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Original Article

Machine Learning based Predictive Assessments of Impacts of Influential Climatic Conditions for the Sustainable Productivity of Paddy Crops

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Abstract *- The excessive inundation of paddy fields and the consumption of groundwater, fertilizers, and insecticides have resulted in substantial unintended consequences. The trajectory of the weather patterns and the correlation between weather and harvests will determine these effects' unique character and scale. Considering the essential environmental concerns affecting paddy ecosystems, this study aims to give a predictive evaluation and outline the ecological implications of rice production and the influence of a changing climate on paddy cultivation in the Region of Interest (RoI). In addition to these realities, it is essential to foresee the climate's effect on paddy fields by employing forward-thinking solutions for dealing with the ever-changing weather patterns that may directly impact rice yields. Philosophy-wise, Machine Learning (ML) differs from most traditional statistics since it emphasizes forecasting rather than description. In this paper, the case study centred on the findings of geographic climate models is conducted using multiplicative Long-Short Term Memory (mLSTM). mLSTM is employed to evaluate the consequences of climatic or environmental changes on rice production in RoI, showing the novelty of the work. To assess the effectiveness of the proposed methodology, the predicted outcomes are compared with the actual results. Sustainable rice production is assured through reasonable and actionable guidelines in the face of mounting environmental challenges.*

Keywords *- Agriculture, Paddy crop, Predictive models, Machine learning, Crop productivity.*

1. Introduction

The farming sector, which is primarily dependent on the weather, will be hit particularly hard by climate science, making it one of the most immediately affected industries overall due to the effects of climatic change [1]. The term "climate change" describes any long-term shift from any known factors of the weather patterns caused by natural variation or by artificial influence. It is predicted that climate change will have significant implications for the ecological sustainability of underdeveloped nations [2], particularly their capacity to accomplish the United Nations Sustainability Progress Objective Those with lower incomes, particularly those in developing countries that rely heavily on agricultural production, are at risk due to climatic changes [3]. The specific repercussions on a region are determined by the current climate state of a nation, as well as other considerations such as geography, society, traditions, economy, and governance [4].

The globe's ecological and agricultural asset infrastructure is already struggling to cope with the increasing requirement for food due to rapid urbanization and rising spending strength in emerging nations [5], with extreme weather further compounding the problem. The climate crisis is one of the limited elements that may significantly alter a region's typical cropping strategy, the yield of crops, and agricultural productivity, as well as the yield from related sectors [6]. In addition, weather patterns in any given location may undergo unsociable hours due to the impact of climatic changes. The delayed seasonal rainfalls, unanticipated downpours, unusual weather, severe rainfalls, warming trends, heavy precipitation, catastrophes, floods, hurricanes, uneven rainfall distribution, and rapidly increasing sea levels are clear indicators of climatic changes [7]. Human actions, including releasing greenhouse emissions, cutting down trees, expanding cities, and developing new economies, are to blame for the current state of the global climate system [8]. Almost every aspect of the ecological and social realms is being influenced by climate science.

Crop production variance is a metric to measure the consequences of climatic changes on farming [9]. From among Indian provinces, Tamil Nadu state is one of the susceptible regions to climatic variability. However, as a bonus, it ranks among the states where certain relationships among economic development, agricultural productivity, and climatic sensitivity are powerful [10]. People in rural regions and those with lower incomes rely heavily on farming, poultry, and cattle for survival. Around seventy per cent of the province's residents live in farming and related industries [11]. Rice, sugarcane, and peanuts were chosen for the research because they are the region's three most widely grown cultivars. This is a dismal number when equated to India's and the globe's average food crop output [12]. Thus, it is clear that India's agricultural output must be significantly enhanced.

This study aims to give a predictive evaluation and outline the ecological implications of rice production and the influence of a changing climate on paddy cultivation in the Region of Interest (RoI). Foreseeing the climate's effect on paddy fields is essential by employing forward-thinking solutions for the ever-changing weather patterns that may directly impact rice yields. Philosophy-wise, ML differs from most traditional statistics since it emphasizes forecasting rather than description. In this research, the case study centred on the findings of geographic climate models is conducted using multiplicative Long-Short Term Memory (mLSTM). mLSTM is employed to evaluate the consequences of climatic/environmental changes on rice production in RoI, showing the novelty of the work. To assess the effectiveness of the proposed methodology, the predicted outcomes are compared with the actual results.

2. Related Works

Carrão et al. [13] state that climate variability occurs globally throughout all temporal frames and results from ecological phenomena. Various time scales like inter-annual scaling, extended geological timeframes, and multi-decadal spontaneous climatic variability provide significant challenges to the accurate characterization of climatic disruption all across the world owing to human activities. Challinor et al. [14] present that for more than a significant duration of time that is usually decades or more, a region's or area's climate has been impacted if there is a substantial variation in observations of the sample estimate or unpredictability of the weather patterns for such a province or territory. Climate variation may result from ecological causes or long-lasting alterations to the atmosphere or soil, primarily attributable to human activity.

Chen et al. [15] state that it is essential to remember that the United Nations Action Plan on Climatic Changes has limited scope for climate science, limiting the term to variations that can be traced back to human activities in some way. Parametric methods with explanatory variables rectify most problems affecting the Ricardian and agronomic approaches. Dastagir [16] presents frameworks with a long history of usage, and they have most recently been employed in research for assessing the impact of the climatic crisis on farming output in India, Asia and the Tanzanian region. The realistically attainable recursive least squares approach estimates panel predictor variables in three stages in several different types of panel research. Kim et al. [17] applied a model for evaluating the possible impacts of climatic variation on average production and the uncertainty of production in agribusiness in the United States and India. Droogers et al. [18] assert that climate variation would harm India's average rice cultivation and yield volatility. Several researchers have used the Probabilistic Maximum Estimation (PME) method to assess agronomic profiles by utilising data over the period. Hingane et al. [19] indicate that the complete variability predictions are commonly excessively confident in the accuracy of the estimated coefficients and hence advise against using them.

