change effect, smart agriculture, machine learning, field data, synthetic data.

I. INTRODUCTION

Crop yield prediction is crucial for addressing food security challenges amid global climate change. Stakeholders, ranging from farmers to policymakers, emphasize the need for accurate and timely yield prediction [1]. Farmers can make more informed financial decisions and apply appropriate management strategies when accurate yield forecasts are available [2]. However, it can be challenging to precisely predict crop yields because of numerous variables such as crop-specific parameters, management strategies, cultivars, soil types, pests, and diseases. Thus climate change is a major factor. Agriculture is highly dependent on the weather and climate. Changing climate and weather patterns can severely affect crop yields [3], [4] and make them unpredictable. For example, Fig. 1(a) and 1(b) depict how daily maximum and minimum temperatures changed over 42 years, from 1980 to 2022 at a location (33.47° - 88.78°) in Mississippi, one major US cotton production site. Over 42 years, the temperature at this location increased by 0.8° C and the world's temperatures rose by at least 1° C. Increase in greenhouse gas levels and heat accumulation [5] have resulted in higher temperatures than pre-industrial levels. These factors affect crops in complex and nonlinear ways [6], [7], [8]. Hence, building a

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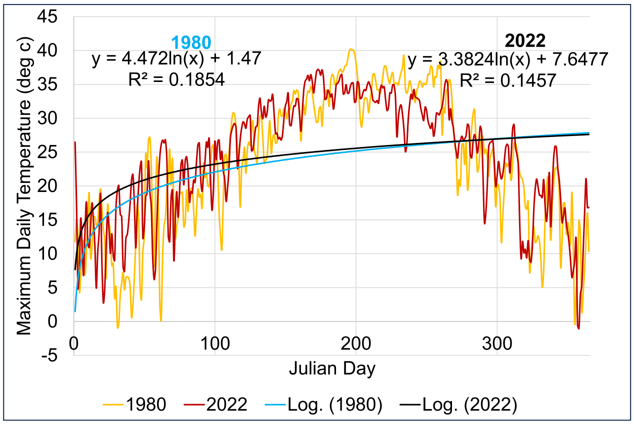
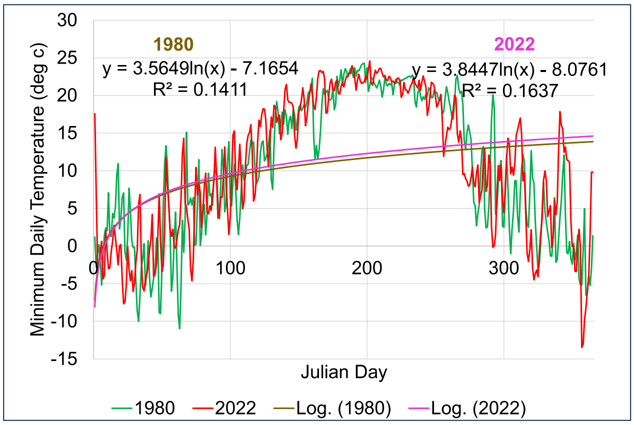


(a)



(b)

FIGURE 1. Daily (a) maximum and (b) minimum temperature variations in 1980 and 2022 at R.R. Foil Plant Science Research Center near Starkville, MS (33.47°, −88.78°). The average maximum temperature was 23.5° C and 24.3° C in 1980 and 2022, respectively, whereas the average minimum temperature was 10.4° C and 10.8° C in those years, respectively. The average maximum temperature increased by 0.8° C and the average minimum temperature increased by 0.4° C in the last 42 years.

robust, reliable, and accurate crop yield prediction model is not easy.

Typically, classical process-based crop growth models are based on the agronomic principles of plants and soils, management strategies, crop phenotypes, and weather variables and are used to predict crop yields [3]. It takes considerable effort and time to build such models and requires the availability of substantial data for calibration and validation of the models. Remote sensing-based approaches have also been employed for crop yield predictions. A wide range of devices, such as satellites, drones, LIDAR and RADAR sensors, and Internet-of-Things (IoT) field sensors are used for remote sensing [9], [10], [11]. Images and soil data collected through this approach were used to calculate various parameters (such as evapotranspiration, normalized difference vegetation index (NDVI), soil type, surface temperature (ST), soil moisture (SM), green vegetation index (GVI), enhanced vegetation index (EVI), temperature condition index (TCI), and vegetation condition index (VCI)) [12]. Indices such as NDVI, green normalized difference vegetation index (GNDVI), VCI, and TCI [12], [13], [14] are also used in statistical models [15], machine learning (ML) and DL-based models [16], [17] and hybrid models [18] to predict crop yield.

However, rapid growth in the IoT has changed this scenario. The proliferation of sensors generating huge amounts of data helped to emerge a new technology called "big data." Advancements in information and communication technologies (ICT), the hardware industry, and various computing platforms (cloud, fog, and edge) [19] enabled the data to be processed and computed more efficiently [20]. Advanced analytical tools such as ML technologies, provide a promising avenue to use these data more proficiently. The effectiveness of ML algorithms has already been demonstrated in the fields of healthcare [21], finance [22], multimedia forensics [23], [24], security and surveillance [25], retail [26], manufacturing [27], self-driving cars [28], virtual assistants [29], and plant/crop/fruits disease prediction [30], [31], [32], [33].

ML models are conceptually different from process-based ones. The advantages of applying ML algorithms are as follows:

- They are data-driven and learn patterns and relationships from a large dataset to predict the output. Therefore, tedious calculation or equation validation with data is not required. Once the input is selected, the remainder of the process is automatic.
- ML-based approaches are highly accurate when trained on high-quality datasets. Therefore, precise yield estimation can be achieved using this method.
- ML-based models are much simpler than process-based ones. Therefore, they are faster whereas process-based models take longer to run.
- As process-based models are computationally heavy they cannot be run on portable devices such as mobile phones. However, ML-based models enable mobile applications for crop models.
- ML models can replicate the nonlinear relationships between various inputs and yields accurately [34].
- Additionally, regularization techniques can make the model robust and generalized for noisy data [35].

Nonetheless, the accuracy of a model depends on various data quality aspects [20] such as volume, variety, meaningfulness, correctness, availability, and reliability. Therefore, an ML model can be developed to predict crop yields accurately when trained on a high-quality dataset. Hence, in the last several years, ML and DL-based approaches have been used extensively to predict crop yields. The ML and DL algorithms used for this approach include neural networks [36], random forests [1], support vector machines [37], convolutional neural networks [38], long short-term memory networks [17], autoencoder [39], faster-RCNN [40], etc. The United States (U.S.) cotton industry is devoted to sustainable production strategies that reduce water, land, and energy consumption while enhancing soil health and yield [41], [42]. Climate-smart agriculture solutions are being developed to increase yields and lower operational costs [43], [44], [45].

A. SOLUTION PROPOSED

Our research goal was to reliably predict cotton yield considering the effects of climate change, specifically high temperatures, in the U.S. southern cotton belt. We compared various ML-based and DNN-based methods for cotton yield prediction and used the best-performing method to evaluate yield estimates over multiple locations. Instead of 30 years of historical data, we focused on the last six years of meteorological data to include the climate change effect.

