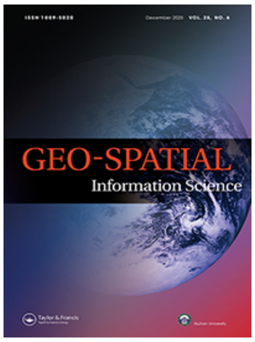

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Global cotton yield trends and the driving factors: insights from a spatiotemporal analysis

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ABSTRACT

Cotton is one of the most economically valuable fiber crops worldwide. Understanding the factors influencing its yield under climate change is crucial for managing climate risks, ensuring a stable textile supply, and promoting sustainable development globally and regionally. This study systematically analyzed the annual yield trends in 82 cotton-producing countries from 1992 to 2021. It investigated the driving factors of cotton yield using eight key indicators, including resource inputs, management practices, and climatic variables. Results show that global cotton yields increased by 27 t km^{-2} annually, with higher growth in high-income and upper-middle-income countries, the latter achieving yields twice the global average. In contrast, lower-middle-income countries experienced slower growth, while low-income countries faced slight declines. Arid regions maintained the highest yields, with significant improvements across tropical, temperate, and arid zones. Using a varying coefficient spatiotemporal regression (geographically and temporally weighted regression (GTWR)), the study further revealed significant regional variations in the driving factors of cotton yield. Globally, cotton-planted areas and labor inputs negatively impacted yields, as larger areas can lead to insufficient management and high labor density indicates a lack of mechanization. In contrast, fertilizer application and sunlight improved yields, while rising temperatures suppressed them. Regional differences were also observed: mechanization enhanced yields in high-income countries, increased land allocation to cotton improved yields in tropical regions, and fertilizer use drove yield growth in low-income regions. This study highlights the spatial and temporal heterogeneity of global cotton production and offers scientific insights to inform region-specific agricultural management policies and sustainable development strategies.

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Climate change; GTWR; spatial heterogeneity; global modeling

1. Introduction

Cotton is among the world's most significant economic crops, serving as both a core raw material for the textile industry and a critical livelihood source for millions of households (Kang et al. 2023; Li et al. 2020). In sub-Saharan Africa, cotton is often referred to as "white gold," contributing approximately $600 billion annually to the global economy (Chabi Simin Najib et al. 2022). Its exceptional ecological adaptability enables cultivation across diverse climatic regions, including arid, temperate, tropical, and subtropical zones, resulting in varied ecological and economic patterns (Hong et al. 2021). Understanding the fluctuations in cotton yield and their driving factors is essential to meet growing global demand, making it a central topic in agricultural research (Zhu, Zheng, et al. 2023).

Climate change profoundly affects agricultural systems worldwide, including cotton farming, through rising temperatures (Ahmad et al. 2017; Zhu et al. 2022), altered precipitation patterns , and the seasonal and interannual variability of extreme weather (Pan et al. 2025). Research shows that cotton yields are strongly influenced by climatic variables such as evaporation rates, sunshine duration, and minimum relative humidity (Sawan and Sabatini 2017). For instance, increasing average temperatures typically reduce cotton yield and quality, with warming trends adversely affecting yield in countries such as China, Pakistan, India, and Syria (Arshad Awan et al. 2021). However, climate change has driven yield increases in some regions, such as Benin in West Africa (Awoye et al. 2017). These variations also prompt shifts in suitable planting areas (Jagermeyr et al. 2021). In Xinjiang of China, for example, rising temperatures have gradually pushed cultivation northward, extending the cotton reproductive period and the interval between fiber formation and the first frost. This adjustment promotes dry matter accumulation and boll maturation,

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enhancing both yield and quality (Han et al. 2022). In water-scarce areas, sustaining yields increasingly depends on efficient water management and adaptive strategies (Asseng et al. 2014). Climate models indicate that optimizing the spatial distribution of cotton cultivation at appropriate time points is a critical strategy to mitigate climate change impacts (Zhu, Sun, et al. 2023).

Modern agricultural technologies have significantly enhanced cotton yields through both resource/management improvements and biotechnological advancements (Cui et al. 2024; Kranthi and Stone 2020; Zhou et al. 2024). Resource inputs and management practices, such as nitrogen fertilizer application and mulching, improve soil temperature and fertility, resulting in substantial yield increases (Hussain et al. 2022; Khan et al. 2021; Wang et al. 2017). Crop rotation systems that incorporate leguminous plants have also contributed to improved yields (Watts et al. 2014; Zhao et al. 2022). Additionally, agricultural mechanization has become crucial for enhancing production efficiency, particularly in response to labor shortages and rising production costs, leading to significant increases in yields per unit area (Abbas 2020; Saliou et al. 2020). Furthermore, deficit irrigation, when applied under optimal climate, soil, and irrigation management conditions, can enhance water-use efficiency, although it may reduce seed cotton yield in some cases, requiring careful consideration of multiple factors for effective application (Cheng et al. 2021; Qi et al. 2022; Wang et al. 2021). In terms of biotechnological advances, India introduced genetically modified pest-resistant cotton (Bt *G. hirsutum*) in 2002, which significantly improved yields, but also increased production costs and posed potential ecological risks (Romeu-Dalmau et al. 2015).

Early global research has predominantly focused on how climatic factors influence cotton production (Zhao et al. 2017), lacking a systematic analysis of the driving mechanisms behind yield changes (Blomqvist, Yates, and Brook 2020). Methodologically, many studies have relied on administrative boundaries to extract climate data from raster layers. This approach involves using administrative boundaries to define the area of interest, allowing the rasterized climate data to be cropped or masked accordingly. Moreover, when taking global cotton-producing regions as the study domain, the cross-regional interdependence and spatial spillover of cotton yield dynamics also warrant careful examination (Fan et al. 2025). For arid regions with small arable areas, this approach often introduces biases and reduces result accuracy. Using cotton cultivation boundaries instead can significantly enhance reliability. Additionally, global agricultural technology data is scarce and difficult to access (Zhao et al. 2019). Therefore, this study employs economic indicators as proxies to indirectly assess the impact of agricultural technology on cotton yields.

This study fills a gap in global cotton yield research by integrating climatic and socioeconomic drivers using geographically and temporally weighted regression (GTWR). Specifically, this study focuses on the spatiotemporal change in global cotton yields from 1992 to 2021 and how key factors drive such change both geographically and temporally. By categorizing regions based on climatic conditions and income levels, it systematically examines the impacts of resource inputs, management practices, and climatic factors on cotton yields. The study aims to provide robust scientific evidence and actionable recommendations to allow global cotton production to be more efficient, and in turn, promote sustainable agricultural development. Further, it aims to offer valuable empirical evidence to advance understanding of the cotton industry's development and supports policymakers and farmers in addressing challenges associated with climate change and market volatility.

2. Data and methods

The research framework consists of two main components. The first component examines the spatiotemporal characteristics of global cotton yields from 1992 to 2021, utilizing data provided by the Food and Agriculture Organization (FAO). The second component employs agricultural economic data from the FAO and ERA5-Land climate data from the European Centre for Medium-Range Weather Forecasts (Muñoz-Sabater et al. 2021; Xie et al. 2022) to systematically analyze the spatiotemporal drivers of global cotton yield growth through a GTWR. Data preprocessing includes spatial data centralization, standardization, and collinearity assessments, followed by model validity verification (Cui et al. 2024).

2.1. Study area

This study examines 82 cotton-producing countries worldwide, which together account for approximately 81.9% of global cotton production, analyzing 30 years of annual changes in cotton yields from 1992 to 2021 (Figure 1). These countries span various geographic regions and display a wide range of climatic conditions and economic contexts. They include traditional major cotton producers such as the United States, China, India, and Pakistan, alongside emerging markets and developing nations. By systematically analyzing cotton yields across these countries, this study aims to reveal their spatiotemporal distribution patterns and trends.

