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Research Article

Forecasting Kenya's Camel Population for Climate Adaptation and Sustainable Livestock Development

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ABSTRACT

Camel production systems are increasingly central to livelihood resilience, climate adaptation, and food security in the arid and semi-arid lands (ASALs) of Kenya, where recurrent droughts and climate variability have undermined conventional cattle-based systems. Consequently, pastoral communities have progressively shifted towards camel-dominant production strategies. Despite the growing economic and ecological significance, systematic empirical forecasting of national camel population trajectories remains limited. Most existing livestock assessments rely on descriptive statistics rather than formal stochastic modelling frameworks. This study developed a comparative univariate time-series forecasting framework. Specifically, it evaluated the forecasting performance of Autoregressive Integrated Moving Average (ARIMA), Holt's linear trend, Exponential Smoothing State Space (ETS), and Linear Trend models using the annual FAOSTAT livestock stock database for Kenya (1961 to 2024). Model performance was evaluated using stationarity diagnostics, residual independence tests, and out-of-sample forecast accuracy metrics, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Forecast comparisons were further evaluated using the Diebold–Mariano predictive accuracy test. The ARIMA (2,1,1) model achieved the lowest AIC (-46.55) and BIC (-36.25). However, the ETS (M, N, N) model demonstrated the highest predictive accuracy with the lowest forecast errors (RMSE = 622,710; MAE = 429,282; MAPE = 11.36%). The projections suggest that Kenya's camel population is likely to stabilise or moderately increase between 2025 and 2029, reflecting continued adaptation to climate variability. These findings provide valuable evidence for livestock planning, climate adaptation, and sustainable development of Kenya's camel sector.

Keywords: Camel population, time-series forecasting, ARIMA, holt's, ETS, climate adaptation, Kenya, livestock planning

INTRODUCTION

The dromedary camel (*Camelus dromedarius*) is an important species in the Arid and Semi-Arid Lands (ASALs) agro-ecosystems of the world, including Africa, Asia and the Middle East, where they contribute substantially to food security, income generation, transportation and livelihood resilience. (Othieno et al., 2022). Camels, unlike conventional livestock, exhibit superior physiological adaptation to arid conditions, including efficient water metabolism, tolerance to high temperatures, and sustained lactation under nutritional stress (Faye & Konuspayeva, 2012). Studies show that pastoralists increasingly adopt camels as a risk management strategy under

climate stress. These attributes position camels as strategic livestock in the context of long-term climate change. Herrero et al. (2010) emphasise that livestock systems must adapt to shifting agroecological constraints, making camel population dynamics an important indicator of adaptive transformation. Camel production has received much attention as a crucial component of resilient livestock systems, which have the ability to support pastoral and agro-pastoral communities facing increased environmental uncertainty.

Globally, the camel population have been steadily increasing over the past four decades to approximately 40 million as of 2020 (Faye, 2020), with more than 80% of the population found in Africa. Sixty per cent (60%) of these are found in the Horn of Africa, where they contribute significantly to export trade, cross-border livestock markets, and in-country trade, as well as food security and livelihoods of local communities (Kinyanjui et al., 2011). Beyond traditionally being used as pack animals, camel livestock keepers derive tremendous benefits from these animals; they are crucial sources of multiple products such as milk, meat, hides and income generation, thus a very important livestock species in the dryland production systems (Elhadi et al., 2015). Camels contribute significantly to household nutrition through sustained milk production during drought periods, thereby stabilising pastoral livelihoods (Mehta et al., 2015).

Globally, livestock production systems have been increasingly affected by climate variability and environmental change, especially in dryland ecosystems where production is dependent on rainfall and natural habitats. The major impacts of environmental risks include changes in rainfall patterns, floods, droughts, loss of biodiversity and increased resource-use conflicts as indicated by the Intergovernmental Panel on Climate Change (IPCC) (Koech et al., 2019; Machan et al., 2022a). There has been evidence of abrupt changes in weather conditions, unreliable weather patterns that have strong negative impacts on livestock production, vegetation index cover and natural resources management (Science, 2009).

Sub-Saharan Africa represents the most vulnerable region to climate change in Africa, with the pastoral communities increasingly experiencing the consequences of recurrent drought and environmental degradation (Gaur & Squires, 2017; Gaur & Squires, 2018). Consequently, livestock systems in East Africa are undergoing structural transformation in response to climate variability and demographic pressures. Among the domesticated animals, the camel is among the livestock species which have shown remarkable resilience under harsh environmental conditions. Their superior physiological adaptations, including efficient water utilisation, high temperature tolerance, browsing flexibility and the ability to maintain production efficiency under nutritional stress, make them very suitable for the arid and semi-arid environments (Faye & Konuspayeva, 2012).

In Kenya, camels have evolved from a marginal livestock species associated primarily with nomadic pastoralism to becoming strategic assets for food systems, income diversification, and climate resilience. The increasing frequency and severity of drought episodes have undermined livestock, affecting mostly pastoralist communities whose main livelihoods are dependent on livestock production (McPeak & Barrett, 2001). However, there have been highlights on the ecological adaptability of camels under water stress and sparse and declining rangeland productivity and conditions (Watson et al., 2016). Consequently, camel production has been understood not only as a climate change adaptation strategy but also as a means to improve climate resilience.

