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Forecasting pastoralist red meat production trajectories in a fragile and climate-vulnerable state: a comparative evaluation of classical, state-space, long-memory, and neural network models in Somalia

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Background: The national economy of Somalia is significantly reliant on the production of pastoralist red meat, a sector that is increasingly debilitated by severe and recurrent climate-related shocks. Accurate forecasting of supply trajectories is crucial for proactive food security planning. However, empirical evaluations of mathematical and machine learning models in fragile states are notably scarce.

Objectives: This study aimed to model, evaluate, and project Somalia's aggregate pastoralist red meat output over a 10-year horizon (2025–2034) using a diverse set of econometric and computational forecasting models.

Methods: Utilizing a historical dataset spanning 64 years (1961–2024), the out-of-sample validation accuracy for the period 2015–2024 was assessed across seven forecasting frameworks. These frameworks included classical models (ARIMA, Theta), state-space models (ETS, TBATS, BATS), long-memory models (ARFIMA), and autoregressive neural networks (ARNN). Stationarity diagnostics were systematically performed using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests.

Results: The stationarity diagnostics confirmed that the historical series is integrated of order one, I(1). Over the out-of-sample window, the long-memory ARFIMA model substantially outperformed all other frameworks, achieving the lowest predictive errors (sMAPE = 3.11%, RMSE = 10,836.89, MASE = 0.85, and Theil's U = 0.69). The non-linear ARNN ranked as the second-best model (sMAPE = 4.49%), while classical and state-space models suffered from systematic bias, predicting overly smoothed trajectories that completely missed real-world shocks. Decadal projections (2025–2034) generated by the fully fitted ARFIMA model forecast a slow, steady decline and stabilization in red meat production, dropping from 175,332.80 to 168,884.30 tons.

Conclusion: This projected plateau indicates that Somalia's traditional pastoral system could be nearing dynamic ecological and structural limits under escalating environmental pressures. Transitioning from reactive, crisis-driven aid to

proactive climate resilience requires targeted investments in digital index-based livestock insurance, commercial fodder value chains, and mobile veterinary infrastructure.

KEYWORDS

ARFIMA, climate-smart agriculture, livestock forecasting, long-memory, neural networks

Introduction

Global agricultural progress depends fundamentally on animal husbandry, a sector that serves as a vital macroeconomic driver in developing regions where agropastoral systems sustain rural populations (Delgado et al., 1999). Animal production does not simply yield protein, fat, and essential micronutrients. It shapes the entire socioeconomic fabric of rural communities by offering employment, cushioning household incomes, facilitating asset accumulation, and creating pathways for gender-inclusive poverty alleviation (Balehegn et al., 2025; Delgado et al., 1999; Erdaw, 2023). For these reasons, resilient livestock systems remain central to global development agendas. They act as essential vehicles for the United Nations General Assembly (2015) Sustainable Development Goals, particularly the targets of ending poverty (SDG 1) and zero hunger (SDG 2) (United Nations General Assembly, 2015). Similarly, sustainable animal husbandry aligns directly with regional frameworks like the African Union (2015) Agenda 2063, which frames agricultural modernization and food security as the main pillars for continental transformation (African Union, 2015).

Globally, the livestock sector has been undergoing a rapid structural transition often conceptualized as the “next food revolution”—a multi-decade shift driven by population growth, rising disposable incomes, and rapid urbanization (Delgado et al., 1999; Thornton, 2010). Looking ahead, meeting the mid-century global demand for terrestrial animal-source foods remains a critical structural challenge (Van Eenennaam, 2024). In sub-Saharan Africa, this sector contributes between 20% and 50% of the agricultural GDP, employing approximately 65%–70% of the regional labor force (Erdaw, 2023). Within the Horn of Africa, and specifically Somalia, the national economy is fundamentally pastoral. Livestock herding serves as the primary source of livelihood for over 60% of the population, contributing approximately 80% of agricultural GDP, 45% of total national GDP, and upward of 80% of foreign currency earnings through exports to the Gulf States (Ojanji and Wright, 2023). Historically, chronic infrastructure deficits and a severe lack of formal credit have restricted the operational efficiency of the livestock value chain (Negassa et al., 2012). Furthermore, forecasting in fragile state contexts is inherently compounded by institutional fragility and acute data scarcity, which often obscure localized transactions such as unrecorded cross-border trade and informal pastoral off-take (Catley et al., 2013; Herrero et al., 2013; Negassa et al., 2012). However, this vital sector faces severe, compounding challenges. Chronic infrastructural underdevelopment, lack of access to formal credit markets, volatile transboundary animal disease outbreaks, and frequent import bans from key destination markets constantly disrupt the value chain (Ojanji and Wright, 2023; Wanyoike et al., 2023). Ultimately, recurrent transboundary disease outbreaks and sudden, cyclical import bans from key destination markets routinely paralyze export trade, causing catastrophic income

shocks for pastoralists (Farah, 2026). These structural vulnerabilities are severely exacerbated by escalating climate-related shocks, including recurrent droughts, temperature extremes, and locust infestations, which decimate pasture biomass, alter disease vector dynamics, and cause catastrophic herd losses (Hussein et al., 2024; Ngongolo and Gayo, 2025; Otte et al., 2023; Wardhere and Mahamed, 2026; Warsame et al., 2023). Analyzing historical weather shows that these extreme rainfall and precipitation shifts are part of a broader, century-long pattern of climatic instability that directly threatens pastoral resilience (Alasow et al., 2025; Mohamed et al., 2022).

To navigate the volatile nature of agricultural supply chains, researchers must project these production trends using quantitative time-series forecasting. Historically, forecasting methodologies have evolved from classical statistical formulations to highly sophisticated computational paradigms. Classical univariate models, most notably the Autoregressive Integrated Moving Average (ARIMA) framework, remain widely utilized due to their parsimonious structure and robust capacity to model linear trends and stochastic dependencies in stationary or first-differenced data (Box et al., 2015; Mgya, 2019; Waiswa, 2023). The Theta model is another widely used tool that separates a time series into multiple curves to capture both long-term trajectories and short-term movements (Assimakopoulos and Nikolopoulos, 2000). To capture more complex data patterns, researchers developed state-space systems like exponential smoothing (ETS) and its advanced versions, BATS and TBATS. These models are excellent at handling bimodal seasonality and changing variance over time (De Livera et al., 2011; Hyndman and Athanasopoulos, 2018). For agricultural data that shows long-term dependencies spanning several decades, long-memory frameworks like the autoregressive fractionally integrated moving average (ARFIMA) model offer a stronger mathematical solution by allowing fractional differencing (Granger and Joyeux, 1980; Rakshit and Paul, 2025). More recently, computational intelligence has entered the field. Autoregressive Neural Networks (ARNN or NNAR) are now used to map highly non-linear patterns, sudden structural changes, and erratic volatility that linear frameworks usually miss (Abdallah and Gouda, 2025; Elmezouar et al., 2021; Makridakis et al., 2020). Nevertheless, each of these forecasting approach possesses certain compromises. While classical and state-space models offer high interpretability and moderate data requirements, they are prone to systematic bias and over-forecasting under extreme structural shocks, whereas neural network architectures offer exceptional predictive flexibility but require extensive memory and carry a high risk of overfitting when applied to short-term or highly volatile historical records (Jainonthee et al., 2025; Makridakis et al., 2020).

