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Decoding climate change : Modeling resilience of sugarcane Co86032 in Padegaon (Maharashtra), India with DSSAT and Random forest

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सार – जलवायु परिवर्तन कृषि उत्पादकता के लिए महत्वपूर्ण चुनौतियाँ प्रस्तुत करता है, विशेषकर उष्णकटिबंधीय क्षेत्रों में जहाँ गन्ने जैसी फसलें अर्थव्यवस्था के लिए महत्वपूर्ण हैं। यह अध्ययन आरसीपी 4.5 परिदृश्य के तहत Co86032 गन्ने की खेती पर जलवायु कारकों के प्रभाव की जांच करता है। डीएसएसएटी और रैंडम फ़ॉरेस्ट मॉडल का एकीकरण तापमान, वर्षा और फसल परिणामों के बीच गैर-रेखीय संबंधों की विस्तृत खोज की अनुमति देता है। हमने उपज, सुक्रोज सामग्री, हरी पत्ती क्षेत्र सूचकांक और फसल सूचकांक जैसे प्रमुख फसल कारकों पर तापमान और वर्षा के पिछले जलवायु डेटा (1986-2021) और भविष्य के अनुमानों (2024-2098) के प्रभावों का विश्लेषण करने के लिए डीएसएसएटी मॉडल और डेटा माइनिंग का उपयोग किया। नतीजे बताते हैं कि उच्च तापमान (टीएक्स) का उपज और सुक्रोज सामग्री पर महत्वपूर्ण प्रभाव पड़ता है, जो तापमान प्रबंधन रणनीतियों की आवश्यकता पर जोर देता है, जैसे कि अनुकूलित रोपण कार्यक्रम और गर्मी-सहिष्णु फसल किस्में।

नतीजे बताते हैं कि उच्च तापमान (टीएक्स), आरसीपी 4.5 परिदृश्य में एक महत्वपूर्ण कारक है, जो गन्ने की उपज और सुक्रोज सामग्री को विशेष रूप से प्रभावित करता है, जिससे अधिकतम तापमान में उतार-चढ़ाव के प्रबंधन पर अधिक ध्यान केंद्रित होता है। यह गर्मी-सहिष्णु प्रजनन कार्यक्रमों और रोपण रणनीतियों को अनुकूलित करके किया जा सकता है। इसके विपरीत, वर्षा (आरएफ) का फसल उत्पादकता के साथ कमजोर संबंध है, जो जल तनाव के प्रबंधन में सिंचाई के बुनियादी ढांचे के महत्व को उजागर करता है। यह बेहतर लचीलेपन और संसाधन उपयोग के लिए तनाव प्रबंधन, फसल विविधीकरण और जलवायु-स्मार्ट खेती तकनीकों के महत्व पर भी जोर देता है। फसल की पैदावार को स्थिर करने के लिए तापमान के रुझान के अनुरूप उन्नत सिंचाई प्रणालियों की सिफारिश की जाती है। पूर्वानुमानित मॉडल (डीएसएसएटी) द्वारा समर्थित अनुकूली और वास्तविक समय निर्णय लेने से इष्टतम फसल प्रबंधन प्रथाएं मिलती हैं और रैंडम फ़ॉरेस्ट मॉडल अलग-अलग जलवायु परिदृश्यों के तहत उपज की भविष्यवाणी को बढ़ाता है। यह संयुक्त मॉडलिंग किसानों और नीति निर्माताओं के लिए व्यावहारिक समाधान प्रदान करता है। इस प्रकार, मौसम आधारित सलाह, सिंचाई योजना और फसल विविधीकरण जैसे सटीक कृषि उपकरण जलवायु प्रभावों को कम करने और बदलती परिस्थितियों में फसल के प्रदर्शन में सुधार के लिए महत्वपूर्ण हैं।

यह अध्ययन यह समझने के महत्व पर प्रकाश डालता है कि जलवायु गन्ने की वृद्धि को कैसे प्रभावित करती है ताकि उद्योगों को जलवायु परिवर्तन के प्रभावों से निपटने के लिए सूचित निर्णय लेने और अनुकूली सटीक कृषि पद्धतियों में सहायता मिल सके।

ABSTRACT. Climate change presents significant challenges to agricultural productivity, especially in tropical regions where crops like sugarcane are crucial for the economy. This study investigates the impact of climatic factors on the Co86032 sugarcane cultivar under the RCP 4.5 scenario. The integration of DSSAT and Random Forest models allows for a detailed exploration of non-linear relationships between temperature, rainfall, and crop outcomes. We used the DSSAT model and data mining to analyze the effects of past climate data (1986-2021) and future projections (2024-2098) of temperature and rainfall on key crop factors such as yield, sucrose content, green leaf area index, and harvest index. Results show that high temperatures (Tx) have a significant impact on yield and sucrose content, emphasizing the need for temperature management strategies, such as optimized planting schedules and heat-tolerant crop varieties.

The results indicate that high temperatures (Tx), a crucial factor in the RCP4.5 scenario, notably affect sugarcane yield and sucrose content, highlighting more focus on the management of maximum temperature fluctuation. This can be done with heat-tolerant breeding programs and optimizing planting strategies. In contrast, rainfall (Rf) has a weaker correlation with crop productivity, highlighting the importance of irrigation infrastructure in managing water stress. It also emphasizes the importance of stress management, crop diversification, and climate-smart farming techniques for improved resilience and resource use. Advanced irrigation systems aligned with temperature trends are recommended to stabilize crop yields. Adaptive and real-time decision-making supported by predictive models (DSSAT) gives optimal crop management practices and the Random Forest model enhances yield predictions under varying climate scenarios. This combined modeling offers practical solutions for farmers and policymakers. Thus, precision agriculture tools like weather-based advisories, irrigation planning, and crop diversification are crucial for mitigating climate impacts and improving crop performance in changing conditions.

This study highlights the importance of understanding how climate influences sugarcane growth to assist industries in making informed decisions and adaptive precision farming practices to tackle the effects of climate change.

Key words – RCP, climate change, Random Forest, DSSAT Model, Sugarcane.

1. Introduction

Sugarcane (Saccharum spp. hybrids), a tropical grass cultivated in both hemispheres, is a significant cash crop in the agro-industrial sector, providing raw materials for various sugar industries and contributing to economies. Tai and Lentini (1998)stated that sugarcane is classified as cold-sensitive and finds its habitat in tropical and subtropical regions where frost is infrequent. Sugarcane plants have distinct responses to diverse stresses and are sensitive to high temperatures and water stress, which significantly impact growth. Elevated temperatures in sugarcane result in alterations to processes like photosynthesis, protein synthesis, and sugar production. According to Sanghera *et al*. (2019), high temperatures reduce sugarcane yield and impact its physiology, biochemistry, and quality. Low temperatures affect the germination rate, seedling establishment, and quality of early harvested crops, especially in the Indian subcontinent. Temperature stress in sugarcane results in alterations to photosynthesis efficiency, oxidative balance, protein synthesis, stomatal closure, membrane health, lipid levels and carbohydrate production.

Research on climate impacts using crop models like DSSAT has been widespread for staple crops such as wheat and rice. However, cultivar-specific studies on sugarcane varieties, particularly Co86032, remain limited, leaving critical gaps in understanding how temperature (Tmax), rainfall variability, and drought uniquely influence its growth stages and yield potential. Existing research tends to generalize findings across multiple crops and regions, neglecting the detailed insights needed for specific varieties and local conditions (PLOS ONE, 2017; Everingham *et al*., 2016).

While DSSAT excels in simulating crop physiology, it struggles to handle non-linear climate interactions, which machine learning models like Random Forest can address. Yet, these models, despite excelling in prediction, lack physiological depth. Integrating DSSAT for physiological insights and Random Forest for complex pattern recognition remains underexplored but is essential for capturing the full impact of future climate scenarios, such as RCP 4.5 projections (Kumar & Jain, 2021).

Additionally, many studies focus either on historical weather trends or future projections but fail to link the two to develop actionable resilience strategies. Bridging historical data (1986-2021) with future projections (2024-2099) offers valuable insights for adaptive crop management, especially in vulnerable regions like Padegaon, Maharashtra. This region faces unique challenges from extreme temperatures and erratic rainfall, requiring predictive, localized adaptation strategies that are often missing from broader agroecological studies. Developing region-specific models and tools will help create tailored crop planning solutions to ensure sustainable productivity in the face of climate variability.

