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Predicting Yellow Stem Borer Occurrence in Rice Using Weather Parameters and LSTM

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Abstract

Incidence of Yellow stem borer (*Scirpophaga incertulas*) (YSB) on Rice (*Oryza sativa L.)* at West Bengal, India is modelled based on field data sets generated during six kharif seasons [2011-20]. The weather variables considered are maximum & minimum temperature (MaxT & MinT) (^{0}C), morning and evening humidity (RHM & RHE) (%), sunshine hours (SS) (hr/d), wind velocity (Wind) (km/hr), total rainfall (RF) (mm) and rainy days (RD). Long Short-Term Memory (LSTM) networks, which are capable of learning long-term temporal dependencies, are used to overcome the limitations of traditional machine learning techniques. The results indicate that LSTM and Gated Recurrent Unit (GRU) models, although more computationally expensive, provide a more accurate solution for pest prediction compared with other methods. Correlation analyses indicate significant positive influence of maximum and minimum temperature on YSB. An empirical comparison of the above models is carried out based on root mean square error (RMSE) and mean square error (MSE). It is observed that, for YSB, the MSE and RMSE values of LSTM and GRU are less as compared to other competing models. Diebold-Mariano (D-M) test was applied for comparison of forecasting performance among the applied models. It is observed that, in the studied pest, predictive accuracy of LSTM is higher than that of other models. The analysis is carried out using R package.

Keywords: YSB, Rice, Deep Learning, Accuracy

Introduction

Natural and artificial environments are increasingly vulnerable to the pervasive effects of climate change, and rice ecosystems are no exception. Rice (*Oryza sativa L.*), a staple food for a significant portion of the global population, is cultivated across various climatic zones and ecoregions in India. The cultivation of rice is largely influenced by factors such as temperature, soil type, water availability, and rainfall. India, the world's second-largest rice producer, cultivates rice across 43 million hectares (Mha), yielding approximately 112 million tons (Mt) of milled rice, with an average productivity of 2.6 tons per hectare (Pathak *et al.* 2022). During the Kharif season, about 84% of the rice acreage approximately 42.7 million hectares is planted, with sowings commencing in June and July (Annual 2019). Despite a pesticide usage rate of 28% in India, insect pests are estimated to cause about 25% output loss in rice cultivation (Dhaliwal *et al.* 2010). West Bengal stands as India's second-largest rice producer, with a production of 14.77 million tons over an area of 5.39 million acres (Chatterjee *et al.* 2017). Remarkably, 78% of total rice acreage is classified as high or medium productivity, accounting for nearly 84% of the state's total rice production. A thorough examination reveals numerous factors acting as constraints on yield potential across the country, with insect pests contributing significantly to yield losses in rice production (Chatterjee *et al.* 2016). In India, approximately 100 insect species feed on rice, with 20 of these classified as severe pests, resulting in production losses of up to 30%. Among these pests, stem borers inflict significant damage on cereal crops worldwide (Lawani 1982; Heinrichs 1985; Kfir *et al.* 2002). The Yellow Stem Borer (YSB) (*Scirpophaga incertulas* Walker) and the Rice Leaf Folder (*Cnaphalocrocis medinalis* Guenee) are among the most prevalent and damaging insect pests in India, causing approximately 10% to 60% of total production losses (Chatterjee and Mondal 2014). YSB is particularly problematic, causing extensive damage during both the vegetative and reproductive stages of rice. During the vegetative stage, the larvae feed on the central shoots of rice tillers, leading to 'dead heart' and 'white ear' symptoms, particularly if feeding occurs during the panicle initiation stage. The economic impact of YSB on rice cultivation is considerable, with output losses ranging from 27% to 34% annually (Prasad *et al.* 2007). The abundance of insect pests and the anticipated severity of damage in rice ecosystems can be monitored through light trap catches, which are frequently employed as a tool for tracking YSB populations throughout the year. Weather conditions play a crucial role in all agricultural operations, including the pest management practices adopted by farmers. Conducive weather patterns can promote an increase in pest prevalence, particularly for YSB, whose biological characteristics are closely linked to prevailing climatic conditions. Establishing relationships between YSB light trap catches and weather parameters provides critical insights into the timing and abundance of pest populations. In India, initial attempts to develop short-term forecasts for YSB using monthly seasonal indices of abiotic factors based on light trap catches and weather characteristics have been reported (Ramakrishnan *et al.* 1994). This underscores the necessity of constructing weather-based predictive models that incorporate historical datasets to accurately forecast YSB intensity for effective forewarning measures. Climate change is a global phenomenon that will inevitably affect insect pest dynamics, making it essential to develop models that can adapt to changing conditions. Several modelling approaches, including Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Average (ARIMA) models, have been employed in recent years to predict YSB occurrences. Notably, some researchers have asserted that Long Short-Term Memory (LSTM) networks provide superior prediction accuracy. For instance, Xue *et al.* (2020) developed a high-precision short-term forecasting model for financial market time series using LSTM, comparing its performance to Backpropagation Neural Networks, standard RNNs, and upgraded LSTM networks. Their findings indicated that LSTM deep neural networks achieved high forecasting accuracy, effectively predicting stock market time series (Xue *et al.* 2020). ARIMA models generate forecasts based on the values of input variables and their associated error terms. Although ARIMA is a linear regression model, it is not limited to linear relationships and can exhibit variations when confronted with complex non-linear practical issues. However, it is noteworthy that linear models typically outperform sophisticated structural models for short-term predictions (Meyler *et al.* 1998). On the other hand, Neural Networks (ANN) are adaptive, data-driven models that do not rely on pre-existing assumptions. Khashei *et al.* (2010) highlighted their utility across various sectors, including banking, business, and engineering. ANN predictions are derived from original data, which is then utilized to formulate broader observations and infer the potential characteristics of the entire dataset. Compared to ARIMA, ANN models excel at addressing non-linear problems, which is particularly relevant in scenarios involving stock market fluctuations. In light of the non-linear nature of pest dynamics, the integration of wavelet analysis with LSTM techniques has emerged as a promising approach for enhancing prediction accuracy. Chen *et al.* (2019) emphasized that utilizing wavelet analysis alongside LSTM could effectively predict commodity pricing, focusing on the temporal aspects of data. The rationale behind employing LSTM in conjunction with recurrent neural networks (RNN) stems from their effectiveness in handling long-term data patterns. However, limitations exist, particularly regarding the lack of external features contributing to the independent variable. In summary, the challenges posed by climate change to rice ecosystems necessitate robust predictive models that can effectively account for the dynamics of pests like YSB. The integration of advanced modelling techniques, such as LSTM and wavelet analysis, offers a pathway to enhance prediction accuracy and inform pest management strategies. As the impact of climate change continues to evolve, ongoing research and adaptation of predictive models will be essential for sustainable rice production and pest management in the face of these changing environmental conditions. The role of weather and climate variability in shaping pest dynamics cannot be overstated, as farmers need reliable tools to anticipate pest outbreaks and implement timely management strategies. As such, the development of weather-based forecasting models stands as a crucial area of research, enabling stakeholders in agriculture to mitigate potential yield losses caused by insect pests. Ultimately, the successful application of these advanced modelling techniques will contribute to the resilience of rice production systems, helping to safeguard food security and support the livelihoods of millions of farmers reliant on this vital crop.