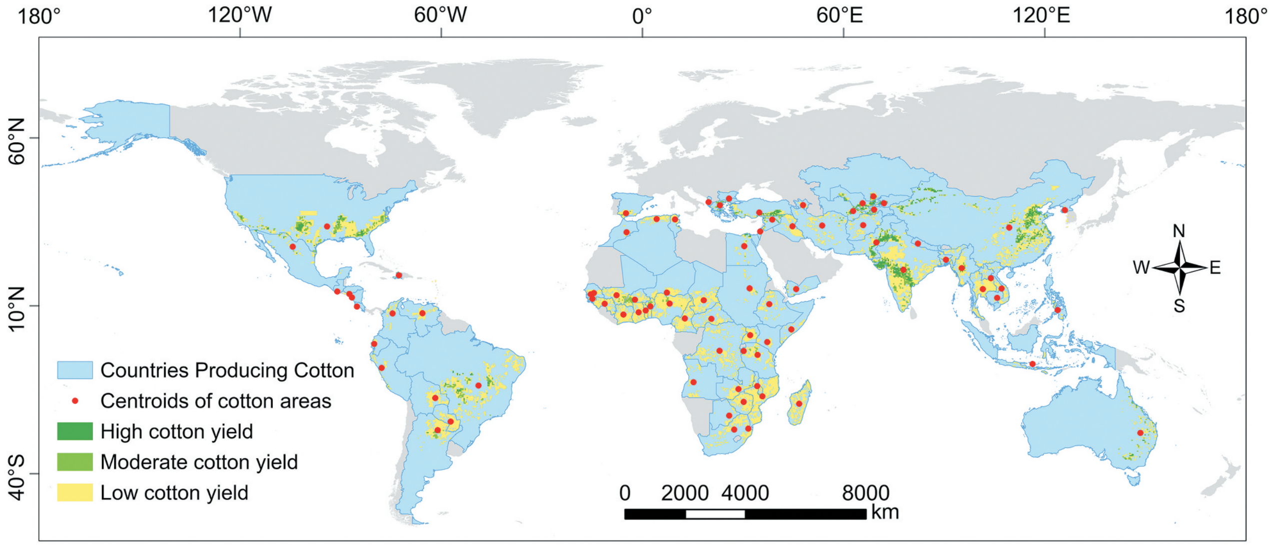

Figure 1. Cotton planting distribution map. Figure sourced from the cotton planting distribution map published in the cotton Explorer by the USDA Foreign Agricultural Service (FAS), International Production Assessment Division (IPAD). The blue background represents the 82 cotton-producing countries worldwide, while the yellow and green areas indicate the spatial distribution of cotton cultivation and corresponding levels of cotton yield. The red dots denote the centroid positions of cotton-growing regions within each country.

2.2. Data sources

The data utilized in this study includes cotton, population, climate, and boundary data (Shen et al. 2024) (Table 1). Datasets serve as the foundational inputs, which will be processed and integrated to address the research objectives. Detailed descriptions of the data processing methods will be provided in subsequent sections.

2.3. Income and climate zone classification

Advancements in agricultural technology and climate change interact, significantly shaping cotton yields. To systematically examine the factors driving spatiotemporal changes in cotton yields, this study employs a dual classification approach based on economic levels and climate types, instead of the conventional seven-continent division. This framework facilitates a comprehensive analysis of yield determinants within the intertwined contexts of economic and environmental factors.

First, to examine the influence of economic levels on cotton yields, this study categorizes countries into four groups: low income, lower-middle income, upper-middle income, and high income; using the World Bank's income classification standards (Figure 2(a)). This categorization reveals differences in agricultural production across these groups, enabling comparisons of cotton yield trends and performance under various driving factors.

Second, to assess the influence of climatic conditions on cotton yields, this study employs the Köppen-Geiger climate classification system (Beck et al. 2018) to categorize 82 countries into five climate types: Equatorial, Arid, Warm Temperate, Boreal, and Polar (Figure 2(b)). This classification effectively captures the temperature and precipitation characteristics of various climate regions, enabling a clear understanding of the distribution patterns and trends of

Table 1. Study datasets, time frames, and sources.

Specific data	Time	Data source
Cotton area harvested, production, yield Nutrient nitrogen N, P_2O_5, K_2O (total) Area of cultivated land Total population, rural population	1992–2021	Food and Agriculture Organization https://www.fao.org/faostat/en/#home.
Total evaporation, temperature, total precipitation Soil water, surface solar radiation	1992–2021	ERA5-Land Monthly Averaged by Hour of Day - ECMWF Climate Reanalysis https://www.ecmwf.int.
Cotton planting distribution map	2021	USDA Foreign Agricultural Service, International Production Assessment Division https://ipad.fas.usda.gov/Default.aspx.
World map by income	2023	The World Bank https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html.
World map by climate	2010	World Map of the Köppen-Geiger climate classification, https://koeppen-geiger.vu-wien.ac.at/present.htm.
Global National Administrative Boundary Data	2016	Resource and Environment Science and Data Center, https://www.resdc.cn/data.aspx?DATAID=205.

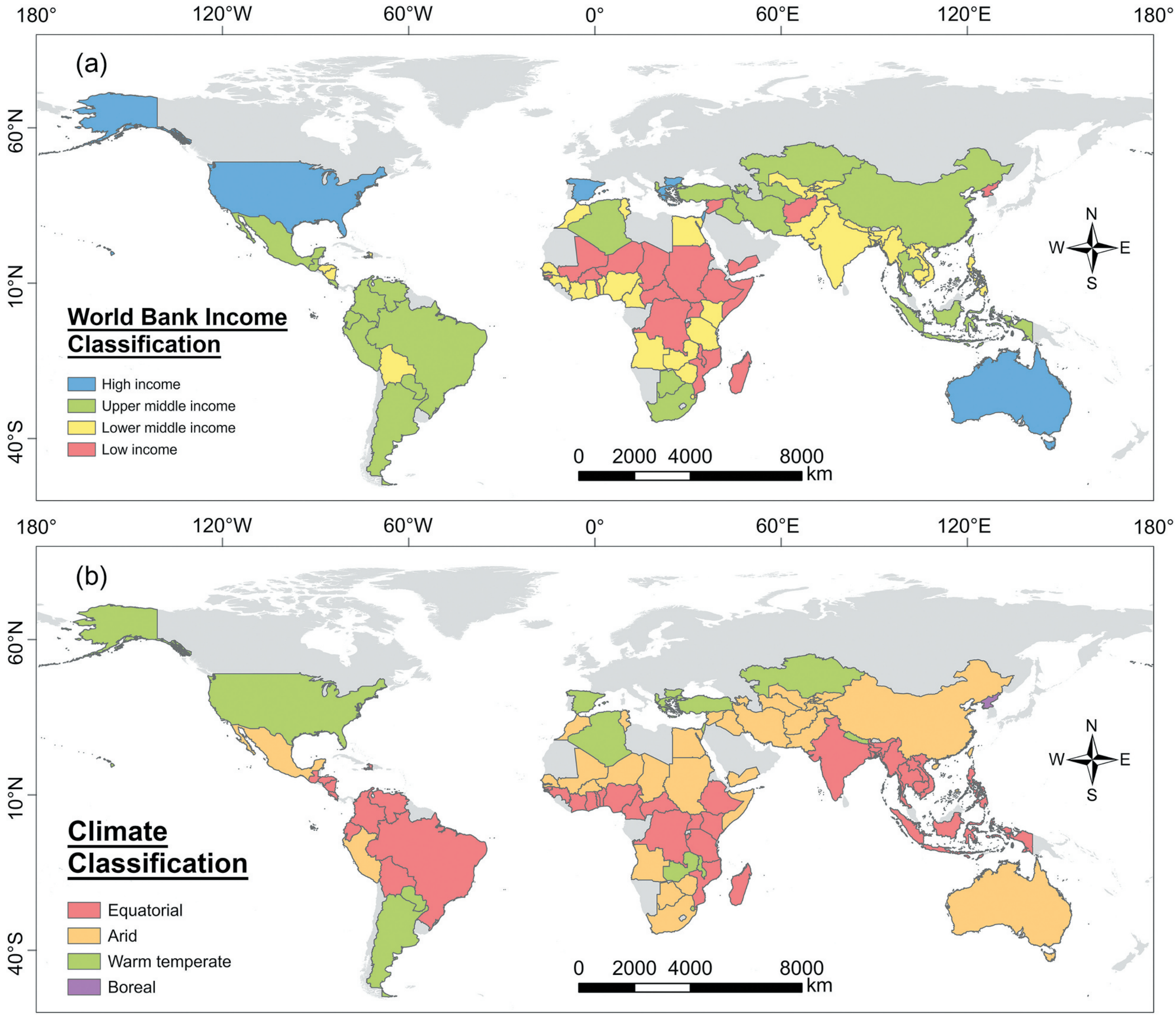

Figure 2. Income and climate classification of 82 global cotton-producing countries: (a) income classification of countries based on the World Bank standards; (b) climate distribution of countries categorized according to the Köppen-Geiger climate classification system.

cotton yields under different climatic conditions. Notably, among the 82 countries, only North Korea falls within the Boreal classification, while the remaining 81 countries are categorized under Equatorial, Arid, or Warm Temperate climate types. None are categorized as Polar.

2.4. Geographically and temporally weighted regression

Geographically and temporally weighted regression is an advanced weighted regression method designed to address heterogeneity across both spatial and temporal dimensions (Comber et al. 2022; Lu et al. 2025). In contrast to geographically weighted regression (GWR) (Brunsdon, Fotheringham, and Charlton 1996; Comber et al. 2022), GTWR incorporates the temporal dimension by constructing dual-weight matrices for space and time, thereby has capacity to dynamically model spatiotemporal data (Huang, Wu, and Barry 2010). The mathematical formulation of the GTWR model is as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \quad (1)$$

The equation above represents the basic structure of the GTWR model, where $\beta_0(u_i, v_i, t_i)$ represents the intercept, $\sum_{k=1}^{p} \beta_k(u_i, v_i, t_i)x_{ik}$ is the summation of the regression coefficients $\beta_k(u_i, v_i, t_i)$ associated with the explanatory variables x_{ik}, and ε_i denotes the random error term.

