PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol 11(sp4): 01–09
https://doi.org/10.14719/pst.5332

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RESEARCH ARTICLE

Evaluating the impact of climatic factors and variability on rice production over varied seasons in irrigated rice system of peninsular India through Empirical approach

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OPEN ACCESS

ARTICLE HISTORY
Received: 01 October 2024
Accepted: 23 October 2024
Available online
Version 1.0 : 10 December 2024

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

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Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
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CITE THIS ARTICLE
Nagaraj RA, Geethalakshmi V, Sureshkumar D, Murugananthi D, Ravikumar R, Manonmani S, Bhuvaneswari K, Karthick V, Mantaw CS. Evaluating the impact of climatic factors and variability on rice production over varied seasons in irrigated rice system of peninsular India through Empirical approach. Plant Science Today.2024;11(sp4):01-09. https:/doi.org/10.14719/pst.5332

Abstract

Rice is the principle and staple food crop of peninsular India, and its production is highly sensitive to climatic factors and variability. The climate change may cause considerable negative impact on rice productivity that could jeopardize food security and livelihood of smallholders. The present study investigates how the changes in mean and variability of climatic factors may impact rice yield during various rice seasons throughout the year. Panel data of districts of Cauvery Delta Region (CDR) from 2000-2022 was used for the analysis and fixed-effects regression with Panel-Corrected Standard Errors (PCSE) model was employed for all three seasons viz, *Kuruvai*, *Samba* and *Navarai*. The results of the study showed that temperature and rainfall significantly impacted rice yields directly and demonstrated the existence of nonlinear relationship between climatic factors and yield. It also revealed intricate, season-specific correlations between rice productivity and environmental variables. The time trend used in the study indicated a significant positive increase in yield continuously through adoption of yield improvement technologies such as high yielding, resistant and climate resilient varieties. This study helps researchers and policymakers in devising proper adaptation strategies to ensure food system security in the region when the climate conditions change and helpful for predicting future productivity.

Keywords

Cauvery delta region; climate change; panel regression; PCSE; rice

Introduction

The global climate change is the serious issue of recent decades poses a severe thread to agricultural production and food security (1-5). Climate change alters the precipitation pattern and mean global temperature is likely to increase by 3.2°C by the year 2100 (3,4). The changes in rainfall and temperature affect agricultural production as weather variables act as direct inputs leading to significant anomalies in food production (5-7). Such changes could have a negative effect on agriculture in the form of reduced productivity, an increase in pests and diseases and labour migration (6). It is anticipated that the effects of climate change would vary around the world, while certain areas and economic systems may benefit from climate change, others may suffer losses especially developing countries (8). In tropical and subtropical regions, the impact was mostly found to be negative. The impact of climate change in India, is likely to be severe as 70 % of population primarily depends upon agriculture (1).

Economic models (particularly Ricardian approach) or crop simulation (agronomic) models were used to quantify impact of climate change on food security (1,6). Crop stimulation models have the potential to exaggerate the harm caused by climate change since they do not consider farmers' responses to changing climate conditions (6). On the other hand, Ricardian approaches have been used for computing the impact of weather variables on yield and farmland values using cross sectional data generally, could be biased if any unobserved time invariant variables such as soil quality, that may be correlated with climate variables (2,9). Hence scientists begin to use, Panel data approach for examining impact of weather variables on agricultural production (2-4,7). Many of the drawbacks of the Ricardian and agronomic models are addressed by panel data models with fixed effects.

Rice is a major and staple food crop worldwide and feeds approximately 557 million people in Asia which accounts for nearly 87 % of global rice consumption and feeds more people than any other crop (1, 10). Response to climate change leads with positive and negative impacts (1 -4,11). The increase in temperature during the reproductive shortens the grain filling duration and reduces the grain volumes (12). The extreme events such as flood, heavy rainfall and drought affect the rice production. Changes in temperature and rainfall in India could potentially reduce average rice yields by 15% to 25% (13). The effect of climatic variables on rice yield in Tamil Nadu was examined and reported that rice yields have deteriorated around 41% with a 4^{0}C upsurge in high temperature (5).

Previous studies focused on the impact of climate change on agriculture globally and included mean values of weather particularly temperature and rainfall (2,3,7,14,15); very few studies included climate variability (2,7) for the analysis. (4) in their study included relative humidity along other variables to assess seasonal influence of weather variables on rice in Bangladesh. Majority of the studies focused on impact of weather variables on annual yield, only very few studies were done on seasonal yield. (16) used cross-sectional time-series data collected at the district level to examine how climate conditions affect wheat and rice yields in India.

