Agriculture and Food

AIMS Agriculture and Food, 11(3): 422–446.
DOI: 10.3934/agrfood.2026022
Received: 05 August 2025
Revised: 21 April 2026
Accepted: 29 May 2026
Published: 09 July 2026

https://www.aimspress.com/journal/agriculture

Research article

Exploring the climatic and non-climatic determinants of cereal production in Bangladesh

A. K. M. Kanak Pervez[1,†], Isfaqur R. Ifty[1,†], Akira Ishida[2,*], Md Mahedi[1] and Md Nazirul Islam Sarker[3,4]

[1] Department of Agronomy and Agricultural Extension, University of Rajshahi, Rajshahi 6205, Bangladesh
[2] Graduate School of Agricultural Science, Kobe University, 1-1 Rokkodai-cho, Nada-ku, Kobe 657-8501, Japan
[3] School of Public Administration, Xi'an University of Finance and Economics, Xi'an 710100, China
[4] Miyan Research Institute, International University of Business Agriculture and Technology, Dhaka 1230, Bangladesh

* **Correspondence:** Email: akira_ishida@people.kobe-u.ac.jp; Tel: +81788035844; Fax: +81788035844.
† Joint first author.

Abstract: Cereal production is a key component of food security and economic stability in Bangladesh; however, it is increasingly influenced by the interplay between climatic stress and non-climatic pressures, including land-use change and ecological degradation. Nevertheless, no study at the national level has jointly quantified the long-term effects of these drivers. Using a multidisciplinary systematic framework involving detrending of the time series through linear regression, followed by iterative refinement and diagnostic validation of model robustness, this study addresses that gap by evaluating annual data spanning 1961–2022. All 11 explanatory variables were subjected to model selection, which revealed that the final model retained four significant predictors: land under cereal production (LUCP), arable land, observed annual precipitation, and forest area. The results indicate that land-use structure and ecological trade-offs are stronger predictors of cereal yield than annual climatic variability alone. The strongest predictor was forest area ($\beta = -0.607$, $p < 0.001$), followed by LUCP ($\beta = 0.300$, $p < 0.001$) and arable land ($\beta = -0.147$, $p = 0.012$), whereas annual precipitation had an independent effect that remained statistically non-significant ($\beta = 0.037$, $p = 0.303$). These findings imply that climate is not the sole determinant of agricultural productivity; rather, the allocation, management, and transformation of land also play critical roles. This evidence underscores the need for policy priorities to focus on sustainable intensification of existing cereal land, restoration of degraded arable land, and integrated governance of land use. Such an approach will directly contribute to achieving Sustainable Development Goal (SDG) 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land).

Keywords: agricultural extension; cereal yields; climatic variables; non-climatic variables; Bangladesh

1. Introduction

Agriculture is an important sector of Bangladesh's economy, contributing approximately 12.5% to the national gross domestic product (GDP) and providing employment for nearly 40% of the labor force [1]. Rice, wheat, and maize collectively account for over 70% of national dietary energy and occupy approximately four-fifths of cultivable land [2]. Although the sector's share of GDP has declined relative to other sectors due to industrialization and urbanization, it remains critical for food security, rural livelihoods, and economic stability.

Both climatic and non-climatic pressures increasingly challenge the sustainability and expansion of agricultural production. The high population density in Bangladesh exerts substantial pressure on arable land (ARL), leading to fragmentation, degradation, and deforestation. The majority of farmers are smallholders, many of whom continue to adopt conventional low-input practices [3]. This situation contributes to a substantial yield gap, primarily driven by poverty and limited access to technology.

In the present study, climatic drivers are defined as meteorological variables external to farm management, including temperature, precipitation (PREC), and atmospheric carbon dioxide (CO_2), whereas non-climatic drivers encompass land use, agricultural inputs, and socio-economic factors (e.g., fertilizer use and land tenure). This taxonomy aligns with established conceptual frameworks [4].

Modern irrigation systems, improved seed varieties, and mechanization are increasingly available; however, their adoption remains uneven due to financial constraints. Climate change constitutes a major challenge, as Bangladesh is highly vulnerable to rising temperatures, erratic PREC, floods, cyclones, and droughts [5]. These climatic variations disrupt crop cycles, reduce soil moisture, and ultimately impair productivity. Nevertheless, the precise effects of climatic variables remain difficult to isolate because non-climatic factors also exert substantial influence. Soil quality declines as a result of deforestation and land-use change, while urbanization reduces the extent of ARL. Continued reliance on traditional practices, low levels of mechanization, and inadequate irrigation infrastructure further constrain productivity [6]. Moreover, the expansion of agriculture into forested areas may initially increase cultivated land; however, it ultimately depletes soil nutrients and accelerates soil erosion.

Current socio-economic conditions exert a substantial influence on farming outcomes. Most rural farmers are poor and lack access to finance, education, and modern agricultural inputs. Food demand continues to increase as the population expands; however, limited land availability and declining soil fertility constrain production. Inadequate infrastructure and inefficient market systems depress farm-gate prices, which in turn limits both investment in and the adoption of improved practices. Distinguishing the relative effects of climatic and non-climatic conditions is therefore critical for effective policy formulation.

Research gap and innovation: Previous research has largely relied on non-climatic variables, with limited evidence regarding the interaction between climatic and non-climatic factors. To date, no national-scale study has jointly quantified land-use, socio-economic, and meteorological determinants of cereal yields across the entire post-Green Revolution period (1961–2022) in Bangladesh. To the best of our knowledge, this is the first national-level study to adopt such an integrated approach. The research question guiding this study is as follows: What climatic and non-climatic variables exert the greatest statistical influence on cereal yields?

By synthesising climatic, land-use, and socio-economic variables within a unified 1961–2022 analytical framework, this study provides the first systematic evidence on the relative contribution of each driver and offers insights to inform land governance and climate adaptation policy in Bangladesh. The findings may assist policymakers in identifying structural constraints on crop yields and in designing targeted interventions.

2. Literature review

The literature on agricultural productivity in Bangladesh can be classified into three interrelated streams: (i) climatic determinants, (ii) non-climatic (socio-economic and land-use) factors, and (iii) integrated approaches. This review synthesizes these strands to identify the research gap that the present study seeks to address.

2.1. Climatic determinants of crop yields

Given Bangladesh's high vulnerability to climate change, numerous studies have examined the relationship between meteorological variables and crop yields. Using time-series analysis, rising temperatures and irregular rainfall significantly reduce rain-fed *aman* rice yields [7] . Similarly, autoregressive distributed lag (ARDL) modelling to assess the long-run effects of temperature and PREC on cereal production [8] . These findings have informed climate adaptation policies, including the promotion of drought- and flood-tolerant rice varieties.

However, climate-focused studies exhibit several limitations. Such approaches often entail omitted variable bias arising from the exclusion of land-use change, input intensification, and technological progress from model specifications [4]. A narrow focus on single crops or individual growing seasons may obscure system-level interactions. Furthermore, multicollinearity among climatic variables, or between climatic and socio-economic trends, is rarely addressed, potentially resulting in coefficient inflation or attribution errors in the estimated parameters.

2.2. Non-climatic determinants

A parallel strand of research has examined the socio-economic and land-cover determinants of agricultural productivity. Previous studies have highlighted the growing importance of irrigation expansion [9], particularly for *boro* rice, which accounts for over 75% of the dry-season cereal area. The application of government-subsidized fertilizer increased from approximately 16 kg/ha in 1970 to more than 100 kg/ha in recent years. Land fragmentation, farm size, and tenure security have also been identified as significant determinants of yield outcomes [6,10]. Access to agricultural inputs, irrigation infrastructure, and market integration is consistently reported as a strong determinant of productivity in these studies.

However, non-climatic studies seldom incorporate weather variability into their modelling frameworks, implicitly assuming that technological and policy factors are the most influential drivers. Although this assumption may hold under relatively stable climatic conditions, it does not necessarily apply to extreme events. Furthermore, the exclusion of climatic variables prevents the assessment of whether adaptation measures, such as the expansion of irrigation, have effectively decoupled yields from rainfall variability, a question of considerable policy relevance.

2.3. Integrated approaches

Recognising the limitations of single-factor studies, recent research has increasingly adopted integrated frameworks that jointly analyse climatic and non-climatic drivers. [4] proposed a systematic approach (SA) that combines variable detrending, stepwise regression, and socio-economic contextual analysis. Their application in Uganda demonstrated that non-climatic factors, such as land area and fertilizer use, often dominate climatic variables in explaining yield variability.

Extending this integrated perspective, the combined effects of digital technology adoption and climate change on food security in Vietnam between 1996 and 2022 [11] . Applying ARDL, dynamic ordinary least squares, and fully modified ordinary least squares methods, the authors found that information and communication technologies, particularly mobile phone and internet usage, significantly promoted food security in both the long and short run [12]. Conversely, temperature changes negatively affected food security across all estimations. These findings demonstrate that integrated approaches combining technological, socio-economic, and climatic factors provide more reliable guidance for policy formulation than single-factor analyses.