Materials and methods

Modern agriculture faces numerous challenges, primarily driven by the urgent need to feed a rapidly growing global population, which is projected to reach approximately 9.7 billion by 2050 (Thayer *et al.* 2020). This population explosion places significant pressure on agricultural systems to produce more food, while simultaneously grappling with the adverse effects of climate change, which disrupts traditional farming practices and exacerbates issues related to natural resource depletion (Nassani *et al.* 2019). Furthermore, shifts in dietary preferences and increasing concerns about food safety and health have compounded the complexity of the agricultural landscape (Conrad *et al*. 2019; Benos *et al*. 2018). To address these multifaceted challenges, there is an urgent need to optimize agricultural practices to enhance productivity while reducing environmental impacts. This imperative has catalysed the evolution of agriculture into a more precise and technology-driven sector, commonly referred to as precision agriculture. By leveraging advanced technologies and data analytics, precision agriculture aims to ensure sustainable farming practices that can deliver maximal productivity in a safe environment (Lampridi *et al.* 2019). Central to the concept of smart farming are four key pillars that underpin its strategy for meeting increasing food demands: (a) optimal management of natural resources, (b) conservation of ecosystems, (c) development of adequate agricultural services, and (d) utilization of modern technologies (Zecca *et al.* 2019). These pillars work in tandem to create a holistic approach to farming that prioritizes efficiency and sustainability. A crucial component of modern agricultural practices is the adoption of Information and Communication Technology (ICT), which has been strongly advocated by policymakers globally. ICT encompasses a wide range of digital tools and platforms designed to enhance agricultural productivity and decision-making. This includes farm management information systems, soil and humidity sensors, accelerometers, wireless sensor networks, drones, low-cost satellites, online services, and automated guided vehicles (Sorensen *et al.* 2019). These technologies provide farmers with real-time data and insights, allowing for more informed decision-making and improved resource management. The integration of ICT in agriculture generates vast amounts of data, commonly referred to as "big data." This data can significantly enhance agricultural practices by offering valuable insights into crop performance, weather patterns, soil conditions, and pest management. However, the sheer volume of data produced poses significant challenges regarding storage, processing, analysis, and interpretation. To unlock the potential benefits of big data, stakeholders must navigate several hurdles associated with the “5-V” requirements: (a) Volume, (b) Variety, (c) Velocity, (d) Veracity, and (e) Value (Meng *et al.* 2016). Traditional data processing techniques often fall short of meeting the demands of the new era of smart farming, which presents a considerable obstacle to extracting meaningful insights from field data (Evstatiev *et al.* 2020). As a result, there is a growing reli which has emerged as a transformative tool in agriculture. As a subset of artificial intelligence, ML harnesses the exponential growth in computational power to analyse complex datasets, uncover patterns, and generate predictions that can inform better farming practices (Swiergosz *et al.* 2020). Machine Learning algorithms can process vast datasets quickly, identifying correlations and trends that may be imperceptible to human analysts. For instance, ML can analyse historical yield data alongside environmental variables such as temperature, rainfall, and soil moisture levels to predict future crop performance under varying conditions. This predictive capability allows farmers to make data-driven decisions, such as when to plant or irrigate crops, ultimately optimizing resource use and enhancing productivity. Moreover, the application of ML in agriculture extends beyond crop management to include pest and disease prediction, soil health monitoring, and supply chain optimization. For example, by analysing data from various sources, including weather forecasts and pest populations, farmers can anticipate potential pest outbreaks and take preventive measures to safeguard their crops. This proactive approach not only minimizes crop losses but also reduces the reliance on chemical pesticides, promoting more sustainable agricultural practices. In addition to ML, the integration of other advanced technologies, such as the Internet of Things (IoT), drones, and remote sensing, further enhances the capabilities of precision agriculture. IoT devices equipped with sensors can provide real-time data on

soil conditions, crop health, and weather patterns, enabling farmers to respond promptly to changing circumstances. Drones equipped with imaging technology can monitor crop health, assess irrigation needs, and detect pest infestations, providing farmers with valuable insights that were previously difficult to obtain. The combination of these technologies creates a comprehensive data ecosystem that empowers farmers to optimize their practices and enhance productivity sustainably. By embracing precision agriculture, farmers can tailor their

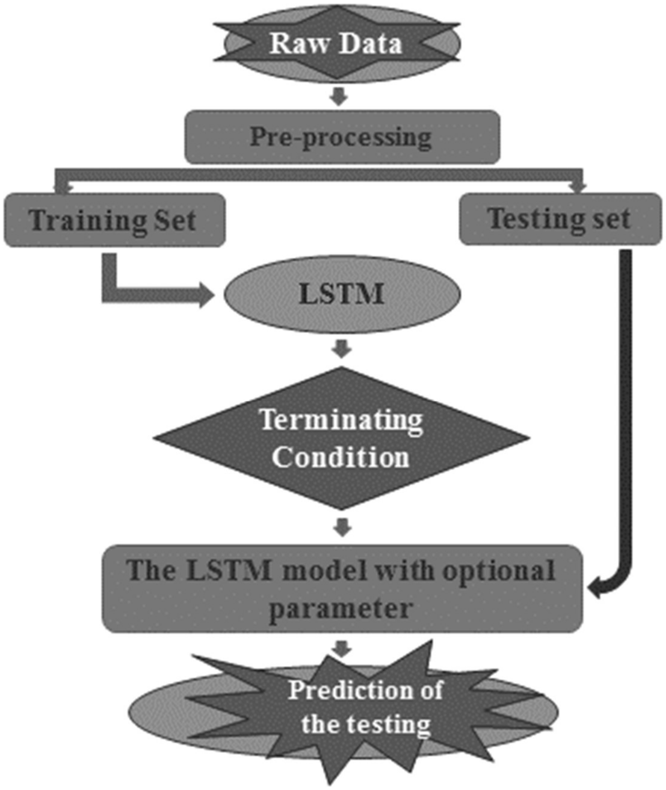

Figure 1: The above diagram shows the protocol followed in this study in implementation of deep learning

practices to the specific needs of their crops, leading to improved yields while minimizing environmental impacts. Despite the promising potential of precision agriculture, several challenges remain. One significant barrier is the digital divide that exists between urban and rural areas, with many smallholder farmers lacking access to the necessary technology and resources to implement these advanced practices. Addressing this divide requires targeted efforts to ensure that all farmers, regardless of their location or economic status, can benefit from technological advancements in agriculture. Additionally, there are concerns regarding data privacy and security, as the increasing reliance on digital technologies raises questions about who owns and controls agricultural data. Ensuring that farmers maintain control over their data and can leverage it for their benefit is essential for fostering trust in precision agriculture systems. In conclusion, modern agriculture must navigate a complex landscape marked by increasing food demand, climate change, and evolving consumer preferences. The transition to precision agriculture presents a viable solution to these challenges, leveraging technology and data analytics to optimize resource use, enhance productivity, and promote sustainability. By focusing on the key pillars of smart farming and harnessing the power of big data and machine learning, the agricultural sector can address the pressing issues of our time while ensuring the long-term viability of food systems. However, it is crucial to bridge the digital divide, address data privacy concerns, and ensure equitable access to technology for all farmers. Through collaborative efforts and continued innovation, modern agriculture can rise to meet the challenges of the future while safeguarding our planet's resources.

