

Bayesian Time-Series Modelling of Cotton Yield under Climatic Variability in Burundi: A Comparison of ARIMA and ARIMAX Models

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Approved: 21 October 2026

Posted: 23 October 2026

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Cite As:

Hatungimana, S., Barankanira, E., Musabanganji, E., Nkurunziza, M., & Nkurunziza, J.D. (2026). *Bayesian Time-Series Modelling of Cotton Yield under Climatic Variability in Burundi: A Comparison of ARIMA and ARIMAX Models*. ESI Preprints.
<https://doi.org/10.19044/esipreprint.10.2026.p524>

Abstract

Background: Cotton is an important cash crop in Burundi, but its productivity has declined over recent decades under the combined influence of climatic variability, agronomic and socio-economic constraints. This study aimed to analyze the temporal dynamics of cotton yield and generate probabilistic forecasts using a times-series modelling framework. **Methods:** Annual cotton yield and climatic data (temperature, precipitation and relative humidity) for the period 1995-2025 were analyzed. Stationarity was assessed using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Bayesian ARIMA and ARIMAX models were estimated using Markov chain Monte Carlo (MCMC) methods in Stan. Model performance was evaluated using the Leave-One-Out Information Criterion (LOOIC) and the Widely Applicable Information Criterion (WAIC). Probabilistic forecasts were

generated for 2026-2030. **Results:** Cotton yield showed marked interannual variability and an overall declining trend during the study period. Although precipitation exhibited greater variability than temperature and relative humidity, none of the climatic variables showed statistically significant posterior effects after accounting for temporal dependence. The Bayesian ARIMA (2,1,0) model outperformed the ARIMAX specifications, while residual diagnostics confirmed an adequate model fit. Forecasts suggested a gradual decline in cotton yield from 2026 to 2030, with progressively wider credible intervals, indicating increasing uncertainty over longer forecasting horizons. **Conclusion:** Historical yield persistence explained cotton yield dynamics better than annual climatic averages alone. The findings suggest that climate effects are likely nonlinear and mediated by seasonal and agronomic factors not captured by annual climatic indicators. Bayesian time-series modelling provides a reliable framework for probabilistic agricultural forecasting and can support climate adaptation strategies and evidence-based decision-making for sustainable cotton production in Burundi.

Keywords: Bayesian time-series modelling, cotton yield, climate variability, probabilistic forecasting, Burundi

1. Introduction

Cotton cultivation represents one of the oldest industrial cash crops introduced in Burundi during the colonial era in the 1920s and 1930s. The crop is mainly cultivated in the lowland regions of Imbo and Moso, where climatic conditions characterized by relatively high temperatures and moderate rainfall are favorable for cotton production. Historically, cotton contributed significantly to rural livelihoods by generating income for farming households and supporting agro-industrial development. However, the sector has progressively declined over the past decades due to several interconnected constraints, including fluctuations in international cotton prices, low agricultural productivity, pest infestations, declining soil fertility, limited access to agricultural inputs, and recurrent socio-political instability that disrupted agricultural systems and rural economies.

To organize and promote cotton production, the Burundian government established the Burundi Cotton Management Company (Compagnie de Gérance du Coton, COGERCO) in 1947. Despite different rehabilitation and recovery initiatives implemented over time, cotton production levels remain relatively low compared to those recorded during earlier decades. Current challenges affecting the sector include climate variability, insufficient fertilizer application, shrinking cultivated areas, weak investment in agricultural infrastructure, and inadequate technical support for producers. However, cotton continues to play an important socio-economic

role in many rural communities because it remains a major source of cash income for smallholder farmers and may contribute to the development of the local textile industry.

Several studies have demonstrated that cotton productivity is highly influenced by climatic conditions. Temperature, rainfall variability, sunshine duration, and seasonal distribution of precipitation are among the major determinants of cotton growth and yield performance. Optimal cotton production generally occurs under temperatures ranging from 20 °C to 30 °C and annual rainfall between 500 and 1,200 mm (Blanc et al., 2008; Sultan et al., 2005). In addition to climatic conditions, soil characteristics strongly influence cotton productivity. Cotton cultivation is generally more successful on deep, fertile, and well-drained clay-loam soils with a pH ranging between 5.5 and 7. Furthermore, agronomic practices such as seed quality, planting density, sowing period, fertilizer application, weed control, and pest management considerably affect crop performance and cotton yield. Integrated soil fertility management practices are therefore considered essential for improving agricultural productivity and sustainability in Sub-Saharan Africa (Bado & Bationo, 2018).

Beyond environmental and agronomic conditions, socio-economic and institutional factors also determine the sustainability and competitiveness of cotton yield. Farmers' access to agricultural inputs, credit services, labor availability, extension support, and profitable markets directly influence production efficiency and farm income. Institutional mechanisms related to market organization, producer supervision, infrastructure development, and value-chain management are equally important for strengthening the resilience and long-term viability of the cotton sector under changing climatic and economic conditions (Bado & Bationo, 2018).

Given the economic importance of cotton and the persistent instability observed in production levels, accurate modeling and forecasting of cotton yield have become essential for supporting agricultural planning and policy decision-making in Burundi. Time-series forecasting techniques are widely used in agricultural studies to analyze historical production trends and predict future output dynamics (Box et al., 2015). Among these approaches, the Autoregressive Integrated Moving Average (ARIMA) model has been extensively applied because of its ability to capture temporal dependence and stochastic variations in agricultural data (Adebisi et al., 2014). However, classical ARIMA models primarily rely on the historical structure of the target series and often fail to explicitly incorporate exogenous climatic variables that significantly influence agricultural productivity. In climate-sensitive agricultural systems, the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model provides a more flexible and realistic framework by integrating both

temporal dependence and external climatic information into the forecasting process. Moreover, classical frequentist ARIMAX approaches may encounter limitations when dealing with small datasets, missing observations, parameter uncertainty, and high variability commonly observed in agricultural production systems in developing countries. Agricultural time series frequently exhibit structural uncertainty and irregular variability, which may negatively affect forecasting performance (Shumway & Stoffer, 2016). To overcome these limitations, Bayesian ARIMAX approaches have increasingly attracted attention in recent years. Bayesian estimation allows the incorporation of prior information into the modelling process while providing probabilistic inference through posterior distributions of model parameters (Gelman et al., 2025). Similarly, Bayesian state-space and time-series models have been shown to effectively handle stochastic variability and uncertainty through Markov Chain Monte Carlo (MCMC) estimation techniques (CARTER & KOHN, 1994).