These integrated studies converge on a common conclusion: understanding agricultural productivity requires the simultaneous consideration of climatic variability and the structural factors that mediate farmers' adaptive capacity. The present study extends this perspective to Bangladesh by applying a modified systematic framework to quantify the relative contributions of climatic and non-climatic determinants across the full post-Green Revolution period (1961–2022).

3. Materials and methods

3.1. Study area

This study focuses on Bangladesh, a lower-middle-income country in South Asia with a predominantly agrarian economy and a strong dependence on cereal production for food security. Bangladesh covers approximately 147,570 km^2 and has a population exceeding 170 million [13]. Agriculture remains central to employment, rural livelihoods, and the national food supply [14]. The principal cereals produced and consumed are rice, wheat, and maize [15].

Bangladesh is highly vulnerable to climatic stressors, including floods, droughts, cyclones, erratic rainfall, and rising temperatures [16,17]. In parallel, cereal production is influenced by non-climatic drivers, such as land fragmentation, deforestation, urbanization, and limited access to agricultural inputs and technology. Given these conditions, Bangladesh provides a relevant case for examining the relative importance of climatic and non-climatic drivers of cereal yield [18].

3.2. Theoretical approach and data acquisition

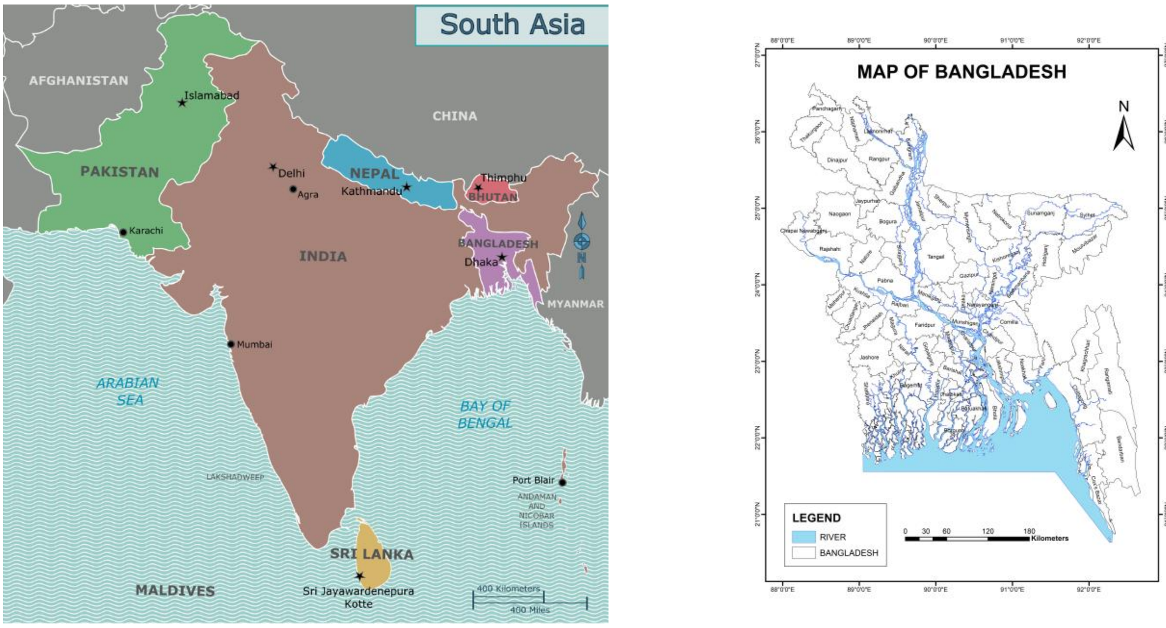
This study aims to identify and characterize the relative contributions and statistical significance of climatic and non-climatic factors (independent variables) to cereal yields (dependent variable) in Bangladesh using a systematic modelling framework. The research utilises national-scale data comprising seven non-climatic variables, four climatic variables, and one dependent variable over 62 years (1961–2022). The dependent variable is cereal yield, measured in kilograms per hectare. Yield statistics were obtained from the World Bank's World Development Indicators (WDI) and represent the total output of principal cereals. Cereals were selected because of their central role in the national food system and their cultivation across multiple seasons throughout the year. The data were available for all years and were used without modification, as they were already reported in a consistent unit of kilograms per hectare.

The use of aggregate cereal yield statistics as a representative indicator of national agricultural production is justified on several grounds. First, comprehensive and continuous time-series data for cereal crops were available from 1961 to 2022. Second, these cereals collectively account for the predominant share of caloric intake and cultivated land in Bangladesh, thereby reflecting national food security patterns. Third, the selected crops span both wet and dry seasons, encompassing the full annual production cycle. Fourth, all yield data were standardized to a uniform unit (kg/ha), enabling comparison and modelling without the need for further adjustment. Finally, incorporating all principal cereals reduces the potential distortion that may arise from analyzing data limited to a single season or crop.

Climatic factors were selected based on their established influence on crop development and the availability of extensive historical data. These include mean annual surface air temperature (°C), annual PREC (mm), CO_2 emissions excluding land use, land-use change, and forestry (LULUCF) (t CO_2e per capita), and forest area (FA) (sq. km). The variables were obtained from the World Bank's *WDI* and the Extreme Weather Watch database.

Although CO_2 emissions do not directly affect agricultural production at the farm level, they influence crop yields indirectly through mechanisms such as elevated temperatures, altered PREC patterns, and increased climatic variability [19,20]. Accordingly, this study incorporates CO_2 emissions (excluding land use and forestry) as an indicator of environmental stress. In Bangladesh, per capita CO_2 emissions (excluding LULUCF) increased from approximately 0.048 metric tons in 1970 to about 0.733 metric tons in 2022, reflecting sustained economic growth and greater reliance on fossil fuels. This increase of more than fourfold, although modest in global terms, indicates rising environmental pressure. Globally, atmospheric CO_2 concentrations rose from approximately 275 ppm in the pre-industrial period to over 417 ppm in 2022 and may exceed 550 ppm by mid-century, potentially resulting in a 2°C increase in global temperature [21]. While elevated CO_2 concentrations can enhance photosynthesis in C_3 crops, such as rice, this effect depends on adequate water and nutrient availability. Associated temperature increases may offset these potential benefits. In this study, CO_2 is therefore treated primarily as an indicator of long-term climatic stress. Mean annual temperature and PREC data were used rather than season-specific values, as cereals are cultivated throughout the year in Bangladesh. The use of annual averages is consistent with previous research by Lobell and Burke (2008) and Sarker et al. (2012), which found that annual climatic variables adequately capture interannual production variability for staple crops when multi-decadal data are analyzed. [22,23].

Non-climatic variables were selected on the basis of data availability and theoretical relevance. The parameters include land under cereal production (LUCP); ARL (hectares); permanent cropland (percentage of total land area); fertilizer use (kilograms per hectare of ARL); gross domestic product (GDP, current US dollars); annual population growth rate (percentage); and value added from agriculture, forestry, and fisheries (current US dollars). These variables capture both direct agronomic inputs and broader socio-economic factors that shape land use and agricultural output. For example, LUCP in Bangladesh increased from 8.6 million hectares in 1961 to over 12.4 million hectares by 2022, while permanent cropland expanded from 2.1% to 7.22% of the total land area (*World Bank data*). Fertilizer use rose from approximately 16 kg/ha in 1970 to more than 300 kg/ha in recent years, indicating a trend towards production intensification (*World Bank data*). These non-climatic drivers were selected on the premise that agricultural production outcomes are determined not only by meteorological conditions but also by structural factors, such as land tenure systems and economic development. Given the uncertainty regarding which of these factors exerts the greatest influence on crop yields, this study developed a modelling framework to evaluate their relative contributions empirically.



(a) (b)

Figure 1. (a) Map of South Asia showing the location of Bangladesh; (b) District-level administrative map of Bangladesh.

3.3. Variable description

The dependent variable in this study is cereal yield (kg/ha), which measures the productivity of cereal crops relative to harvested land area. It serves as a key indicator for assessing agricultural performance and food security in Bangladesh.

The seven independent non-climatic variables were obtained from the World Bank Group. Seven non-climatic factors are considered particularly significant in influencing agricultural yields in Bangladesh, including:

• LUCP (hectares) refers to the total area cultivated for cereal crops, including rice, wheat, and maize, measured in hectares. Cereal production is central to food security and agricultural income in Bangladesh. An expansion of land allocated to cereal cultivation may reflect increased agricultural activity and potentially enhance aggregate production [24].

• GDP (current US dollars) denotes the total market value of all final goods and services produced within Bangladesh in a given year. Measured in current US dollars, GDP serves as an indicator of overall economic performance. Higher GDP levels may be associated with improved infrastructure, greater access to agricultural inputs, and increased public investment in rural development, which can contribute to higher crop yields.

• Population growth (annual %) measures the annual rate of increase in Bangladesh's total population. Rapid population growth can exert pressure on land, water, and food resources. An expanding population increases food demand, thereby intensifying the need for higher agricultural yields.