Statistical analyses

Random forest

A random forest (RF) is a predictor consisting of a collection of randomized base regression trees $\{r_n(\mathbf{x},\Theta_m,D_n), m \geq 1\}$, where $\Theta_1,\Theta_2,...$ are i.i.d. outputs of a randomizing variable Θ. These random trees are combined to form the aggregated regression estimate

$$r_n(X,D_n) = E_\Theta [r_n(X,\Theta,D_n)], \qquad (2)$$

where E_Θ denotes expectation with respect to the random parameter, conditionally on **X** and the data set D_n. In the following, to lighten notation a little, we will omit the dependency of the estimates in the sample, and write for example $r_n(\mathbf{X})$ instead of $r_n(\mathbf{X},D_n)$. Note that, in practice, the above expectation is evaluated by Monte Carlo, that is, by generating M (usually large) random trees, and taking the average of the individual outcomes. The randomizing variable Θ is used to determine how the successive cuts are performed when building the individual trees, such as selection of the coordinate to split and position of the split (Figure 2).

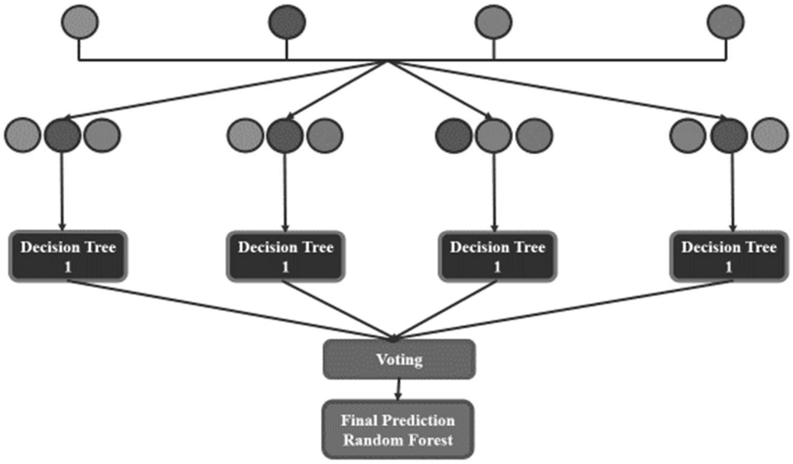

Figure 2: Workflow of random forest regression machine learning algorithm

Long Short-Term Memory (LSTM) Model

The Long Short-Term Memory (LSTM) neural network, introduced by Hochreiter and Schmidhuber in 1997, was designed to effectively address the challenges posed by long-term data dependencies, making it particularly suitable for tasks requiring the analysis of sequential data over extended periods (Hochreiter & Schmidhuber, 1997). This capability is especially beneficial in financial applications, where high-frequency time series data often exhibit complex patterns that traditional models struggle to capture. The LSTM model was specifically developed to overcome the limitations of standard recurrent neural networks (RNNs), such as the issues of gradient expansion and gradient disappearance, which can hinder learning in deep networks and result in suboptimal performance (Ta *et al.,* 2020). The architecture of an LSTM consists of three critical memory modules: the input gate, output gate, and forget gate, as illustrated in figure 5. Each of these gates plays a pivotal role in the network's ability to manage information; the input gate determines what information to store in the memory, the output gate decides what to output from the memory, and the forget gate controls the retention of information, allowing the

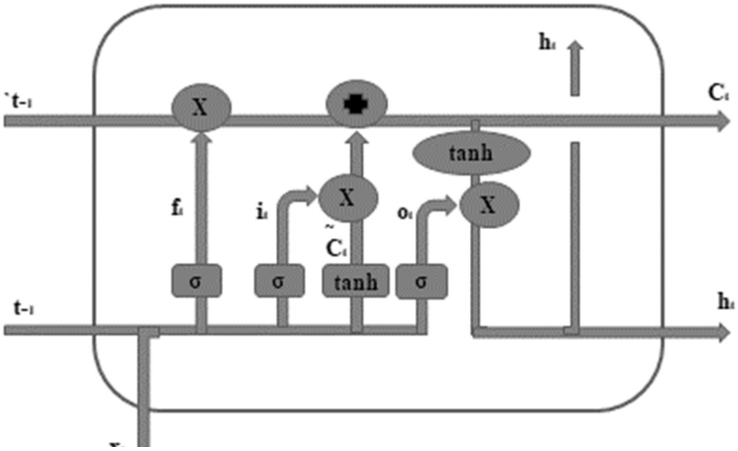

Figure 4. Schematic representation of LSTM

model to retain relevant data while discarding less important or irrelevant information. This selective memory management enables LSTMs to learn from sequences of varying lengths and maintain context over time, enhancing their effectiveness in various applications, including natural language processing, speech recognition, and time series forecasting. Given the robustness of Hochreiter and Schmidhuber's original LSTM model, we have chosen to implement it in our study to leverage its strengths in capturing temporal dependencies and improving prediction accuracy. The operational premise of Long Short-Term Memory (LSTM) networks revolves around effectively analyzing information at a given time ttt by employing a systematic approach to information flow through its gates. Initially, the forget gate is activated to discard unnecessary information, ensuring that only relevant data persists. Following this, the input gate filters the useful information, utilizing a specified probability to determine which data should be retained and which should be ignored. This step is crucial as it allows the model to selectively focus on the most pertinent inputs. Subsequently, the output gate extracts the refined useful information that will be passed on to the next LSTM unit, contributing to the network's capacity to maintain context across time steps. The selection of the activation function plays a significant role in this process, as it influences the model's learning capabilities and convergence. In our implementation, we have utilized the standard sigmoid function and the hyperbolic tangent (tanh) function as activation functions, both of which are effective in controlling the information flow within the network. The overall LSTM process can be succinctly summarized in five steps: (1) the forget gate processes the input to determine what information to discard, (2) the input gate evaluates new information to decide what to store, (3) the cell state is updated based on the outputs of the forget and input gates, (4) the output gate determines what information to output to the next LSTM unit, and (5) the activation functions transform the outputs for further processing. This structured approach enables LSTMs to effectively capture long-term dependencies in sequential data.