Even with these advanced forecasting tools available, very few empirical studies focus on aggregate livestock and meat production in fragile, conflict-affected countries. Most studies in Somalia focus

on predicting environmental outcomes, like tracking carbon dioxide and methane emissions, or modeling macroeconomic trends using rigid linear assumptions (Abdullahi et al., 2025; Egeh et al., 2023; Hassan et al., 2026). While some researchers have used biophysical simulations—such as system dynamics to model small ruminant sales in Somaliland—these studies do not compare the actual predictive accuracy of different mathematical and machine learning models over the long term (Wanyoike et al., 2023), which leaves a major gap in both methodology and practice. No published research has compared classical, state-space, long-memory, and neural network models to forecast pastoralist red meat production in Somalia. This study directly addresses this gap. By evaluating traditional linear econometric systems against flexible, non-linear machine learning models, this research seeks to identify which tools perform best in volatile, data-poor, and crisis-prone environments (Elmezouar et al., 2021; Esse et al., 2025).

Using time-series tools for agricultural forecasting rests on the theory of stochastic data-generating processes. This theory states that past production data contains hidden, repeating patterns—such as deterministic trends, cyclical shifts, and structural breaks—that can be modeled to predict future states (Box et al., 2015). In livestock economics, these trajectories are shaped by physical constraints like biological growth cycles, herd demographic structures, and climatic feed-feedback loops (Muigai et al., 2016; Srivastava et al., 2025). While sudden environmental shocks cause short-term spikes in the data, the long-term trend is driven by deeper structural changes that can be captured using integrated, state-space, or neural network algorithms (Ahmed et al., 2026; Hussein et al., 2024; Wardhere and Mahamed, 2026; Warsame et al., 2023). Transitioning from reactive, crisis-driven aid to proactive, evidence-based agricultural planning requires these forecasting principles (Ahmed et al., 2026; Satyanarayana and Risheen, 2023). By establishing robust, mathematically validated baseline projections of aggregate meat output, policymakers can formulate target livestock interventions, design optimal import-export regulatory protocols, allocate development resources efficiently, and construct adaptive climate-smart early warning systems (Ngongolo and Gayo, 2025; Srivastava et al., 2025).

Given these complex challenges, this study aims to model, evaluate, and project pastoralist red meat production in Somalia over a 10-year period from 2025 to 2034 using a diverse set of forecasting models. For a country highly vulnerable to climate shifts and political instability, having reliable, data-driven livestock projections is vital for national planning, food security preparations, economic stabilization, and building climate resilience (Hussein et al., 2024; Otte et al., 2023; Wanyoike et al., 2023). Specifically, the objectives of this research are to: (a) evaluate the stationarity and structural breaks in historical Somali pastoralist red meat production; (b) build and compare the out-of-sample forecasting accuracy of classical (ARIMA, Theta), state-space (ETS, TBATS, BATS), long-memory (ARFIMA), and neural network (NNAR) models; and (c) generate long-term forecasts with clear uncertainty bounds. This research offers both theoretical and practical value. On a theoretical level, it pushes the empirical boundaries of agricultural forecasting in fragile settings by testing whether machine learning can improve upon classic econometric models. From a practical standpoint, it provides Somali policymakers, development partners, and non-governmental

organizations with a reliable decision-making tool. This tool is designed to help them shift away from short-term emergency relief and toward proactive, climate-smart food security planning (Ahmed et al., 2026; Negassa et al., 2012; Ojanji and Wright, 2023).

Materials and methods

Research design and study area

To examine historical patterns and project aggregate meat production trajectories in Somalia, this study employs a quantitative, comparative, time-series research design. Sourced from the Crops and Livestock Products (QCL) database of the Food and Agriculture Organization of the United Nations (FAOSTAT), the dataset represents the national annual aggregate meat production expressed in metric tons over a 64-year historical horizon from 1961 to 2024 ($T = 64$).

The study area, Somalia, is characterized as a fragile, drought-prone, and climate-sensitive country in the Horn of Africa, where livestock production constitutes the cornerstone of both pastoral livelihoods and macroeconomic stabilization (Ojanji and Wright, 2023). Given the high frequency of severe droughts and geopolitical shocks, constructing a robust quantitative framework is crucial to evaluate how physical and non-linear climate perturbations translate into long-term dependencies within agricultural supply chains (Srivastava et al., 2025).

Data reshaping and preprocessing

To establish a rigorous and transparent modeling baseline, all data cleaning, reshaping, and preprocessing steps were performed programmatically using the R programming language (R Core Team, 2023). Unlike previous studies that utilize pre-aggregated meat indicators, the raw disaggregated annual production series (expressed in metric tons) was downloaded directly from FAOSTAT. To focus strictly on the pastoralist red meat sector, the dataset was filtered using the *dplyr* and *tidyr* packages in R to include only the four primary pastoral livestock species: camels (*Meat of camels, fresh or chilled*), cattle (*Meat of cattle with the bone, fresh or chilled*), sheep (*Meat of sheep, fresh or chilled*), and goats (*Meat of goat, fresh or chilled*).

Poultry and chicken meat (*Meat of chickens, fresh or chilled*) were explicitly excluded from the aggregate series. This exclusion is justified because commercial poultry in Somalia is highly underdeveloped, relies heavily on imported inputs, and does not operate within the traditional rangeland-based pastoral systems of the country.

After filtering, the long-format data was reshaped into a wide-format matrix using the *pivot_wider()* function. The strictly pastoralist total red meat production series (*Total_Meat_Production*) was then calculated by taking the row-wise sum of the four pastoral species for each year using the *rowSums()* function. Any potential missing entries were handled using listwise deletion via *na.omit()*, yielding a continuous, unbroken series of 64 observations.

For model estimation, diagnostic checking, and predictive accuracy evaluation, the analysis utilized several R packages, including *forecast* (for ARIMA, ETS, TBATS, ARFIMA, and

NNAR models), *tseries* (for unit-root tests), *TStudio* (for train-test partitioning), *psych* (for descriptive statistics), and *Metrics* (for forecast evaluation metrics).

Data partitioning and stationarity diagnostics

To ensure a rigorous and unbiased evaluation of the forecasting models, the complete time-series dataset ($T = 64$) was partitioned into a training sample (1961–2014, $n = 54$) and a holdout testing sample (2015–2024, $h = 10$) using a programmatic split (Hyndman and Athanasopoulos, 2018). The out-of-sample testing partition served as a blind validation window to assess the predictive accuracy of each forecasting paradigm.

Because covariance stationarity is a prerequisite for classical univariate statistical forecasting models, the stationarity of the aggregate meat production series (Y_t) was systematically evaluated. The analysis applied the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests (Box et al., 2015). The mathematical formulation of the ADF test involves fitting an autoregressive model to control for higher-order serial correlation in the series, expressed as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varepsilon_t$$

where ΔY_t is the first-difference operator defined as:

$$\Delta Y_t = Y_t - Y_{t-1}$$

and α is a constant, β is the coefficient on a time trend t , p is the lag order of the autoregressive process, and ε_t is a zero-mean white noise error term (Box et al., 2015). The null hypothesis of non-stationarity ($H_0: \gamma = 0$) is tested against the alternative hypothesis of stationarity ($H_1: \gamma < 0$) using the t-statistic of γ . Symmetrically, the PP test was implemented as a non-parametric correction to control for heteroskedasticity and autocorrelation in the error term (Box et al., 2015). The optimal differencing order (d) was verified using the automatic unit root differencing algorithm (*ndiffs*), establishing that a first-order difference ($d = 1$) was sufficient to achieve stationarity, $I(1)$ (Box et al., 2015).

To further ensure robustness against potential test-decade bias, an expanding-window rolling-origin cross-validation (tsCV) was operationalized alongside the primary single-split holdout evaluation (Hyndman and Athanasopoulos, 2018). This method iteratively recalculates forecast errors across multiple sequential training partitions, providing a stringent check on model stability (Tashman, 2000).