Previous studies have demonstrated the effectiveness of Bayesian time-series models in crop forecasting and climate-related analyses. Bayesian ARIMA-type models improve predictive performance by combining temporal dependence structures with probabilistic parameter estimation within a coherent inferential framework for time-series forecasting (*Forecasting*, n.d.; Gelman et al., 2025). Recent empirical applications have further shown that ARIMAX models are widely used in agricultural forecasting when climatic covariates such as rainfall, temperature, and relative humidity are incorporated to improve predictive accuracy. To illustrate, ARIMAX models have been successfully applied in wheat yield forecasting using weather variables in India and in mustard yield prediction by integrating rainfall and temperature as exogenous regressors (Kaushik, 2024; Paul & Ghosh, 2013). In addition, hybrid and extended ARIMAX frameworks have demonstrated improved performance in crop yield prediction under climatic variability by explicitly modelling exogenous meteorological effects (Alam et al., 2018). More recent studies have also highlighted the better performance of ARIMAX models over classical ARIMA in capturing climate-driven agricultural dynamics, particularly under rainfall variability and environmental uncertainty (Goyal et al., 2024). Despite the growing application of Bayesian and ARIMAX-based forecasting approaches in agricultural studies, very limited research has focused on modelling and forecasting cotton yield in Burundi using Bayesian ARIMA and ARIMAX techniques under climatic variability conditions.

Therefore, the main objective of this study was to analyze and forecast cotton yield dynamic in Burundi using a Bayesian ARIMA and ARIMAX time-series modelling approaches. Specifically, the study aims to (i) evaluate the statistical properties of cotton yield and climatic time series,

(ii) identify the temporal dynamics of cotton yield, (iii) compare the ARIMA and ARIMAX models, and (iv) determine the probabilistic forecasts of cotton yield for 2026-2030. That may support agricultural planning and evidence-based decision-making in the cotton sector. The findings of this study are expected to contribute to the development of climate-resilient agricultural strategies and the long-term sustainability of cotton production in Burundi.

2. Materials and Methods

2.1. Study area and data source

This study was conducted at the national level in Burundi, where cotton production is predominantly concentrated in the lowland regions of Imbo and Moso, and where agricultural productivity is strongly influenced by climatic variability. Data were obtained from multiple sources. In fact, cotton-based data (production and cultivated area) were obtained from Burundi Cotton Management Company (Compagnie de Gérance du Coton, COGERCO). Climatic data (rainfall, temperature and relative humidity) were collected from the National Geospatial Information Authority (Institut Géographique du Burundi, IGEBU) and, as well as cotton-based data, cover a 31-year period (1995-2025).

2.2. Outcome and explanatory variables

The available agricultural database included cotton production (tons) and cultivated area (hectares). The dependent variable was the cotton yield (tons/hectare) and was computed as the ratio of cotton production and cultivated area for each year. Climatic variables used as explanatory variables included mean temperature (°C), rainfall (mm), and relative humidity (%). These climatic variables have been used in previous studies and have shown that temperature and rainfall variability significantly affect cotton growth, water availability, and final agricultural productivity under rain-fed conditions (Blanc et al., 2008; Sultan et al., 2005).

2.3. Data analysis

Descriptive statistics (frequency, minimum, mean, standard deviation, median, maximum) were computed for each variable: cotton yield (YIELD), relative humidity (RHUM), rainfall (RAINF) and temperature (TEMP). Timeline was drawn for each variable to assess their trend and their variability over time. Pearson correlation coefficients were computed between these variables to assess the relationship between cotton yield and climatic variables.

The stationarity properties of cotton yield and climatic variables were examined using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and

Box-Jenkins methodology was used to achieve stationarity (Box et al., 2015). The orders of differencing, autoregressive and moving average of the ARIMA process were identified using partial autocorrelation function (PACF) and autocorrelation function (ACF) respectively. The candidate models were compared using Akaike Information Criterion (AIC). The empirical strategy was extended to a Bayesian ARIMAX framework to incorporate exogenous climatic influences.

Let $Z_t = \Delta YIELD_t = YIELD_t - YIELD_{t-1}$ denote the differenced yield, one ARIMA model and seven ARIMAX models with specified exogenous variables were defined respectively as:

$$\begin{aligned}
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta TEMP_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta RHUM_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta RAINF_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta TEMP_t + \beta_2 \times \Delta RHUM_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta TEMP_t + \beta_2 \times \Delta RAINF_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta RHUM_t + \beta_2 \times \Delta RAINF_t + \varepsilon_t \\
 Z_t &= \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \beta_1 \times \Delta TEMP_t + \beta_2 \times \Delta RHUM_t + \beta_3 \times \Delta RAINF_t + \varepsilon_t
 \end{aligned} \tag{1}$$

where α denotes the intercept, ϕ_1 and ϕ_2 denote the autoregressive parameters associated with the first and the second lags of the differenced cotton yield respectively, t stands for the time (years) and, $t-1$ and $t-2$ the previous years. The first and the second order autoregressive terms were used to capture the influence of the previous year's and the two-year-lagged-differenced variable on the current differenced variable, $\beta = (\beta_1, \beta_2, \beta_3)$ measure the effects of climatic variables $X = (TEMP, RHUM, RAINF)$ on cotton yield and $\varepsilon_t \sim N(0, \sigma^2)$ is a normally distributed error.