This study addresses the gap in understanding non-linear relationships between climatic parameters (such as temperature, and rainfall) and sugarcane growth. Prior studies have largely focused on linear models, which fail to capture these complex interactions under climate variability. The Co86032 sugarcane variety was selected due to its agronomic importance, occupying more than 50% of plantation areas in Maharashtra. Its drought tolerance, resistance to smut disease, and high productivity make it an ideal subject for studying climate resilience strategies in sugarcane cultivation.

Understanding the effects of rising global temperatures and their impact is crucial for agricultural sustainability and planning. Precipitation patterns, as seen in scenarios like RCP4.5, are essential to predict how these changes will impact crop performance. This study examines how weather conditions affect the growth of the Co86032 sugarcane cultivar in Padegaon using the DSSAT model for analysis. Leveraging advanced techniques of machine learning (ML) like random forest (RF) algorithms has been vital in enhancing prediction accuracy and refining crop management strategies to adjust to shifting climate conditions. The Co86032 sugarcane variety has a significant economic and agronomic role, being the dominant cultivar, covering 53.62% of sugarcane plantations for over 20 years in Maharashtra. Its adaptability to drought and resistance to smut disease make it suitable for assessing resilience to climate change. Co86032 also excels in cane yield and Commercial Cane Sugar (CCS) production, which is influenced by temperature and water availability, key factors of the study. Therefore, the sugarcane cultivar Co86032 facilitates a focused investigation into genetic and environmental interactions crucial for developing climate-smart agricultural practices to maintain sustainable productivity amid climate challenges.

2. Literature Review

Advanced predictive analysis in agriculture, employing machine learning methods such as random forests (RF), has demonstrated strong performance in forecasting sugarcane yields, achieving accuracy rates of over 86% one year before harvest. These models handle intricate data patterns and multiple factors such as rainfall, temperature, and solar radiation, which are not necessarily linear or follow a specific order. Studies from the Tamil Nadu region reveal that C3 crops like rice and groundnut are more vulnerable to climate conditions, while C4 crops like sugarcane exhibit resilience. However, C4 crops are not immune to extremes like drought and elevated temperatures, which can reduce yield by 1.51%. Climate change and agricultural practices are projected to cause a potential yield reduction of 3.84% to 6.62% by 2100. To mitigate climate change impacts, Thiago Vizine Da Cruz & Ricardo Luiz Machado (2023)explored the importance of continued governmental support for advancing sugarcane cultivar development, which enhances yield, contributes to environmental sustainability, and aligns with the achievement of Sustainable Development Goals. These efforts are critical to avoiding stressful yield reductions in future climate scenarios.

Research by Everingham *et al*. (2016) and Jyoti *et al*. (2020) further indicates that sugarcane yields are highly sensitive to temperature and rainfall variations, emphasizing the importance of agricultural adaptations. Sugarcane cultivar Co 86032 (Nira), introduced in 1996, has been the dominant variety in Maharashtra for over two decades due to its high cane and Commercial Cane Sugar (CCS) yield, adaptability and resistance to smut and drought.

Despite the promising advancements in predictive agricultural models, several limitations remain that restrict their effectiveness. The DSSAT model relies heavily on linear relationships and static environmental assumptions, limiting its ability to capture non-linear environmental impacts, particularly those exacerbated by climate change, such as extreme events and rainfall variability (Kumar and Jain, 2021; Sonkar *et al*., 2019; Everingham *et al*., 2016). This approach can result in biased predictions as it treats climate variables independently and struggles to accommodate dynamic climate scenarios, such as those predicted under RCP 4.5 (Kumar and Jain, 2021). On the other hand, while RF models can effectively capture non-linear relationships, they pose challenges in interpretability, making it difficult for stakeholders to derive actionable insights (Everingham *et al*., 2016). Additionally, RF models demand extensive datasets, which may not always be available, and their computational complexity can act as a barrier for smaller research setups (Saunders *et al*., 2020).

Existing crop models like DSSAT struggle to accurately represent non-linear climate effects, such as extreme rainfall events, while Random Forest models, although powerful, face challenges in interpretability and data requirements (Saunders *et al*., 2020). This study integrates DSSAT with Random Forest to bridge these gaps, leveraging the strengths of both models to enhance predictive accuracy and provide actionable insights for agricultural decision-making.

Furthermore, both models individually tend to overlook the importance of genetic traits and crop-specific strategies, which are crucial for crops like sugarcane, given their complex physiological responses to environmental stressors (Patel & Wang, 2020; Liu & Thompson, 2020). This critique highlights the need for integrated modeling approaches that combine the strengths of machine learning insights with crop physiology. Cultivar-specific strategies, such as those focused on Co 86032, are essential to developing climate-smart agricultural practices that enhance resilience and sustainability amid climate variability.

3. Materials and methods

3.1. *Study area*

Padegaon station, located in the Satara district of Maharashtra, India (latitude 18º12' N and longitude 74º10' E, altitude 556 m above mean sea level), is an agrometeorological station (Fig. 1). The average annual temperatures at Padegaon station vary from 38.0°C to 9.6°C, with annual precipitation ranging from 400 to 517 mm, peaking between July and September. The sugarcane variety Co 86032, introduced in 1996 and covering53.62% of Maharashtra's sugarcane area by 2016-17, has significantly impacted the state’s economy, generating

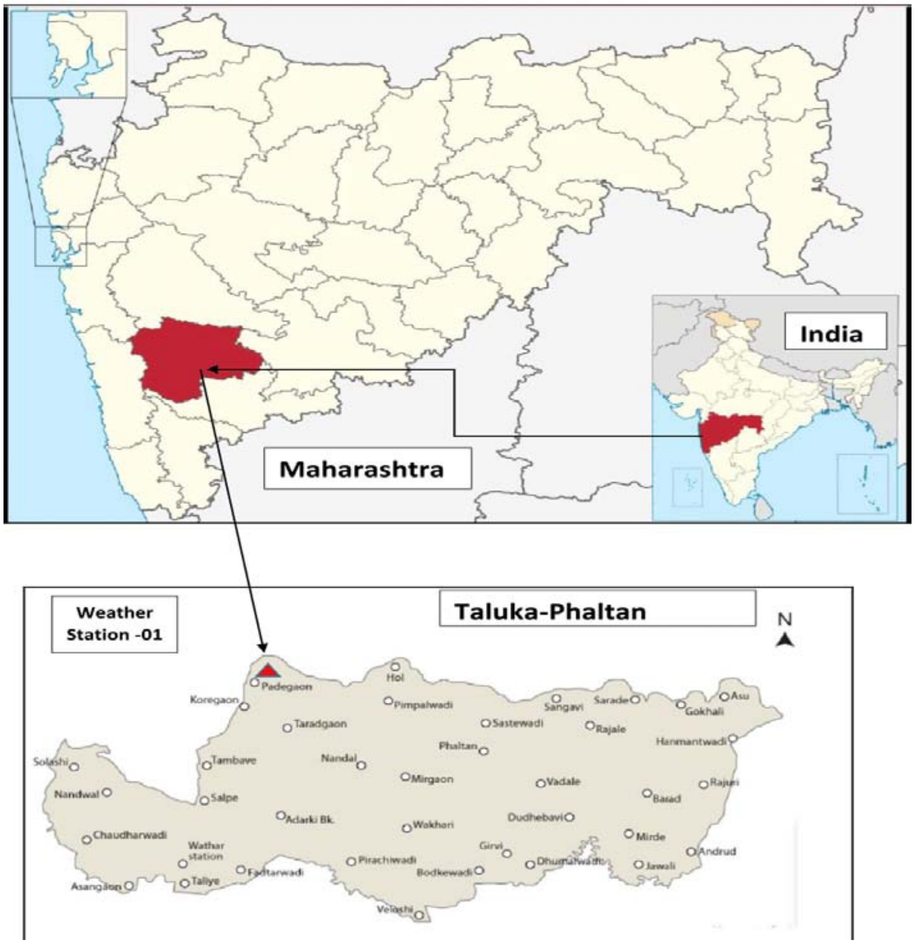


Fig. 1. Geographical location of the Central Sugarcane Research Centre, Padegaon, Maharashtra, India, and the Weather Station, Taluka-Phaltan, District-Satara