B. SIGNIFICANCE OF THE SOLUTION

- Because temperature is the largest driver among weather variables for plant growth and development, accounting for this relatively rapid climate change is important for incorporating an ML approach to estimate cotton yield. Our study addresses climate change and underscores its significance.
- Our study also showed how synthetic data use could apply state-of-the-art technology such as AI/ML in agriculture. The scarcity of publicly available datasets necessitates this for sustainable agriculture research.
- In this study, we calculated the accumulated heat from temperature variation during the season. This strategy simplifies the entire method and requires less computation. Consequently, it offers a more portable and edge-based solution.

The rest of the paper is organized as follows: Section II describes the methodology and experimental verification. The results are documented, discussed, and compared with existing works in Section III. Finally, Section IV summarizes how the results of this research move the knowledge base regarding ML applications to cotton yield forecasting and the importance of using synthetic data in agricultural research.

II. MATERIALS AND METHODS

Temperature is a key factor in cotton development. However, genetic traits can influence crop responses at different developmental stages. Cultivar responses to other environmental and field conditions, such as day length and water or nitrogen stress, vary across time and space, making the scenario dynamic and complex [46]. For example, Fig. 2 shows the variation in the weather elements at a representative site in Hockley, TX, at (33.51°, -102.5°) for the cotton season in 2022.

The primary focus of this study is to build an ML-based, robust cotton model that can precisely predict cotton yield while addressing the dynamic effects of these multiple inputs. Fig. 3 presents an overview of the proposed approach.

A. INPUT SELECTION

Weather [46], cultivar [47], soil type [48], and nitrogen [49] were selected as the input variables. The effects of rainfall, wind speed, and solar radiation were not considered because temperature is the most important weather element to influence cotton growth [44]. However, any variable from a weather dataset is time-series data, which demands more dynamic computation and increases the complexity of any crop model. To reduce complexity, we converted the time series temperature data to a scalar value, the accumulated heat, as described in Section II-D, without sacrificing model accuracy.

B. DATASET DETAILS

Two types of cotton yield data were used: field data and synthetic data. Field data were collected over the southern cotton belt in the 1980s and the early 1990s and archived with the Adaptive Cropping Systems Laboratory, USDA-ARS, Beltsville, Maryland. The dataset included multiple field plots, covering a range of soil types, cultivars, and nitrogen fertilizer concentrations. Plants were irrigated as determined by the farm managers to supplement precipitation to avoid water stress. Table 1 lists the details of the field dataset used in this study [50].

However, more rapid climate change has recently been observed worldwide. For example, the atmospheric CO_2 concentration ($\approx$ 337 ppm) in 1980 surged to 412 ppm in 2019 [51]. Therefore, the most recent effects of climate change over the past several years were not reflected in field data. In addition, more training data are needed to train the ML model without overfitting as ML models predict well when trained on a large diverse dataset [20], [52].

To address this issue, we generated synthetic yield data using a process-based cotton model called GOSSYM [53], [54], [55]. The development and applications of GOSSYM have been extensively documented in multiple scientific articles [54], [56], [57]. It is fundamentally a material balance model that simulates crop growth and development, carbon and nitrogen uptake, movement, and allocation in plants, as well as water and nitrogen in the soil. GOSSYM predicts crop responses to meteorological inputs [58], such as daily total solar radiation, maximum and minimum air temperatures, daily total wind speed, rainfall, fertilizer applications, and irrigation. Over the years, this model has undergone numerous enhancements and adjustments utilizing advanced concepts and insights acquired from experiments conducted in laboratory settings, field-scale scenarios, and controlled environments [56], [57]. The most recent iteration of GOSSYM involved enhancements in the soil, photosynthesis, and transpiration mechanisms [59]. The GOSSYM model incorporates 50 parameters related to weather, management, soil processes, and species- and cultivar-dependent characteristics. These parameters have been extensively discussed and documented in previous studies [56], [60].

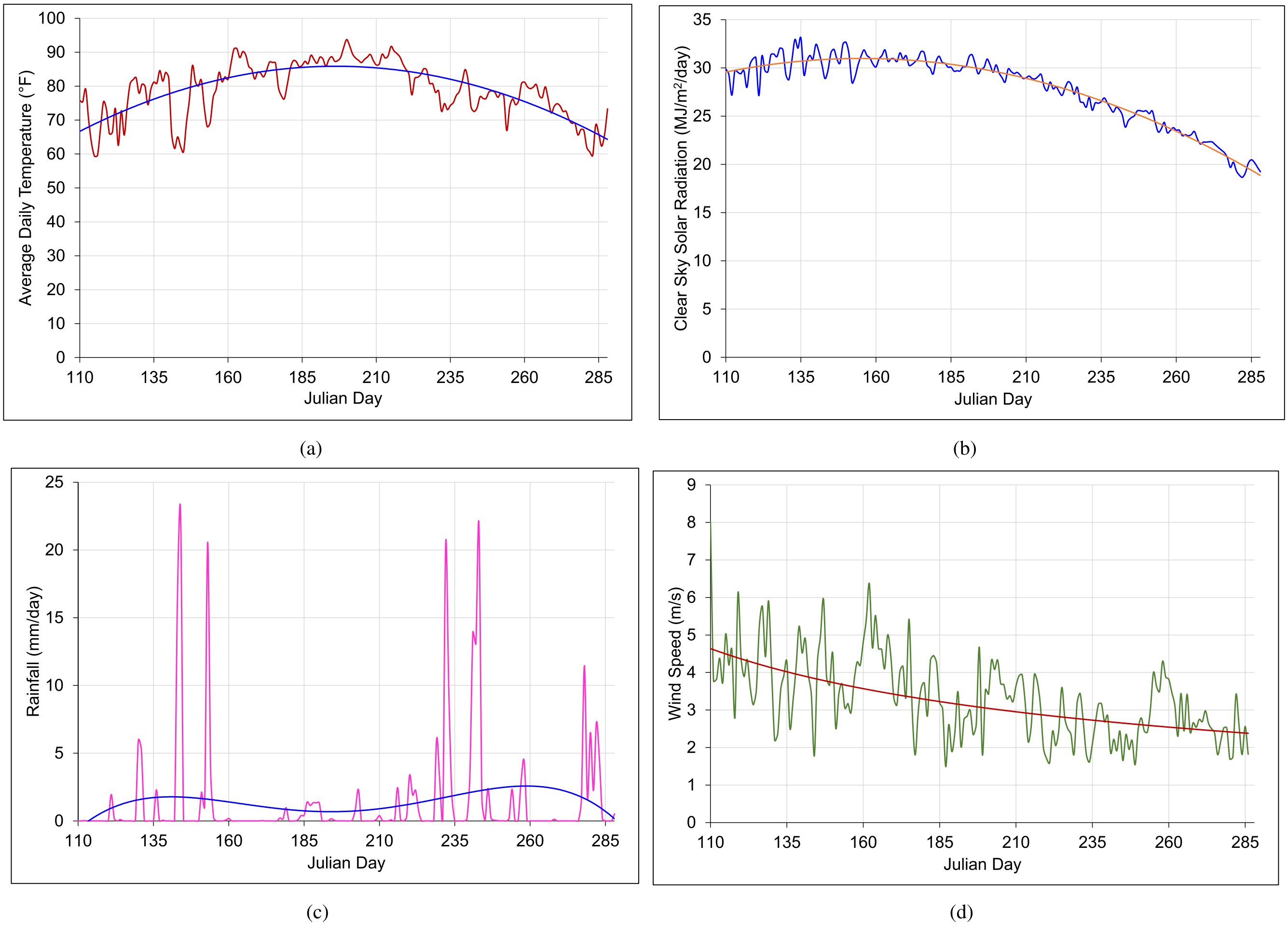


FIGURE 2. Variation in weather variables from Julian day 110 to 288 in 2022 at location Hockley, TX (33.51°, −102.52°). a) Average daily temperature vs Julian day, b) Clear sky solar radiation vs Julian day, c) Rainfall vs Julian day, and d) Wind speed vs Julian day.

