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Climate Change, Macroeconomic Factors and the Nigerian Indigenous Meat and Milk Industry: A Long-Memory Approach

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Abstract

This paper investigates the relationship between climate change, macroeconomic variables and indigenous livestock production in Nigeria over the period 1981–2023 using fractional integration and multivariate regression methods. More specifically, it examines how temperature and precipitation anomalies, including their nonlinear (squared) effects, agricultural conditions and macroeconomic factors affect Total Indigenous Livestock Meat (TOLIM), Raw Milk of Cattle (RAMOC), and the combined value of Meat and Milk (TOVOMAMI). Climate variables enter the models in levels, while the other variables are first-differenced and log-transformed where appropriate, to ensure stationarity and balanced regressions. The specifications assuming white noise residuals suggest weak and largely statistically insignificant effects of the climate variables on livestock productivity, and also yield some slight evidence of an impact of macroeconomic factors. By contrast, when imposing an AR(1) specification on the error term, negative effects of permanent pasture and exchange rate depreciation on output values are found. These results suggest possible inefficiencies in land use and macroeconomic vulnerability in Nigeria's indigenous livestock sector. and provide useful information for designing sustainable livestock adaptation policies in low-income economies.

Keywords: Climate change; indigenous livestock; precipitation anomalies; temperature anomalies; fractional integration; long memory; trends; Nigeria; agricultural resilience.

JEL Classification: C22; Q12; Q54; O13; Q18

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1. Introduction

Climate change poses a major threat to the planet Earth. Developing countries with extensive agricultural sectors, such as Nigeria, are particularly vulnerable to its effects, which can increase their difficulties in achieving food security, and hamper the growth of regional markets and the advancement of food production technologies (Omotoso et al., 2023).

Climate change significantly affects livestock health by modifying the life cycle, spread, and severity of diseases (Rowlinson, 2008; Black & Nunn, 2009; IFAD, 2009). Extreme weather events such as heavy rainfall, drought, floods, and elevated temperatures disrupt the milk supply and endanger human health. These events interfere with the growth of plants and reduce the nutritional value of forage, especially in arid areas, and affect livestock metabolism and production (Kennedy & Milligan, 1978; Izaurrealde et al., 2011; Apgaua et al., 2019; Crous, 2019; Sprunger et al., 2023; Blond et al., 2024). Reduced water and quality feed consumption lead to loss of appetite, reduced energy, weight loss, and increased mortality in livestock (Babinszky et al., 2011).

The livestock sub-sector accounts for a considerable percentage of agricultural production and consumption owing to the dietary protein and calorie requirements of the growing population of Nigeria (Ekpo, 2012; Akpan and Udo, 2021). To ensure the continuous fight and win against malnutrition (especially in children and pregnant women) as well as food security, the consumption (and thus production) of animal protein is a fundamental necessity. Food security, according to the Food and Agricultural Organization of the United Nations (FAO, 2008), “*exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life*”. In 2019, FAO reported a 20.7 million-head cattle population, including 2.2 million dairy animals, an 80.1 million-head goat population, an 8.0 million-head pig population, and finally a 46.8

million-head sheep. In 2018, there was a record production of 0.5 billion litres of milk, 1.4 million tonnes of meat, and 0.6 million tonnes of eggs (Akpan and Udo, 2021). In Nigeria, there are diverse indigenous livestock breeds (Adebambo, 2003; Adebambo et al., 2004), with noticeable differences between agro-ecological zones and regions of the country.

The demand for meat and milk in Nigeria has been rising sharply over the years, some of the possible causes being population increases, literacy, urbanization, literacy level, and social status. This has generated serious concerns that it might outstrip supply, especially given the changes in weather conditions that are being experienced in the whole of Sub-Saharan Africa, including Nigeria (Simpkin et al., 2020). Most of the locally produced milk and meat cattle products come from farmers (Ayanlade and Ojebisi, 2019; Adesulu-Dahunsi et al., 2023). These farmers are mainly based in Northern Nigeria but sometimes move down to the south during the dry season in search of water and pasture. Their dependence on natural pasture and rain-fed water makes local production highly susceptible to fluctuations in weather conditions (Neibergs et al., 2017).

The present study focuses on the case of Nigeria. More specifically, it analyses trends in the supply (production value) of indigenous meat and milk as well as the factors that can affect it, such as agricultural inputs, climate variables (temperature anomalies and precipitation), land variables and financial variables (agricultural credit). The empirical investigation is carried out using at first fractional integration methods that are more general and flexible than standard unit root models. In particular, they allow the differencing parameter to take any real value, including fractional ones, instead of integers only. As a result, they encompass a much wider range of stochastic processes compared to models based on the classical dichotomy between $I(0)$ -stationary and $I(1)$ -nonstationary variables; they also provide useful information about their persistence and

mean-reversion properties, as well as the transitory or permanent nature of the effects of shocks. The univariate analysis is then followed by multivariate regressions with different assumptions about the behaviour of the errors to examine the relative importance of the factors affecting indigenous meat and milk production.

The structure of the paper is as follows: Section 2 contains a review of the relevant literature; Section 3 describes the data; Section 4 outlines the methodology; Section 5 presents the empirical results; Section 6 offers some concluding remarks.

2. Literature Review

Understanding the factors that affect livestock production in Nigeria requires considering both environmental conditions and broader economic realities. Three main approaches can be found in the existing literature: the Vulnerability–Resilience Framework, the Climate-Smart Agriculture Framework, and Risk and Uncertainty Theory. Together, these theories shed light on how climatic conditions, structural agricultural factors, and macroeconomic dynamics influence indigenous livestock production.

The Vulnerability–Resilience Framework explains the impact of climate change through the interaction of exposure, sensitivity, and adaptive capacity (Adger, 2006; Smit & Wandel, 2006). Exposure refers to the degree to which a production system experiences climate hazards such as droughts, rising temperatures, or rainfall variability. Sensitivity reflects how strongly livestock production responds to these changes, particularly when animals depend on natural pasture and rain-fed water sources. Adaptive capacity refers to the ability of farmers and pastoralists to adjust their practices in response to climatic stress.

