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EXIGENCY FOR ADOPTION OF CLIMATE RESILIENT TECHNIQUES (AI-ML) IN SUSTAINABLE HORTICULTURE PRODUCTION IN INDIA: AN ECONOMETRIC ANALYSIS

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ABSTRACT

The global scientific community is increasingly recognizing the urgent need to address the complex challenges facing the agricultural sector, particularly those arising from significant shifts in climatic conditions. In India, the rising demand for horticultural crops, both domestically and internationally, has compelled farmers to focus on producing high-value crops, particularly fruits and vegetables, in a cost-effective manner. This demand, coupled with the relatively shorter production cycles, potential for crop diversification, more efficient land use, and opportunities for integrating advanced technologies, has led to a growing preference among farmers for horticultural production over traditional staple food crops. This paper aims to analyze the multifaceted impact of climate change on food security and to assess its long-term effects on the production of horticultural crops in India. To achieve this, the study utilizes climatic and agricultural data from the 15 leading horticultural-producing states of India, spanning the period from 1987-88 to 2020-21. A Panel Autoregressive Distributed Lag (ARDL) model is employed to examine the long-term effects of climate change on horticultural production. Keeping in view the regional variability in geographic, climatic, and socio-economic conditions, the ARDL model is particularly suited to capture heterogeneity by incorporating multiple cross-sectional units. The factors influencing horticultural crop production are categorized into climate-related and non-climate-related variables. The results indicate that, in the long run, climate variables exhibit a significantly negative relationship with horticultural production, suggesting an unfavourable impact. In contrast, non-climatic factors such as the area under cultivation and the annual average wage rate are positively correlated with horticultural production and have a significant effect. Overall, the study concludes that, in the long term, climate change exerts a more substantial influence on horticultural crop production than other factors. This finding highlights the critical need for the adoption of climate-resilient technologies in horticultural farming to mitigate the adverse effects of climate change and ensure sustainable production.

Keywords: Horticulture, Climate, Technological Innovation (AI-ML), Panel ARDL

Climate change, as defined by the Intergovernmental Panel on Climate Change (IPCC), refers to any significant alteration in climate patterns over time, whether driven by natural variability or human activities (IPCC, 2022). This phenomenon poses a profound threat to global food security by disrupting agricultural productivity through a series of complex and interconnected climatic shifts, including rising temperatures, erratic rainfall patterns, and extreme weather events (Chaves *et al.*, 2003; Cline, 2007). While moderate climate fluctuations may have limited effects, more severe climate scenarios are likely to cause substantial damage to key agricultural sectors, including staple crops, horticulture, and livestock, thereby exacerbating challenges in meeting the growing global demand for food (Massetti and Mendelsohn, 2011; Bozzella *et al.*, 2017). In response to these challenges, the adoption of sustainable agricultural practices has become crucial for both mitigating the adverse impacts of climate change and adapting to the evolving environmental conditions. Innovations such as conservation agriculture, Internet of Things (IoT)-based monitoring systems, Artificial Intelligence (AI), and digital farming technologies have shown considerable promise in enhancing agricultural productivity while minimizing ecological footprints. According to World Bank reports, countries such as Israel, the United States, Bangladesh, and China have pioneered the implementation of climate-smart agricultural strategies, aimed at strengthening resilience and ensuring long-term food security in the face of climate uncertainties.

India's agricultural sector is grappling with the dual challenge of feeding a population projected to surpass that of China by mid-2023 (State of World Population Report, UNFPA), while simultaneously addressing rising poverty and food insecurity (Chand and Chauhan, 1999). Historical initiatives such as the Green Revolution and the Five-Year Plans played a pivotal role in achieving food self-sufficiency (Kannan and Sundaram, 2011; Chand, 2010; Yadav and Anand,

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2019). However, despite these achievements, recent data from the Ministry of Statistics and Programme Implementation (MoSPI) indicates a concerning trend. According to the second advanced estimate of National Income for 2022-23, the Gross Value Added (GVA) of agriculture and allied sectors in India has declined from 20.3% in 2020-21 to 18.3% in 2022-23, highlighting the growing challenges within the sector. While government initiatives such as *Aatmanirbhar Bharat* aim to foster agricultural resilience, persistent inefficiencies in policy implementation and insufficient infrastructure continue to impede sustainable growth in the sector. Recent reports, including the IPCC's 2022 assessment, forecast dire consequences for India's agriculture, with anticipated reductions in labour productivity, shrinking cultivable land, and escalating water scarcity, factors that threaten national food security and disproportionately impact small and marginal farmers (Praveen and Sharma, 2020). Projections suggest that, by 2050, staple crop production could experience significant declines, with GDP losses ranging from 3% to 10% annually by 2100.