GOSSYM was previously calibrated with cultivar parameters for 12 cotton cultivars, including those from the Delta, Acala, Stripper, and PIMA cultivar groups [56], [61]. These parameters were derived from multiple modeling studies of these cultivars. The cultivars used in this study were selected based on identical parameter sets. To include the most recent effects of climate change, the last six years, 2017-2022, were selected as the study period. The POWER Data Access Viewer [62] tool was used to download the daily weather data required to drive the GOSSYM model. We chose the first three leading cotton-producing states: Texas, Mississippi, and Georgia, based on their historical cotton production practices. We also selected three locations within each of the three states, as study areas (Table. 2).

Three different soil types, two cultivars, and four different amounts of applied nitrogen were selected for each location. This range of values was selected based on their presence in field data (Table 1) to ensure compatibility. Table 3 lists the input variations for the generated datasets. Sufficient irrigation was applied in addition to rainfall to avoid water stress. To make the data consistent with that of Table 1 we assumed that the plants were sown on May 1st and harvested on September 30th of each year [63], [64], [65], [66].

TABLE 1. Details of the field data obtained from experimental trials from seven states in the U.S. cotton belt from 1980 through the early 1990s.

Items	Details	Remarks
Study States	California, Texas, Missouri, New Mexico, Mississippi, Tennessee, Alabama	[63]
Number of Locations	48	Field Data
Number of Study Years	7	Field Data
Number of Soil Types	10	Field Data
Number of Cultivars	2	Field Data
Nitrogen Amount	0-300 kg/ha	Field Data

There were 48 instances of field data and 1296 instances of generated data. 1075 data samples (80%) were randomly selected and used for training and validation, and 269 data samples (20%) were used for testing purposes.

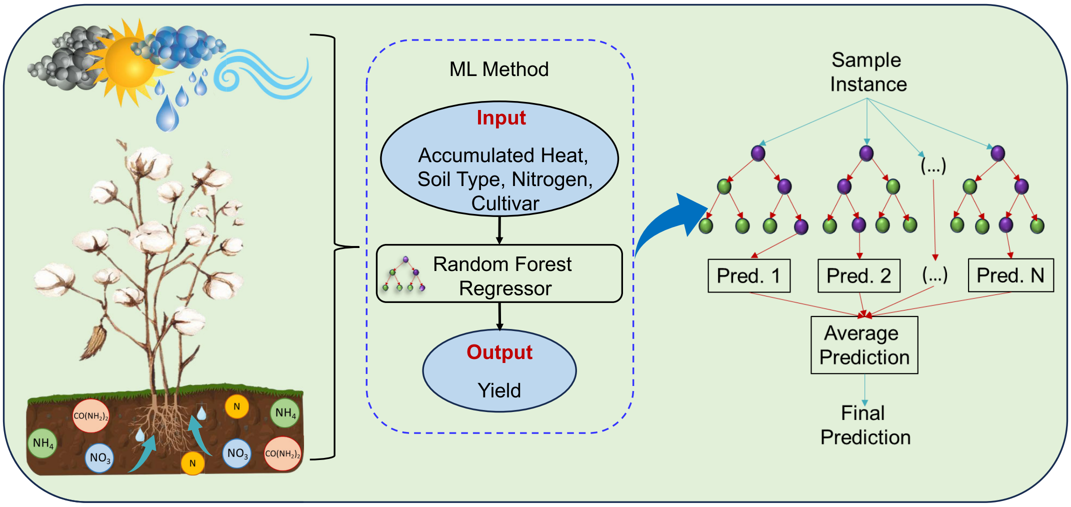


FIGURE 3. Overview of cotton yield prediction using random forest regressor.

TABLE 2. Details of the study area used for generating synthetic yield data using the GOSSYM cotton model.

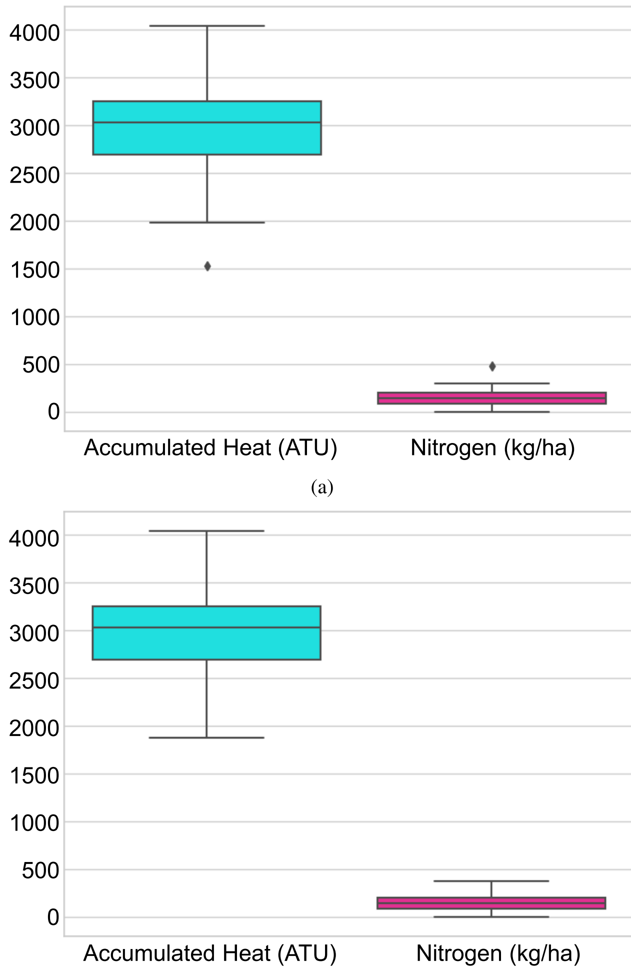
State	County	Lat.	Long.	Alt. (m)
Texas	Hockley	33.51	-102.52	1095.1
	Cameron	25.88	-97.40	5.48
	Calhoun	28.48	-96.62	4.27
Georgia	Bulloch	32.25	-81.74	56
	Mitchell	32.22	-84.46	44
	Dooly	32.14	-83.72	118
Mississippi	Starkville	33.28	-88.46	50
	Coahoma	34.26	-90.55	53
	Monroe	33.77	-88.67	83

TABLE 3. Details of the synthetic dataset generated through GOSSYM.

Study Location	Year	Cultivar	Soil	Nitrogen
Locations (From Table.2)	2017 - 2022	2 Upland Varieties (DPL90, NuCot33)	Clay, Sandy Loam, Sandy Clay Loam	4 Different values (0, 100, 200, 300 kg/ha) match the field data.

