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REVIEW ARTICLE

Climate change impacts on agriculture and forests: Analytical methods review

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Abstract

Climate and climate change are critical factors influencing global ecosystems, agriculture and forestry. Climate refers to the long-term patterns of temperature, precipitation and atmospheric conditions, while climate change refers to significant alterations in these patterns over time. This review examines the impacts of climate change on natural systems, with particular focus on variations in temperature, precipitation and related climatic variables. The review integrates advanced statistical methodologies, including homogeneity tests, trend analysis and change-point detection, to analyze climate data and identify patterns of variability and shifts over time. Homogeneity tests are used to detect sudden changes or inhomogeneities caused by non-climatic variables (from station relocations or instrumental changes). Trend analysis is employed to detect long-term changes in climate variables such as temperature and precipitation, providing information on existing climate changes. Change-point detection tests help identify specific points at which significant shifts in climatic patterns occur, which may influence sudden transitions in ecosystems. Collectively, these tools enhance our ability to detect, interpret and respond to the evolving nature of climate change, thereby supporting timely and informed adaptation strategies in the fields of agriculture and forestry.

Keywords : change-point; climate variability; homogeneity; impact; trend analysis

Introduction

Climate is one of the most essential components of the Earth system. Weather and climate are determined by a wide range of factors, including temperature, precipitation, air pressure and humidity (1). Climate is defined as the average weather conditions of a region, based on historical data of meteorological elements (2). Climate change is defined as the shift in an areas' climate caused by both natural and man-made conditions such as the greenhouse effect (3). Climate change is characterized by long-term variations in temperature, precipitation, air pressure and humidity (4).

According to the IPCC (2023) report, climate change represents a serious socioeconomic and environmental issue, affecting terrestrial, freshwater, cryosphere, coastal and open ocean ecosystems. Its impacts are increasing and could become irreversible (5). Globally, the agricultural industry is facing serious challenges from climate change and variability. It is well-known that adverse effects on crop production will come from changes in temperature, rainfall patterns, sea level and atmospheric CO_2 concentration (6). Future climate change is expected to severely affect crop productivity and water requirements, as climatic factors directly influence agricultural output (7). Additionally, the growing global population has marked increased the demand for food (8). In order to maintain agricultural productivity, reduce susceptibility and enhance the resilience of agricultural systems' to t climate change, adaptation strategies are necessary (9).

Climate change also poses a threat to biodiversity by altering optimal temperature ranges, thereby disrupting ecological systems and accelerating species loss (10).

It is widely accepted that non-climatic variables like urbanization and site relocations cause fluctuations in the majority of long-term climate datasets. These non-climatic variables frequently produce inhomogeneities at different times and in varying degrees of magnitude (11). To determine whether the data in a given set exhibits a significant trend or an abrupt change in the distribution, various kinds of statistical tests, both parametric and non-parametric, are often used (12, 13). These trends include variations in temperature, rainfall, wind speed, humidity levels and other weather parameters (14).

It is important to note that parametric tests are generally more effective when the data are normally distributed and independent, whereas non-parametric tests are more suitable for skewed or ordinal data (15). Non-parametric tests require data independence and are less susceptible to non-normal distributions, extreme values and missing values (16). However, non-climatic factors (e.g. station relocation, urbanization) do not influence actual climate patterns but affect the measurement or representation of climate data which could affect the results of climatic-related studies. Therefore, it is strongly suggested that the long-term time series of weather parameters be tested for homogeneity prior to use (17).

Sudden changes in time series data are known as change points. Change point detection is a valuable tool for modelling and time series prediction across various fields, including medical condition monitoring, climate change detection, speech and image analysis and human activity recognition (18). Because of the growing risk associated with climate change and the rising greenhouse gas concentrations, change point detection-based techniques for climate analysis, monitoring and prediction have gained importance during the past few decades (19).

The objective of this review is to explore and synthesize previous studies on statistical techniques used to analyze climate variables. Furthermore, climate change impact on the agriculture sector and the forest ecosystems are also discoursed for a clear understanding of potential significance of various tests to analyze the climate variability to take necessary actions accordingly.

Methodology

This review discusses three major statistical methods used in climate data analysis: homogeneity tests, trend analysis and change-point detection. To illustrate the applications of these methods, a simulated dataset was generated using the *rand()* function in R. This dataset does not represent real-world observations; it is intended solely for the purpose of demonstrating the application and visualization of statistical techniques. All plots and analyses were performed using R software (version 4.3.2).