Over the past two decades, Indian agriculture has experienced a notable shift towards horticultural production and consumption, moving away from the traditional emphasis on food grains. This transformation is driven by a combination of factors, including policy reforms, the rise of health-conscious consumers, changing dietary preferences, and heightened awareness of nutrition. Forecasting per capita consumption of food grains and horticultural crops is crucial for anticipating future demand, revealing the growing prominence of horticultural products in the Indian diet. Projections indicate a steady increase in the per capita availability of horticultural crops, signaling a promising transition toward a more resilient, nutritious, and sustainable food system, in contrast to food grains (Krithi and Varman, 2024). The rising demand for horticultural crops can be attributed to their shorter production cycles, greater potential for diversification, and compatibility with modern agricultural technologies. These characteristics make horticultural crops a promising solution to mitigate the impacts of climate change. However, the sector faces significant challenges, including inadequate market linkages and the increasing risks associated with climate change, which threaten its long-term sustainability. Addressing these issues requires the adoption of ICT-based climate-smart strategies, the development of robust agricultural infrastructure, and the integration of precision farming technologies, such as sensors, drones, and AI-driven pest and irrigation management systems, to optimize productivity (Jiber *et al.*, 2011; Awuor *et al.*, 2013; Mammo, 2014). AI tools, in particular, are being increasingly leveraged to aid in climate-adaptive crop selection and monitoring, allowing farmers to mitigate risks and improve their resilience to climate variability. India has launched several initiatives, including the National Mission for Sustainable Agriculture, the *Rashtriya Krishi Vikas Yojana*, and the National Horticulture Mission, to promote agricultural sustainability and horticultural growth. However, these efforts require enhanced implementation strategies and a stronger focus on region-specific climate challenges affecting horticultural production. To strengthen the sector's resilience, there is a pressing need to expand research and investment in climate-resilient horticultural practices. Such efforts can boost farmers' income, enhance their livelihoods, and ensure the long-term sustainability of Indian agriculture. Integrating AI and machine learning technologies, alongside other smart farming practices, will be critical to adapting to unpredictable climatic conditions and securing a resilient agricultural future for India.

A comprehensive review of the literature reveals various studies examining the effects of climate change on agricultural production across a wide range of crops. Researchers have employed both time-series and panel data models to analyze these impacts. Several cross-country panel studies, including those by Xiang *et al.* (2022), Lisha *et al.* (2022), and Mirza *et al.* (2021), have investigated the broader effects of climate change on agricultural production. Additionally, empirical studies by Zaied and Cheikh (2015), Zhai *et al.* (2017), Chandio *et al.* (2020), Attiaoui and Boufateh (2019), and Chandio *et al.* (2023) have specifically focused on the effects of climate change on agricultural production in countries such as Tunisia and China. Shakoor *et al.* (2011) examined the impact of climate change on agricultural production in Pakistan, while Bomdzele and Molua (2023) studied the short-term impacts of both climate and non-climate factors on the export-oriented cocoa production in Cameroon, Central Africa. Warsame *et al.* (2023) explored how climate change and political instability affect maize production in Somalia. Focusing on India, Singh *et al.* (2024) analyzed the impact of climate change on cereal production, while Jena (2021) explored the relationship between agricultural productivity and climate change in Odisha. Kumar and Upadhyay (2019) also contributed to the study of climate change's effect on agricultural productivity in India. Saqib *et al.* (2022) focused specifically on the effects of climate change on horticultural crops, although the general literature on this topic remains sparse, with most studies addressing the impacts on specific crops like sugarcane and fruits. Chandio *et al.* (2024) modeled the impact of climate change on the production of major fruits in Pakistan, and Khan *et al.* (2021) similarly explored the effects on fruit production in China. A significant portion of the literature has employed the Ricardian approach and panel regression models to capture the relationship between climate change and agricultural production. However, in studies examining both the short- and long-run effects, the Panel ARDL model has become increasingly popular. For example, Duaza and Radzman (2022), Abdi *et al.* (2023), and Tanveer and Kalim (2024) utilized this approach to explore the dynamic relationship between climate variables and agricultural productivity, highlighting both immediate and long-term effects.