• Value added of agriculture, forestry, and fisheries (current US dollars) represents the net output of these sectors after deducting intermediate inputs. Higher value added indicates greater efficiency within the primary sector, which may enhance crop yields through improved access to technology, advanced agricultural practices, and capital investment.

• ARL (hectares) refers to land suitable for tillage and the cultivation of crops requiring seasonal replanting. In Bangladesh, ARL constitutes a critical resource for sustaining cereal production. Expansion of ARL may reflect increased agricultural capacity; however, if it results from deforestation or inappropriate land conversion, it may contribute to environmental degradation.

• Permanent cropland (% of land area) denotes the proportion of total land allocated to crops that do not require annual replanting, such as tea, coffee, and fruit trees [25]. In Bangladesh, growth in this variable may signal agricultural diversification and greater long-term production stability.

• Fertilizer consumption (kilograms per hectare of ARL) measures the average application of fertilizer per hectare of cultivated land. Fertilizer is a key input for improving soil nutrient availability and increasing crop production. In Bangladesh, optimal fertilizer application can substantially enhance crop yields.

The four independent climatic drivers are temperature, PREC, CO_2 emissions excluding land use and forestry, and FA, which are defined as follows:

• Mean surface air temperature (°C) represents the annual average of daily air temperatures at the Earth's surface across Bangladesh. Temperature is a major climatic variable influencing plant developmental stages, physiological processes, and yield outcomes.

• Annual PREC (mm) refers to the total rainfall recorded within a calendar year in Bangladesh. PREC is essential for sustaining rain-fed agriculture, which accounts for a substantial share of agricultural production in the country. Regular and timely rainfall supports healthy plant development, particularly during critical growth stages.

• CO_2 emissions per capita, excluding LULUCF, measured in tons of CO_2 equivalent (t CO_2e per capita), represent annual per capita emissions associated with industrial activity and fossil fuel consumption, excluding emissions from land-use change and forestry practices [26]. Elevated CO_2 concentrations may stimulate plant growth by enhancing photosynthetic activity, particularly in C_3 crops [27].

• FA (sq. km) denotes the total area of land classified as forest, measured in square kilometres. This indicator reflects trends in deforestation and reforestation over time. Continued reductions in forest cover, although potentially increasing agricultural land in the short term, can disrupt hydrological cycles, intensify soil erosion, and accelerate biodiversity loss, thereby threatening the long-term sustainability of cereal production systems [28].

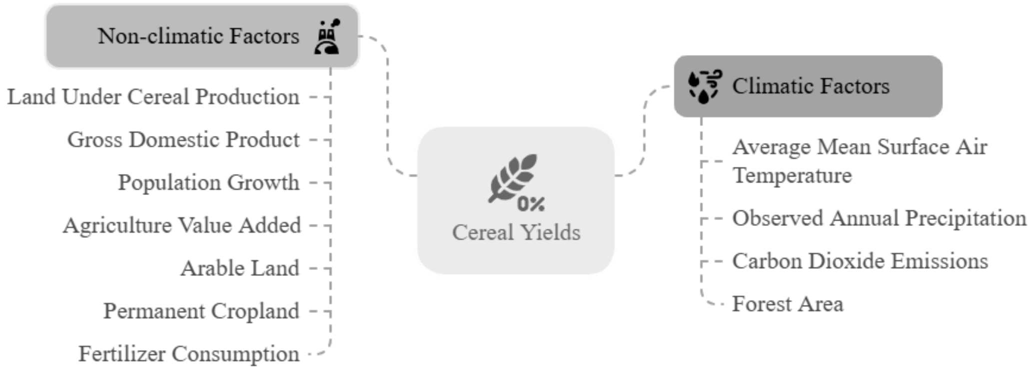


Figure 2. Categorization of climatic and non-climatic determinants of crop yields.

3.4. Analytical methodology

This study adopts the SA proposed by Müller et al. (2013), which comprises a four-step procedure to identify the principal climatic and non-climatic determinants of cereal yields in Bangladesh [29]. The analytical framework integrates detrending, multiple linear regression (MLR), iterative model refinement, and diagnostic testing to ensure both robustness and interpretability.

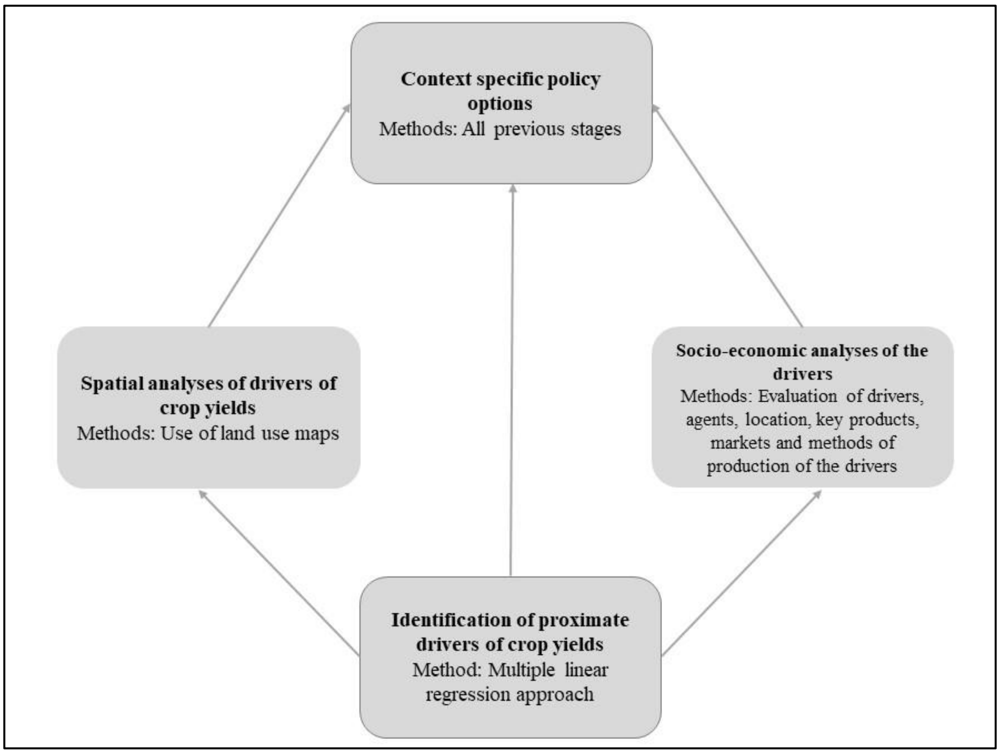


Figure 3. Schematic representation of the key stages of the modified systematic approach (SA).

Step 1: Data preparation and detrending

All variables (one dependent and eleven independent variables) were first detrended to remove long-term linear trends associated with technological progress, structural transformation, and gradual environmental change. This procedure enables the analysis to focus on interannual variability rather than long-term growth patterns.

The detrending procedure follows the approach of [4], whereby each time-series variable is normalized using its expected value derived from a linear trend model:

$$\mathrm{EXP}y = ax + b \tag{1}$$

where *EXPy* denotes the expected value of the variable, *x* represents the time variable (year), *a* is the slope coefficient indicating the rate of change, and *b* is the intercept term. This transformation removes linear trend effects associated with time.

Step 2: Estimation of the initial model (IM)

An initial multiple linear regression (MLR) model was estimated, incorporating all eleven explanatory variables (both climatic and non-climatic):

$$Y_{CY\_IM} = \alpha_0 + \alpha_1 X_{LUCP} + \alpha_2 X_{GDP} + \alpha_3 X_{POPGR} + \alpha_4 X_{AFF} + \alpha_5 X_{ARL} + \alpha_6 X_{PCP} + \alpha_7 X_{FERT} + \alpha_8 X_{TEMP} + \alpha_9 X_{PREC} + \alpha_{10} X_{CO2} + \alpha_{11} X_{FA} + \varepsilon \tag{2}$$

where Y_{CY_IM} represents cereal yield in the Initial Model (dependent variable). The term α_0 denotes the regression intercept, and ε denotes the stochastic error term. The coefficients α_1 to α_{11} are the partial regression coefficients corresponding, respectively, to X_{LUCP} (land under cereal production, hectares), X_{GDP} (gross domestic product, US$), X_{POPGR} (annual population growth rate, %), X_{AFF} (agriculture, forestry, and fisheries value added, current US$), X_{ARL} (arable land, hectares), X_{PCP} (permanent cropland, % of land area), X_{FERT} (fertilizer consumption, kilograms per hectare of arable land), X_{TEMP} (mean surface air temperature, °C), X_{PREC} (observed annual precipitation, mm), X_{CO2} (carbon dioxide (CO_2) emissions excluding LULUCF per capita (t CO_2e/capita), and X_{FA} (forest area, square kilometres). Each coefficient measures the partial effect of its associated explanatory variable on cereal yield, holding all other variables in Equation (2) constant.

Step 3: Model refinement and variable selection

The initial specification required an iterative refinement process to obtain a more robust and interpretable model. The final model was selected based on combined statistical, diagnostic, and theoretical criteria rather than a single decision rule.