Isik and Devadoss [20] found that a rise of just one to two degrees Celsius in temperature will reduce paddy grain productivity by 3 - 17 per cent throughout India. They are employing the InfoCrop framework. In contrast, yields are proportionally unaffected, mainly in the northern Indo-Gangetic flatlands. Kittel [21] proposes a method that assesses the influence of climatic factors on agricultural yields or cropland assets by using the cross-sectional disparities between different types of farmland usage and climatic patterns. For the estimation of semi-Ricardian concepts in India, net income is employed as a substitute for the leasehold valuation of farmland because of a lack of information on land costs. Krause et al. [22] discovered that a predicted 2-degree Celsius increase in temperature and a 7% increase in rainfall lessen agricultural income by 9%. Although research in India suggests that farmers would be negatively affected by climatic changes, the lack of such information and the failure to account for spatial analysis and temporal-reliant aspects, including soil characteristics, makes it difficult to provide reliable predictions.

3. The Proposed Model

We have formulated a novel multiplicative Long-Short Term Memory (mLSTM) model in this research. The presented mLSTM aims to analyze the consequences of climatic or environmental change on rice production in RoI. The anticipated results are associated with the initial outcomes to assess the presented approach's efficiency. Figure 1 depicts the diagrammatical representation of CDA with geographical attributes.

3.1. Review on RoI

The Cauvery Delta Area chosen as the RoI for research investigation, often known as CDA, can be found in Tamil Nadu's easternmost region. The Bay of Bengal surrounds it on its eastern side, the Palk Strait on its southern side, the Trichy district on its western side, the Perambalur and Ariyalur districts on its north-west side, the Cuddalore district on its northern side, and the Puddukkottai district on its south-western side. The real RoI is 1.447 million hectares of cultivation land. Around 57 per cent of the total CDA is located in the former Tanjore district, which included the towns of present-day Nagapattinam, Thanjavur, and Thiruvarur district, with the remaining 43 per cent spread out among the present-day regions of Ariyalur, Pudukkottai, Trichy, and Cuddalore districts. Located at the 10.00°N-11.30°N latitude and 78.15°E-79.45°E longitude, the CDA has a vast land mass that covers around 11 per cent of the state's cultivation area. More than four million people find gainful employment in agriculture due to the 95.6 cm of yearly monsoon rains[23]. Across this basin, the precipitation differs widely.

The rainfall due to the southwest monsoon typically hits the western part of the watershed, especially during the June to September months.

In contrast, significant rainfall due to the northeast monsoon hits the eastern part of the basin during the October to December months of every year. Other than that window, precipitation is negligible. Most rainwater is stored in the multiple reservoirs built across the river, mostly filled during the southwest monsoon period. On the other hand, the northeast monsoon period provides an enormous amount of rainfall in CDA.

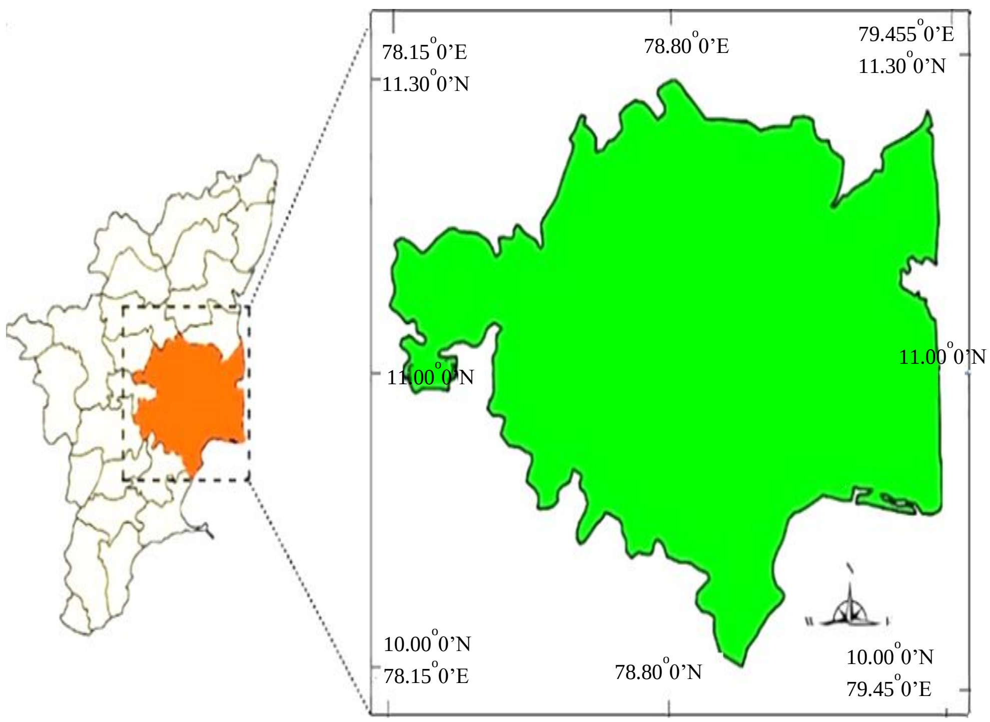


Fig. 1 Geographical layout of RoI

3.2. Climate Change Scenario

As an initial process, this study intends to evaluate the influence of prospective paddy cultivation under distinct representative concentration pathways. This is accomplished by incorporating various climatic condition scenarios empirically developed using the MarkSim weather forecast generator in conjunction with mLSTM.

The Intergovernmental Panel on Climate Change (IPCC) created a methodology to encapsulate these assertions inside a series of eventualities called Representative Concentration Pathways (RCPs).

Potential strategic climatic evolution is modelled using the characteristics of every scenario. In addition, geological, crop, and climatic data are inputted to determine the water requirement for irrigation.