Existing studies have consistently highlighted that climate factors, such as rainfall, temperature (both minimum and maximum), and precipitation, significantly influence agricultural production. As India continues to expand its adoption of technology across various sectors, it is crucial to investigate how factors like technological advancements and modern irrigation methods might shape the future of agricultural crop production. While there has been some focus on climate change's effects on crop productivity, there remains a notable gap in research concerning the immediate and long-term impacts of climate variability on horticultural crops in India. Despite efforts to forecast the future of agricultural crops, questions persist about why technological progress and government policies designed to mitigate climate change have not yielded more effective results. What are the reasons for the limited success of these initiatives? Moreover, what policy recommendations can be made to enhance climate resilience in agricultural production, considering both climate-related interventions and the adoption of new technologies? Additionally, it is essential to examine the non-climate factors that influence agricultural productivity in India. While much of the research focuses on the direct impacts of climate change, the role of economic, infrastructural, and institutional factors cannot be overlooked. For the purpose of this study, horticultural crops, more vulnerable to climate impacts, are specifically considered, as they are increasingly significant to India's agricultural sector. Though a substantial body of research exists on agriculture and climate change, there is a dearth of scientific studies that utilize robust statistical and econometric methodologies to comprehensively assess these impacts. This gap in the literature signals a critical need for more rigorous, data-driven analyses. Therefore, recognizing the limitations of the existing literature in this area, this study seeks to make a significant contribution by analyzing the impact of both climate and non-climate factors on horticultural crops in India. The study further aims to explore the long-run and short-run effects of climate change, providing empirical evidence to inform policy and technology adoption strategies. In doing so, this research aspires to enhance understanding of how India can build climate resilience in its agricultural sector, particularly in the context of horticultural production.

MATERIALS AND METHODS

Data sources

To investigate the impact of climate change on agricultural production in India, this study analyzes data from the 15 leading horticultural producing states over the period from 1987-88 to 2020-21. Among agricultural crops, horticultural products such as fruits, vegetables, spices, and flowers are particularly vulnerable to climate change. Consequently, this study treats horticultural production (measured in metric tonnes) as the dependent variable. The independent variables are categorized into two groups: climate variables and non-climate variables. The climate variables include maximum annual temperature, minimum annual temperature, and annual rainfall, all sourced from the India Meteorological Department (IMD), Government of India (GOI). Non-climate variables comprise factors such as the area sown under horticultural crops, total horticultural crop production, fertilizer consumption for horticultural production, total irrigated area for horticulture, and the annual average wage rate of horticulture workers. Data for these variables are obtained from the Ministry of Agriculture and Farmers Welfare, the Reserve Bank of India, CMIE (Fruits and Vegetables, Spices, Plantation), and Agricultural Wages India 2019-2020, respectively.

This study employs a robust balanced panel and utilizes the Panel Autoregressive Distributed Lag (ARDL) econometric model to examine the relationship between climate change and horticultural production. The Panel ARDL model is particularly suited for capturing the dynamic interplay between climate and non-climate factors, as well as their combined effects on horticultural production over time. Given the data spans 33 years across the 15 leading horticultural producing states, it allows for an in-depth analysis of the cross-sectional variations in the impact of climate change on horticultural crops. The Panel ARDL framework is advantageous as it enables the differentiation between short-term fluctuations and long-term trends. The short-term analysis provides insights into immediate responses to climatic shifts, aiding in crisis management and facilitating rapid decision-making. In contrast, the long-term analysis offers a deeper understanding of sustainability, adaptation strategies, and policy formulation. By integrating both perspectives, this study presents a comprehensive view of the complex interactions between climate and non-climate factors affecting horticultural production in India. As highlighted in the *Literature Review* section, numerous studies have employed the Panel ARDL model to explore the relationship between climate variables and agricultural production, further validating its effectiveness in this context.

Table 1. Variables and their sources used in the study

Variable	Unit	Source
Maximum annual temperature (climate factor)	In Degree Celsius	India Meteorological department (IMD), GOI
Minimum annual temperature (climate factor)	In Degree Celsius	India Meteorological department (IMD), GOI
Annual rainfall (climate factor)	In MM	India Meteorological department (IMD) , GOI
Area sown (area of production)	In 000 Hectare	Ministry of Agriculture and Farmers Welfare, GOI
Total production of horticultural crops	In 000 Metric Tonne	Ministry of Agriculture and Farmers Welfare, GOI
Fertilizer consumption (proxy for technical efficiency)	In kg per hectare	RBI Ministry of Agriculture and Farmers Welfare, GOI
Total irrigated area (proxy for technical efficiency)	In 000 hectare	Ministry of Agriculture and Farmers Welfare, GOI CMIE (FandV, Spices, Plantation)
Average annual wage rate	In Rs per 8 hour	Agricultural Wages India 2019-2020 Directorate of Economics and Statistics Department of Agricultural Cooperation and Farmers Welfare Ministry of Agriculture and Farmers Welfare RBI