Theoretical formulations of forecasting models

Classical baselines: ARIMA and Theta

The Autoregressive Integrated Moving Average, $ARIMA(p, d, q)$ with drift model, is formulated to capture linear stochastic dependencies in first-differenced data (Box et al., 2015). The general mathematical structure of the stationary differenced series $w_t = (1 - B)^d Y_t$ is expressed as:

$$\Phi_p(B)(1 - B)^d Y_t = c + \Theta_q(B)\varepsilon_t$$

where B is the backshift operator defined as $B^k Y_t = Y_{t-k}$; $\Phi_p(B) = 1 - \phi_1 B - \dots - \phi_p B^p$ represents the autoregressive (AR) polynomial of order p ; $\Theta_q(B) = 1 + \theta_1 B + \dots + \theta_q B^q$ represents the moving average (MA) polynomial of order q ; c is the drift parameter; and $\varepsilon_t \sim WN(0, \sigma^2)$ is assumed to be white noise (Box et al., 2015; Waiswa, 2023).

The Theta model decomposes the raw time series Y_t into two or more θ -lines, $Y_t(\theta)$, by scaling the local second-order differences of the series (Assimakopoulos and Nikolopoulos, 2000). The second-order difference at time t is expressed as:

$$Y_t''(\theta) = \theta Y_t \theta_Y$$

where $Y_t'' = Y_t - 2Y_{t-1} + Y_{t-2}$ for $t = 3, \dots, T$. For a standard two-line decomposition, $\theta_1 = 0$ captures the long-term deterministic linear trend via simple regression, while $\theta_2 = 2$ represents the short-term curvatures and is extrapolated using a Simple Exponential Smoothing (SES) formulation (Assimakopoulos and Nikolopoulos, 2000).

State-space formulations: ETS, BATS, and TBATS

The Exponential Smoothing (ETS) framework represents the underlying components of the time series—specifically level (ℓ_t), trend (b_t), and seasonality (s_t)—within a state-space formulation (Hyndman and Athanasopoulos, 2018). For the selected $ETS(M, A, N)$ model (Multiplicative Error, Additive Trend, No Seasonality), the measurement and state transition equations are defined as:

$$\begin{aligned} Y_t &= (\ell_{t-1} + b_{t-1})(1 + e_t) \\ \ell_t &= (\ell_{t-1} + b_{t-1})(1 + \alpha e_t) \\ b_t &= b_{t-1} + \beta(\ell_{t-1} + b_{t-1})e_t \end{aligned}$$

where e_t represents the multiplicative error term, and α and β are smoothing parameters constrained such that $0 < \alpha, \beta < 1$ (Hyndman and Athanasopoulos, 2018).

To accommodate non-constant variance and autocorrelation in the residuals, the TBATS model incorporates Box-Cox transformations (ω), ARMA mathematical errors, trend damping (ϕ), and trigonometric seasonal representations (De Livera et al., 2011). The general formulation is expressed as:

$$Y_t^{(\omega)} = \begin{cases} \frac{Y_t^\omega - 1}{\omega}, & \omega \neq 0 \\ \ln Y_t, & \omega = 0 \end{cases}$$

$$Y_t^{(\omega)} = \ell_{t-1} + \phi b_{t-1} + \sum_{i=1}^J s_{t-1}^{(i)} + d_t$$

where d_t is modeled as an $ARMA(p, q)$ process to resolve short-term autocorrelations in the residuals, and the state variables (ℓ_t, b_t) are updated dynamically via smoothing transitions (De Livera et al., 2011).

Long-memory modeling: ARFIMA

Where time-series data exhibit long-range persistence and slow-decaying autocorrelations over multiple decades, the Autoregressive

Fractionally Integrated Moving Average (ARFIMA(p, d, q)) model is utilized (Granger and Joyeux, 1980). The integration parameter d is allowed to take non-integer, fractional values, expanding the differentiation operator via binomial expansion:

$$\Phi(B)(1-B)^d Y_t = \Theta(B)\varepsilon_t$$

The fractional differencing operator $(1-B)^d$ is mathematically expanded as an infinite lag polynomial:

$$\begin{aligned}(1-B)^d &= \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)} B^k \\ &= 1 - dB - \frac{d(1-d)}{2!} B^2 - \frac{d(1-d)(2-d)}{3!} B^3 - \dots\end{aligned}$$

where $\Gamma(\cdot)$ represents the standard gamma function (Granger and Joyeux, 1980). When $0 < d < 0.5$, the process is stationary and invertible, exhibiting long-memory properties where the autocorrelation function decays hyperbolically rather than exponentially (Granger and Joyeux, 1980; Rakshit and Paul, 2025).

Computational intelligence: autoregressive neural networks (ARNN)

To capture potential non-linearities, structural breaks, and high-frequency volatility, an Autoregressive Neural Network—specifically a feedforward single hidden-layer NNAR(p, k) structure—is established (Makridakis et al., 2020). The inputs to the network consist of lagged values of the time series, $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$, which are mapped to a hidden layer of k nodes using a non-linear activation function (logistic sigmoid). The mathematical representation of the forecast value $\hat{Y}_t$ is defined as:

$$\hat{Y}_t = w_0 + \sum_{j=1}^k w_j \psi \left(v_{0j} + \sum_{i=1}^p v_{ij} Y_{t-i} \right)$$

where w_0 and v_{0j} represent the bias terms; w_j and v_{ij} denote the connection weights; and $\psi(z) = (1 + e^{-z})^{-1}$ is the sigmoid transfer function (Abdallah and Gouda, 2025; Makridakis et al., 2020). The weights are iteratively optimized using backpropagation to minimize the sum of squared errors over the in-sample training partition.

Model diagnostics and information criteria

To verify the statistical adequacy of the estimated models and ensure that residuals behave as white noise, the Ljung-Box portmanteau diagnostic test was applied (Box et al., 2015). The Ljung-Box Q^* -statistic evaluates the joint null hypothesis that all autocorrelations of the residuals up to lag m are equal to zero ($H_0: r_1 = r_2 = \dots = r_m = 0$). Symmetrically, the Q^* -statistic can be expressed as:

$$Q^* = n(n+2) \sum_{k=1}^m \frac{\hat{r}_k^2}{n-k}$$

where n represents the sample size; $\hat{r}_k$ denotes the sample autocorrelation of the residuals at lag k ; and m represents the total number of lags tested (typically $m = 10$ for non-seasonal

annual data). Under the null hypothesis, Q^* asymptotically follows a chi-squared distribution, $\chi^2(m-K)$, where K represents the number of estimated parameters in the underlying forecasting model (Box et al., 2015).

To balance model fit and parsimony during the optimization phase, candidate models were compared using information criteria derived from likelihood theory. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were derived as:

$$\text{AIC} = -2 \ln(L) + 2K$$

$$\text{BIC} = -2 \ln(L) + K \ln(n)$$

where L is the maximized value of the likelihood function for the estimated model; K represents the total number of estimated parameters; and n denotes the number of observations (Box et al., 2015). The optimal model is selected by identifying the specification that minimizes both criteria, preventing overfitting while ensuring adequate data representation.

Model evaluation and predictive accuracy metrics

To conduct a rigorous, head-to-head comparison of classical, state-space, long-memory, and neural network models during the out-of-sample testing period (2015–2024), six robust error metrics were calculated. These metrics are mathematically defined as:

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{h} \sum_{t=T+1}^{T+h} (Y_t - \hat{Y}_t)^2}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{h} \sum_{t=T+1}^{T+h} |Y_t - \hat{Y}_t|$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{100}{h} \sum_{t=T+1}^{T+h} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|$$

$$\text{Symmetric Mean Absolute Percentage Error (sMAPE)}$$

$$= \frac{200}{h} \sum_{t=T+1}^{T+h} \frac{|Y_t - \hat{Y}_t|}{|Y_t| + |\hat{Y}_t|}$$

$$\text{Mean Absolute Scaled Error (MASE)} = \frac{\frac{1}{h} \sum_{t=T+1}^{T+h} |Y_t - \hat{Y}_t|}{\frac{1}{n-1} \sum_{i=2}^n |Y_i - Y_{i-1}|}$$

$$\text{Theil's U} = \frac{\sqrt{\frac{1}{h} \sum_{t=T+1}^{T+h} (Y_t - \hat{Y}_t)^2}}{\sqrt{\frac{1}{h} \sum_{t=T+1}^{T+h} Y_t^2} + \sqrt{\frac{1}{h} \sum_{t=T+1}^{T+h} \hat{Y}_t^2}}$$

where $h = 10$ represents the forecast horizon; $n = 54$ represents the length of the in-sample training partition; Y_t represents the actual meat production volume; and $\hat{Y}_t$ denotes the predicted meat production volume (Hyndman and Athanasopoulos, 2018).