C. DATA FEATURE ENGINEERING

Data feature engineering and input data feature selection are crucial for the performance of an ML model. We applied two feature engineering techniques: transforming categorical data into numeric forms and removing outliers. Fig. 4(a) shows the data distribution for the accumulated heat and nitrogen inputs. The diamond shape (⧫) represents the outliers for each variable, which can have detrimental effects on the accuracy of ML methods. Hence, we removed all outliers from the inputs. Fig. 4(b) shows the data distribution of the inputs after removing outliers. There were two categorical inputs in the dataset: soil type and cultivar. These were changed to the representative numerical values.



(b)

FIGURE 4. Data distribution for the inputs: Accumulated Heat (ATU) and Nitrogen (kg/ha). (a) shows the outliers (shown in black diamond shape ⧫) present in the dataset for the inputs. (b) shows the data distribution after removing the outliers.

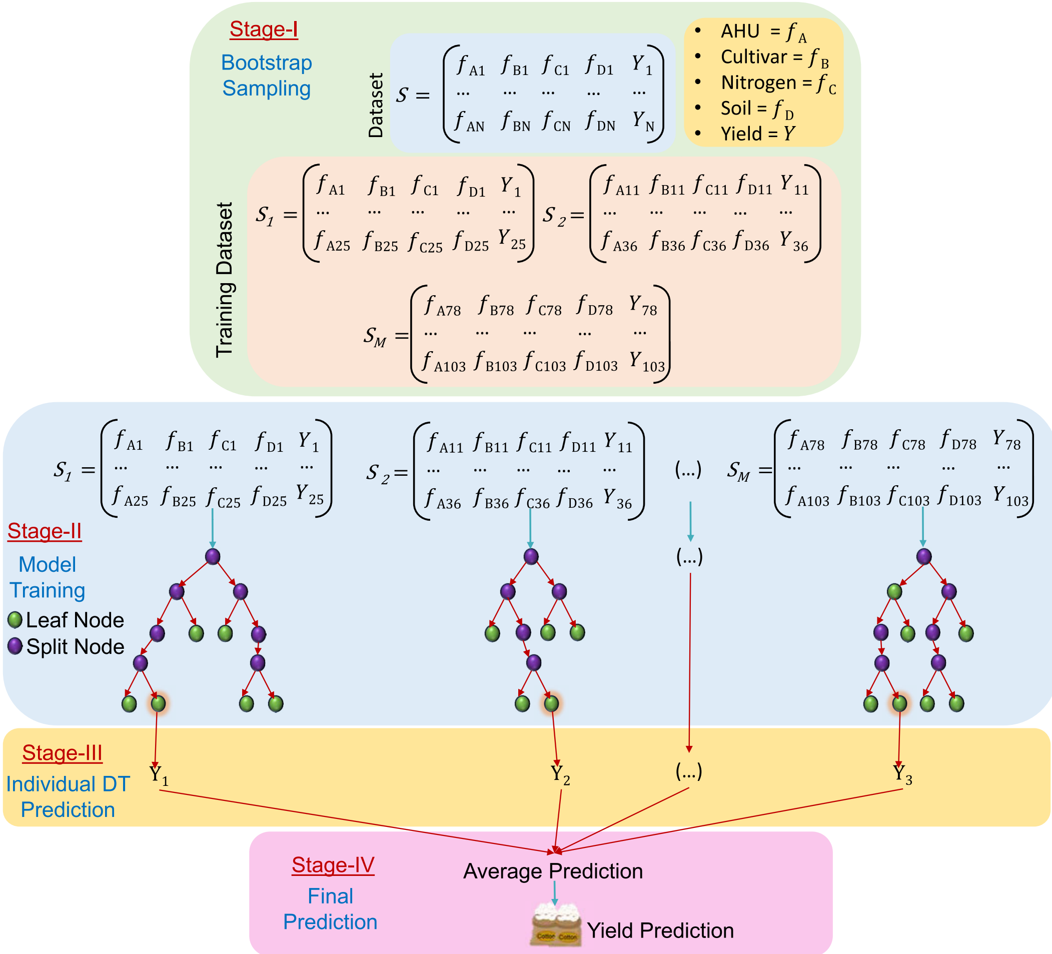


FIGURE 5. The process of how random forest regressor predicts the yield.

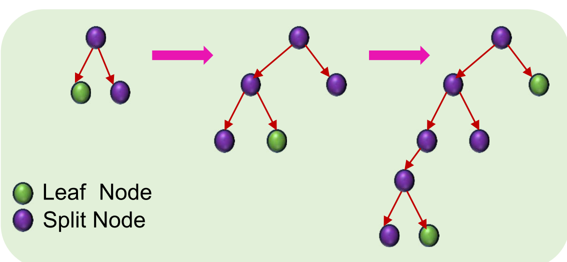


FIGURE 6. Leaf-wise expansion of decision tree for LightGBM.

D. ACCUMULATED HEAT CALCULATION

Cotton growth and the rate of development are primarily temperature-driven [46], [67]. Because cotton crops develop more slowly on days with cool temperatures than on days with warm temperatures, temperature measurements during the cropping season are frequently recorded on-farm or at nearby weather stations to help estimate when a crop reaches a particular developmental stage (Main). The heat unit for cotton, DD_{60}, indicates that the accumulated temperature effect occurs over the course of a day. DD_{60} was calculated by taking the daily average of the highest and lowest temperatures recorded in Fahrenheit ($^{\circ}F_{max}$ and $^{\circ}F_{min}$ respectively) as in Eq. 1.

$$DD_{60} = \frac{(^{\circ}F_{max} + ^{\circ}F_{min})}{2} - 60 \tag{1}$$

The total accumulated heat (AH) was calculated using Eq. 2 summing over the season.

$$AH = \sum_{n=1}^{N} DD_{60_n} \tag{2}$$

where $N = (Earliest\ Day\ of\ Harvest - Day\ of\ Sowing)$.

To calculate the accumulated heat for a past year, that weather data of a specific year is downloaded from POWER [62]; however, we can use 10 years of historical data for a future prediction.

E. MODELS

This study evaluated five different ML algorithms to determine the best-performing algorithm for cotton yield

```
Workflow
1. Load the dataset.
2. Remove the outliers from the
   input and output variables.
3. Transform the categorical values
   to numerical values.
4. Randomly divide the dataset into
   Training and Test parts.
5. Split the Training dataset into
   Train and Valid parts.
6. Select the ML model.
7. Select the loss function and
   optimizer.
8. Train the model.
9. Cross-validate the model.
10.Test the model with unseen data.
```

(a)

```
Algorithm-1
1. Download weather data.
2. For the past year, download the
   specific year's data.
3. For a future year, take the last
   10 year's average data.
4. Get the daily maximum and minimum
   temperatures.
5. Calculate Accumulated Heat.
6. Provide the soil type, cultivar,
   and amount of nitrogen to the
   trained model.
7. The model will predict the cotton
   yield.
```

(b)

FIGURE 7. (a) Workflow of cotton yield prediction model development. (b) Algorithm for cotton yield prediction.

prediction. As cotton yield is a nonlinear function of weather parameters, cultivar, soil, and fertilizers added, we selected several ML algorithms that work well with nonlinear functions.