Kenya currently hosts one of the largest camel populations in sub-Saharan Africa, and it is the leading camel milk producer globally, with an annual production volume exceeding 1.165 million

metric tonnes (Oselu et al., 2022). The pastoral communities in the North-Eastern parts of Kenya rear about 4.722 million camels, accounting for about 80% of all camels in the country. Herds are concentrated in the ASAL counties such as Marsabit, Turkana, Mandera, Wajir, and Isiolo, and the national population is approximately 4.3 million, remaining the dominant livestock in the ASAL (Oselu et al., 2022).

Besides providing transportation of goods across the deserts, meat, fur, and milk, camels substantially contribute to household food security through sustained milk production even in the periods of prolonged drought, thus stabilising nutrition and productivity when other livestock populations decline (Mehta et al., 2015). The increasing commercialisation of camel milk and expansion of urban demand further reinforce the sector's economic relevance in Kenya's livestock sector (Noor et al., 2013). The Food and Agriculture Organisation (FAO, 2019) recognise non-cattle livestock, including camels, as critical to the future of livestock development in Africa's drylands. They are key pathways for enhancing resilience, improving pastoral livelihoods and supporting sustainable developments in the dryland ecosystems.

Structural growth in camel numbers over recent decades reflects adaptive responses to environmental risk, increasing climate variability, and policy recognition of camels as drought-resilient livestock (Watson et al., 2016; Barrett et al., 2004). In response to climate change, recurrent drought, erratic rainfall, rangeland degradation and increased competition for natural resources, development organisations have promoted herd structuring towards camel production systems due to their exceptional adaptations to harsh climatic conditions. Since the early 2000s, development initiatives have supported camel distribution programmes across northern Kenya to strengthen household resilience and increase adaptation to climate variability (Machan et al., 2022). As a result, herd restructuring toward camel-dominant systems has accelerated, increasing their populations particularly within Kenya's Arid and Semi-arid Lands (ASALs).

The importance of camels has also been strategically recognised by the Kenya National Climate Change Policy (2014), which identifies climate-resilient agricultural systems as a priority to strengthen adaptation and reduce climate variability impacts on the vulnerable communities. Despite the policy giving a full focus on resilient agricultural systems, camel production becomes an integral part of the resilient livestock systems, which provide a niche for promoting drought-tolerant species which can sustain productivity regardless of the increasing climate variability (Machan et al., 2022). Furthermore, the Kenyan camel population reflects not only the biological adaptation but also the broader socioeconomic, institutional and policy responses to the change in climate

The complex interactions of the environment, biology, socioeconomics, and management actors all influence the camel population dynamics. The principal driver of population decline among the herds in the ASALs remains climate change, since it affects the availability of pasture. Water resources, disease occurrence and livestock mortality (Ibrahim et al., 2024). Disease outbreak is one of the many drivers of camel population dynamics, as stated by Othieno et al. (2022) in a study on health and production challenges to identify infection drivers and risky behaviours in camels. It influences the herd performance in the pastoral communities, constraining camel productivity and population growth. Additionally, changes in demand for camel products, expansion in camel milk commercialisation, policy interventions, and shifts in pastoral livelihood strategies all contribute to shaping the long-term population trajectories. Generally, these dynamics generate very complex temporal patterns characterised by long-term trends, stochastic variation, and potential structural changes. Thus, highlighting the need for

robust statistical approaches that can accurately model and forecast the camel population while capturing population dynamics (Hyndman, 2021).

Understanding the livestock population dynamics is important in sustainable livestock development, policy formulation and evidence-based planning. Reliable population projections facilitate producers, government agencies, as well as development agencies in expecting future livestock dynamics, optimising resource use and allocation, strengthening veterinary services and extension, as well as improved preparedness for climatic and market-related shocks. According to Kulyk et al. (2023), agricultural forecasting has become an intrinsic decision support tool as it provides quantitative information crucial for strategic planning, investment decisions, infrastructural development and food security investment. Robust livestock population forecasting is therefore increasingly important as it hints at the long-term changes in herd structures and dynamics, thus supporting adaptive management strategies.

Despite the increasing economic and ecological benefits due to camel keeping in Kenya, studies have mostly focused on production systems, health constraints, adaptation to climate change, breeding practices, milk production and socioeconomic relevance, all of which are very important in understanding the camel production systems (Othieno et al., 2022; Watson et al., 2016). However, limited studies have provided insights into the long-term temporal dynamics in national camel populations.

A significant methodological gap is therefore evident, which is the forecasting of camel population future trajectories using rigorous statistical time series approaches. This gap, therefore, limits the policymakers and planning proactive decisions based on the livestock numbers and not overly relying on historical observations alone.

Camel populations present dynamic behaviours driven by multiple interacting factors, which frequently generate non-stationary time series characterised by long-term trends, stochastic fluctuations, and structural changes. Therefore, descriptive analyses are generally not enough to capture such dynamic characteristics or produce reliable projections. With the present gap, statistical approaches capable of accounting for all these temporal dependencies and stochastic variations become handy in accurate and reliable population projections, which can support livestock planning (Box et al., 1994; Hyndman & Athanasopoulos, 2021).

