



RESEARCH ARTICLE

Machine learning assessment of climatic stress and productivity dynamics in the Himalayan vegetable agroecosystem

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Received: 23 February 2026; Accepted: 01 June 2026; Available online: Version 1.0: 27 August 2026

Cite this article: Shivam B, Subhash S, Samriti P, Nisha T, Ashu C, Kuldeep ST. Machine learning assessment of climatic stress and productivity dynamics in the Himalayan vegetable agroecosystem. Plant Science Today. 2026;13(sp5):01–13. <https://doi.org/10.14719/pst.14203>

Abstract

Mountain vegetable systems are critical for income generation and nutritional security in the Indian Himalayas, but accelerating climatic warming is increasingly threatening their long-term sustainability. To evaluate climate–production dynamics in Himachal Pradesh during 1996–2025, this study employed a multi-method framework integrating Mann–Kendall (MK) trend analysis, Sens' slope estimation (SSE), compound annual growth rate modelling (CAGR) modelling, decomposition analysis (DA), spearman correlation (SC) and extreme gradient boosting (XGBoost)-based machine learning. Results revealed substantial warming, with maximum and minimum temperatures increasing by approximately 0.12 °C year⁻¹, accompanied by a sharp decline in chilling hours (–31.88 hr year⁻¹). Although vegetable production increased considerably during the study period, decomposition analysis showed that production growth was driven primarily by rapid expansion of cultivated area, with tomato and pea production increases attributable to area effects by 96.23 % and 81.43 %, respectively. In contrast, productivity growth remained weak or negative for several climate-sensitive vegetables. Machine-learning analysis identified critical thermal thresholds above 22–23 °C, while exploratory (XGBoost) models demonstrated satisfactory performance, with R^2 values ranging between 0.78–0.89, mean absolute error (MAE) values between 5–8 % and mean absolute percentage error (MAPE) values below 10 %. Overall, the findings suggest that current vegetable production growth in Himachal Pradesh reflects structural buffering through area expansion rather than genuine productivity-based climate resilience, highlighting the need for climate-adaptive and productivity-centred management strategies in Himalayan agroecosystems.

Keywords: CAGR; chilling hours; decomposition; Himalayas; mountain agriculture; tomato; XGBoost

Introduction

Vegetable cultivation has emerged as a central pillar of agricultural diversification, income enhancement and nutritional security in India. Owing to its wide range of agro-climatic conditions, the country can produce a diverse spectrum of vegetables throughout the year, supporting both domestic consumption and market-oriented agriculture. India ranks second globally in vegetable production, reflecting the growing economic importance of the sector within national agriculture (1). According to the National Horticulture Database, vegetables in India covered an area of 11.23 million hectares (Mha) with a total production of 209.39 million tonnes (Mt) underscoring the dominant role of vegetables in the horticultural economy (2).

The increasing prominence of vegetables is particularly evident in hill and mountain states, where limited land availability and fragmented holdings constrain the expansion of traditional food grains. Himachal Pradesh, located in the Western Himalayan region, has emerged as a major hub of off-season vegetable production,

supplying both regional and distant urban markets. Recent estimates indicate that the area under vegetable cultivation in Himachal Pradesh reached 88.76 thousand hectares, with a total production of 1679.55 thousand tonnes in 2025, highlighting the growing contribution of vegetables to the states' agricultural economy and rural livelihoods (3). For a large proportion of farmers in the region, vegetables now constitute a primary source of income due to their higher returns per unit area and strong market demand (4). Despite these gains, agricultural systems in the Himalayan region operate under inherently fragile environmental conditions. Steep slopes, shallow soils, high erosion susceptibility and limited cultivable land impose significant structural constraints on agricultural sustainability (5). These vulnerabilities are further exacerbated by climate change, which has manifested in the Himalayas through rising temperatures, increasing rainfall variability and greater climatic uncertainty (6). Such changes pose serious risks to vegetable production systems, particularly for crops that are sensitive to temperature and moisture conditions during critical phenological stages (7).

Evidence suggests that even modest warming can have pronounced impacts on crop productivity in mountain regions. Temperature-sensitive crops, especially cool-season vegetables, depend on moderate thermal regimes and adequate chilling accumulation for optimal growth and yield formation (7, 8). Studies have shown that a 1 °C increase in temperature can reduce the productivity of Himalayan crops such as potatoes and peas by up to 10 %, underscoring the vulnerability of these systems to warming trends (9, 10). Given the economic importance of such crops, temperature-induced productivity losses have direct implications for farm incomes and the long-term viability of vegetable-based livelihoods. At the same time, climate change does not affect all vegetables uniformly. Differences in crop physiology, growing seasons and management practices result in heterogeneous responses to rising temperatures (11, 12). While some warm-season vegetables may exhibit relative tolerance or short-term stability under warming conditions, others experience yield stagnation or decline (13). Farmers often respond to climatic stress through adaptive strategies such as expanding cultivated area, shifting production to more climatically suitable locations, or intensifying input use (14). Although these responses can sustain aggregate production in the short term, they may also mask underlying declines in productivity and increase long-term vulnerability (15).

Failure to distinguish between structural expansion and genuine productivity gains can result in misleading assessments of climate resilience in vegetable production systems (4). Apparent growth in total output may coexist with declining climatic suitability, creating an illusion of resilience (16). From a sustainability perspective, resilience depends not only on short-term coping mechanisms but also on the capacity of agricultural systems to maintain productivity under persistent environmental stress (17). Understanding whether production growth reflects true productivity improvement or is primarily driven by structural buffering is therefore critical for evaluating adaptation pathways in climate-sensitive regions. While numerous studies have examined climatic trends or crop productivity responses independently, limited research has integrated climatic trend detection, structural production decomposition and non-linear response modeling to distinguish between area-led buffering and genuine productivity resilience in mountain vegetable systems. Crop-wise responses to climatic variables such as rising temperature and declining chilling hours remain insufficiently understood in Himalayan vegetable agroecosystems. Against this backdrop, the present study examines the relationship between long-term climatic change and vegetable production in Himachal Pradesh, with a specific focus on crop-wise responses to climatic variability and the structural drivers of production change.

Materials and Methods

Study area

The study was conducted in Himachal Pradesh, a mountainous state located in the Western Himalayan region of India. The state spans latitudes 30°22'–33°12' N and longitudes 75°45'–79°04' E, covering an area of about 55673 km². Himachal Pradesh exhibits pronounced altitudinal variation, ranging from approximately 350 m to over 6000 m above mean sea level, resulting in diverse agro-climatic conditions. The climate varies from sub-tropical in the lower hills to temperate and alpine in higher elevations, with cold winters

and mild summers in mid- and high-hill regions (18). Agriculture in the state is predominantly rainfed and carried out on small, fragmented landholdings, rendering it highly vulnerable to climatic variability. Vegetable cultivation forms a major component of the states' agricultural economy, particularly for off-season crops such as tomato, peas, cabbage, cauliflower and capsicum. The ecological fragility of the Himalayan landscape combined with increasing climatic stress makes Himachal Pradesh an appropriate case for assessing long-term climate impacts on vegetable production.

Data sources

Climate data

Annual climate data for the period 1996–2025 were obtained from the India Meteorological Department (IMD) to capture long-term climatic variability and trends in Himachal Pradesh. The climatic variables considered in the analysis include: maximum temperature ($T_{\max}$, °C), minimum temperature ($T_{\min}$, °C), rainfall (mm), relative humidity (%) and estimated chilling hours. Chilling hours were estimated as the cumulative annual hours with temperatures below 7.2 °C, a commonly used threshold for assessing winter chill accumulation in temperate cropping systems. State-level annual averages were used to ensure consistency with aggregate agricultural production and cultivated area statistics. The use of aggregated climatic data facilitates identification of dominant long-term climatic trends while minimising short-term local variability. Although such aggregation may partially mask localised altitudinal and microclimatic heterogeneity across the diverse Himalayan landscape of Himachal Pradesh, it remains appropriate for evaluating broad state-level climate production relationships and long-term structural changes in vegetable production systems.