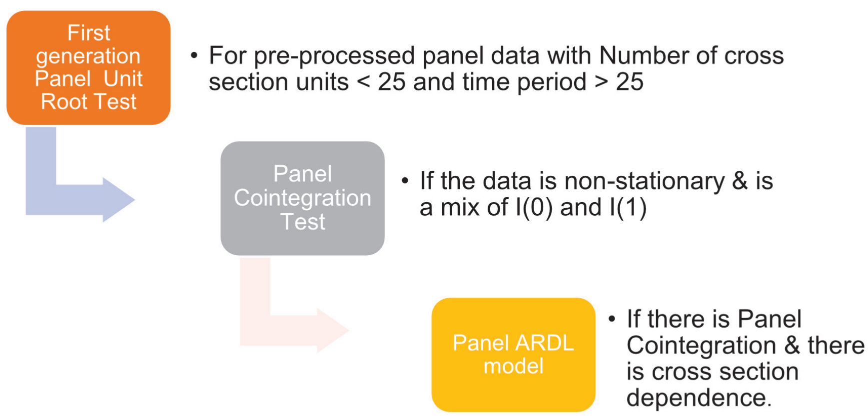

Fig. 1. Methodology for choosing the panel ARDL model
(Source: Sohag *et al*., 2018; Sek *et al*., 2024; Frimpong *et al*., 2024)

The Panel Autoregressive Distributed Lag (ARDL) approach was proposed and popularized by Pesaran and Shin, 1998; Pesaran and Smith, 1995). In this study, the Pooled Mean Group (PMG) technique is employed to estimate the Panel ARDL model. The PMG estimators are likelihood-based, and they assume that the long-run coefficients are identical across states or groups. To assess the presence of cross-sectional dependence in the model, several diagnostic tests are applied, including the Breusch-Pagan LM test, the Pesaran scaled LM test, and the Pesaran CD test (Pesaran, 2004, 2007, 2021). The Panel ARDL model is particularly suitable when the variables in the model are stationary at different levels, that is, when the variables exhibit a mixture of I(0) and I(1) stationarity. This condition is verified using the Pesaran Panel Unit Root test. The Panel Unit Root test is a statistical method used to determine the stationarity or presence of a unit root in time-series variables within a panel dataset. By checking for stationarity, the study ensures the robustness and validity of the ARDL model, providing reliable estimates of the relationships between climate change and horticultural production.

The Panel ARDL model is explained in terms of the extended production function which is assumed to be Cobb-Douglas production function given in equation (1):

$$Y_{it} = X_{1,it}^{\propto_1} . X_{2,it}^{\propto_2} . X_{3,it}^{\propto_3} . - - - X_{n,it}^{\propto_n} \quad .... \textbf{(1)}$$

Taking log of equation (1) on both the sides, we get

$$lnY_{it} = \propto + \propto_1 lnX_{1,it} + \propto_2 lnX_{2,it} \propto_3 lnX_{3,it} \propto_4 lnX_{4,it} - - - \propto_n lnX_{n,it} .... \quad ..... \textbf{(2)}$$

Specifically, Panel ARDL equation is given below:

$$lnY_{it} = \propto_0 + \sum_{k=1}^{p} \propto_{1,ik}\ lnY_{i,t-k} + \sum_{k=1}^{q1} \propto_{2,ik}\ lnX_{1,t-k} + \sum_{k=1}^{q2} \propto_{3,ik}\ lnX_{2,t-k} + \ \dots\dots\dots\dots + \sum_{k=1}^{qn} \propto_{m,ik}\ lnX_{m,t-k} + \epsilon_{it} \quad \dots\dots\dots \ (3)$$

where t = 1, 2, 3 … T is time (in years)

i = 1, 2, 3 …n represents cross-section units (states)

p = number of lags of dependent variable

q = number of lags of independent variable (based on lag length criteria)

Y = dependent variable (horticulture production)

X_1 to X_m = independent variables (minimum temperature, maximum temperature, rainfall, area sown, irrigated area, fertilizer consumption, wage rate)

$\propto_0$ fixed effect and $\propto_1 - \propto_m$ = coefficients of independent variables

$\in_{it}$ = error term

The long run equation i.e. equation (3) states that the coefficients $\propto_1$, $\propto_2 \dots \propto_m$ can either be positive or negative. These coefficients are the elasticities of variables, stating that a unit change in any of the coefficient will lead to a considerable positive or negative effect on the dependent variable in long run. However in the short run there may be some amount of disequilibrium. The speed at which the disequilibrium is getting adjusted could be examined through the panel error correction equation as given in equation (4).