We utilized the preexisting Decision Support System for Agrotechnology Transfer (DSSAT) v4.8 data-generating technique and the suggested mLSTM undertake a comparative investigation of the outcome of climatic conditions on rice crops in the concerned RoI. MarkSim generates foundational data for various climate change scenarios using morphological and environmental traits. Paddy crop types grown at different seasons in CDA are described in detail in Table 1[24]. In addition, periodic discussions and analyses of each variety's climate effects and crop productivity outcomes were conducted.

3.3. Crop Simulation Model

Table 1. Crop types and their growing seasons

Season	Months
Sornavari	March/April to June/July
Kar	April/May to July/August
Early Samba	July/August to January/February
Samba	September/October to January/ February
Late Samba	September/October to January/ February
Thaladi/Pishanam	September/October to February/ March
Navarai	November/December to February /March

3.4. mLSTM Description

Models trained in specific river basins against statistical information are the most often used method for estimating the effects of climatic changes on hydrological ecosystems.

However, any approach is unrealistic in light of climate change and other human factors since climatic shifts have a multiplicative effect on watershed features[25, 26]. Minimalistic approaches, incorrect parameterization adaptation, a significant decline in effectiveness when modelling at a regional level or massive dimension, and failure to account for dynamic ecological conditions are presently the most significant obstacles. Thus, in this research study, we incorporated mLSTM, a variant of LSTM, to overcome those obstacles.

Since there might be gaps of undetermined length among crucial occurrences in a temporal data series, Short-Term Long Memories (LSTM) networks excel at categorizing, analyzing, and predicting the target objectives based on historical and dynamical serial correlation.

LSTMs were created as a unique model for various solutions, especially for the vanishing gradient issue that might arise during training standard Recurrent Neural Networks (RNNs). The core process of mLSTM has derived a hybrid construction incorporating the factorized hidden-to-hidden transition of multiplicative-RNN (mRNNs) with the gating framework from LSTMs.

The structure of mRNN was developed to facilitate the explicit goal of facilitating a temporal-based, input-reliant transition process. For ease of comprehension, an mRNN can be expressed in terms of the intermediate state I_s, as shown in Equations (1) and (2).

$$I_s = \left[\left(I_t \cdot \omega_{I_s I_t}\right) \odot \left(\mathbb{h}_{t-1} \cdot \omega_{I_s \mathbb{h}_t}\right)\right] \quad (1)$$

$$\overrightarrow{\mathbb{h}}_t = \left[\left(I_s \cdot \omega_{I_s \mathbb{h}_t}\right) \odot \left(I_t \cdot \omega_{I_t \mathbb{h}_I}\right)\right] \quad (2)$$

$\omega_{I_s I_t}$ Represents the diagonal matrix that changes depending on the input,
$\omega_{\mathbb{h}_t}$ Is the matrix of hidden weights and their inputs,
$\overrightarrow{\mathbb{h}}_t$, denotes the hidden vector at a time, t
$\mathbb{h}_{t-1}$, previously hidden state

Because of the mRNN's complicated transitioning process, climate-oriented data may have difficulty adapting over the longer term if it is processed by the typical RNN components (units). Connecting the LSTM's gating components to the mRNN's I_s (which is formulated in equation (1)) yields the sequence of the processes (from equations (3) to (6)), which combines the advantages of both structures and the diagrammatical representation is depicted in figure 2.

$$\widehat{\mathbb{h}}_t = \left[\left(I_t \cdot \omega_{\mathbb{h}_t}\right) + \left(I_s \cdot \omega_{I_s \mathbb{h}_t}\right)\right] \quad (3)$$

$$I_t = sig(f)\left[\left(I_t \cdot \omega_{I_t}\right) + \left(I_s \cdot \omega_{I_t I_s}\right)\right] \quad (4)$$

$$O_t = sig(f)\left[\left(I_t \cdot \omega_{O_t}\right) + \left(I_s \cdot \omega_{O_s}\right)\right] \quad (5)$$

$$f_t = sig(f)\left[\left(I_t \cdot \omega_{f_t}\right) + \left(I_s \cdot \omega_{f_s}\right)\right] \quad (6)$$

$sig\ (f)$ represents the sigmoidal (logistic) function, and I_t, O_t, f_t represent the input, output, and forget gates subsequently.

In each trial, we ensured that the I_s dimensionality was equivalent to that of h_t. Using I_s with all base components, our model has almost twice as many recurrent inter-state weights as LSTM while retaining the equivalent sum of h_t. This structure aims to merge the input-reliant adaptability of mRNNs, the latent state control, and the long-term memory capacity of LSTMs.

The complicated changes that emerge from the factorized $\omega_{\mathbb{h}_t}$ may be further simplified to regulate with the intervention of LSTMs' gating components. Furthermore, more input-reliant transition patterns are possible with LSTM components than with standard mRNNs attributed to the prevalence of f_t and sigmoid inputs.

Instead of being trained to recreate the data, the architecture's key component receives supervised training. This means that constructing an abstract model of the feed is not the primary concern.

The novel aspect of this structure is the training processes, which rely on Hessian-free tuning rather than a conventional methodology like back-propagation. Although this strategy is effective, we are conscious of other gated networks trained using such a level of procedures.

3.5. Predictive Assessment Measures

Rice is adaptable and may be cultivated in many different environments and temperatures. Humidity, solar irradiance, and precipitation all have a role in determining paddy yield, either directly via their effects on the plant's physiology throughout the grain-making phase or indirectly via creating an environment conducive to the growth of crop pests.

Therefore, the climatic scenarios were constructed using several elements, including all the primary components that significantly affect rice cultivation, which is precisely depicted in figure 3.