The Cauvery Delta Region, also popularly known as the " Rice granary of South India" is a region in southern India that produces 30 percent of the State's rice, where the rice is cultivated in all 3 seasons throughout the year (1,11,17). The research studies on the effect of climatic variables on Cauvery delta region have been limited so far (5, 10). Hence this present study is aimed at estimating the effects of both mean weather variables and variability on average yield of *Kuruvai*, *Samba* and *Navarai* seasons in Cauvery delta region of Tamil Nadu state. In addition to that, non-linear climate effects on yield are used to account for farmers adaptation.

Materials and Methods

Study area description

Cauvery Delta Region (CDR) comprises of four districts namely., Thanjavur (10.67 N; 79.24 E), Thiruvarur (10.67 N; 79.53 E), Nagapattinam (10.57 N; 79.76 E) and Mayiladuthurai (11.15 N; 79.70 E), which are in the eastern part of the state on the lower Cauvery subbasin (Fig.1). Mayiladuthurai is bifurcated from Nagapattinam district recently in 2020; hence Nagapattinam and Mayiladuthurai were considered as a single district in the study. This zone receives an average annual rainfall of 1052 mm and receives its half of the annual rainfall during northeast monsoon (October to December). This region is warmer in the months of April, May and June, during which temperature reaches 36^{o}C. Agriculture is the primary occupation of this region and rice is major crop that is grown in four seasons viz., *Kuruvai*, *Samba*, thaladi and *Navarai*, accounts for 65 percent of cropping area followed by black gram is cultivated in 14 percent and green gram in 10 percent of rice area as rice follow pulses which is the predominant cropping pattern under irrigated conditions in this region.

CDR depends upon the Mettur reservoir water for irrigation. During *Kuruvai* (June to September) short duration rice varieties have been cultivated with well irrigation since mettur canal water reaches delta by the last week of June. *Samba* (August to January) is cultivated in large area with long duration variety as canal water is available throughout the cropping season. The farmers who opt for *Kuruvai* would go for thaladi season as second crop which begins in September and ends in mid of January and medium duration varieties are commonly grown in the thaladi season. The farmers with borewells or other supplementary irrigation sources prefer *Navarai* (January-May) cultivation.

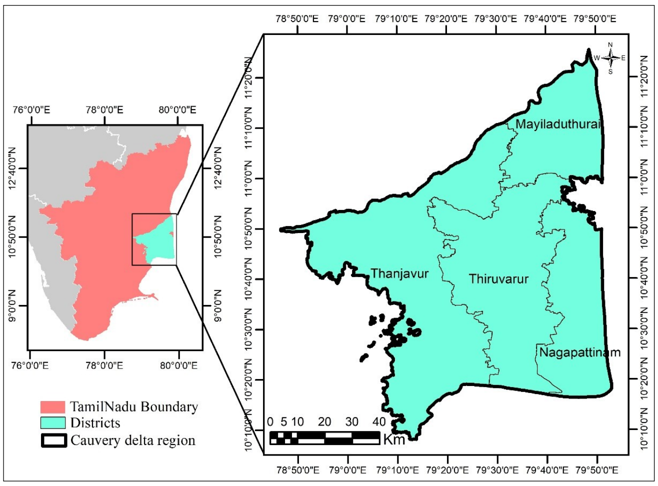

Fig. 1. Study area map.

Crop data and weather variables

Agricultural yield and weather variables were collected from three districts of Cauvery delta region of Tamil Nadu over 23 years (2000-2022). Rice is grown throughout the year in 3 distinct seasons. The seasonal rice production and area data were collected from season and crop reports published by Government of Tamil Nadu for study years. Regarding weather data, temperature and rainfall data were extracted from India Meteorological Department (IMD) gridded data for study districts through Google Collab platform. The relative humidity for the same point was extracted from NASA POWER data access viewer. For all variables, standard deviation was computed as variability across months for agricultural seasons.