TABLE 1

Summary of soil and genetic input parameters

Soil Depth	Lower limit	Upper limit	Saturation	EXTR	INIT	Root DIST	Bulk density	pH	NO_3	NH_4	ORG-C
0-5	0.16	0.29	0.6	0.13	0.3	1	1.35	7.1	1.5	0.2	0.31
5-15	0.16	0.29	0.6	0.13	0.3	1	1.35	7.1	1.5	0.2	0.31
15-25	0.16	0.29	0.6	0.13	0.3	1	1.35	7.1	1.5	0.2	0.28
25-35	0.16	0.29	0.6	0.13	0.3	1	1.35	7.1	1.5	0.2	0.28
35-45	0.07	0.17	0.3	0.1	0.3	1	1.35	7.1	1.5	0.2	0.17
45-55	0.07	0.17	0.3	0.1	0.3	1	1.35	7.1	1.5	0.2	0.17
55-70	0.15	0.17	0.6	0.02	0.313	0.1	1.35	8.1	1.5	0.2	0.3
70-85	0.15	0.17	0.6	0.02	0.32	0.1	1.35	8.1	1.5	0.2	0.3
85-95	0.14	0.28	0.6	0.14	0.32	0.1	1.35	8.1	1.5	0.2	1.4
95-117	0.16	0.3	0.63	0.14	0.32	0.1	1.34	8.5	1.5	0.2	1.38
117-140	0.16	0.3	0.63	0.14	0.3	0.1	1.34	8.5	0.01	0.01	1.38

Soil Albedo : 0.09
Evaporation limit : 5.00
Min Factor : 1.00
Runoff curve : 84.00
Drainage rate : 0.25
FerlityFactor : 1.00
N-Fertilizer : 660kg/ha IN 4 Applications

TABLE 2

Genetic Coefficient of Sugarcane Crop Cultivar Co86032

Parameter	Description	Value
MaxPARCE	Maximum radiation conversion efficiency (g/MJ)	9.88
APFMX	Maximum fraction of dry mass to aerial dry mass (t/t)	0.93
STKPFMAX	Fraction of aerial dry mass to stalk at high temperatures (t/t)	0.78
SUCA	Maximum sucrose content in stalk base (t/t)	0.62
TBFT	Temperature for 50% maximum sucrose partitioning (°C)	26
Tthalfo	Thermal time to half canopy (°C days)	250
TBase	Base temperature for canopy development (°C days)	16
LFMAX	Maximum number of green leaves	12
MXLFAREA	Maximum leaf area for leaves above a certain count (cm²)	629
MXLFARNO	Leaf number above which leaf area is limited	15
PI1	Phyllocron interval for early leaf numbers (°C days)	94
PI2	Phyllocron interval for later leaf numbers (°C days)	199

₹905.08 crore in that year alone and over₹100,787 crore in 22 years. To enhance resilience under changing climate conditionsstrategies such as DSSAT simulations for optimized management, Random Forest models for predictive yield adjustments based on temperature and rainfall, and regression analysis to identify key climate impact factors are employed. This station encompasses 125.30 hectares of land, of which 94.14 hectares are under sugarcane cultivation. Located in a drought-prone area, the station sources irrigation from the Nira Right Bank Canal, two farm ponds (1.81 crore liters capacity), three wells, and five bore wells.

3.2. *Datasets*

The forecast model requires time-series weather data; therefore, daily weather data spanning from 1986–2021 and experimental data on the sugarcane crop for 2022 were obtained from the Central Sugarcane Research Station, Padegaon, Satara, Maharashtra, India. Further, the study has considered the projected data from 2024 to 2099, sourced from CMIP outputs. The choice of this extended period allows the analysis to capture both historical trends and future variability, providing a comprehensive understanding of long-term climate dynamics. Evaluating multiple decades ensures that transient climate phases, extreme events, and gradual shifts are considered, essential for crops like sugarcane with long growth cycles. Shorter periods may overlook critical trends or rare events, limiting the robustness of projections. In contrast, this extended period helps identify gradual patterns in temperature and rainfall changes, offering more reliable insights for long-term agricultural planning. It ensures the predictions are rooted in observed historical trends while applyingthem to future scenarios, supporting more informed decision-making for sustainable sugarcane management.

The RCP 4.5 scenario, a moderate emissions pathway, peaking by 2040 before delining reflects realistic climate mitigation strategies, balancing environmental relevant to agriculture (PLOS ONE, 2017) and economic considerations. This scenario allows for a nuanced understanding of future agricultural challenges and opportunities, balances between high-emission(RCP 8.5) and low-emission(RCP 2.6) pathways. This moderate scenario (RCP4.5) offers a practical basis for evaluating resilience strategies and is suited for climate change impact on sugarcane Co86032 in Maharashtra(Thompson & Patel, 2022).

3.3. *DSSAT v4.8 Crop Model*

The DSSAT model replicates crop growth, maturation, and nutrient cycles across diverse environmental settings. It monitors carbon, water, and nitrogen levels and tracks key growth stages. Fundamental data required by the model include meteorological weather data, soil data (Table 1), genetic coefficients (Table 2) and crop experimental details. The model was validated by Alocilja *et al*. (1987) and incorporates the Hargreaves-Samani equation to estimate daily solar radiation.

Genetic coefficients for the sugarcane cultivar Co 86032 were calibrated and validated at Navsari Agricultural University, Gujarat, as per the Research Accomplishments and Recommendations of 2019 (Table 2). The DSSAT model was utilized to assess the influence of climate factors on sugarcane growth, yield, and biomass production. DSSAT simulations for optimized management, Random Forest models for predictive yield adjustments based on temperature and rainfall, and regression analysis to identify key climate impact factors**.**

3.4. *Random Forest (RF) Model*

The Random Forest (RF) model is a widely used ensemble learning method known for its robustness and effectiveness in capturing complex, non-linear relationships in data. By constructing multiple decision trees and aggregating their predictions, RF enhances both accuracy and stability over single-tree models, making it particularly valuable in fields like agriculture, where data variability and intricate interactions between variables, such as climatic factors and crop responses, are prevalent (Everingham *et al*., 2016). Its significance lies in its adaptability to high-dimensional datasets and resilience to missing or noisy data, distinguishing it from other models like Support Vector Machines and Neural Networks. This reliability and versatility make RF a powerful tool for modeling agricultural systems, providing critical insights for decision-making under diverse environmental conditions. While RF excels in these areas, it also comes with specific limitations related to computational demands and interpretability. Furthermore, achieving optimal performance in RF requires careful tuning of hyperparameters to balance accuracy, efficiency, and complexity. The following sections explore these limitations and describe the hyperparameter tuning approach adopted to maximize the model's utility in predicting crop responses under varying climate conditions.

3.4.1. *Potential Limitations of the Random Forest (RF) Model*

The Random Forest (RF) model, while highly effective in capturing complex, non-linear relationships and minimizing overfitting through ensemble learning, does present some limitations. Firstly, RF is computationally intensive, especially when managing large datasets, which can challenge applications with limited computational resources (Everingham *et al*., 2016). Furthermore, the model's accuracy and stability are data-dependent; smaller or constrained datasets may reduce its predictive reliability. Additionally, although RF provides feature importance insights, its interpretability is lower than simpler models, potentially limiting the practical, actionable insights available for stakeholders (Hamilton *et al*., 2018). These factors underscore the importance of balancing model complexity with resource availability when deploying RF in data-intensive applications.

3.4.2. *Hyperparameter Tuning for Optimal RF Model Performance*

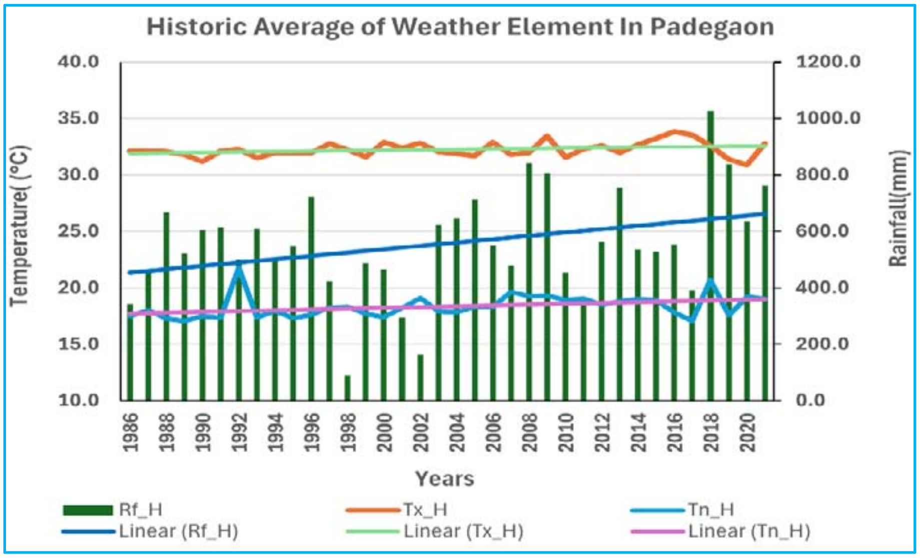
To enhance the RF model's predictive performance and efficiency, key hyperparameters were meticulously tuned. The number of estimators, representing the total trees in the ensemble, was optimized to prevent both underfitting (too few trees) and overfitting (too many trees). Adjusting tree depth further prevented excessive complexity, thereby improving model generalization. Parameters such as minimum samples per leaf ensured that each leaf contained a sufficient data volume, reinforcing predictive reliability. Additionally, bootstrap sampling introduced robustness by creating random subsets for each tree, reducing variance and improving stability. This tuning process, executed through grid search and cross-validation, provided an optimal balance between accuracy and computational efficiency, enabling the model to capture intricate interactions between temperature, rainfall, and sugarcane growth with high reliability (Saunders *et al*., 2020).

