



# Agricultural Employment in Somalia: The Nexus of Climate Change, Conflict, and Agricultural Productivity

Abdikadir Ahmed Mohamed<sup>\*</sup>, Abdi Majid Yusuf Ibey<sup>†</sup>, Abdifatah Mohamed Abdikarim<sup>†</sup>, Galad Mohamed Barre<sup>†</sup>

Faculty of Economics and Management, Jamhuriya University of Science and Technology, Mogadishu, Somalia

<sup>\*</sup> Correspondence: Abdikadir Ahmed Mohamed ([abdikadir.ahmed@just.edu.so](mailto:abdikadir.ahmed@just.edu.so))

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**Abstract:** Agriculture is central to Somalia's economy, employing nearly half of the population and serving as a key source of rural livelihoods. However, the sector is increasingly undermined by climate change, deforestation, and armed conflict. In a context marked by high unemployment and institutional fragility, understanding how these challenges affect agricultural employment is essential for policy design. This study aims to analyze the short- and long-run effects of climate change (rainfall, temperature, CO<sub>2</sub> emissions, and deforestation), conflict (internal and external), and agricultural productivity (crop and livestock production) on agricultural employment in Somalia between 1991–2022. Using Autoregressive Distributed Lag (ARDL) and Generalized Method of Moments (GMM) models, the study captures dynamic interactions while addressing endogeneity and model robustness through stability and diagnostic tests. The results show that rising temperatures and CO<sub>2</sub> emissions significantly reduce agricultural employment, while deforestation contributes to long-term job losses by degrading arable land. Rainfall variability supports employment in the short run but lacks long-term significance. Internal conflict exhibits a paradoxical stabilizing effect due to labor immobility, while external conflict leads to displacement and labor market disruption. Livestock production emerges as a consistent driver of rural employment, whereas crop production remains stagnant and fails to absorb labor. By integrating environmental and political stressors within a unified econometric framework, this study contributes to the literature on employment dynamics in fragile contexts. The findings underscore the need for climate-resilient farming practices, conflict-sensitive rural development, reforestation, and investment in the livestock sector to safeguard livelihoods and promote economic resilience in Somalia.

**Keywords:** Agricultural employment; Climate change; Conflict; Agricultural production; Autoregressive Distributed Lag (ARDL); Generalized Method of Moments (GMM); Somalia

## 1 Introduction

Somalia is widely recognized as one of the most climate-vulnerable countries in the world. It regularly experiences extreme weather events such as prolonged droughts, erratic rainfall, and periodic flooding. Over the past two decades, the country has endured more than thirty climate-related disasters, including recurrent droughts that have devastated crops and livestock and displaced millions [1]. More than 70% of Somalia's population depends on climate-sensitive agricultural activities for their livelihoods [2]. These disruptions have intensified food insecurity and undermined the ability of rural populations to sustain agricultural practices, not merely in terms of formal wage employment, but in terms of physical access to farming, livestock rearing, and productive rural engagement.

This inability to engage in agriculture is exacerbated by political instability, which has persisted for decades and remains a defining feature of Somalia's governance landscape. Weak institutions, fragmented authority, and frequent armed conflicts have disrupted economic systems and stifled efforts to build long-term resilience [3, 4]. As a result, many farming communities have been displaced from their land, while others have had to abandon agricultural activities due to insecurity or lack of support. In many rural areas, deforestation primarily driven by charcoal production adopted as a survival strategy has further reduced arable land and degraded natural ecosystems [5, 6]. Meanwhile, in urban centers, conflict has forced populations to migrate to rural areas, increasing pressure on

already fragile agricultural systems [7]. Together, these dynamics have disrupted the flow of agricultural labor and exacerbated unemployment in both rural and urban settings.