Statisticians employ polynomial regression to model the nonlinearity between y and x using n^{th}-degree polynomial of x. The nonlinear connection between x and the conditional mean of y, $E(y|x)$, is fitted using a *polynomial regression*. *Polynomial regression* fits a nonlinear model well; however it is a linear statistical estimation problem because the unknown parameters are linear. When there is more than one independent variable, the problem becomes a linear statistical estimation problem that involves multiple variables. Therefore, *linear regression* is a subset of *polynomial regression*, which is regarded as a specific instance of *multiple linear regression* [68], [69], [70]. Additionally, in this case, inputs were not highly correlated. Hence, we used *multiple linear regression* (*MLR*) as the base method.

TABLE 4. Details of the loss functions of the models.

Model / Loss Function	Loss Function Expression
Random Forest / MSE [76]	$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$
LightGBM / Huber [77]	$L_\delta(a) = \begin{cases} \frac{1}{2}(\hat{y}_i - y_i)^2 & for\|\hat{y}_i - y_i\| \leq \delta, \\ \delta.(\|\hat{y}_i - y_i\| - \frac{1}{2}\delta), & otherwise. \end{cases}$
Support Vector Regressor / Epsilon Insensitive [78]	$L_\epsilon = \begin{cases} 0 & for\|\hat{y}_i - y_i\| \leq \epsilon, \\ \|\hat{y}_i - y_i\| - \epsilon, & otherwise. \end{cases}$
Multiple Linear Regression / MAE [79]	$MAE = \frac{1}{N}\sum_{i=1}^{N}\|\hat{y}_i - y_i\|$
Neural Network / MAE [79]	$MAE = \frac{1}{N}\sum_{i=1}^{N}\|\hat{y}_i - y_i\|$

$\hat{y}_i \rightarrow$ predicted value; $y_i \rightarrow$ true value
$N \rightarrow$ number of samples; $\delta \rightarrow$ threshold parameter
MAE $\rightarrow$ Mean Absolute Error; MSE $\rightarrow$ Mean Squared Error.

1) MULTIPLE LINEAR REGRESSION

As mentioned earlier *multiple linear regression* (*MLR*) is the same as a basic linear regression algorithm with multiple inputs. MLR fits the best-fit line in the data distribution. The MLR algorithm satisfies the following linear equation:

$$y = \sum_{n=1}^{N} \alpha_i x + \epsilon \tag{3}$$

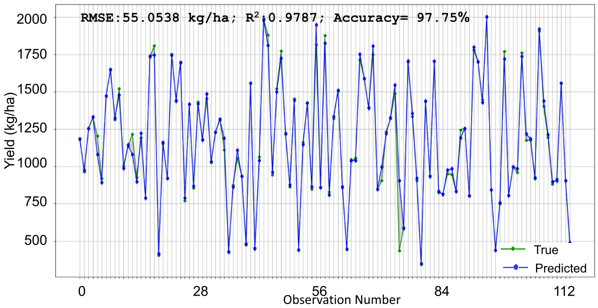
where α_i is the regression coefficient of the i-th independent variable, ϵ the model error, x is the input variable, N is the number of input variables, and y is the output variable.

2) SUPPORT VECTOR MACHINE

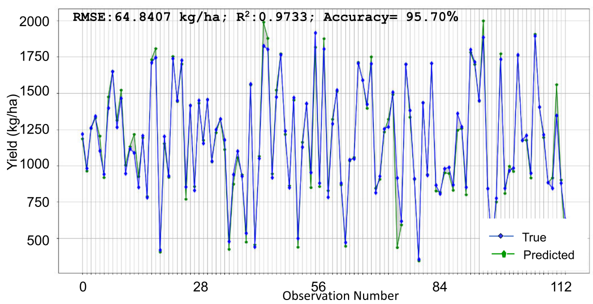
Support Vector Machine [71] is another supervised learning method that predicts the outcome by finding the correct hyperplane in the M-dimensional features space of N samples, maximizing the margin, and minimizing the prediction error. A *kernel* in an SVM maps the data into a higher-dimensional space, making it suitable for use in cases where there are nonlinear relationships between inputs and outputs. We used a support vector regression (SVR) algorithm to predict cotton yields.

TABLE 5. Performance metrics of four ML-type models for the cotton yield estimated from test dataset formed with field and simulated data.

Model	*RMSE* (kg/ha)	R^2	*NSE*	Accuracy (%)
Random Forest	**55.05**	**0.98**	**0.98**	**97.75**
LightGBM	64.84	0.97	0.97	95.70
SVR	341.15	0.18	NA	71.89
MLR	347.59	0.17	NA	69.13



(a)



(b)

FIGURE 8. Yield Prediction for test cases by (a) Random forest regressor (b) LightGBM regressor. Results show true and predicted yields for part of the test dataset. Most of the predicted yields comply with the true yields for both cases.

3) RANDOM FOREST

Random Forest [72] is a robust ML algorithm consisting of an ensemble of decision trees. It learns through supervised learning methods and uses a bootstrap aggregating (bagging) technique to determine the result. For N training samples, a Random Forest (RF) is built with N decision trees. Each unpruned decision tree uses slightly varied training samples, resulting in slightly different but overfitted performance. This makes the trees distinct, thereby reducing the forecast error or variance. Given the N samples and M features, the training samples of size n are repeatedly subsampled, where any sample may be present more than once and $n \leq N$. Additionally, a small subset m of features is selected from M features $m \leq M$. Consequently, using the bootstrap technique, each tree obtains n samples with m features. Finally, an average of each decision tree's results is used to generate the final prediction for the regression problem using aggregation. The branching techniques of RF regressors enable their use in nonlinear input-output relationships. Fig. 5 shows how the cotton yield was predicted using the RF algorithm.

4) LIGHTGBM

Light Gradient Boosting Machine (LightGBM) is a gradient boosting decision tree-based ensemble algorithm [73]. It expands leaf-wise (Fig. 6) instead of level-wise compared to other Decision Trees. It uses histogram-based and cost-effective algorithms because their time complexity is related to the number of bins but not to the data volume once histograms are created. Various boosting types can be used with LightGBM, for example, GBDT, DART, GOSS, etc.

5) NEURAL NETWORK

Our last ML model is an artificial neural network, specifically a multilayer perceptron (MLP). This feed-forward network was constructed with four input nodes and one output node to match the number of input features and outputs. The numbers of hidden layers and nodes in these layers varied. The ReLU activation function was used for the hidden layers, to include the nonlinearity of the inputs in the model. The mean absolute error loss function and Adam optimizer [74] were used.

F. YIELD PREDICTION

Fig. 7(a) depicts the workflow for model development and Fig. 7(b) shows the pseudocode for cotton yield prediction. The algorithms were trained using supervised learning. The best-performing algorithm was cross-validated 10-fold. We used a random grid search method to identify the most appropriate RF parameters from the estimator values: max depth, min samples split, min samples leaf, and bootstrap set to True and False. The best RF was obtained with 4000 estimators with bootstrapping True, and the maximum depth of the tree was 31. For the LightGBM regressor, the number of leaves was 100 with a maximum tree depth of 10, the boosting type was GBDT, and the metric was *Huber*.

For the linear regressor, a two-step Keras [75] sequential model with a normalizer as the first layer, and a linear layer with one output as the second layer was used with multiple inputs. A radial basis function kernel was used for the SVR algorithm. Various DNNs with varying numbers of layers were evaluated. Finally, the trained model was used for the yield prediction. Table 4 presents the various loss functions used in this study.