4. Results and discussions

4.1. *Integration of Climate & DSSAT Output Data, Statistical Analysis, and ML Techniques*

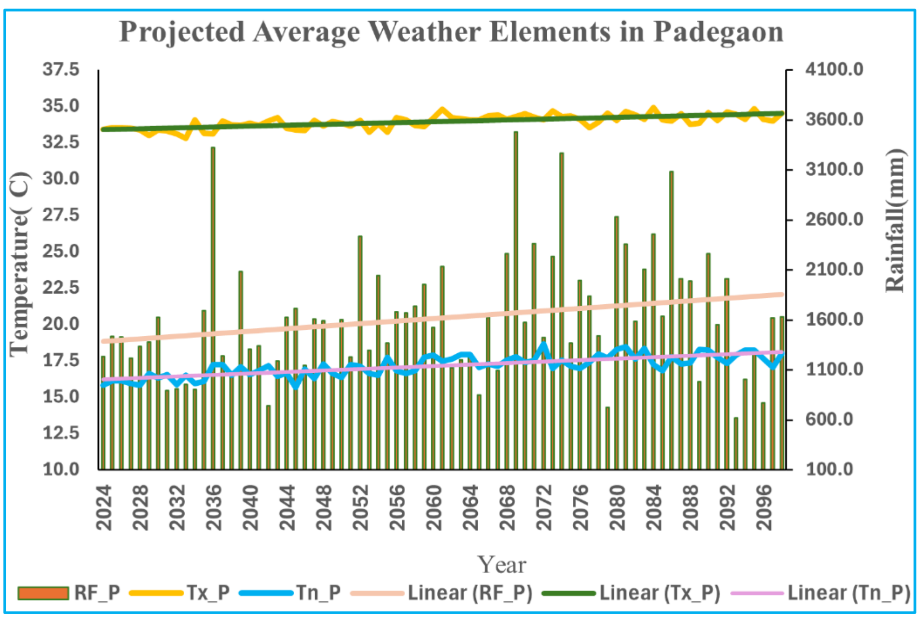
The study investigates the performance of sugarcane cultivar Co86032 under the RCP4.5 climate change scenario. It uses historical and projected data to propose strategies for enhancing productivity. Pearson correlation coefficient and regression analysis, along with machine learning techniques, provide insights into the relationship between climatic variables and sugarcane yield and growth pattern.

The present research primarily explores the influence of climatic factors on the sugarcane cultivar Co86032 via the review of historical and future research data. This study utilizes sophisticated modeling methods to evaluate the impact of temperature and precipitation on the growth, yield, and biomass output of sugarcane in different



Tx_Obs = 0.0187x + 31.892 R^2 = 0.0882   Tn_Obs = 0.0361x +17.676 R^2 = 0.1381   RF_Obs = 5.9716x + 446.8 R^2 = 0.112

Fig. 1. Mean annual Maximum & Minimum Temperature & Rainfall over Padegaon for Historic Period



Tx_Prj = 0.0149x + 33.382 R^2 = 0.4792   Tn_P = 0.0254x +16.19 R^2 = 0.58   RF_Prj = 6.3002x + 1381.2 R^2 = 0.0508

Fig. 2. Yearly average of Maximum & Minimum Temperature & Rainfall over Padegaon for Projected Period

climatic scenarios. Graph analysis in Fig. 1 depicts the mean values of temperatures & precipitation for Padegaon from 1986 to 2021. The observed trend line for Tx indicates a small rise in the highest recorded temperature during the historical timeframe and suggests significant fluctuation in historical recorded temperature data. 'Tn' also exhibits a little bit more rate of rise in comparison to the Tx, and suggests a more pronounced pattern of increasing minimum temperatures over time. An upward trend in rainfall is observed, still, low R^2 reflects the significant variability and fewer predictable variations in precipitation across the historical data. Although there are

TABLE 3

Pearson's Correlation Coefficient of Crop Variables for historic & Projections

Parameters for Pearson Correlation Coefficient (CC)	Historic	Projected
Sugarcane Yield & Maximum Temperature(Tx) in °C	0.035	0.397
Sugarcane Yield & Minimum Temperature(Tn) in °C	0.023	0.103
Sugarcane Yield & Rainfall (mm) in °C	0.016	0.160
Harvest index(HI) &Maximum Temperature(Tx) in °C	0.000	0.376**
Harvest index(HI) & Fresh cane yield (t/ha)	0.251***	0.796***
Harvest index(HI) & Stalk (millable) at harvest (t/ha)	0.36***	0.843***
Harvest index(HI) & Aerial dry at harvest (t/ha)	0.36***	0.843***
Harvest index(HI) & Sucrose of dry mass at harvest (t/ha)	0.627***	0.949***
Harvest index(HI) & Yield (kg/ha)	0.627***	0.95***
Emergence day (DAP) & Fresh cane yield (t/ha)	-0.366***	0.537***
Fresh cane yield (t/ha) & Stalk (millable) at harvest (t/ha)	0.993***	0.996***
Fresh cane yield (t/ha) & Aerial biomass at harvest (t/ha)	0.993***	0.996***
Fresh cane yield (t/ha) & Sucrose of dry mass (t/ha)	0.908***	0.937***
Fresh cane yield (t/ha) & Yield (kg/ha)	0.908***	0.937***
Stalk (millable) & Sucrose of dry mass at harvest (t/ha)	0.951***	0.963***
Stalk (millable) dry mass at harvest (t/ha) & Yield (kg/ha)	0.951***	0.963***
Aerial dry biomass at harvest (t/ha) & Sucrose of dry mass at harvest (t/ha)	1***	0.964***
Aerial dry biomass at harvest (t/ha) & Yield (kg/ha)	1***	0.963***

Table 3 Analysis reveals an increase in the sensitivity of sugarcane yield and growth parameters to temperature changes in future projections, highlighting the growing impact of climate change

noticeable increasing patterns in temperature, and a more pronounced variability as well as the uncertain trend found for rainfall over Padegaon.

4.2. *Assessing Climate Effects on Sugarcane: Historical & Future Projections*

Fig. 2 displays the projected (2024-2099) climate data (Tx, Tn &Rf) forPadegaon, spanning the years from 2024-2099. In comparison to past patterns, the Tx exhibits a more significant rise and a larger R^2 signifies a more robust and steady upward trend, which reflects a more imminent future warming. Furthermore, there is a substantial increase in the Tn with greater R^2 emphasizing a more evident and consistent pattern of rising of projected Tn under RCP4.5 scenarios. Estimated rainfall indicated a significant rise, but the relatively low R^2 value implies variability in projected rainfall patterns will likely continue and unpredictable. Overall, the projected data suggests a stronger and more consistent pattern of rising temperatures and a highly variable rainfall pattern.