Several forecasting models have been employed in agricultural and livestock studies, including the Autoregressive Integrated Moving Average (ARIMA) model, Holt's Linear Exponential Smoothing, Exponential Smoothing State Space (ETS) model and Linear trend models each having a distinct role depending with the nature of the data, The ARIMA remains the most widely used approach due to its ability to model autocorrelations and non-stationary time series following appropriate differencing (George et al., 2015). The ETS model functions by providing a flexible framework for modelling level trend, and seasonal components while automatically selecting appropriate error, trend and seasonal structures (Hyndman & Athanasopoulos, 2002, 2021). The Holt Linear trend approach, just as it suggests, exhibits a simple exponential smoothing which incorporates trend components, thus suitable for non-seasonal series showing persistent linear growth (Gardner & Jr., 2006).

Consequently, the linear trend model provided a simple deterministic benchmark against which more sophisticated forecasting approaches can be evaluated. The forecasting models differ in terms of their assumptions regarding trend behaviour, autocorrelation structure, and stochastic functions. Comparative evaluation of these models is therefore important in selecting the

forecasting model that is most reliable in predictive performance under environmental conditions which are variable and accompanied by structural changes (Green et al., 2015).

Not only are accurate models required for robust forecasting model estimation, but also comprehensive model validation. Livestock populations are often affected by structural changes from drought, disease outbreaks, and policy reforms. Market fluctuation, in addition to environmental shocks, influences forecast performance (Perron & Pierre, 1989). Therefore, model performance should be evaluated in terms of its adequacy using the residual diagnostic tests, which verify the adequate capturing of temporal dependence. Similarly, the predictive performance of the competing models should be assessed using forecast accuracy measures and statistical comparisons (Diebold, 2015; Hyndman & Athanasopoulos, 2021).

Evidence-based decision-making backed with a reliable forecast on camel population dynamics is extremely important in Kenya's livestock sector. Accurate population trajectories inform livestock development and planning, climate adaptation strategies, veterinary service delivery, disease surveillance, feed and resource management infrastructural development, and market planning. As Kenya seeks to promote climate-resilient agricultural systems within its ASALs, scientifically robust forecasting models have become handy in supporting policy formulations, resource allocations and the sustainable management of the camel sector.

This study, therefore, aimed to forecast the camel population in Kenya using the FAOSTAT database (1961 to 2024) on the previous years' camel population, while identifying the most accurate and reliable model for the population projections. ARIMA, ETS, Holt's linear trend, and the linear trend were the univariate forecasting models employed in this study. The models were further evaluated using statistical diagnostics and forecast accuracy measures. The resulting projections therefore provide valuable evidence for livestock planning, climate change adaptations, resource allocation, and the sustainable development of the camel sector in Kenya.

MATERIAL AND METHODS

Data Source and Study Design

Quantitative time series forecasting approach was employed in this tidying analysis historical camel population dynamics and generate future population projections for Kenya. Annual camel population data were obtained from the Food and Agriculture Organisation Statistical Database (FAOSTAT) agricultural stock database, in which harmonised livestock statistics are reported by member countries. The annual data obtained consisted of annual camel population records for Kenya spanning the period 1961 to 2024, reported in headcount units.

The study employed four forecasting methods in which comparative performance was evaluated, the approaches which included: Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing State Space (ETS), Holt's Linear Trend, and Linear Trend models. The analytical framework included exploratory data analysis, stationary testing, model estimation, residual diagnostics, forecast validation and the projection of future camel population.

Data Analysis Plan

R statistical software environment (R Core Team, 2024) was crucial in the statistical analyses, in which several specialised packages were used in different stages of analysis. The most fundamental packages included: forecast for time series modelling, tseries for stationary testing involving the Augmented Dickey-Fuller (ADF) test, metrics for forecast accuracy evaluation, while ggplot was used for graphical visualisation and scales for output formatting.

Forecasting Models

ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model followed the Box-Jenkins methodology. Autocorrelation functions (ACF), partial autocorrelation function (PACF), and information criteria were used in guiding the model identification (George E. P. Box et al., 2015).

ETS Model

The forecast package provided the automatic selection procedures, which were used to fit the exponential smoothing state space (ETS) model. The ETS model framework accommodates different combinations of error, trend, and seasonal components. It then selects the most appropriate structure using the likelihood-based criteria.

Holt's Linear Trend Model

Holt's linear trend model was used to analyse the data; it exhibited a trend component without incorporating the seasonality. This forecasting method, therefore, applies exponential smoothing to the series' levels and trend components (Gardner & Jr., 2006). It is very handy for forecasting non-seasonal time series data sets.

Linear Trend Model

Ordinary least squares regression was used to fit a linear trend model, with the camel population as the dependent variable and time as the explanatory variable. This model crucially provided a baseline forecasting approach against which the more advanced time series modelling was evaluated.

Model Validation and Diagnostic Testing

Each model's fit adequacy was evaluated through residual diagnostic analysis; whereby residual plots were examined to identify randomness and any remaining systematic patterns. The presence of serial dependence was evaluated using the autocorrelation function (ACF). The Ljung-Box portmanteau test was used as a standard diagnostic for assessing whether the models exhibited significant autocorrelation, and non-significant p-values to confirm that the residuals approximate white noise and that the fitted models adequately captured the temporal dependence structure of the series analysed (Ljung & Box, 1978).