Results

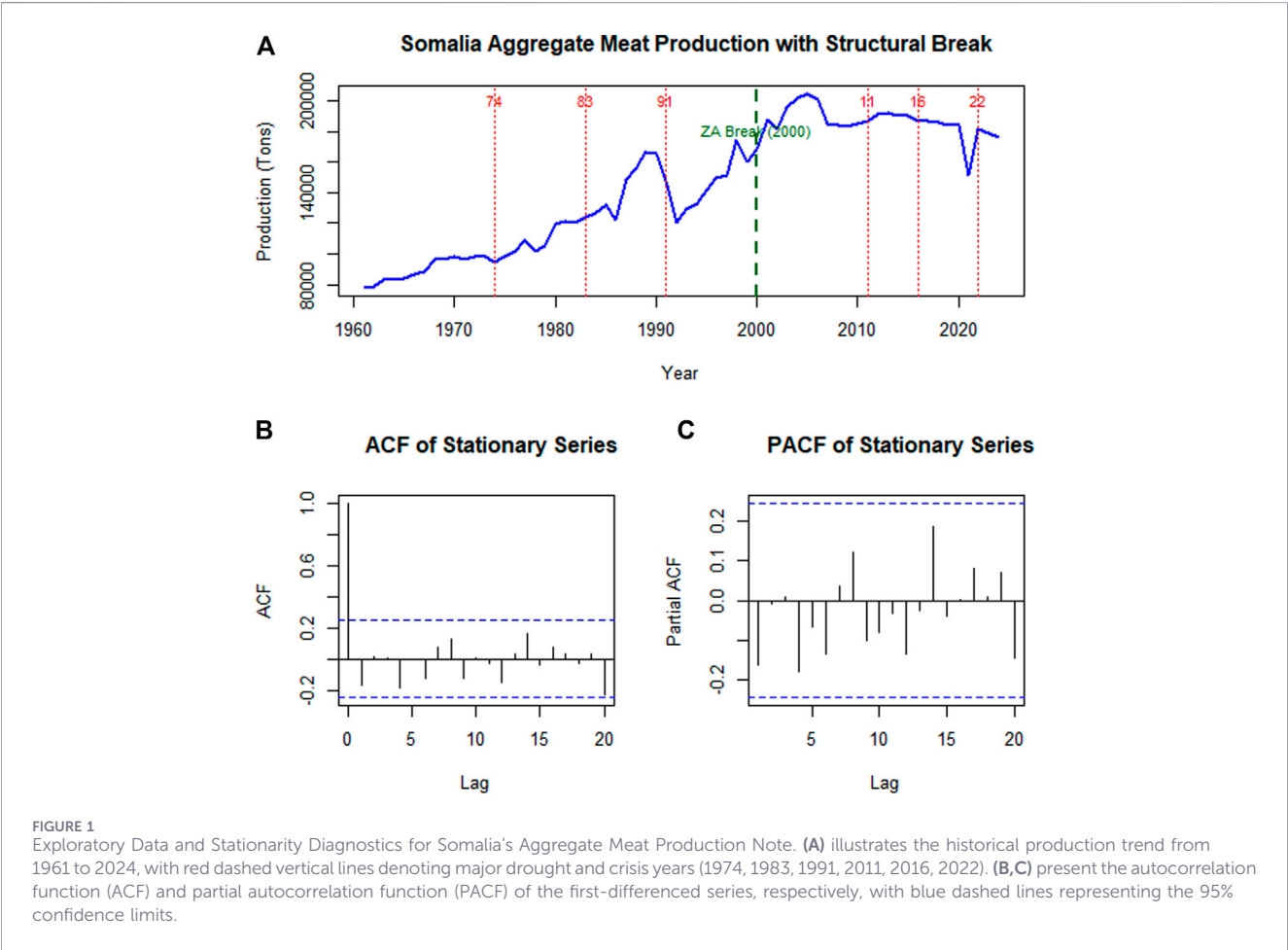
Data preprocessing and cleaning

Before the forecasting models were constructed, the historical dataset was systematically cleaned and prepared. Raw annual livestock production data for Somalia was obtained from the

TABLE 1 Descriptive statistics of somalia’s pastoralist red meat production (1961–2024).

Variable	<i>n</i>	<i>M</i>	<i>SD</i>	Median	Min	Max	Skewness	Kurtosis
Production	64	144,214.20	40,268.65	149,102.00	77,582.00	204,660.00	−0.15	−1.52

M = mean; *SD*, standard deviation. Values are expressed in metric tons.



Crops and Livestock Products (QCL) database of the Food and Agriculture Organization of the United Nations (FAOSTAT), spanning from 1961 to 2024. To prevent mathematical and structural anomalies during differencing or lag calculations, a complete, unbroken series was required. Listwise deletion was applied to identify any missing entries or gaps in the annual reporting. Fortunately, diagnostics indicated zero missing values ($NA = 0$). This verification process yielded a clean, continuous dataset of 64 annual observations ($T = 64$) representing the aggregate metric tonnage of pastoralist red meat production in Somalia. We used this verified series for both training and testing.

Descriptive and exploratory data analysis

Table 1 shows the basic descriptive statistics for Somalia’s annual pastoralist red meat production, measured in metric tons.

On average, the country produced 144,214.20 tons of meat annually ($SD = 40,268.65$) between 1961 and 2024. The standard

error of the mean (SE) is 5,033.58. The calculated median value of 149,102.00 tons is close to the mean, with a near-symmetric distribution ($skewness = -0.15$), indicating that historical production levels remained relatively balanced over the long term despite intermittent crisis-driven fluctuations. The kurtosis is -1.52 . This negative kurtosis points to a platykurtic distribution, meaning the historical data has a flatter peak and lighter tails than a standard normal bell curve. This shape reflects prolonged periods of stable but low production in the early decades, followed by a transition to higher output levels in the later decades.

The historical trend of meat production was also mapped to see how it changed over the years (Figure 1). Vertical dashed lines were incorporated to mark major drought and shock years: 1974, 1983, 1991, 2011, 2016, and 2022. Sharp drops in the aggregate production curve are visible immediately following these environmental and political perturbations.

To investigate species-specific dynamics, aggregate production was decomposed into individual trajectories for camels, cattle, sheep, and goats (Figure 2).