Model and estimation Models

Econometric Model

Least-squares dummy variable (LSDV) model which allows cross sectional heterogeneity by allowing each entity to have an intercept value was deployed in the present investigation. The description of variables is given in table 1. Models are commonly used in panel models are the fixed- and random-effects (2,4). To determine the effects of weather variables on rice yield and to exploit cross sectional and temporal attributes of panel data models with fixed effects is used to control unobserved district level heterogenicity that may correlate with explanatory variables (2). This is also known as a time-invariant model that implies, although the intercept may differ across growing district, each districts intercept does not vary over time. Furthermore, district is not random sample as we use all district in this region for which data is available, we used fixed effects to control both time-specific and district specific effects. Many researchers supported this decision (2-4,6,14,18,19). The fixed-effects model (FEM) has an advantage over the random-effects model in that it permits the correlation between time-invariant distinctiveness and regressors. Conversely, the random-effects model presupposes that there is no association between explanatory factors and unobserved time-invariant traits. In this Study, we develop three models for three seasons that includes five independent variables (i.e., cropping area, maximum temperature, minimum temperature, rainfall and relative humidity) and standard deviation of maximum and minimum temperature, rainfall and relative humidity to examine the impact of these variables on rice yield. Temperature and rainfall are known as the primary determinants of crop growth and yield (2-4). Time trend variable was also included in the study for capturing the effect of changes in technology, variety and irrigation and other practices on the yield of the crops (2). The model proposed for the current study with variable in i^{th} district in year t for three season is given below,

Model 1 Quadratic Model for *Kuruvai* rice

$$Y_{it} = \beta_0 + \beta_1 Area_{it} + \beta_2\ Tmax_{it} + \beta_3 Tmin_{it} + \beta_4\ RF_{it} + \beta_5 RH_{it} + \beta_6\ Area^2_{it} + \beta_7 Tmax^2_{it} + \beta_8 Tmin^2_{it} + \beta_9 RF^2_{it} + \beta_{10} RH^2_{it} + \beta_{11} SdTmax_{it} + \beta_{12}\ SdTmin_{it} + \beta_{13}\ SdRainfall_{it} + \beta_{14}\ SdRH_{it} + \beta_{15} Tmax_i \times Tmin_{it} + \beta_{16} Tmax_{it} \times RF_{it} + \beta_{17} Tmax_{it} \times RH_{it} + \beta_{18}\ Tmin_{it} \times RF_{it} + \beta_{19} Tmin_{it} \times RH_{it} + \beta_{20} RF_{it} \times RH_{it} + \beta_{21} Time\ trend_{it} + \alpha_i + \delta_i + \varepsilon_{it}$$

Model 2 Quadratic Model for *Samba* rice

$$Y_{it} = \beta_0 + \beta_1 Area_{it} + \beta_2 Tmax_{it} + \beta_3 Tmin_{it} + \beta_4 RF_{it} + \beta_5 RH_{it} + \beta_6 Area^2_{it} + \beta_7 Tmax^2_{it} + \beta_8 Tmin^2_{it} + \beta_9 RF^2_{it} + \beta_{10} RH^2_{it} + \beta_{11} SdTmax_{it} + \beta_{12}\ SdTmin_{it} + \beta_{13} SdRainfall_{it} + \beta_{14} SdRH_{it} + \beta_{15} Tmax_{it} \times Tmin_{it} + \beta_{16} Tmax_{it} \times RF_{it} + \beta_{17} Tmax_{it} \times RH_{it} + \beta_{18}\ Tmin_{it} \times RF_{it} + \beta_{19}\ Tmin_{it} \times RH_{it} + \beta_{20} RF_{it} \times RH_{it} + \beta_{21} Time\ trend_{it} + \alpha_i + \delta_i + \omega_{it}$$

Model 3 Quadratic Model for *Navarai* rice

$$Y_{it} = \beta_0 + \beta_1 Area_{it} + \beta_2 Tmax_{it} + \beta_3 Tmin_{it} + \beta_4\ RF_{it} + \beta_5\ RH_{it} + \beta_6 Area^2_{it} + \beta_7 Tmax^2_{it} + \beta_8 Tmin^2_{it} + \beta_9\ RF^2_{it} + \beta_{10} RH^2_{it} + \beta_{11} SdTmax_{it} + \beta_{12}\ SdTmin_{it} + \beta_{13} SdRainfall_{it} + \beta_{14}\ SdRH_{it} + \beta_{15}\ Tmax_{it} \times Tmin_{it} + \beta_{16} Tmax_{it} \times RF_{it} + \beta_{17} Tmax_{it} \times RH_{it} + \beta_{18}\ Tmin_{it} \times RF_{it} + \beta_{19}\ Tmin_{it} \times RH_{it} + \beta_{20} RF_{it} \times RH_{it} + \beta_{21}\ Time\ trend_{it} + \alpha_i + \delta_i + \varphi_{it}$$