The information criteria and the Bayesian Information Criterion were used in the assessment of the model explanatory performance, whereby lower values indicated a superior model while penalising the excessive model complexity.

Forecast Accuracy Assessment

The data set was divided into two subsets, that is, training and testing data, to evaluate the predictive performance. Model estimation used the period 1961 to 2019, while the observations from 2020 to 2024 were reserved for out-of-sample validation. This approach provided a basis for the assessment of the ability of each model to predict previously unseen observations and minimised the risk of overfitting.

The three commonly applied error measures for forecast accuracy included:

$$RMSE = \sqrt{\frac{\sum (Y_t - \hat{Y}_t)^2}{n}}$$

$$MAE = \frac{\sum |Y_t - \hat{Y}_t|}{n}$$

$$MAPE = \frac{100}{n} \sum \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|$$

where Y_t represented the observed value, $\hat{Y}_t$ the forecast value, and n the number of observations. Models with the lowest RMSE, MAE and MAPE were considered the most superior in the predictive accuracy.

Comparative Forecasting Evaluation

The Diebold-Mariano test was used to assess the models in terms of their competing forecast accuracies. The test evaluates whether the forecast values generated differed significantly, whereby statistical significance indicates superior predictive performance of the models relative to each other (Diebold & Mariano, 1995).

Forecast Projections

After model evaluation and selection, the Kenyan camel population were generated on a five-year forecast that is the period 2025 to 2029. The forecast trajectories from the ARIMA, ETS, Holt's linear trend and linear trend models were used to assess and compare the future population dynamics and their implications for livestock management and development planning, climate adaptation, and sustainable management of Kenya's camel production systems.

RESULTS AND DISCUSSION

Historical Camel Population Dynamics, Structural Transformations and Climate Adaptation

A gradual but moderate rate of growth in the camel population was shown in the long-run pattern from 1961 through to the late 1990s. Camel numbers increased steadily from lower than 1 million head to approximately 1 million by the late 1990s. This phase was characterised by low volatility and incremental expansion.

By the early 2000s, a pronounced structural shift was observed. From 2005 to 2007, there was a sharp rise in camel population, which indicated a regime change in herd expansion. This period presented a substantially larger population increase than the prior decades.

There was a series of volatility in the period between 2008 and 2022, with notable fluctuations including camel population reaching above 4.5 million animals, a visible decrease in camel population around 2022 and a subsequent partial pickup towards 2023 and 2024. The series appeared to stabilise at approximately 4.8 million head in 2024, following an earlier population decline

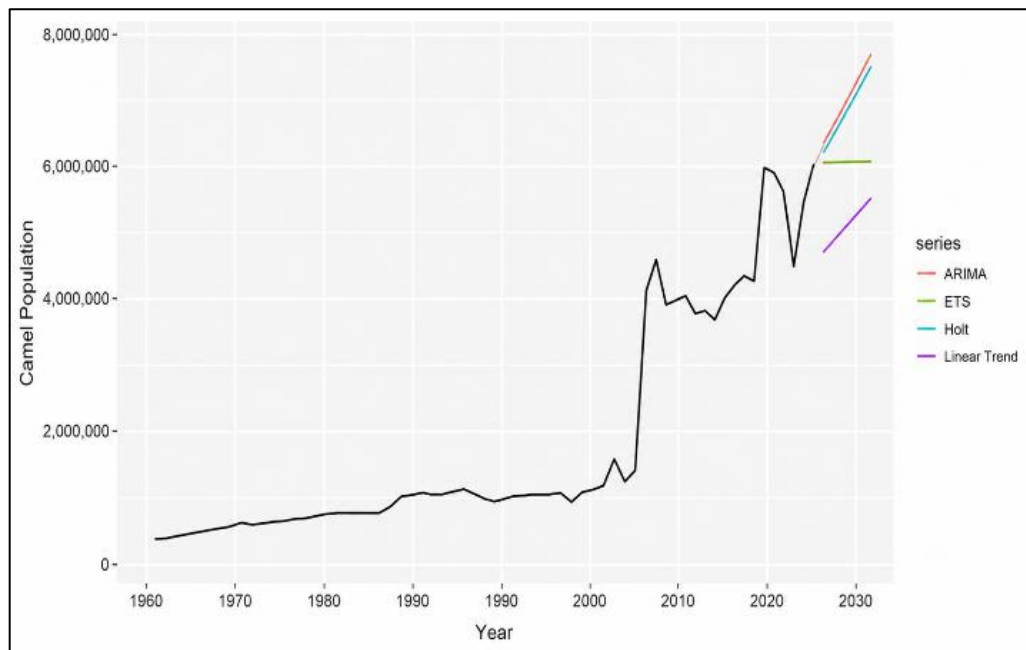


Figure 1. Graphical Analysis: Historical and Forecasted Camel Population Dynamics

Figure 1 shows the historical trajectory of the camel population in Kenya from the early 1960s to 2024, along with projected values from 2025 to 2029 generated by four competing forecasting approaches. The graphical evidence revealed several distinct structural phases in the historical series before considering the forecast behaviour.