Vegetable data

Crop-wise annual data on area and production of major vegetables in Himachal Pradesh were obtained from official state agricultural statistics for the study period 1996–2025. The analysis includes key vegetable crops representing both cool-season and warm-season categories, namely okra, cucurbits, capsicum, chillies, peas, tomato, beans, onion, garlic, cabbage and cauliflower. These crops together account for a substantial share of the states' vegetable area and production and reflect the diversity of vegetable production systems in the region. Productivity (yield) was computed as production per unit area and used where required to examine yield dynamics and support decomposition and climate sensitivity analyses. Although this measure does not explicitly account for input intensity, technological change or management practices, it provides a consistent indicator for evaluating long-term productivity trends and climate–production relationships at the state level.

Trend analysis of climatic variables

Long-term trends in climatic variables were assessed using the non-parametric Mann–Kendall (MK) test, which is widely applied in climate studies due to its robustness against non-normality and outliers. The magnitude of detected trends was quantified using Sen's slope estimator (SSE), providing an estimate of the rate of change per year. These methods are suitable for identifying monotonic trends in climatic time series without assuming a specific distribution. Since the analysis was based on long-term annual climatic observations, the influence of short-term temporal variability was expected to be relatively limited for broad state-level trend assessment.

Mann-Kendall (MK) test

The MK test is widely used in hydro-climatic studies because of its robustness to non-normal data distributions and its low sensitivity to outliers and inhomogeneities commonly present in long-term climatic datasets (19). The MK test statistic (S) indicates the direction of the trend, where positive and negative values represent increasing and decreasing trends, respectively (20, 21). The statistic is computed as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \quad (\text{Eqn. 1})$$

where X_i and X_j are the data values at times i and j ($j > i$) and n is the length of the time series. The sign function is defined as:

$$\text{sgn}(X_j - X_i) = \begin{cases} +1, & \text{if } X_j - X_i > 0 \\ 0, & \text{if } X_j - X_i = 0 \\ -1, & \text{if } X_j - X_i < 0 \end{cases} \quad (\text{Eqn. 2})$$

For sample sizes greater than ten ($n \geq 10$), the test statistic S approximately follows a normal distribution with a mean of zero. The variance of S , accounting for tied values, is given by:

$$\text{Var}(S) = \frac{1}{18} \left[n(n-1)(2n+5) - \sum_{p=1}^q t_p(t_p-1)(2t_p+5) \right] \quad (\text{Eqn. 3})$$

where q is the number of tied groups and t_p is the number of observations in the p^{th} tied group.

The standardised MK test statistic Z_{MK} was computed as:

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases} \quad (\text{Eqn. 4})$$

where (S) represents the Mann-Kendall statistic, n denotes the number of observations and $\text{Var}(S)$ is the variance of S . The significance of trends was evaluated using a two-sided test. The null hypothesis of no monotonic trend was rejected when

$|Z_{MK}| > Z_{1-\alpha/2}$ at the chosen significance level.

Sens' slope test

The magnitude of the detected trend was estimated using Sens' slope method (22, 23). This non-parametric approach provides a robust estimate of trend magnitude and is particularly suitable for hydro-climatic time series containing outliers or non-normal distributions. To obtain the slope estimate Q , the slopes of all possible pairs of data values were calculated as follows:

$$Q_i = \frac{Y_j - Y_i}{X_j - X_i}, j > i \quad (\text{Eqn. 5})$$

where Q_i represents Sens' slope estimator, indicating the magnitude of trend change per unit time. Where Y_i and Y_j represent observed values at times X_i and X_j , respectively. The Sens' slope estimator (Q_{med}) was then computed as the median of these N slope estimates:

$$Q_{\text{med}} = \begin{cases} Q_{\frac{N+1}{2}}, & \text{if } N \text{ is odd} \\ \frac{1}{2} (Q_{\frac{N}{2}} + Q_{\frac{N}{2}+1}), & \text{if } N \text{ is even} \end{cases} \quad (\text{Eqn. 6})$$

A positive value of Q_{med} signifies an increasing trend, whereas a negative value indicates a decreasing trend over time.

Crop-specific climate sensitivity analysis

Spearman's rank correlation coefficient (ρ) was used to examine the association between climatic variables and vegetable production. This non-parametric measure evaluates the strength and direction of monotonic relationships without requiring assumptions of normality or linearity, making it suitable for long-term climatic and agricultural time-series data (24).

The coefficient is computed as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (\text{Eqn. 7})$$

where ρ is Spearman's rank correlation coefficient, d_i represents the difference between paired ranks and n is the number of observations. Values of ρ range from -1 to +1, indicating negative to positive associations. Given the long-term monotonic trends present in both climatic and productivity series, the reported correlations should be interpreted primarily as exploratory associations rather than strict causal relationships.

Crop-wise Spearman correlations were estimated between vegetable production and key climatic variables, with particular emphasis on maximum temperature (T_{max}). Statistical significance was assessed using corresponding p -values and results were interpreted in terms of the strength and direction of climate-production relationships.

Machine learning-based response analysis

To capture non-linear responses and potential temperature thresholds, a machine learning approach was adopted. Crop-specific response functions were estimated using XGBoost-based regression models, with T_{max} as the primary predictor and vegetable production as the response variable. Machine learning was employed to move beyond linear assumptions and to identify plateauing or declining responses that may not be evident from correlation analysis alone. Model outputs were interpreted in terms of relative response patterns rather than precise prediction, consistent with the exploratory objective of the study.

Extreme gradient boosting (XGBoost)

Extreme gradient boosting (XGBoost) was employed to analyse crop-specific responses to temperature (25). The method constructs an ensemble of decision trees sequentially, where each new tree minimises the gradient of the loss function by correcting the residual errors of the preceding model. This framework is well suited for capturing non-linear relationships and interaction effects between climatic variables and vegetable production. XGBoost was selected because of its strong capability to model complex non-linear relationships, interaction effects and threshold responses between climatic variables and crop productivity. Compared with conventional regression approaches, XGBoost provides greater flexibility in capturing heterogeneous crop responses to warming and climatic variability, making it particularly suitable for climate-sensitive agricultural systems.

To improve model robustness and minimise overfitting, multiple combinations of learning rate, maximum tree depth and number of estimators were evaluated within the XGBoost framework. The final model configuration included a learning rate of 0.05, maximum tree depth of 3 and 100 estimators, which provided stable response patterns while minimising overfitting. Model performance was evaluated using coefficient of determination (R^2) and root mean square error (RMSE). Maximum temperature ($T_{\max}$) was used as the principal predictor variable because the primary objective of the study was to examine the influence of climatic warming and rising temperature stress on vegetable production systems in Himachal Pradesh. Considering the relatively short time-series dataset, the machine-learning analysis was conducted primarily for exploratory assessment of non-linear response patterns and warming-induced thermal thresholds rather than predictive forecasting. Model interpretation emphasised stability of response behaviour while preserving the temporal structure of the climatic series, thereby reducing limitations associated with conventional random partitioning in small datasets.

Decomposition of production change

Decomposition analysis was employed to quantify the relative contribution of area expansion and yield change to variations in crop production over time. The approach follows the classical decomposition framework proposed, which is based on the fundamental production identity (26):

$$P = A \times Y \text{ (Eqn. 8)}$$

where P denotes production, A represents cultivated area and Y indicates yield.

$$\Delta P = (\Delta A \times Y_0) + (\Delta Y \times A_0) + (\Delta A \times \Delta Y) \text{ (Eqn. 9)}$$

Changes in production between two periods were decomposed as: where A_0 and Y_0 are area and yield in the base period, respectively.