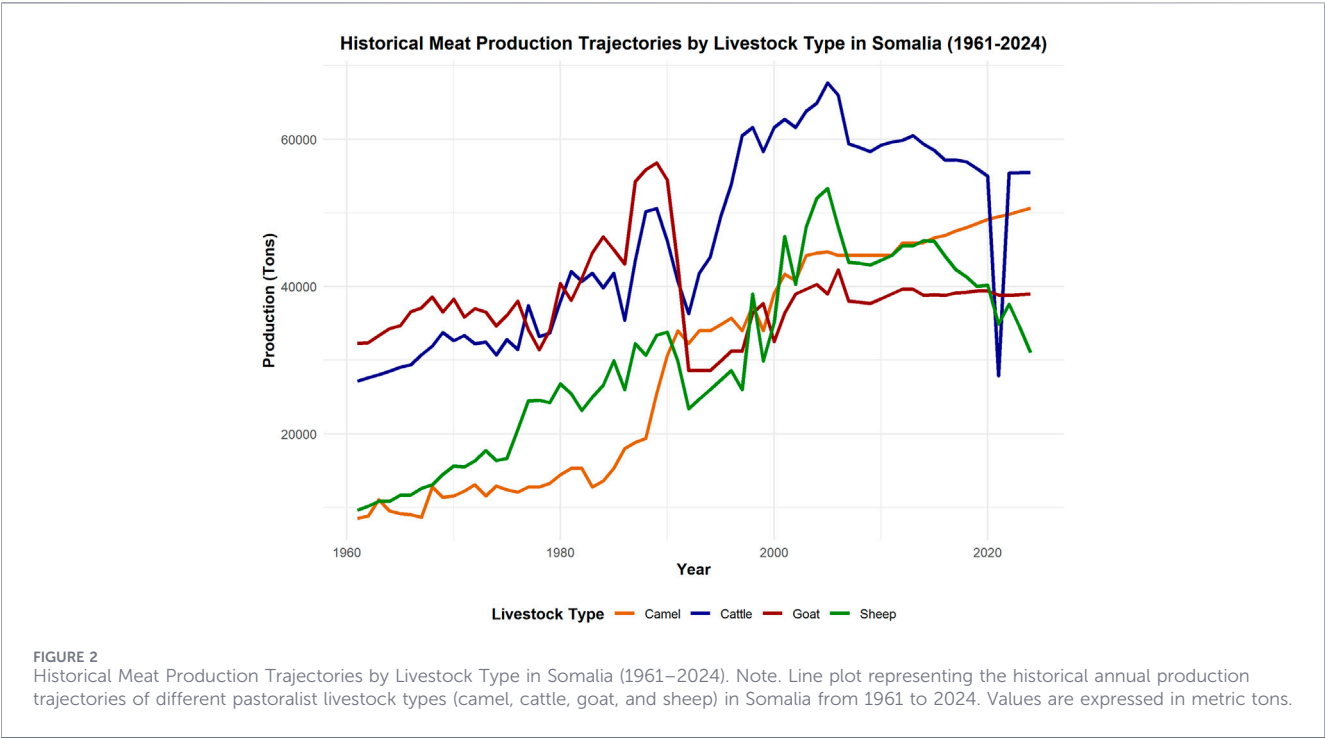


TABLE 2 Unit-root test results for somalia’s pastoralist red meat production.

Series	ADF statistic	ADF <i>p</i>	PP statistic	PP <i>p</i>	Decision
Level series [I(0)]	−2.08	0.544	−11.61	0.424	Nonstationary
First difference [I(1)]	−4.82	<0.001	−71.36	<0.001	Stationary

Rejection of the null hypothesis indicates covariance stationarity.

This comparison reveals a prominent socio-ecological pattern. Camel meat production (the orange line) has risen steadily and demonstrates remarkable resilience over the 64-year horizon, barely dropping during droughts and reflecting the species’ high climate adaptation and survival capacity. In contrast, cattle meat production (the dark blue line) is highly unstable, collapsing dramatically during the 1991 civil conflict and the multi-season meteorological drought of 2022. Goats (dark red line) and sheep (green line) remain comparatively stable, with goats exhibiting stronger post-drought recovery rates.

Stationarity and differencing analysis

Most classic time series models assume that the underlying data generating process is covariance stationary. To test this assumption, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests were systematically executed. These tests evaluated both the raw level series and the first-differenced series, as summarized in Table 2.

The level series failed to reject the null hypothesis of a unit root under both the ADF ($p = 0.544$) and PP ($p = 0.424$) tests, indicating nonstationarity. Following first differencing, both tests strongly rejected the null hypothesis ($p < 0.001$), confirming that the transformed series was stationary. The differencing order

recommended by the automated procedure ($d = 1$) was therefore adopted for subsequent modeling. The stationarity conclusion was further supported by the rapid decay observed in the ACF and PACF plots of the differenced series (Figure 1).

To rigorously account for potential structural shifts in the historical series (1961–2024)—as highlighted by recurrent climatic shocks—the Zivot-Andrews unit-root test allowing for a break in both intercept and trend was implemented. The test statistic of −4.3992 indicates that the series exhibits unit-root behavior with a structural breakpoint identified around the year 2000 (position 40), as summarized in Table 3. This formal breakpoint aligns with structural adjustments following regional shifts and precedes subsequent decadal shocks, reinforcing the integration order I(1) established by the standard ADF and PP diagnostics and validating the historical crisis markers incorporated in Figure 1.

Model estimation and residual diagnostics

Forecasting models were estimated using the in-sample training partition (1961–2014, $n = 54$). The automatic selection process using the AICc criterion chose an ARIMA (0,1,0) model with drift as our best baseline. The estimated drift coefficient is 2,127.85 (SE = 1,221.37). This shows that there was a modest upward trend of about 2,127.85 tons of red meat per