The short run Panel Error Correction Equation given in equation (4) is derived from the long-run panel ARDL equation given in equation (3)

$$ln\Delta Y_{it} = \propto_i + \sum_{k=1}^{p} \propto_{1,ik}\ ln\Delta Y_{i,t-k} + \sum_{k=0}^{q1} \propto_{2,ik}\ ln\Delta X_{1,t-k} + \sum_{k=1}^{q2} \propto_{3,ik}\ ln\Delta X_{2,t-k} + - - - + \sum_{k=1}^{qn} \propto_{m,ik}\ ln\Delta X_{m,t-k} + \delta_i ECM_i + \epsilon_{it} \dots \ (4)$$

Where δ = ECM coefficient which determines the Speed of adjustment in disequilibrium in the short run.

RESULTS AND DISCUSSION

The descriptive statistics for the variables included in the study are presented in Table 2. The mean, minimum, and maximum values of each variable are provided, offering an overview of their central tendency and range. Additionally, the standard deviation (SD) is calculated for all variables, which measures the extent of variability within the dataset over the years. The SD results indicate considerable variation in several key variables, including average annual rainfall, area sown under horticultural crops, total irrigated area, minimum temperature, maximum temperature, total horticultural production, and the average annual wage rate of horticulture workers.

As outlined in the *Methods* section, it is essential to test for cross-sectional dependence and stationarity of the data before applying the Panel ARDL model. Cross-sectional dependence refers to the interdependence or correlation between cross-sectional units, which violates the assumption of independent observations. Panel unit root tests are used to assess the stationarity or presence of a unit root in time-series variables within a panel dataset. Violations of either of these conditions can lead to spurious results. To test for cross-sectional dependence, the Breusch-Pagan LM test, the Pesaran scaled LM test, and the Pesaran CD test were employed. The results, presented in Table 3, indicate that the p-values of all three tests are less than 0.05, leading to the rejection of the null hypothesis, which suggests the presence of cross-sectional dependence between the units. Additionally, the Ramsey RESET test indicates that there is a potential for omitted variable bias in the model. When testing for multicollinearity, the variance inflation factors (VIF) for all variables are found to be below 3, which suggests that there is no severe multicollinearity and the results are within an acceptable range. Finally, the Breusch-Pagan Lagrange Multiplier (LM) test for random effects gives a significant result, confirming the presence of random effects in the model.

Table 2. Descriptive statistics of key agricultural and climatic variables

Variable	Min	Max	Mean	Standard Deviation
Average annual minimum temperature (In Celsius)	-2.00	21.65	8.80	5.63
Average annual maximum temperature (In Celsius)	34.50	47.00	41.38	3.12
Average annual rainfall (In MM)	208.94	3647.00	1322.46	680.50
Area sown (In ‘000 Hectares)	135.00	2682.98	1265.82	607.70
Horticulture production (In Metric tonnes)	1636.20	40813.85	15284.37	3.84
Fertilizer consumption (In Kg)	35.10	259.13	143.15	58.31
Total irrigated area (In 000 Hectares)	1.00	1809.17	511.97	480.95
Average daily wage rate (In Rs.)	50.09	2012.50	188.66	148.30

Source: Authors’ estimation based on secondary data

Table 3. Hypothesis testing for model selection and diagnostics

Applied Tests	Hypothesis	*P*-values/ Probability
Breusch-Pagan LM test for independence	H_0: There is no cross-section dependence between units. H_1: There is a presence of cross section dependence between units.	*0.0000*
Pesaran scaled LM Test		*0.0000*
Pesaran CD Test		*0.0000*
Ramsey RESET test using powers of the fitted values of Dependent variable (Horticulture production)	H_0: Model has no omitted variables H_1: Model has omitted variables	*0.0000*
Multicollinearity testing-variance Inflation factors	VIF ≤ 1: No correlation 1 < VIF ≤ 5: Moderate correlation. VIF > 5: High correlation	Mean VIF = 2.19
Breusch-Pagan Lagrange Multiplier (LM) test for random effects model	H_0: There are no random effects. H_1: Random effects are present.	*0.000*
Modified Walt test for heteroskedasticity	H_0: There is no heteroskedasticity in the state-wise panel H_1: There is a presence of heteroskedasticity in the state-wise panel	*0.000*
Wooldridge test for serial correlation and autocorrelation	H_0: There is no serial correlation in the residuals H_1: There is serial correlation in the residuals	*0.000*
Hausman specification test	Determine whether fixed effect or random effect can be preferred.	The data fails to meet the asymptotic assumption of the Hausman test, which may be attributed to the presence of cross-sectional dependence.