where, Yit is yield of rice in i^{th} district in year t; $Tmax_{it}^2$, $Tmin_{it}^2$, RF_{it}^2, RH_{it}^2 and $Area_{it}^2$ are squared terms of Tmax, Tmin, Rainfall, Relative Humidity and area respectively in i^{th} district in year t. $Tmax_{it}$ x $Tmin_{it}$, $Tmax_{it}$ xRF_{it} , $Tmin_{it}$ x RF_{it}, $Tmin_{it}$ x RH_{it}, RF_{it} x RH_{it} are interaction effect; $SdTmax_it$, $SdTmin_{it}$, $SdRF_{it}$ and $SdRH_{it}$ are Standard deviation of Tmax, Tmin, RF and RH in i^{th} district in year t. $Time\ trend_{it}$ is technology advancement such as high

Table 1. Description of variables in model

Variable	Description and Unit
Yield (Y)	Average yield of rice per hectare (kg/ha)
Maximum Temperature (Tmax)	Average Maximum temperature in cropping season (°C)
Minimum Temperature (Tmin)	Average Minimum temperature in cropping season (°C)
Rainfall (RF)	Total rainfall during the cropping season (mm)
Relative Humidity (RH)	Average RH in cropping period (%)
SdTmax	Standard Deviation in Maximum temperature in cropping season (°C)
SdTmin	Standard Deviation in Minimum temperature in cropping season (°C)
SdRF	Standard Deviation in Rainfall in cropping season (mm)
SdRH	Standard Deviation in Relative Humidity in cropping season (%)
Area	Area of Rice cultivating during cropping season (ha)

yielding varieties, irrigation technologies. α_i denote district -specific effects (i.e. Time invariant); δ_i denote time specific effects that are district invariants (i.e. District- and year-specific regression constants), which equals 1 for observations from ith district and otherwise 0; ε_{it}, ω_{it} and φ_{it} are error terms of *Kuruvai*, *Samba* and *Navarai* respectively. For Model 1 (*Kuruvai*), Model 2 (*Samba*) and Model 3 (*Navarai*) the climate variables computed from June to September, August to January and January to May respectively. Tmax, Tmin, Rh are computed as seasonal average while RF is computed as sum.

In each of these models, the specification incorporated quadratic terms for independent variables to account for the non-linear impact of independent variables on rice yield. The inclusion of an interaction term among the independent factors allowed for the assessment of the possible impact of the climatic variables on the effect of other independent variables (3). As a result, calculating the effect of an increase of 1 unit in the independent variable corresponds to a certain percentage change in yield, presuming that other independent variables remains constant.

Estimation Models

A model cannot be regressed for prediction unless several diagnostic tests have been performed to confirm that the model's error structure satisfies the underlying assumptions (2-4). In our study, three key assumptions need to be satisfied: errors must be homoscedastic; errors must be cross-sectionally independent and autocorrelation is not present. To check if heteroscedasticity was present, the modified Wald test was used. It tests the alternative hypothesis that the error variances are unequal with the null hypothesis, which states that all the error variances are equal. To determine whether autocorrelation exists, a test recommended by Wooldridge was carried out. In this test, the alternative hypothesis is that there is a first-order correlation and the null hypothesis is that there is no first-order autocorrelation. To determine if Cross-sectional Dependence (CD) exists under the null hypothesis of CD, the Bresusch-Pagan test was lastly employed. We also conducted a unit root test to confirm that our time series data were stationary. If a time series of panel data contains a unit root (non-stationary), it implies that there is a systematic pattern that is unpredictable. The existence of a unit root or regressing nonstationary data will produce a spurious regression (20). Usually, a regression is spurious if trending variables over time are regressed, which likely indicates a non-existing relationship. In this study, Number of years (T=23) is relatively larger than number of districts (N=3) and there may be contemporaneous correlated across the panel. PCSE approach for panel data with fixed effects that yields an unbiased standard error estimate and an efficient coefficient (21).

Results

The effect of weather variable on rice yield was analyzed using the PCSE approach. The data was tested for the model estimation. The descriptive statistics was also computed for the selected variables.

Descriptive Statistics

The descriptive statistics of variables of Cauvery Delta Region used in this model for period of 2000-2022 for different seasons is given in Table 2. The average yield of *Kuruvai* is higher followed by *Navarai* and *Samba* season. The average Tmax of *Kuruvai*, *Samba*, *Navarai* is 34.5, 32.2 and 34.8°C respectively. The yield of *Samba* season is generally less due to heavy rainfall damage during northeast monsoon season. The cropping area, mean rainfall and relative humidity of *Samba* is higher than other 2 seasons. The CD of Tmax and Tmin found to be higher in *Navarai* season. The mean value of SdTmax is higher in *Samba* than *Navarai* but their SD is vice versa. The mean value of SdTmin is higher in *Navarai* than *Samba* and *Kuruvai*.