Kenya's camel population exhibited a replicative growth which reflected a deeper structural transformation within pastoral systems. Similar structural shifts have been identified in other livestock time series studies, where changes in regime and long-term upward trend are characteristic features in need of differenced ARIMA to achieve stationarity (Mgaya, 2019; Palabiçak & Binici, 2023). This is in agreement with evidence of substantial camel population expansion and commercialisation over the past three decades (Hughes & Anderson, 2020; Othieno et al., 2022). Frequent incidences of severe drought cycles have been increasingly experienced in recent decades, therefore reshaping herd composition and pushing livestock keepers to more drought-resilient species (Wako et al., 2017; Ndiritu, 2021).

Camels possess adaptive physiological traits including browsing flexibility, superior water-use efficiency and thermal tolerance, which exemplifies their resilient nature under drought stress. For these reasons, ASAs have been dominated by camels compared to cattle (Wako et al., 2017; Watson et al., 2016). Empirical work from the ASAL regions of Northern Kenya and neighbouring regions has shown that camels can survive and continue to produce under severe drought conditions while other animal species succumb. In contrast, cattle mortality due to drought has been documented to be an average of 13 to 45%, underscoring the comparative resilience advantage that underpins herd structuring towards camel production systems (Nkedianye et al., 2011a). This has therefore improved household resilience under certain climatic conditions (Thornton et al., 2009; Herrero et al., 2010). Consequently, the observation of camel population expansion as evidenced in this study is likely to reflect the adaptive herd restructuring rather than simple demographic growth (Hughes & Anderson, 2020; Thiakunu et al., 2023).

Climate adaptations don't imply monotonic expansion. Drought shocks do introduce short-run volatility, mortality incidences and market disruption. Recent studies among pastoralists in Kenya documented recurrent drought and perceived increase in drought drive complex, non-

linear adaptation responses (Ndiritu, 2021; Wako et al., 2017). According to Abrhaley and Tesfay (2025), the ETS specification provided stabilisation, which suggested that recent population dynamics are influenced by cyclical climatic pressures and not uninterrupted structural growth. These findings are consistent with projections that camels' habitat suitability in the Horn of Africa may expand and contract under the future scenarios.

The interpretation also aligns with the climate adaptation theory, which emphasises the dynamic adjustment rather than a linear transformation. Adaptive social-ecological systems are a pastoral mode of operation in which species composition shifts in response to evolving risk profiles, with heterogeneous outcomes across households depending on assets and access to support (Volpato & King, 2018).

Residual Diagnostics and Model Adequacy

A residual analysis to assess the adequacy of the fitted ARIMA (2,1,1), ETS (M, N, N), linear trend and Holt (AAN) models was conducted. For each specification, the time plot of residuals and the corresponding autocorrelation function (ACF) were examined; this was in addition to Ljung-Box test p-values, which were used to formally evaluate residual independence.

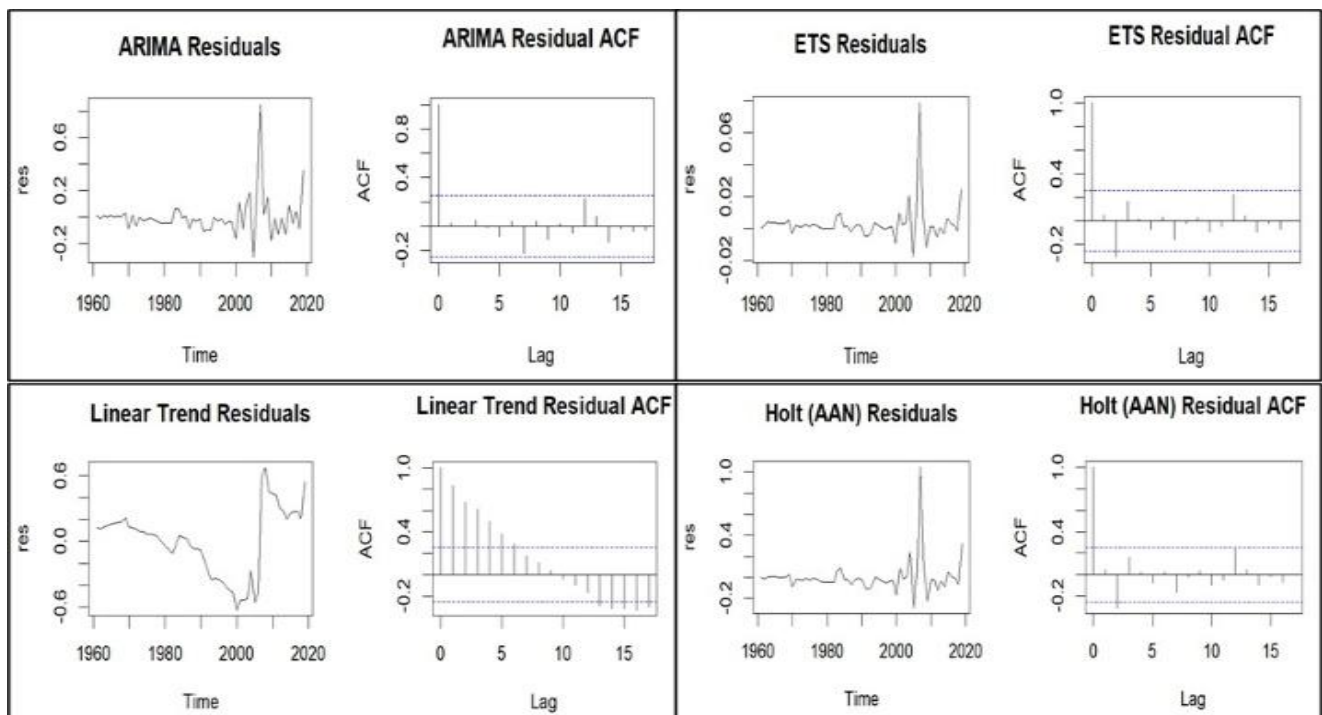


Figure 2. Model Residual Diagnostics

For the models, ARIMA, ETS and Holt's, the fluctuations centred approximately around zero with no persistent upward or downward drift except for the linear trend model, which showed pronounced structural patterns, and its deviations were not randomly distributed around zero.