Tests of homogeneity

Homogenization is the process of identifying and correcting irregularities in climate data (20). It is a critical step in any climatological study. The two stages of homogenization processes involves: break detection, which is normally applied to time series aggregated at annual, seasonal, or monthly scale; and adjustment calculations (21). The results will show incorrect trends if the homogeneity is not checked before trend analysis (22, 23). To be able to distinguish between changes caused by observation techniques and natural climate shifts, it is crucial to homogenize climate data for a precise understanding of climatic variability and change (24).

Table 1 presents a comparison of homogenization methods that can be used for climate data. Fig. 1 is a self - generated figure showing the difference between trends in raw and homogenized data. The raw data represents original temperature values, while the homogenized data shows adjusted values after correcting for potential inconsistencies. Several Bayesian approaches such as BAMS, BARE, Bayesian change-point algorithm, BHNT are widely used for testing homogeneity. Also, there are some software packages for homogenization such as Climatol, RHTest, AnClim ,ProClimDB, USHCN and HOMER which can be used to perform homogeneity tests and correct the irregularities (20).

Trend analysis

Trend analysis of climatic variables is a key technique for assessing the climate characteristics of a specific region, as it provides estimates of variability (46). The main focus of trend analysis is on identifying the overall direction and magnitude of change, rather than explaining the underlying climatic mechanisms, or how they evolve over time (47). Trend results, particularly from historical records and climate change model scenario projections, help the prediction of the climate before mitigation and adaptation efforts can be undertaken (48).

Table 2 represents a comparison of trend detection methods suitable for climate data. Fig. 2 is the self -generated figure through R software which shows the increasing trend in temperature data.

Change point detection techniques

A change-point refers to an abrupt shift in the behavior of a time series (59). Change-point detection is a rapidly growing subject in the data science literature (60), with numerous applications in time series analysis. These techniques are used to estimate the actual number of structural changes present in the data. When structural change occur naturally, accurate estimation of change-points is necessary to assess long-term climatic changes effectively (61).

Table 3 represents a comparison of change-point detection methods application to climate data. Fig. 3 is a self-generated figure; created using R software, showing the detected change-point in the temperature dataset.

Impact of climate change in agriculture

Climate change poses major challenges to agriculture and food security, as increasing extreme weather events have led to decreased crop yields worldwide. Weeds, diseases, insects and pests are also considerably impacted by changes in climate parameters in various ways (68). Climate change is reshaping global agriculture by altering traditional planting patterns, thereby posing substantial risks to food security. Farming systems are being disrupted by the interplay of rising temperatures, changing precipitation regimes and a higher incidence of extreme weather events (69).

Expected consequences of climate change include rising sea levels, increased average surface temperatures and more frequent extreme events. These changes are anticipated to significantly influence the distribution, quality and quantity of crop production, posing a major threat to economy and mankind (70). Additionally, climate change may alter the physical, chemical and biological properties of soil. In this context, soil health refers to the soils' capacity to maintain its essential functions-physical, chemical and biological; despite stresses arising from temperature fluctuations, changes in precipitation and atmospheric nitrogen deposition (71).

Due to specific growth requirements and limited adaptability, certain crops are more sensitive to climate