We implemented this work using different packages and frameworks such as scikit-learn, Numpy, Pandas, and Keras [75]. The models were trained and tested on an Intel Xeon server with 16 cores CPU, 64 GB RAM, and an NVIDIA RTX A4000 GPU.

G. PERFORMANCE METRICS

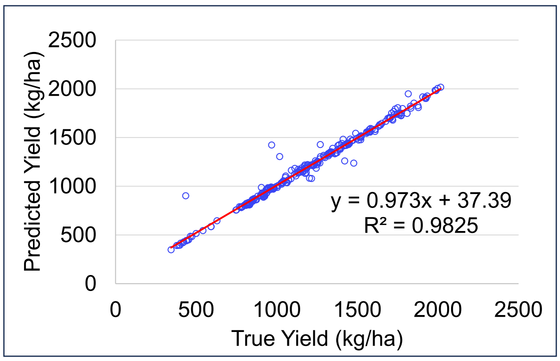
Several performance metrics have been calculated to evaluate the performance of the proposed method. The calculated metrics are *root mean square error* (*RMSE*), R^2, *Nash-Sutcliffe efficiency* (*NSE*), and *accuracy*. *RMSE* quantifies how well the regression line fits a data distribution. This is the average difference between the model predictions

TABLE 6. Performance metrics of the two Neural Networks for the cotton yield estimated from the test dataset formed with field and simulated data.

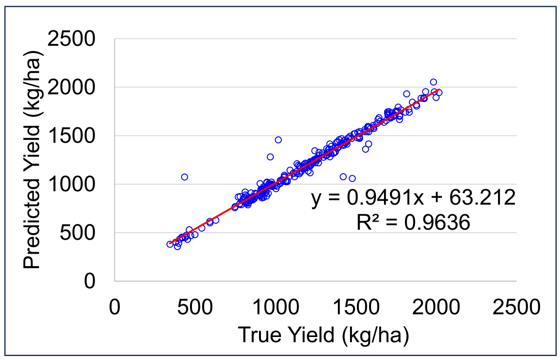
Network	Network Architecture	Number of Trainable Parameters	Accuracy(%)	RMSE (kg/ha)	R^2	Data Provided	Minimum Data Needed
NN1	FC (16, ReLU) FC (16, ReLU) FC (8, Sig) FC (4, Sig) FC (2, Sig) FC (1)	537	63.42	406.34	-0.0007	1075	5370
NN2	FC (8, ReLU) FC (4, ReLU) FC (2, ReLU) FC (1)	89	71.35	340.18	0.3000	1075	890

TABLE 7. Comparative analysis between the current results with the RF regressor and other related research associated with estimating cotton yields.

Crop	Method	Study Area	Study Period	*RMSE* (kg/ha)	R^2	Remarks
Cotton	MODIS + RF	5 locations in Maharashtra, India	2001-2017	62.77	0.69	[82]
Crop	Rainfall, pH, Temperature, Season, Crop, Nitrogen, and Electrical Conductivity + RF	537 locations in India	N.A.	-	0.882	[83]
Rice	Satellite Data+ DT + RF	1 location in India	1981-2030	281	0.67	[84]
Cotton	Spatial-Temporal M.T.L.	A 48-ha location in west TX, USA	2001-2003	83.7	-	[85]
Cotton	Spatial Temporal + RF + GBM	2 locations in New South Wales, Australia	2014, 2016, 2017	170 (RF), 190 (GBM)	0.44 0.39	[86]
Cotton	Accumulated Heat + RF	9 locations in USA	2017-2022	55.05	0.98	Current Work



(a)



(b)

FIGURE 9. Yield Prediction by a) Random Forest Regressor and b) LightGBM Regressor. Results show true versus predicted yields for the test dataset. Most of the predicted yields comply with the true yields.

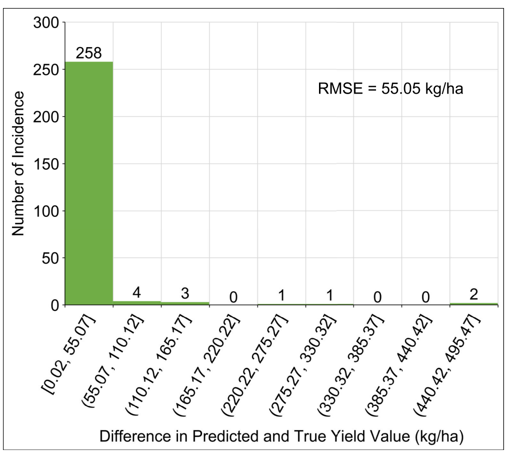


FIGURE 10. Performance histogram for RF regressor.

and the dataset values. A lower value of *RMSE* corresponds to a better-performing model. Eq. 4 is the measure of *RMSE*.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(y_i - \hat{y}_i)^2}{N}} \tag{4}$$

where $\hat{y}_i$ is the predicted value for the i^{th} sample and the actual value is y_i. N is the total number of samples.

R^2 or R squared is coefficient of determination. This indicates the percentage of the dependent variable's variability accounted for by the regression of the independent variables. This indicates how well the model explains the variability in the observed data.

Another performance metric is the *Nash-Sutcliffe* efficiency (*NSE*). This normalized metric quantifies how well a model predicts based on the observed data. R^2 is expressed by Eq. 5 and *NSE* is expressed as in Eq. 6.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \tag{5}$$