Table 2. Descriptive statistics

		Kuruvai		***Samba***		***Navarai***	
Variable	**Obs.**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Y	69	3635.5	710.4	2688.7	1152.3	3461.2	907.1
Tmax	69	35.4	0.4	32.2	0.3	34.8	0.5
Tmin	69	26.0	0.3	23.9	0.3	25.1	0.4
RF	69	245.1	133.4	852.9	347.7	132.2	130.4
RH	69	69.0	4.7	78.0	2.6	70.4	4.0
SdTmax	69	0.8	0.3	2.2	0.2	1.8	0.3
SdTmin	69	0.5	0.2	1.6	0.2	1.9	0.2
SdRF	69	47.6	28.4	131.5	71.2	42.8	49.1
SdRH	69	3.6	1.8	5.9	2.6	3.0	1.4
Rice Area	69	29696.2	13772.1	102183.1	17242.8	5307.3	5639.0

Values are pertaining to the period from 2000-2022

Econometric diagnostic test results

Econometric tests

The tests examined 3 models for panel heteroscedasticity, autocorrelation and cross-sectional correlation and the results are presented in Table 3. Model1 (*Kuruvai* season) and Model2 (*Samba*) showed no significant violations of the tested assumptions at the 5% level. However, Model 2's autocorrelation test (p = 0.0552) was close to the significance threshold. Model 3 (*Navarai* season) exhibited significant heteroscedasticity (p = 0.0046), but no significant autocorrelation or cross-sectional correlation. These findings suggest that while Models 1 and 2 may be suitable for standard panel regression techniques, Model 3 requires adjustments to address heteroscedasticity alternative estimation methods. In our study, number of years (T=23) is relatively larger as compared to number of districts (N=3), they may contemporaneous correlated across the panel Ordinary least square (OLS) estimation does not fulfill error assumptions we go for Panel-corrected standard errors (PCSE) method (2). PCSE can provide more conservative estimates of standard errors, which may be valuable even when tests don't show significant violations. For Model 2, the autocorrelation test (p = 0.0552) is very close to the conventional significance threshold. PCSE could address potential issues that the test might not have captured due to sample size or other factors. Though Model 1 and Model 2 are not violating the assumptions to ensure consistency and robustness among all model we used PCSE for all models. We use Im, Pesaran and Shin (IPS) panel unit root test for stationarity and test rejected null hypothesis of unit root and confirmed stationarity of given series of each variable and there is no need of taking lagged variables in the model. The results of IPS unitroot test is presented in Table 4.

Regression Results

The regression results with panel corrected standard error estimates of *Kuruvai* model is presented in Table 5. The results showed that the minimum temperature correlated positively with yield under 10% significance however the squared Tmin is negatively correlated under 5% significant implies the strong nonlinear relationship between temperature with *Kuruvai* yield, the increase in minimum temperature will decrease the yield. The mean maximum temperature, rainfall and relative humidity negatively correlated with the yield, but the relationship is not significant. Tmax and RH is negatively correlated, but in contrast Tmin and Rainfall are positively nonsignificant in both cases. The interaction terms of Tmin × RF is positively significant at 1% significance. Tmax × Tmin, Tmax × RH, Tmin× RH and RF× RH is positively correlated with yield while Tmax × RF has negative effect on yield and all are non-significant. The time trend positively correlated under 1% significance. Climatic factors and technology explain 72.46% of variations in rice yield.

The regression results of *Samba* model are presented in Table 6. It showed a significant negative correlation with area which causes decline in yield and same results from squared area shows a significant nonlinear relationship between area and yield. The increase in area beyond threshold level does not increases the yield. The mean Tmax is positively correlated under 5% significance while squared term shows non-significant decrease in yield. The mean values of Rainfall and Squared rainfall negatively correlated with *Samba* yield with 5% and 10% significance. The Mean values of Tmin, RH and its squares are non-significantly positively correlated. Tmin× RH the interaction is negatively correlated while RF× RH is positively correlated under 10% significance. Though Tmax × Tmin, Tmax × RF, Tmax × RH and Tmin× RF positively correlated but non-significant. Time factor positively correlated with 1% significance.