Table 1. Homogenization methods

Method	Features	Reference
Non- parametric tests		
Von Neumann ratio test	The presence of irregularities is determined by value of the ratio	(25)
Wald-Wolfowitz runs test	Used to assess randomness in a sequence of data The test counts the total number of runs in the sequence and compares it to the expected number of runs under the null hypothesis of randomness. If the number of runs is significantly higher or lower than expected, the sequence is non-random. Suitable for small sample sizes.	(26)
Mann-Kendall test	To test the presence of trends	(27)
Wilcoxon-Mann-Whitney or Mann-Whitney U test	Evaluates whether two samples come from populations with the same distribution	(28)
Kruskal-Wallis test	Used to compare 2 or more independent groups of data	(29), (30)
Pettitt's test	Identifies breakpoints in the middle of the series	(31)
Classical Tests	Determine the consistency of meteorological records and making necessary adjustments	(32)
Craddock's test	Identify inconsistencies If the ratio of the reference series and candidate series remains constant, the records are consistent	(33)
Potter test	Commonly applied to precipitation series	(34)
Buishand Range test	Uses cumulative deviations from the mean to identify breaks or shifts in a dataset.	(35)
Regression Methods		
Two phase regression	Uses series of regression fits to candidate series sub sections using reference series which act as predictor variables If the best fit is observed by the reduction of residual sum of squares, then the end points of each sub section indicating inhomogeneities	(36)
Multiple linear regression	Application of multiple linear regression models If autocorrelation is identified in the residuals of the regression models, then inhomogeneities may be present in the tested series	(11)
Method of cumulative residuals	Used for exploratory analysis	(37)
Homogenisation procedure		
SNHT	Likelihood ratio test Detection of single break point	(38)
SNHT with trend	Identifies trend-type inhomogeneities	(39)
MASH	Use of Metadata Multiple breakpoints can be detected	(40)
PRODIGE	Detects unknown number of breaks using penalized log-likelihood procedure	(41)
Geostatistical simulation approach	Break is detected whenever the interval of probability p (e.g. 0.95) centered in the local probability density function calculated for candidate series does not have the observed value of the candidate station	(42)
ACMANT	Bivariate test is applied for identifying the inhomogeneities	(42)
ACMANT2	ACMANT extension for precipitation series	(44)

Standard Normal Homogeneity Test, Multiple Analysis of Series for Homogenization, Adapted Caussinus–Mestre Algorithm for homogenizing Networks of Temperature series

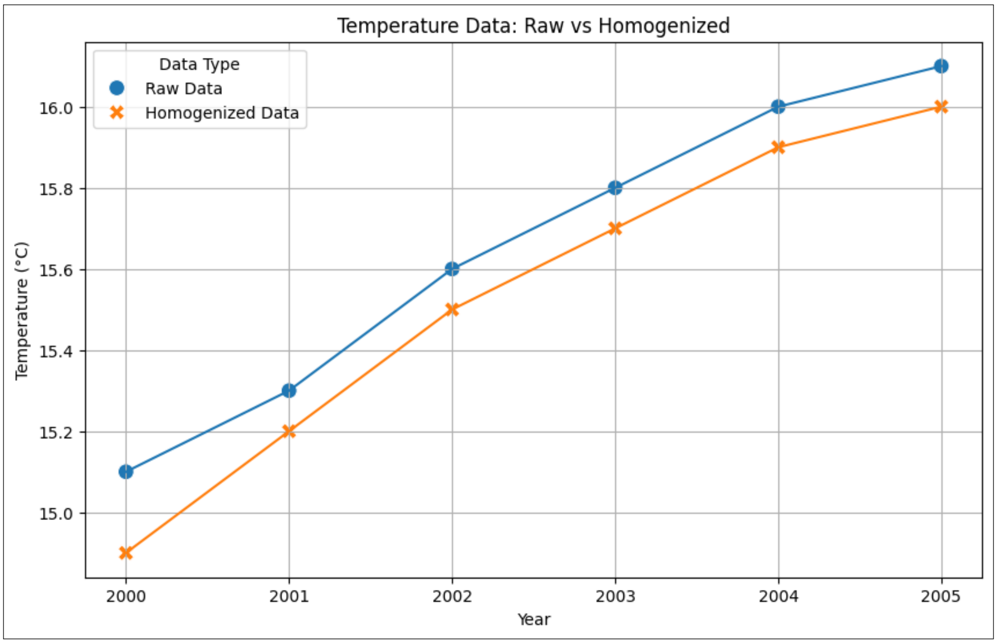

Fig. 1. Temperature data comparison between raw and homogenized data (self-generated figure).