The Bayesian ARIMA and ARIMAX models were estimated within a Bayesian framework. Posterior distributions of the model parameters were obtained using Markov chain Monte Carlo (MCMC) methods. Let $\theta = (\alpha, \phi_1, \phi_2, \sigma)$ and $\theta = (\alpha, \phi_1, \phi_2, \beta_1, \beta_2, \beta_3, \sigma)$ denote the vector of ARIMA and ARIMAX model parameters respectively. Conditional on the observed data and climatic covariates, the first-differenced cotton yield was assumed to follow a Gaussian distribution:

$$Z_t | \theta, X_t \sim N(\mu_t, \sigma^2)$$

where $\mu_t = \alpha + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + X_t^T \beta$ corresponds to the conditional mean specified by ARIMAX models. For the ARIMA model, the term $X_t^T \beta$

is omitted. The parameter σ denotes the residual standard deviation. Accordingly, the conditional density of the first-differenced cotton yield at time t is:

$$p(Z_t | \theta, X_t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(Z_t - \mu_t)^2}{2\sigma^2}\right].$$

Assuming conditional independence of the observations, the likelihood function is:

$$L(\theta | Z, X) = \prod_{t=3}^n \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(Z_t - \mu_t)^2}{2\sigma^2}\right] = (2\pi\sigma^2)^{-\frac{n-2}{2}} \exp\left[-\frac{1}{2\sigma^2} \sum_{t=3}^n (Z_t - \mu_t)^2\right] \quad (2)$$

Regularizing prior distributions were specified to stabilize estimation while allowing the data to dominate posterior inference. Zero-centered normal priors were assigned to the intercept and autoregressive coefficients, with their scales chosen relative to the empirical variability of the differenced cotton yield series. Student-t priors with three degrees of freedom were used for the regression coefficients and residuals to provide heavier tails while retaining regularization (Baumeister & Hamilton, 2018; Box et al., 2015; Muhammed & Athar, 2023). Prior scales were assessed with respect to their implications on the response scale, following the prior-predictive approach recommended by Wesner and Pomeranz (Wesner & Pomeranz, 2021).

$$\alpha \sim N(0, 0.1^2)$$

$$\phi_1, \phi_2 \sim N(0, 0.5^2), |\phi| < 1$$

$$\beta_j \sim t_3(0, s_j), s_j = \frac{sd(Z_t)}{sd(\Delta X_i)} \quad (3)$$

$$\sigma \sim t_3^+(0, s_\sigma), s_\sigma = sd(Z_t), \sigma > 0$$

The priors in (3) were then combined with the information contained in the observed data in (2) through Bayes' theorem to find the posterior distribution:

$$\begin{aligned} p(\theta | Z_t, X) &\propto p(Z_t | \theta, X) p(\theta) \propto p(Z_t | \theta, X_t) p(\alpha) \prod_{i=1}^2 p(\phi_i) \prod_{j=1}^3 p(\beta_j) p(\sigma) \\ &\propto (2\pi\sigma^2)^{-\frac{n-2}{2}} \exp\left[-\frac{1}{2\sigma^2} \sum_{t=3}^n (Z_t - \mu_t)^2\right] \exp\left[-50\alpha^2 - 2(\phi_1^2 + \phi_2^2)\right] \prod_{j=1}^3 \left(1 + \frac{\beta_j^2}{3s_j^2}\right)^{-2} \left(1 + \frac{\sigma^2}{3s_\sigma^2}\right)^{-2} \end{aligned} \quad (4)$$

For the ARIMA model, the product involving the climatic regression coefficients is omitted.

Because the resulting posterior distribution in (4) does not belong to a standard closed-form probability family, posterior inference was performed using Markov Chain Monte Carlo (MCMC) simulation implemented in Stan. Four independent Markov chains were run in parallel to ensure robust exploration of the posterior distribution. Each chain was executed for 10,000 iterations, of which the first 2,000 iterations were discarded as burn-in (warm-up) to remove the influence of initial values and allow the chains to reach their stationary distribution. This burn-in proportion (20%) is consistent with standard practices in Bayesian computation and ensures convergence stability (Gelman, 2006; Gelman et al., 2025). No thinning was applied (thinning interval = 1), in line with recent recommendations in the Bayesian literature indicating that thinning is generally unnecessary when chains exhibit good mixing and sufficient effective sample sizes (Link & Eaton, 2012). Posterior samples retained after warm-up were used for inference, summary statistics, and predictive analysis. Convergence was assessed using multiple diagnostic tools including autocorrelation functions, effective sample sizes, and the Gelman-Rubin convergence statistic ($\hat{R}$). Convergence was considered satisfactory when ($\hat{R} < 1.1$), indicating that all chains converged to the same posterior distribution (Brooks et al., 2011).

Model performance was evaluated using classical forecast accuracy metrics, including the Leave-One-Out Information Criterion (LOOIC) and the Widely Applicable Information Criterion (WAIC). These metrics allowed comparison of alternative specifications while accounting for model complexity (Vehtari et al., 2017). These indicators were computed by comparing observed cotton yield values with posterior mean fitted values derived from the Bayesian ARIMA and ARIMAX models. Residual diagnostics were conducted using the Ljung-Box test to verify the absence of serial autocorrelation in model residuals, confirming that the temporal dependence structure was adequately captured (Gelman, 2006, 2008).

The final model was used to generate probabilistic forecasts of cotton yield (2026-2030). Forecast distributions were obtained directly from posterior predictive simulations. The resulting forecasts were summarized using posterior means and 95% credible intervals, providing a robust probabilistic framework for agricultural decision-making.

3. Findings

3.1. Descriptive statistics

The mean cotton yield (YIELD) and its standard deviation [SD] were 0.68 t/ha and 0.30 respectively (**Table 1**). Cotton yield exhibited substantial variability over the study period (1995-2025), with values ranging from 0.27 t/ha in 2019 to 0.91 t/ha in 1998 (**Figure 1**). Relative humidity (RHUM) remained comparatively stable throughout the study period, with a mean of 71.72% (SD=0.98) and a narrow range between 69.45% and 73.54%.