Table 7 presents the regression results of *Navarai* model and results shows that the Tmin is negatively correlated with *Navarai* rice under 5% significance. Here the variability of relative humidity positively correlated with the yield. Tmin× RH interaction correlated positively with 10% significance. The Time variable is positively correlated with 1% significance. Tmax × Tmin and Tmax × RF is positively corelated, while Tmax × RH and Tmin× RF is found to be negative and non-significant.

Table 4. Panel unit root test statistics

Variable	t bar statistics		
	Kuruvai	***Samba***	***Navarai***
Yield	-2.59*	-4.29**	-3.11**
T Max	-4.90**	-4.20**	-5.36**
T Min	-2.31*	-2.49*	-4.01**
Rainfall	-4.72**	-3.71**	-3.91**
Relative Humidity	-3.50**	-4.76**	-4.57**
Area	-2.91*	-2.77*	-5.07**

*and ** indicate statistical significance at 5% and 1%, respectively

Table 3. Econometric diagnostics tests

Model	Econometic assumptions	Type of Test	Statistics	*p* values
Model 1 (*Kuruvai* season)	Panel heteroscedasticity	Modified Wald test	6.30	0.0978
	Presence of autocorrelation	Woodridge test	4.349	0.1724
	Cross sectional Correlation	Breusch-Pagan Test	0.181	0.9806
Model 2 (*Samba* season)	Panel heteroscedasticity	Modified Wald test	0.03	0.9986
	Presence of autocorrelation	Woodridge test	16.629	0.0552
	Cross sectional Correlation	Breusch-Pagan Test	1.394	0.7069
Model 3 (*Navarai* season)	Panel heteroscedasticity	Modified Wald test	13.02**	0.0046
	Presence of autocorrelation	Woodridge test	0.488	0.5573
	Cross sectional Correlation	Breusch-Pagan Test	3.052	0.3837

** indicate statistical significance at 5%

Table 5. Regression results of *Kuruvai* Model

Dependent variable = Yield	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Area	0.01*	0.01	1.76	0.079	0.00	0.02
Tmax	-26621.40	36664.80	-0.73	0.468	-98483.09	45240.29
Tmin	89805.21*	46838.77	1.92	0.055	-1997.10	181607.50
RF	-102.59	66.00	-1.55	0.120	-231.94	26.76
RH	-454.85	2211.68	-0.21	0.837	-4789.67	3879.97
SdTmax	-85.28	430.38	-0.20	0.843	-928.80	758.24
SdTmin	525.23	684.61	0.77	0.443	-816.57	1867.03
SdRF	1.58	3.24	0.49	0.625	-4.77	7.93
SdRH	-67.01	45.56	-1.47	0.141	-156.30	22.28
$Area^2$	-0.00000006	0.000000096	-0.62	0.538	-0.00000025	0.00000013
$Tmax^2$	-81.22	447.16	-0.18	0.856	-957.64	795.21
$Tmin^2$	-2605.28**	1005.49	-2.59	0.010	-4576.00	-634.56
RF^2	-0.01**	0.00	-2.27	0.023	-0.01	0.00
RH^2	-7.06	5.25	-1.34	0.179	-17.34	3.23
Tmax × Tmin	1201.25	933.35	1.29	0.198	-628.08	3030.58
Tmax × RF	-1.89	1.55	-1.22	0.222	-4.92	1.14
Tmax × RH	18.85	39.38	0.48	0.632	-58.33	96.04
Tmin× RF	6.51***	2.15	3.03	0.002	2.30	10.73
Tmin× RH	28.17	56.65	0.50	0.619	-82.85	139.20
RF× RH	0.02	0.15	0.15	0.883	-0.27	0.32
Time	63.73***	16.28	3.91	0.000	31.82	95.64
Constant	-663271.10	1022861.00	-0.65	0.517	-2668041.00	1341499.00
District FE and Time FE			Yes			
Observations			66			
Wald Chi2			111.01***			
P Value			0.0000			
R^2			0.7246			

*, **, *** indicate statistical significance at 10%,5% and 1%, respectively. FE denoted fixed effects