Table 3 has detailed Pearson's correlation coefficients for sugarcane crop variables. This reveals a significant shift from weak historical correlations to stronger future correlations. For instance, while historical data showed weak correlations between sugarcane yield and Tx (0.035) or Tn (0.023), future projections indicate a moderate positive correlation with Tx (0.397) and increased sensitivity in other variables such as harvest index and fresh cane yield. The findings highlight a notable increase in the sensitivity of sugarcane growth parameters to temperature changes under future climate scenarios. This shift underscores the growing impact of climate change on sugarcane and necessitates integrated predictive models like DSSAT and Random Forest for

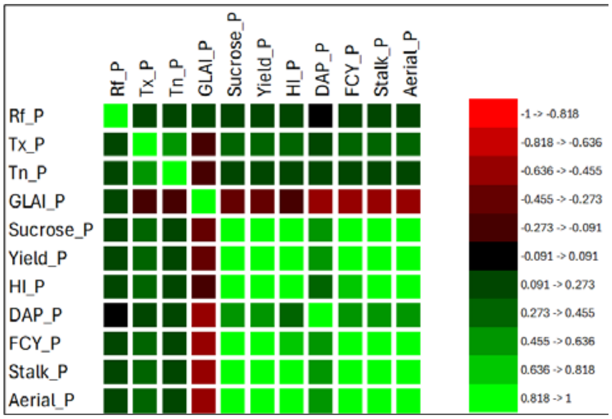


Fig. 4. Projected correlation heat map showing relationships between future climate variables and sugarcane crop parameters

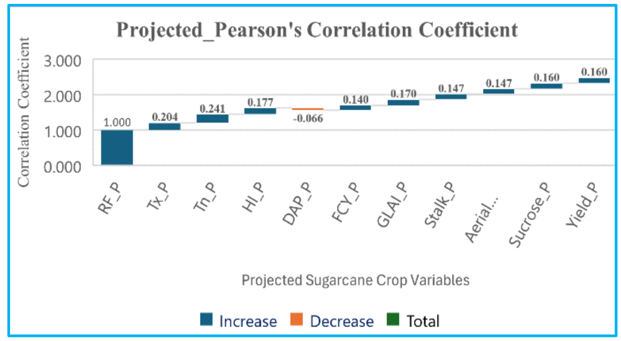


Fig. 6. Projected Pearson's correlation coefficient shows the strength of the relationship between projected climate variables and sugarcane crop parameters

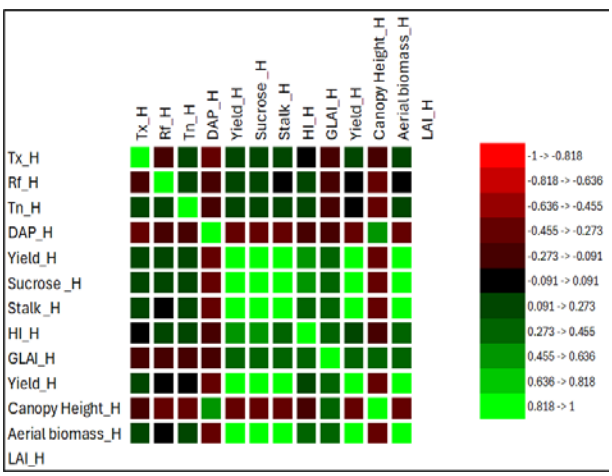


Fig. 5. Historical correlation heat map illustrating relationships between past climate variables &sugarcane crop parameters

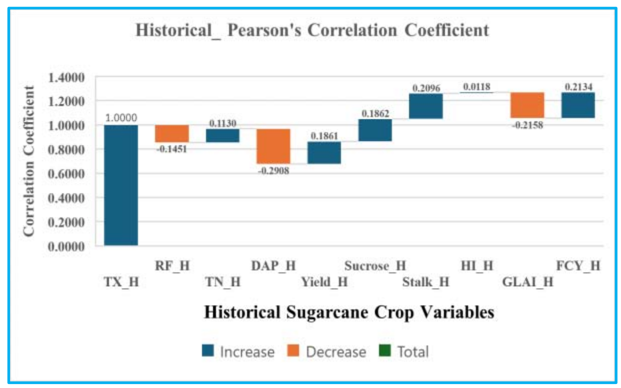


Fig. 7. Historical Pearson's correlation coefficient shows the strength of the relationship between projected climate variables and sugarcane crop parameters

crop performance forecasts. Genetic traits, especially sucrose content, are crucial for developing climate-resilient cultivars.

4.3. *Regression Analysis of Maximum Temperature (Tx) (°C)*

Table 3 & Figs. 4 to 7 depicted the study of Pearson correlation coefficients for the analysis of climate factors on the Co86032 sugarcane cultivar in Padegaon for historical &projected data. The assessment of Tx effect on sugarcane crop parameters revealed sucrose dry mass (0.483, p=0.001), aerial dry biomass (1.212, p=0.001), sugarcane yield (482.8, p=0.001), and stalk dry mass (0.944, p=0.001) showed highly significant positive relationships with Tx. This finding suggested that higher temperatures are beneficial to boost sucrose content and biomass production, *i.e.*, the overall yield of sugarcane. The positive coefficients shown suggest a substantial increase in these parameters with Tx increment. However, Tx has a non-significant and weak negative relationship with green leaf area (-0.16, p=0.488), and harvest index (-0.001, p=0.977) showed Tx variation not affected significantly by leaf area and efficiency of biomass conversion into harvestable yield. Thus, the sucrose, aerial dry biomass, sugarcane yield, and stalk dry mass growth are highly responsive to Tx changes, while leaf area and harvest index may require additional factors to be influenced.

4.4. *Regression Analysis of Minimum Temperature (Tn) (°C)*

A distinct picture of Tn showed where most of the sugarcane growth parameters have non-significant and weak correlation such as green leaf area (0.036, p=0.828), harvest index (0.021, p=0.140), sugarcane yield (-94.1, p=0.370), sucrose dry mass (-0.09, p=0.376), aerial dry biomass (-0.15, p=0.564) and stalk dry mass (-0.11, p=0.569). This implied that Tn has not significantly influenced these crop parameters. It also revealed that Tn has less sensitivity to sugarcane growth and productivity, the crop may already be functioning under an ideal Tn range. Thus, it can be concluded that Tx plays an important role in sugarcane development whereas Tn might not be a limiting factor in the observed climatic conditions.

4.5. *Regression Analysis of Rainfall (mm)*

Rainfall's impact on sugarcane parameters provided mixed results, i.e., green leaf area (0.0, p=0.03) showed a significant positive relationship with rainfall. This suggested that increased precipitation enhances the leaf area important for photosynthesis and overall plant health. However, other parameters like harvest index (0.0, p=0.65), sucrose dry mass (0.0, p=0.337), aerial dry biomass (0.0, p=0.41), and stalk dry mass (0.0, p=0.409) showed non-significant correlations with rainfall. Moreover, the interaction effects of rainfall with Tx & Tn on the harvest index are also weak and have no significant impact on its efficiency measures. Rainfall's impact on sugarcane growth is limited and may be attributed to several agronomic and environmental factors. Table 3, revealed that the sugarcane growth parameters (yield, biomass accumulation, and sucrose content) havea stronger temperature dependence (R^2 = 0.188 for maximum temperature) than on rainfall (R^2 = 0.0508), likely due to high precipitation variability over Padegaon. Further, the crop's ability to utilize stored soil moisture and deep root systems, along with, irrigation infrastructure (canal-fed systems and farm ponds of Padegaon), mitigates the impact of rainfall deficits. This finding is consistent with Everingham *et al.* (2016), who found that supplementary irrigation decouples rainfall from yield outcomes in sugarcane systems. Moreover, seasonal rainfall variability does not always align with critical growth stages like germination or sucrose accumulation, further diminishing its effect on productivity. Tmax plays a more dominant role in regulating key physiological processes such as photosynthesis and sucrose partitioning (Thompson & Patel, 2022), while positive correlation between rainfall and green leaf area (p = 0.03) with other agronomic traits, including biomass, harvest index, remained unaffected. Thus, sugarcane yield shows a stronger response to temperature-driven processes than to rainfall variability. This indicated the importance of temperature management strategies, alongwithoptimized irrigation practices for sugarcane yield stability under future climate scenarios. Further, sugarcane yield's lower correlation with rainfall suggests that it may be overshadowed by other climatic factors like temperature and soil moisture content, emphasizing the need for integrated management.

4.6. *Baseline/Intercept of Sugarcane Parameters*

The baseline values of sugarcane crop parameters showed a strong inherent capacity for leaf area(27.6) development without environmental stresses. However, intercepts for harvest index, sucrose dry mass, aerial dry biomass, and sugarcane yield are non-significant i.e. not strongly inherent in climatic factors. The regression models based on p-values explained moderate variability in these traits, highlighting the importance of understanding climatic variables on sugarcane growth. The study revealed that temperature, rainfall, and crop physiology significantly influence sugarcane growth parameters like sucrose content, biomass, and yield, highlighting the need for targeted agricultural practices to optimize productivity under changing conditions. The baseline values indicate a strong inherent potential for leaf area development, but other growth parameters rely heavily on climatic factors. Based on Table 3, Figs. 4 to 7, the subsequent sections have thoroughly examined key sugarcane growth and development parameters, examining their role in the overall growth cycle and their response to varying climatic conditions.