Step1: The previous unit's output value and the current unit's input value are integrated into the forget gate. The forget gate's output value is calculated by the following formula:

$$f_t = \sigma\{W_f * (h_{t-1} * x_t)\} + b_f \qquad (3)$$

where W_f is the forget gate's weight, and b_f is the bias, x_t is the input value, and h_{t-1} is the output value of the prior unit.

Step 2: The output value of the prior unit and the input value of the current time are incorporated into the input gate. The output value and candidate cell state values are computed by the following formulas

$$i_t = \sigma\{W_i * (h_{t-1} * x_t)\} + b_i \qquad (4)$$

$$\widetilde{C_t} = tanh\{W_c * (h_{t-1} * x_t)\} + b_c \qquad (5)$$

where W_i is the weight of this gate, and b_i is the bias W_c and b_c are the weight and bias of the candidate input respectively.

Step 3: Updation of the current cell is done using the formula given below:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \qquad (6)$$

Step 4: the output gate takes h_{t-1} and x_t as input values, and the output of the output gate is calculated by the following formula

$$o_t = \sigma\{W_o * (h_{t-1} * x_t)\} + b_o \qquad (7)$$

where, W_i and b_i are the weight and bias of this gate respectively.

Step 5: The final output of the LSTM unit is generated by computing the output gate output and the cell state, as indicated in the following formula

$$h_t = \ o_t * tanh\ (C_t) \qquad (8)$$

Validation of forecasts

The dataset of Yellow Stem Borer (YSB) population and weather variables was split into two parts for analysis. For each location, 90% of the observations were used for model development, while the remaining 10% were reserved for validation. A comparative assessment of the prediction performance of various models including RNN, GRU, LSTM, Bidirectional LSTM, Deep LSTM, SVR, and RF was conducted. The evaluation was based on root mean square error (RMSE), calculated using the following formula to assess accuracy in pest prediction across different methodologies.

$$\text{RMSE}=\sqrt{\sum_{\text{i}=1}^{n}\frac{\left(\text{Predicted}(y_i)-\text{observed}(y_i)\right)^2}{n}} \qquad \text{RMAPE}=\frac{1}{n}\frac{\sum_{\text{i}=1}^{n}\left|\left(\text{observed}(y_i)-\text{predicted}(y_i)\right)\right|}{\text{observed}(y_i)}\times 100$$

$$\text{Model Accuracy}=100-\text{RMAPE}$$

The root mean square error (RMSE) was calculated with value representing the number of observations used for validation, The Diebold-Mariano test (Diebold and Mariano 1995) was also applied to compare predictive accuracy between pairs of models. Additionally, other evaluation metrics included the coefficient of correlation (R), coefficient of determination (R²), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) (De Myttenaere *et al.* 2016; Lehmann *et al.* 1998). Lower MAE, MAPE, and MSE values indicate smaller errors and better model performance. Conversely.

Materials and Methods

Study locations

The study was part of an Information and Communication Technology (ICT)-based pest surveillance program on rice, conducted at experimental research stations in Barasat, West Bengal, India. Surveillance was implemented in 10 villages located within a 30 km radius of the meteorological observatory at the experimental station. Two one-acre rice fields from each village were selected for surveillance during the study seasons. Weekly observations were carried out on Yellow Stem Borer (YSB) populations, starting from the early vegetative stage of the rice crop and continuing until harvest. For each field, five random spots were chosen, and two rice plants per spot were randomly selected for observation, following a whole-plant sampling method. The sampling plan followed a random selection process for spots and plants, ensuring unbiased observation across the field. In addition to pest data, general information on each surveillance field was collected, including field area, rice cultivar grown, sowing dates, and production practices. This comprehensive surveillance design enabled the collection of robust field data for modeling pest incidence in relation to weather variables. The fixed surveillance plans ensured consistent data collection throughout the season, while the random sampling approach minimized potential sampling biases.

Data accrual and reporting system

The pest surveillance for rice was conducted using a structured proforma, based on the format provided by the National Centre for Integrated Pest Management (NCIPM) under the National Initiative on Climate Resilient Agriculture (NICRA) (ref: NCIPM Pest Surveillance). This proforma, which included specific variables for Yellow Stem Borer (YSB), was used for recording spot-wise observations on a weekly basis. Data collection involved client software developed for offline data entry and online upload, allowing for efficient accumulation of field data each week. The reporting system, developed to function online, enabled the extraction of data from each field across various spots for each week of observation, based on Standard Meteorological Weeks (SMW) corresponding to the growing season. Field observations for Yellow Stem Borer (YSB), represented as numbers per week per trap, were conducted weekly in 10 villages situated within a 30 km radius of the meteorological observatory at Barasat, West Bengal In each of the rice fields selected, five random spots were chosen, and 10 plants per spot were selected randomly for YSB observations. Weekly monitoring began at the vegetative stage of the rice crop and continued until harvest. The surveillance focused on rice fields where farmers typically grew the major rice varieties during the Kharif season, with a row and plant spacing of 90 x 30 cm. This spacing was maintained for consistent and accurate observation of YSB populations during the study period (2011-2020). The data collected on YSB numbers per week and per trap were vital for assessing pest incidence and trends across different growing seasons. By integrating this field data with weather variables, a comprehensive analysis of YSB population dynamics and its correlation with climatic factors was made possible, contributing to the overall pest management strategy within the framework of climate-resilient agriculture.

Meteorological observations

The weather data, including maximum and minimum temperatures (°C), morning and evening humidity (%), total rainfall (mm), and the number of rainy days, were recorded on a Standard Meteorological Week (SMW) basis from the Meteorological Observatory in West Bengal. This data was utilized to assess the influence of various weather parameters on the population dynamics of the yellow stem borer (YSB) measured in terms of numbers per week per trap (Nos./weeks/trap). The findings aim to establish correlations between climatic conditions and YSB occurrences to inform pest management strategies.