Table 6. Regression results of *Samba* Model

Dependent variable = Yield	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Area	-0.023***	0.009	-2.61	0.009	-0.041	-0.006
Tmax	12789.120**	6235.48	2.05	0.040	567.802	25010.44
Tmin	7186.161	4861.94	1.48	0.139	-2343.066	16715.39
RF	-132.514**	54.509	-2.43	0.015	-239.349	-25.679
RH	1375.507	5348.694	0.26	0.797	-9107.740	11858.75
SdTmax	-730.857	865.739	-0.84	0.399	-2427.675	965.961
SdTmin	-368.519	853.114	-0.43	0.666	-2040.591	1303.554
SdRF	-6.085*	3.487	-1.74	0.081	-12.919	0.750
SdRH	163.565	107.887	1.52	0.129	-47.888	375.019
$Area^2$	-920.406**	403.476	-2.28	0.023	-1711.205	-129.607
$Tmax^2$	-438.904	843.232	-0.52	0.603	-2091.609	1213.801
$Tmin^2$	0.000015	0.000926	0.02	0.987	-0.001799	0.002
RF^2	-10.431	19.329	-0.54	0.589	-48.316	27.454
RH^2	0.00000006	0.00000004	1.6600	0.097	-0.00000001	0.00000014
Tmax × Tmin	1140.967	1104.570	1.03	0.302	-1023.951	3305.885
Tmax × RF	2.302	1.440	1.60	0.110	-0.521	5.126
Tmax × RH	221.395	137.548	1.61	0.107	-48.195	490.985
Tmin× RF	1.003	1.009	0.99	0.320	-0.974	2.981
Tmin× RH	-299.227*	158.007	-1.89	0.058	-608.914	10.460
RF× RH	0.435*	0.230	1.89	0.059	-0.016	0.885
Time	68.801***	25.401	2.71	0.007	19.016	118.586
Constant	-295376.7	290719.4	-1.02	0.310	-865176.4	274422.9
District FE and Time FE			Yes			
Observations			66			
Wald Chi2			134.01***			
P Value			0.0000			
R^2			0.6895			

*, **, *** indicate statistical significance at 10%,5% and 1%, respectively. FE denoted fixed effects

Table 7. Regression results of *Navarai* Model

Dependent variable = Yield	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Area	0.007	0.040	0.170	0.861	-0.071	0.085
Tmax	-25.051	3968.264	-0.010	0.995	-7802.706	7752.603
Tmin	-7865.765**	3776.832	-2.080	0.037	-15268.220	-463.311
RF	-175.514	106.894	-1.640	0.101	-385.022	33.994
RH	1767.735	2996.886	0.590	0.555	-4106.053	7641.524
SdTmax	469.489	441.688	1.060	0.288	-396.203	1335.181
SdTmin	-314.210	624.623	-0.500	0.615	-1538.449	910.029
SdRF	-3.612	9.254	-0.390	0.696	-21.750	14.527
SdRH	277.110**	111.385	2.490	0.013	58.799	495.421
$Area^2$	0.0000003	0.000001	0.240	0.810	-0.0000023	0.0000029
$Tmax^2$	-630.344	612.460	-1.030	0.303	-1830.742	570.055
$Tmin^2$	-1496.159	1160.787	-1.290	0.197	-3771.259	778.941
RF^2	-0.003	0.006	-0.460	0.645	-0.014	0.009
RH^2	-12.738	14.557	-0.880	0.382	-41.268	15.792
Tmax × Tmin	2058.514	1688.465	1.220	0.223	-1250.816	5367.845
Tmax × RF	4.616	2.892	1.600	0.110	-1.052	10.284
Tmax × RH	-124.761	85.434	-1.460	0.144	-292.208	42.687
Tmin× RF	-0.014	0.081	-0.180	0.861	-0.172	0.144
Tmin× RH	163.571*	91.536	1.790	0.074	-15.836	342.978
RF× RH	0.260	0.261	0.990	0.320	-0.252	0.772
Time	74.799***	30.447	2.460	0.014	15.125	134.474
Constant	62236.01	131304.2	0.470	0.636	-195115.5	319587.6
			Yes			
District FE and Time FE			66			
Observations			74.03***			
Wald Chi2			0.0000			
P Value			0.7107			

*, **, *** indicate statistical significance at 10%,5% and 1%, respectively. FE denoted fixed effects