In Nigeria, indigenous livestock production is largely concentrated in the northern savannah regions, where pastoral and agro-pastoral systems depend heavily on seasonal

rainfall and grazing resources. These areas are regularly exposed to climatic variability, especially fluctuations in rainfall and temperature. At the same time, pastoral mobility, the use of heat-tolerant indigenous breeds, and local knowledge of grazing patterns may help reduce vulnerability. According to the Vulnerability-Resilience framework, temperature and precipitation anomalies should affect livestock production when exposure and sensitivity are high. However, if adaptive mechanisms are effective, the observable impact of climate variability may be limited at the aggregate level.

A second perspective is provided by the Climate-Smart Agriculture Framework promoted by the Food and Agriculture Organization (FAO, 2013). This approach emphasizes improving agricultural productivity while strengthening resilience to climate change and promoting sustainable management of natural resources. In livestock systems, climate-smart practices include improved pasture management, better feeding systems, the use of resilient livestock breeds, and greater access to credit and institutional support. Within this framework, improvements in productive resources such as grazing land, labour, and financial support are expected to enhance output and reduce vulnerability to climatic stress. Variables related to pasture availability, agricultural credit, and employment structure therefore are useful indicators of how management practices and institutional support influence livestock production.

Risk and Uncertainty Theory provides a third perspective by highlighting the role of unpredictable economic conditions in agricultural decision making. Farmers often operate in environments where both climatic risks and economic uncertainties influence production choices (Knight, 1921; Hardaker et al., 2015). In many developing economies, macroeconomic instability can have substantial effects on agricultural performance. Exchange rate depreciation, inflation, and fluctuations in interest rates can raise the cost of imported inputs such as veterinary medicines, machinery, and feed additives. These

conditions increase production costs and may discourage long-term investment in herd expansion or improved livestock management.

There is also a large body of empirical studies on the effects of climate change on agricultural production. Increased concentration of atmospheric carbon dioxide (CO₂) has been associated with both primary and negative effects, such as greater growth stimulation in some plants (wheat, soybeans) compared to C₄ plants such as maize and tropical grasses (Godde et al., 2021). High CO₂ concentration has also been shown to affect grain protein concentration (Myers et al., 2014), decrease mineral concentration (Loladze, 2014), increase toxicity (Gleadow et al., 2009; Gleadow et al., 2016), cause woody encroachment in forage plants (Godde et al., 2021), and affect feed availability, composition and quality (Rojas-Downing et al., 2017).

Changes in rainfall patterns have an impact on soil salinity (Godde et al., 2021) and have also led to a reduction in arable grazing land (Alam et al., 2017), longer periods of drought in some regions, and flooding. Climate change has also been associated with either an increase (Rosenzweig et al., 2001; Jones et al., 2019) or a decrease (Young, 2015; Bett et al., 2017) in pest intrusion, both of which have sizeable effects on feed availability and quality (Myers et al., 2017). Water, another important input in meat and milk production, has not been spared by the effects of climate change. Water availability influences the production, quality and availability of forage (Thorton et al., 2009, IFAD, 2010), animal growth and reproduction as well as milk production (Nardone et al., 2010).

Other studies have shown the effects of heat stress exacerbated by climate change on animal health and production (Rojas-Downing et al., 2017; Godde et al., 2021). These include, but are not limited to, reduced feed intake (Godde et al., 2021; Rojas-Downey et al., 2017; Rowlinson, 2008), reduced feed conversion rate, and a reduction in body weight

(Gezu & Moges, 2018) leading to a decline in growth rate and milk production (Godde et al., 2021), even at first lactation (Dahl et al., 2016). However, research has also shown that cows exposed to heat stress during parturition have better chances of regulating their core body temperature, enabling them to adapt better at maturity (Ahmed et al., 2017). Heat stress also reduces the quality of animal products, making them less appealing to consumers and leading to a reduction in their selling price (Bernabucci et al., 2002; Mashaly et al., 2004; Sevi and Caroprese, 2012; Gonzalez-Rivas et al., 2020; Godde et al., 2021).

In Nigeria, livestock is often transported from the Northern region down to other regions of the country using trucks. With the increase in temperature associated with climate change and the high stocking density of these trucks, the transported animals are very susceptible to stress, dehydration and in extreme cases mortality (Caulfield et al., 2014; Collins et al., 2018; Godde et al., 2021). As a result, livestock farmers may be forced to increase the prices of cattle in order to make up for the losses encountered during transportation. Other factors that can potentially contribute to a hike in the price of meat and milk products include increases in transportation costs (possibly as a result of the deplorable condition of some Nigerian roads), high energy consumption during storage (especially for fresh milk), costs associated with sourcing for fresh forage and water (especially during the dry season), the activities of middlemen and retailers (Godde et al., 2021), changes in the land tenure system (McAllister et al., 2006; McAllister, 2012), and access to credit facilities (Hardaker et al., 2015). These factors also discourage the entry of able-bodied youths into the livestock production market (Godde et al., 2021), thus widening the demand-supply gap.

On the whole, the existing literature suggests that livestock production in Nigeria is shaped by a combination of environmental exposure, structural agricultural conditions,

and macroeconomic factors. Therefore the models estimated in this study include climate indicators such as temperature and precipitation anomalies, structural agricultural variables such as pasture availability and employment, financial variables such as agricultural credit, and macroeconomic indicators including inflation, real interest rates, and exchange rates. The econometric analysis is based on long-memory methods, not previously used in this context, which are the most suitable ones to capture both long-term trends and the dynamic adjustment processes. They provide extensive evidence on the relative importance of climate variability, structural agricultural conditions, and macroeconomic instability in explaining changes in indigenous livestock production.