The model exhibited autocorrelations within the 95% confidence bounds; thus, the models ARIMA, ETS and Holt lacked statistically significant serial correlations. There were no evident patterns of persistence or cyclical decay.

Table 1: Ljung-Box test results for the residual autocorrelation of the fitted forecasting models

Forecasting Model	Ljung-Box p-value
ARIMA (2,1,1)	0.8746
ETS (M, N, N)	0.3799
Linear Trend	0.3609
Holt (AAN)	<0.05

Further, with the Ljung-Box p-values, ARIMA (0.8746), ETS (0.38), and Holt (0.3609) all exceeded 0.05 (Table 1), thereby indicating that residual correlations were not significant. With a linear trend having a p-value of 0.0, this indicated a highly significant correlation, and it failed to adequately capture the dynamic structure of the camel population trend, leaving temporal dependence unmodelled. With this comparative diagnostic summary, the linear trend violated the independence assumption.

These diagnostic analyses indicated that ARIMA, ETS, and Holt's models adequately captured the temporal dependence structure in camel population dynamics. Conversely, the Linear trend model failed to account for important stochastic variation. Therefore, the subsequent forecasting comparisons primarily focused on models that satisfied residual dependence assumptions.

Model Selection, Forecast Accuracy and Predictive Performance

The four time-series models were estimated using a training sample, and model adequacy and relative parsimony were assessed using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Table 2. Model Estimation and Information Criteria

Forecasting Model	AIC	BIC
ARIMA (2,1,1)	-46.55	-36.25
ETS (M, N, N)	33.82	40.05
Linear Trend	33.50	39.74
Holt (AAN)	35.96	46.35

Note: AIC=Akaike Information Criterion; BIC= Bayesian Information Criterion

The lowest AIC and BC values were recorded from the ARIMA (2,1,1) model, AIC (-46.55) and BIC (-36.25). This indicated a superior sample fit relative to other specifications. The ETS model had AIC and BIC of 33.82 and 40.05, respectively, linear trend AIC (33.5) and BIC (39.74), while Holt (Aan) had BIC and AIC of 35.96 and 46.35, respectively. The lower AIC and BIC as presented by the ARIMA model indicated that this model provided the best statistical representation of the historical stochastic structure of camel population dynamics. This finding is consistent with other national livestock time series analyses in which the ARIMA model was fitted and achieved lower AIC and BIC than simpler benchmark approaches; however, they still required out-of-sample validation, crucial for confirming predictive performance reliability (Mgaya, 2019; Palabiçak & Binici, 2023).

Table 3. Out-Of-Sample Forecast Accuracy

Forecasting Model	RMSE	MAE	MAPE
ARIMA	1,228,470	1,134,078	27.6%
ETS	622,710	429,282	11.36%
Linear	1,331,291	1,238,255	27.7%
Holt	1,243,121	1,105,751	27.2%

Note: RMSE = Root Mean Squared Error; MAE= Mean Absolute Error ; MAPE=Mean Absolute Percentage Error

Forecast performance was evaluated and predictive accuracy quantified using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) over the hold period (Hyndman & Koehler, 2006). These metrics are crucial in providing a basis for model comparison.

As presented in Table 3, the lowest forecast errors across all the accuracy measures were achieved by the ETS (M, N, N) model with RMSE (622,710), MAE (429,282), and MAPE (11.36%). The accuracy measures (MAE and MAPE) in all other models exceeded one million, with MAPE of over 27%.

The ETS model exhibited superiority in RMSE, MAE, and MAPE, indicating the robustness of its predictive advantage. With an MAPE of 11%, the ETS model represented a marked improvement in predictive precision. Consistent with this study, the superiority of ETS in out-of-sample accuracy, despite better in-sample fit shown by ARIMA, has been reported in similar livestock time series contexts, for instance, forecasting Kenyan livestock by (Titus et al., 2021) and the Somali lands camel and cattle export volumes, whereby ETS (A, N, N) was selected based as the optimal model for cattle data projections (Esse et al., 2025).

Reconciling Explanatory Fit and Predictive Performance

The empirical findings in this study revealed a clear divergence between in-sample explanatory adequacy and out-of-sample predictive performance. Despite the ARIMA (2,1,1) model having the lowest AIC and BIC values, which symbolised a superior historical fit, the ETS (M, N, N) model specifications outperformed all four models explored in this study's forecast accuracy. These findings were consistent with comparative evidence in which the ETS model often yielded lower forecast errors despite ARIMA's better in-sample fit (Gao, 2025; Ali et al., 2025). A highly parameterised stochastic model may fit historical data closely but underperform in short-term predictions when structural shifts or volatility are present, evidence demonstrated by the broader forecasting divergence alignment (Yao, 2025; Hyndman & Athanasopoulos, 2008).