The model calculates the weight matrix using some kernel weighting function, where for this study a Gaussian kernel is used as represented by:

$$w_{ij} = \exp\left(-\frac{d_{ij}^2}{2b^2}\right) \times \exp\left(-\frac{(t_i - t_j)^2}{2c^2}\right) \quad (2)$$

where w_{ij} denotes the weight of the i-th sample relative to the j-th sample, d_{ij} is the spatial distance between samples i and j, $t_i - t_j$ represents the time difference between samples i and j, and b and c are the spatial and temporal bandwidths that control the range of weighting.

GTWR computes localized regression coefficients through the localized weighting, that enables it to capture spatiotemporal heterogeneity in the relationships between the dependent variable and each independent variable, in turn. This makes it highly suitable for analyzing dynamically changing spatial phenomena, particularly when investigating the combined effects of geographic and temporal factors on complex processes.

This study employed the GTWR analysis tool in the GWmodelS software (Lu et al. 2014, 2023, 2024) to systematically analyze regional differences in the driving factors (independent variables) of global cotton yield (dependent variable). Based on the GTWR results, the contributions of each driving factor were calculated and categorized into two types: (i) Absolute contribution rate, a metric obtained by summing the absolute values of each variable, quantifies the overall strength of their impact, reflecting their comprehensive contribution to system fluctuations irrespective of direction (positive or negative); and (ii) Net contribution rate, a metric calculated by summing positive and negative contributions and dividing by the total contribution value, which indicates the net influence direction of each variable and its overall promotive or inhibitory effect on cotton yield. The GTWR model is validated via a set of standard model performance diagnostics (Cui et al. 2024).

2.5. Data preprocessing and checks for collinearity

2.5.1. Data preprocessing

To address the impact of seasonal differences between the Northern and Southern Hemispheres during climate data processing, this study adjusted ERA5-Land monthly averaged climate data according to the distinct cotton growing seasons in each hemisphere. In the Northern Hemisphere, data from April to September were used, while in the Southern Hemisphere, data from October of the previous year to March of the current year were analyzed. This approach effectively reduces potential errors caused by seasonal variations and provides a more accurate climatic context for subsequent analysis.

This study also utilized the spatial layout of cotton planting areas, extracted from the Cotton Planting Distribution Map published by the USDA Foreign Agricultural Service and the International Production Assessment Division (Boryan et al. 2011). Using this information, climate data for each country's cotton planting regions were clipped, and the average climate values within these regions were calculated to ensure the representativeness and reliability of the regional data.

To enable the GTWR analysis, the centroid positions of cotton planting areas in each country were calculated and used as the coordinate data in the GTWR analysis. This process provided essential location data for GTWR, facilitating a precise spatial representation of the relationship between climatic factors and cotton production. The climatic factor data were integrated with resource input and management data for each country's cotton planting areas and assigned to the calculated centroids.

Cotton growth is influenced by a combination of interacting climatic and management factors. Climatic variables, such as temperature, precipitation, and evapotranspiration, play a critical role in shaping soil moisture, photosynthesis, and crop development (Hersbach et al. 2020). Concurrent land management practices – including cropland allocation, labor input, and fertilizer application – are essential for sustaining agricultural productivity (Ludemann et al. 2024). These factors are not independent but are intertwined with socioeconomic and resource constraints, collectively determining agricultural outcomes. Following a comprehensive review of the primary drivers of cotton growth and the availability of reliable datasets, nine variables, divided into two categories – climatic factors and resource management – were selected for analysis (Table 2).

Dimensions of the final preprocessed dataset consisted of 82 sites (countries) each with nine key drivers of cotton yield found annually across 30 years (1992 to 2021).

2.5.2. Collinearity and variable reduction

Collinearity is a prevalent issue in any form of regression analysis, characterized by strong correlations among independent variables. It can result in unstable model coefficients, inflated standard errors, and reduced interpretability and predictive accuracy of the model (Shrestha 2020). Thus, investigating for collinearity is crucial before constructing a regression model to ensure robustness.

This study utilized the variance inflation factor (VIF) to assess the degree of collinearity among independent variables. VIF quantifies the linear relationship between an independent variable and all other independent variables. The formula for calculating VIF is as follows:

$$\mathrm{VIF}(X_i) = \frac{1}{1 - R_i^2} \tag{3}$$

In this context, R_i^2 represents the coefficient of determination obtained when an independent variable X_i

Table 2. Description of independent variables used in the GTWR model.

Category	Variable	Description
Climatic factors	Evapotranspiration (Eva)	Evapotranspiration influences soil moisture retention and is crucial for cotton growth. Excessive evapotranspiration may cause soil drought, while moderate levels help maintain water balance in cotton fields.
	Precipitation (Pre)	Precipitation is a fundamental climatic factor for cotton cultivation. Adequate precipitation provides essential water for cotton growth, whereas excessive or insufficient rainfall can adversely affect cotton yields.
	Soil water content (SW)	Soil water content directly affects the root water absorption of cotton plants. Low soil moisture can restrict growth, whereas adequate levels support healthy cotton development.
	Surface solar radiation (SSR)	Surface solar radiation supplies energy for cotton growth and influences photosynthetic efficiency. Sufficient surface solar radiation promotes high yields, while insufficient radiation may limit production.
	Temperature (Tem)	Temperature is a vital climatic factor for cotton growth, influencing germination, development, and maturation. Optimal temperatures enhance yield, while extreme temperatures can significantly reduce production.
Resource and management factors	Cotton area share (CAS)	Cotton area share reflects the proportion of land allocated to cotton cultivation in different regions, serving as a crucial indicator of production scale (Chapepa, Mudada, and Mapuranga 2020). Regions with larger planting areas often allocate more agricultural resources and technologies, thereby boosting cotton yields.
	Labor density (LD)	Labor density, a micro-level indicator (Ushifusa and Tomohara 2012), represents the labor supply dedicated to cotton cultivation per unit of land area. Higher labor density regions can invest more workforce into field management tasks, such as weeding, fertilizing, and pest control, enhancing both yield and quality.
	Rural population share (RPS)	Rural population share is a macro-level indicator that reflects the structure of agricultural labor and the stage of economic development in a region. A higher rural population share typically indicates greater reliance on agriculture, lower economic growth, and limited industrialization and urbanization. These factors are often associated with lower levels of mechanization and can directly affect cotton yield.
	Fertilizer usage (Fer)	Fertilizer input is a pivotal factor influencing cotton yield (Nguyen et al. 2024). The dataset categorizes fertilizer use into nitrogen, phosphorus, and potassium; however, incomplete data for some countries necessitated calculating the total usage of these three nutrients. Proper fertilizer application enhances soil fertility, promotes healthy cotton growth, and improves fiber quality, significantly increasing yield.

(one of the nine factors, above) is regressed against all other independent variables (the remaining eight factors described above). The higher VIF values indicate more severe collinearity: a VIF between 1 and 5 suggests acceptable levels of collinearity, values exceeding 5 indicate strong collinearity, and values above 10 signify severe collinearity, which necessitates corrective measures such as variable removal, the application of principal component analysis to the independent data, or the use of some penalized regression.

This study analyzed collinearity among the independent variables, grouping data from all 30 years and all 82 sites together (i.e. ignoring temporal effects and spatial effects). The results revealed that when the SW variable was included, the VIF values for Eva, Pre, and SW were 6.4, 6.1, and 9.6, respectively, indicating significant collinearity. As the VIF value for SW, neared the critical threshold of 10, SW was likely the primary source of collinearity. To mitigate the effects of collinearity, the SW variable was excluded. Following its removal, the VIF values for Eva and Pre dropped to 4.1 and 4.3, respectively, indicating that the collinearity issue was effectively addressed. The *VIF* values for other variables also declined, as detailed in Table 3.

In summary, the collinearity analysis conducted in this study identified strong linear correlations among certain variables. Removing the SW variable significantly reduced collinearity, which should enhance GTWR's robustness and explanatory capacity. This adjustment should improve model stability, enabling more reliable analysis of the factors influencing the dependent variable in subsequent steps. A key assumption made, however, was that collinearity only had a global, not local, influence, as temporal and spatial effects were not considered. A localized assessment would require adapting the GTWR model to a penalized form, an extension beyond the scope of this study. In the future, incorporating such adaptations could offer more precise insights into local collinearity and its impact on the results (e.g. see Lu et al. 2014; Comber et al. 2022 for the spatial-only case).

3. Results

3.1. Spatiotemporal dynamics of cotton yield

Annual global cotton yield trends from 1992 to 2021 indicate an overall upward trajectory over the past 30 years (Figure 3(c)). The global average cotton yield

Table 3. Comparison of VIF values (before and after removing SW).