Similarly, temperature (TEMP) showed limited variability with mean 21.09°C (SD=0.25°C), indicating relatively stable thermal conditions over time. In contrast, rainfall (RAINF) displayed pronounced variability, ranging from 862.80 mm to 1480.60 mm, with a mean value of 1162.60 mm (SD=136.58 mm).

Table 1: Descriptive statistics

	Frequency	Minimum	Mean	SD	Median	Maximum
YIELD (t/ha)	31	0.27	0.68	0.30	0.70	0.91
RHUM (%)	31	69.45	71.72	0.98	72.06	73.54
RAINF (mm)	31	862.80	1162.60	136.58	1166.30	1480.60
TEMP (°C)	31	20.74	21.09	0.25	21.02	21.70

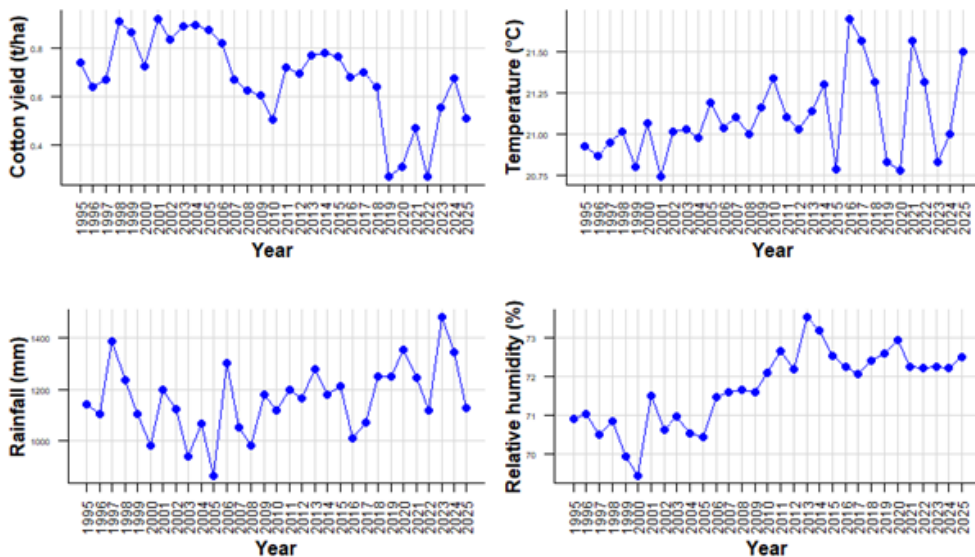


Figure 1: Temporal trend of cotton yield and climatic variables

Cotton yield showed an increasing trend over the study period. It varied from 0.74 t/ha in 1995 to a maximum of approximately 0.91 t/ha in 2001 before progressively declining after 2010. The lowest cotton yield values were observed during the recent period, reaching 0.27 t/ha in 2019 and 2022, followed by a partial recovery to 0.68 t/ha in 2024. Rainfall decreased from 1234.4 mm in 1997 to 862.8 mm in 2005 and then increased

to 1480.6 mm in 2023 before declining to 1125.0 mm in 2025. Relative humidity showed a decreasing trend over the study period. It showed a general increasing trend over time, rising from 70.92% in 1995 to 73.54% in 2013. Subsequently, relative humidity slightly declined and stabilized around 73.21%-72.50% during the period 2014-2025. Temperature increased from 20.9°C in 1995 to 21.7°C in 2016. The minimum temperature values were observed in 2001, 2015, and 2020 and the maximum values were observed in 2016, 2021 and 2025 respectively.

The more relative humidity, rainfall and temperature increased, the more cotton yield decreased (**Table 2**). Correlation between cotton yield and relative humidity was moderate. Correlation between cotton yield and rainfall was weak and correlation between cotton yield and temperature was very weak.

Table 2: Correlation matrix

	YIELD (t/ha)	RHUM (%)	RAIN (mm)	TEMP (°C)
YIELD (t/ha)	1.00	-0.48*	-0.30	-0.18
RHUM (%)		1.00	0.43*	0.28
RAIN (mm)			1.00	-0.30
TEMP (°C)				1.00

*: p-value<0.005

3.2. Stationarity and model identification

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test rejects the null hypothesis of stationarity for cotton yield, temperature and relative humidity-related series, indicating non-stationarity for these variables and implying the presence of a unit root. However, the first-order difference results showed stationarity, indicating that all variables become stationary after differencing (**Table 3, Figure 2**). Hence, all these variables were classified as integrated order one [*I* (1)]. Importantly, none of these variables appeared to be integrated of order two, which validated the suitability of the ARIMA/ARIMAX modeling framework.

Table 3: Stationarity test

Variables	Non-differenced series			Differenced series		
	KPSS statistic	P-value	Status	KPSS statistic	P-value	Status
YIELD (t/ha)	0.6346	0.020	Non-stationary	0.0723	0.010	Stationary
RHUM (%)	0.5838	0.024	Non-stationary	0.0554	0.010	Stationary
RAIN (mm)	0.4089	0.073	Stationary	0.0600	0.010	Stationary
TEMP (°C)	0.8612	0.010	Non-stationary	0.0790	0.010	Stationary