(a) Statistical screening

An initial screening criterion was a p-value threshold of 0.10. Such a relatively liberal threshold is commonly employed in exploratory modelling to avoid the premature exclusion of variables that may become significant after adjusting for multicollinearity and model instability.

(b) Multicollinearity diagnostics

Variance inflation factor (VIF) analysis formed part of the model selection procedure. Variables exhibiting excessively high levels of multicollinearity—typically indicated by VIF values ≥ 10, and in some cases substantially higher—were considered to inflate the instability of coefficient estimates. These variables were removed sequentially until the resulting model exhibited acceptable multicollinearity.

(c) Stability of coefficients and model consistency

At each stage, the model was re-estimated and evaluated with respect to:

a) Stability of coefficient signs;
b) Consistency in coefficient magnitudes;
c) Overall model performance.

(d) Theoretical relevance

In addition to statistical criteria, variables were retained or excluded based on their conceptual relevance to Bangladesh's agricultural production system. Land-use, climatic, and ecological variables were prioritized where they aligned with established agronomic and environmental relationships.

Step 4: FOM

Following the iterative refinement process, a FOM was derived with a reduced set of variables satisfying statistical significance, diagnostic validity, and theoretical consistency:

$$Y_{\mathrm{CY\_FOM}} = \alpha_0 + \alpha_1 X_{LUCP} + \alpha_2 X_{Precipitation} + \alpha_3 X_{ARL} + \alpha_4 X_{FA} + \varepsilon \tag{3}$$

where α_1, α_2, α_3, and α_4 are the partial regression coefficients associated with LUCP, annual PREC, ARL, and FA, respectively. These four variables represent the most influential predictors of cereal yield in Bangladesh, as determined through iterative model refinement. This two-stage regression strategy ensures comprehensive initial variable inclusion followed by a parsimonious final specification, thereby mitigating risks of overfitting and multicollinearity.

The reduced model achieves parsimony while preserving explanatory power and interpretability.

Step 5: Diagnostic testing and model validation

To ensure robustness, several diagnostic tests were conducted:

a) The VIF was calculated to assess multicollinearity, and all retained variables exhibited acceptable VIF values (VIF < 10);
b) Autocorrelation was evaluated using the Durbin–Watson (DW) statistic. The DW statistic indicated the presence of positive autocorrelation, which is expected in time-series data;
c) Overall model significance was assessed using the F-statistic and the adjusted R^2.

The final model specification is therefore considered the most stable and interpretable when evaluated across the initial, intermediate, and full model specifications.

The DW test was applied to examine the presence of autocorrelation in the residuals. The DW statistic indicated positive autocorrelation, a common characteristic of long-term time-series data [30]. In the presence of autocorrelation, the results should be interpreted as structural associations rather than precise statistical inference, as coefficient estimates may be less efficient [31]. However, this limitation does not invalidate the overall findings, as the primary objective of the study is to identify dominant correlates of cereal yield rather than to establish causal or predictive relationships. The use of detrended data and iterative model refinement reduces the risk of spurious correlation; nevertheless, more advanced time-series techniques, such as autoregressive models or heteroskedasticity and autocorrelation-consistent estimators, could be employed in future research to address this issue more comprehensively [32].

Step 6: Scope and interpretation

The estimated relationships reflect correlations rather than causal effects. The modelling framework is appropriate for exploring dominant correlates of cereal yield within a long-term national context. Given the aggregation of annual data, the results should be interpreted as representing composite structural relationships rather than localized or causal mechanisms.

4. Results

The MLR results indicate that both climatic and non-climatic factors contribute to cereal yield in Bangladesh; however, non-climatic drivers remain comparatively more influential overall. The IM, which included all eleven climatic and non-climatic predictors, was statistically significant (adjusted R^2 = 0.987; F-statistic = 223.595). Nevertheless, several variables in the full specification exhibited weak statistical significance and overlapping explanatory power, necessitating further refinement prior to substantive interpretation. Accordingly, the model was simplified iteratively on the basis of statistical significance, diagnostic evaluation, and conceptual relevance to obtain a more stable and interpretable specification.

Table 1. Results of the initial regression model including all eleven independent variables

Independent Variables	B	Std. Error	Beta	t	Sig.
LUCP (hectares)	0	0	0.217	4.26	0
GDP (current US dollars)	−2.26E−09	0	−0.302	−0.53	0.602
Population growth (annual %)	−832.367	455.169	−0.444	−1.829	0.082
Agriculture, forestry, and fisheries value added (current US dollars)	2.15E−08	0	0.304	0.479	0.637
Arable land (hectares)	0	0	−0.076	−1.368	0.186
Permanent cropland (% of land area)	243.309	69.811	0.44	3.485	0.002
Fertilizer consumption (kilograms per hectare of arable land)	−0.097	1.351	−0.009	−0.072	0.944
Mean surface air temperature (°C)	−43.067	63.182	−0.017	−0.682	0.503
Annual precipitation (mm)	0.09	0.074	0.028	1.211	0.24
CO_2 emissions per capita excluding LULUCF (t CO_2e per capita)	109.574	1286.773	0.023	0.085	0.933
Forest area (square kilometres)	0.771	1.475	0.146	0.523	0.607

Dependent variable: cereal yield (kg per hectare*),* Bangladesh.
R = 0.996; adjusted R^2 = 0.987; F-statistic = 223.595; Durbin–Watson (DW) = 2.154.

The final diagnostic-validated model retained four variables: LUCP, ARL, annual PREC, and FA (square kilometres). This final model was also highly significant (R = 0.986; adjusted R^2 = 0.969; F-statistic = 242.897) and explained a substantial proportion of the variation in cereal yield in Bangladesh. Although this specification is marginally less precise than the baseline model in terms of the Akaike information criterion and total explained variance, it substantially reduces instability among explanatory variables while preserving strong overall explanatory power.

FA (square kilometres) was the most pronounced predictor in absolute terms ($\beta = -0.607$, $t = -7.735$, $p < 0.001$), followed by LUCP ($\beta = 0.300$, $t = 4.764$, $p < 0.001$) and ARL ($\beta = -0.147$, $t = -2.709$, $p = 0.012$). The final model retained annual PREC; however, its coefficient was not statistically significant ($\beta = 0.037$, $t = 1.051$, $p = 0.303$). These findings indicate that land-use structure and ecological trade-offs exhibit a stronger association with variation in cereal yield in Bangladesh than annual climatic variability.

The positive coefficient associated with LUCP suggests that per-hectare cereal productivity increases as the proportion of land allocated to cereal cultivation expands. This pattern may reflect crop specialization and improved access to irrigation, infrastructure, extension services, and production support. In contrast, the negative coefficient for ARL suggests that expansion of cultivated area alone does not necessarily increase productivity, particularly when cultivation extends into marginal, saline, flood-prone, or lower-quality land. The negative association between FA and cereal yield should not be interpreted as a direct causal relationship. Rather, it likely reflects broader land-use trade-offs in which agricultural expansion, ecological degradation, and long-term production risks are interconnected.

These results are consistent with the alternative hypothesis (H_1) that climatic and non-climatic factors do not exert equal effects on cereal yields; therefore, the rejection of equal pairwise influence among individual drivers supports rejection of the null hypothesis (H_0). Although three of the four retained variables relate to land use, the inclusion of FA indicates that ecological conditions also play a significant role in cereal production outcomes. Nevertheless, the limited independent effect of annual PREC suggests that rainfall variability at the national scale may be partially mitigated by irrigation, cropping adjustments, and other adaptive practices, particularly within cereal production systems across Bangladesh.

Bangladesh receives substantial total annual rainfall with pronounced seasonal variation; however, irrigation serves as a key mechanism for stabilising cereal production, especially during the boro season [33]. This context explains the comparatively limited contribution of annual PREC relative to land-use variables in the preferred model specification. Overall, the results indicate that cereal yield determinants in Bangladesh are more strongly associated with land-use practices, agricultural specialization, and environmental pressures than with short-term climatic variability alone.

4.1. Agents, locations, production systems, and market dimensions of key drivers of cereal yields in Bangladesh

This section examines the socio-economic and spatial dimensions of the four variables retained in the FOM: annual PREC, LUCP, ARL, and FA. Each variable is interpreted in relation to key agents, geographic distribution, production systems, and market linkages to provide a deeper understanding of how these factors influence cereal productivity in Bangladesh.

4.1.1. Annual PREC

Annual PREC was retained in the final model ($t = 1.051$; $p = 0.303$) but was not statistically significant, indicating that its independent contribution to yield variation is relatively limited when considered alongside land-use variables. Nevertheless, rainfall remains one of the fundamental agro-climatic determinants of agricultural systems in Bangladesh [34,35].

Bangladesh receives substantial annual rainfall, with a pronounced seasonal concentration during the monsoon period. Accordingly, the agricultural effects of PREC cannot be explained solely by total rainfall amounts, but also by its timing, intensity, and spatial distribution [36]. Excessive rainfall may lead to flooding and waterlogging, whereas insufficient rainfall can constrain crop growth, particularly in the comparatively drier north-western regions.