Accordingly, total production change was partitioned into three components: Area effect ($\Delta A \times Y_0$), representing the contribution of changes in cultivated area, yield effect ($\Delta Y \times A_0$), capturing the contribution of productivity improvement and interaction effect ($\Delta A \times \Delta Y$), reflecting the joint influence of simultaneous changes in area and yield. This decomposition framework enables clear identification of whether production growth is primarily driven by structural expansion or by genuine productivity enhancement.

Trend projection of cultivated area

To illustrate the persistence of structural responses under ongoing climatic change, Holts' linear trend method was applied to project vegetable cultivated area. Holts' approach is suitable for time series characterised by a persistent trend without seasonality and was used here to indicate the direction of future area expansion rather than to generate precise forecasts. Area projection was employed to complement the decomposition analysis and to highlight the role of structural buffering in sustaining production growth.

Holts' linear trend method consists of three equations representing the forecast, level and trend components of a time series (27):

$$\hat{y}_{t+k} = a_t + k c_t \text{ (Eqn. 10)}$$

$$a_t = \gamma y_t + (1 - \gamma)(a_{t-1} + c_{t-1}) \text{ (Eqn. 11)}$$

$$c_t = \delta(a_t - a_{t-1}) + (1 - \delta)c_{t-1} \text{ (Eqn. 12)}$$

where Eq. (10) represents the forecast equation, Eq. (11) denotes the level equation and Eq. (12) represents the trend equation.

Here, γ and δ are the smoothing parameters for the level and trend components, respectively, with values ranging between 0 and 1. The terms a_t and c_t denote the estimated level and trend of the time series at time t , while y_t represents the observed value at time t . According to Eq. (10), the k -step-ahead forecast is obtained as the sum of the most recent estimated level and k times the estimated trend.

Compound annual growth rate (CAGR) analysis

The growth performance of area, production and productivity of vegetables was analysed using the compound annual growth rate (CAGR). It provides a smoothed measure of growth over time and is widely used in agricultural growth analysis to capture long-term trends while minimising the influence of short-term fluctuations (28).

CAGR was estimated using a log-linear (exponential) growth function, expressed as:

$$\ln(Y_t) = a + bt + \varepsilon_t \text{ (Eqn. 13)}$$

where: Y_t represents the variable of interest (area, production, or productivity) in year t , a is the intercept, b is the growth coefficient, t denotes time in years and ε_t is the random error term.

Analytical framework

The analytical framework was designed to sequentially integrate climatic trend detection, production dynamics assessment, climate-productivity relationship analysis and non-linear response modelling. Initially, the MK test and SSE were employed to identify long-term climatic trends. CAGR analysis and decomposition techniques were subsequently used to evaluate structural changes in vegetable area, production and productivity. Spearman correlation analysis was then applied to assess crop-specific associations between climatic variables and productivity. Finally, XGBoost-based machine learning was used to identify non-linear response patterns and critical thermal thresholds. This integrated multi-method framework enabled comprehensive assessment of both climatic stress and structural adaptation dynamics within Himalayan vegetable production systems (Fig. 1).

Results

Long-term trends in climatic variables

The MK trend test combined with SSE revealed statistically significant long-term changes in key climatic variables during the study period (1996–2025) (Table 1). Maximum temperature ($T_{\max}$) and minimum temperature ($T_{\min}$) exhibited strong increasing trends (Kendall $\tau = 0.982, p < 0.001$), with Sens' slope indicating an average rise of approximately $0.12^\circ\text{C year}^{-1}$. Rainfall showed a weak and statistically non-significant declining trend (Kendall $\tau = -0.146, p > 0.05$), indicating high interannual variability rather than a monotonic change. Relative humidity declined significantly over time (Kendall $\tau = -0.437, p < 0.001$), while chilling hours exhibited a sharp and highly significant decreasing trend

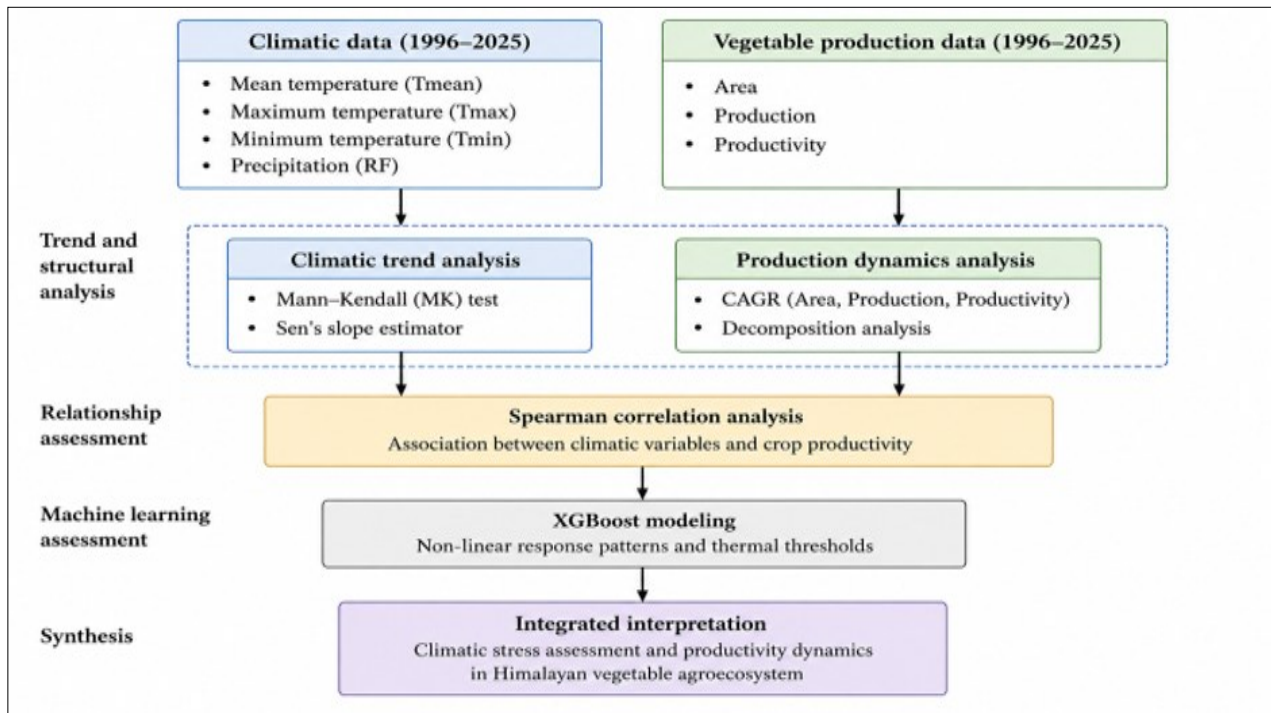


Fig. 1. Integrated analytical framework for assessing climatic stress and productivity dynamics in Himalayan vegetable agroecosystems.

Table 1. Mann–Kendall trend test and Sens' Slope estimates for major climatic variables (1996–2025)

Variable	Kendalls' tau (τ)	P-value	Sens' slope (β)
T_{max}	0.981609	$p < 0.001$	0.118519
T_{min}	0.981609	$p < 0.001$	0.118519
Rainfall	-0.14584	$p > 0.001$	-2.05882
Relative Humidity	-0.43673	$p < 0.001$	-0.05385
Chill	-0.98161	$p < 0.001$	-31.875

(Kendall $\tau = -0.982$, $p < 0.001$), with Sens' slope indicating a reduction of nearly 32 chilling hr year⁻¹.