Variable	CAS	LD	RPS	Fer	Eva	Pre	SW	SSR	Tem
VIF (Including SW)	1.31	2.32	2.32	2.01	6.41	6.08	9.58	3.45	1.38
VIF (Excluding SW)	1.25	2.12	2.28	1.98	4.07	4.26	–	2.03	1.19

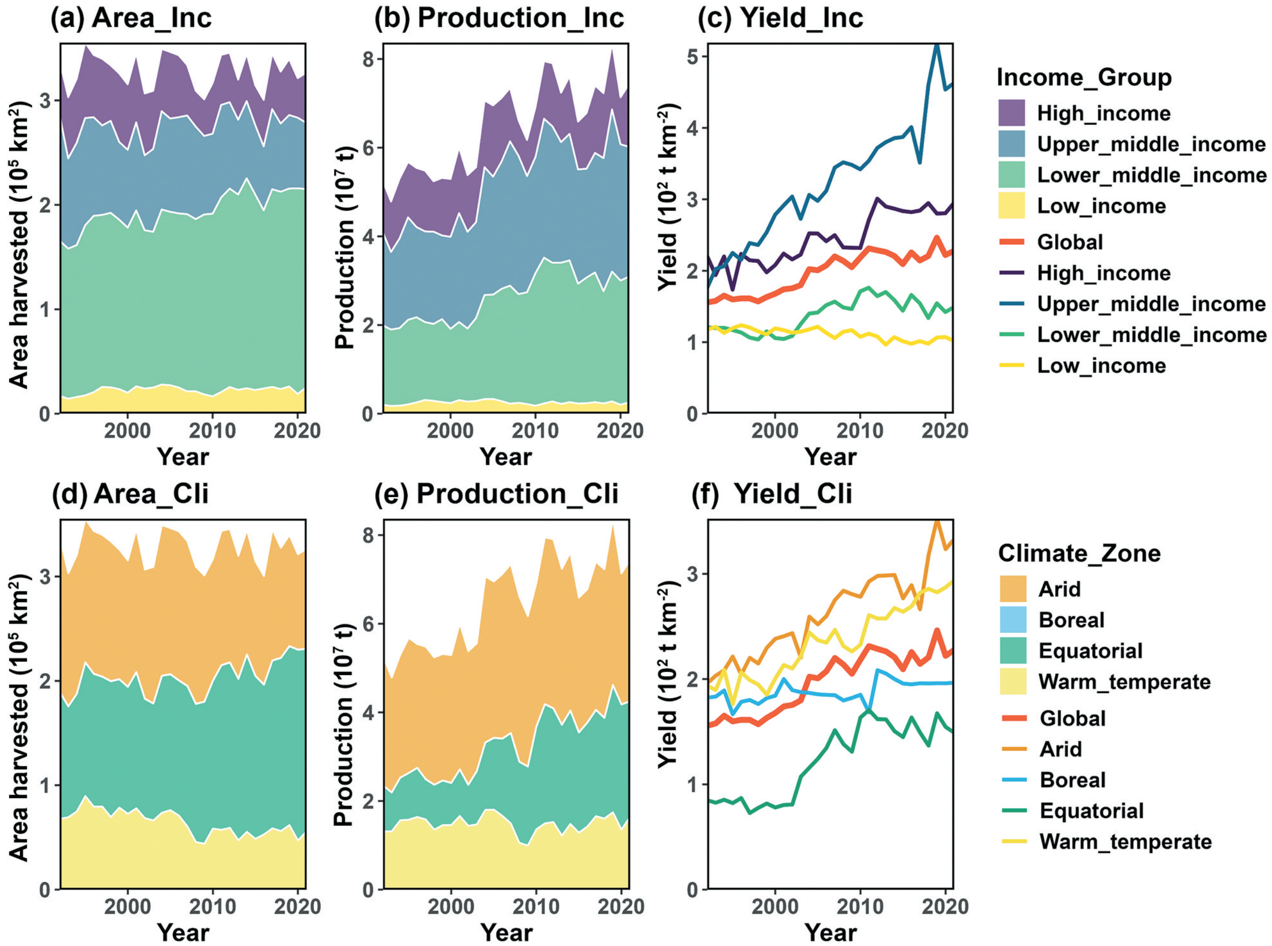

Figure 3. Annual global cotton yields, planted area, and total production for the period 1992–2021 based on income and climate classification: (a)–(c) are data presentations categorized by economic income for each country in the world. (a) Change in cotton planted area, (b) change in total cotton production, and (c) change in cotton yields. (d)–(f) Are data presentations categorized by climate type. (d) Change in area under cotton cultivation, (e) change in total cotton production, and (f) change in cotton yields.

increased from 156 t km^{-2} in 1992 to 228 t km^{-2} in 2021, representing an average annual growth of approximately 27 t km^{-2}. This growth can be attributed to several factors, including the widespread adoption of Bt cotton in India and China, which reduced pest-induced losses by approximately 24%, greater use of precision agriculture tools, improved nutrient management, and increased investment in cotton research and mechanization in major producing countries. Among income groups, upper-middle-income countries achieved the highest yields and largest growth, reaching 460 t km^{-2} —more than twice the global average. High-income countries recorded yields slightly above the global average, following a growth trend consistent with the global pattern. Lower-middle -income countries exhibited yields below the global average, with notable increases between 2000 and 2010, followed by relative stability. Low-income countries maintained consistently low yields, averaging around 100 t km^{-2}, with a slight decline over time. After 2010, yield changes across all income groups, except upper-middle-income countries, were minimal, with most growth concentrated before 2010. Globally, the total cotton planting area remained stable (Figure 3(a)), fluctuating between 3.0×10^5 and 3.5×10^5 km^2. Lower-middle-income countries accounted for more than half of the global cotton planting area, displaying an upward trend. In contrast, the planting areas in upper-middle-income and high-income countries continued to decline, while those in low-income countries showed no significant changes. In terms of total production, global cotton output increased from 5.264×10^7 t in 1992 to 7.434×10^7 t in 2021 (Figure 3(b)). Middle-income countries dominated global production, contributing over 77% and showing steady annual growth. By contrast, total production in high-income and low-income countries remained relatively stable.

From a climate classification perspective, cotton yield across the three global climate types exhibited a strong upward trend (Figure 3(f)). Yields in temperate and arid regions surpassed the global average, with arid regions slightly outperforming temperate regions. Conversely, tropical countries, while maintaining yields below the global average, experienced significantly faster growth between 2003 and 2010 compared to other climate types. In terms of planting area, although the global total remained relatively stable, tropical countries experienced a continuous increase, accounting for 53.6% of the global cotton planting area by 2021 (Figure 3(d)). Meanwhile, planting areas in arid and temperate regions showed a consistent decline. Regarding total production, prior to 2003, cotton production across the three climate types remained relatively stable, with arid regions contributing more than half of the global total (Figure 3(e)). After 2003, cotton production in tropical countries grew rapidly, nearing the total production of arid regions by 2020. In contrast, production in temperate regions remained relatively stable, while production in arid regions fluctuated significantly but maintained an overall steady trend.

As illustrated in Figure 4, emerging economies such as those for China, Brazil, Mexico, Turkey, Argentina, Peru, and South Africa have strongly outperformed other countries in cotton yield and yield growth. This underscores the critical role of the cotton industry in these nations, reflecting both the high priority it receives and its substantial contribution to economic development. In contrast, regions such as Africa and Southeast Asia, which are traditionally low-yield areas, have experienced a continuous decline in cotton yield over the past 30 years. This trend highlights the limited investment and technological support for the cotton industry in these regions, which impedes stable growth. Furthermore, the decline in yield in these areas demonstrates the global concentration effect of the cotton industry, wherein production increasingly shifts to countries with abundant resources and strong policy support, thereby exacerbating regional yield disparities.