The principal agents associated with rainfall-dependent cereal systems include smallholder farmers, irrigation users, local water managers, and agricultural extension services. With respect to crop-specific reliance, *aman* rice is particularly dependent on monsoon PREC, whereas *boro* rice relies predominantly on irrigation [37].

In the context of the final model, the statistical insignificance of PREC does not imply climatic irrelevance. Rather, it reflects the increasing role of irrigation infrastructure, cropping adjustments, and context-specific management practices that reduce direct dependence on interannual rainfall variability.

4.1.2. LUCP

LUCP is positively and significantly associated with cereal yield ($\beta = 0.300$, $p < 0.001$), indicating that a greater concentration of land allocated to cereal cultivation corresponds to higher per-hectare productivity.

In 2022, LUCP in Bangladesh was approximately 12.4 million hectares, underscoring the central role of cereals, particularly rice, in national food security [38]. The principal agents involved are smallholder farmers with fragmented landholdings, supported by government programmes, agricultural extension services, and input supply systems.

Major cereal-producing regions include Rajshahi, Rangpur, Bogra, Mymensingh, and parts of Khulna and Jessore, where irrigation infrastructure and agricultural support systems are relatively well developed. The dominant cropping systems comprise *boro* rice (irrigated), *aman* rice (rain-fed), *aus* rice, wheat, and maize, characterized by increasing adoption of improved and hybrid varieties [39].

The positive association between LUCP and yield likely reflects crop specialization, although enhanced access to irrigation, mechanization, and extension services may also contribute to productivity gains [40,41]. These production systems are closely integrated into national markets, with cereals forming the foundation of the country's food supply, while maize supports the livestock feed and agro-processing sectors.

4.1.3. ARL

ARL is negatively and significantly associated with cereal yield ($\beta = -0.147$, $p = 0.012$), indicating that expansion of cultivated area does not automatically translate into higher yields.

ARL in Bangladesh has been substantially affected by urbanization, environmental stress, and land degradation. In 2022, approximately 8.2 million hectares of ARL were under cultivation; however, much of the newly cultivated land comprises marginal or environmentally sensitive areas, including saline coastal zones, flood-prone regions, and degraded soils [42,43].

The principal actors involved in the expansion of ARL include smallholders, landless migrants, and informal settlers who convert wetlands, forest margins, or other ecologically sensitive areas into cropland. Such land is typically characterized by low-input cropping systems, limited irrigation, and suboptimal soil management, resulting in lower productivity compared with more established agricultural areas [44].

The observed negative association therefore reflects declining average land quality and diminishing returns to the expansion of ARL, rather than a direct adverse effect of ARL per se. These finding highlights that improving land quality and input-use efficiency may be a more sustainable strategy than simply expanding the cultivated area.

4.1.4. FA

In absolute terms, FA is the strongest predictor ($\beta = -0.607$, $p < 0.001$), exhibiting a negative association with cereal yield. However, this relationship should be interpreted with caution and not as a direct cause-and-effect mechanism.

Over time, population pressure, agricultural expansion, settlement growth, and resource extraction have contributed to the decline of forest cover [45]. Key affected areas include the Chittagong Hill Tracts, the Madhupur forest region, and buffer zones surrounding the Sundarbans.

In many instances, forest land has been converted into cereal-based agricultural systems. Although such conversion may increase cultivated area in the short term, it often results in soil erosion, declining soil fertility, biodiversity loss, and disruption of hydrological systems, which may constrain long-term agricultural productivity [28].

The inverse association between FA and cereal yield therefore reflects land-use trade-offs and ecological pressures rather than a direct causal linkage. Similar patterns have been observed in other developing countries, where agricultural expansion frequently occurs at the expense of natural ecosystems [46].

Table 2. Results of the final diagnostic-validated regression model.

Independent variables	B	Std. Error	Beta	t	Sig.	VIF	Rank of |t|
LUCP (hectares)	0	0	0.3	4.764	0	3.96	2
Arable land (hectares)	0	0	−0.147	−2.709	0.012	2.936	3
Annual precipitation (mm)	0.116	0.11	0.037	1.051	0.303	1.219	4
Forest area (square kilometres)	−4167.79	538.81	−0.607	−7.735	0	6.154	1

Model summary: R = 0.986; R^2 = 0.973; adjusted R^2 = 0.969; F-statistic = 242.897; Durbin–Watson = 0.861.
Dependent variable: cereal yield (kg per hectare), Bangladesh.

Table 3. Socio-economic analysis of the main predictors of cereal yield in Bangladesh.

	Annual precipitation	LUCP (land under cereal production)	Arable land (hectares)	Forest area (square kilometres)
Agents	Rain-fed farmers, irrigation users, water managers, and extension services	Smallholder farmers, agribusinesses, and government support programmes	Farmers, landless migrants, agro-investors, and local cultivators	Forest Department, tribal communities, timber operators, fuelwood collectors, and illegal loggers
Location	Monsoon-dependent floodplains, delta regions, drought-prone north-west, and low-lying rice areas	Northern floodplains, central districts, and western and south-western cereal zones	Nationwide, particularly marginal lands in Barisal, Khulna, Rajshahi, Satkhira, and Noakhali	Sundarbans buffer zones, Chittagong Hill Tracts, Madhupur forest region, and north-eastern woodlands
Products/Uses	Supports soil moisture, crop water availability, and rain-fed aman systems	Rice, wheat, maize, and other cereal systems	Seasonal food crops, rice, vegetables, fodder, and cash crops	Timber, fuelwood, non-timber forest products, and ecological services
Production Characteristics	Seasonal dependence; effects vary by timing, flooding intensity, and irrigation buffering	Small-scale farming, manual transplanting, tube-well irrigation, and partial mechanization	Mixed systems; many marginal plots are low-input and poorly serviced	Conservation, extraction, and land conversion interact with surrounding farming systems
Markets	Indirect effects through production stability and cereal supply	Domestic markets, the national food system, limited regional trade, and feed markets	Local and national supply chains	Local timber and fuelwood markets; indirect implications for long-term agricultural sustainability

4.2. Robustness and consistency of findings

To assess robustness, several model specifications were examined: the full model including all variables (as presented in Table 4), intermediate reduced models in which subsets of variables were removed based on hypothesized association strength, and the FOM. Across these alternative specifications, the principal finding remains consistent: national-scale modelling indicates that land-use and ecological variables exert a stronger influence on cereal yield than climatic variables.

This pattern is consistent with previous studies demonstrating that structural and management factors, such as land allocation, irrigation, and fertilizer use, often outweigh short-term climatic variability in explaining agricultural productivity outcomes in developing countries [47].

To enhance interpretability, multicollinearity was addressed by eliminating redundant variables, thereby retaining only robust and theoretically relevant predictors in accordance with established econometric modelling practices [48,49]. Although the model explains a substantial proportion of the variation in cereal yield, this explanatory power should be interpreted cautiously, as strong goodness-of-fit in time-series models may partly reflect shared trends among variables rather than genuine structural relationships [50,51].

Accordingly, the estimated relationships should be interpreted as statistical associations rather than causal effects, given the use of aggregated national-level data and the presence of residual autocorrelation. Similar limitations have been acknowledged in long-term agricultural analyses, where complex interactions among socio-economic, environmental, and institutional factors cannot be fully captured within a single regression framework [52].

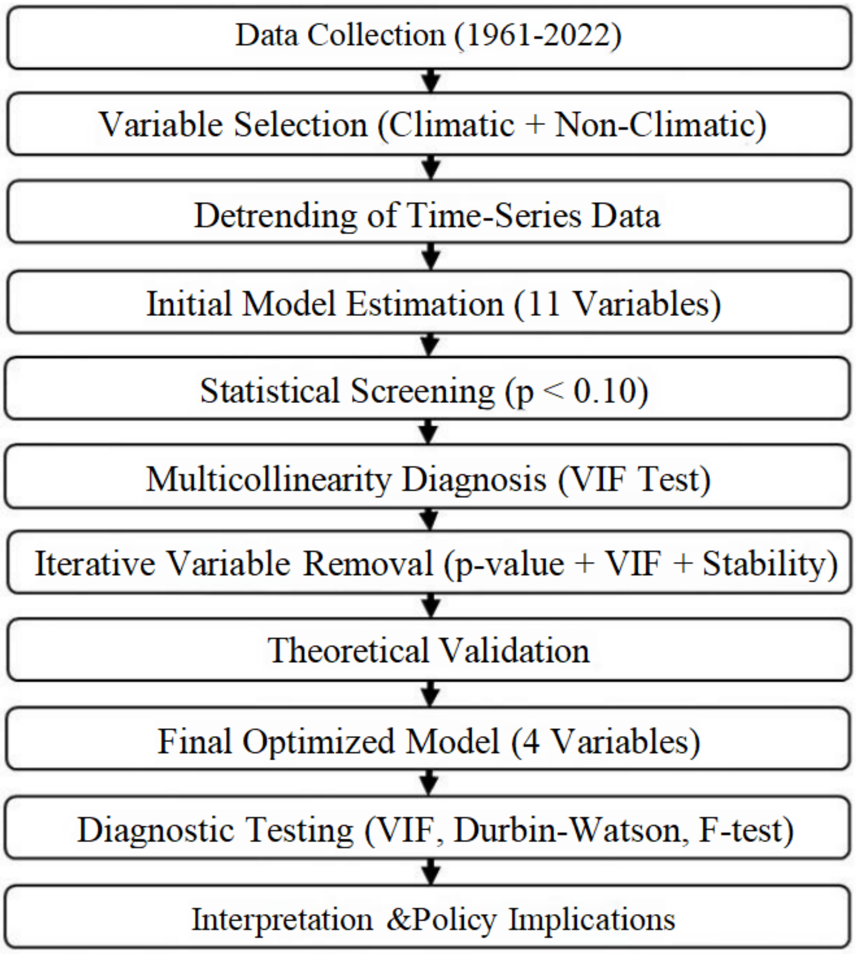


Figure 4. Analytical workflow for model development and validation.