Seasonal dynamics and status of YSB

Graphical representation of data from various studies reveals an increasing trend in pest epidemics, including Yellow Stem Borer (YSB) in rice, largely driven by climate change. Understanding the impact of climate change on host-pathogen interactions is essential for developing effective pest management strategies (Shepard 1995). A ten-year study on YSB conducted over consecutive Kharif seasons (2011–2020) in Barasat, West Bengal, indicated that YSB infestations began in the second week of August, with peak incidences occurring between the third week of October and November. The highest YSB incidence was recorded in 2019, while the lowest was observed in 2014 (Figure 6). Baldini *et al.* (2017) categorize data into experimental and model-based, based on type and accessibility. In this study, seasonal variations in YSB occurrence were graphically represented in Figure 2, highlighting the pest's patterns across years. Among the various pests affecting rice, Yellow Stem Borer (*Scirpophaga incertulas*) is considered one of the most destructive, as it inflicts damage during both the vegetative and reproductive stages of the crop (Rubia 1989). Across rice-growing regions in India, YSB is a top priority pest, causing yield losses of 27–34% annually (Prasad 2007). Light trap catches, commonly used to monitor insect populations in rice ecosystems, provide an indication of pest abundance and the potential severity of damage. YSB moth catches from light traps are frequently employed as a year-round monitoring tool in pest management strategies. Changes in the onset, peak, and severity of insect pests, including YSB, have been documented in India through laboratory experiments and field data. These studies highlight the relationship between changing weather patterns and pest outbreaks, reinforcing the need for adaptive pest control measures (Annual 2016). As climate change continues to alter weather conditions, these studies underline the importance of long-term monitoring of YSB populations and weather variables. This data provides critical insights into pest dynamics, helping to formulate more targeted management approaches for the control of YSB and other pests in rice cultivation.

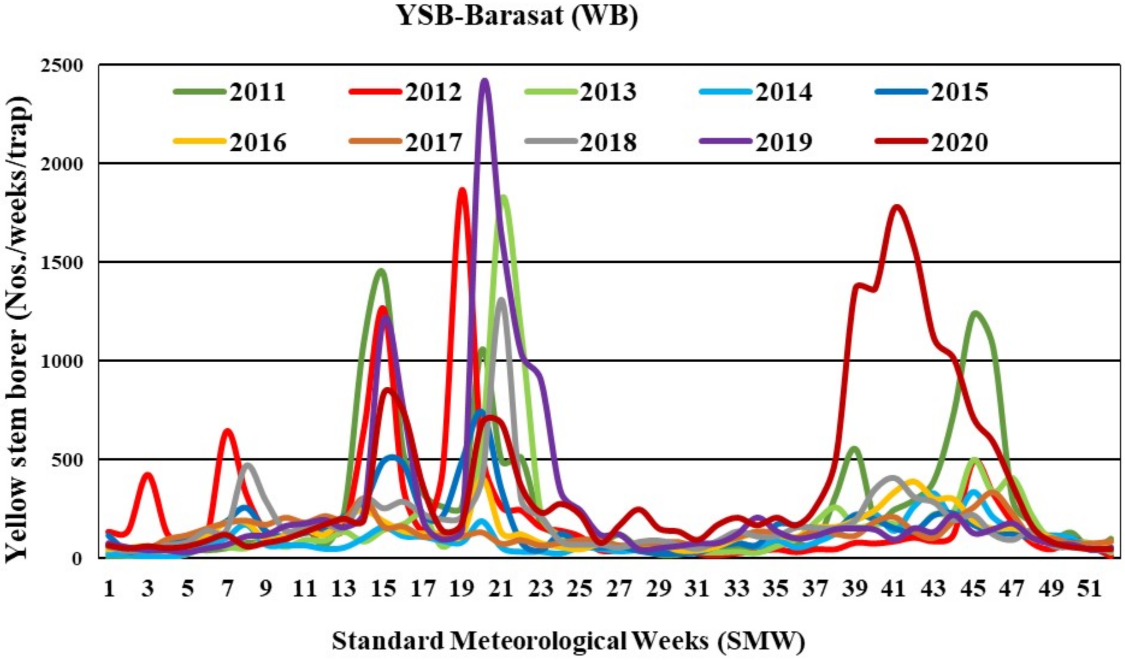

Figure 6. The seasonal variation of YSB occurrence in rice

Analysis of variance (ANOVA)

Comparative analysis of YSB occurrence across the years

Comparisons of Yellow Stem Borer (YSB) mean population across different seasons were analysed using one-way analysis of variance (ANOVA) after applying an arcsine transformation. Mean comparisons were conducted through Duncan's Multiple Range Test (DMRT), as shown in Table 1 (Vargas *et al.* 2010). The analysis revealed that YSB populations were significantly lower in 2014 compared to other years, with 2020 showing notably higher incidences. The YSB incidence during other seasons was generally on par with each other (Shelly et al. 2014).

These results highlight the seasonal variability of YSB populations and the importance of long-term monitoring for effective pest management strategies.

Table 1. Comparative analysis of YSB occurrence across the years

2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
269.45^{b}	216.74^{b}	181.55^{bc}	98.73^{c}	167.21^{b}	134.39^{b}	135.2^{b}	185.49^{b}	264.62^{b}	367.32^{a}

*** Means followed by the superscript of same at $p<0.05$ based on DMRT**

Descriptive statistics of YSB occurrence

The descriptive statistics of Yellow Stem Borer (YSB) occurrence (numbers per week per trap) are presented in Table 2. Upon reviewing the table, it is evident that the variability in YSB population, measured by standard deviation, was high, with values ranging up to 281.89. The maximum YSB occurrence recorded was 2,374 (numbers per week per trap). The distribution of YSB data exhibited positive skewness and leptokurtic characteristics, indicating a higher frequency of smaller values with occasional large peaks. Rainfall variability, measured through the coefficient of variation (CV), was also high, with the lowest recorded occurrence being 2.00 (numbers per week per trap). Understanding the shape of data is crucial in determining where most information lies and for identifying outliers. In a one-dimensional case, the key parameters of interest are the population mean and variance. The effect of non-normal data on statistical inference, particularly for these two parameters, can be fully characterized by skewness and kurtosis. These concepts are familiar to graduate students in the social sciences (Tabachnick et al. 2001). YSB occurrence was found to be positively skewed and leptokurtic, indicating that most data points were concentrated on the lower side of the distribution, with a few extreme occurrences driving up the mean. Among the weather-related regressor variables, most, except maximum temperature (MaxT) and minimum temperature (MinT), exhibited positive skewness as well (Blanca *et al.* 2013). In terms of kurtosis, MaxT, MinT, and relative humidity in the evening (RHE) followed a platykurtic distribution, meaning that their distribution had lighter tails than a normal distribution. Conversely, other regressor variables, such as rainfall and wind speed, exhibited leptokurtic distributions, characterized by fatter tails and a higher peak (An L *et al.* 2008). The use of skewness and kurtosis in analyzing the distribution of YSB populations and related weather variables helps in understanding the data's underlying structure and informs better modeling. The high variability and non-normality of the data pose challenges for traditional statistical inference, highlighting the need for appropriate transformations or non-parametric approaches in such cases. All analyses were conducted using R software (R Core Team 2013), a robust platform for statistical computing that allows for the handling of complex datasets and the implementation of advanced statistical techniques. These insights into the distribution and variability of YSB populations, as well as the corresponding weather variables, are essential for developing accurate models for pest prediction and management.