Table 2. Methods of trend analysis

Method	Description	Reference
Least squares linear regression test	Slope based test Used to describe the presence of linear trend in time series	(49)
MK	Evaluates the hypothesis of randomness (no trend) against the alternative of a monotonic trend in a time series	(27)
Spearman rank correlation test	Test statistic tSRC can be approximated using a t-distribution for large samples with n-2 degrees of freedom and significance level α If tn-2, α /2< tSRC< tn-2, 1-α /2, null hypothesis will not be rejected detecting trend in the series	(50)
Sens Slope estimation	To estimate magnitude of a trend in a time series	(51)
Trend-free pre-whitening with MK test	Aims to remove both the effects of trends and serial correlation to ensure accurate trend detection Alternative to standard pre-whitening methods and variance correction approaches	(52)
Modified Mann-Kendall Test	Introduced to correct the variance of the MK test statistic to account for autocorrelation	(53)
Block bootstrap with MK and SR	Suggested for testing trends or changes in hydrological datasets as BBS adapts well to the complex properties of hydrological data, such as seasonality or serial correlation while resampling it	(54)
Sequential Mann–Kendall test	The sequential MK test calculates two statistics: u(t) (progressive analysis) and u'(t) (reverse analysis). When these two sequences diverge significantly from zero and from each other, it indicates the presence and beginning of a trend Detects both the presence of trends and their starting points in time series data	(55)
Innovative trend analysis approach	The method plots two halves of a time series, scatter points above or below the 1:1 line indicates increasing or decreasing monotonic trends	(56)
Adaptive Cumulative Sum	Automatically configures its parameters during operation Detects changes more effectively, even with small deviations or when the data's underlying probability distribution is unknown Reduces false positives and negatives compared to traditional CUSUM and other change detection methods	(57)
Singular spectrum analysis	It decomposes a time series into independent and interpretable components like trends, periodic patterns and noise Doesn't require a prior parametric model of the time series	(58)

Mann Kendall ,Spearman Rank

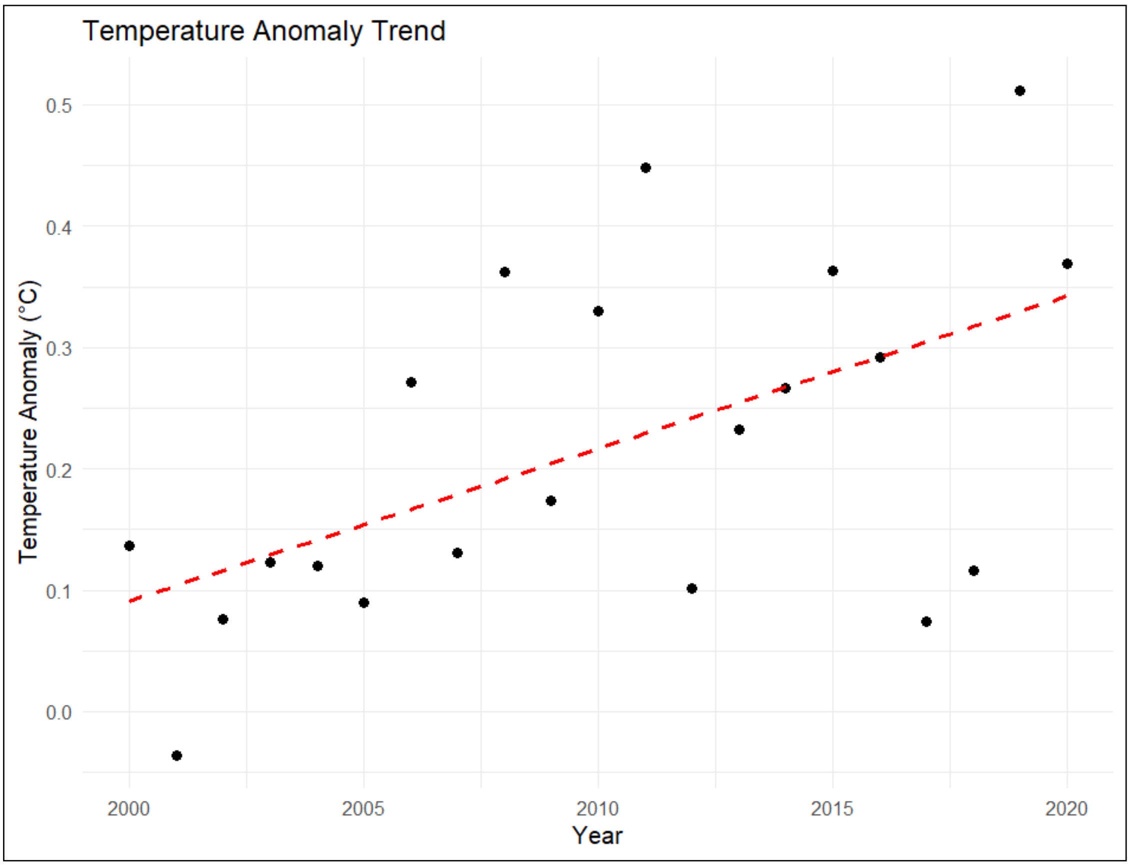

Fig. 2. Increasing trend line of temperature data (self-generated figure).