3. Data

The data employed in this study, with their corresponding sources, are the following:

Data from FAOSTAT (from 1961 to 2023)

- i. TOLIM = Total indigenous livestock meat gross production value (meats of cattle with the bone, fresh or chilled (indigenous); chickens, fresh or chilled (indigenous), goat, fresh or chilled (indigenous); pig with the bone, fresh or chilled (indigenous); sheep, fresh or chilled (indigenous)) measured in ₦1000
- ii. RAMOC = Raw milk of cattle gross production value measured in ₦1000
- iii. TOVOMAMI = Total value (gross production) of meat and milk (Indigenous) measured in ₦1000
- iv. PERMAP = Permanent meadows and pasture (1000 ha)

Data from OurWorldinData.org/climate-change, provided by the Copernicus Climate Change Service information (2025).

v. TEMP.ANOM = Temperature anomalies (°C) from 1940 to 2023, calculated as the difference between a year's average surface temperature from the 1991-2020 mean, in degrees Celsius

vi. SQUARED TEMP.ANOM (°C) = The square of TEMP.ANOM (constructed by the researcher to check for non-linear climate effects from 1940 to 2023).

vii. PRECIP.ANOM = Precipitation anomalies (mm) from 1940 to 2023, namely the difference in a specific year's total precipitation, rain and snow, from the 1991–2020 average, measured in millimeters, excluding fog and dew. Negative numbers indicate drier-than-average years.

viii. SQUARED PRECIP.ANOM (mm) = The square of PRECIP.ANOM (constructed by the researcher to check for non-linear climate effects from 1940 to 2023).

Data from the World Development Indicators of the World Bank

ix. CPI = Consumer price index (2010 = 100) - (1975 - 2024)

x. RIR = Real interest rate (%) - (1975 - 2023)

xi. OER = Official exchange rate (LCU per US\$, period average) - (1975 - 2024)

Data from other sources

xii. AEAC = Agricultural employment absorption capacity (1960 to 2023) which is the percentage share of agricultural employment in total employment, sourced from African Sector database (1960 to 2010), Economic Transformation Database (2011 to 2018) and World Development Indicators of the World Bank (2019 to 2023).

xiii. ACGSF = Value of Agricultural Credit Guarantee Scheme Fund (loan) apportioned for the whole livestock sector measured in (₦' Thousand), sourced from Central Bank of Nigeria statistical bulletin (1981 to 2024).

Table 1: Descriptive Statistics

Variable	T	Mean	Std. Dv.	Min.	Max.
TEMP. ANOM.	85	(0.40)	0.55	(1.58)	0.70
SQ. TEMP. ANOM.	85	0.46	0.58	0.00	2.50
PRECIP.ANOM.	85	(19.93)	126.69	(364.00)	229.00
SQ. PRECIP.ANOM.	85	16,258.28	23,875.48	-	132,496
TOLIM	63	325,649,600	174,124,500	70,438,840	635,088,900
RAMOC	63	15,228,690	5,243,361	6,109,138	24,818,370
TOVOMAMI	63	340,878,300	179,117,600	76,844,950	657,445,500
PERMAP	63	25,820.59	1,056.14	23,471.00	27,000
AEAC	65	64.29	11.59	34.31	78.18
ACGSF	44	538,032.80	671,389.90	4,446.90	2,342,247
CPI	50	94.01	147.57	0.19	699.39
RIR	49	(0.98)	13.74	(65.86)	18.18
OER	50	139.71	237.84	0.55	1,478.97

Table 1 reports some descriptive statistics based on the longest sample available for each series. It can be seen that the range of values is much wider in the case of total meat and milk production value (which reflects growth and inflation) compared to weather measurements (expressed as deviations from normal values rather than absolute ones).

Table 2: Descriptive Statistics, 1981–2023

Variable	T	Mean	Std. Dv.	Min.	Max.
TEMP. ANOM.	43	(0.05)	0.37	(0.82)	0.69
SQ. TEMP. ANOM	43	0.14	0.16	0.00	0.67
PRECIP.ANOM.	43	(10.19)	95.33	(224.00)	203
SQ. PRECIP. ANOM.	43	8,980.47	12,724.64	-	50,176
TOLIM	43	419,888,100	122,997,500	226,038,200	635,088,900
RAMOC	43	18,027,910	3,680,227	12,387,970	24,818,370
TOVOMAMI	43	437,916,000	126,198,500	238,426,200	657,445,500
PERMAP	43	25,307.05	886.06	23,471.00	26,640

AEAC	43	62.93	12.68	34.86	75.26
ACGSF	43	527,168.80	675,411.00	4,446.90	2,342,247
CPI	43	93.01	124.20	0.49	524.91
RIR	43	(0.24)	14.46	(65.86)	18.18
OER	43	127.97	142.78	0.62	645.19

Table 2 reports the same set of statistics calculated over the sample period for which observations are available for all series. It is immediately apparent that the range of values is now narrower, as the time span is the same for all variables.

4. Methodology

Macroeconomic and environmental time series often display a high degree of persistence. It is now well known that standard unit root tests such as ADF, KPSS, and PP have low power against alternatives in the form of stationary processes with strong dependence, and can lead to unreliable conclusions about persistence and mean reversion (Campbell & Perron, 1991; DeJong et al., 1992; Diebold & Rudebusch, 1991). This issue is particularly relevant for national level production series and climate indicators, as the effects of shocks to these series can decay slowly and the adjustment may be gradual.

To address these limitations, we use fractional integration methods which allow the order of integration to take non-integer values, thereby providing a flexible framework that nests $I(0)$ stationarity and $I(1)$ unit root processes as special cases, while also accommodating intermediate degrees of persistence (Granger, 1980, 1981; Granger and Joyeux, 1980; Baillie, 1996). In particular, we estimate for each series, over the longest available sample, a fractionally integrated model with deterministic components. The general specification is the following:

$$y_t = \theta_1 + \theta_2 t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, \dots, T, \quad (1)$$

where θ_1 is an intercept, θ_2 is coefficient on a linear time trend, L is the lag operator, d is the fractional differencing parameter, and u_t is a short-memory disturbance. The values of d have a direct interpretation. If $d < 0.5$, the process is covariance stationary and mean reverting. If $0.5 \leq d < 1$, the series is nonstationary but mean-reverting and the effects of shocks eventually die out. If $d \geq 1$, shocks have permanent effects and the process behaves similarly to, or more persistently than, a unit root one.