5. Discussion

5.1. Land-use dynamics and ecological trade-offs as dominant drivers

The results suggest that variability in cereal yields across Bangladesh is driven more strongly by land-use structure and ecological dynamics than by annual climatic variability. This finding is consistent with a growing body of literature attributing agricultural productivity in many developing countries not only to climatic factors but also to structural determinants, such as land allocation, irrigation, and input use [53,54].

The positive association between LUCP and cereal yield reflects crop specialization and production intensification. Areas with higher concentrations of LUCP in Bangladesh—typically more productive regions—benefit from improved irrigation, input provision, and extension services, leading to enhanced productivity. Similar trends have been reported in South Asia, where intensification and technological adoption have substantially increased cereal production [55].

In contrast, the negative association between ARL and yield indicates that expansion of cultivable land does not necessarily translate into higher agricultural productivity. This finding aligns with literature demonstrating that agricultural expansion into marginal or environmentally fragile areas often results in lower average yields due to soil degradation, salinization, and water constraints [56]. These results therefore underscore that land quality and management practices, rather than land quantity alone, are critical determinants of productivity.

The negative correlation between FA and cereal yield should not be interpreted as a mechanistic causal relationship. Rather, it reflects broader land-use trade-offs and ecological pressures. In Bangladesh, forest conversion has frequently been associated with agricultural expansion and settlement development [57]. Although such conversion may increase cultivated land in the short term, it can lead to ecological degradation over time, including soil erosion, loss of ecosystem services, and disruption of hydrological systems [58]. Similar dynamics have been documented in other developing regions, where deforestation accompanies agricultural expansion [59]. Accordingly, the forest variable captures this interaction—land conversion, ecological stress, and long-term productivity risk—rather than indicating a direct adverse effect of forest cover.

5.2. Climatic influence and the role of adaptation

Although PREC was retained in the final model, its statistical effect was weaker than that of land-use variables. This finding should be interpreted with caution. Climate remains one of the fundamental determinants of agricultural production; however, its impacts are mediated by adaptation and infrastructure, particularly within the context of Bangladesh.

Although Bangladesh receives substantial annual rainfall, agricultural yields are influenced more by the distribution, timing, and management of water across seasonal and annual cycles than by cumulative annual totals [60,61]. Moreover, the expansion of irrigation—particularly for *boro* rice—has reduced reliance on rainfall in many cereal production systems. Farmers adapt cropping patterns, planting dates, and water management practices in response to climatic variability [62].

Accordingly, the relatively weak independent effect of PREC in the model likely reflects the buffering role of irrigation and adaptive practices rather than an absence of climatic influence. This interpretation is consistent with integrated agricultural studies that emphasise the interaction between climatic and non-climatic determinants [63]. Therefore, these findings do not diminish the importance of climate; rather, they highlight that its effects are embedded within broader production systems.

5.3. Policy and sustainability implications

The findings give rise to several important policy implications. First, the positive association between LUCP and cereal yield suggests that productivity gains can be achieved through sustainable intensification rather than expansion into new land. Optimising investments in irrigation efficiency, seed systems, soil fertility management, and extension services remains essential for improving cereal productivity [64]. These measures also contribute directly to SDG 2 (Zero Hunger) by enhancing food security.

Second, the inverse relationship between ARL and yield suggests that we should focus more on improving the quality than on expanding the amount of land resources. Policy efforts should promote restoration of degraded land, adaptation through climate-resilient farming practices, and sustainable soil management. Such strategies will help to contribute towards SDG 2 and SDG 13 (Climate Action) by strengthening the resilience of vulnerable agricultural systems.

Third, interpreting FA as reflecting ecological trade-offs underscores the need for integrated land-use planning. The adoption of agroforestry and conservation-based agricultural practices could reduce unsustainable forest conversion, thereby balancing food production with ecosystem protection [65]. These interventions contribute to SDG 13 and SDG 15 (Life on Land) by promoting climate resilience and biodiversity conservation.

In conclusion, the overall findings indicate that cereal production in Bangladesh should prioritize productivity improvements on existing agricultural land, restoration of degraded areas, and protection of ecological systems rather than further expansion of cultivated land.

5.4. Limitations and scope of interpretation

The results should be interpreted with caution. First, the analysis was conducted at the annual national level, which may obscure regional, seasonal, and crop-specific differences in climatic exposure and agricultural responses. Second, the regression results represent statistical associations rather than causal pathways; therefore, they should not be interpreted as direct cause-and-effect mechanisms. Third, residual autocorrelation and the use of aggregated variables may reduce the efficiency and precision of coefficient estimates.

Furthermore, the relatively weak effect of PREC in the final model must be interpreted in light of the use of annual averages, which do not capture intra-seasonal variability or extreme weather events. Future research could address these limitations by employing disaggregated data, incorporating seasonal indicators of variability, and applying more advanced time-series modelling approaches.

Nonetheless, the evidence indicates that long-term variation in cereal yield in Bangladesh is more closely associated with land-use structure, ecological dynamics, and adaptive capacity than with annual climatic variability alone. This finding underscores the need for integrated policy approaches that address climatic and non-climatic drivers simultaneously.

6. Conclusions and recommendations

6.1. Conclusion

Using a modified systematic modelling framework, this study examined the relative impacts of climatic and non-climatic factors on cereal yield in Bangladesh over the period 1961–2022. The results of the final model, validated through diagnostic testing, indicate that cereal yield is more closely associated with land-use structure and ecological dynamics than with annual climatic variability alone. LUCP was retained as a significant positive predictor of cereal yield, whereas ARL and FA were retained as significant negative predictors. Annual PREC was also included in the final model; however, its independent effect was statistically weak at the national annual scale.

These findings indicate that agricultural productivity in Bangladesh is shaped not only by climatic conditions but also by the spatial allocation, management, and long-term transformation of land resources. They underscore the importance of analysing structural and ecological factors alongside climatic variables when assessing long-term agricultural performance.

Nevertheless, the estimated relationships represent statistical associations rather than conclusive causal effects. In particular, the negative coefficient on FA should not be interpreted as implying that forest cover directly reduces cereal yield. Instead, it reflects broader land-use trade-offs associated with agricultural expansion and ecological degradation, which may generate long-term production vulnerability. The weak independent role of PREC should therefore not be interpreted as climatic irrelevance; rather, it suggests that rainfall effects are mediated through irrigation systems, cropping adjustments, and adaptive practices within Bangladesh's farming systems.

In summary, the findings emphasise the need for integrated analytical and policy frameworks that account for both climatic and non-climatic determinants of agricultural productivity.

6.2. Policy recommendations

Based on this study, several important implications for agricultural policy and sustainable development in Bangladesh emerge.

First, the positive association between LUCP and cereal yield suggests that productivity improvements should be pursued through sustainable intensification on existing cereal land rather than horizontal expansion into new areas. Key policy measures include improving irrigation efficiency and water management systems; promoting improved seed varieties and modern inputs; and strengthening agricultural extension services and farmer training. These actions contribute directly to SDG 2 (Zero Hunger) by increasing productivity while preserving resource efficiency.

Second, the negative association between ARL and cereal yield indicates that integrating marginal or degraded areas into cultivation does not necessarily lead to higher productivity. Therefore, policy should prioritize improvements in land quality, including soil fertility restoration, land rehabilitation, enhanced drainage and salinity management, and the adoption of climate-resilient or stress-tolerant crop varieties. Such interventions enhance resilience and generate co-benefits for SDG 2 (Zero Hunger) and SDG 13 (Climate Action).

Third, the findings regarding FA underscore the need to manage trade-offs between agricultural expansion and ecological sustainability. Land-use governance should be strengthened by reducing unsustainable conversion of forest land to agriculture, promoting broader adoption of agroforestry and integrated production systems, and reinforcing forest protection and buffer-zone maintenance. These actions are critical for achieving SDG 13 (Climate Action) and SDG 15 (Life on Land) by maintaining ecosystem services and ensuring long-term agricultural sustainability.

Fourth, although PREC exhibited a relatively weaker statistical effect in the final model, climate variability remains an important underlying driver of agricultural outcomes. Strengthening climate adaptation within agricultural systems requires the expansion of climate-resilient infrastructure, including irrigation systems; enhancement of climate information services for farmers; and adoption of adaptive cropping practices and seasonal planning. Such adaptation measures strengthen adaptive capacity and reduce vulnerability to climate-related risks.