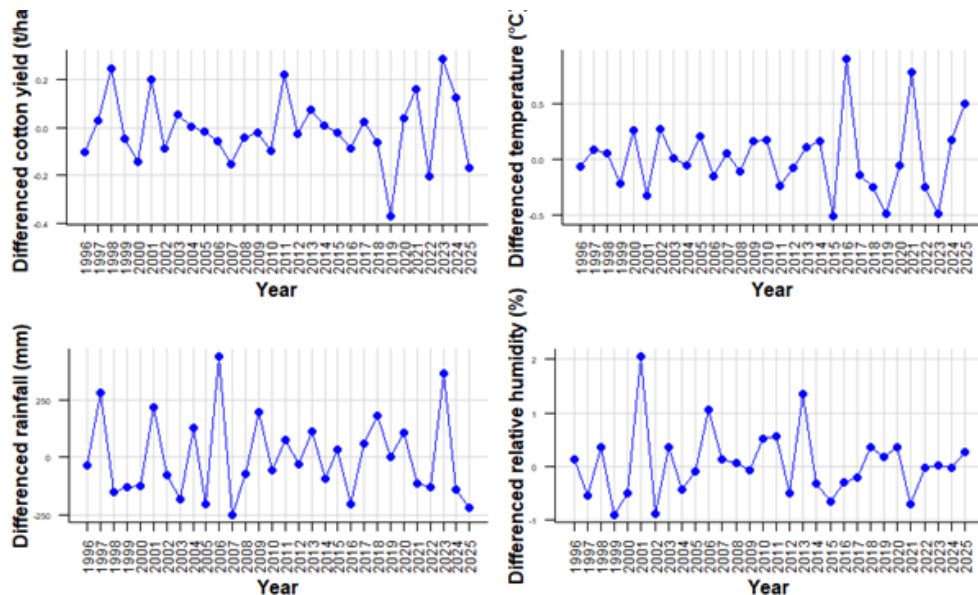


Figure 2: Temporal trend of differenced cotton yield and climatic variables

Following first-order differencing ($d=1$), the autoregressive (p) and moving average (q) orders were identified using the partial autocorrelation function (PACF) and the autocorrelation function (ACF) of the first-order difference of cotton yield series, respectively (**Figure 3**, **Figure 4**). Inspection of ACF and PACF plots indicated that the serial dependance was mainly concentrated at the first few lags. Since the plots did not clearly identify a single ARIMA model, and then, four candidate models with $p=1$ or 2 and $q=0$ or 1 were considered.

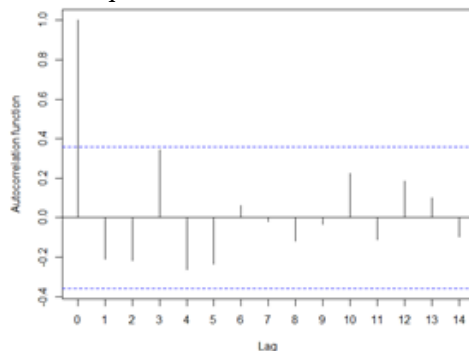


Figure 3: Autocorrelation function

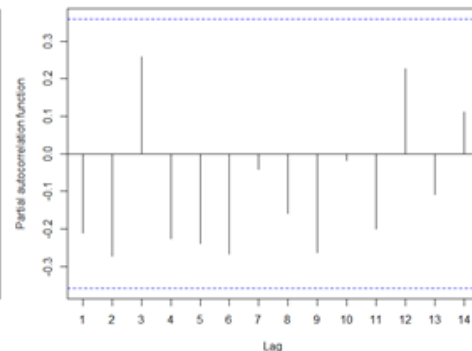


Figure 4: Partial autocorrelation function

The AIC values of the models ARIMA(1,1,0), ARIMA(1,1,1), ARIMA(2,1,0) and ARIMA(2,1,1) were -9.79, -22.80, -26.07 and -24.07 respectively. The ARIMA(2,1,0) model showed the lowest value (-26.07),

indicating the best balance between model fit and complexity. Therefore, it was selected for modelling the cotton yield dynamic.

3.3. Bayesian ARIMA and ARIMAX estimation results

Posterior parameter estimates of the Bayesian ARIMA and ARIMAX models were presented in **Tables 4** and **5**. Overall, the Markov chain Monte Carlo (MCMC) estimation exhibited satisfactory convergence for all models. The potential scale reduction (R-hat) was approximately 1 for all parameters, while the effective sample size (ESS) ranged from 16721 to 30324, indicating efficient posterior sampling and reliable parameter estimation. Across all models, the posterior mean of the intercept (α) remained close to zero, varying from -0.0105 to -0.0080.

Furthermore, the corresponding 95 % credible intervals (CrI) consistently included zero, suggesting no evidence of a systematic drift in the differenced cotton yield series after accounting for temporal dependance and climate covariates. The autoregressive parameters ϕ_1 and ϕ_2 were consistently negative across all specifications. However, the 95 % credible intervals always included zero, indicating considerable posterior uncertainty regarding the magnitude of short-term serial dependance. This result suggested that although the estimated temporal dependance tended to be negative, its effect was not strongly supported by the posterior distributions.

Regarding climatic covariates, the posterior estimates indicated heterogenous effects. Importantly, the 95 % credible intervals of all climatic coefficients included zero in every ARIMAX specification, indicating that none of the individual and combined climatic variables show strong posterior evidence of a statistically significant association with cotton yield changes after accounting autoregressive structure of the series.

The posterior estimates of the residual standard deviation (σ) were stable across competing models, ranging from 0.1436 to 0.1473. This consistency indicates that the inclusion of climatic covariates produced only limited significant changes in the residual variability of the differenced cotton yield series. The associated uncertainty remained substantial, as reflected by credible intervals overlapping zero, while the climatic variables slightly modified the posterior means of the regression coefficients. Consequently, the contribution of annual temperature, relative humidity and rainfall to explaining short-term variations in cotton yield appears limited when considered individually or jointly within the ARIMAX framework.