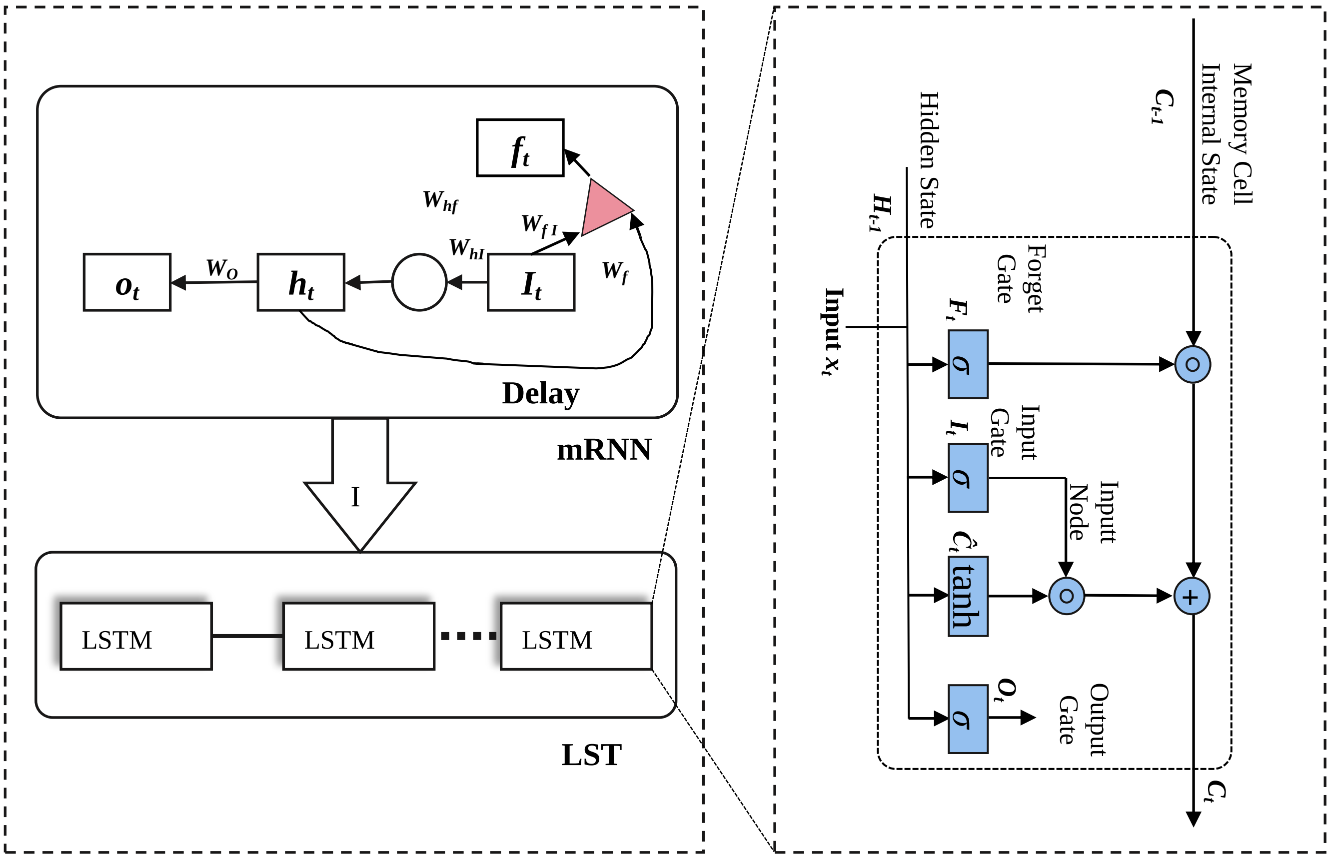


Fig. 2 Structure of mLSTM

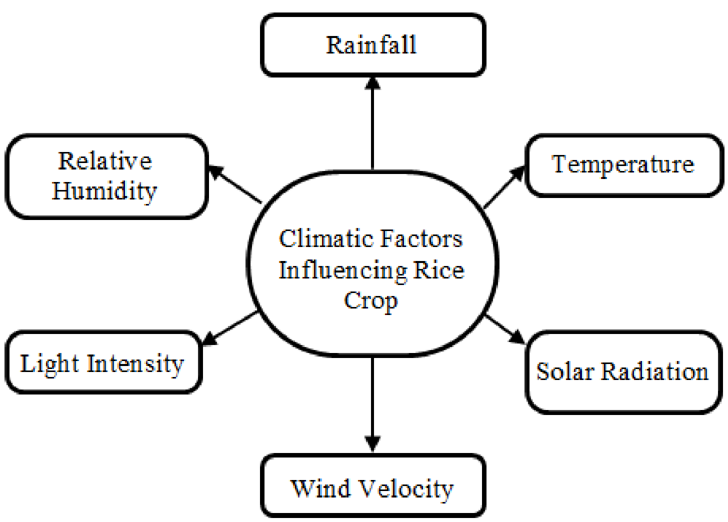


Fig. 3 Primary impactful components of p addy crop

Very high temperatures stunt the development of plants. In addition, changes in tillering, seedling development, and ripeness were affected by temperature fluctuations, which may further impact grain production. After implantation, the growth rate is affected by temperature, which is approximately linear between 20 and 35 degrees Celsius. Eventually, the tillering velocity and the absolute growth rate are somewhat influenced by temperature.

The relative importance of seasonal versus annual precipitation was evaluated to comprehend the spatial variability of rainfall. The unpredictability was examined using the annual mean, maximum (max), and minimum (min) ambient temperature data.

The number of NPIkelet plants produce rises with decreasing temperatures during the initial growing period. The average mass of grains seems to be influenced by the ambient temperature it experiences before ripening. Figure 4 shows the ideal temperatures for a rice crop at various phases of development. Rice is very vulnerable to frost, which may cause several issues, including germination failure, a slowdown in the emergence of the seedlings, retardation, darkening of the leaves, deterioration of the NPIke length and apex, imperfect panicle activity, a lag in inflorescence, excessive NPIkelet mortality, and uneven ripening.