4.7. *Analysis of Sugarcane Growth Parameters*

4.7.1. *Harvest Index (HI) Relationships*

(*i*) Correlation between Tx and the Harvest Index (HI) shows a moderate positive correlation with temperature (r = 0.376**), suggesting that warmer temperatures up to a certain point help sugarcane reach physiological maturity faster and may boost sucrose accumulation. Therefore, it would be beneficial to develop a sugarcane genotype that can efficiently convert biomass under various temperature conditions. This trend is expected to become even more significant by 2099, suggesting a growing sensitivity to rising temperatures or possible changes in growth stages. This finding aligns with observations from Kumar and Lee (2021), who reported similar resilience traits in sugarcane.

(*ii*) *The Harvest Index (HI)* shows strong connections with the yield of fresh cane. yield (historical: r = 0.251***; projected: r = 0.796***), stalk dry mass (historical: r = 0.36***; projected: r = 0.843***), and aerial dry biomass (historical: r = 0.36***; projected: r = 0.843***). This highlights how climate significantly affects yield and biomass distribution, with projected data suggesting a potential increase in these effects due to more severe climate variations. This aligns with Smith and Jones's (2019) discussion on how climate affects the distribution of biomass in sugarcane, emphasizing the impact of climatic variability on agricultural practices.

(*iii*) *Rainfall Dynamics* : Fresh cane yield and its related metrics such as stalk dry mass and aerial biomass consistently showed significant positive correlations with rainfall. These strong correlations underscore the importance of adequate water availability for optimal growth and yield of sugarcane.

4.7.2. *Yield and Sucrose Content*

(*i*) Yield and Sucrose Relationships: Both historical and projected correlations between yield and sucrose content are notably high. These results highlight the significant impact of climatic factors on sugar accumulation and overall productivity, reinforcing the need for sugarcane breeding programs to enhance sucrose yield traits in response to anticipated climatic stresses, aligning with studies by Patel and Wang (2020) which highlighted the impact of climate on crop health and vigor.

4.7.3. *Emergence Day and Yield*

In the past, early sprouting has been linked to higher fresh cane yield, suggesting that sprouting sooner leads to better yield. negative correlation between early emergence and fresh cane yield (r = -0.366***) is expected to continue, though with less strength. In the past, early sprouting has been linked to higher fresh cane yield suggesting that sprouting sooner leads to better yield. This trend is expected to continue, though with less strength (r = 0.537***), as conditions change. This information guides the adjustment of planting practices to adapt to changing climate conditions.

4.8. Regression Analysis of Future Projections

4.8.1. *Projected Sugarcane Yield Dynamics*

Table 3 shows the DSSAT model projected (2024-2098) sugarcane yield parameter under the RCP4.5 scenario revealing that Tx is the most vital climate driver, influencing yield variability significantly. The model's R^2 value of 0.188 indicated that 19% of the yield variability could be explained by the climatic variables. The accumulation of stalk biomass and aerial dry biomass is notably affected by Tx, highlighting the need for effective thermal management to enhance sugarcane's physiological reactions. Sucrose content is a vital factor for yield, mainly influenced by Tx. This underscores the importance of temperature control in improving sugar production, highlighting how sensitive sugarcane yield is to temperature stress and how temperature impacts physiological responses in the crop. While annual rainfall projections and Tn have lower statistical significance, their interconnected effects indicate a complex, multifaceted influence on yield results, warranting further investigation with advanced models incorporating interactive and nonlinear dynamics. These findings are consistent with the literature of Everingham *et al.* (2016) and Sonkar *et al*. (2019), who identified sucrose content as a dominant factor in yield prediction and emphasized improving sugarcane's sucrose content and biomass production to maintain yield stability and quality under changing climate.

4.8.1.1. *Temperature-Rainfall Interactions and Their Impact on Sugarcane Growth*

The interaction between maximum temperature (Tx) and rainfall exhibits non-linear impacts on sugarcane growth, significantly affecting parameters like biomass, sucrose content, and harvest index. Regression analysis indicates that Tx independently has a strong influence on sucrose content, biomass, and yield ($p = 0.001$), while rainfall shows weaker or non-significant correlations across several growths. Periods of high Tx combined with limited rainfall exacerbate drought stress, reducing photosynthetic efficiency and biomass accumulation (Mehdi *et al*., 2024). In contrast, high temperatures accompanied by adequate rainfall during active vegetative phases promote optimal growth by accelerating metabolic processes and enhancing water-use efficiency as corroborated by Mehdi *et al*. (2024). However, excessive rainfall during high-temperature periods can result in water logging, impairing root oxygenation and nutrient uptake, leading to yield reductions (Everingham *et al*., 2016).

The study also highlights that rainfall has a positive but limited impact on the Green Leaf Area Index (GLAI), which supports photosynthesis and plant health. However, the benefits of rainfall are reduced under extreme heat, which impairs stomatal conductance and reduces leaf turgor Mehdi *et al*. (2024). Moreover, rainfall during cooler periods (Tn) shows negligible influence on crop outcomes, indicating that sugarcane benefits most when rainfall aligns with moderate heat stress conditions.

4.8.1.2. *Strategic Implications*

The interaction between temperature and rainfall is critical for aligning irrigation practices with temperature fluctuations to enhance yield stability. Precision irrigation systems can prevent water stress during heatwaves, ensuring crop resilience under high-temperature conditions (Sonkar *et al*., 2019). The results emphasize the need for integrated water management systems that optimize irrigation to align with climatic conditions, especially during critical growth phases. Policymakers should focus on expanding irrigation infrastructure and promoting real-time weather data usage for effective irrigation scheduling to mitigate the combined stress of heat and moisture deficits (Patel & Wang, 2020).

In summary, the complex interplay between Tx and rainfall requires adaptive strategies for sugarcane cultivation, integrating climate-resilient management practices to mitigate risks from both drought and waterlogging. Managing these climatic interactions effectively will be essential to sustaining sugarcane productivity under future climate scenario.

4.8.2. *Projected Sugarcane Stalk Biomass Dynamics*

The regression analysis stated in Table 3 for sugarcane stalk dry mass revealed a noticeable dependency on climatic variables, with maximum temperature exerting the most significant influence. This correlation underscores the critical role of temperature extremes in affecting sugarcane's metabolic and growth patterns. The minimal impact from other variables like rainfall and minimum temperature suggests that unmodeled factors may obscure their effects, highlighting the necessity for a comprehensive analysis to fully capture climate impacts on biomass growth. This finding is supported by Sanghera G.S. (2020) who explains how temperature affects sugarcane growth and changes physiological and metabolic responses in the crop.

4.8.3. *Projected Aerial Dry Biomass Dynamics*

The analysis shows that Tx significantly affects the aerial dry biomass. This accounts for 19% of the variance, indicating the crucial influence of thermal conditions on the physiological and morphological traits of sugarcane. These conditions impact photosynthesis and growth duration. The minimal impact of other climatic factors underscores the dominant role of temperature, underscoring the need for climate-adapted strategies in sugarcane cultivation. This discovery is consistent with the research by Henderson, A., Yong (2023), Anderson, L. and Ng, (2021), who investigated the impact of thermal conditions on sugarcane biomass productivity. This study also confirms a comparable outcome and elaborates on the effects of high temperatures on crop biomass and productivity, recommending adaptive strategies.

4.8.4. *Projected Sucrose Production Dynamics*

Sucrose content directly impacts the economy of the crop. The analysis shows that temperature plays a crucial role in increasing sucrose levels in sugarcane, which is important for optimizing sugar production. However, the limited effects of rainfall and Tn indicate the necessity for more advanced modeling techniques to understand how climate affects sucrose content. These findings are supported by Brooks, C. & Chen, Y. (2023), who studied the impact of temperature variation on sugarcane metabolism. These findings emphasize temperature management in agricultural practices and directly impact the economy.

4.8.5. *Projected Rainfall & Green Leaf Area (GLA) Dynamics*

The projected rainfall analysis identified rainfall as the primary factor influencing the Green Leaf Area Index (GLAI), accounting for 15% of the variance. This emphasizes the crucial role of efficient water management in supporting leaf growth and photosynthesis, vital for preserving plant health in changing climatic conditions. This result aligns with Morris and Liu's (2022) research on water availability's effect on leaf morphology revealed rainfall's impact on GLAI. The study provides insights into adaptive strategies for crop resilience under climate variability.