Table 4: Posterior parameter estimates for the Bayesian ARIMA

Model	Parameter	Mean	SD	P2.5%	P97.5%	ESS	R-hat
ARIMA(2,1,0)	α	-0.0066	0.0266	-0.0589	0.0455	27381	1.0000
	ϕ_1	-0.2291	0.1847	-0.5909	0.1368	26829	1.0001
	ϕ_2	-0.2408	0.1874	-0.6131	0.1297	26618	1.0000
	σ	0.1446	0.0206	0.1109	0.1913	24761	1.0000

Table 5: Posterior parameter estimates for the Bayesian ARIMAX

Model	Parameter	Mean	SD	P2.5%	P97.5%	ESS	R-hat
ARIMA(2,1,0) + Temperature	α	-0.0059	0.0268	-0.0581	0.0471	28656	1.0000
	ϕ_1	-0.2213	0.1936	-0.5983	0.161	25515	1.0000
	ϕ_2	-0.2414	0.1909	-0.614	0.1362	27698	1.0001
	β_{TFMD}	-0.0161	0.0844	-0.1848	0.1507	25137	1.0002
	σ	0.1473	0.0216	0.1122	0.1961	21969	1.0001
ARIMA(2,1,0) + Humidity	α	-0.0105	0.0263	-0.0625	0.0416	25151	0.9999
	ϕ_1	-0.1453	0.1995	-0.5342	0.2518	24452	1.0000
	ϕ_2	-0.2705	0.1883	-0.6392	0.1003	24166	1.0000
	β_{DHIM}	0.0502	0.0456	-0.0399	0.1409	24037	1.0000
	σ	0.1436	0.0208	0.1099	0.1908	19537	1.0000
ARIMA(2,1,0) + Rainfall	α	-0.0046	0.0262	-0.0561	0.046	17996	1.0000
	ϕ_1	-0.1432	0.1988	-0.5313	0.2516	17763	0.9999
	ϕ_2	-0.2169	0.1869	-0.5826	0.1545	17730	1.0001
	β_{DAINE}	0.0002	0.0002	-0.0001	0.0005	29839	0.9999
	σ	0.1436	0.0209	0.1094	0.1901	15866	1.0000
ARIMA(2,1,0) + Temperature + Humidity	α	-0.0104	0.0273	-0.0648	0.0431	27025	1.0000
	ϕ_1	-0.1447	0.2036	-0.551	0.2563	25718	1.0000
	ϕ_2	-0.2683	0.194	-0.6449	0.1232	26772	0.9999
	β_{TFMD}	-0.0018	0.0847	-0.1688	0.1654	24467	1.0002
	β_{DHIM}	0.0500	0.0467	-0.0419	0.1418	26218	1.0000
ARIMA(2,1,0) + Temperature + Rainfall	σ	0.1467	0.0219	0.1113	0.1966	21936	1.0001
	α	-0.0051	0.0269	-0.0583	0.0473	22013	1.0001
	ϕ_1	-0.1411	0.2035	-0.5400	0.2686	21421	1.0001
	ϕ_2	-0.1993	0.1947	-0.5811	0.1885	22050	1.0002
	β_{TFMD}	0.0399	0.0963	-0.1479	0.2284	22067	1.0000
ARIMA(2,1,0) + Humidity + Rainfall	β_{DAINE}	0.0002	0.0002	-0.0001	0.0006	27766	0.9999
	σ	0.1461	0.0217	0.1108	0.1952	17497	1.0000
	α	-0.0079	0.0268	-0.0609	0.0447	21563	1.0001
	ϕ_1	-0.0997	0.2068	-0.5067	0.3076	19295	1.0000
	ϕ_2	-0.2393	0.1927	-0.6141	0.143	19531	1.0002
ARIMA(2,1,0)	β_{DHIM}	0.0371	0.0487	-0.0592	0.1324	18984	1.0000
	β_{DAINE}	0.0001	0.0002	-0.0002	0.0005	30324	1.0002
ARIMA(2,1,0)	σ	0.1445	0.0216	0.1095	0.1939	16721	1.0000
	α	-0.0080	0.0272	-0.0615	0.0453	24849	1.0002

+ Rainfall	ϕ_1	-0.095	0.2097	-0.4990	0.3206	23340	1.0000
+ Humidity	ϕ_2	-0,2237	0,1978	-0,6029	0,1749	23920	1,0001
+ Precipitation	β_{TEMP}	0,0392	0,0963	-0,1506	0,2302	24252	1,0002
	β_{RHUM}	0,0368	0,0489	-0,0597	0,1333	22807	1,0000
	β_{RAINF}	0,0002	0,0002	-0,0002	0,0006	28865	1,0000
	σ	0,1470	0,0223	0,1112	0,1978	17460	1,0003

Predictive performance of the Bayesian ARIMA and ARIMAX models were compared using the Leave-One-Out Information Criterion (LOOIC) and the Widely Applicable Information Criterion (WAIC). According to those Bayesian model selection criteria, the ARIMA(2,1,0) model achieved the lower LOOIC (-25.1817) and WAIC (-25.4388), indicating the best overall balance between model fit and complexity (**Table 6**). Among the ARIMAX models, the model including annual rainfall (RAINF) ranked second, suggesting that rainfall provides the greatest contribution to predictive performance among the climatic covariates considered. Overall, these results suggest that although the inclusion of climatic variables can marginally improve prediction errors, they do not explain strongly Burundian cotton yield.

Table 6: Predictive performance comparison of the Bayesian ARIMA and ARIMAX models

Rank	Model	LOOIC	WAIC
1	ARIMA(2,1,0)	-25.1817	-25.4388
2	ARIMA(2,1,0) + RHUM	-24.6210	-25.0802
3	ARIMA(2,1,0) + RAINF	-24.3137	-24.8181
4	ARIMA(2,1,0) + TEMP	-22.5298	-23.0637
5	ARIMA(2,1,0) + RHUM + RAINF	-22.0193	-23.2196
6	ARIMA(2,1,0) + TEMP + RAINF	-21.9942	-22.7404
7	ARIMA(2,1,0) + TEMP + RHUM	-21.7222	-22.4454
8	ARIMA(2,1,0) + TEMP + RHUM + RAINF	-19.8920	-21.2611

3.4. Model validation and residual diagnostics

The residual diagnostics indicated satisfactory model adequacy. The residuals were centered and close to zero (mean=0.0005), with a standard deviation of 0.1363 and values ranging from -0.3734 to 0.2866. The Ljung-Box test yielded a statistic of 8.1143 with a p-value of 0.2298 (>0.05), indicating no significant residual autocorrelation (**Table 7**). Thus, the null hypothesis of no autocorrelation was not rejected and then, the residuals were consistent with a white-noise process and support the adequacy of the Bayesian ARIMA model.