Source: Authors' estimation based on secondary data

Similarly in Table 4, the results of panel unit root test are presented. The null and alternative hypothesis for panel unit root test is as follows.

H_0: There is panel unit root (non- stationarity)
H_1: There is no panel unit root (stationarity)

It is estimated that, with the exception of minimum temperature and wage rate, the CIPS (Cross-Sectionally Augmented Panel Unit Root Test) values for all other variables do not fall within the 5% significance level, thus failing to yield significant results. Consequently, given that the panel data comprises both stationary and non-stationary variables, the Panel ARDL (AutoRegressive Distributed Lag) model is an appropriate method for examining the long-run relationships among the variables in this study.

Table 4. Results of the Pesaran Panel Unit Root Test for stationarity

Variable	CIPS value	Stationary/Not
Min temperature	-2.613	Stationary
Max temperature	-3.587	Non-Stationary
Average rainfall	-3.871	Non-Stationary
Area of production	-4.334	Non-Stationary
Fertilizer consumption	-4.352	Non-Stationary
Irrigated area	-3.740	Non-Stationary
Wage rate	-2.501	Stationary

(CIPS Critical Values: 10% = -2.67, 5% = -2.78, 1% = -3.01)
Source: Authors' estimation based on secondary data

The next step is to test for a long-run relationship among climate and non-climate variables, and the independent variables using 3 among the seven-panel cointegration tests suggested by Pedroni (1999). Pedroni (1995, 1997, 2004) proposes a residual-based test for identifying the cointegration for dynamic panels having multiple regressors. Here, long-run slope coefficients and short-run dynamics are permitted to be heterogeneous across individual states. The hypothesis is given as:

H_0: No cointegration
H_1: All panels are cointegrated

The cointegration result states that all the three tests has *p*-values less than 0.05, stating that there is a presence of cointegration among all panels.

Table 5. Results of the Pedroni Test for Cointegration

Pedroni Cointegration Test	Statistics	*P*-value
Modified Phillips-Perron t	5.6959	*0.0000*
Phillips-Perron t	-2.0005	*0.0227*
Augmented Dickey-Fuller t	-2.8224	*0.0024*

Source: Author's estimation based on secondary data

Since both the mentioned conditions are satisfied, it is conducive to use Panel ARDL model to analyze the long run impact of climate and non-climate factors on horticulture production.

It has been identified that, the function build considering the climatic and non-climatic factors affecting horticulture production is:

HP = f (min, max, rain, frt, area, irr, wgs) ------ (5)

where,

HP = Total horticulture production (In Metric tonnes)

min = Average minimum temperature (In Degree celsius)

max = Average maximum temperature (In Degree celsius)

rain = Annual rainfall (In MM)

area = Area sown under horticulture (In 000 hectare),

frt = Fertilizer consumed for horticulture production (In kg per hectare),

irr = Total irrigated area under horticulture (In 000 hectare)

wgs = Average annual wage rate of horticulture workers (In Rs per 8 hour)

t = time period.

The optimal lag length is 2 according to AIC (Akaike information criteria) of lag selection. The results of panel ARDL model which shows the long run and short run equilibrium among variables and the impact of the climatic and non-climatic factors on horticulture production in India are presented in Table 6.

The long-run equation (equation 6) is formed from the results presented in table 5:

$HP_t = -0.04465\ (min_t) - 0.18053\ (max_t) - 0.099052\ (rain_t) + 1.07036\ (area_t)$

$-0.14289\ (frt_t) - 0.27810\ (irr_t) + 0.3140\ (wgs_t)$ ……..(6)