Although agriculture remains the backbone of Somalia's economy, contributing significantly to national GDP and rural income, its capacity to provide stable and sustainable employment has been weakened by environmental and political shocks [8]. Rising temperatures, declining and unpredictable rainfall, soil degradation, and the absence of climate adaptation mechanisms have all contributed to a steady erosion of agricultural potential [9, 10]. These changes are not only reducing productivity but are also rendering many farming areas unworkable, contributing to what could be better described as "employment displacement" rather than mere wage-based unemployment. In this context, agricultural employment must be understood as the capacity to engage in productive rural labor, which is now threatened by both climate and conflict-related disruptions.

Despite growing academic interest in climate-related challenges in fragile economies, research that simultaneously examines the interplay of climate change, conflict, agricultural production, and labor market outcomes in Somalia remains limited. Existing studies, such as Ahmed et al. [11] and Hassan and Mohamed [12], focus on climate variables and agricultural productivity but often neglect how these environmental stressors affect employment outcomes a critical concern in Somalia's informal, rural labor markets.

A recent study by Nor and Mohamad [13], explores the environmental impacts of agricultural productivity, GDP per capita, and renewable energy consumption using Autoregressive Distributed Lag (ARDL) methods. While their work provides valuable insights into the link between agriculture and environmental degradation, it does not investigate labor outcomes, nor does it account for conflict dynamics or the employment implications of deforestation and CO<sub>2</sub> emissions.

This study addresses these gaps by focusing on agricultural employment as the core outcome variable and incorporating a broader set of climate stressors rainfall, temperature, CO<sub>2</sub> emissions, and deforestation alongside both internal and external conflict. It also distinguishes between crop and livestock production, reflecting sector-specific labor dynamics. Methodologically, the study combines ARDL to capture short- and long-run effects with GMM to control for potential endogeneity, offering a more dynamic and robust analysis of agricultural employment trends in fragile contexts like Somalia.

The study is guided by several core research questions: How do climate-related variables such as rainfall, temperature, CO<sub>2</sub> emissions, and deforestation affect agricultural employment in Somalia? What is the impact of internal and external conflict on rural labor engagement and access to agricultural livelihoods? How do crop and livestock production mediate or amplify the effects of environmental and political stressors? And finally, to what extent can dynamic modeling approaches capture both the immediate and delayed effects of these variables on employment in fragile agricultural systems?

In line with these questions, the main objectives of the study are threefold. First, it aims to identify the key climate and conflict-related factors influencing agricultural employment in Somalia. Second, it seeks to examine the interplay between environmental variables and agricultural productivity (both crops and livestock) in shaping rural employment patterns. Third, it intends to develop policy-relevant recommendations that address the structural vulnerabilities of Somalia's agricultural labor systems and enhance their resilience to future shocks.

The structure of this article is organized as follows. The next section provides a detailed review of the theoretical and empirical literature on climate change, conflict, and agricultural employment, with a focus on fragile state contexts. The third section presents the methodological framework, including data sources, variables, and the specification of the econometric models used. The fourth section discusses the empirical findings, highlighting both short-run and long-run effects of the independent variables on agricultural employment. The final section concludes with a synthesis of key insights, implications for policy and practice, and suggestions for future research.

## 2 Literature Review

Climate change, as defined by the Intergovernmental Panel on Climate Change (IPCC) [14], refers to long-term alterations in temperature, precipitation, and other weather patterns, primarily caused by human activities such as fossil fuel combustion, deforestation, and industrial emissions. These environmental disruptions are increasingly affecting ecosystems, food systems, and human livelihoods. In fragile states like Somalia, which depend heavily on rain-fed agriculture, the consequences are particularly severe. Agriculture in Somalia encompassing both crop cultivation and livestock rearing employs nearly half the population and is highly sensitive to climatic variability, environmental degradation, and socio-political instability.