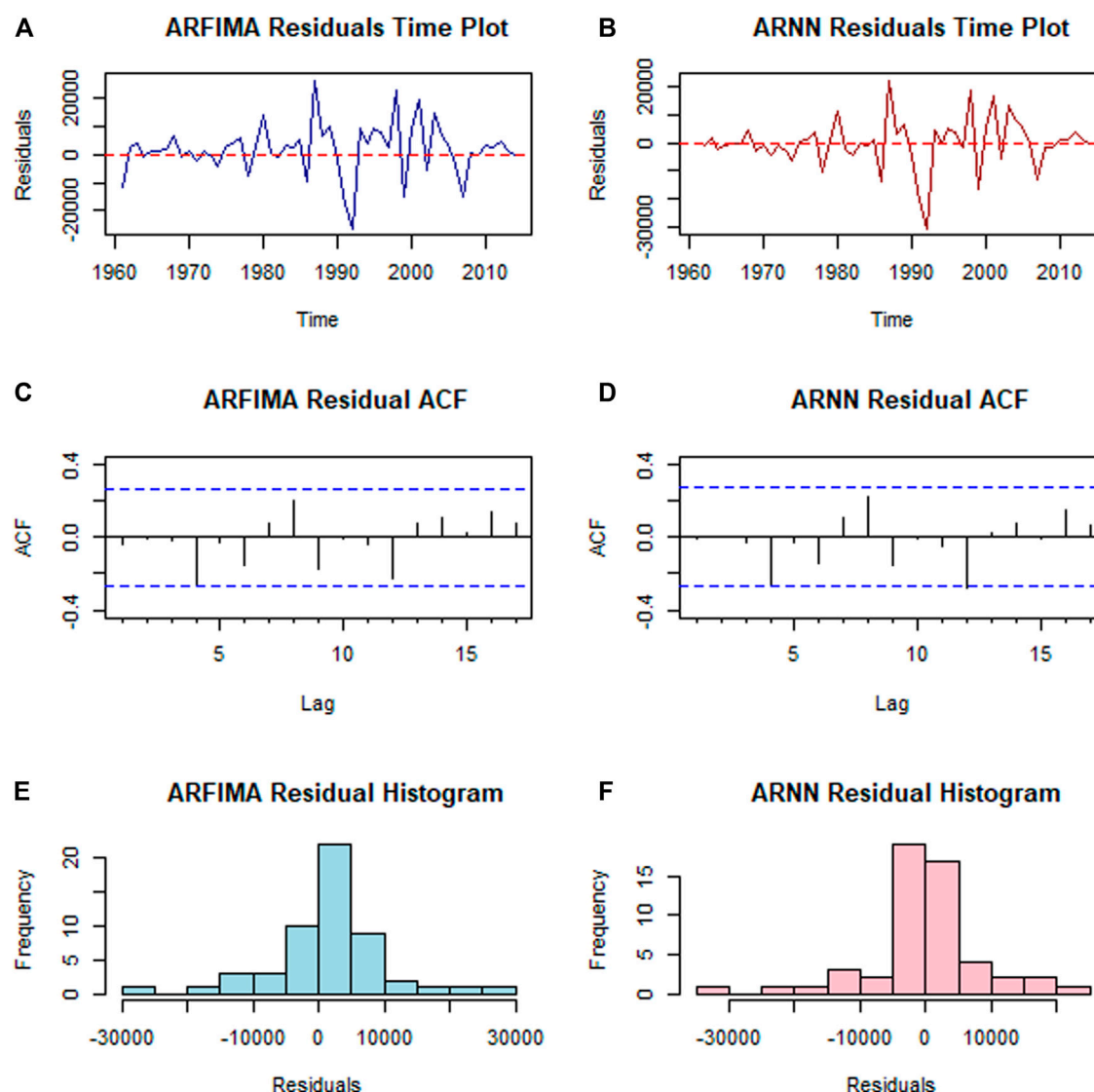


FIGURE 3
Residual Diagnostics for the Winning ARFIMA and Runner-Up ARNN Models. Note. Residual diagnostics comparing the ARFIMA and ARNN models. Panels (A,B) represent the residuals time plot; panels (C,D) represent the residual ACF plots; panels (E,F) represent the residual histograms with normal distribution curves. Blue dashed lines in ACF plots denote the 95% confidence limits.

year during this training period. The statistical significance of this drift is marginal ($t = 1.74$, $p \approx 0.082$), which reflects the high volatility of the series. For diagnostics, this baseline model has a residual variance (σ^2) of 80,582,454, a log-likelihood of -557.13 , an AIC of 1118.25, and a BIC of 1122.19. Diagnostic checks were run on the residuals to ensure that the estimated models are statistically sound and errors behave as white noise. First, the training ARIMA (0,1,0) with drift was evaluated. The Ljung-Box test showed no significant serial correlation ($Q^* = 12.12$, $df = 10$, $p = 0.277$), confirming that the residuals are random. Next, the full-sample ARIMA (0,1,0) was tested. The Ljung-Box test again confirmed model adequacy ($Q^* = 7.86$, $df = 10$, $p = 0.643$). To investigate further, a 6-panel composite plot was constructed to compare the residuals of the two best-performing models, ARFIMA and ARNN (Figure 3).

Comparative evaluation of forecasting performance

The forecasting performance of the estimated models was evaluated over a 10-year blind test window (2015–2024). Six robust accuracy metrics were calculated to compare model performance side-by-side, as summarized in Table 4 and illustrated in Figure 4.

The ARFIMA model consistently achieved the best performance across all accuracy measures. Specifically, it produced the lowest RMSE (10,836.89), MAE (5,387.34), MAPE (3.34%), and sMAPE (3.11%). Its Theil's U statistic (0.69) was substantially below 1.0, indicating superior predictive accuracy relative to a naïve random-walk benchmark.

The ARNN model ranked second overall, achieving an RMSE of 12,825.75 and an sMAPE of 4.49%. Although the neural network

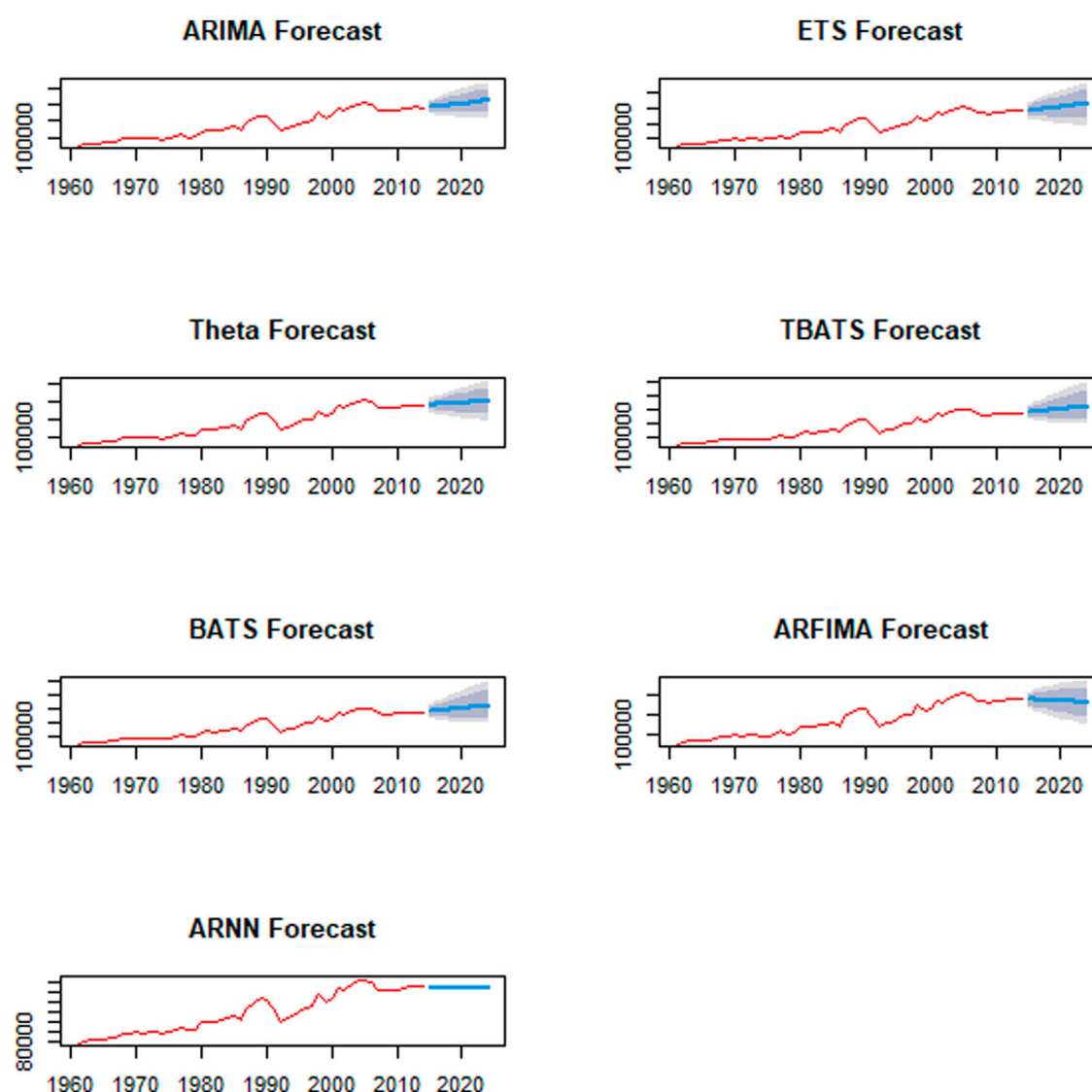


FIGURE 4
Comprehensive Out-of-Sample Forecasting Comparison (2015–2024). Note. Trajectories of the out-of-sample forecasts (2015–2024) across seven models (ARIMA, ETS, Theta, TBATS, BATS, ARFIMA, ARNN) evaluated against observed test data. Shaded regions represent 80% and 95% confidence intervals. For the ARNN (NNAR) panel, explicit prediction intervals are omitted due to the computational constraints of generating bootstrap simulation bands within the small-sample training regime ($n = 54$).

TABLE 3 Zivot-Andrews unit root test results with structural break.