The ETS model was selected by the automatic procedure, which incorporated a multiplicative error without a deterministic trend component. This structural choice implied that recent camel population dynamics are best characterised by level adjustment rather than a continued exponential acceleration. This model selection was compatible with the evidence of the recent stabilisation and regional heterogeneity in camel growth and performance, as evidenced in the Arid and Semi-arid lands (ASALs) (Hughes & Anderson, 2020; Othieno et al., 2022; Thiakunu et al., 2023).

Notably, the FAO data set presented the year 2022, which was included in the test period, in which drought episodes were experienced in the Horn of Africa, leading to livestock mortality and disruption in production among the Kenyan arid and semi-arid lands (Ndiritu, 2021). The ARIMA

model normally incorporates drifts; in this paper, it extrapolated a positive growth and consequently overpredicted the population level during these volatile periods. This echoed other applications where the ARIMA Trend component performed poorly under abrupt structural or climate shocks (Gao, 2025; Ali et al., 2025).

The findings of this study reinforced the methodological distinction as articulated by Shmueli (2010), that explanatory power does not guarantee predictive reliability. Forecasting agricultural and livestock trends, especially in climate-sensitive systems, predictive validation using hold-out samples often provides stronger inferential credibility than information criteria alone, as found in recent ARIMA-ETS comparisons and climate-sensitive export and macroeconomic forecasting applications (Yao, 2025).

Table 4. Pairwise Diebold-Mariano test results for comparing forecast accuracy among the fitted models

Model Comparison	DM Statistic	p-value
ARIMA vs ETS	3.375	0.0279
ARIMA vs Linear Trend	-0.249	0.8155
ARIMA vs Holt (AAN)	-0.190	0.8589
ETS vs Linear Trend	-1.716	0.1614
ETS vs Holt (AAN)	-2.947	0.0421
Linear Trend vs Holt (AAN)	0.194	0.8557

The Diebold-Mariano test showed significant predictive performance (Table 4) between the ARIMA and ETS models ($p = 0.0279$) and between the ETS and Holt (AAN) models ($p=0.0421$). The remaining model comparisons showed no significant differences ($p>0.005$). These results showed that the ETS model differed significantly from both the ARIMA and Holt models, and when considered together with its lower RMSE, MAE and MAPE, the ETS model demonstrated the superior and the strongest overall predictive performance for the camel population forecasting in Kenya, further emphasising the importance of model evaluations (Diebold & Francis, 2015).

Forecast Projections and Disease Dynamics

Table 5. Forecast Projections of Camel Population (2025-2029)

Year	ARIMA	ETS	Linear	Holt
2025	4,981,977	4,779,431	3,807,116	4,895,042
2026	5,193,051	4,779,431	3,962,360	5,099,185
2027	5,413,067	4,779,431	4,123,934	5,311,842
2028	5,642,405	4,779,431	4,292,096	5,533,367
2029	5,881,460	4,779,431	4,467,115	5,764,131

Upward Growth Trajectories

Sustained growth in the camel population was seen in the ARIMA model. The population increased from 4,981,977 in 2025 to 5,881,460 by 2029, which reflected a stochastic trend which is embedded in the differenced ARIMA specification. Similarly, increased population levels were seen in Holt's model. camel population rose from 4,895,042 in 2025 to 5,764,131 in 2029. This was at a slightly moderate rate compared to the ARIMA model.

Two forecasts (ARIMA and Holt's models) exhibited sustained upward trajectories. Their projections showed a monotonic increase over the five-year forecast period, with the camel population exceeding 5.5 million by 2028–2029. The slope remained positive throughout, suggesting the continuation of the recent growth momentum.

Constant-level projection

One forecast ETS (M, N, N) remained constant throughout the projection horizon, with an estimated population of 4.78 million camels. This model trajectory indicated neither slope nor acceleration, thus showing stabilisation at the most recent observed level.

Disease Dynamics as A Moderating Force

While camel population expansion has been supported by climate adaptation, the disease menace has represented a critical moderating factor in herd dynamics. Camel populations in Kenya are affected by both endemic and emerging diseases, which include Rift Valley Fever (RVF), brucellosis, trypanosomiasis, and respiratory infections, among other zoonoses (Muturi et al., 2021; Hughes & Anderson, 2020). Outbreaks of Rift Valley Fever (RVF) are associated with anomalous rainfall and flooding events, which influence mosquito vector populations (Anyamba et al., 2012).

With intensifying climate variability, the interaction between increased rainfall and vector ecology heightens outbreak risk. A study in northern Kenya regarding serological evidence indicated substantial RVF exposure in camels, besides other infections (Muturi et al., 2021; Hughes & Anderson, 2020). Such episodic disease events can increase mortality incidences, impose trade restrictions, contribute to population volatility and constrain herd recovery after drought (Othieno et al., 2022; Muturi et al., 2021). In pastoral systems, brucellosis disease has been widely documented to reduce reproductive efficiencies through abortions and infertility. Systematic reviews in Kenyan camels reported appreciable brucella seroprevalence with robust links to human exposure (Muturi et al., 2021; Hughes & Anderson, 2020). The wider ecological changes, dynamic vegetations, and vector distribution in the ASAs similarly influence trypanosomiasis and other vector-borne diseases (Hughes & Anderson, 2020).