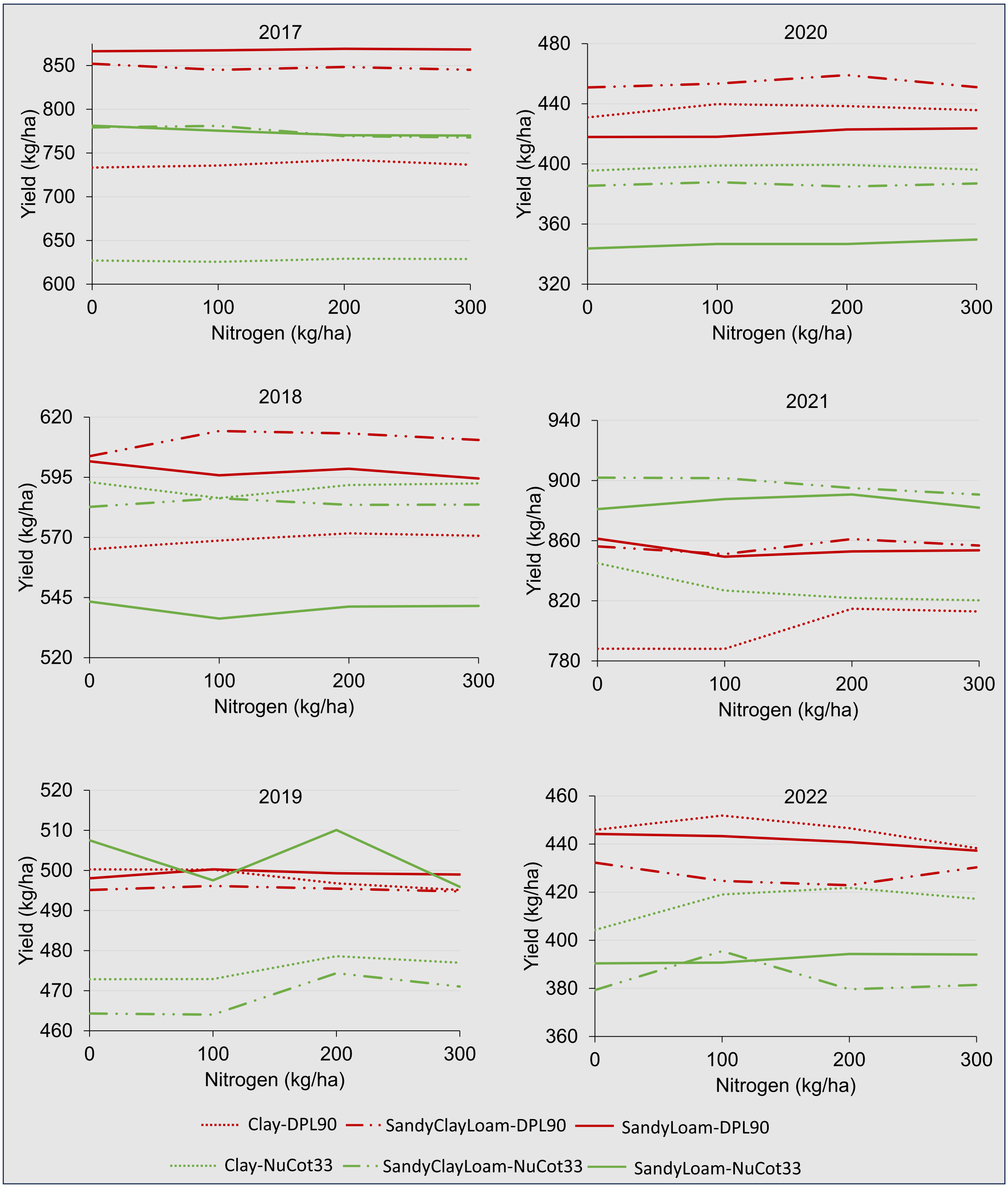


FIGURE 11. Yield vs Nitrogen plots for the years 2017-2022, and all three soil types and two cultivars form the Synthetic dataset for the location Hockley, TX.

$$NSE = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2} \quad (6)$$

where $\hat{y}_i$ is the predicted value for the i^{th} sample, y_i is the actual value, $\bar{y}$ is the average y value, and N is the total number of samples. Although both metrics are expressed with similar formulas, they are used from different perspectives. NSE focuses on accuracy whereas R^2 indicates the fitness of the model.

III. RESULTS AND DISCUSSIONS

Initially, we experimented with five models and selected the best-performing model using existing data. We evaluated the models using the test dataset, which was kept aside before training. Table 5 lists the performance metrics derived from all the algorithms. Random Forest performed best among all models with 97.75% accuracy and a high R^2 of 0.98. The next-best-performing algorithm was LightGBM. It also had a high R^2 value of 0.97 and a high accuracy of 95.70%. Both algorithms achieved high NSE of 0.98 and 0.97 respectively. This proves that these two models are a good fit for the observed data. A perfect fit between the model and the observed data is represented by $NSE = 1$. When the observed mean is a better predictor than the model, then $\infty < NSE < 0$ is true, and a value of $NSE = 0$ means that the model predictions are equally accurate as the mean of the observed data [80], [81]. However, SVR and MLR did not perform well. An accuracy of only ≈70% was obtained with a very low R^2, and $RMSE$ values were nearly 5× compared with those of RF and LightGBM. The NSE was not calculated for these two algorithms.

The metrics for the neural network are shown in Table 6 which shows the two tested scenarios. Here, NN2 performed better than NN1 which performed randomly (a negative R^2 proves that) with the existing dataset. To train a neural network with considerable accuracy, additional data are required. the amount of data required depends on several factors: the complexity of the problem, the number of trainable parameters of the network, the number of input features, etc. [20]. The number of trainable parameters for NN2 was 89; therefore as a rule of thumb, a minimum of (89×10)=890 training samples were needed while assuming that the problem was not complex. However, for NN1, the minimum number of training data samples required was 5370, which was much higher than the provided training data samples of 1075.

We chose the two best-performing models, RF and LightGBM regressors, from the five models listed in Tables 5 and 6. The true and predicted yield plots for the RF and LightGBM regressors, respectively are shown in Fig. 8(a) and 8(b). The RF regressor predicted 95.91% of the test samples well below the $RMSE$ value of 55.05 kg/ha. The LightGBM predicted 88.10% of the test samples well below the $RMSE$ value of 64.84 kg/ha.

The predicted yield versus true yield is plotted in Fig. 9 where Fig. 9(a) depicts the yield plot for the RF regressor and Fig. 9(b) shows that of the LightGBM regressor. Although both the RF and LightGBM regressors performed well, the RF regressor performed marginally better than the LightGBM regressor. The deviation from the fitting line was less for the RF regressor than for the LightGBM regressor. Appendix describes the yield predicted by the RF model and the corresponding actual yield for the test dataset. Fig. 10 shows that among the 269 test samples, the prediction error of 258 samples was $\leq RMSE$ in the case of RF regressor.

Fig. 11 shows the yield vs nitrogen plots for 2017-2022, all three soil types, and two cultivars from the synthetic dataset for Hockley, TX. In the last six years, the maximum yield has been achieved when the nitrogen amount was 200 kg/ha. Table 7 compares our study with other literature sources that use the RF regressor as a predictive tool for simulating crop yields. These studies used a variety of data types as inputs, including satellite images, spatiotemporal data, and numerical data. RF performs well with noisy data, supporting its use as a popular ML algorithm for crop yield prediction.

In our study, the RF regressor was the best-performing ML algorithm for cotton yield prediction. However, another ML algorithm, LightGBM, also performed very well. This ensures the robustness of the method when using the accumulated heat to predict cotton yield and suggests an ML ensemble approach. Comparing the results in Table 7, our study was spatially and temporally diverse. More recently weather data have been used to address recent climate change effects. A very small part of the weather data was from earlier years to avoid bias in weather data. Hence, the proposed method was considerably more robust.

IV. CONCLUSION

In this study, we predicted cotton yields in U.S. locations with a high accuracy using simple ML approaches with accumulated heat information and an RF regressor. This study stands out by reducing the computational effort by converting time-series weather data to a scalar value, AH, without affecting the accuracy of the model. We introduced another alternative ML algorithm, the LightGBM regressor, which performs competitively with an RF regressor.

Machine and deep learning techniques perform well when trained on large datasets. However, it is not always possible to access large publicly available datasets, which hinders the application of ML/DL-based approaches. Synthetic data use in training AI/ML models is a common method in the case of data scarcity; however, it is not widely used in agriculture. Our study used generated and field data to build and test an AI-based cotton model. It demonstrates the potential use of synthetic data in training ML/DL models in agriculture.