Table 2: Descriptive statistics of response variable with repressor variables

Statistic	YSB	MaxT	MinT	RHM	RHE	Rainfall	RainyD
Mean	203.21	32.21	21.81	93.14	63.22	31.42	2.52
Median	121.53	31.11	22.94	93.86	61.15	7.09	2.00
Minimum	3.00	15.30	6.13	47.00	22.84	0.00	0
Maximum	2373	35.41	25.32	221.29	113.24	428.13	5.00
Mode	58.00	31.41	22.91	96.29	56.12	0.00	0.00
Range	2373.00	22.04	20.72	174.29	81.43	421.80	6.00
SD	282.90	3.94	5.39	7.30	13.91	39.61	2.04
Skewness	3.87	-0.74	-0.64	9.70	0.02	3.05	2.03
Kurtosis	16.73	0.06	-0.92	185.70	-0.55	13.05	0.17
CV	141.06	13.65	32.40	7.86	22.12	**146.74**	121.53

$^{\#}$ SD: standard deviation; CV: coefficient variation

Goodness of fit tests

Before proceeding with further analysis, normality checks were conducted using the Kolmogorov-Smirnov and Anderson-Darling tests, which revealed that the Yellow Stem Borer (YSB) population in Barasat, West Bengal, significantly deviated from normality, as shown in Table 3 (Ramesh *et al.* 2019). Due to this non-normality, a nonparametric modeling approach was employed to predict YSB occurrence (numbers per week per trap) based on climatic variables.

Table 3: Goodness-of-fit tests for normal distribution

Goodness-of-Fit Tests for Normal Distribution

Test	**Statistic**		**p-Value**	
Kolmogorov-Smirnov	D	0.25	Pr > D	<0.010
Cramer-von Mises	W-Sq	12.83	Pr > W-Sq	<0.005
Anderson-Darling	A-Sq	71.59	Pr > A-Sq	<0.005

*****: significant at $p< 0.01$; *: significant at $p< 0.05$**

Pearson Correlation Coefficients

Correlation analyses were conducted between Yellow Stem Borer (YSB) populations, measured as numbers per week per trap, and various weather parameters based on standard meteorological weeks (SMW) over a ten-year period from the crop seasons of 2011 to 2020. The correlation analysis revealed that YSB populations were significantly positively correlated with both maximum and minimum temperatures, indicating that as temperatures rise, so does the incidence of YSB. This finding is consistent with studies conducted in Purulia, West Bengal, which explored the influence of different weather parameters on YSB population fluctuations (Animesh 2018).

The detailed correlation between meteorological parameters and YSB population dynamics is presented in Table 4, illustrating how weather conditions can significantly affect pest populations. Weather serves as a crucial determinant in the population dynamics of pests, as highlighted by Agrawal and Mehta (2007) and Laxmi and Kumar (2011a, 2011b). Temperature, in particular, plays a vital role in the life cycle, behaviours, and reproduction of pests like YSB, affecting their survival and proliferation rates. Historically, many researchers have employed regression models both linear and nonlinear to develop insect pest disease forewarning systems, showcasing the importance of statistical methods in pest management and forecasting (Desai *et al.* 2004; Chattopadhyay *et al.* 2005a, 2005b; Dhar *et al.* 2007; Kumar *et al*. 2012; Kumar *et al*. 2013). These models allow for the analysis of complex relationships between various environmental factors and pest populations, providing valuable insights for developing effective pest management strategies.

As such, the positive correlation found between YSB populations and temperature underscores the need for ongoing monitoring of climatic conditions to anticipate pest outbreaks and implement timely control measures. Understanding these relationships not only aids in pest prediction but also contributes to broader efforts in sustainable agriculture, where climate resilience and integrated pest management are essential for minimizing crop losses. The data generated from these correlation analyses can inform farmers and agricultural policymakers about the potential risks posed by YSB under varying temperature scenarios, enabling them to make more informed decisions regarding pest control and crop management practices. In summary, the correlation analyses conducted over the ten-year study period provide crucial insights into the relationship between YSB populations and weather parameters, particularly temperature. This knowledge is essential for the development of predictive models that can aid in effective pest management strategies, helping to mitigate the impact of YSB and enhance rice production sustainability. By combining statistical analysis with practical agricultural knowledge, researchers and practitioners can better navigate the challenges posed by climate change and pest dynamics in rice cultivation.

Table 4: Correlation Coefficients of YSB with Climate variables

Pearson Correlation Coefficients, Prob > |r| under H0: Rho=0

Trap	MaxT	MinT	RHM	RHE	Rainfall	RainyD
YSB	0.24***	0.16***	-0.05	0.01	-0.06	-0.05

*****: significant at $p< 0.01$; *: significant at $p< 0.05$**

The data was categorized into three groups based on structural changes, represented by pink, green, and blue colours for the first, second, and third groups, respectively. Correlation analysis revealed that Yellow Stem Borer (YSB) populations were significantly positively correlated with both maximum and minimum temperatures across these groups. Specifically, maximum temperature exhibited a strong positive correlation in all three groups, while minimum temperature showed a significant positive correlation only in the third group. Additionally, relative humidity in the morning (RHM) was found to be significantly positively correlated in the first group, as illustrated in Figure 7. These correlations highlight the critical role of climatic factors in influencing YSB populations, which are key contributors to pest outbreaks in rice cultivation. The two major factors responsible for significant yield loss in rice are regular pest outbreaks and adverse weather conditions, as noted by Pathak (1994). Understanding these relationships is essential for developing effective pest management strategies and improving crop resilience. By analysing the interactions between YSB populations and various weather parameters, researchers can better anticipate pest outbreaks and mitigate their impacts on rice yields. This understanding is vital for farmers and agricultural stakeholders seeking to optimize production while minimizing losses caused by both pests and unfavourable weather conditions.