Test specification	Test statistic	1% critical value	5% critical value	10% critical value	Indicated breakpoint	Decision/Result
Zivot-Andrews (intercept and trend)	−4.3992	−5.57	−5.08	−4.82	Year 2000 (position 40)	Non-stationary with break

The test allows for a structural break in both the intercept and the trend (“both” model specification) with a lag order of 1.

model successfully captured nonlinear patterns, its predictive accuracy remained inferior to that of the ARFIMA model. Classical and state-space models generally produced larger forecasting errors, suggesting limited ability to capture the long-memory characteristics and structural variability of Somalia’s livestock production system.

To ensure that the out-of-sample superiority of the ARFIMA model is robust beyond a single train/test split (2015–2024), an expanding-window rolling-origin cross-validation (tsCV) was executed. The cross-validation root mean squared errors robustly confirm this ranking, yielding an aggregate RMSE of 10,595.91 for the long-memory ARFIMA model compared to 11,900.06 for the

TABLE 4 Out-of-sample forecast accuracy comparison (2015–2024).

Model	Family	RMSE	MAE	MAPE (%)	sMAPE (%)	MASE	Theil's U
ARFIMA	Long-memory	10,836.89	5,387.34	3.34	3.11	0.85	0.69
ARNN	Neural network	12,825.75	7,962.89	4.80	4.49	1.26	0.82
Theta	Classical	20,880.50	16,614.78	9.69	8.95	2.63	1.36
ARIMA	Classical	26,071.04	21,604.07	12.51	11.41	3.41	1.71
BATS	State-space	26,799.13	22,257.56	12.88	11.72	3.52	1.76
TBATS	State-space	26,799.13	22,257.56	12.88	11.72	3.52	1.76
ETS	State-space	27,732.65	23,242.01	13.43	12.20	3.67	1.82

Lower values indicate superior forecasting performance. BATS, and TBATS, produced identical accuracy metrics because the annual non-seasonal frequency ($s = 1$) caused the trigonometric seasonal components of TBATS, to drop out during algorithmic convergence, resulting in an identical state-space specification to the BATS, model.

TABLE 5 Projected pastoralist red meat production in somalia (2025–2034) based on the ARFIMA model.

Year	Forecast	Lower 80%	Upper 80%	Lower 95%	Upper 95%
2025	175,332.80	162,430.50	188,235.10	155,600.40	195,065.20
2026	174,540.20	156,524.00	192,556.30	146,986.90	202,093.50
2027	173,767.70	151,979.00	195,556.40	140,444.80	207,090.60
2028	173,014.90	148,168.10	197,861.70	135,015.00	211,014.80
2029	172,281.30	144,844.00	199,718.70	130,319.50	214,243.20
2030	171,566.40	141,877.30	201,255.60	126,160.80	216,972.10
2031	170,869.70	139,189.90	202,549.60	122,419.60	219,319.90
2032	170,190.80	136,729.80	203,651.80	119,016.60	221,365.00
2033	169,529.10	134,460.20	204,598.00	115,895.80	223,162.40
2034	168,884.30	132,353.80	205,414.80	113,015.70	224,752.90

Forecasts were generated using the ARFIMA, model fitted to the complete historical series.

runner-up non-linear ARNN model. This confirms that ARFIMA’s predictive dominance is stable across expanding estimation windows and not an artifact of specific test-decade idiosyncrasies.

Decadal forecasts of pastoralist red meat production (2025–2034)

Given its superior forecasting performance, the ARFIMA model was fitted to the full historical dataset (1961–2024) to generate projections for the period 2025–2034. Forecast estimates and associated prediction intervals are presented in Table 5.

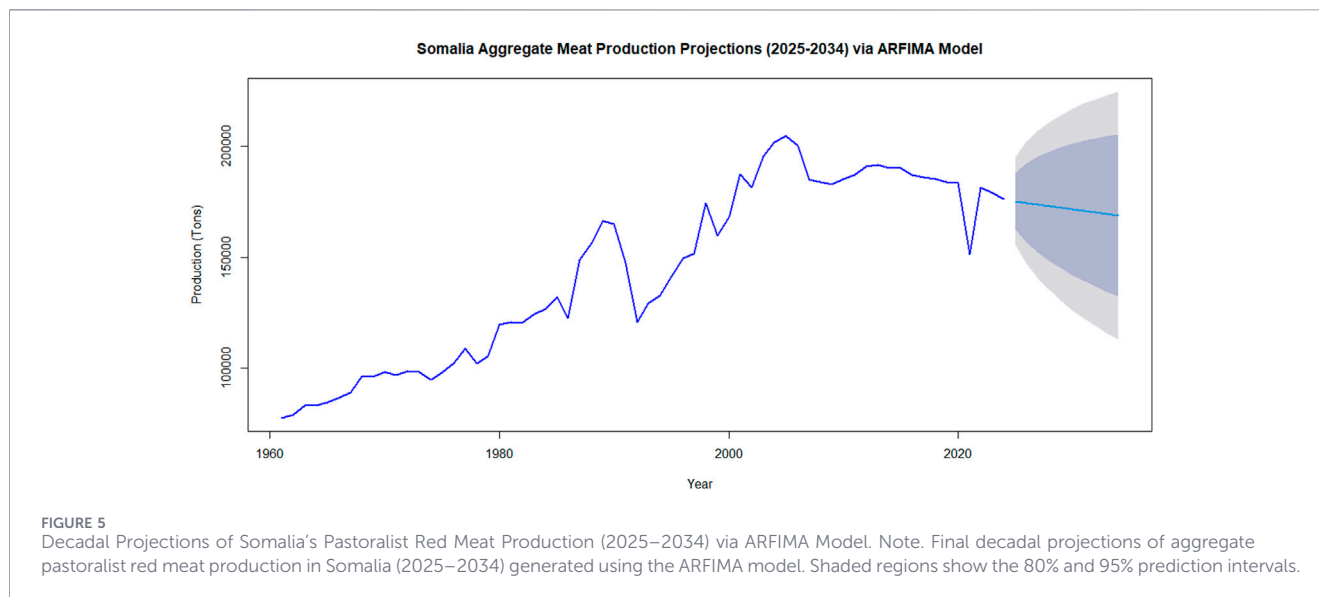
As Figure 5 shows, the ARFIMA model predicts a slow, steady decline and stabilization in pastoralist red meat production. The point estimates drop from 175,332.80 tons in 2025 to 168,884.30 tons by 2034. The gray confidence bands widen over time, which aligns with statistical expectations since forecasting further into the future naturally accumulates greater uncertainty.

In short, the forecasts suggest the sector is stabilizing with a slight downward trend. This behavior could indicate that Somalia’s traditional pastoral system is nearing its natural ecological carrying capacity under escalating environmental stress. Actual future production will remain heavily dependent on rainfall patterns,

veterinary infrastructure investments, and international market access.

Discussion

The empirical findings reveal that aggregate pastoralist red meat production in Somalia is governed by long-memory dependencies that require advanced univariate forecasting frameworks. The long-memory ARFIMA model exhibited clear superiority over the 10-year out-of-sample validation period (2015–2024), achieving the lowest error metrics across all criteria ($sMAPE = 3.11\%$, $RMSE = 10,836.89$, and $Theil's U = 0.69$). This statistical dominance over classical ARIMA and state-space models highlights the mathematical importance of the fractional differencing parameter d ($0 < d < 0.5$) in representing long-range dependencies in dryland agrarian datasets. In a fragile environment like Somalia, pastoralist livestock metrics are heavily determined by animal growth cycles, reproductive capacities, and rangeland biomass carrying capacity. When extreme climatic or political shocks occur—such as the historic multi-season droughts of 2011, 2016, and 2022—their impacts do not quickly dissipate. Instead, they linger as multi-year



dependencies in national herd structures, depressing off-take and meat production capacity for several subsequent years (Negassa et al., 2012; Ojanji and Wright, 2023). The ARFIMA model successfully represents this slow-decaying shock persistence, whereas traditional models like the ARIMA(0,1,0) with drift assume that shock impacts are either infinitely persistent or rapidly decay, leading to much larger forecast errors.