This method is suitable for practical applications because of its simplicity compared to process-level model approaches. This method is also much simpler to use than process-based models, with less computational overhead in terms of eventually porting to mobile applications which can benefit farmers to use our application. However, our model has some limitations too:

- The method is likely limited to interpolating yields within the same range of the training data space as in any other supervised learning method. Retraining the model using data from new locations can address this limitation.
- It is built at the local level. More regional locations need to be included to obtain a regional-level model.
- However, we must add more locations and significantly more diverse soil, cultivar, and nitrogen variations to the training data to create a more global model.
- The goal of this study was to validate the proposed method. Because our field data were from the 1990s, we used the same cultivars to generate recent synthetic

TABLE 8. Test results for Random Forest Regressor.

True Yield	Predicted Yield	True Yield	Predicted Yield	True Yield	Predicted Yield	True Yield	Predicted Yield
1185.93	1181.58	472.91	484.56	915.83	926.62	1156.36	1190.09
963.14	974.9	1567.92	1556.14	1905.69	1917.96	1175.12	1164.82
1255.19	1254.62	1557.47	1557.67	1403.22	1440.58	1386.65	1425.24
1329.12	1331.1	453.4	450.33	1193.76	1212.09	1256.29	1242.28
1203.04	1082.9	1063.8	1038.23	881.95	898.2	1610.06	1563.15
918.68	892.39	1988.13	1982.04	915.72	905.22	1982.43	1986.05
1473.64	1473.49	1878.2	1808.9	1559.83	1555.16	1726	1767.85
1651.32	1646.84	942.7	961.04	901.57	904.92	1008.94	1008.27
1313.37	1323.74	1520.82	1499.71	464.32	486.91	1222.72	1221.83
1521.21	1478.53	1771.48	1730.03	1701.03	1701.87	1347.5	1389.24
1003.33	988.58	1215.8	1220.44	917.08	887.28	1851.15	1854.1
1131.49	1146.37	861.3	873.79	1922.35	1902.41	1171.65	1205.34
1215.62	1080.37	1451.46	1440.53	955.25	963.49	1579.99	1566.05
925.23	897.9	438.3	443.91	1332.77	1348.76	1216.46	1218.74
1191.4	1222.39	1160.81	1146.13	898.62	903.35	1018.08	1304.94
787.68	790.61	1426.58	1424.32	1743.06	1738.88	1716.03	1689.66
1731.67	1739.08	848.35	864.24	806.97	811.96	1557.47	1557.67
1808.18	1748.16	1815.6	1949.57	1248.79	1251.46	453.4	450.33
404.26	416.86	856.44	859.31	947.06	978.1	1063.8	1038.23
1150.86	1161.57	1875.97	1827.61	1423.87	1422.16	1988.13	1982.04
919.03	920.33	828.45	809.59	379.62	392.92	1878.2	1808.9
1752.48	1743.61	1320.72	1335.92	979.84	983.33	942.7	961.04
1442.5	1439.87	1512.02	1506.8	1290.84	1316.9	1134.21	1174.55
1700.05	1696.04	868.06	860.47	1643.23	1627.82	1270.94	1304.36
768.91	789.65	445.87	446.87	923.61	912.8	1581.7	1594.08
1417.19	1417.67	1034.36	1041.94	1556.77	1543.77	1090.39	1163.98
856.18	869.19	1056.85	1039.36	1697.14	1701.33	813.6	811.3
1430.43	1418.97	1712.62	1751.57	1933.92	1927.47	1219.93	1219.95
1174.7	1180.95	1590.54	1585.7	923.82	903.48	819.22	815.72
1456.16	1483.61	1396.02	1392.55	1719.4	1678.61	975.67	984.75
1026.84	1031.98	1750.13	1806.73	1611.6	1582.48	2017.4	2016.61
1228.43	1227.32	845.12	850.95	1248.65	1221.61	830.64	833.36
1320.58	1313.57	904.96	988.07	869.07	863.81	1338.08	1347.1
1112	1184.03	1232.88	1218.23	775.49	785.31	1110.78	1124.93
422.88	429.9	1320.89	1327.86	926.39	939.53	1175.96	1133.25
873.78	862.1	1489.07	1543.67	1572.88	1558.16	1118.82	1107.79
1054.98	1104.92	434.896	902.52	856.89	869.65	1269.8	1429.12
936.11	932.36	592.46	585.33	1228.79	1225.48	628.84	645.67
343.77	349.45	1700.26	1707.93	1421	1259.78	850.03	845.91
1434.59	1438.35	1335.1	1355.33	1150.82	1166.54	746.44	756.26
938.2	934.13	1579.64	1556.77	780.72	789.62	926.39	932.7
1706.05	1703.06	974.14	982.05	926.39	932.7	972.86	979.93
824.4	833.9	1832.28	1802	1072.93	1067.45	1047.96	1053.26
816.97	812.77	932.49	961.69	1522.74	1513.22	823.28	810.53
950.05	975.74	1053.46	1090.42	968.3	1424.01	1148.19	1146.25
945.34	985.78	1375.44	1370.71	1360.56	1334.21	926.39	932.7
830.41	832.6	779.3	780.92	909.54	932.07	1522.6	1517.96
1244.32	1184.69	978.1	970.43	1267.58	1281.14	1133.01	1135.96
1256.12	1251.66	390.71	393.23	1411.82	1482.69	1373.52	1343.89
799.61	806.21	1184.01	1188.08	1523.5	1511.06	1437.12	1438.99
1780.74	1797.38	1734.81	1792.64	1158.49	1149.9	984.68	982.02
1698.34	1703.34	810.92	824.52	904.19	904.53	1437.12	1438.99
1444.76	1427.8	1142.27	1166.58	1063.54	1038.19	1676.62	1667.82
1999.26	2004.67	1318.84	1335.55	398.91	395.49	1210.65	1214.8
842.33	843.69	1291.45	1304.47	1921.98	1914.22	1365.19	1340.31
438.48	439.79	1430.89	1424.28	1344.65	1351.06	1215.26	1220.24
749.55	757.4	1387.29	1384.67	591.77	585.36	1073.23	1063.71
1770.98	1724.02	944.77	963.58	1508.65	1475.16	1266.95	1238.62
808.93	804.06	1414.62	1413.84	1041.2	1056.06	1464.55	1466.89
995.98	997.53	1029.47	1021.32	1688.54	1696.68	1224.39	1210.66
959.91	985.55	936.61	929.8	1608.84	1585.06	591.77	585.36
1760.46	1734.66	1299.02	1294.53	1033.38	1036.84	1508.65	1475.16
1174.06	1218.15	1239.84	1261.96	1380.11	1417.36	1041.2	1056.06
1176.32	1188.7	1829.82	1821.97	1574.56	1582.97	1688.54	1696.68

data to maintain the parity. However, we need to retrain the model with the current data for application in today's field.

As part of future research, we will apply this method to new locations in the southern cotton belt in the U.S. and scale it up to a regional and national level. We will also work on extending the methods to other crops in the U.S. to establish the validity of the method.

We believe that the high accuracy of this study will encourage further research in agriculture to use synthetic data to develop AI-based crop models and reduce the gap between advanced technologies and the agricultural industry.

APPENDIX

See Table 8.

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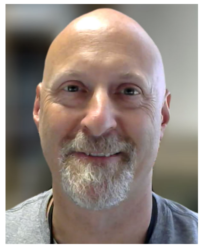

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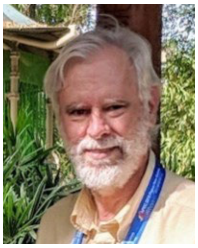

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