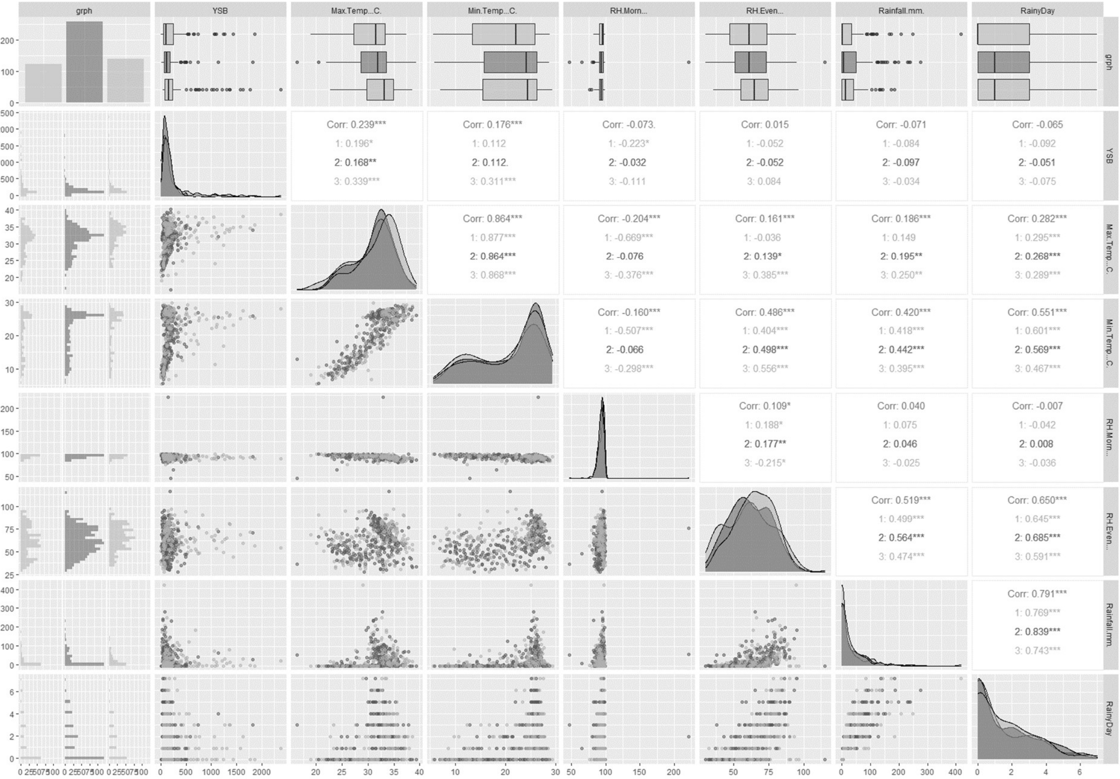

Figure 7: Correlation Coefficients of YSB occurrence with Climate variables

Validation of forecasts

Short-term forecasts for Yellow Stem Borer (YSB) using light trap catches and weather parameters have been attempted in India, employing standard meteorological weeks (SMW) and seasonal indices of abiotic factors (Ramakrishnan *et al.* 1994). Additionally, day degree and regression models (Krishnaiah *et al.* 1997) have been developed over the last decade; however, their application in the field remains limited at present. Consequently, there is a pressing need to develop more robust weather-based models that incorporate recent datasets to enhance the accuracy of YSB occurrence predictions for effective forewarning. In developing these models, it is crucial to consider the variability in YSB occurrence data over the years, which can be categorized into different levels of pest occurrence. These categories help in understanding the relationship between pest dynamics and weather conditions. For instance, congenial weather conditions significantly impact YSB populations and their infestation patterns, as noted by Krishnaiah (2004). Identifying and analyzing these conditions can lead to more accurate predictions of YSB outbreaks, allowing for timely interventions and better management strategies. To achieve this, the integration of historical data with current weather patterns will be essential in creating a comprehensive predictive model. This model would utilize various climatic variables, such as temperature, humidity, and rainfall, to assess their influence on YSB populations effectively. By doing so, it will be possible to establish a clearer understanding of how weather influences pest behavior, aiding farmers in making informed decisions about pest control measures. Furthermore, enhanced predictive capabilities can lead to better resource allocation, ensuring that pest management strategies are deployed where and when they are most needed. This proactive approach not only helps in reducing yield losses due to pest outbreaks but also contributes to more sustainable agricultural practices. Ultimately, developing and implementing these weather-based models will be crucial in improving the resilience of rice crops against the threats posed by YSB and other pests in a changing climate.

Table 5. Values in relation to RNN, GRU, LSTM, Bidirectional LSTM, Deep LSTM, ARIMA-X and ANN predicting of YSB.

Model	RMSE	MAE

RNN	331.42	163.84
GRU	**307.78**	152.84
LSTM	316.73	**144.36**
Bidirectional LSTM	315.11	154.04
Deep LSTM	347.78	162.15
SVR	415.89	215.62
RF	336.13	173.35

The success of the predictive model lies not only in forecasting expected outputs based on ten years of historical data but also in its ability to maintain the same level of accuracy for all incoming and future datasets. A robust model should be capable of handling changes in data without compromising its predictive performance, ensuring consistent results across varying conditions. When comparing evaluation metrics such as Root Mean Square Error (RMSE) and Mean Square Error (MSE) presented in Table 5, it becomes evident that the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models outperform the other methodologies by a noticeable margin, as illustrated in Figure 8. This margin of difference can be attributed to several key factors, as discussed in Figure 9. One reason for the superior performance of LSTM and GRU models is their capacity to learn long-term dependencies in data, making them particularly well-suited for time-series predictions, such as those involving pest populations. These models effectively capture the intricate relationships between climatic variables and pest dynamics, allowing for more accurate forecasts. Additionally, their ability to adapt to shifts in data patterns contributes to their robustness, enabling them to provide reliable predictions even in the face of changing environmental conditions. Forecasting the development of YSB populations with high accuracy, along with accurately describing their dynamics, is critical for implementing effective pest management strategies. By minimizing yield losses attributed to pest outbreaks, growers can enhance the sustainability and profitability of their rice production systems. Knowledge of the timing of YSB attacks in relation to crop phenology and the prevailing weather factors is essential for devising efficient, economical, and environmentally friendly management practices. When growers are equipped with predictive insights into YSB occurrence, they can take timely actions to manage the pest effectively. For instance, understanding the correlation between YSB populations and specific weather conditions enables farmers to implement preventive measures ahead of anticipated outbreaks. This proactive approach can include the timely application of insecticides or the deployment of biological control agents, thereby minimizing crop damage and reducing reliance on chemical treatments. Furthermore, effective pest management informed by accurate forecasting contributes to sustainable agricultural practices, promoting ecological balance and preserving beneficial organisms in the ecosystem. In conclusion, the development of robust predictive models, such as LSTM and GRU, represents a significant advancement in understanding and managing YSB populations in rice cultivation. By harnessing these models, stakeholders in agriculture can improve their pest management strategies, ultimately leading to enhanced crop resilience and reduced yield losses. The ability to predict YSB occurrences accurately allows for more effective resource allocation and timely interventions, fostering a more sustainable approach to rice production in the face of ongoing climate challenges.