According to the IPCC framework, vulnerability to climate change is defined by three elements: exposure, sensitivity, and adaptive capacity. Somalia's agriculture is highly exposed due to frequent droughts, erratic rainfall, and rising temperatures. Its sensitivity is pronounced because of dependence on subsistence agriculture, limited irrigation, and fragile soil conditions. Moreover, adaptive capacity remains low due to institutional weaknesses, poor access to technology, and insufficient climate financing. These conditions make agricultural employment highly precarious, particularly for vulnerable rural populations.

In this study, agricultural workers refer to individuals involved in crop farming, livestock management, or both whether self-employed smallholders, pastoralists, or wage laborers. This includes workers engaged in informal sectors that dominate Somalia's rural economy. Understanding their exposure to climate risks is vital for evaluating employment outcomes in this fragile context.

Several Somalia-specific studies have linked climate variability to agricultural employment and productivity. For instance, the study [11] shows that climate-induced food insecurity has significantly weakened rural employment. Hassan and Mohamed [12], using an ARDL model, find that rainfall variability depresses short-term productivity but can support long-term agricultural output if coupled with investment and demographic growth. Similarly, Nor and Mohamad [13] demonstrate that CO<sub>2</sub> emissions reduce agricultural employment by degrading productive land and increasing vulnerability. These findings align with the researchers [6], who emphasize that displaced rural populations often resort to charcoal production, contributing to deforestation and long-term labor market deterioration.

Broader evidence from Sub-Saharan Africa and Asia complements these findings. Alehile [15], using a nonlinear ARDL model for Nigeria, reveals that both positive and negative rainfall and temperature shocks negatively affect agricultural employment in the long run. Though some short-term benefits exist, they are offset by lagged adverse effects. Uddin and Al Mamun [16], in a PMG-ARDL study on South Asia, show that rising temperatures may temporarily boost employment but ultimately reduce it over time. Rainfall effects were insignificant, possibly due to institutional and adaptive gaps. These findings reinforce the idea that climate impacts on labor are complex, non-linear, and context-dependent.

A range of global studies also highlight the interaction between climate shocks and employment. Jiang and Guo [17], using microdata from China, find that heatwaves extend rural labor migration, reducing local labor availability. Javeed [18] shows that irregular rainfall and temperature shifts compel farmers to abandon agriculture in favor of informal urban work. Feriga et al. [19] examine labor dynamics under climate stress, finding that heat exposure reduces productivity, increases absenteeism, and accelerates labor reallocation away from agriculture. In Southern Africa, Madzivhandila and Niyimbanira [20] show that floods and droughts lead to job losses and food insecurity among informal rural workers. Piya et al. [21] add that droughts reduce land-based employment, driving livelihood diversification in vulnerable regions.

Deforestation, both as a cause and consequence of rural displacement, emerges as a critical theme. In Somalia, charcoal production is a major contributor to deforestation [22] degrading arable land and further reducing employment options in agriculture. This reflects findings by Semeraro et al. [23], who argue that poor countries suffer dual threats from reduced productivity and increased competition for limited resources. As forests decline, so do communal labor systems, especially those supporting livestock grazing and small-scale farming.

The role of carbon emissions and global warming is extensively debated. While Rehman et al. [24] and Ozdemir [25] suggest short-term fertilization benefits from CO<sub>2</sub>, long-term effects include desertification, soil nutrient loss, and water scarcity. In the EU context, Łacka et al. [26] find that while emissions initially boost yields, their effects diminish over time due to accumulated environmental degradation. Crucially, EU countries can mitigate this decline through technological investment a strategy largely unavailable in Somalia due to weak institutional capacity.

Gender and social inequalities further compound these challenges. Murugesan and Swaminathan [27] show that women are more vulnerable to climate-induced employment loss due to limited access to resources and decision-making structures. Mehra et al. [28] highlight how extreme heat and food insecurity reduce female labor participation, impacting agricultural output and household well-being.