Growth dynamics of vegetable area and productivity

Growth in area under vegetables

Log-linear growth analysis and compound annual growth rate (CAGR) estimates reveal a significant expansion in cultivated area under all selected vegetables (Table 2). Okra recorded the highest area growth (CAGR = 8.10 % year⁻¹, $\beta = 7.82$, $p < 0.001$), followed by garlic (8.10 % year⁻¹), cauliflower (7.27 % year⁻¹), tomato (6.05 % year⁻¹) and chillies (5.36 % year⁻¹). Even crops with relatively modest expansion, such as cucurbits (CAGR = 1.39 % year⁻¹), showed statistically significant growth. High coefficients of determination (R^2 ranging from 0.51–0.96) suggest that temporal trends explain a large share of the variation in vegetable area, confirming a pronounced structural shift toward vegetable cultivation.

Growth in vegetable productivity

In contrast to area expansion, productivity growth was modest, heterogeneous and crop-specific (Table 3). Beans exhibited the highest productivity growth (CAGR = 2.46 % year⁻¹), followed by capsicum (2.29 % year⁻¹), okra (1.09 % year⁻¹) and tomato (0.11 % year⁻¹). Several crops showed near stagnation in productivity, including cabbage (0.05 % year⁻¹) and cauliflower (0.01 % year⁻¹). Cucurbits (-1.54 % year⁻¹) and garlic (-0.46 % year⁻¹) experienced declining productivity, although the latter trend was statistically insignificant. Lower R^2 values for productivity trends compared to area trends indicate that productivity is influenced by additional factors such as climate variability and management practices, beyond simple time progression.

Decomposition of changes in vegetable production

The decomposition analysis partitioned changes in vegetable production into area, yield and interaction effects between the base year (1995) and terminal year (2025) (Table 4). The long-term study

Table 2. Compound annual growth rate and log-linear growth estimates of area under selected vegetables

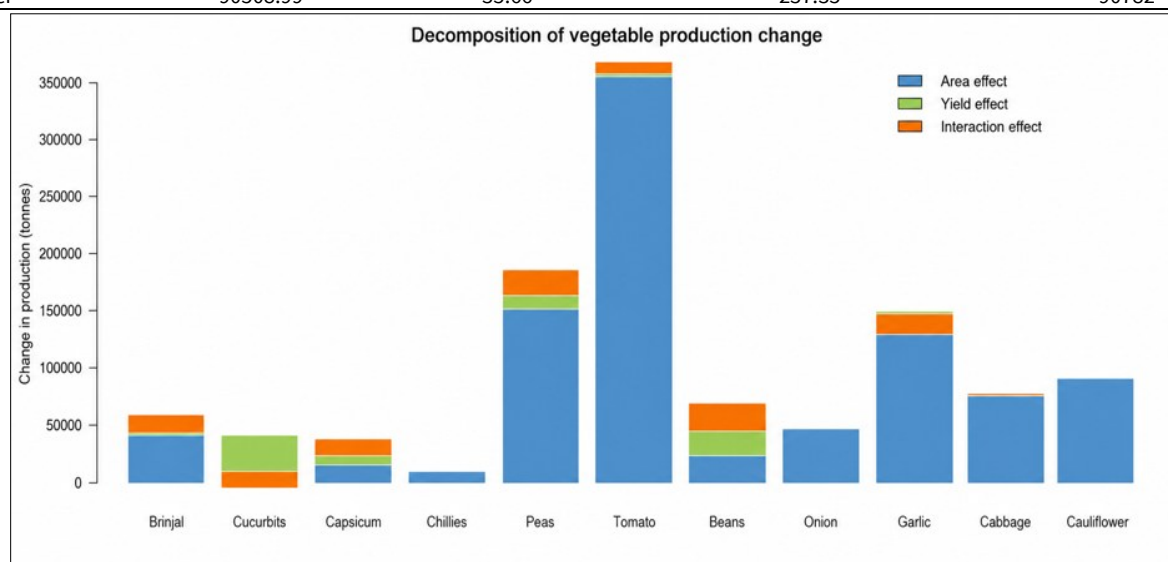
Crop	CAGR of area (%)	Growth rate (β , % year ⁻¹)	P-value	R^2
Beans	2.6	3.042	$p < 0.001$	0.937
Bhindi	8.1	7.822	$p < 0.001$	0.905
Cabbage	3.58	3.969	$p < 0.001$	0.767
Capsicum	3.8	3	$p < 0.001$	0.742
Cauliflower	7.27	7.36	$p < 0.001$	0.919
Chillies	5.36	5.461	$p < 0.001$	0.828
Cucurbits	1.39	1.36	$p < 0.001$	0.513
Garlic	8.1	7.869	$p < 0.001$	0.955
Onion	5.95	5.86	$p < 0.001$	0.874
Peas	3.95	4.434	$p < 0.001$	0.787
Tomato	6.05	4.274	$p < 0.001$	0.788

Table 3. Compound annual growth rate and log-linear growth estimates of vegetable productivity

Crop	CAGR of Productivity (%)	Growth Rate (β , % year ⁻¹)	P-value	R ²
Beans	2.46	2.077	$p < 0.001$	0.763
Bhindi	1.09	2.497	$p < 0.001$	0.783
Cabbage	0.05	0.487	$p < 0.001$	0.254
Capsicum	2.29	4.59	$p < 0.001$	0.784
Cauliflower	0.01	0.8	$p < 0.001$	0.51
Chillies	0.18	1.194	$p < 0.001$	0.491
Cucurbits	-1.54	-0.453	$p > 0.01$	0.11
Garlic	-0.46	0.258	$p > 0.01$	0.029
Onion	-0.03	1.562	$p < 0.001$	0.369
Peas	0.49	1.101	$p < 0.001$	0.851
Tomato	0.11	1.005	$p < 0.001$	0.357

Table 4. Decomposition analysis of vegetable production change between base and terminal years

Crop	Area effect	Yield effect	Interaction effect	Total change
Bhindi	41800	1797.72	15414.28	59012
Cucurbits	41151	-30387.23	-14904.77	-4141
Capsicum	15626.4	7422.96	14497.86	37547.22
Chillies	9081.64	137.91	489.2	9708.75
Peas	150991.46	11200.8	23239.74	185432
Tomato	354802.89	2535.22	11377.89	368716
Beans	23100.27	21333.83	23632.91	68067
Onion	47564.52	-90.6	-393.92	47080
Garlic	148762.41	-2162.38	-18515.04	128085
Cabbage	75506.32	678.19	1200.48	77385
Cauliflower	90508.99	35.66	237.35	90782

**Fig. 2.** Relative contribution of area, yield and interaction effects to total production change across vegetables.

period was selected to capture broad structural changes in vegetable production systems while minimising the influence of short-term annual fluctuations. Results indicate that area expansion was the dominant driver of production growth for most vegetables (Fig. 2). Tomato recorded the largest absolute increase in production (368716 t), of which 96.23 % was attributable to area expansion. Similar dominance of area effects was observed for peas (81.43 %), cabbage (97.57 %) and cauliflower (99.70 %). Beans and capsicum displayed comparatively stronger yield and interaction effects,

together accounting for over 60 % of total production change, suggesting relatively better productivity performance. In contrast, cucurbits experienced a net decline in production (-4141 t) despite positive area expansion, due to large negative yield and interaction effects.