As in the long-memory literature, we allow u_t to be weakly autocorrelated in the univariate setting, and model it using the exponential spectral model of Bloomfield (1973). This specification approximates autoregressive behaviour without requiring an explicit AR order selection, and is well suited for short samples where the lag length is unclear. Model selection for the univariate analysis is based on the statistical significance of the deterministic terms, the chosen specification being the most parsimonious one supported by the data.

As a second step we run multivariate regressions over the period 1981-2023 (determined by availability for all series) selecting their specification on the basis of the univariate estimates of d . In particular, climate anomaly variables that behave as $I(0)$ are entered in levels, while variables consistent with $I(1)$ behaviour are entered in first differences to avoid spurious regressions and to maintain a balanced specification in a short sample. The regressions are run for each of the following three dependent variables: total indigenous livestock meat value, raw milk of cattle value, and the combined value of meat and milk. The baseline specification is the following:

$$y(t) = \alpha + \beta_0 t + \beta_1 \text{TEMP.ANOM}(t) + \beta_2 \text{SQUARED TEMP.ANOM}(t) + \beta_3 \text{PRECIP.ANOM}(t) + \beta_4 \text{SQUARED PRECIP.ANOM}(t) + \beta_5 \text{PERMAP}(t) + \beta_6 \text{AEAC}(t) + \beta_7 \text{ACGSF}(t) + \beta_8 \text{CPI}(t) + \beta_9 \text{RIR}(t) + \beta_{10} \text{OER}(t) + u(t), \quad (2)$$

where y_t denotes the first difference of the logged dependent variable, and therefore the coefficients can be interpreted as percentage changes. The squared climate terms are included to capture potential nonlinear effects, for example thresholds and asymmetric responses, where moderate deviations may be absorbed but extreme anomalies impose disproportionate costs.

As already mentioned, climate anomaly variables are entered in levels given their $I(0)$ behaviour, whilst economic and structural variables are entered in first differences, and in logs where appropriate, consistently with the univariate evidence suggesting that they are close to $I(1)$ processes. This mixed specification is also consistent with the economic structure of the sector. Climate anomalies represent deviations from a long run reference period and therefore behave differently from nominal or value-based aggregates that trend strongly due to inflation, population growth, and structural change.

We make two alternative assumptions about the error term u_t . First, we estimate the baseline regression under the assumption of serially uncorrelated errors, so inference relies on the standard OLS framework. Second, given the fact that macro time series regressions frequently exhibit residual autocorrelation, we formally test for it using the Breusch-Godfrey LM tests. When autocorrelation is detected, we estimate the model allowing u_t to follow an AR(1) process, i.e.

$$u_t = \rho u_{t-1} + \varepsilon_t, \quad |\rho| < 1, \quad (3)$$

where ε_t is a white noise. This correction improves the reliability of standard errors and reduces the risk of overstating statistical significance when the residuals are serially correlated.

It is important to distinguish clearly between the univariate and multivariate stages. Bloomfield-type errors are used in the univariate fractional integration analysis to capture weak autocorrelation without imposing an explicit AR structure. In the

multivariate regression analysis, we assume instead white noise errors as the baseline and AR(1) errors when the diagnostic tests indicate serial correlation. The reason for this difference is that the AR framework also measures persistence throughout the AR coefficient and is competing with the fractional differencing parameter in describing it and thus producing anomalous results in some cases.

5. Empirical Results

As a first step, standard unit root tests are carried out. Their results are reported in Tables 3 and 4.

Table 3: Unit Root Test Results (ADF & KPSS)

Test	Test Statistic	1% C.V	5% C.V	10% C.V	Decision
TEMP. ANOM.					
ADF	-6.831	-4.04	-3.45	-3.15	Reject $H_0 \rightarrow$ Stationary
KPSS	0.063	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary
SQ. TEMP. ANOM.					
ADF	-4.617	-4.04	-3.45	-3.15	Reject $H_0 \rightarrow$ Stationary
KPSS	0.162	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary
PRECIP. ANOM.					
ADF	-5.924	-4.04	-3.45	-3.15	Reject $H_0 \rightarrow$ Stationary
KPSS	0.15	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary
SQ. PRECIP. ANOM.					
ADF	-6.072	-4.04	-3.45	-3.15	Reject $H_0 \rightarrow$ Stationary
KPSS	0.12	0.216	0.146	0.119	Marginal ($\approx 10\%$) $\rightarrow$ Weak evidence against stationarity
TOLIM					
ADF	-2.988	-4.04	-3.45	-3.15	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.069	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary

RAMOC					
ADF	-2.896	-4.04	-3.45	-3.15	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.052	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary
TOVOMAMI					
ADF	-2.98	-4.04	-3.45	-3.15	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.069	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary
PERMAP					
ADF	-1.217	-4.04	-3.45	-3.15	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.161	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary
AEAC					
ADF	-0.093	-4.04	-3.45	-3.15	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.341	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary
ACGSF					
ADF	-1.824	-4.15	-3.5	-3.18	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.109	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary
CPI					
ADF	-1.386	-4.15	-3.5	-3.18	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.279	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary
RIR					
ADF	-4.185	-4.15	-3.5	-3.18	Reject $H_0 \rightarrow$ Stationary (at 1%)
KPSS	0.071	0.216	0.146	0.119	Fail to Reject $H_0 \rightarrow$ Stationary
OER					
ADF	2.461	-4.15	-3.5	-3.18	Fail to Reject $H_0 \rightarrow$ Non-stationary
KPSS	0.22	0.216	0.146	0.119	Reject $H_0 \rightarrow$ Not Stationary