Table 3. Methods of change point detection

Technique	Features	Reference
Standard normal homogeneity test	Likelihood ratio test Checks for a single abrupt shift in the mean of the standardized series	(38)
Nonparametric SNH test	Non-parametric SNHT detects changepoints by applying the Wilcoxon rank-sum statistic across all possible split points in the series	(62)
Two-phase regression of Wang	Identifying and analyzing changes in the relationship between an independent variable and a dependent variable at an unknown breakpoint within a dataset	(63)
TPR of Lund and Reeves	Two-phase regression divides a time series into two segments, each with its own linear regression model The changepoint marks where the statistical properties (mean or slope) of the time series change	(64)
New generalized method	Hierarchical changepoint method	
Akaike's information criteria	Penalized likelihood methods Compare competing models by balancing goodness-of-fit with model complexity to avoid overfitting	(65)
Sawa's Bayes criteria	An AIC or SBC selector chooses the model with the minimum AIC or SBC statistic.	(66)
BFAST	Detect multiple abrupt and gradual changes in time series data Separate changes into components like trend, seasonality and noise	(67)

Standard Normal Homogeneity, Two Phase Regression, Breaks For Additive Seasonal and Trend

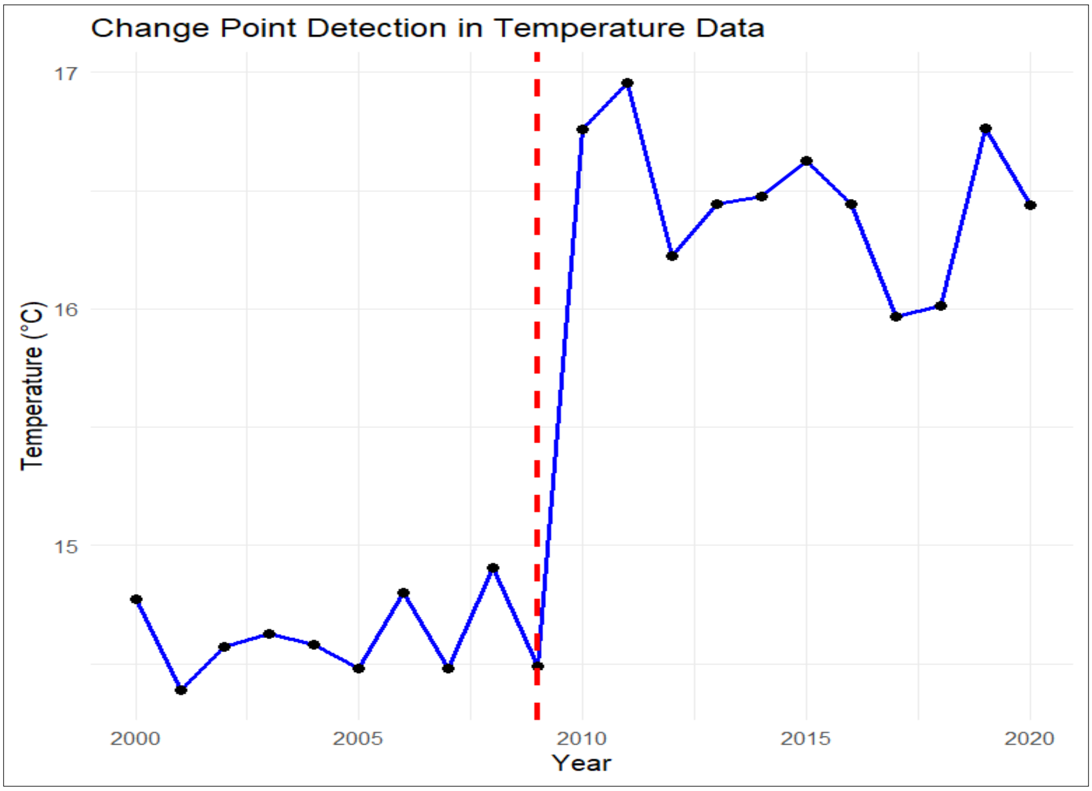

Fig. 3. Change point detection in temperature data: The blue line indicates recorded temperatures, while red dashed line indicating detected change point (self-generated figure).

change. For example, coffee is highly vulnerable to variations in precipitation patterns and temperature, affecting coffee-growing countries such as Central America. Similarly, the production of cocoa, which is common all-over in West Africa, is being hampered by increasing humidity, temperature stress and disease vulnerability. Prolonged drought conditions reduce soil moisture levels, thereby impairing plant growth and productivity (69).