4.8.6. *Projected Harvest Index (HI) Dynamics*

Table 4 shows the result of the analysis of climatic factors using the RF model, including nocturnal temperatures and rainfall interactions, which have a moderate influence (22%) on the Harvest Index, impacting biomass distribution. This finding is consistent with the research by Reynolds and Patel (2024), which explores how various climatic factors interact to impact crop maturity and biomass distribution, highlighting the challenges of managing climatic conditions for better harvest results. This underscores the necessity of carefully managing temperature and water conditions to enhance crop maturity and yield in different environmental settings.

4.9. *Genetic and Climatic Drivers of Sugarcane Yield : Random Forest Insights*

Random Forest (RF) model analysis for the historical (1986 to 2021) and projected period (2024-2099) under the RCP4.5 scenario emphasized the significant influence of genetic traits on sugarcane yield and quality compared to climatic factors. The analysis during the historical period demonstrated considerable variability, in a Mean Squared Error (MSE) of 1,563,890.96, highlighting the substantial impact of sucrose accumulation on yield optimization. During this time, "Sucrose of dry mass at harvest" was identified as the most important predictor, with an importance score of 0.576, aligning with Saunders *et al*. (2020) emphasis on sucrose content in precision

TABLE 4

Performance output parameter of RF Model

Names of RF-Model output	Historic Output	Projected Output
Mean Squared Error	1563891	883.0246133
Year	0.0014049	0.001131915
Maximum Temperature	0.0035333	0.001025868
Rainfall	0.0040755	0.002987109
Minimum Temperature	0.0026575	0.005027118
Emergence day(DAP)	0.0074482	0.002355584
Sucrose of drymass at harvest(t/ha	0.576467	0.754194866
Stalk millable dry mass at harvest(t/ha)	0.1737185	0.057005973
Harvest index at maturity	0.0034282	0.032228848
Green LAI	0.0079228	0.000805636
Fresh cane yield(t/ha)	0.0501957	0.033351198
Aerial dry biomass at harvest(t/ha)	0.1651515	0.109885886
Canopy height(m)	0.0039969	-

agriculture models. Moreover, the significant roles of "Stalk (millable) dry mass at harvest" and "Aerial dry biomass at harvest" in crop performance, scored 0.174 and 0.165 respectively, aligning with Johnson E., *et al*. (2019) study, where biomass characteristics as critical determinants of sugarcane productivity have been highlighted.

In contrast, the projected data analysis for the 2024-2099 period revealed a marked improvement in model accuracy, indicated by a reduced MSE of 883.02. This phase of the analysis reaffirmed the critical role of the "amount of sugar obtained from the harvested crop," which exhibited an increased importance score of 0.754 may be attributed to genetic traits that influence the crop performance rather than climatic factors. This attribution is denoted in the research study of Liu *et al.* (2021). However, the reduction in importance scores for characteristics related to plant size, and structure suggests a strategic shift in plant resource allocation, favoring sucrose production over biomass accumulation under projected climatic stresses. The analysis recommends prioritizing genetic enhancements and improved farming practices to optimize sugarcane yield in upcoming climate conditions. This approach enhances specific features of the crop, particularly sucrose content, and ensures sustainability and productivity.

5.9.1. *Projected Sugarcane Yield Performance Using A Random Forest Perspective*

This analysis compares the influences of intrinsic crop traits and climatic variables on sugarcane yield through Random Forest models for historical (1986-2021) and future (2024-2099) periods. "Sucrose of dry mass at harvest" emerges as the most significant yield predictor in both periods, with its importance increasing in the future model from 0.576 to 0.754, indicating heightened sensitivity to sucrose accumulation under future climatic stress (Liu and Thompson, 2020). The analysis shows a significant enhancement in model accuracy, with the Mean Squared Error (MSE) decreasing from 1,563,890.96 in the past to 883.02 in the future, indicating improved predictive performance under the RCP4.5 scenario.

While intrinsic crop traits like sucrose content and aerial dry biomass remain dominant in yield determination, climatic factors (temperature &rainfall) exhibit a slight increase in importance in the future model. Specifically, Tn increased from 0.003 in the historical period to 0.005 in the future period and rainfall from 0.004 to 0.003. This trend suggests that while still secondary, the impact of climatic variables might become more pronounced due to the evolving climate conditions. Notably, "Fresh cane yield" and "Harvest index at maturity" gain is significant in the future, hence expanding their importance in yield prediction amidst climate shifts.

Johnson, T. & Lee, A. (2021) discuss the resilience of sugarcane to moderate climatic shifts, yet the expected increase in climatic extremes could challenge this resilience, highlighting the necessity for robust adaptive cultivation strategies. The analysis emphasizes the importance of improving crop management techniques and implementing focused breeding initiatives to enhance sugarcane productivity amidst various environmental obstacles.

5. Adaptation & Mitigation Strategies

Research conducted by an agrometeorologist focuses on the resilience of sugarcane to changing climate conditions, underlining the crucial role of advancements in agronomy and genetic improvements. The research highlights the critical need for strategic development to improve essential crop traits such as sucrose content and biomass, pivotal for yield optimization under improved adaptive management strategies. Integrating sophisticated predictive models, like random forests, with traditional crop modeling techniques, refines resilience predictions and strengthens crop management strategies. The research particularly highlights the significance of prioritizing the trait "sucrose of dry mass at harvest" in sugarcane breeding programs and management strategies, to improve productivity under climate stress. Additionally, it calls for further research to develop cultivars specifically optimized for these critical traits. The study also, predicts a heightened influence of climate changes on sugarcane farming, emphasizing the urgent need for comprehensive management approaches due to the anticipated rise in extreme weather events. These strategies focused on optimizing genotypes for stress resilience, refining planting schedules to align with climatic changes, and enhancing water management practices to mitigate risks. This viewpoint is consistent with the perspectives shared by Singh and Patel (2019), who advocate for integrating these methods to enhance sugarcane production sustainability amidst climate variations.

This study underscores the importance of integrating agronomic and genetic innovations with region-specific adaption strategies to sustainably boost sugarcane production. Customized strategies, encompassing effective water management, optimum planting timelines, and focused crop protection, are crucial to tackle the distinct problems of drought-prone and humid regions. These solutions synchronize agricultural operations with distinct regional climatic circumstances, guaranteeing resilience and productivity in fluctuating environments. The practical consequences for farmers and policymakers underscore the necessity of adapting these tactics to various climatic zones, promoting climate-smart agricultural practices in sugarcane growing.

5.1. *Region-Specific Adaptation Strategies for Sugarcane Cultivation*

In drought-prone regions like Padegaon, where water scarcity and high evapotranspiration rates challenge productivity, adaptation strategies must focus on efficient water management (optimizing water use) and drought resilience. This includes implementing drip irrigation systems, which reduce water usage while enhancing soil moisture for sugarcane growth and rainwater harvesting techniques, which collect and store seasonal rainfall for use during dry spells. Cultivating drought-tolerant varieties such as Co86032 can further sustain productivity, as these are adapted to thrive under limited water availability.

For coastal and humid regions like Dapoli in Ratnagiri, high humidity and variable rainfall pose risks of fungal diseases and waterlogging. Disease-resistant cultivars can help mitigate the impact of humidity-induced pathogens, while improved drainage systems are essential to prevent water logging during heavy rains. Integrated pest management (IPM) strategies also play a critical role in controlling the spread of pests and diseases in these conditions.

In semi-arid regions, where conservation of soil moisture is crucial, soil moisture monitoring systems provide real-time data that allow for precise irrigation scheduling, ensuring water is applied only when necessary. This practice conserves resources and supports crop resilience during dry periods. Additionally, planting cover crops can help retain soil moisture and reduce evaporation rates.

5.2. *Integrated Practical Implications for Farmers and Policymakers*

Based on the result & discussion analysis, some integrated practical implicationsthat would benefit farmers and policymakers in the optimization of sugarcane yield amidst climatic variability are stated as follows:

5.2.1. *Practical Implications for Farmers*

(a) *Temperature Management*

(*i*) Adopt mulching techniques to reduce soil temperature and improve moisture retention.

(*ii*) Promote intercropping with shade-giving crops to manage heat stress on young plants.

(*iii*) Use drip irrigation to improve water-use efficiency, especially during periods of high maximum temperature (Tmax).

(*iv*) Maintain canal-fed systems and farm ponds to supplement water availability during dry spells.