Discussion

Samba yield is significantly impacted positively by the maximum temperature (Tmax), whereas *Kuruvai* yield is significantly impacted positively by the minimum temperature (Tmin) and *Navarai* yield is significantly impacted negatively by the Tmin. A rise in pests and diseases during *Kuruvai* and *Navarai* can result in a decrease in crop productivity. However, higher temperatures also increase the efficiency of photosynthetic activity and fertilizer use, which may reduce insect infestations (2, 22, 23). According to a report, a drop in the minimum temperature produces spikelet sterility and productivity loss. Seasonal variations in temperature effects highlight the significance of taking seasonal climate trends into account when planning agricultural operations (24). However, take note that the effects of fertilizing with carbon dioxide (CO_2) were not included in the model. Increased atmospheric greenhouse gas concentrations are projected to cause CO_2 fertilization, which will balance off the negative consequences of climate change and promote plant growth (3, 25-27). Elevated CO_2 enhances C3 crop yields by 10 to 30%, however crop responses are contingent on agronomic conditions, species types and nutrient and water availability (28). Because this region receives greater rainfall during the northeast monsoon, rainfall has a major negative impact on *Samba* yield and a substantial positive impact on *Kuruvai* or *Navarai* yields. An excessive amount of precipitation could be harmful to *Samba* crop because of increased risk of floods or disease (1,11). Additionally, we found that the yield and rainfall have a quadratic relationship, which is consistent with the earlier findings (2,6). There were no apparent direct effects of relative humidity, but there was a strong interaction with minimum temperature for both *Samba* and *Navarai*.

The effects of relative humidity tend to be more complicated, acting through interactions with other elements rather than acting directly. *Samba* yield is significantly harmed by the standard deviation of rainfall (SdRF). If 1 mm increase in the standard deviation of rainfall during *Samba* results in a 6.1 kilogram per hectare drop in projected production. This validates the findings of earlier studies in Taiwan (2, 29-31). The yield is impacted differentially by weather variability depending on the season. *Samba* yield is greatly impacted negatively by squared area, *Kuruvai* yield is significantly impacted negatively by squared Tmin and squared RF. certain non-linear effects imply optimal ranges or diminishing returns for certain variables (2,6). For *Kuruvai*, the RF × RH interaction is considerable, while for *Samba*, the Tmin × RF interaction is quite significant. These data support the impact of climate variables on rice yield in Peninsular Malaysia during the main rice-growing season as reported (3). The necessity of holistic management strategies is highlighted by the intricate interactions between environmental elements.

The Time trend's strong significance makes it evident that farmers can mitigate the negative effects of climate change by increasing yield through crop breeding programs, the System of Rice Intensification (SRI) technology, advanced irrigation techniques and other practices that adopt climate-resilient breeding varieties. These measures also partially offset the negative effects. The requirement for specialized agricultural practices for every growing season is highlighted by the differences in impacts across seasons. Developing crop types that are tolerant to climate change and modifying planting dates may be essential, considering the substantial effects of temperature and rainfall. Rainfall's detrimental effect on *Samba* yields points to the necessity for better water management techniques or drainage systems (11). The upward temporal pattern suggests that funding agricultural research and technology transfer could increase yields even further.

Conclusion

In conclusion, this research offers an in-depth understanding of the weather variables affecting agricultural yields during the *Kuruvai*, *Samba* and *Navarai* growing seasons. It also reveals intricate, season-specific correlations between crop productivity and environmental variables. According to our research, variables like rainfall, temperature and cultivated area have different effects on yield, highlighting the variability in yield drivers throughout seasons. The steady upward temporal trend that is shown in all seasons is indicative of both significant technology developments and farmer adaptations, showing the inventiveness and resiliency of farming communities. These findings have significant ramifications for both agricultural policy and practice, as they highlight the need for climate-resilient techniques to be more heavily invested in, season-specific methods, better water management systems and ongoing funding for agricultural research and technology transfer. Although our model has strong explanatory power, in order to obtain a greater knowledge of yield determinants, future research could benefit from adding more variables and using mixed methods approaches. Such in-depth analyses will be essential for maintaining food security and encouraging sustainable agricultural practices as climate change continues to transform agricultural landscapes. This will allow for the development of more potent strategies for enhancing productivity and resilience in the face of ongoing global challenges.

Acknowledgements

The authors duly acknowledge the Agro Climate Research centre and Tamil Nadu Agricultural University, Coimbatore for providing the technical support. The Authors are thankful to the World Resource Institute (WRI) for the financial support rendered through WRI/CARDS project entitled “AgriAdapt Climate Risk Tool for Indian Rice Value Chain “(WRI/CARDS/CBE/2024/R001)”.

Authors' contributions

RA collected the data, carried out the analysis and wrote the article under the guidance of VG, KB, DM, RR, SM, DS and VK are contributed by improving the manuscript. KB and KS carried out the corrections and improved manuscript. CSM, RR and DM helped in summarizing and editing the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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