Climate-productivity relationships

Spearman's rank correlation analysis revealed statistically significant associations between maximum temperature (T_{max}) and vegetable

Table 5. Spearman's rank correlation between maximum temperature and vegetable productivity

Vegetable	Spearman r (T_{max})	P-value	Interpretation
Bhindi	1.000	$p < 0.001$	Strong positive
Cucurbits	0.998	$p < 0.001$	Strong positive
Capsicum	0.998	$p < 0.001$	Strong positive
Chillies	-0.193	$p > 0.1$	Weak / NS
Peas	-0.583	$p < 0.001$	Moderate negative
Tomato	-0.998	$p < 0.001$	Strong negative
Beans	0.995	$p < 0.001$	Strong positive
Onion	0.406	$p < 0.05$	Moderate positive
Cabbage	0.918	$p < 0.001$	Strong positive
Cauliflower	0.895	$p < 0.001$	Strong positive
Garlic	0.927	$p < 0.001$	Strong positive

productivity (Table 5). Productivity of peas ($\rho = -0.583, p < 0.001$) and tomato ($\rho = -0.998, p < 0.001$) exhibited strong negative relationships with $T_{\max}$, highlighting their sensitivity to warming conditions. Chillies showed a weak and statistically non-significant association ($\rho = -0.193, p > 0.05$). Conversely, okra, capsicum, beans, cabbage, cauliflower and garlic exhibited strong positive correlations with $T_{\max}$ ($\rho = 0.89, p < 0.001$), indicating greater thermal tolerance or adaptive responses through crop management and varietal selection.

Non-linear productivity responses from machine learning analysis

Machine-learning analysis using XGBoost regression captured non-linear responses of vegetable productivity to $T_{\max}$ (Fig. 3 and 4). The response curves revealed distinct threshold and saturation effects across crops. Cool-season vegetables such as peas, cabbage and cauliflower exhibited productivity plateaus or declines beyond 22–23 °C, indicating critical thermal thresholds. Tomato showed a pronounced decline in productivity response at higher temperatures, consistent with its strong negative correlation with $T_{\max}$. The exploratory XGBoost models demonstrated satisfactory performance, with R^2 values ranging between 0.78–0.89, MAE values between 5–8 % and MAPE values below 10 %, supporting the stability of the identified thermal response patterns.

Yield variability and regime shifts

State-space transition analysis based on rolling mean yield and yield variability identified distinct productivity regimes across vegetables. Several crops, particularly peas, tomato and cabbage, transitioned from low-variability-moderate-yield regimes to higher-variability

regimes in recent years (Fig. 5). These regime shifts coincide with periods of rising $T_{\max}$ and declining chilling hours, suggesting increasing climatic instability in yield formation processes. Warm-season vegetables exhibited relatively stable regime structures, reinforcing their comparative climatic resilience.

Projection of structural responses

Holts' linear trend model applied to total vegetable area demonstrated strong predictive performance (RMSE = 1719 ha; MAE = 1263 ha; MAPE = 2.64 %; pseudo $R^2 = 0.994$). Forecasts indicate continued expansion of vegetable area under prevailing trends. While this expansion supports aggregate production growth, it also increases dependence on land-based adjustment mechanisms, raising concerns about long-term sustainability under continued climatic warming (Fig. 6).

Discussion

Persistent warming and erosion of thermal suitability

The present study found that vegetable production in Himachal Pradesh has been occurring under a rapidly warming climatic regime characterised by statistically significant increases in maximum and minimum surface air temperatures. Sens' slope estimates indicated warming rates of approximately 0.2 °C year⁻¹, reflecting substantial cumulative warming over the study period. Similar warming trends across Himalayan regions were also reported in various studies. Research indicates increasing temperature intensity and climatic instability across the northwestern Himalayas and India (9, 16, 29). Likewise, research has demonstrated the increasing vulnerability of Himalayan ecosystems

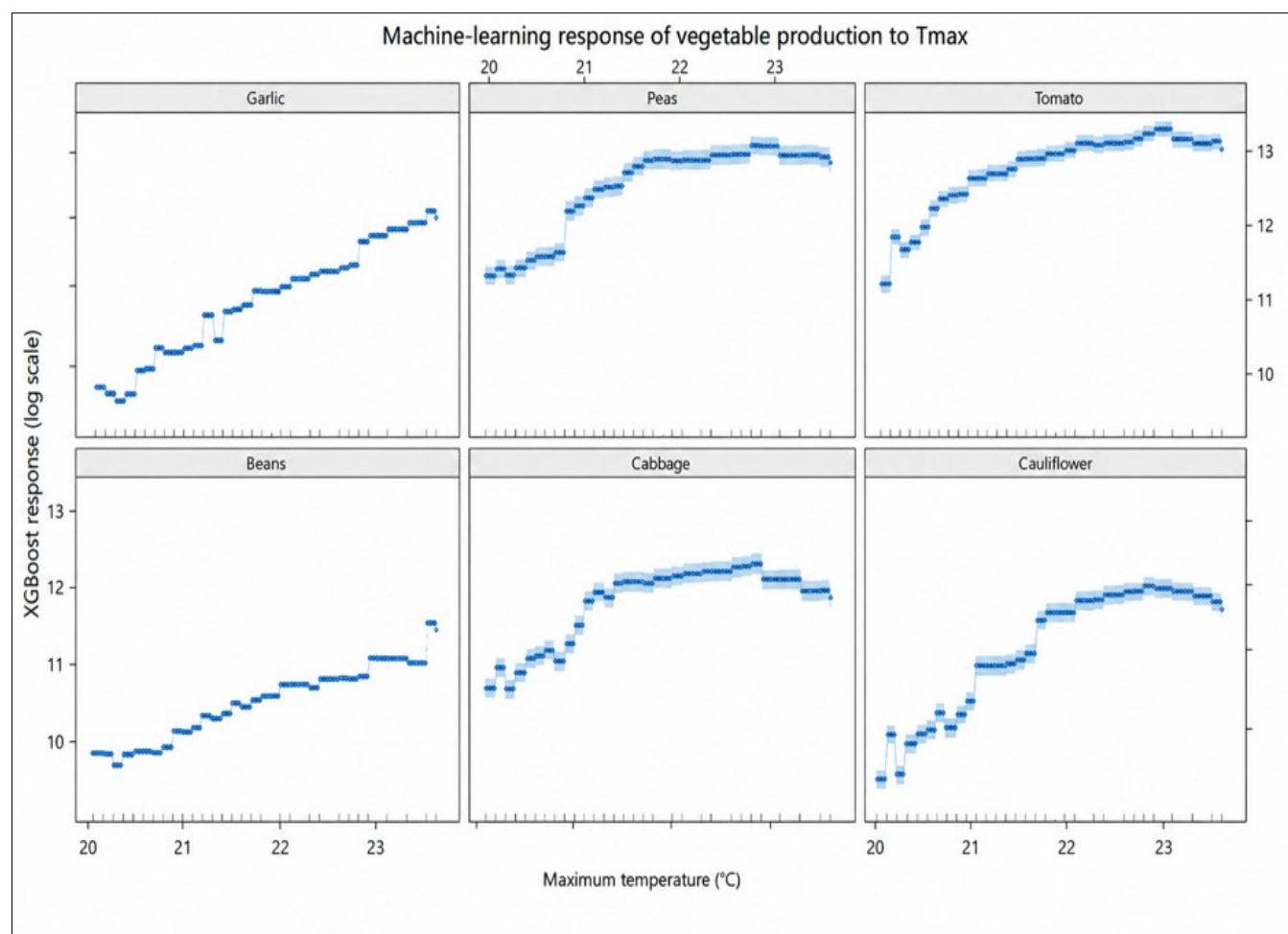


Fig. 3. Non-linear response of cool-season vegetable productivity to maximum temperature based on XGBoost regression analysis.