Table 4: Summary of the Unit Root Test Results

Variable	ADF Stat	1% CV	5% CV	10% CV	KPSS Stat	1% CV	5% CV	10% CV	Stationary in Levels?
TEMP.ANOM	-6.831	-4.04	-3.45	-3.15	0.063	0.216	0.146	0.119	Yes
SQ.TEMP.ANOM	-4.617	-4.04	-3.45	-3.15	0.162	0.216	0.146	0.119	Yes (marginal)
PRECIP.ANOM	-5.924	-4.04	-3.45	-3.15	0.15	0.216	0.146	0.119	Yes
SQ.PRECIP.ANOM	-6.072	-4.04	-3.45	-3.15	0.12	0.216	0.146	0.119	Yes (borderline)
TOLIM	-2.988	-4.04	-3.45	-3.15	0.069	0.216	0.146	0.119	No
RAMOC	-2.896	-4.04	-3.45	-3.15	0.052	0.216	0.146	0.119	No
TOVOMAMI	-2.98	-4.04	-3.45	-3.15	0.069	0.216	0.146	0.119	No
PERMAP	-1.217	-4.04	-3.45	-3.15	0.161	0.216	0.146	0.119	No
AEAC	-0.093	-4.04	-3.45	-3.15	0.341	0.216	0.146	0.119	No
ACGSF	-1.824	-4.15	-3.5	-3.18	0.109	0.216	0.146	0.119	No
CPI	-1.386	-4.15	-3.5	-3.18	0.279	0.216	0.146	0.119	No
RIR	-4.185	-4.15	-3.5	-3.18	0.071	0.216	0.146	0.119	Yes
OER	2.461	-4.15	-3.5	-3.18	0.22	0.216	0.146	0.119	No

The ADF and KPSS tests provide mixed evidence regarding the stochastic properties of the series. The climate anomaly variables generally appear stationary in levels according to the ADF test, while the KPSS statistics provide only weak or marginal evidence against stationarity. By contrast, most economic and structural variables, including livestock production values, pasture area, employment absorption, credit, prices, and the exchange rate, display characteristics consistent with non-stationary behaviour. However, as already stated, these unit root tests, as well as others such as Phillips and Perron (PP, 1988) and Elliot et al. (ERS, 1996) have very low power if the true data generating process is fractionally integrated (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Schmid, 1996). Therefore, next we test for the fractional order of integration of the series. In particular, we estimate equation (1) including a constant, a linear time trend and $I(d)$ detrended series, and assume that the errors follow an autocorrelated process as in the exponential spectral model of Bloomfield (1973).

Table 5 displays the estimates of d from equation (1) under three different specifications: with θ_1 and θ_2 set equal to zero, i.e., without deterministic terms (column 2); when θ_2 set equal to 0, i.e. with a constant only (column 3); without restrictions, i.e. with both a constant and a linear time trend (column 4). To select our preferred model we follow a “general to specific” approach, i.e., we start with the specification including both an intercept and a linear time trend; then, if the time trend coefficient is found to be statistically insignificant, we move on to the case with an intercept only; finally, if the intercept is also insignificant, we select the model without deterministic terms.

Table 5: Estimates of d in a model with autocorrelated errors

Country	No terms	An intercept	An intercept and a linear time trend
TOLIM (in logs)	0.83 (0.51, 1.23)	0.94 (0.62, 1.39)	0.98 (0.74, 1.32)
TOVOMAM (in logs)	0.84 (0.52, 1.25)	0.98 (0.62, 1.39)	0.99 (0.75, 1.34)
RAMOC (in logs)	0.85 (0.54, 1.23)	0.75 (0.57, 1.44)	0.94 (0.68, 1.32)
PERMAP (in logs)	0.85 (0.54, 1.23)	1.15 (0.86, 1.59)	1.15 (0.84, 1.61)
TEMP. ANOM.	0.55 (0.38, 0.76)	0.44 (0.32, 0.59)	-0.27 (-0.64, 0.19)
SQ. TEMP. ANOM.	0.66 (0.43, 0.97)	0.49 (0.31, 0.89)	0.21 (-0.14, 0.89)
PRECIP. ANOM.	0.02 (-0.24, 0.39)	0.02 (-0.21, 0.35)	0.03 (-0.24, 0.39)
SQ. PRECIP. ANOM.	0.31 (0.08, 0.64)	0.20 (0.03, 0.44)	0.12 (-0.16, 0.61)
CPI (in logs)	0.94 (0.68, 1.38)	0.97 (0.72, 1.42)	0.87 (0.62, 1.24)
RIR	0.10 (-0.17, 0.49)	0.09 (-0.17, 0.42)	-0.52 (-0.97, 0.28)
OER (in logs)	0.80 (0.56, 1.49)	0.78 (0.58, 1.47)	0.75 (0.45, 1.26)
AEAC	0.75 (0.42, 1.15)	1.17 (0.98, 1.37)	1.16 (0.99, 1.39)
ACGSF (in logs)	0.34 (0.20, 1.10)	0.85 (0.62, 1.21)	0.78 (0.12, 1.22)

Note: The values of d are the estimates of the differencing parameter, with the 95% confidence bands in parenthesis. In bold the selected specification for each series based on the statistical significance of the deterministic terms.

Table 6 displays the estimated coefficients of the selected models for each series. It can be seen that the coefficient on the time trend is significant in all cases. except for

PERMAP, when only the intercept is significant, and for PRECIP ANM., when neither deterministic term is significant.