The long-run equilibrium results reveal that all climate variables, minimum temperature, maximum temperature, and rainfall, exhibit a statistically significant negative relationship with horticultural production. Specifically, both minimum and maximum temperatures have been found to negatively impact horticultural crops (Cammarano *et al.*, 2022; Tokunaga *et al.*, 2015; Jatuporn and Takeuchi, 2023; Zaied and Zouabi, 2016; Attiaoui and Boufateh, 2019). Several studies (Alagidede *et al.*, 2016; Akram and Gulzar, 2013; Tahir *et al.*, 2024; Jan *et al.*, 2021; Cabas *et al.*, 2010; Aye and Ater, 2012; Holst *et al.*, 2013) have highlighted that rising temperatures can detrimentally affect agricultural productivity. Additionally, rainfall demonstrates a negative relationship with horticultural production, as evidenced by Nciizah and Wakindiki (2014), Poudel and Kotani (2013), and Weersink *et al.* (2010). Regarding non-climatic variables, both fertilizer consumption and irrigated area exhibit a negative impact on long-run horticultural production, with the relationship being statistically significant at the 5% level. In contrast, the area under cultivation shows a positive and statistically significant effect in the long run (Tahir *et al.*, 2024). Furthermore, wage rates for horticultural workers are positively correlated with production and remain statistically significant (Chandio *et al.*, 2022). Over time, an increase in fertilizer application can lead to a significant decline in soil fertility, thereby reducing production levels (Pasini *et al.*, 2022; Celikkol Erbas and Guven Solakoglu, 2017). Similarly, the expansion of irrigated areas is negatively associated with production, as excessive water usage can deplete soil organic carbon levels, which in turn adversely affects soil health and fertility (Yao *et al.*, 2024).

The short-run equation with ECM is formed from the results given in Table 5:

$HP_t = 0.550 + 0.196\ (HP_{t-1}) - 0.111\ (min_t) – 0.626\ (max_t) + 0.030\ (rain_t) +0.320\ (area_t)$

$- 0.010\ (frt_t) - 0.179\ (irr_t) -0.068\ (wgs_t) - 0.045\ (ECT_{t-1})$

…. (7)

The short-run equation, represented by equation (7), outlines the error correction model (ECM) designed to restore long-run equilibrium. In this context, the values of the error correction term (ECT) 0 and 1 represent no adjustment and full adjustment to equilibrium in the long run, respectively. A negative ECT value within the range of 0 to 1 is essential for a stable error correction mechanism (Asongu *et al.*, 2016), whereas a positive ECT signals a deviation from equilibrium. Consequently, the negative ECT value of -0.454 (ECT_{t-1}) in equation (7) indicates that the system is adjusting towards equilibrium after an exogenous shock, with approximately 45% of the error being corrected in the long run. When comparing the short-run and long-run models, it is observed that while annual average rainfall has a positive relationship with horticultural production in the long run, it is negative and statistically insignificant in the short run (Busayo and James, 2021). According to Ghosh *et al.* (2019), rainfall during the monsoon season plays a critical role in food production in India. In states like Uttar Pradesh and Madhya Pradesh, it has a positive impact in the short run. However, in regions such as Punjab and West Bengal, excessive rainfall can negatively affect crop yields, such as rice, illustrating a more complex relationship. This suggests that unanticipated heavy rainfall can damage crops, infrastructure, lead to soil erosion, and increase flood risks, ultimately reducing long-term crop production. All other variables maintain the same sign as in the long-

Table 6. Long-Run and Short-Run Equilibrium Results of the Panel ARDL Model

Variable	Coefficient	Probability*	Variable	Coefficient	Probability*
	Long run equation			Short run equation	
Min temp	-0.044658 (0.013051)	0.0000*	Δ Horticulture Production (-1)	0.19605 (0.157825)	0.2273
Max temp	-0.180530 (0.083028)	0.0318*	Δ Min temp	-0.111406 (0.112881)	0.3258
Rainfall	-0.090529 (0.019125)	0.0000*	Δ Max temp	-0.626323 (0.332002)	0.0618
Area under cultivation	1.070366 (0.03075)	0.0000*	Δ Rainfall	0.030447 (0.05413)	0.5749
Fertilizer	-0.142896 (0.023444)	0.0000*	Δ Area under cultivation	0.129976 (0.265086)	0.6249
Irrigated area	-0.278105 (0.058276)	0.0000*	Δ Fertilizer	-0.010058 (0.067740)	0.8822
Wage rate	0.3144011 (0.014478)	0.0000*	Δ Irrigated area	-0.17971 (0.264113)	0.4976
-	-	-	Wage rate	-0.068384 (0.05800)	0.2409
-	-	-	ECM	-0.454203 (0.234150)	0.0549
-	-	-	C	0.550842 (0.262749)	0.0383

Note: i) The Figures in parentheses are Standard Error values
ii) *Significance at p≤0.05

Source: Authors' estimation based on secondary data

run model but are statistically insignificant in the short run.