During paddy cultivation, the amount of sunlight a crop needs changes at each stage. Minimal differences in agronomic traits are seen when crops are shaded during the growing season. Conversely, shading strongly affects the density of NPIkelets during the reproductive stage. As a result of a drop in the proportion of loaded NPIkelets, grain production is drastically reduced before maturity. The most significant impact of solar radiation on crop productivity occurs during vegetative development. During dry weather, the sun's rays are most potent in the temperate zone. As a result, parched crop yields are often lower than their moist counterparts.

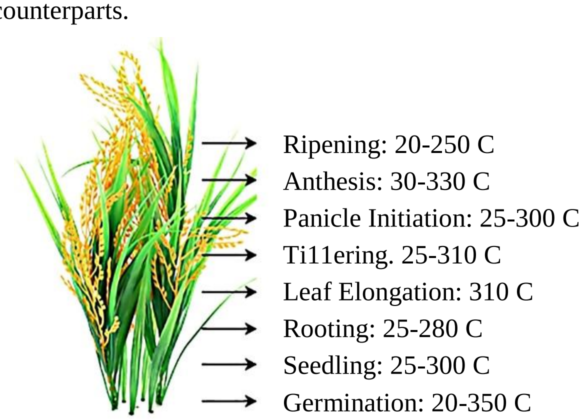


Fig. 4 Ideal temperatures of paddy crop in varied growing stages

A little breeze during rice's growth cycle boosts grain output by increasing volatility in the canopies because that is where most of the paddy crops' photosynthesis occurs. The photosynthesis rate rises as air velocity rises. Low wind speeds are adequate because winds faster than 0.9 meters per second have little impact on boosting the photosynthetic process. The paddy stalks get desiccated when the breeze is dry.

There is a statistically significant correlation between sunlight intensity and crop yield. Poor radiance during the rainy season is often attributed to lousy rice harvests in the RoI.

The ideal humidity level for paddy blossoming is between 70 and 80 per cent. Low levels of humidity (less than 40 per cent) prevent blossoming. The reduction of pigmentation and the subsequent acceleration of vegetative growth are relied on by low humidity levels. A water deficit may decrease production at any growth phase. Rice plants are especially vulnerable to water shortages during the divisional minimization stage or through crowning. Reduced yield results from a high rate of dryness imposed by moisture stress during heading. Until sterility has taken hold, the crop will never recover. However, production may not be affected by a moisture deficit in the vegetative growth phase. The proportional drop in grain production that occurs when paddy crops are immersed at various stages of development depends on the paddy crop's maturity.

3.5.1. Paddy Productivity Index (PPI)

Both climatic (precipitation events, warmth, humidity levels, and intensity of solar irradiation) and agronomic (seedlings, geographical data, and action plans) variables influence crop yield (covering the use of fertilizers, pesticides, and water management). Differentiating the effects of non-meteorological elements, especially technological inputs, may be difficult. The observed productivity was matched with the countdown linear relation over a specific time to investigate the rhythm of patterns and measure the annual growth depending on technology sources. To figure out the technological effectiveness in productivity ($\boldsymbol{\tau_p}$) for this analysis which is expressed in equation (7).

$$\tau_p = (\delta \cdot t_n) + \varphi \tag{7}$$

Wherein δ and φ are experimental coefficients and t_n = *1, 2* reflect the years 2020 and 2021 for rice production. The Paddy Productivity Index (PPI) has been employed to standardize the dataset, which is further supported by extracting some proportion of the technological-centric productivity from the productivity gains (actual results). The annualized PPI after normalization is expressed in equation (8) for any given nth agricultural year.

$$I_{ppi} = {[A_p - \tau_p]_n}/{[\tau_p]} \times 100 \tag{8}$$

Where A_p represents factual productivity per year, and τ_p is the scientific pattern of productivity for any given n^{th} year.

3.5.2. Normalized Precipitation Indicator

The NPI's ease of use and effectiveness has made it a popular drought gauge. It aids in detecting and tracking droughts using just the most basic data sources: seasonal rainfall records from the last few decades. Furthermore, numerical value replacement aids in evaluating unusual or excessive precipitation, allowing for the investigation and assessment of weather patterns in different climatic regimes. As opposed to competing indicators, NPI excels in three key areas: (a) empirical stability, (b) the ability to represent both short- and long-durative dryness, and (c) the ability to conduct water stress vulnerability assessments.The long-term observation recordings could be fitted to likelihood function-based simulators, and after that, they could be transformed into a standard curve. The NPI is indicative of the set of reference deviations that being a perspective, deviates from the lengthy norm (usually a mean) and expresses as,

$$\beta_{npi} = {(\mathbb{P}_n - \overline{\mathbb{P}})}/{\sigma} \tag{9}$$

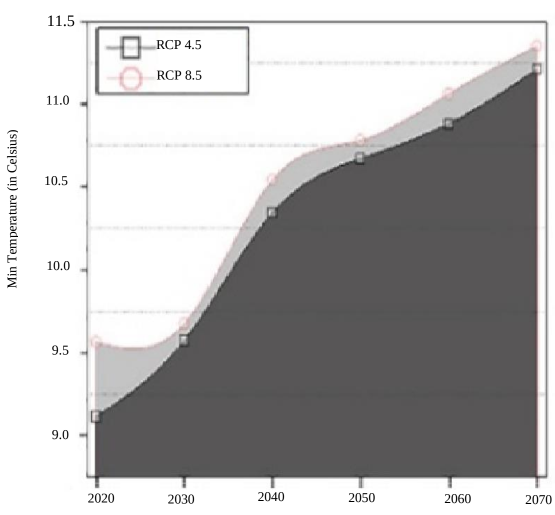
where $\mathbb{P}_i$, $\overline{\mathbb{P}}$ and σ are precipitation in the nth year, the long-term average, and the standard deviation of average rainfall, respectively.