Between 1992 and 2021, India, China, Brazil, and the United States emerged as the four countries with the strongest annual increases in global cotton production (Figure 5(a)). India was the only country to achieve a substantial expansion in cotton planting area, far surpassing other nations, and leading the world in total production growth. In contrast, China experienced a notable reduction in planting area yet maintained its position among the top three global

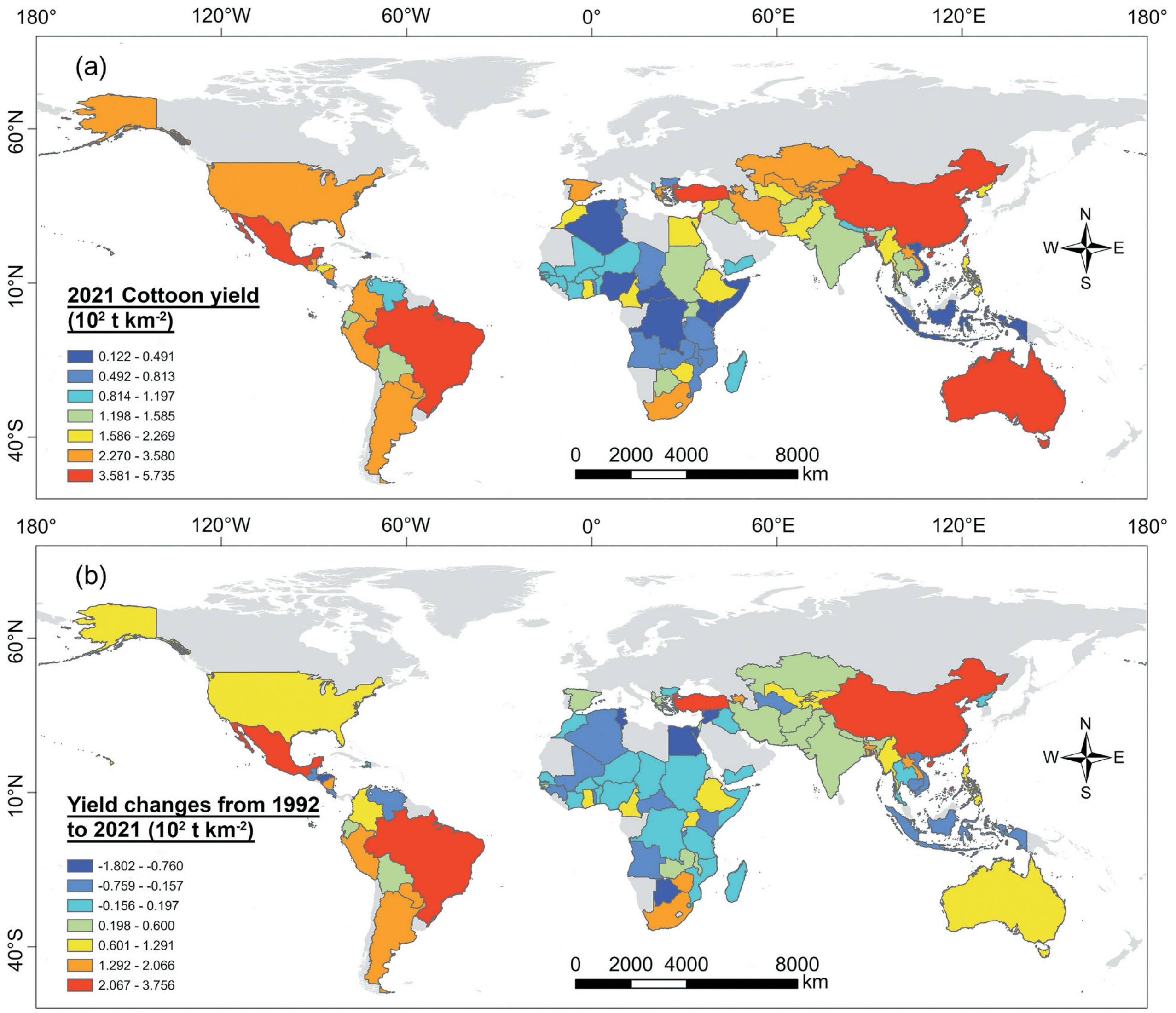

Figure 4. Distribution of cotton yields by country in the world: (a) is the cotton yield by country in 2021, and (b) is the change in cotton yield by country from 1992 to 2021.

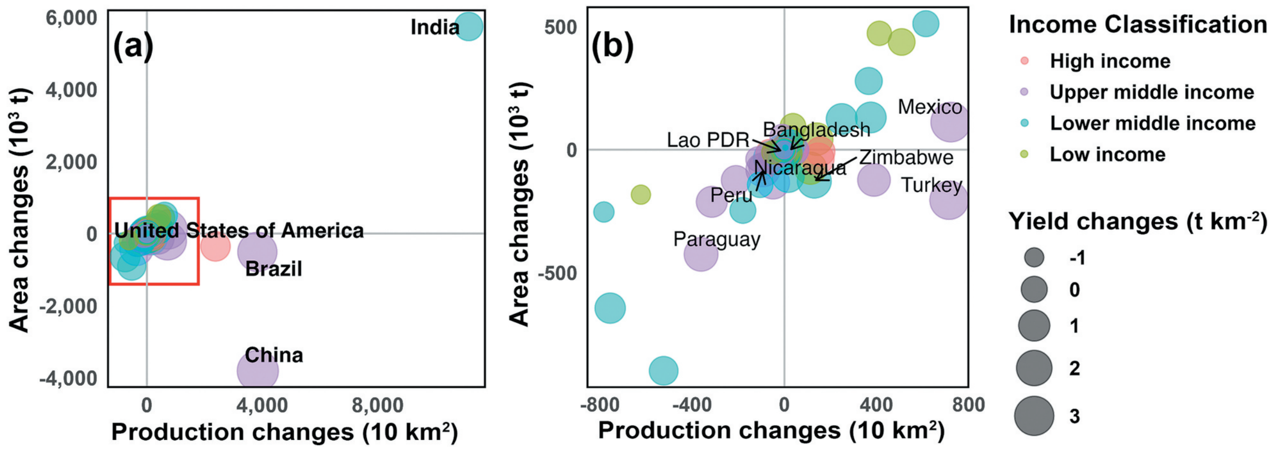

Figure 5. Changes in cotton production, planted area and total production by region, 1992–2021: (b) is a zoomed-in display of the data near the origin in (a), with the *y*-axis indicating the change in cotton acreage from 1992 to 2021, the *x*-axis indicating the change in total cotton production over the same period, and the size of the bubbles indicating the magnitude of the change in cotton yields from 1992 to 2021.

producers, demonstrating exceptional production efficiency. Brazil also exhibited remarkable growth in total production, nearly matching that of China, despite a slight decline in planting area. The United States ranked fourth in production growth, with minimal changes in planting area. In comparison, other countries showed relatively modest changes in both planting area and total production.

Figure 5(b) illustrates the distribution of cotton planting area and total production among the remaining 78 countries (i.e. excluding India, China, Brazil, and the United States). For most countries, total production fluctuated proportionally with changes in planting area, and the distribution of countries across the four income groups was relatively uniform, showing no significant clustering. Figure 5(b) identifies eight additional countries, alongside China and Brazil from Figure 5(a), as the top 10 contributors to the largest increases in global cotton production, all of which are middle-income countries. Among these 10 nations, the top four are China, Brazil, Mexico, and Turkey; Peru ranks sixth, and Paraguay ranks ninth, all classified as upper-middle-income countries. The remaining four countries, Bangladesh, Nicaragua, Zimbabwe, and Laos, all fall within the lower-middle-income category.

3.2. Spatiotemporal drivers of cotton yield

Utilizing the GTWR model allowed us to assess the intensity of various drivers' influence on cotton yield across different regions and time points, providing insights into how heterogeneity in relationships affects cotton yield. The model employed a Gaussian kernel function and great circle distances, with an optimal adaptive bandwidth of 23 nearest neighbors determined through cross-validation. The model demonstrated excellent fit, with an R^2 of 0.92 and an adjusted R^2 of 0.90, indicating that it explains most of the variability in the data. Cross-validation results further confirmed the model's robustness. The estimated GTWR coefficients are the key outputs, reflecting changes in data relationships and capturing the heterogeneity of each driver's effect on cotton yield.

Figure 6 presents the distributions of GTWR coefficients at the 82 sites (countries) across 30 years (-1992–2021), for the eight factors influencing cotton yield, grouped across different income levels (high-income, upper-middle-income, lower-middle-income, low-income) and climate types (equatorial, arid, warm temperate). By combining violin and box plots, the figure illustrates the distribution patterns and variability of the coefficients, reflecting the (spatial and temporal) heterogeneity of these factors' impacts on cotton yield, conditional to income and climate.