Changes in temperature, atmospheric carbon dioxide levels, rainfall and solar radiation have impact on crop growth and production. Despite the effects of climate change, agricultural productivity can be maintained by some adaptation techniques such as modified sowing dates, water and nutrient scheduling (72). Water resources will also be impacted from the direct and indirect effects of climate change. Many parts of India have an unequal distribution of water resource is highly uneven, ranging from the northeast, which receives the most rainfall on Earth, to the arid northwest, which receives less rainfall (73).

Climate change affects insect and pest populations directly by activities like reproduction, development, survival rates and indirectly by disturbing the interactions with natural enemies, competitors and vectors (74). It also influences the occurrence and distribution of plant diseases, as factors such as temperature, light and water play key roles in pathogen and host dynamics. It also affects the survival, vigor, rate of multiplication, sporulation, direction and distance of dispersal of inoculums, as well as the rate of spore germination and penetration of pathogens into host plants (75). According to the IPCC (2023), global warming is projected to range between 1.5° C and 4.4°C by 2100, depending on greenhouse gas emissions (5). Rising temperatures and other climate-related variables are likely to impact host plant resistance, reducing their ability to withstand pathogen attacks (76).

Impact on forests

Vegetation dynamics and ecological quality are significantly influenced by climatic conditions (77). Climate change impacts various forest ecosystems differently, depending on their structure, location and biodiversity. Anthropogenic climate change is affecting global biodiversity, with many species experiencing negative impacts, although some may benefit or expand depending on on regional climatic shifts, species-specific traits and ecosystem characteristics. As species distributions shift in response to rising temperatures and fluctuating precipitation patterns, many species face an elevated risk of extinction. The primary climatic variables influencing species vulnerability are annual precipitation and the diurnal temperature range (78).

Eleven million ha (2 %) of global humid tropical protected areas area are under the highest combined threats from deforestation and climate change. Areas with low current deforestation risk but high climate vulnerability span 135 million ha (26 %), with 35 % located in South America, underscoring the importance of protected area resilience. Regions classified as lower risk-based on current deforestation and climate models-cover 89 million ha (17 %) and are primarily in Africa (34 %) and Asia (17 %), though some of these areas may still face significant localized pressures, suggesting the need for targeted conservation strategies (79).

Mediterranean regions, spread across several continents, are particularly affected by increasing summer temperatures and declining winter precipitation. These changes heighten fire risk in Mediterranean forest ecosystems, resulting in more frequent and severe wildfires (80). Changes in temperature, precipitation, wind speed and relative humidity due to climate change are likely to alter future fire regimes. The fire season is expected to extend by 3 to 61 days nationwide, with over 55 % of forest areas likely to experience a more intense pre-monsoon fire season (81).

The loss of forest cover not only harms biodiversity and disrupts ecosystem services, but also reduces the amount of carbon that can be absorbed from the atmosphere, which in turn speeds up climate change.

Conclusion

From this review, it is concluded that statistical tests such as homogeneity tests, trend tests and change-point detection are invaluable tools for understanding the impacts of climate change on agriculture and forest ecosystems. Homogeneity tests ensure the reliability of climate data by identifying inconsistencies arising from non-climatic factors like station relocations or instrument changes. Trend analysis help uncover long-term patterns, such as rising temperatures or shifting rainfall, which influence ecosystem dynamics. Change-point detection tests identify the timing of abrupt changes.

By using these techniques, researchers can identify gradual trends and detect critical climatic turning points. This enables a deeper understanding of how climate change affects ecosystems, offering a foundation for developing effective strategies to mitigate adverse impacts and enhance resilience in agriculture and forests. This enables a deeper understanding of how climate change affects ecosystems and provides scientific evidence that can inform targeted policy interventions, guide resource allocation and support the development of adaptive and mitigation strategies aimed at enhancing the resilience of agriculture and forest systems in the face of climate change.

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Authors' contributions

PSN and PSG conceptualized the review topic and drafted the sections on climate change analysis. RGS and SS reviewed and edited the manuscript. DM and KA provided critical insights and helped refine the paper. All authors reviewed and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that there is no conflict of interest related to this article.

Ethical issues: None

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