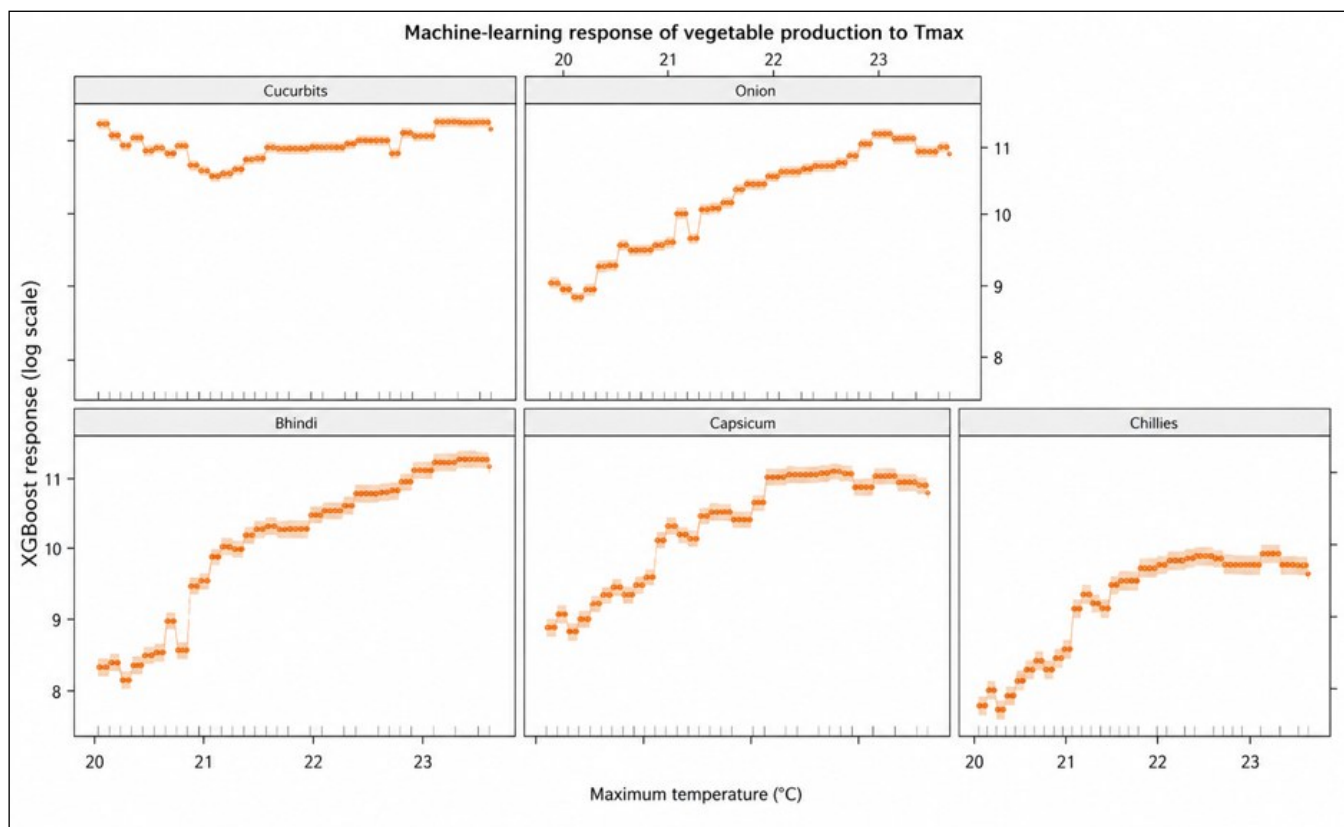


Fig. 4. Non-linear response of warm-season vegetable productivity to maximum temperature based on XGBoost regression analysis.

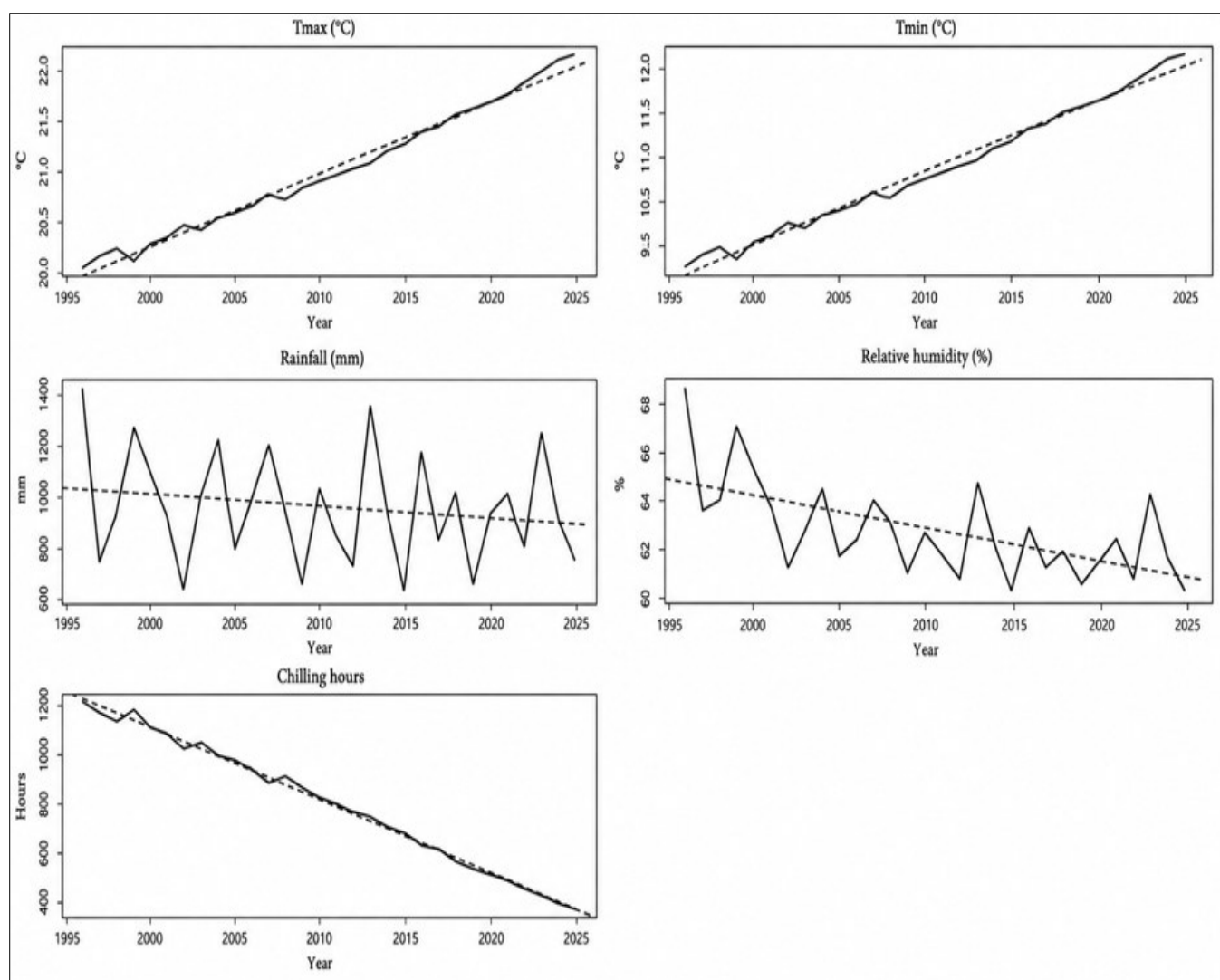


Fig. 5. Long-term trends in major climatic variables (1996–2025).