Table 7: Validation statistics and white-noise diagnostics of the Bayesian ARIMA residuals

Model	Mean	SD	Min	Max	Ljung-Box statistic	P-value
Bayesian ARIMA(2,1,0)	-0.0005	0.1363	-0.3734	0.2866	8.1143	0.2298

The diagnostics of the Bayesian ARIMA model showed that the residual series fluctuated randomly around zero without any apparent trend or systematic pattern, indicating that the model captured the temporal dynamics of cotton yield. The ACF and PACF functions of the residuals showed that all autocorrelation coefficients remain within the 95 % confidence bounds, providing no evidence of significant residual serial correlation (**Figure 5**). These graphical findings were consistent with the Ljung-Box test ($p=0.1709$), confirming that the residuals behaved as white noise. Overall, the diagnostic results indicated that the Bayesian ARIMA(2,1,0) model was statistically adequate and satisfied the assumptions required for reliable inference and forecasting.

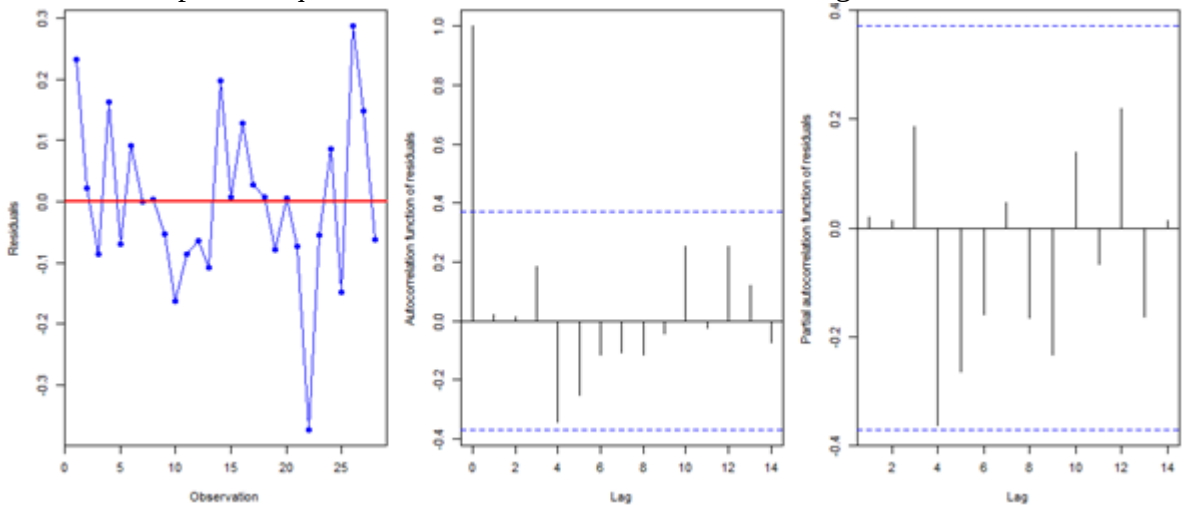


Figure 5: Residual diagnostics of Bayesian ARIMA(2,1,0) model

3.5. Probabilistic forecasting of cotton yield

The Bayesian ARIMA(2,1,0) model generated probabilistic forecasts of cotton yield for the period 2026-2030 (**Table 8**). The predicted mean yield showed a slight increasing trend over the forecasting horizon, from 0.512 t/ha in 2026 to 0.516 t/ha in 2030. However, the forecasts remained relatively stable compared with the historical variability observed during the study period. The 95 % credible intervals became progressively wider over time, indicating increasing uncertainty as the forecasting horizon increased. This widening uncertainty reflected the difficulty of predicting long-term cotton yield dynamics using historical yield patterns alone. Overall, the Bayesian ARIMA(2,1,0) model suggested a possible increase in future cotton yield, while highlighting considerable uncertainty associated with long-term projections.

Table 8: Probabilistic forecasts of cotton yield for 2026-2030

Year	Mean forecast (t/ha)	95 % CrI
2026	0.512	0.209 to 0.814
2027	0.541	0.149 to 0.917
2028	0.533	0.086 to 0.964
2029	0.517	0.012 to 1.005
2030	0.516	-0.054 to 1.066

Overall, the Bayesian forecasts indicated a relatively stable evolution of cotton yield between 2026 and 2030, with a slight upward trend. However, the progressive widening of the 95 % credible intervals reflected increasing uncertainty as forecasting horizon extends. These results highlighted usefulness of the Bayesian ARIMA(2,1,0) model for providing probabilistic forecast, while emphasizing the need for cautions interpretation of long-term projections.

4. Discussion

This study aimed to investigate the temporal dynamics and future evolution of cotton yield in Burundi using Bayesian times-series modelling under climatic variability in Burundi. The results revealed substantial interannual fluctuations in cotton yield over the period 1995-2025, with a general declining tendency despite relatively stable temperature and relative humidity conditions. The findings highlight the complexity of cotton production dynamics, where climatic variability, historical production patterns, and non-climatic factors interact to influence yield performance.

The observed variability in cotton yield is consistent with previous studies showing that agricultural production in tropical regions is highly sensitive to environmental fluctuations and socio-economic constraints. Cotton is particularly affected by rainfall variability because water availability influences germination, vegetative development, flowering, and boll formation. Previous research conducted in West Africa demonstrated that variations in rainfall amount and seasonal distribution significantly affect cotton productivity (Blanc et al., 2008). In Burundi, the strong fluctuations observed in precipitation compared with relative stability of temperature and relative humidity suggest that rainfall variability may represent an important environmental factor influencing cotton production. However, the declining trend in cotton yield despite increasing precipitation levels indicates that climatic variables alone cannot fully explain recent production dynamics.