Ultimately, the findings indicate that agricultural productivity is shaped by land-use decisions and their interaction with ecological conditions and climate. This underscores the need for policies to be implemented within integrated frameworks rather than through sector-specific interventions, with close coordination among agricultural, environmental, and climate policy domains to ensure coherent and effective outcomes.

6.3. Future research

In summary, the future of cereal productivity in Bangladesh depends less on land expansion and more on the efficient use of land, ecological sustainability, and adaptive capacity. Although climate change remains a critical challenge, the results indicate that structural and management factors warrant greater attention in long-term agricultural development. Future research could build on this analysis by employing district-level panel data, crop-specific models, and more advanced econometric techniques capable of identifying causal relationships and non-linear climatic effects. Such work would enable a more refined understanding of regional heterogeneity and strengthen the evidence base for long-term agricultural planning in Bangladesh.

Author contributions

Conceptualization: A K M Kanak Pervez, Akira Ishida; Methodology: A K M Kanak Pervez, Akira Ishida, Md Nazirul Islam Sarker; Validation: Akira Ishida, Md Mahedi, Md Nazirul Islam Sarker; Formal analysis: A K M Kanak Pervez, Isfaqur R. Ifty; Investigation: A K M Kanak Pervez, Isfaqur R. Ifty, Md Mahedi; Resources: Md Mahedi; Data curation: A K M Kanak Pervez, Isfaqur R. Ifty, Md Mahedi; Writing – original draft: A K M Kanak Pervez, Isfaqur R. Ifty; Writing – review and editing: A K M Kanak Pervez, Isfaqur R. Ifty, Akira Ishida, Md Mahedi, Md Nazirul Islam Sarker; Visualization: Isfaqur R. Ifty; Supervision: Akira Ishida; Project administration: A K M Kanak Pervez. All authors have read and agreed to the published version of the manuscript.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

1. Miah MD, Hasan R, Uddin H (2020) Agricultural development and the rural economy: The case of Bangladesh. In: Barai MK (Ed.), *Bangladesh's Economic and Social Progress: From a Basket Case to a Development Model*, Singapore, Springer, 237–266. https://doi.org/10.1007/978-981-15-1683-2_8
2. D'Odorico P, Davis KF, Rosa L, et al. (2018) The global food-energy-water nexus. *Rev Geophys* 56: 456–531. https://doi.org/10.1029/2017RG000591
3. Akanmu AO, Akol AM, Ndolo DO, et al. (2023) Agroecological techniques: Adoption of safe and sustainable agricultural practices among the smallholder farmers in Africa. *Front Sustain Food Syst* 7: 1143061. https://doi.org/10.3389/fsufs.2023.1143061
4. Epule TE, Ford JD, Lwasa S, et al. (2018) The determinants of crop yields in Uganda: what is the role of climatic and non-climatic factors? *Agric & Food Secur* 7: 10. https://doi.org/10.1186/s40066-018-0159-3
5. Srivastav AL, Dhyani Rajni, Ranjan M, et al. (2021) Climate-resilient strategies for sustainable management of water resources and agriculture. *Environ Sci Pollut Res* 28: 41576–41595. https://doi.org/10.1007/s11356-021-14332-4
6. Sims B, Kienzle J (2017) Sustainable agricultural mechanization for smallholders: What is it and how can we implement it? *Agriculture* 7: 50. https://doi.org/10.3390/agriculture7060050
7. Ghose B, Islam ARMdT, Islam HMT, et al. (2021) Rain-fed rice yield fluctuation to climatic anomalies in Bangladesh. *Int J Plant Prod* 15: 183–201. https://doi.org/10.1007/s42106-021-00131-x
8. Chandio AA, Jiang Y, Fatima T, et al. (2022) Assessing the impacts of climate change on cereal production in Bangladesh: evidence from ARDL modeling approach. *Int J Climate Change Strategies Manage* 14: 125–147. https://doi.org/10.1108/IJCCSM-10-2020-0111
9. Dey NC, Saha R, Parvez M, et al. (2017) Sustainability of groundwater use for irrigation of dry-season crops in northwest Bangladesh. *Groundwater Sustainable Dev* 4: 66–77. https://doi.org/10.1016/j.gsd.2017.02.001
10. Sarker MR, Galdos MV, Challinor AJ, et al. (2021) A farming system typology for the adoption of new technology in Bangladesh. *Food Energy Secur* 10: e287. https://doi.org/10.1002/fes3.287
11. Li C, Chandio AA, Abid N, et al. (2025) Exploring the impact of digital technologies adoption and climate change on food security: Policy framework for achieving sustainable development goals. *Int J Climate Change Strategies Manage* 17: 1140–1160. https://doi.org/10.1108/IJCCSM-07-2025-0214
12. Merlin ML, Chen Y (2021) Analysis of the factors affecting electricity consumption in DR Congo using fully modified ordinary least square (FMOLS), dynamic ordinary least square (DOLS) and canonical cointegrating regression (CCR) estimation approach. *Energy* 232: 121025. https://doi.org/10.1016/j.energy.2021.121025
13. Khan SR (2022) Resource potentials of the marine areas of Bangladesh. *Bangladesh Geosciences and Resources Potential*, CRC Press. https://doi.org/10.1201/9781003080817-9
14. Sahoo G, Wani AM, Swamy SL, et al. (2022) Livelihood strategy and sustainability aspects in industrialization as a source of employment in rural areas. In: Hassan MI, Sen Roy S, Chatterjee U, et al. (Eds.), *Social Morphology, Human Welfare, and Sustainability*, Cham, Springer International Publishing, 643–670. https://doi.org/10.1007/978-3-030-96760-4_26

15. Islam MdR, Rahman MdA, Anik AR, et al. (2023) The role of minor cereals in food and nutrition security in Bangladesh: Constraints to sustainable production. *Food Secur* 15: 1151–1160. https://doi.org/10.1007/s12571-023-01364-6
16. Haq A, Md S (2022) Extreme weather events and spiraling debt: A double whammy for Bangladeshis affected by climate change. *Front Psychol* 13: 879219. https://doi.org/10.3389/fpsyg.2022.879219
17. Mahedi M, Pervez AKMK, Ishida A, et al. (2026) Living with drought: climate change perceptions, adaptation, and mitigation among farmers in rural Bangladesh. *Front Clim* 8: 1744133. https://doi.org/10.3389/fclim.2026.1744133
18. Sidhu BS, Mehrabi Z, Kandlikar M, et al. (2022) On the relative importance of climatic and non-climatic factors in crop yield models. *Climatic Change* 173: 8. https://doi.org/10.1007/s10584-022-03404-0
19. Bhatti UA, Bhatti MA, Tang H, et al. (2024) Global production patterns: Understanding the relationship between greenhouse gas emissions, agriculture greening and climate variability. *Environ Res* 245: 118049. https://doi.org/10.1016/j.envres.2023.118049
20. Xing Y, Wang X (2024) Impact of agricultural activities on climate change: A review of greenhouse gas emission patterns in field crop systems. *Plants* 13: 2285. https://doi.org/10.3390/plants13162285
21. Friedlingstein P, O'Sullivan M, Jones MW, et al. (2022) Global Carbon Budget 2022. *Earth Syst Sci Data* 14: 4811–4900. https://doi.org/10.5194/essd-14-4811-2022
22. Lobell DB, Burke MB (2008) Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environ Res Lett* 3: 034007. https://doi.org/10.1088/1748-9326/3/3/034007
23. Sarker MdAR, Alam K, Gow J (2012) Exploring the relationship between climate change and rice yield in Bangladesh: An analysis of time series data. *Agric Syst* 112: 11–16. https://doi.org/10.1016/j.agsy.2012.06.004
24. Gerssen-Gondelach S, Wicke B, Faaij A (2015) Assessment of driving factors for yield and productivity developments in crop and cattle production as key to increasing sustainable biomass potentials. *Food Energy Secur* 4: 36–75. https://doi.org/10.1002/fes3.53
25. Melvani K, Myers TLB, Stacey N, et al. (2022) Farmers' values for land, trees and biodiversity underlie agricultural sustainability. *Land Use Policy* 117: 105688. https://doi.org/10.1016/j.landusepol.2021.105688
26. Akenji L, Bengtsson M, Toivio V, et al. (2021) 1.5-degree lifestyles: Towards a fair consumption space for all, Hot or Cool.
27. Boretti A (2025) Evaluating water use efficiency and CO_2 absorption in plants under rising atmospheric carbon dioxide levels. *J Atmos Sol-Terr Phys* 266: 106409. https://doi.org/10.1016/j.jastp.2024.106409
28. Ekka P, Patra S, Upreti M, et al. (2023) Land degradation and its impacts on biodiversity and ecosystem services. In: Raj A, Jhariya MK, Banerjee A, et al. (Eds.), *Land and Environmental Management through Forestry*, Wiley, 77–101. https://doi.org/10.1002/9781119910527.ch4
29. Müller R, Pistorius T, Rohde S, et al. (2013) Policy options to reduce deforestation based on a systematic analysis of drivers and agents in lowland Bolivia. *Land Use Policy* 30: 895–907. https://doi.org/10.1016/j.landusepol.2012.06.019
30. Okamura H, Osada Y, Nishijima S, et al. (2021) Novel robust time series analysis for long-term and short-term prediction. *Sci Rep* 11: 11938. https://doi.org/10.1038/s41598-021-91327-8