The direction and intensity of variables' effects on cotton yield growth vary significantly across countries with different income levels and climate types. Globally, factors such as labor density, fertilizer usage, surface solar radiation, and precipitation generally exert positive influences on cotton yield in most regions, underscoring the importance of agricultural inputs and climatic resources as primary drivers of yield improvement. Conversely, the rural population share often shows negative coefficients in multiple regions, indicating that higher rural population proportions may suppress cotton yield at a macro level. In contrast, labor density predominantly displays positive coefficients, suggesting that sufficient labor availability contributes to improved yield at a micro level. Additionally, temperature and evapotranspiration typically exhibit negative coefficients, reflecting the adverse effects of high temperatures and elevated evapotranspiration on cotton yield. These negative impacts are particularly pronounced in tropical and

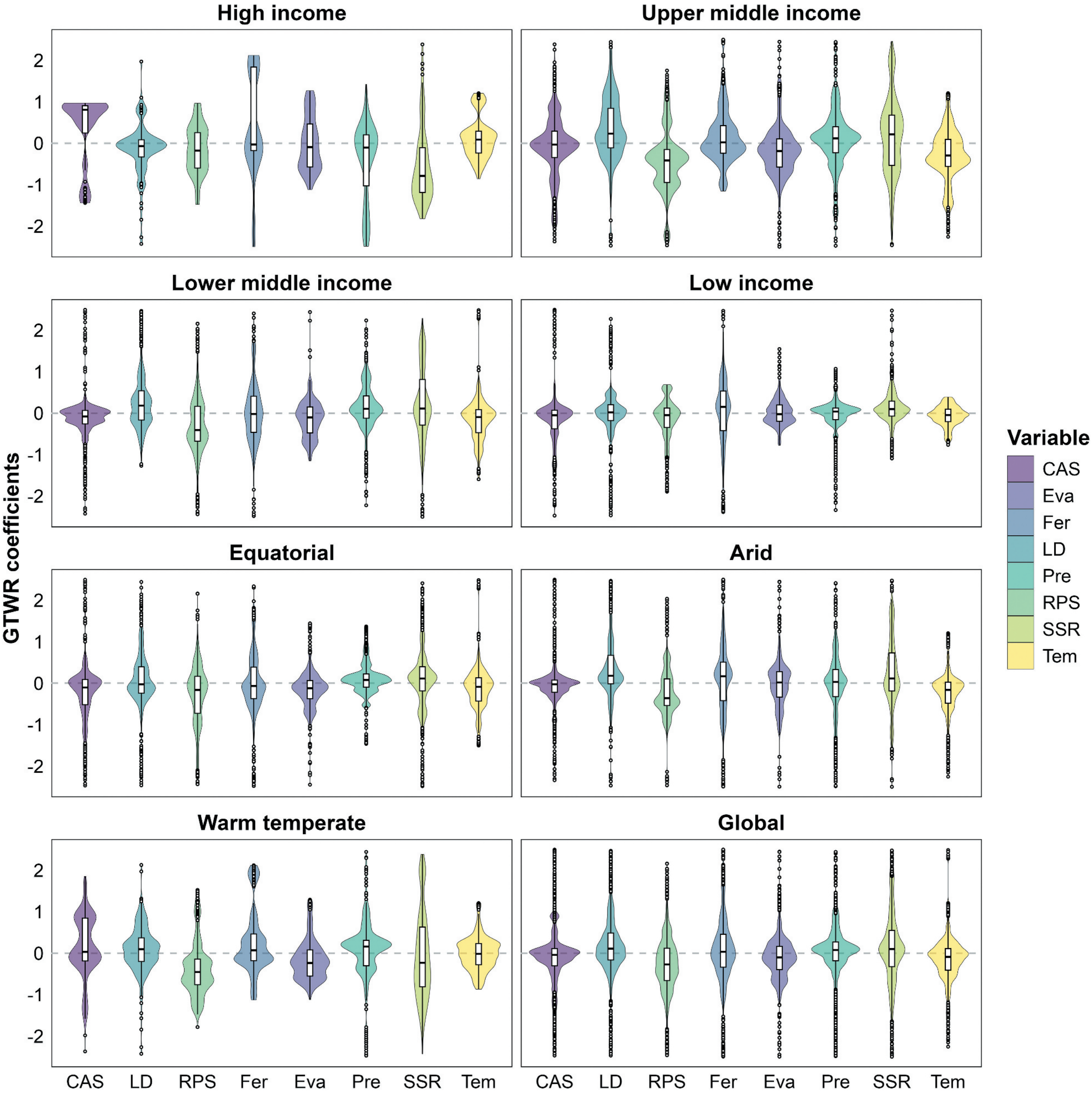

Figure 6. Distribution of GTWR coefficients for the eight drivers of cotton yields by different categories. The width of the violins indicates the density of the coefficients in each value interval, i.e. the concentration of coefficients in different intervals. The box line plot shows a five-number generalization of the coefficients, including the minimum, lower quartile (Q1), median, upper quartile (Q3), and maximum, which helps us to visualize and understand the trend of concentration and the degree of dispersion of the coefficients. The eight drivers (independent variables) are: (1) CAS: cotton area share; (2) LD: labor density; (3) RPS: rural population share; (4) Fer: fertilizer input; (5) Eva: Evapotranspiration; (6) Pre: Precipitation; (7) SSR: surface solar radiation; (8) Tem: Temperature.

arid regions, underscoring the substantial challenges posed by high temperatures and rapid water evaporation to cotton production in these areas. The distribution characteristics of the GTWR regression coefficients indicate that cotton yield is shaped by a combination of multiple factors, with their effects varying significantly across different income levels and climate types.

To quantify the influence of each variable, this study calculates both the absolute contribution rate and the net contribution rate based on the GTWR model coefficients. The absolute contribution rate measures the total magnitude of a variable's impact on cotton yield, irrespective of whether the effect is positive or negative. In contrast, the net contribution rate captures the overall direction of the variable's effect, indicating whether it promotes or inhibits yield. It considers both the magnitude and the sign (positive or negative) of the effect, providing a clearer understanding of whether the variable has a beneficial or detrimental impact on cotton yield. By combining these two metrics, the study offers a more comprehensive evaluation of how different variables influence cotton yield under various conditions, thus facilitating the identification of interrelationships and dynamic interactions among factors within complex systems.

The global spatial distribution of net contribution rates derived from GTWR coefficients reveals substantial spatial heterogeneity in the influence of different drivers on cotton yield across countries (Figure 7). Although GTWR provides coefficient maps for each year of the 30-year period, no clear temporal patterns could be observed. As such, annual GTWR coefficient maps are not presented and instead only the net contribution rates, as depicted in Figure 7 In China, surface solar radiation makes a significant positive contribution, highlighting the critical dependence of cotton yield increases on abundant sunlight resources. In the United States and Central Asia, evapotranspiration contributes positively, indicating that appropriate evapotranspiration levels enhance water absorption and photosynthesis, thereby promoting plant vigor and increasing cotton yield. In contrast, in Brazil and Australia, labor density has a significant negative effect on cotton yield, suggesting that excessive labor reduces production efficiency or leads to poor land management. This underscores the potential for labor density to negatively impact cotton farming in these regions, as illustrated in Figure 6. In India, precipitation positively influences cotton yield, reflecting the importance of adequate rainfall for growth. However, evapotranspiration in India shows a strongly negative contribution, likely due to excessive evaporation losses or inadequate water resource management, which constrain effective water use and hinder cotton growth and yield.

These differences highlight the intricate interactions between natural and socio-economic factors influencing cotton production across countries. A comprehensive assessment of the effects of climatic conditions, resource inputs, and socio-economic structures on cotton yield is essential. Accordingly, the contribution rates of each of the eight drivers to cotton yield under the eight classification conditions, encompassing global scale, different climate types, and varying economic income levels, are depicted in Figure 8.

Globally, cotton area and labor density exhibit the highest absolute contribution rates to yield, at 26.7% and 22.0%, respectively, emphasizing the critical role of effective land and labor resource management in enhancing yield. However, both drivers have the negative net contribution rates, at −3.9% and −6.7%, respectively, suggesting that expanding planting areas and increasing labor input may decrease management efficiency, thereby adversely impacting yield. In contrast, fertilizer use and solar radiation show positive net contribution rates (4.7% and 3.6%, respectively), underscoring the beneficial effects of agricultural inputs and solar energy on improving cotton yield. Temperature has a net contribution rate of −1.8%, which is negative across all income groups except high-income countries, further highlighting the suppressive impact of rising temperatures on global cotton yield. The global ranking of driver contributions is as follows: CAS (26.7%) >LD (22.0%) >Fer (11.7%) >SSR (11.1%) >RPS (9.9%) >Pre (7.3%) >Eva (5.7%) >Tem (5.6%).

The impact of the eight study drivers on cotton yield varies significantly across regions. In high-income countries, labor density shows a notably negative net contribution to yield (−28.2%), far exceeding that in other regions. The net contribution of cotton area share to yield is positive (5.9%), sharply contrasting with other global regions. Additionally, high-income countries are unique in displaying a positive net contribution of temperature (1.2%) and a negative net contribution of surface solar radiation (−3.4%). In tropical countries, cotton area share also has a positive net contribution to yield (5.4%). Precipitation and evapotranspiration exhibit pronounced spatial heterogeneity in their contributions to yield. Precipitation shows a negative net contribution in high-income countries, low-income countries, and arid regions but a positive contribution in other areas. In contrast, evapotranspiration has a positive net contribution in high-income and low-income countries but a negative contribution in other regions.

Overall, the GTWR model results highlight clear spatial differences in the driving factors of cotton yield across regions with varying income levels and climatic zones. To achieve sustainable improvements in cotton yield, each region should optimize management strategies based on its key resources.