The negative trend observed in cotton yield may therefore reflect the combined influence of climatic and non-climatic factors. Previous studies have emphasized that agricultural productivity in Sub-Saharan Africa is

strongly affected by limitations in input availability, soil fertility decline, pest pressure, market instability and institutional constraints (Bado & Bationo, 2018). In the Burundian context, reductions in cultivated areas, limited fertilizer and insecticide use, weak extension services, and historical disruptions in agricultural systems may have contributed to declining cotton productivity. These results support the view that climate change impacts on agriculture should not be considered independently from socio-economic and management factors, particularly in smallholder farming systems where adaptive capacity remains limited (Thornton et al., 2014).

The stationarity analysis confirmed that cotton yield and climatic variables exhibited non-stationary behavior in their original form but became stationary after first differencing. This result justified the application ARIMA approaches and agrees with the Box-Jenkins methodology, which emphasizes the importance of transforming non-stationary time series before modelling temporal dependence (Box et al., 2015). The identification of an ARIMA (2,1,0) structure suggests that cotton yield dynamics were mainly characterized by short-term dependence rather than strong long-term autoregressive persistence. Similar findings have been reported in agricultural forecasting studies where crop yields often exhibit stochastic variations around long-term trends and where simple ARIMA structures can provide reliable forecasts when historical information is limited (Hyndman & Athanasopoulos, 2018). Although climatic variables were incorporated through the Bayesian ARIMAX framework, their individual posterior effects were not statistically supported. The result does not necessarily imply that climate changes are irrelevant for cotton production; rather, it indicates that their direct contribution to explaining annual yield changes was limited after accounting for temporal dependence. Similar conclusions have been reported in climate yield studies where climatic effects are often nonlinear, cumulative, and dependent on specific crop growth stages rather than annual averages alone. Annual aggregation of temperature, relative humidity and precipitation may therefore mask important intra-seasonal climate effects, such as rainfall timing during flowering or extreme temperature events during critical development phases.

The relatively limited improvement of Bayesian ARIMAX models compared with the Bayesian ARIMA model also deserves attention. The Bayesian information criteria favored the simpler ARIMA 2,1,0) model. Similar observation has been reported in forecasting studies where additional explanatory variables improve theoretical representation but do not always enhance predictive accuracy, especially when sample sizes are small and explanatory variables contain considerable uncertainty (Hyndman & Athanasopoulos, 2018).

The residual diagnostics confirmed the adequacy of the selected Bayesian ARIMA model. Residuals were centered around zero, showed no significant autocorrelation according to the Ljung-Box test, and behaved approximately as white noise. These results indicate that the model successfully captured the main temporal structure of cotton yield variations. Similar advantages of Bayesian time-series approaches have been highlighted in agricultural applications because they provide a flexible framework for parameter uncertainty estimation and probabilistic forecasting, which are particularly valuable when historical datasets are relatively short (Gelman et al., 2025).

The probabilistic forecasts generated by the Bayesian ARIMA model indicated a possible increase in cotton yield between 2026 and 2030. The widening credible intervals reflect the accumulation of uncertainty inherent in long-term agricultural forecasting. Similar patterns have been observed in climate sensitive crop forecasting, where uncertainty increases progressively because future yield depends on multiple interacting environmental and socio-economic process. Therefore, these forecasts should not be interpreted as deterministic predictions but rather as probabilistic scenarios that can support agricultural planning and risk management.

From an agricultural policy perspective, the results highlight the need for integrated strategies to improve cotton resilience in Burundi. Since climatic variables alone did not fully explain yield variability, interventions should combine climate adaptation measures with improvements in agronomic management, access to inputs, soil fertility restoration, pest control and institutional support. Strengthening climate information services and developing improved forecasting systems could also help farmers and decision-makers anticipate production risks and optimize resource allocation.

This study has some limitations. First, the relatively short annual series (1995-2025) limits the ability to detect complex nonlinear climate-yield relationships. Second, only annual climatic averages were considered, whereas crop response is strongly influenced by seasonal climate conditions and extreme events. Third, other important determinants of cotton yield, such as fertilizer application, pest incidence and socio-economic factors, were not included due to data limitations. Future research could therefore explore higher-resolution climatic indicators, incorporate agronomic and socio-economic variables, and evaluate more flexible models such as hierarchical models or machine-learning approaches combined with climate projections.

Conclusion

This study demonstrates that Bayesian time-series modelling provides a valuable framework for analyzing and forecasting cotton yield dynamics under uncertainty. The results suggest that historical yield

persistence remains the dominant predictor of future cotton production in Burundi, while climatic influences require more detailed temporal and agronomic representation. These findings contribute to improving understanding of climate-sensitive agricultural systems and provide useful evidence for designing more resilient cotton production strategies. This study showed that Bayesian time-series modelling provides a robust framework for analyzing and forecasting cotton yield dynamics under climatic variability in Burundi. The Bayesian ARIMA (2,1,0) model outperformed the ARIMAX specifications, suggesting that historical yield persistence explained future yield variation better than annual climatic averages. Although climatic variables did not exhibit statistically significant individual effect, this likely reflects the complexity of climate-crop interactions rather than the absence of climate influence. The probabilistic forecasts indicated possible increase in cotton yield between 2026 and 2030, with increasing uncertainty over longer forecasting horizons. Overall, these findings highlight the need for integrated adaptation strategies that combine improved agronomic practices, institutional support, and more detailed climate information to enhance the resilience and sustainability of cotton production in Burundi.

Conflict of Interest: The authors reported no conflict of interest.

Data Availability: All data are included in the content of the paper.

Funding Statement: The authors did not obtain any funding for this research.

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