Table 6: Estimated coefficients from the selected models

Country	No terms	An intercept	An intercept and a linear time trend
TOLIM (in logs)	0.98 (0.74, 1.32)	18.172 (222.78)	0.0329 (3.45)
TOVOMAM (in logs)	0.99 (0.75, 1.34)	18.247 (238.85)	0.0322 (3.47)
RAMOC (in logs)	0.94 (0.68, 1.32)	15.609 (318.86)	0.0209 (4.22)
PERMAP (in logs)	1.15 (0.84, 1.61)	10.203 (1009.33)	-----
TEMP. ANOM.	-0.27 (-0.64, 0.19)	-11.85 (-42.08)	0.0180 (28.65)
SQ. TEMP. ANOM.	0.21 (-0.14, 0.89)	1.009 (6.15)	-0.0127 (-4.02)
PRECIP. ANOM.	0.03 (-0.24, 0.39)	-----	-----
SQ. PRECIP. ANOM.	0.12 (-0.16, 0.61)	32939.48 (4.76)	-366.20 (-2.70)
CPI (in logs)	0.87 (0.62, 1.24)	-1.824 (-19.73)	0.1675 (18.41)
RIR	-0.52 (-0.97, 1.28)	-10.639 (-11.74)	0.4071 (10.57)
OER (in logs)	0.75 (0.45, 1.26)	-0.733 (-2.79)	0.1563 (9.40)
AEAC	1.16 (0.99, 1.39)	78.983 (47.49)	-0.740 (-1.94)
ACGSF (in logs)	0.78 (0.12, 1.22)	9.858 (21.08)	0.0981 (2.77)

Note: The values in column 2 are the estimates of d and their associated 95% confidence band. Columns 3 and 4 report the estimates of the intercept and the time trend coefficient, with their t-values in parenthesis.

It is noteworthy that the estimates of d are very heterogeneous across the series, and the confidence bands are very wide in all cases, which probably reflects the short sample size for most of the series. The estimated values of d are above 1 for PERMAP (1.15) and AEAC (1.16), negative for RIR (-0.52), and in the interval (0, 1) in the other cases. Note, however, that the confidence intervals include the values 0 and 1 in all cases; thus, the null hypothesis of $d = 0$ (corresponding to the trend stationary representation of the series) cannot be rejected in the cases of the four climate series along with RIR, while the unit root representation (i.e., $d = 1$) cannot be rejected in the remaining cases. In the

case of RIR, the confidence interval is so wide that both hypothesis, $d = 0$ and $d = 1$, cannot be rejected. On the whole, evidence of $I(0)$ stationarity is found in the cases of the four-climate series, TEMP ANOM., SQ TEMP ANOM., PRECIP. ANOM. and SQ. PRECIP. ANOM., whilst for the rest of the series the $I(1)$ hypothesis of a unit root cannot be rejected.

On the basis of these results, next we estimate equation (2) with all the series in first differences, except for the four climate variables, which are expressed in levels. The results are reported in Table 7, 8 and 9 for RAMOC, TOLIM and TOVOMAM respectively as the dependent variable.

Table 7: Regression Results for RAMOC

	Dependent variable: RAMOC))
TEMP_ANOM	0.031 (0.040)
SQ_TEMP_ANOM	0.033 (0.078)
PRECIP_ANOM	-0.00002 (0.0001)
SQ_PRECIP_ANOM	0.00000 (0.00000)
Dlog_PERMAP	-1.232 (1.016)
D_AEAC	0.0004 (0.007)
D_RIR	0.0003 (0.001)
Dlog_CPI	0.055 (0.108)
Dlog_OER	0.006 (0.048)
Dlog_ACGSF	0.009 (0.022)
Constant	-0.007 (0.025)
Observations	42
R2	0.111
Adjusted R2	-0.176
Residual Std. Error	0.065 (df = 31)

F Statistic	0.387 (df = 10; 31)
=====	
Note: p-values in brackets; *p<0.1; **p<0.05; ***p<0.01	

Table 7 shows that a 1°C increase in temperature anomaly is associated with a 3.1% increase in the gross production value of raw milk (RAMOC), but this result is not statistically significant. The squared term is also positive, which suggests a convex (U-shaped) but insignificant relationship. A small negative effect of precipitation anomalies on RAMOC is found, though again it is insignificant. Its square suggests a very weak non-linear precipitation effect. A 1% increase in permanent meadow and pasture is associated with a 1.23% decrease in RAMOC, which is unexpected but not significant. Agricultural employment absorption capacity changes have a negligible and insignificant impact.

The results also show an insignificant positive relationship between the real interest rate and RAMOC, and a significant positive CPI impact. Finally, there is a very small and insignificant effect of the exchange rate, and a positive, but insignificant effect of agricultural credit. Overall, none of these factors are statistically significant. The R^2 is in fact low (0.11), and the model does not explain the variation in RAMOC well.

Table 8: Regression Results for TOLIM

	Dependent variable:
	TOLIM))
TEMP_ANOM	-0.027 (0.035)
SQ_TEMP_ANOM	-0.004 (0.069)
PRECIP_ANOM	-0.0001 (0.0001)
SQ_PRECIP_ANOM	0.00000 (0.00000)

Dlog_PERMAP	-1.443 (0.889)
D_AEAC	-0.002 (0.006)
D_RIR	0.0003 (0.001)
Dlog_CPI	0.025 (0.094)
Dlog_OER	-0.074* (0.042)
Dlog_ACGSF	-0.015 (0.020)
Constant	0.023 (0.022)
Observations	42
R2	0.218
Adjusted R2	-0.034
Residual Std. Error	0.056 (df = 31)
F Statistic	0.866 (df = 10; 31)
=====	
Note: p-values in brackets; *p<0.1; **p<0.05; ***p<0.01	

Table 8 shows a slight negative but insignificant effect of temperature anomalies on gross production value of Total Livestock Meat - Indigenous (TOLIM) (-2.7%), with no evidence of non-linear effects. There is also a very small negative impact of precipitation anomalies on TOLIM. A 1% increase in PERMAP is estimated to lead to a 1.4% decrease in TOLIM, but again this coefficient is insignificant. We also find a weak negative effect of the agricultural employment share, a negligible impact of the real interest rate, an insignificant CPI effect (this coefficient implying that a 1% increase in CPI would lead to an increase of 2.5% in TOLIM), and a negative effect of a depreciation of the exchange rate on the gross production value of total livestock meat (indigenous). Further, agricultural loans to the livestock sector have a negative but insignificant effect. Of all the variables, only the exchange rate (Dlog_OER) has a weak, significant effect. The model explains 22% of variation in TOLIM ($R^2 = 0.218$), but the F-statistic is not significant.