4. Discussion

This study has revealed that global cotton yield has experienced a fluctuating upward trend over the 30-year period, 1992–2021, with upper-middle-income countries making particularly notable contributions, achieving yield levels twice the global average. This observation aligns with the findings of the report World Cotton Production and Consumption: An Overview (2020), which highlights the pivotal role of cotton as a significant economic crop in agriculture, particularly in developing countries (Khan et al. 2020). Additionally, related research predicts that global cotton yield will increase at an annual rate of 1.5%, while the annual growth rate of planting area will be approximately 0.5%, collectively driving an average annual yield growth of 1% (Gul et al. 2022). These reported trends are consistent with the findings of this study, further confirming the reliability and scientific validity of this study's outputs.

This study found that emerging economies such as China, Brazil, Mexico, Turkey, Argentina, Peru, and South Africa lead other nations in cotton yield and

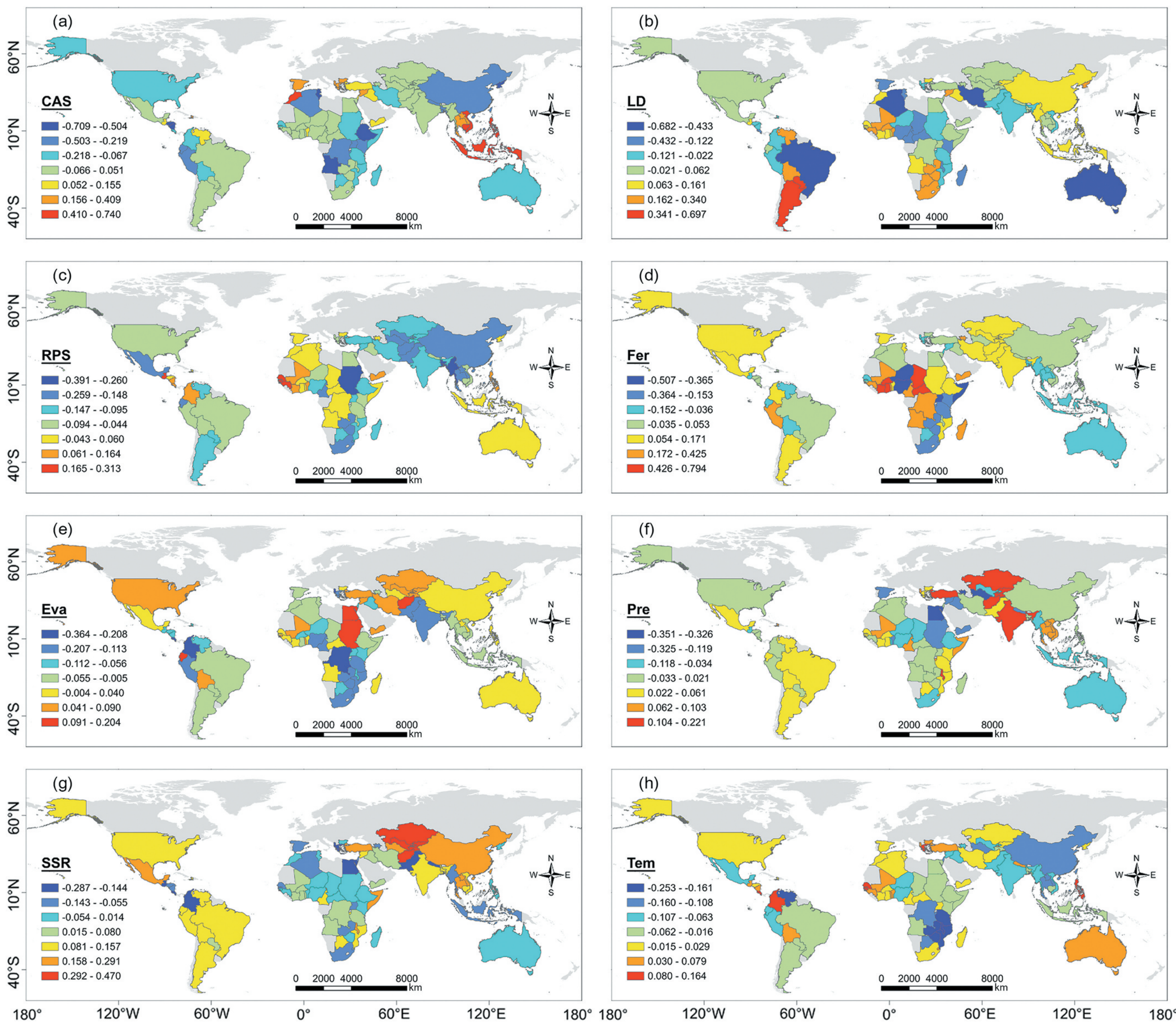

Figure 7. Spatial distribution of the net contribution rates of the eight drivers influencing cotton yield: (a) cotton area share; (b) labor density; (c) rural population share; (d) fertilizer input; (e) evapotranspiration; (f) precipitation; (g) surface solar radiation; (h) temperature.

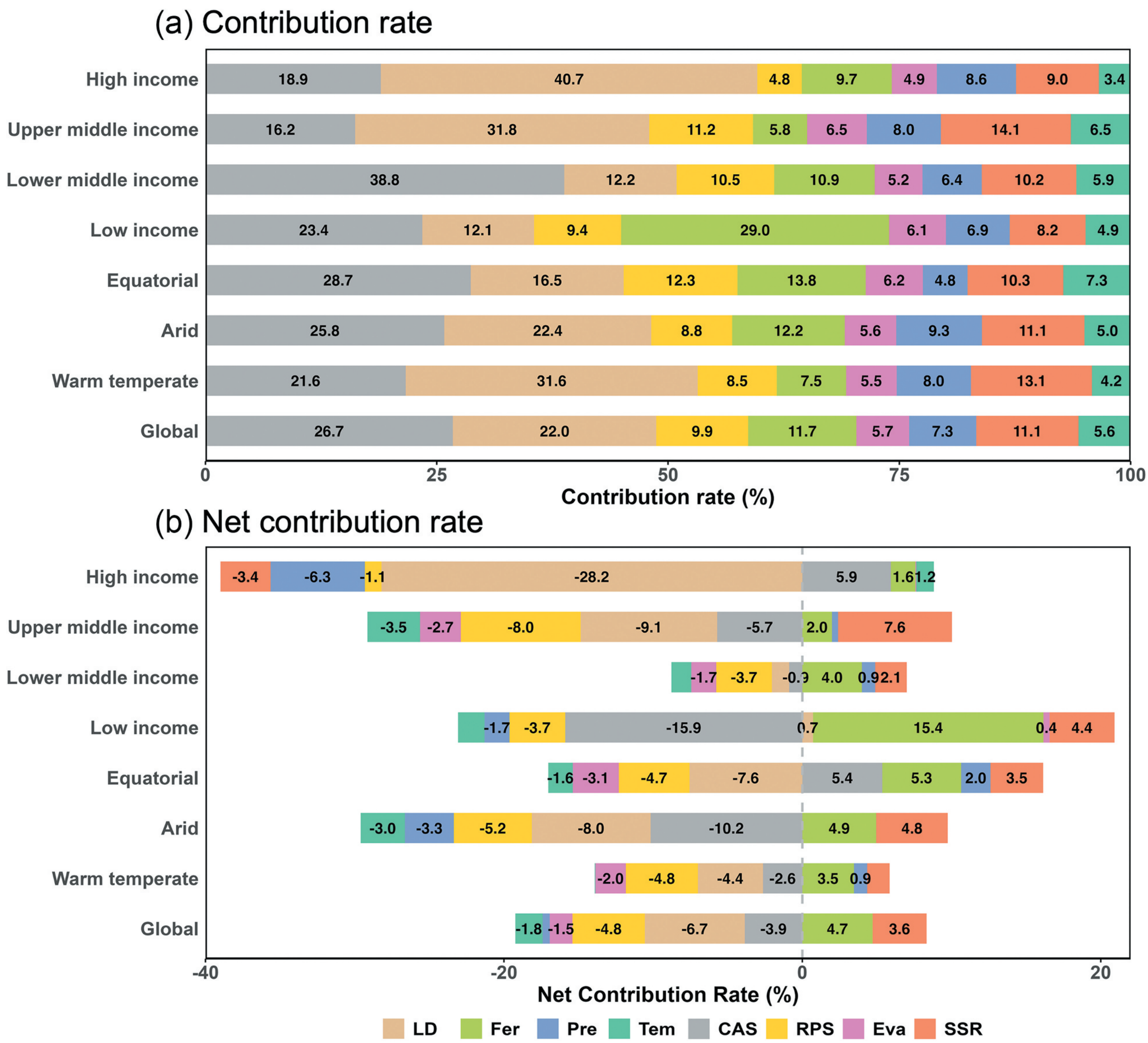

Figure 8. Absolute and net contribution rates of the eight drivers of cotton yield: (a) contribution rates of drivers under eight classification conditions; (b) net contribution rates of drivers under eight classification conditions.

growth. The cotton industry in these countries is crucial, as it generates significant economic benefits and plays a key role in driving overall economic development (Arshad et al. 2022). This trend is closely associated with the adoption of advanced agricultural technologies and increased investment in agriculture (Guo et al. 2022). However, while cotton production contributes to economic growth, it may also exacerbate vulnerability in smallholder economies, especially if the benefits of yield increases are not equitably distributed. In many cases, smallholder farmers are exposed to market fluctuations, climate risks, and limited access to technological advancements, which could undermine the long-term sustainability of cotton farming in these regions. Policymakers should consider developing more inclusive agricultural policies that promote equitable access to advanced technologies and ensure that the economic benefits of cotton production are more evenly shared among smallholders. Additionally, investment in rural infrastructure and education could help mitigate the risks faced by smallholder farmers, enabling them to better adapt to market and environmental changes.