(b) *Optimized Green Leaf Area Maintenance*

(*i*) Use foliar sprays and nutrient management to promote healthy leaf growth and boost photosynthesis, even during suboptimal rainfall conditions.

(*ii*) Implement rainwater harvesting to capture rainfall during key vegetative phases and enhance leaf area for better plant health.

(c) *Synchronized Planting and Management Practices*

(*i*) Adjust planting schedules to align with projected rainfall patterns and Tmax conditions for improved yields.

(*ii*) Use crop simulation models (e.g., DSSAT) to determine optimal planting windows based on forecasted climate scenarios.

(d) *Transitional Zones*

(*i*) Adopt diversified cropping systems with shorter-duration crops to reduce the risks of sugarcane monocropping.

(*ii*) Develop climate-resilient cropping calendars using long-term forecasts to better plan planting and harvesting activities.

(e) *Hilly Regions and Plateaus*

(*i*) Extend diversified cropping strategies to mitigate risks from erratic weather conditions.

(*ii*) Leverage predictive models to maintain stable yields by adjusting farming practices based on changing climatic conditions.

(f) *Urban and Peri-Urban Areas*

(*i*) Explore vertical farming, hydroponics and aeroponics to optimize space and water use while increasing productivity.

(*ii*) Establish greenhouse-based sugarcane nurseries to supply climate-resilient planting material and ensure sustainable urban agricultural production.

(*iii*) Promote local production to reduce dependency on external supply chains and minimize disruption risks.

(g) *Arid and Semi-Arid Zones*

(*i*) Focus on water-saving technologies like drip irrigation and rainwater harvesting to manage water scarcity.

(*ii*) Cultivate drought-tolerant sugarcane varieties to cope with limited rainfall and extreme heat.

(h) *Coastal Regions*

(*i*) Strengthen disease management practices to address challenges posed by humid conditions.

(*ii*) Implement water control measures to prevent waterlogging and maintain healthy crop growth.

5.2.2. *Recommendations for Policymakers*

(a) Incentives for Irrigation Infrastructure

(*i*) Develop policies to support canal-fed systems, farm ponds, and rainwater harvesting structures to ensure water availability during dry periods.

(*ii*) Provide subsidies for drip irrigation systems to encourage efficient water management practices.

(b) *Support Predictive Modeling and Data-Driven Agriculture*

(*i*) Create region-specific advisory services that offer tailored planting schedules and irrigation guidelines based on local Tmax and rainfall patterns.

(c) *Develop Climate-Smart Urban Agriculture*

(*i*) Encourage urban and peri-urban agriculture through policies promoting vertical farming, hydroponics, and aeroponics.

(*ii*) Provide subsidies and grants for the establishment of greenhouse-based nurseries to supply climate-resilient planting material.

(d) *Invest in Water-Saving Technologies and Drought-Resilient Crops*

(*i*) Facilitate the adoption of drip irrigation and rainwater harvesting systems, especially in arid and semi-arid regions.

(*ii*) Support breeding programs for the development and distribution of drought-tolerant sugarcane varieties.

(e) *Enhance Disease Management in Coastal Areas*

(*i*) Implement disease surveillance and early warning systems to help farmers combat the impacts of pests and diseases in coastal regions.

(*ii*) Provide training programs to improve water management practices and reduce the risks associated with waterlogging.

(f) Training Programs for Climate-Smart Agriculture

5.3. *Adaptation Strategies for Different Climatic Zones*

To apply these strategies effectively across varied climatic zones, it is essential to tailor practices to local conditions. In arid and semi-arid zones, expanding rainwater harvesting infrastructure can provide a sustainable water source, while promoting the use of drought-tolerant varieties helps ensure productivity under extreme temperatures. Additionally, soil moisture monitoring systems should be widely adopted to optimize water use efficiency in these water-scarce areas.

In coastal regions, where frequent heavy rainfall and high humidity are common, implementing IPM strategies and drainage infrastructure will reduce the risk of crop loss from fungal outbreaks and water logging. Policymakers can support farmers by providing resources and training on effective drainage management and pest control methods specific to humid environments.

For regions with transitional climates, where weather patterns are less predictable, adopting diversified cropping systems can mitigate risks associated with monoculture farming. Predictive models, such as DSSAT or Random Forest-based tools, can be utilized to forecast climate patterns and guide planting schedules and water management, enhancing resilience in regions with fluctuating climatic conditions.

6. Conclusion

This study on sugarcane cultivar Co86032 concludes that climatic factors significantly influence yield outcomes under both historical and projected scenarios. It emphasizes the importance of sucrose content as a key trait for productivity, advocating for targeted breeding programs to enhance this trait and boost yields. The findings call for an integrated approach to sugarcane agriculture, combining advanced genetic research, precision agriculture technologies and climate-resilient farming practices to ensure sustainability. Importantly, the research highlights that intrinsic crop characteristics, such as sucrose content and biomass productivity, have a greater impact on yield than weather conditions alone. This underscores the need for continuous future research to enhance these traits and develop adaptable farming practices in response to changing climates.

Future researchshould focus on integrating real-time data from IoT devices with crop models to enable dynamic irrigation scheduling and pest control. Additionally, ensemble machine learning models, such as XGBoost and LSTM, can improve yield predictions by capturing temporal patterns. Policymakers must support the adoption of these technologies through subsidies and training programs to ensure sustainable agricultural practices.

In addition, integrating advanced machine learning models, such as GBM, LSTM, and XGBoost, with real-time data offers significant potential for improving sugarcane yield predictions and crop management. These models capture non-linear relationships and temporal patterns, enabling precise forecasts. Ensemble models further enhance predictive accuracy and support adaptive practices under changing climatic conditions (Everingham *et al*., 2016). IoT-based sensors and remote sensing platforms provide continuous environmental inputs, enhancing the responsiveness of crop models like DSSAT for better irrigation planning and yield forecasting (Reynolds & Patel, 2024).

Incorporating genomic data into crop models aids the identification of heat- and drought-tolerant traits, promoting the development of climate-resilient sugarcane cultivars. Collaborative public-private breeding programs will accelerate the availability of these improved varieties (Liu *et al*., 2021). Scenario-based simulations using pathways like RCP 2.6 and RCP 6.0 offer vital insights for assessing climate risks and guiding adaptive policies, such as early sowing and crop insurance schemes (Kumar & Lee, 2021).

Precision agriculture technologies, such as automated irrigation, drones, and spatial analytics, play a crucial role in optimizing resources and boosting productivity, while early warning systems enable proactive responses to extreme weather, enhancing resilience in vulnerable areas. By integrating agricultural, environmental, and economic data, these innovations support sustainable crop management and food security.

6.1. *Strengthen the Link to Policy Recommendations for Practical Impact*

Promote Advanced Technology Adoption : Policies should actively support the use of adaptive agricultural technologies, ensuring farmers and stakeholders have access to tools that enable resource-efficient practices amid climate variability.

Encourage Innovation for Resilience : Effective policies are crucial to advancing innovations that improve productivity and resilience in sugarcane agriculture, including:

(*i*) Drought-resistant cultivars,

(*ii*) Water-saving technologies (*e.g*., drip irrigation, rainwater harvesting),

(*iii*) Predictive modeling tools such as Random Forest and DSSAT for data-driven decisions on region-specific planting and irrigation schedules.

Government Incentives and Partnerships

(*i*) Targeted incentives for adopting IoT and remote sensing technologies are essential.

(*ii*) Public-private partnerships can further genomic research, supporting the development of resilient crop varieties.

Region-Specific Advisory Services : Establish localized advisory services to guide farmers on:

(*i*) Temperature regulation,
(*ii*) Pest management,
(*iii*) Water resource optimization tailored to specific climatic zones.

Capacity Building through Training : Invest in training programs focused on:

(*i*) Precision agriculture techniques,

(*ii*) Integrated pest management (IPM),

(*iii*) Real-time disease monitoring to strengthen adaptive capacities.

Scenario-Based Policy Approach : Implement policies rooted in scenario-based planning, with emphasis on:

(*i*) Crop insurance,

(*ii*) Adaptive water management programs to enhance long-term resilience.

Align Research with Actionable Policies : Bridging research with targeted policy actions fosters sustainable resource use and productivity in sugarcane farming, enhancing the practical impact of climate adaptation as conditions evolve.

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Author's contribution

ShahenazMulla : Investigation, Methodology, Conceptualization, writing original draft and writing review and editing, Formal analysis.

Sudhir K. Singh : Provided supervision, formal analysis, methodology, and wrote the original draft.

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