Table 9: Regression Results for TOVOMAMI

	Dependent variable: TOVOMAMI)
TEMP_ANOM	-0.025 (0.033)
SQ_TEMP_ANOM	-0.002 (0.065)
PRECIP_ANOM	-0.0001 (0.0001)
SQ_PRECIP_ANOM	0.00000 (0.00000)
Dlog_PERMAP	-1.429* (0.842)
D_AEAC	-0.001 (0.006)
D_RIR	0.0003 (0.001)
Dlog_CPI	0.025 (0.089)
Dlog_OER	-0.071* (0.039)
Dlog_ACGSF	-0.014 (0.019)
Constant	0.022 (0.021)
Observations	42
R2	0.225
Adjusted R2	-0.024
Residual Std. Error	0.053 (df = 31)
F Statistic	0.903 (df = 10; 31)
=====	
Note: p-values in brackets: *p<0.1; **p<0.05; ***p<0.01	

Table 9 shows that there is a negative, but insignificant, relationship between temperature anomaly and total value (gross production) of meat and milk, indigenous (TOVOMAMI), and that non-linearities are not present. It also suggests that precipitation has an insignificant, slight negative linear effect. Permanent meadow and pasture appear to affect TOVOMAMI, which is counterintuitive and possibly reflects land inefficiency, degradation or competition. Changes in agricultural employment seem to have no impact

on TOVOMAMI, and both the real interest rate and the consumer price index (inflation) have insignificant positive effects. Devaluations of the official exchange rates have a significant negative effect on TOVOMAMI, as they increase input costs (machineries, fertilizers, etc.). Agricultural credit from the federal government of Nigeria, through the Central Bank of Nigeria, allocated to the whole livestock sector, does not significantly affect TOVOMAMI. As in the case of TOLIM, permanent meadow and pasture (Dlog_PERMAP) as well as the exchange rate (Dlog_OER) are only weakly significant. The model explains ~23% of the variance ($R^2 = 0.225$), and the overall fit is low.

Table 10: Breusch-Godfrey Autocorrelation tests

Model	LM Statistic	df	p-value	Interpretation
TOLIM	5.42	2	0.0666	Mild evidence of autocorrelation ($p < 0.1$). Consider correcting it.
RAMOC	1.89	2	0.3895	No evidence of autocorrelation. Residuals appear to be white noise.
TOVOMA MI	5.88	2	0.0529	Borderline significant autocorrelation ($p \approx 0.05$).

The Breusch–Godfrey LM test examines the null hypothesis of no serial correlation in the regression residuals. The reported statistics correspond to tests for second-order autocorrelation (lag order = 2). A low p-value leads to rejection of the null hypothesis, indicating the presence of residual autocorrelation.

Table 10 reports the Breusch–Godfrey LM tests for residual autocorrelation. The results suggest that the RAMOC model does not exhibit serial correlation, as the null hypothesis of no autocorrelation cannot be rejected. By contrast, the TOLIM and TOVOMAMI models show some evidence of residual autocorrelation at the 10 percent significance level. To account for this possibility, the regressions are re-estimated allowing for AR(1) disturbances. This correction improves the reliability of the estimated standard errors and provides a robustness check for the baseline results.

Tables 11 and 12 report the corresponding results assuming AR (1) errors.

Table 11: AR(1) Regression Results for TOLIM

	TOLIM with AR(1) errors
Intercept	0.034* (0.017)
TEMP_ANOM	-0.005 (0.029)
SQ_TEMP_ANOM	-0.029 (0.064)
PRECIP_ANOM	0.000 (0.000)
SQ_PRECIP_ANOM	0.000 (0.000)
Dlog_PERMAP	-2.338** (0.808)
D_AEAC	0.004 (0.005)
D_RIR	0.001 (0.001)
Dlog_CPI	0.040 (0.076)
Dlog_OER	-0.109** (0.034)
Dlog_ACGSF	-0.011 (0.016)
Num.Obs.	42
R ²	0.132
p-values in brackets; p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001	

Notes: The dependent variable is the first difference of the logarithm of total indigenous livestock meat production value (TOLIM). Climate variables enter the model in levels as temperature and precipitation anomalies and their squared terms, while economic and structural variables are included in first differences, and in logarithmic form where appropriate. The regression allows for AR(1) disturbances to account for residual autocorrelation detected in the baseline specification. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11 shows that, when accounting for autocorrelation in the residuals in the form of an AR(1) process, more precise estimates are obtained. While the effects of temperature anomalies and precipitation effects remain small and statistically insignificant, two variables now emerge as statistically significant. More specifically:

- A 1% increase in permanent meadow and pasture (PERMAP) is associated with a 1.65% decrease in TOLIM ($p = 0.0069$), which suggests a negative impact possibly due to land misallocation, degradation, or inefficient use.
- A 1% increase in the exchange rate (depreciation) is associated with a 7.4% decline in TOLIM ($p = 0.0031$), reflecting the impact of currency weakness on input costs, possibly raising the cost of feed or infrastructure.

Other variables such as temperature anomalies (TEMP_ANOM), the consumer price index (CPI), and real interest rates remain statistically insignificant, though the sign of the coefficients is largely consistent with prior expectations. Overall, the model fit improves slightly, and the residual diagnostics support the inclusion of the AR(1) term, enhancing the reliability of inference.

Table 12: AR(1) Regression Results for TOVOMAMI

	TOVOMAMI with AR(1) errors
Intercept	0.033* (0.016)
TEMP_ANOM	-0.005 (0.027)
SQ_TEMP_ANOM	-0.025 (0.060)
PRECIP_ANOM	0.000 (0.000)
SQ_PRECIP_ANOM	0.000 (0.000)
Dlog_PERMAP	-2.231** (0.760)
D_AEAC	0.004 (0.005)
D_RIR	0.001 (0.001)
Dlog_CPI	0.036 (0.072)

	TOVOMAMI with AR(1) errors
Dlog_OER	-0.104** (0.032)
Dlog_ACGSF	-0.010 (0.015)
Num.Obs. 42 R ² 0.145	
p-values in brackets: $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

Notes: The dependent variable is the first difference of the logarithm of the total value of indigenous meat and milk production (TOVOMAMI). Climate variables (temperature and precipitation anomalies and their squared terms) enter the regression in levels, while economic and structural variables are included in first differences and in logarithmic form where appropriate. The regression allows for AR(1) disturbances in order to correct for residual autocorrelation detected in the baseline model. Standard errors are reported in parentheses.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample consists of annual observations for the period 1981–2023.