Analysis using the spatiotemporal GTWR model revealed significant variations in the drivers influencing cotton yield across different income levels and climate regions. Globally, drivers such as labor density, fertilizer use, solar radiation, and precipitation positively impact cotton yield in most regions, underscoring the importance of agricultural inputs and climatic resources in driving yield improvements. Favorable climatic conditions and adequate agricultural resources are particularly conducive to higher yields. In contrast, the negative relationships (via negative GTWR coefficients) for rural population share indicated that areas with higher rural population proportions may experience suppressed cotton yields, primarily due to underdeveloped economies and low levels of agricultural mechanization (Baffes 2011; Potapov et al. 2022). In China's key cotton-producing regions, prior studies have identified nitrogen fertilizer application and agricultural mechanization as the main drivers of sustained yield growth (Huang et al. 2022). For example, nitrogen application methods can significantly affect nitrate nitrogen concentration in the root zone, nitrogen absorption efficiency, and final yield in cotton fields with sandy soils in the Taklamakan Desert (Shareef et al. 2019). Similarly, in Pakistan, labor density has shown a positive correlation with cotton yield, emphasizing the vital role of labor input in regions with limited mechanization (Arshad et al. 2022).

The impact of labor density on cotton yield varies across regions. In high-income countries, where agriculture is often highly mechanized and incorporates technological innovations such as IoT sensors (Wu, Guo, Huang, Han, et al. 2024; Wu et al. 2023), artificial intelligence, and data analytics (Goel et al. 2021; Wu, Guo, Huang, Zhang, et al. 2024), labor density has a notably negative effect on cotton yield. The study found that in high-income countries (Thorp, Thompson, and Bronson 2020), labor density contributes a net rate of −28.2% to cotton yield, reflecting a significantly more negative effect compared to other regions. This highlights the drawbacks of over-relying on labor in mechanized agriculture, where automation and technological advances should ideally optimize efficiency and reduce the need for manual labor. Policymakers should promote further automation and technological integration to enhance productivity and sustainability, reducing labor dependence and ensuring agricultural systems remain efficient and competitive in an increasingly technological landscape. Excessive labor input may lead to inefficient resource allocation or reduced management effectiveness. In contrast, advanced mechanization in high-income countries likely offsets labor demands by reducing reliance on manual labor (Nouri et al. 2020). Expanding planting areas also positively impacts cotton yield, with a net contribution rate of 5.9%, suggesting that mechanized systems benefit from large-scale production. Conversely, cotton production in low-income countries relies heavily on basic inputs, particularly fertilizers, which show a significantly positive contribution rate of 15.4%, far exceeding the global average of 4.7%. This finding aligns with research showing that fertilizers are critical for improving yields in underdeveloped agricultural systems (Addis et al. 2021).

The impact of climate change on global cotton production is significant and cannot be overlooked. This study found that the net contribution of temperature to cotton yield is −1.8%, indicating that rising temperatures are linked to reduced yields. In most countries, temperature negatively affects cotton yield. A meta-analysis of model-based simulations found that a 1°C increase in average temperature results in a 7.8% decline in cotton yield (Li et al. 2021), consistent with the results of this study. As temperatures rise and precipitation patterns shift, cotton-growing regions are likely to experience more extreme climatic events, such as droughts and floods, further exacerbating spatial disparities in yields (Jans et al. 2021). The adverse effects of high temperatures and increased evapotranspiration are especially pronounced in arid regions. Consequently, improving the climate resilience of cotton production, optimizing irrigation technologies, and enhancing water resource management are critical challenges that must be urgently addressed (Asseng et al. 2014; Huang et al. 2022).

Although this study examined the effects of various factors, including climatic conditions, fertilizer inputs, cropping structure, and socio-economic variables on cotton yield, genetically modified (GM) cotton was not included due to limitations in data availability and quantification. Nevertheless, the significant influence of GM cotton on yield is undeniable. For example, since Brazil began promoting Bt cotton (a GM variety) in the 1990' s, cotton yields have increased substantially, with exports reaching 1.618×10^6 t in 2023, generating $3.07 billion in revenue. In Mexico, after the introduction of Bt cotton in 1996, 96% of cotton fields were planted with this variety by 2008, leading to notable yield improvements. Similarly, in Argentina, the adoption of Bt cotton in 1998 has been widely embraced by small-scale farms, reducing pesticide costs and significantly boosting yields (Nagaraj et al. 2024). In India, the cultivation of Bt cotton has steadily expanded since 1996, now covering 93% of the country's cotton fields, resulting in a remarkable yield increase. However, the widespread adoption of Bt cotton has also led to challenges, such as poor pest resistance in certain regions, emphasizing the importance of considering long-term impacts and potential risks when promoting new technologies (Nagaraj et al. 2024).

Beyond GM cotton, several other avenues warrant further investigation. For example, quantifying the interactions among various factors and examining the potential impacts of climate change on future cotton production remain critical areas for in-depth research. In addition, techniques based on remotely sensed vegetation indices and cotton phenology can also provide important support for cotton yield analysis and assessment (Du et al. 2025). Moreover, future studies could incorporate more granular local and farm-level data to inform the

GTWR model and provide more targeted policy recommendations for improving cotton production across different countries.

5. Conclusions

Comprehensive research on the spatiotemporal dynamics of global cotton yield and its driving mechanisms offers valuable insights for addressing climate change and informing agricultural management decisions. This study utilized a dual classification framework based on economic levels and climate types to examine the patterns of cotton yield across 82 cotton-producing countries from 1992 to 2021, integrating economic and environmental contexts. By applying GTWR, this study quantitatively assessed the varying impacts of eight driving factors on cotton yield across different income levels and climate types.

Study findings demonstrate that global cotton yield followed a fluctuating upward trajectory over the past 30 years, with an average annual increase of approximately 27 t km^{-2}. Yields in high-income and upper-middle-income countries showed significant growth, with upper-middle-income countries making a substantial contribution to global yield gains and achieving yields twice the global average. In addition, yields in tropical, temperate, and arid climatic zones increased significantly, with the arid climatic zone maintaining the highest yield consistently over time. Cotton yield can be influenced by multiple factors, with regional and income-level variations in dependencies and responses. The eight key drivers of global cotton yield are ranked in descending order of contribution rates as follows: CAS > LD >Fer >SSR >RPS >Pre >Ev >Tem.

Fertilizer application and surface solar radiation are the key factors that significantly enhance cotton yield, whereas rising temperatures negatively impact it. In high-income countries, cotton area share and temperature both positively influence yield, while surface solar radiation has the opposite effect, distinguishing these regions from others. The impacts of precipitation and evapotranspiration exhibit regional variability: precipitation negatively affects yield in both high-income and low-income countries, whereas evapotranspiration's effects are mixed, depending on the region.

These findings underscore the intricate spatial and temporal variability in global cotton production, highlighting the necessity for region-specific agricultural policies. Future research should incorporate farm-level data and climate projections to further refine these insights and enhance policy effectiveness. To achieve sustainable growth in cotton yields, it is essential to optimize agricultural resource allocation based on each country's unique resources and climate.

Author contributions

CRediT: **Hong Fan:** Conceptualization, Data curation, Software, Writing – original draft, Writing – review & editing; **Jianghua Zheng:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing; **Binbin Lu:** Methodology, Software, Writing – review & editing; **Xurui Mao:** Investigation, Software; **Juan Yang:** Validation; **Linzhi Han:** Funding acquisition, Investigation; **Paul Harris:** Funding acquisition, Methodology, Software, Writing – review & editing.

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Data availability statement

The datasets used in this study are as follows: Cotton area harvested, production, and yield data (1992–2021) are available from the Food and Agriculture Organization (FAOSTAT): https://www.fao.org/faostat/en/#home. Soil water and surface solar radiation data are provided by ECMWF: https://www.ecmwf.int. Cotton planting distribution map (2021) is available from the USDA Foreign Agricultural Service (FAS), International Production Assessment Division (IPAD): https://ipad.fas.usda.gov/Default.aspx. World map by income data (2023) is accessible through The World Bank: https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html. Other data supporting the results of this study are available from the author upon request.

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