The literature also explores the relationship between agricultural productivity and employment generation. Madhurima et al. [29] and Rasikh et al. [30] show that optimizing cropping patterns and input use can enhance employment in India and Afghanistan, especially when credit and technology are accessible. Conversely, Charlton [31] argues that agricultural transformation and mechanization in commercial farms may reduce labor demand while increasing seasonal and migrant labor dependency. Mlambo [32] and Asaleye et al. [33] provide evidence that agricultural output correlates negatively with unemployment in Africa, while Osabohien et al. [34] emphasize agriculture's potential for inclusive growth if human capital constraints are addressed.

Further global studies underscore the foundational role of agriculture in reducing poverty and enhancing food security. For example, Syahputri et al. [35] show that agriculture remains a key source of employment and nutrition in rural economies, yet climate change undermines these gains by increasing production risks. Aboye et al. [36], based on fieldwork in Ethiopia, reveal how farmers adjust livelihood strategies in response to irregular rainfall and pasture shortages—often switching from livestock to informal labor or aid dependency. Prince et al. [37] reinforce that floods, droughts, and pest outbreaks disrupt both planting cycles and livestock production, further destabilizing employment.

Despite this growing body of research, several limitations persist. Many studies rely on static or regionally aggregated models that fail to reflect dynamic, localized interactions among climate, conflict, and labor. For instance, PMG and fixed-effects models often miss feedback loops and lagged effects. To overcome the limitations of

static models, recent studies have increasingly applied dynamic techniques such as ARDL and NARDL, and others, few integrate political instability and sector-specific characteristics like livestock dependence. Moreover, studies focusing on Europe or Asia (e.g., Ali [38] and Łacka et al. [26]) assume technological buffers and market access conditions often absent in Somalia.

In response to these gaps, this study develops a context-specific framework to assess the combined effects of rainfall, temperature, CO<sub>2</sub> emissions, deforestation, and conflict (both internal and external) on agricultural employment in Somalia. Unlike previous studies that examine these variables in isolation, this research adopts a dynamic and integrated econometric approach. It also accounts for Somalia's unique socio-economic conditions, such as dependence on livestock, weak governance, and conflict-induced displacement. By exploring these complex interactions, the study contributes a nuanced understanding of how environmental and political stressors jointly influence rural labor markets in fragile economies.

### 3 Conceptual Framework

This study is guided by a conceptual framework that explores the dynamic causal pathways linking climate change, conflict, and agricultural output to agricultural employment in Somalia, as shown in Figure 1. The framework identifies key variables rainfall, temperature, CO<sub>2</sub> emissions, deforestation, livestock production, crop production, and conflict as primary drivers of agricultural employment. Each variable is expected to influence employment through distinct channels: rainfall (+) supports labor demand during good seasons; temperature (-), CO<sub>2</sub> emissions (-), and deforestation (-) reduce productivity and land quality, lowering labor absorption; internal and external conflict (-) disrupt labor markets and mobility; while livestock (+) and crop production (+) are directly tied to employment creation. These relationships are structured to reflect one-way causal impacts, aligning with the study's methodological focus on ARDL and GMM models to capture short- and long-term effects. This framework draws on labor demand theory and the endogenous growth approach, highlighting how environmental and political conditions affect employment through productivity and sectoral shocks.