3.5.3. Circadian Temperature Variation

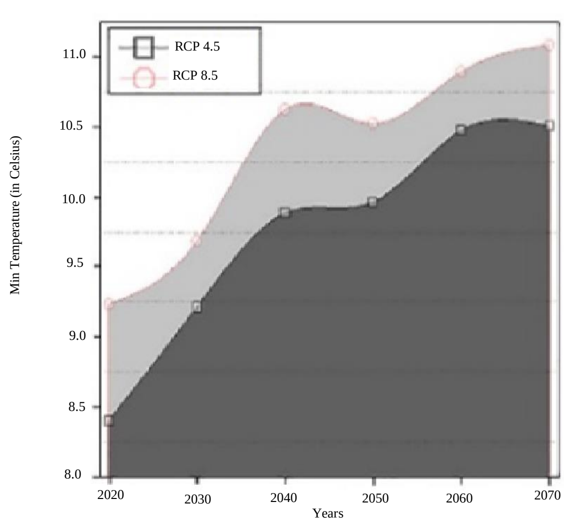
Circadian Temperature Variation (CTV = maximum–minimum temperature) influences crop development and harvest success. Documentary records and climate sensitivity predict significant shifts in CTV. We used CTV and NPI because they are valuable indices for gauging the effect of climatic variability on agricultural output.

4. Performance Validation

We used DSSAT v4.8 and mLSTM to analyze potential changes in rice harvests associated with climatic change. A DSSAT model estimated crop development and production by examining physical and morphological factors. mLSTM is an advanced ML technique that predicts agronomical factors based on temporal attributes.The yearly average future climate projections using mLSTM and DSSAT are shown in Figures 5a and 5b for two climate scenarios, respectively. Both methods forecast a progressive rise in the yearly minimum temperature in the RoI. Minimum temperatures are projected to rise to 11.6°C (in RCP 4.5) and 11.3°C (under RCP 8.5) through mLSTM experiments and to around 10.4°C (under RCP 4.5) and 11.1°C (under RCP 8.5) via DSSAT trials, over the period 2020–2070. According to different climatic variability patterns, the yearly minimum temperature will shift from 1.0 to 2.1 degrees Celsius to 0.8 to 1.7 degrees Celsius. Similarly, figures 6a and 6b for two climatic scenarios forecast a progressive rise in the yearly maximum temperature in the respective RoI. Maximum temperatures are projected to rise to 39.5°C (in RCP 4.5) and 39.8°C (under RCP 8.5) through mLSTM experiments and to around 38.9°C (under RCP 4.5), and 39.1°C (under RCP 8.5) via DSSAT trials, over the period 2020–2070. According to different climatic variability patterns, the yearly maximum temperature will shift from 1.3 to 2.2 degrees Celsius to 0.9 to 1.6 degrees Celsius.



(a) mLSTM



(b) DSSAT

Fig. 5 Future minimum temperature prediction under two concerned climatic scenarios (RCP 4.5 and RCP 8.5)

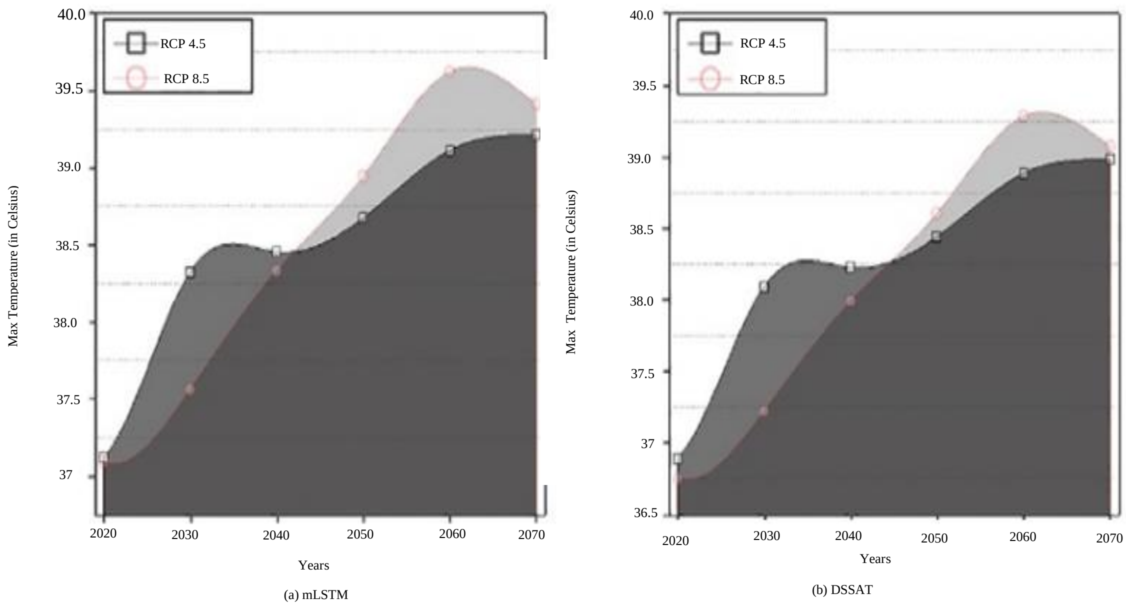


Fig. 6 Future maximum temperature prediction under two concerned climatic scenarios (RCP 4.5 and RCP 8.5)

There are three distinct growth seasons in the CDA: the rainy season (November–February), the post-monsoon (March–June), and the subsequent rainy climate (October–November). We separated our estimates of the climate predictions into three distinct seasons based on the various possibilities. The effect of potential temperature increases on rice production is evaluated under different settings, with other factors held constant when possible. Minimal temperature-centric normalized deviations should be included for best-predicting results. Consequently, the expected change in the outcomes of each scenario over a year is shown in figures 7(a) to 7(d). There is a significant upward pattern in the temperature variations throughout the vegetative stage (March–June), accompanied by a decrease during the winter months (November–February). These findings provide evidence that small changes in environmental conditions lead to increased rice production. The rationale is that there may be insufficient accumulated temperatures in the RoI under examination. A decrease in rice output of 0.23 per cent has been linked to just a modest temperature rise of 0.8 degrees Celsius.