Table 12 shows that, in the case of TOVOMAMI, when introducing the AR(1) correction two variables become statistically significant:

- A 1% increase in PERMAP is now significantly associated with a 1.7% decrease in total livestock value ($p = 0.0062$). This again suggests land use inefficiencies or inverse productivity trends.
- A 1% depreciation of the exchange rate (OER) reduces TOVOMAMI by 6.9%, and this effect is significant at 1% ($p = 0.0028$). This aligns with prior expectations that depreciation raises input costs.

The effects of temperature anomaly and precipitation effects remain weak, and so do those of CPI, RIR, and ACGSF. Overall, the model performance improves when introducing the AR(1) correction; the improved precision of the estimates highlights the importance of accounting for autocorrelation in macro-level agricultural data.

Note that the lack of statistical significance of several factors is a likely consequence of the small sample size (42 observations), and thus caution should be applied when interpreting the findings.

6. Conclusions

This study examines the relative importance of climatic variability, structural agricultural conditions, and macroeconomic factors in explaining changes in Nigeria's indigenous livestock production between 1981 and 2023. More specifically, after analysing the properties of the individual series by estimating fractional integration models, we run multivariate regressions to investigate the effects of temperature anomalies and its square, precipitation anomalies and its square, permanent meadows and pasture (PERMAP), consumer price index (CPI), real interest rate (RIR), official exchange rate (OER), agricultural employment absorption capacity (AEAC), value of Agricultural Credit Guarantee Scheme Fund (loan) apportioned for the whole livestock sector (ACGSF) on three respective dependent variables, total indigenous livestock meat gross production value (TOLIM), raw milk of cattle gross production value (RAMOC), and Total value (gross production) of meat and milk - Indigenous (TOVOMAMI) from 1981 to 2023.

Livestock production in Nigeria is concentrated largely in the northern savannah zones, where pastoral and agro-pastoral systems dominate and where production depends heavily on natural pasture, seasonal rainfall, and mobility across ecological zones. The sector operates within a broader agricultural space characterized by limited mechanization, weak rural infrastructure, recurrent farmer herder conflict, and strong dependence on imported inputs such as veterinary drugs and feed components. Against this background, the analysis applies fractional integration methods and multivariate time series regressions to examine long run persistence and the main structural drivers of livestock output.

The fractional integration results indicate a considerable degree of persistence in the livestock production series, with most point estimates of the differencing parameter

being close to one. However, the confidence intervals are wide and generally encompass both zero and one, which is not surprising given the relatively short sample period. For this reason, unit root behaviour cannot be formally rejected. In other words, the evidence does not provide definitive proof of fractional integration.

Nevertheless, the estimates are consistent with the idea that livestock production in Nigeria adjusts slowly and that shocks may have effects that linger over time. Such persistence is plausible in a sector where herd rebuilding takes years rather than months, where investment decisions are made cautiously under uncertainty, and where institutional support, credit access, and infrastructure remain limited. In this sense, the results align with the structural realities of Nigeria's livestock systems, even if they do not allow for strong statistical claims about long memory.

The multivariate empirical results show that temperature and precipitation anomalies do not have statistically significant effects on national livestock production values. Although the estimated coefficients often have negative signs, they are generally not statistically different from zero. At the national level, this suggests that year to year climate variability may not be the primary driver of fluctuations in indigenous meat and milk production. In Nigeria, pastoral mobility, the use of heat tolerant indigenous breeds, and seasonal herd movements across ecological zones may partially cushion short term climatic shocks. At the same time, national aggregates may conceal important regional variation, particularly in the far north where drought episodes are more severe. The absence of strong aggregate climate effects therefore does not imply that climate stress is unimportant, but rather that its measurable impact at the aggregate level appears limited over the sample period.

By contrast, macroeconomic instability, particularly exchange rate depreciation, appears to affect more strongly livestock production once autocorrelation is taken into

account. Nigeria's livestock sector depends on imported veterinary pharmaceuticals, feed additives, machinery, and fuel. When the currency depreciates, the domestic cost of these inputs rises sharply. The negative and statistically significant relationship between exchange rate depreciation and livestock output suggests that currency instability increases production costs and discourages investment. In this context, macroeconomic fragility appears to constrain livestock productivity more directly than interannual temperature or rainfall fluctuations.

The negative association between permanent pasture expansion and livestock value is also economically meaningful. Nigeria's grazing lands have faced pressure from desertification in the north, encroachment by crop farming in the Middle Belt, urban expansion, and insecurity in conflict affected regions. An increase in reported pasture area does not necessarily translate into higher productivity per animal. It may reflect declining land quality, overgrazing, or the expansion of marginal lands with low carrying capacity. The results therefore indicate that land expansion alone does not ensure higher output and that productivity improvements require better pasture management, water infrastructure, and feed systems rather than simply more hectares.

On the whole, the findings in this study imply that policies focusing exclusively on climate adaptation are unlikely to address the main constraints facing Nigeria's indigenous livestock industry. While drought management and heat stress mitigation remain important, stabilizing the macroeconomic environment, improving rural infrastructure, strengthening veterinary services, and supporting access to affordable inputs may have more immediate effects on production. In addition, the limited explanatory power of national level regressions suggests that future research should focus on regional data, particularly in northern states where climate exposure, insecurity, and land pressure are most pronounced.

To conclude, our analysis suggests that at the aggregate level (though not necessarily at the regional one) the effects of climate change on Nigerian indigenous livestock might be weaker than those of structural economic conditions. In Nigeria's current agricultural setting, characterized by exchange rate volatility, land degradation, infrastructure deficits, and security challenges, macroeconomic and structural factors may play a more decisive role than short-term climate variability in determining livestock sector performance.

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