#### 3.1 Methodology

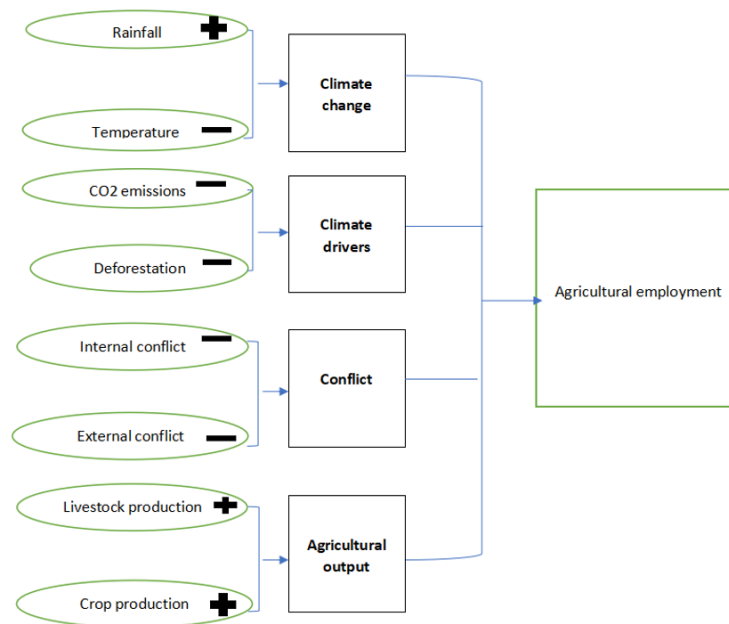
This study investigates the effects of climate variables, agricultural production, and political variables on agricultural employment in Somalia, using time series data from 1991 to 2022. The selection of this period ensures the availability of consistent and comprehensive data, allowing for robust and reliable analysis while maintaining data integrity. The dependent variable in this study is Agricultural Employment (AE), measured as the percentage of the total workforce employed in agriculture. This indicator is critical for understanding rural livelihoods and economic stability in agrarian economies like Somalia [39].

The independent variables include climate factors such as rainfall (RF), temperature (TP), carbon dioxide CO<sub>2</sub> emissions [13], and deforestation [40]. Political variables such as internal and external conflicts [41] are also included, alongside agricultural output variables like Crop Production (CP) and Livestock Production (LP) [42]. These variables are selected based on their demonstrated relevance to agricultural outcomes, as evidenced by studies [43–47], which emphasize the role of climate, conflict, and agricultural production in shaping employment dynamics.

To improve consistency and interpret the results in percentage terms, some of the variables, including rainfall, temperature, carbon dioxide emissions, crop production, and livestock production, were transformed into their natural logarithms. This transformation also helps stabilize variance and allows the coefficients to be interpreted as elasticities, which aligns with the standard approach in econometric modeling. The data for these variables were sourced from reputable databases, including the World Bank, the Climate Change Knowledge Portal (CCKP), and the International Country Risk Guide published by Political Risk Service (PRS-ICRG). Table 1 provides a detailed description of the variables and their sources.

#### 3.2 Econometric Model Specification

The formulation of the specifications of the agricultural employment model in the present study has been guided by Abdelgawwad and Kamal [48], Samatar [49], who used ARDL, and Osabohien et al. [34], Suproń and Myszczyński [50] who used Generalized Method of Moments (GMM). Based on this framework, the first step of the research estimates the impacts of climatic variables, agricultural production, and livestock production on the agricultural employment sector in Somalia. To address the research objectives, this study employs two complementary econometric models: the ARDL and the GMM. The ARDL approach is particularly well-suited for time series data that are characterized by small sample sizes and mixed integration orders [I(0) and I(1)], which is the case for Somalia [51]. Unlike conventional cointegration methods, ARDL allows for the estimation of both short-run and long-run relationships without requiring pre-testing for unit root at the same order. Additionally, it accommodates different lag structures across variables, which is important in contexts with irregular data dynamics.