While other parameters are held constant, it is discovered that a decrease in rainwater is correlated with a rise in crop productivity. In contrast, a rise in precipitation is linked to decreased crop yield. Figure 8 displays the outcomes of an examination of precipitation variability. If annual precipitation increases by 10% or 20% over the next five decades, rice output will drop by 4.23 and 13.32 per cent, respectively. Similarly, we have included potential future precipitation decreases in our analysis. A 10% and 20% reduction in rainfall throughout the paddy vegetative stage would improve grain productivity by 6.18% and 18.26%, respectively. This may be because we incorporate additional rainfall predictor variables for October and November into our empirical model, considering that rainfall in these months might negatively impact paddy crop production as it reaches maturity. Therefore, the study should focus on regions wherein changes in rainfall patterns will significantly affect crop needs.

While the initial rainy season receives the most rainfall, the overall amount of precipitation that occurs throughout the monsoon season (October and November) and further will peak in the second month of that wet season and then progressively decrease in the third month. As a consequence of the climatic shift, it is expected that the rainy season will increase precipitation while the dry period (March–June) will remain drier. Even during second dry periods, the highest and lowest temperatures and the most intense solar irradiation will be experienced. Consistent with prior research findings, RCP 8.5 has the most significant emissions of greenhouse gases since all the climatic variables were created more often under this scenario than under RCP 4.5 scenarios.

Figure 8 depicts the estimated rainfall distribution, showing significant geographical and temporal variance expected to reduce progressively throughout the 2060s. The worst drop in precipitation occurred within the RCP 8.5 projections, which spanned from 2050 to 2065.

However, projections for future precipitation show a broad range, from 950 mm to 885 mm. Precipitation in August and September seemed to have a relatively insignificant effect on rice production. However, rainfall in

October and November had a statistically significant adverse effect on rice production, which differed from 0 at the 1% significant level. The findings imply that a 3 per cent precipitation increase without any temperature shift will reduce annual rice production by ~1%. This is to be anticipated and is probably owing to the premise that the crop yield is at its peak during harvest in October and November. The rains before the commencement of harvesting affect rice productivity adversely. While monsoon rains typically occur between July and September, a variation in their timing to September and October will severely impact rice production and crop quality.

From the observable results of figure 9, it is evident that there is a rise in solar irradiance in the upcoming decades, with the highest incremental shift occurring as in the RCP 8.5 scenario. There is a correlation between the quantity of precipitation and the rise in solar radiation; heavy rainfall is associated with decreased solar irradiance. Wet-season productivity is 30–40% worse than dry-season productivity. In the rainy season, reduced production was attributed to reduced incoming solar irradiance rather than the persistence of the average temperature in CDA.

Figures 9 and 10 demonstrate the findings of the various correlations between annual NPI and CTV. For the pertinent RoI, we find a significant correlation between annual NPI and CTV of 0.78 (R^2) at a significance level of 0.03. Based on this data, it is concluded that 9.15% and 12.42% of the variation in rice output in CDA, respectively, can be attributed to anomalies in rainfall patterns (NPI) and temperature (CTV). On the other hand, for samba rice, the correlation was less, representing just 0.28% and 0.24% of the CDA's natural variation. Correlations were also at an all-time low, especially during the growing and harvesting stages of the Navarai crop season.

Though long-term NPI readings might provide some insight into the frequency and severity of dry and wet periods in the CDA, they may not indicate a clear pattern. Our observations showed that March through June were the most susceptible to drought and lower precipitation. CTV's decline can be attributed to the fact that lower temperatures are rising at a faster rate than higher temperatures. Maximum temperatures have also risen over time, albeit slower than minimum temperatures. This has led to a decline in CTV throughout the late samba season. Our data suggest a declining pattern of CTV due to a more rapid rise in winter temperatures than in summer ones. Increasingly rapid reductions in winter monsoon intensity correlate to ever-higher maximum temperature rise rates.

For the years 2020–2070, there will be a substantial and considerable linear relationship (R2 value at P 0.03) between the productivity of periodic rice crops (Sornavari, kar, early samba, samba, late samba, thaladi, and navarai) and the year in CDA (Table 2).

The profitability of paddy cultivation was maximum in the dry area out of all the ecological systems. Mild temperature increases of 1.2 °C and 1.8 °C are observed to enhance yields by 3.13% and 4.18%, respectively. Although higher temperatures might boost rice output, increased evapotranspiration will raise the need for more irrigation.