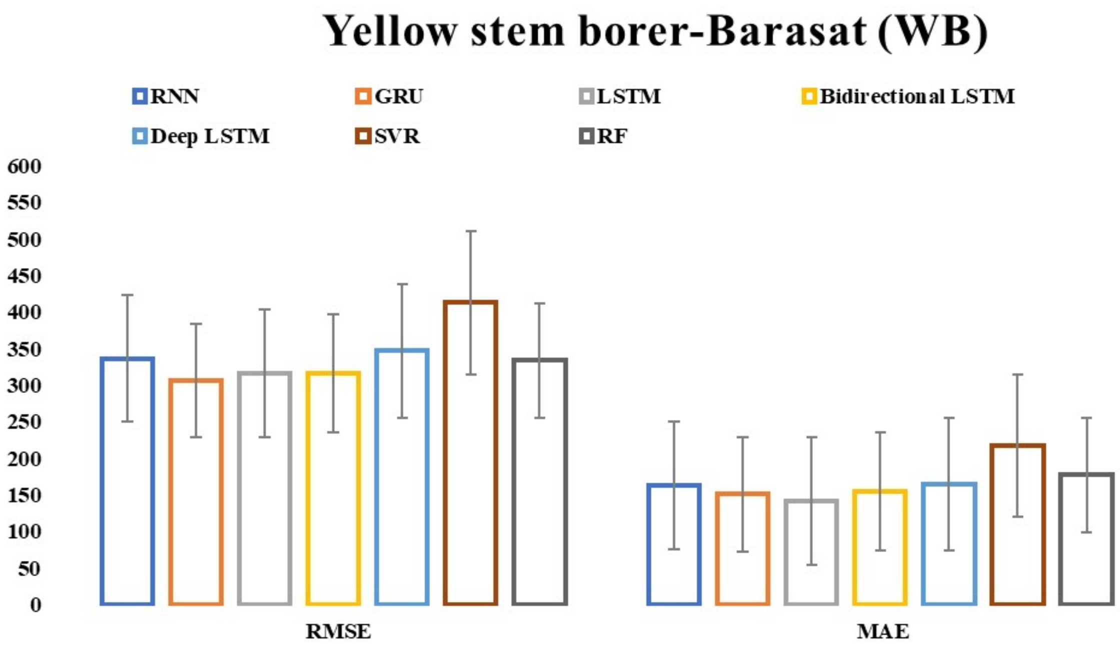

Figure 8. RMSE and MSE of different models for predicting YSB

Test results for yellow stem borer (WB)

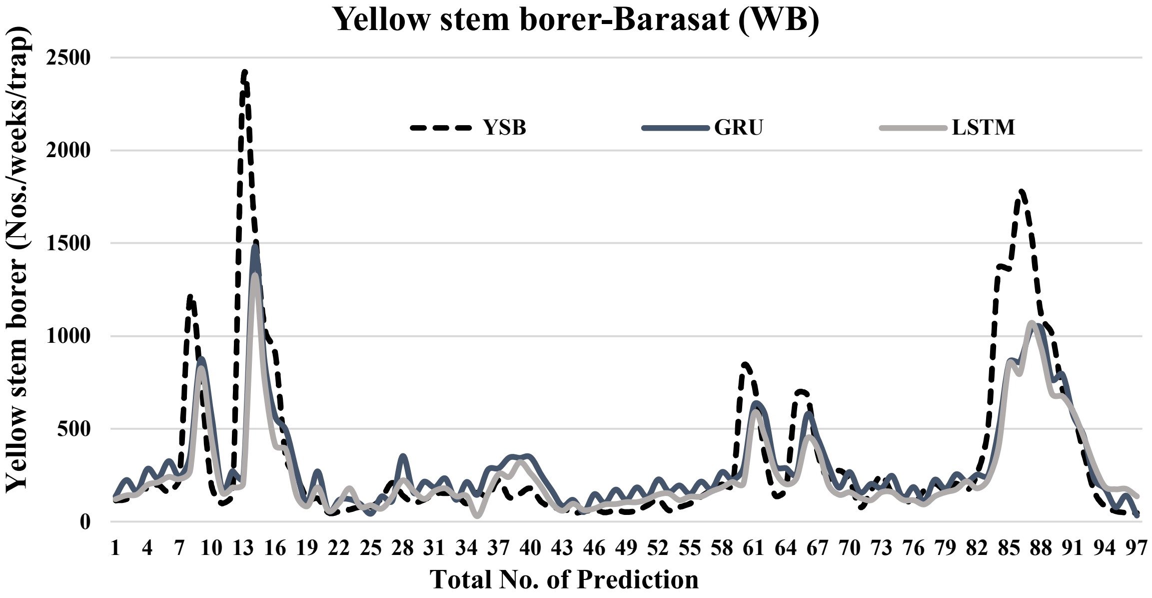

Figure 9. Different models for predicting YSB occurrence

Concussion

Climate change significantly affects rice-growing areas, leading to wide fluctuations in temperature and erratic rainfall patterns. Understanding the seasonal dynamics of pests in relation to these weather variations is crucial for effective agricultural management. The present study conducted at Barasat, West Bengal, revealed a decline in the incidence of Yellow Stem Borer (YSB) in rice, with the highest occurrences noted between 23 and 34 Standard Meteorological Weeks (SMW) during the 2019-2020 seasons. This decline may be indicative of changing environmental conditions and pest management practices in the region. In exploring approaches to model the incidence of YSB, various deep learning techniques were employed, showcasing differing performance levels. Empirical results demonstrated that the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models significantly outperformed other models such as Recurrent Neural Networks (RNN), Bidirectional LSTM, Deep LSTM, ARIMA-X, and Artificial Neural Networks (ANN). This superior performance was further validated by the Diebold-Mariano (D-M) test, which confirmed the predictive accuracy of the LSTM and GRU models over the competing methods. The ability to integrate disease-weather interactions into predictive models has led to higher accuracy rates in forecasting YSB occurrences. By harnessing these advanced modelling techniques, the current models could serve as a vital tool for predicting YSB scenarios in future seasons, especially under projected climate change conditions. Such predictive capabilities are essential for farmers and agricultural stakeholders, as they provide critical insights that can guide timely interventions and pest management strategies. While the techniques utilized in this study are primarily data-driven, making it challenging to generalize conclusions across all diseases and pests, the methodologies can be replicated for other pest and disease scenarios to enhance prediction accuracy. By applying similar modelling approaches to different contexts, researchers can gain valuable insights into pest dynamics and develop tailored management strategies that account for the specific challenges posed by climate change. Moreover, as climate change continues to evolve, the need for robust predictive models will become increasingly critical. These models not only aid in understanding current pest dynamics but also play a pivotal role in preparing for future challenges in agricultural production. As variations in climate continue to influence pest populations and behaviours, the importance of developing adaptable and accurate forecasting tools cannot be overstated. In conclusion, the findings of this study highlight the adverse impacts of climate change on rice cultivation and the significance of understanding pest dynamics in this context. By employing advanced deep learning techniques to model YSB occurrences, researchers can provide valuable insights that contribute to more effective pest management strategies. As we navigate the complexities of climate change and its implications for agriculture, continued investment in research and the development of predictive models will be essential for ensuring the sustainability and resilience of rice production systems. The insights gained from this study could pave the way for future research aimed at mitigating the effects of climate change on pests and enhancing agricultural productivity in the face of evolving environmental challenges.

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