These results directly challenge a prominent body of agricultural forecasting literature. Several studies argue that parsimonious, short-memory models, such as classical ARIMA or simple exponential smoothing (ETS), are sufficient for agricultural forecasting in sub-Saharan Africa, suggesting that complex long-memory parameters add unnecessary parameterization without improving accuracy (Mgaya, 2019; Waiswa, 2023). Specifically, the findings of this study challenge the traditional, unconditional use of short-memory Box-Jenkins models for East African livestock metrics, which suffer from severe systematic bias when applied to shock-prone arid zones (Waiswa, 2023). Additionally, these findings challenge recent assertions in the forecasting literature that highly flexible machine learning architectures, particularly Autoregressive Neural Networks (ARNN/NNAR), are always superior to statistical models in modeling highly volatile agrarian data. While the ARNN model performed as the second-best forecasting instrument in this study ($sMAPE = 4.49\%$; $Theil's U = 0.82$), the absolute superiority of the ARFIMA model contradicts the general assumption that neural networks always outperform statistical models. This reveals that in data-scarce, highly volatile, and finite historical datasets ($T = 64$), neural networks remain highly prone to overfitting, highlighting the structural limitations of machine learning in small-sample time series regimes (Elmezouar et al., 2021).

This statistical performance can be traced to the unique biophysical and socio-political dynamics of the Somali livestock sector. The biological recovery of camel, cattle, sheep, and goat populations following severe droughts is a multi-year process that cannot be adequately modeled by short-memory frameworks. During extreme climatic anomalies, mass livestock mortality occurs alongside pasture depletion, which disrupts breeding cycles

and depresses meat production for several subsequent years (Hussein et al., 2024). This biological reality is supported by historical evidence indicating that the 2016/17 drought in Somalia caused a massive deficit of 14.8 million births (with goats losing 10.5 million and sheep losing 4 million births) and 4 million excess animal deaths (Otte et al., 2023). This massive reproductive gap directly explains the prolonged, slow-decaying lags observed in the disaggregated species trajectories (Figure 2). While cattle meat production (the dark blue line) is highly vulnerable and took years to recover after the 1991 civil war and the 2022 drought, camel meat production (the orange line) exhibited high climate resilience and a steady upward trend, driven by the biological capacity of camels to maintain milk and meat offtake under extreme water scarcity where other ruminants typically experience severe production declines (Muigai et al., 2016).

Furthermore, this study provides distinct contributions to the empirical literature on agricultural forecasting in fragile states. While previous modeling efforts in Somalia have heavily focused on macroeconomic variables or environmental indicators under rigid linear assumptions, this research represents the first comprehensive, head-to-head comparison of classical, state-space, long-memory, and machine learning models for aggregate red meat production. By demonstrating the absolute mathematical superiority of the fractionally integrated ARFIMA process over highly complex neural networks, this study pushes the empirical boundaries of time-series analysis in data-scarce and volatile environments. Additionally, the programmatic preprocessing baseline established in R (R Core Team, 2023) and the strict exclusion of commercial poultry provide a highly targeted, replicable methodology for evaluating dryland pastoral systems, filling a major methodological gap noted in previous regional agricultural assessments (Esse et al., 2025; Wanyoike et al., 2023).

Despite these contributions, several strengths and limitations of this study must be acknowledged. A primary strength of this research is the use of a comprehensive 64-year historical dataset (1961–2024) validated over a rigorous 10-year out-of-sample testing window (2015–2024), which minimized the risk of in-sample overfitting and simulated real-world predictive performance. Another strength is the integration of both parametric statistical

algorithms and computational networks, balancing econometric interpretability and non-linear flexibility. Conversely, a prominent limitation of this univariate design is the inability to explicitly incorporate exogenous, climate-driven covariates, such as the Normalized Difference Vegetation Index (NDVI) or precipitation anomalies (Mohamed et al., 2022). Furthermore, data scarcity and the finite sample size ($n = 54$ training observations) restricted the architectural depth of the autoregressive neural network, preventing the implementation of deep learning configurations (Jainonthee et al., 2025); though this constraint is methodologically managed through a single hidden-layer structure suited to small-sample regimes (Jainonthee et al., 2025). In addition, as a single-country analysis focused exclusively on Somalia's pastoral economy, the empirical findings reflect specific socio-ecological dynamics; consequently, while the methodological framework is broadly transferable, direct generalizability of these specific production trajectories to other regional pastoral systems should be approached with appropriate context (Erdaw, 2023). Finally, a critical methodological consideration relates to the underlying macro-level data source. The FAOSTAT (QCL) production series relies on national aggregations that, within the Somali pastoral context, heavily incorporate informal cross-border trade, unrecorded subsistence slaughter, and traditional off-take—variables that are notoriously difficult to capture via direct accounting (Catley et al., 2013; Herrero et al., 2013). While FAOSTAT provides the longest continuous macro-level baseline available ($T = 64$) and remains standard for macro-comparisons, these estimation methods introduce inherent reporting uncertainties. Consequently, our decadal projections reflect broader structural and systemic trajectories rather than localized transactional ledgers, necessitating a nuanced interpretation by food-security policymakers.

At the local level, the forecasting results of this study align closely with recent empirical surveys of pastoralist asset depletion. Meteorological droughts in Southwest Somalia (Bay, Bakool, and Lower Shabelle) are documented to have caused catastrophic herd losses of up to 62.1% for goats, 68.6% for cattle, 74.7% for sheep, and 63.5% for camels (Wardhere and Mahamed, 2026). Widespread asset collapse and the drying up of conventional water catchments reported by local pastoralists directly explain the gradual contraction and stabilization predicted by the ARFIMA model (declining from 175,332.80 tons in 2025 to 168,884.30 tons by 2034). This projected plateau suggests that traditional pastoral systems in Somalia may be approaching critical rangeland carrying capacities under compounding anthropogenic and environmental pressures. Specifically, chronic pasture depletion, reduced biomass regeneration, and multi-season droughts systematically constrain the long-term demographic and biological expansion of herds, forcing agropastoral systems toward a dynamic ecological equilibrium (Otte et al., 2023; Warsame et al., 2023). Under these conditions, the massive collapse of livestock assets forces pastoralists into distress decisions, disrupting the long-term stability of domestic meat production and driving chronic food insecurity (Otte et al., 2023; Wardhere and Mahamed, 2026). In this context, transitioning from reactive emergency relief to proactive planning requires mathematically validated baselines to construct climate-smart early warning systems (Ngongolo and Gayo, 2025; Srivastava et al., 2025).

Conclusion

Synthesizing the empirical evaluations, this study demonstrates that long-memory frameworks are fundamentally better suited than classical or machine learning paradigms for projecting aggregate livestock trajectories in fragile dryland environments. By capturing slow-decaying shock persistence, the ARFIMA model establishes a robust, mathematically validated baseline indicating a structural production plateau through 2034. To preempt potential ecological thresholds and safeguard food security, institutional stakeholders must leverage these quantitative baselines—shifting away from reactive emergency interventions toward proactive investments in commercial fodder systems, mobile veterinary infrastructure, and index-based livestock insurance. Future extensions should build upon these univariate findings by integrating high-resolution spatial and climatic covariates within hybrid architectures.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <https://www.fao.org/faostat/en/#data/QCL>.

Author contributions

AB: Conceptualization, Methodology, Formal analysis, Software, Writing – review and editing. DS: Conceptualization, Project administration, Resources, Writing – review and editing. AM: Validation, Supervision Writing – original draft. SH: Data curation, Investigation, Visualization, Writing – original draft. All authors contributed to the article and approved the submitted version.

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Conflict of interest

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