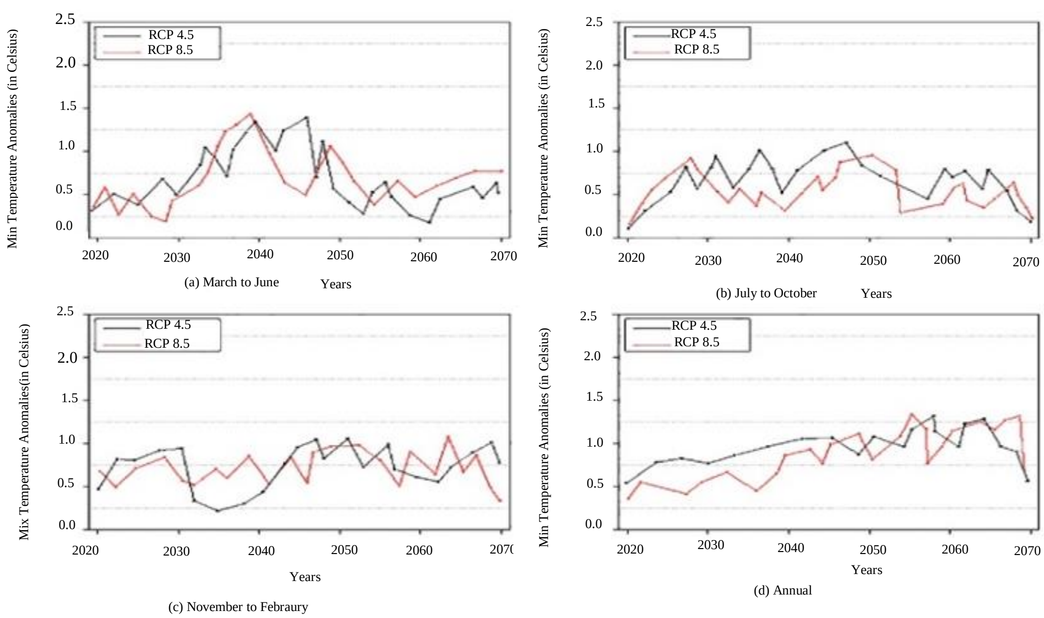


Fig. 7 Minimal temperature-centric normalized anomalies

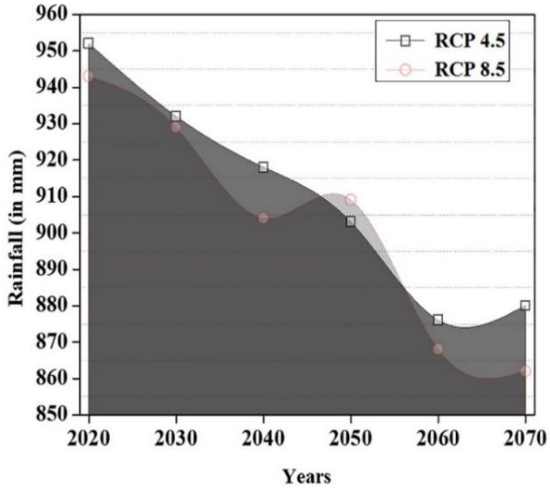


Fig. 8 Predictive assessments on rainfall

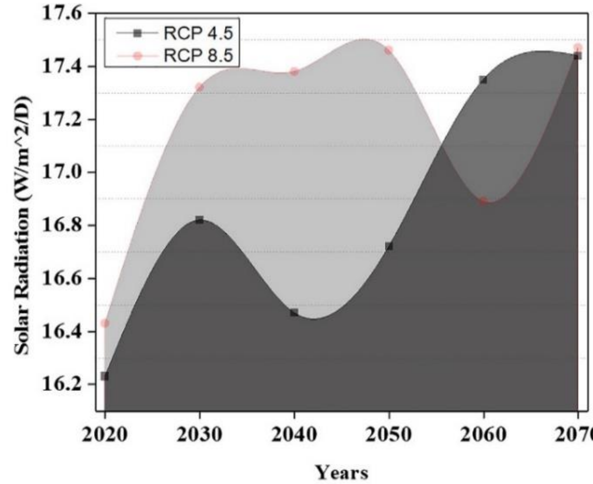


Fig. 9 Predictive assessments on solar radiations

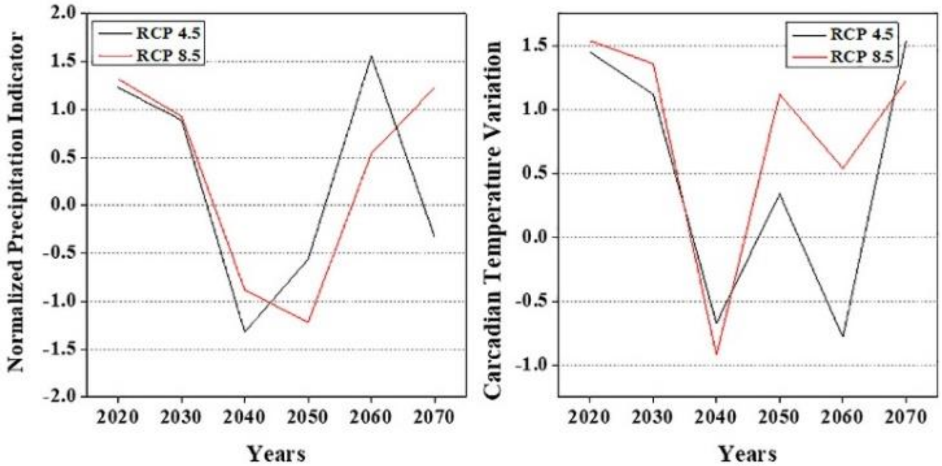


Fig. 10 Predictive assessments using NPI and CTV indicators

Table 2. Analysis of various rice crop productivity

Rice Crop	Productivity	R^2
Sornavari	1.632+(ti x 0.0413)	0.71
Kar	1.711+(ti x 0.0301)	0.74
Early Samba	1.612+(ti x 0.0358)	0.69
Samba	1.805+(ti x 0.0601)	0.84
Late Samba	1.523+(ti x 0.0531)	0.71
Thaladi/Pishanam	1.432+(ti x 0.0243)	0.65
Navarai	1.389+(ti x 0.0289)	0.62

5. Conclusion

This research examined the effects of climatic variations on paddy crop production on a broader cumulative scale by employing time-series data. We applied the mLSTM, and DSSAT approaches in RCP 4.5 and RCP 8.5 to assess the impact in two discrete cases. The research's outcomes suggest that climate factors, such as precipitation and temperature, are crucial in determining rice harvests. A substantially noteworthy difference exists between the mean highest temperature from March to June and July to September and the mean lowest temperature from October to December. In addition, rice production and precipitation in October and November have a strong inverse correlation. To obtain complete knowledge on the subject of changing climate and rice production, scientific investigations in the future will have to concentrate on data analysis in various scenario settings. These findings could be utilized by cultivators, scientists, and regulators to better plan for and respond to changing climates in the rice-producing economy. In future, hybrid deep learning-based models can be designed to improve the paddy crop productivity prediction performance.

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