The short-run equation is inherently heterogeneous, allowing for state-specific results based on the coefficients and significance of each variable. As depicted in Graph 2, the majority of states exhibit negative coefficients (e.g., Uttar Pradesh, Assam, Chhattisgarh, Kerala, etc.), which indicates convergence toward the long-run equilibrium. States with larger negative coefficients demonstrate a faster rate of adjustment to equilibrium. In contrast, states such as Haryana, Odisha, and Tamil Nadu display positive coefficients, suggesting a divergence from the long-run equilibrium, implying that these states are not yet adjusting toward equilibrium. Additionally, states like Maharashtra and Punjab have coefficients close to zero, signifying a slow or negligible adjustment towards equilibrium. This analysis highlights the significant regional variations in convergence behaviour. While some states, such as Uttar Pradesh, exhibit faster convergence, others, such as Tamil Nadu, show signs of divergence, reflecting differing regional dynamics in the adjustment process towards long-run equilibrium.

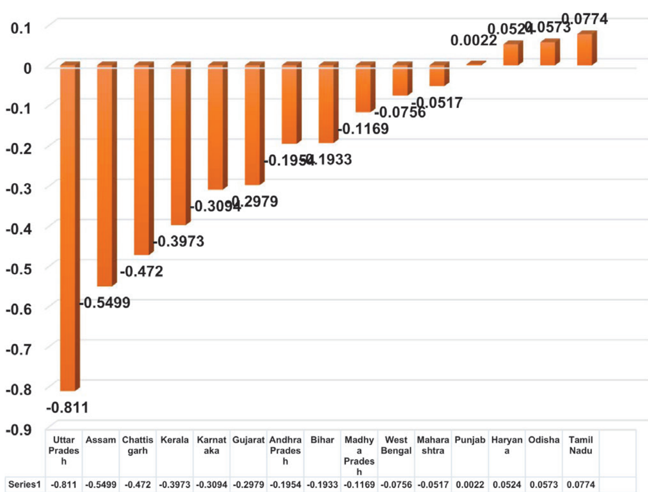

Fig. 2. Long run convergence of 15 horticulture producing states (Coefficients of adjustment)

Source: Authors' estimation

CONCLUSION

This study highlights the potential risks and vulnerabilities posed by climate change on horticultural production. To understand both the long-run and short-run effects on horticultural output, we employ the Panel ARDL technique (PMG estimation) to analyze the climatic and non-climatic variables across 15 of India's top horticulture-producing states. In the long run, the climate variables, maximum temperature, minimum temperature, and rainfall demonstrate a negative and statistically significant relationship with horticultural production. On the other hand, non-climatic factors such as area under cultivation and annual average wage rate exhibit a positive and significant impact on horticultural output. However, in the short run, the signs of the relationships between the variables differ from those observed in the long run, suggesting that while long-run equilibrium exists among the variables, short-run disequilibrium prevails. The error correction term (ECM_{t-1}) in equation (7) indicates that 45 percent of the disequilibrium among the variables is corrected in each period. These findings highlight the vulnerability of horticultural crops to climate change in the long run, necessitating efforts to mitigate these effects.

In light of these results, the study calls for the adoption of climate-resilient technologies, such as AI-ML-based innovations, to enhance horticultural production in India. Furthermore, there is an urgent need for policies and initiatives aimed at empowering farmers with the necessary knowledge, resources, and tools to adapt more effectively to the changing climatic conditions. International examples provide valuable insights into how technology can help mitigate the impacts of climate change on agriculture. For instance, Israel, one of the driest countries in the world, has developed advanced solutions to adapt to climate change through innovations in technology (World Bank Group). Similarly, the United States has embraced data-driven agriculture, offering smallholder farmers the tools for better data management and decision-making to address climate-related challenges (Gray *et al.*, 2018). China has introduced smart greenhouse technologies that continuously monitor and optimize conditions such as temperature and humidity, improving soil quality and crop growth (Guo *et al.*, 2024). In the Netherlands, vertical farming[1] offers an efficient, sustainable, and pesticide-free cultivation method that uses minimal water and space, significantly reducing the land required for horticultural production (Besten, 2019; Ji *et al.*, 2019). Kenya, through its digital agriculture initiatives, has expanded agricultural production by incorporating various technological solutions (Richard, 2024). However, India faces significant challenges in adopting such climate-resilient techniques. These include economic barriers like high implementation costs, limited access to credit, small and fragmented land holdings, and infrastructural constraints such as inadequate internet connectivity, unreliable power supply, and insufficient storage and logistics. Technical barriers, including low digital literacy and the digital divide, further complicate the situation, as do policy and institutional challenges such as regulatory hurdles, lack of government support, and insufficient extension services. To address these issues, there is a pressing need for expanded research and targeted policies that support the adoption of climate-resilient technologies and empower Indian farmers to navigate the challenges posed by climate change.

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