31. Onyekwere SC, Otuyelu O (2021) Inward foreign direct investments (FDI) and location choice determinants: Empirical evidence from India. *Daengku: J Humanit Soc Sci Innovation* 1: 111–129. https://doi.org/10.35877/454RI.daengku580
32. Rho Y, Shao X (2015) Inference for time series regression models with weakly dependent and heteroscedastic errors. *J Bus & Econ Stat* 33: 444–457. https://doi.org/10.1080/07350015.2014.962698
33. Hossain M, Biswas P, Islam MR (2023) Cold-tolerant and short-duration rice (*Oryza sativa* L.) for sustainable food security of the flash flood-prone Haor wetlands of Bangladesh. *Sustainability* 15: 16873. https://doi.org/10.3390/su152416873
34. Chakraborty S, Pan S, Pal SC, et al. (2025) Evaluating the impact of rainfall patterns on sustainable agricultural crop production. *Discov Sustain* 6: 516. https://doi.org/10.1007/s43621-025-01392-6
35. Mondol MF, Hasan MF, Tania MJ, et al. (2025) An ensemble machine learning framework for predicting agricultural droughts in the Ganges Delta of Bangladesh. *Earth Syst Environ* 10: 6429–6450. https://doi.org/10.1007/s41748-025-00943-1
36. Chang D, Li S, Lai Z (2023) Effects of extreme precipitation intensity and duration on the runoff and nutrient yields. *J Hydrol* 626: 130281. https://doi.org/10.1016/j.jhydrol.2023.130281
37. Jion MostMMF, Kamruzzaman M, Mallick J, et al. (2025) Agricultural drought risk in aman rice season: A case from western region of Bangladesh. *Theor Appl Climatol* 156: 561. https://doi.org/10.1007/s00704-025-05827-y
38. Korie N, Njeru L, Mburu J, et al. (2023) Assessment of factors influencing adoption of tomato post-harvest loss-reduction technologies in Kaduna state, Nigeria. *EAJSTI* 4: No.2. https://doi.org/10.37425/eajsti.v4i2.599
39. Sajid Hasan A (2017) Study on the impact of climate change on the production of BR11 aman rice in Bangladesh.
40. Nyamayevu D, Nyagumbo I, Chiduwa M, et al. (2024) Understanding crop diversification among smallholder farmers: Socioeconomic insights from Central Malawi. *Sustainability* 16: 9078. https://doi.org/10.3390/su16209078
41. Sumo TV, Ritho C, Irungu P (2022) Effect of farmer socio-economic characteristics on extension services demand and its intensity of use in post-conflict Liberia. *Heliyon* 8: e12268. https://doi.org/10.1016/j.heliyon.2022.e12268
42. Dubey A, Singh PK, Singh S, et al. (2025) Impact of climate change and land degradation on agriculture. In: Chatterjee U, Ghosh A, Roy SK (Eds.), *Eco-Resilience: Climate Change, Land Degradation and Sustainable Solutions*, Cham, Springer Nature Switzerland, 49–95. https://doi.org/10.1007/978-3-032-00708-7_3
43. Singh J, Asim M, Tshering P (2025) Comprehensive review of land resource policies of South Asia. In: Rani S (Ed.), *Land and Water Nexus in South Asia: Exploring the Interplay of Resources*, Cham, Springer Nature Switzerland, 407–447. https://doi.org/10.1007/978-3-031-87429-1_15
44. Sharma UC, Datta M, Sharma V (2022) Land use and management. In: *Soils in the Hindu Kush Himalayas*, Cham, Springer International Publishing, 295–462. https://doi.org/10.1007/978-3-031-11458-8_7
45. Maja MM, Ayano SF (2021) The impact of population growth on natural resources and farmers' capacity to adapt to climate change in low-income countries. *Earth Syst Environ* 5: 271–283. https://doi.org/10.1007/s41748-021-00209-6

46. Azadi H, Ho P, Hasfiati L (2011) Agricultural land conversion drivers: A comparison between less developed, developing and developed countries. *Land Degrad Dev* 22: 596–604. https://doi.org/10.1002/ldr.1037
47. Ahmed Z, Gui D, Murtaza G, et al. (2023) An overview of smart irrigation management for improving water productivity under climate change in drylands. *Agronomy* 13: 2113. https://doi.org/10.3390/agronomy13082113
48. Chan JY-L, Leow SMH, Bea KT, et al. (2022) Mitigating the multicollinearity problem and its machine learning approach: A review. *Mathematics* 10: 1283. https://doi.org/10.3390/math10081283
49. Osman EGA (2025) Entropy based solutions for detecting and treating multicollinearity in econometrics. *Discov Anal* 3: 18. https://doi.org/10.1007/s44257-025-00047-0
50. Okorie IE, Afuecheta E, Nadarajah S (2023) Time series and power law analysis of crop yield in some east African countries. *PLoS ONE* 18: e0287011. https://doi.org/10.1371/journal.pone.0287011
51. Silva JV, Heerwaarden J van, Reidsma P, et al. (2023) Big data, small explanatory and predictive power: Lessons from random forest modeling of on-farm yield variability and implications for data-driven agronomy. *Field Crops Res* 302: 109063. https://doi.org/10.1016/j.fcr.2023.109063
52. Therond O, Duru M, Roger-Estrade J, et al. (2017) A new analytical framework of farming system and agriculture model diversities. A review. *Agron Sustain Dev* 37: 21. https://doi.org/10.1007/s13593-017-0429-7
53. Cornia GA (1985) Farm size, land yields and the agricultural production function: An analysis for fifteen developing countries. *World Dev* 13: 513–534. https://doi.org/10.1016/0305-750X(85)90054-3
54. Rahman S, Anik AR, Sarker JR (2022) Climate, environment and socio-economic drivers of global agricultural productivity Growth. *Land* 11: 512. https://doi.org/10.3390/land11040512
55. Ali Chandio A, Sethi N, Prasad Dash D, et al. (2022) Towards sustainable food production: What role ICT and technological development can play for cereal production in Asian–7 countries? *Comput Electron Agric* 202: 107368. https://doi.org/10.1016/j.compag.2022.107368
56. Naorem A, Jayaraman S, Dang YP, et al. (2023) Soil constraints in an arid environment—Challenges, prospects, and implications. *Agronomy* 13: 220. https://doi.org/10.3390/agronomy13010220
57. Islam I, Cui S, Hoque MZ, et al. (2022) Dynamics of tree outside forest land cover development and ecosystem carbon storage change in Eastern Coastal Zone, Bangladesh. *Land* 11: 76. https://doi.org/10.3390/land11010076
58. Moghadam NT, Malekmohammadi B, Schirmer M (2024) Vulnerability assessment of hydrological ecosystem services under future climate and land use change dynamics. *Ecol Indic* 160: 111905. https://doi.org/10.1016/j.ecolind.2024.111905
59. Masolele RN, Marcos D, De Sy V, et al. (2024) Mapping the diversity of land uses following deforestation across Africa. *Sci Rep* 14: 1681. https://doi.org/10.1038/s41598-024-52138-9
60. Jui MJF, Haque MdM, Billah M (2025) A spatiotemporal analysis of four decades of temperature-precipitation interactions and their agricultural consequences in Bangladesh. *Discov Atmos* 3: 36. https://doi.org/10.1007/s44292-025-00063-5
61. Mainuddin M, Peña-Arancibia JL, Karim F, et al. (2022) Long-term spatio-temporal variability and trends in rainfall and temperature extremes and their potential risk to rice production in Bangladesh. *PLOS Climate* 1: e0000009. https://doi.org/10.1371/journal.pclm.0000009

62. Wang X, Folberth C, Skalsky R, et al. (2022) Crop calendar optimization for climate change adaptation in rice-based multiple cropping systems of India and Bangladesh. *Agric For Meteorol* 315: 108830. https://doi.org/10.1016/j.agrformet.2022.108830
63. Kidane R, Wanner T, Nursey-Bray M, et al. (2022) The role of climatic and non-climatic factors in smallholder farmers' adaptation responses: Insights from Rural Ethiopia. *Sustainability* 14: 5715. https://doi.org/10.3390/su14095715
64. Sharma R, Rallapalli S, Magner J (2025) Optimizing water-efficient agriculture: evaluating the sustainability of soil management and irrigation synergies using fuzzy extent analysis. *Sci Rep* 15: 29382. https://doi.org/10.1038/s41598-025-15426-6
65. Pandey PC, Pandey M (2023) Highlighting the role of agriculture and geospatial technology in food security and sustainable development goals. *Sustainable Dev* 31: 3175–3195. https://doi.org/10.1002/sd.2600