Around 2002, a volatility spike was observed, which likely reflected compounded stress from drought and disease. Concurrent drought and disease outbreaks are well-documented cases of massive acute livestock mortality in Kenyan pastoral systems, where drought creates nutritional stress while population congregation amplifies pathogen transmission and compounds herd losses (Nkedianye et al., 2011). This finding is consistent with the reports of respiratory and other health challenges in the Kenyan camel herds in recent years (Othieno et al., 2022; Muturi et al., 2021). The dynamics of diseases are greatly influenced by climate change through vector habitat alteration, extended transmission seasons and intensified livestock mobility. Therefore, disease-climate interactions partly explained the recent population stabilisation rather than positive growth.

Notably, in this context, a forecasting model which heavily extrapolates the long-run drift may fail to account for the nonlinear epidemiological shocks. Recent data, as emphasised by adaptive smoothing models (Gao, 2025; Yao, 2025), may better capture herd adjustments following disease and or climate disturbances. This is exemplified by other comparative ARIMA-ETS forecasting studies, which were observed in other volatile systems (Ali et al., 2025; Gao, 2025; Yao, 2025).

Moderate Linear Growth

The linear trend showed a steady but comparatively linear projection. The camel population increased from 3,807,116 in 2025 to 4,467,115 in 2029. While it increased annually, its growth rate is visibly lower than that of the two steeper upward trajectories (ARIMA and Holt's models). This model remained substantially lower than the highest projected path.

Divergence over the forecast horizon

Notably, the divergence among the models widened over time, with the spread between the highest (ARIMA model) and the lowest (Linear trend model) forecasts that exceeded 1.4 million camels by 2029. The increasing dispersion reflected the differences in assumptions regarding the persistence of historical growth trends.

Policy Implications for Camel Sector Planning

The ETS model carried a superior predictive accuracy, a practical implication for short-term horizon planning. Time series models for national livestock planning have been comparatively demonstrated in the sub-Saharan setting, where ARIMA and ETS models have been applied to FAOSTAT data, providing a quantitative baseline for livestock resources management decisions (Kulyk et al., 2023b; Mgaya, 2019). In climate-volatile areas, adaptive forecasting tools and models are crucial in informing strategic feed reserve allocation, veterinary drug procurement, drought contingency funding and provision for market stabilisation mechanisms (Ndiritu, 2021; Othieno et al., 2022). According to Ndiritu (2021), as a climate adaptation strategy, early warning information and forecast planning in Kenya influences households' choices and capacity to cope with climate extremes. Camel population forecasting using a stochastic trend model may overestimate herd sizes during drought cycles. This may potentially lead to misallocation of resources such as feeds, veterinary drugs and equipment. More responsive models, such as the ETS model, can better align contingency planning with actual livestock population dynamics (Ali et al., 2025; Gao, 2025; Yao, 2025).

Camel population expansion represents an endogenous climate adaptation strategy in Kenya. Integration of camel population dynamics into adaptation modelling, prioritisation of camel-specific extension services into national climate policy frameworks, are crucial for such adaptations. This is besides mobility support for sustainable grazing corridors and climate-informed disease surveillance. Camels are increasingly getting recognised as the ship of the desert. In terms of their adaptations and livelihood security, this recognition comes with emphasis on climate-smart livestock systems with species diversification for resilience building (Wako et al., 2017; Watson et al., 2016b). To enhance participatory governance capacity, forecasting models become an integral adaptation toolkit. This methodology provides a better target and support to vulnerable producers (Ndiritu, 2021; Wako et al., 2017).

Despite resilience improvement by camel population expansion, overstocking remains a risk. In the presence of weak institutional governance, fragile ecosystems remain at risk, and even drought-resistant species can exert pressure on the ecosystem. This is if camel habitats normally shift in response to changing climate suitability (Abrhaley & Tesfay, 2025). When planning is based on forecasting models, it provides possible livestock populations. This is very important for policy enactment touching on sustainable stocking densities and community rangeland management, thereby meeting the broader ASAL resource management under climate stress (Ndiritu, 2021; Wako et al., 2017). Camel population projections enable preventive rather than

reactive ecological management, thus contributing to livelihood resilience and ecosystem integrity (Volpato & King, 2018).

CONCLUSION

The present study forecasted camel population dynamics in Kenya using the annual FAOSTAT data from 1961 to 2024, in which ARIMA, ETS, Holt's linear trend and linear trend models were compared. While the best sample fit was provided by the ARIMA (2,1,1) based on the AIC and BIC criteria. The ETS (M, N, N) demonstrated the best out-of-sample accuracy, with a record of the lowest RMSE, MAE, and MAPE values. The historical trend in population growth revealed a substantial increase in Kenya's climate-resilient camel population, underscoring the importance of camels in climate-resilient pastoral systems. The analysis results indicated that the camel population is likely to remain stable or moderately increase in the five-year forecasted period, between 2025 and 2029. Therefore, this study highlights the importance of evaluating predictive performance alongside the model fit when selecting forecasting approaches, which provide useful evidence for livestock planning and climate adaptation strategies in the Kenyan ASAL regions.

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