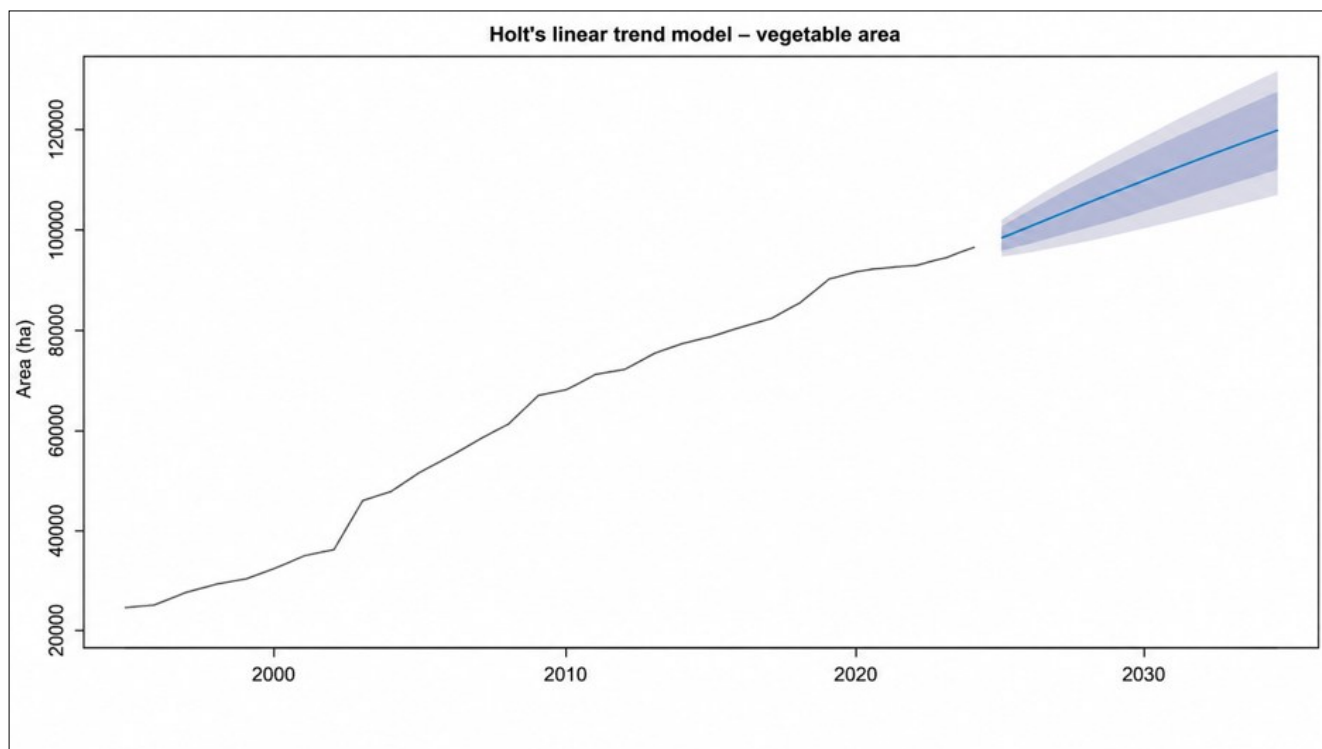


Fig. 6. Forecast of total vegetable area using Holt's linear trend model.

and agricultural systems under continued climatic warming (30, 31). The study further observed a sharp decline in chilling hours, indicating substantial alteration in winter thermal conditions. Reduced chilling accumulation may adversely affect flowering synchronisation and reproductive development in cool-season vegetables. Similar concerns regarding changing winter thermal regimes in Himalayan environments were also reported (9, 16). In contrast, rainfall did not exhibit a significant long-term trend, whereas relative humidity declined significantly, suggesting that temperature-related stress has emerged as the dominant climatic constraint affecting vegetable systems in the region. Similar observations were recorded in the previous studies, which emphasised increasing climatic stress and vulnerability in Himalayan agricultural systems (4). Overall, the findings suggest that continued warming may progressively erode the thermal suitability and long-term stability of Himalayan vegetable production systems (15, 32–35).

Area expansion outpacing productivity growth

The present study revealed a growing divergence between rapid expansion of cultivated area and relatively weak productivity improvement in Himachal Pradesh. While vegetable cultivation expanded consistently across crops, productivity gains remained modest, stagnant, or even negative for several vegetables. Similar trends of area-led production growth with slower productivity improvement were also reported (13). Likewise, research highlighted that lower land productivity and limited modernisation increase climatic and environmental vulnerability in resource-constrained agricultural systems (36). The weaker and more variable productivity trends observed in the present study further suggest increasing sensitivity of vegetable yields to climatic variability and associated external stresses. These findings indicate that recent increases in vegetable production have been sustained primarily through expansion of cultivated land rather than improvements in yield efficiency. However, continued reliance on area expansion may become increasingly unsustainable in Himalayan agroecosystems

characterised by limited arable land, fragmented holdings and ecological fragility.

Dominance of structural buffering revealed by decomposition analysis

The decomposition analysis indicated that recent vegetable production growth in Himachal Pradesh has been driven predominantly by expansion of cultivated area rather than sustained productivity improvement. The dominance of area effects across most vegetables suggests that farmers have largely compensated for climatic stress through structural adjustments in cultivation patterns instead of achieving substantial yield enhancement. In contrast, the relatively small or negative contribution of yield effects for several crops indicates limited productivity resilience under warming conditions. Similar concerns regarding declining productivity resilience and increasing climatic vulnerability in vegetable systems have been highlighted (37, 38). Research indicates that rising temperatures and climatic stress can increasingly constrain vegetable productivity despite expansion in cultivation (37, 38). Likewise, research emphasised that warming-induced stress may progressively reduce the effectiveness of conventional adaptation mechanisms in vegetable production systems (39). The findings therefore suggest that area expansion has functioned primarily as a short-term buffering mechanism rather than evidence of durable climate resilience. Under continued warming and declining thermal suitability, the sustainability of this adjustment pathway may become increasingly uncertain in Himalayan Mountain agroecosystems.

Temperature productivity linkages and crop-specific sensitivity

The correlation analysis revealed substantial heterogeneity in crop responses to rising temperature, indicating that climatic warming does not affect all vegetables uniformly. Tomato and peas exhibited strong negative associations with T_{max} , suggesting high sensitivity of cool-season vegetables to increasing thermal stress. Similar negative effects of rising temperature on crop productivity and reproductive

stability were also reported in previous studies. Research highlighted the adverse influence of warming on agricultural productivity in climate-sensitive regions (40, 41). These responses are likely associated with declining chilling availability and increasing heat stress during flowering and reproductive stages, which may negatively affect pollination, fruit set and yield stability. In contrast, vegetables such as okra, capsicum, beans, cabbage, cauliflower and garlic showed positive associations with temperature. However, these relationships should not be interpreted as unlimited benefits of warming. Rather, they may reflect relative thermal tolerance within the observed climatic range, combined with adaptive management practices and gradual spatial adjustment of cultivation toward more suitable environments. Similar observations regarding crop-specific climatic adaptability and resilience strategies were reported in previous studies. Chillies exhibited comparatively weak temperature sensitivity, indicating either broader thermal adaptability or stronger influence of non-climatic factors such as varietal selection, input management, irrigation, technological change and agronomic practices (42, 43). Comparable findings were reported in previous studies (44). Research emphasised that crop productivity responses are shaped by interactions between climatic stress and management-related factors (44). Overall, the findings highlight the crop-specific nature of climatic vulnerability within Himalayan vegetable production systems and suggest that the reported relationships should be interpreted primarily as indicators of climatic association and relative sensitivity rather than definitive evidence of causality.

Non-linear responses and thermal thresholds identified through machine learning

The XGBoost-based machine-learning analysis provided important insights into non-linear crop responses that could not be fully captured through correlation analysis alone. Tomato and peas exhibited clear thermal thresholds around 22–23 °C, beyond which productivity declined sharply, indicating high sensitivity of reproductive processes to increasing temperature. Similar heat-stress effects on flowering, pollen viability and fruit set in tomato and pea crops were also reported in previous studies (45–47). Cabbage and cauliflower displayed yield saturation at higher temperatures despite positive linear associations, suggesting that apparent productivity stability may conceal approaching physiological limits. In contrast, warm-season vegetables such as okra and capsicum exhibited comparatively flatter response curves, indicating relatively greater thermal tolerance within the observed climatic range. Similar non-linear crop responses under climatic warming were also highlighted in previous studies (11). However, these responses should not be interpreted as evidence of unlimited climatic resilience. Similar concerns regarding declining agricultural productivity under continued warming were emphasised in previous studies (48, 49). Overall, the findings suggest that continued warming may progressively push even relatively tolerant vegetable crops beyond critical productivity thresholds in Himalayan agroecosystems.

Increasing yield variability as an early warning signal

State-space transition analysis revealed increasing yield variability for peas, tomato, cabbage and cauliflower, with transitions from low-variance to high-variance regimes during recent years. This increase in variability coincided with accelerated warming and declining chilling hours, suggesting growing climatic instability in Himalayan vegetable systems (16, 37). Similar observations regarding the

influence of climatic variability on agricultural productivity and system vulnerability were reported in previous studies (41, 43). Elevated variability increases production risk and income instability even when mean productivity appears relatively stable. Warm-season crops exhibited comparatively stable variance regimes, indicating relatively greater short-term resilience under the current climatic range. However, given the magnitude of observed warming trends, this stability may be temporary rather than permanent. Similar shifts in climatic suitability and agricultural instability across Himalayan systems were also highlighted in previous studies (34). Overall, the findings suggest that increasing yield variability may serve as an important early warning indicator of declining climate resilience in mountain vegetable agroecosystems.

Persistence and limits of area-led adaptation

Holts' linear trend projections indicated that expansion of cultivated area is likely to remain a dominant adaptation strategy under ongoing climatic change. The strong forecasting performance suggests a relatively stable trajectory of continued area expansion in vegetable cultivation. Similar structural adjustment patterns in agricultural systems under changing climatic and policy conditions were also reported in a previous study (50). The present findings suggest that farmers are increasingly maintaining production through land-use adjustments under rising climatic stress. However, continued dependence on area expansion raises important sustainability concerns in fragile Himalayan agroecosystems characterised by limited arable land, slope instability and erosion susceptibility. Similar concerns regarding climatic warming, ecological instability and shifting agricultural suitability in Himalayan regions were highlighted in previous studies (32–34). Overall, the findings suggest that structural expansion alone may not be sufficient to sustain vegetable production under continued warming and declining chilling availability without corresponding improvements in productivity resilience and climate-adaptive management practices.

Integrated interpretation and implications for resilience

Collectively, the findings demonstrate that vegetable production growth in Himachal Pradesh reflects structural resilience rather than productivity-based climate resilience. Rapid expansion of cultivated area, with CAGR values exceeding 5 % for several crops, has masked stagnating or declining productivity, particularly for climate-sensitive vegetables such as peas and tomato. Similar trends of area-led production growth with limited productivity improvement were also reported in previous studies (13). The convergence of strong warming trends, declining chilling availability, weak productivity growth, dominance of area effects, non-linear thermal thresholds and increasing yield variability indicates that the current production trajectory remains adaptive but fragile. Comparable concerns regarding climate-induced agricultural vulnerability and declining resilience under continued warming were emphasised (41, 42). Overall, the findings suggest that continued warming may increasingly expose vulnerabilities that structural area expansion alone cannot offset without targeted interventions focused on varietal improvement, microclimate management and climate-informed crop planning in Himalayan vegetable agroecosystems.

Study limitations and future research directions

The present study is based on aggregated state-level climatic and production data, which may not fully capture the substantial altitudinal and agro-climatic heterogeneity across Himachal Pradesh. Consequently, the findings should be interpreted primarily

as broad regional trends rather than location-specific responses. Future studies using district-level or elevation-specific datasets may provide more refined understanding of localised climate–productivity interactions within Himalayan vegetable systems. The study primarily focused on long-term climatic trends, productivity dynamics, structural adaptation patterns and exploratory machine-learning assessment of warming-induced thermal responses. The XGBoost analysis was intended mainly to identify non-linear response behaviour and thermal thresholds using maximum temperature as the principal climatic indicator rather than to develop a comprehensive multivariable predictive model. Other important climatic and management-related factors, including rainfall variability, soil moisture, irrigation, technological change, varietal improvement and input management, were not explicitly incorporated. In addition, the relatively short annual time-series dataset may limit predictive generalisation of the machine-learning results. Economic dimensions such as farm income, profitability, production costs, labour availability and market risk were also not explicitly incorporated because of limitations in long-term consistent farm-level datasets. Future research integrating high-resolution climatic, agronomic, physiological and economic data could therefore provide a more comprehensive assessment of climate resilience and adaptation effectiveness in Himalayan vegetable production systems.

Policy Implications

The findings underscore the need for a strategic reorientation of vegetable development policy in Himachal Pradesh from area-led growth toward productivity-based climate adaptation. Continued reliance on expansion of cultivated area as the primary adjustment mechanism is environmentally unsustainable in fragile hill ecosystems and insufficient to counter rising thermal stress. Policy efforts must therefore prioritise stabilising and enhancing yields under warming conditions. Given the strong temperature sensitivity of key vegetables such as peas and tomato, targeted investment in the development and dissemination of heat-tolerant and low-chill varieties is critical. Crop-specific thermal thresholds identified in this study provide a scientific basis for revising varietal recommendations and sowing calendars at the regional scale. Declining winter chill further necessitates climate-informed spatial reallocation of vegetable systems, with cool-season crops gradually shifting to higher elevations, while lower elevations transition toward more thermally resilient alternatives. These adjustments should be supported through climate zoning, strengthened extension services and localised advisory systems. Increasing yield variability also highlights the importance of risk management instruments. Crop insurance and income stabilisation schemes must explicitly account for climate-induced variability and threshold risks rather than relying on historical averages. Finally, investments in protected cultivation, microclimate modification and water-efficient technologies are essential to enable farmers to transition from land-based buffering toward sustainable, productivity-driven climate resilience.

Conclusion

This study demonstrates that vegetable production in Himachal Pradesh has expanded under a rapidly warming climatic regime characterised by statistically significant increases in annual maximum and minimum surface air temperatures and a persistent decline in chilling hours. Despite these adverse climatic trends,

vegetable output increased approximately three times during 1995–2025. However, decomposition analysis revealed that nearly 80–95 % of production growth for major vegetable crops was driven by expansion in cultivated area, whereas yield contributions remained marginal for peas (0.49 % year⁻¹) and cabbage (0.05 % year⁻¹) and negative for cucurbits (−1.54 % year⁻¹). Strong negative associations between temperature and productivity for peas and tomato indicate increasing climatic vulnerability of cool-season vegetable systems. Machine-learning analysis further identified non-linear and crop-specific productivity responses, with critical thermal thresholds above 22–23 °C beyond which productivity declined sharply. Increasing yield variability across several crops additionally suggests emerging instability in vegetable production systems. Overall, the findings indicate that recent vegetable production growth in Himachal Pradesh has been sustained more through structural expansion than genuine productivity-centred climate resilience. Under continued warming and increasing land constraints, this growth trajectory may become increasingly unsustainable, highlighting the need for adaptation strategies focused on varietal improvement, microclimate management and climate-resilient production planning in Himalayan Mountain agroecosystems.

Acknowledgements

I sincerely acknowledge the institutional support and the provision of all necessary facilities that enabled the successful conduct of this study. The encouragement and assistance received throughout the research process are gratefully recognised.

Authors' contributions

SB contributed to conceptualisation, methodology, data collection, formal analysis, visualisation, writing-original draft preparation and manuscript revision. SS contributed to supervision, conceptualisation, methodology, review and editing. SP contributed to data validation, interpretation of results, review and editing. NT contributed to data curation, literature review and manuscript review. AC contributed to methodological support, data interpretation and manuscript review. KST contributed to supervision, critical review and final approval of the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

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

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this manuscript, ChatGPT (OpenAI) was used for language refinement, grammatical editing and improvement of readability. All authors read and approved the final manuscript.

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