**Figure 1.** Conceptual framework

**Table 1.** Nature of the data

| Variable                      | Notation        | Measurement  | Source     |
|-------------------------------|-----------------|--|------------|
| DV: Employment                |                 |  |            |
| Agricultural employment       | AEM             | Employment in agriculture (% of total employment) (modeled ILO estimate)   | World Bank |
| Climate Variables             |                 |  |            |
| Rainfall                      | RF              | Average annual precipitation (mm)  | CCKP       |
| Temperature                   | TP              | Average annual temperature in (°C )  |            |
| Carbon dioxide                | CO <sub>2</sub> | CO <sub>2</sub> emissions (kt)   | World Bank |
| Deforestation                 | DF              | Arable land (% of land area)   |            |
| Agricultural Output Variables |                 |  |            |
| Crop production               | CP              | Crop production index (2014–2016 = 100)  | World Bank |
| Livestock production          | LP              | Livestock production index (2014–2016 = 100)   |            |
| Conflict Variables            |                 |  |            |
| Internal conflict             | IC              | It is assessment rating contains three components: (a) civil war/coup threat, (b) terrorism/political violence, (c) civil disorder | PRS-ICRG   |
| External conflict             | EC              | It is assessment rating contains three components: (a) war, (b) cross-border conflict, (c) foreign pressures                       |            |

The GMM model is employed to address endogeneity concerns, especially where explanatory variables (e.g., climate and conflict indicators) may be correlated with the error term. GMM is robust to heteroscedasticity and autocorrelation and is effective in estimating dynamic models with lagged dependent variables [52, 53]. Although GMM is more common in panel datasets, its principles are valid for time series settings when simultaneity and omitted variable bias are present. This dual-model strategy helps enhance the robustness of results, particularly in fragile economies where data limitations and institutional shocks are common. ARDL model for this study [12] is specified as follows:

$$AEM_t = \beta_0 + \beta_1 RF_t + \beta_2 TP_t + \beta_3 CO2_t + \beta_4 DF_t + \beta_5 IC_t + \beta_6 EC_t + \beta_7 CP_t + \beta_8 LP_t$$

$AEM_t$  are agricultural employment at t time;  $RF_t$ ,  $TP_t$ ,  $CO2_t$ ,  $DF_t$ , are rain fall, temperature and carbon dioxide and Deforestation at time t;  $IC_t$ ,  $EC_t$  are internal, and External conflict respectively at time t.  $CP_t$ ,  $LP_t$ , are crop production and livestock production at t time.  $\beta_0$  is the intercept,  $\beta_1$ , to  $\beta_8$  are coefficients.



### 3.3 Estimation Procedure

The ARDL approach encompasses estimation of both the short-run and long-run dynamics. Here, the presence of the long-run relationship is verified by using the bounds testing approach for cointegration. If the F-statistic exceeds the critical value bounds, cointegration is confirmed, indicating the presence of a long-term relationship among the variables.

The ARDL model specifies the error correction model-ECM, which helps to encapsulate the short-term dynamics while preserving the long-term equilibrium. The typical formulation of the ECM applicable to each model may be presented as follows:

$$\begin{aligned} AEM = & \beta_0 + \sum_{i=1}^{\rho} \varphi_1 \Delta RF_{t-i} + \sum_{i=1}^{\rho} \varphi_2 \Delta TP_{t-i} + \sum_{i=1}^{\rho} \varphi_3 \Delta CO_{t-i} \\ & + \sum_{i=1}^{\rho} \varphi_4 \Delta DF_{t-i} + \sum_{i=1}^{\rho} \varphi_5 \Delta IC_{t-i} + \sum_{i=1}^{\rho} \varphi_6 \Delta EC_{t-i} + \sum_{i=1}^{\rho} \varphi_7 \Delta CP_{t-i} \& \\ & + \sum_{i=1}^{\rho} \varphi_8 \Delta LP_{t-i} + \delta_1 RF_{t-1} + \delta_2 TP_{t-1} + \delta_3 CO_{t-1} + \delta_4 DF_{t-1} + \delta_5 ICC_{t-1} \\ & + \delta_6 EC_{t-1} + \delta_7 CP_{t-1} + \delta_8 \log LP_{t-1} + \delta_9 EC_{t-1} + \varepsilon_t \end{aligned}$$

$\beta_0$  is the intercept,  $\varphi$  is the coefficient for the long run,  $\delta$  represents the short run,  $\rho$  is the number of lags,  $\Delta$  is the operator of first difference,  $EC_{t-1}$  is the speed of adjustment parameter and  $\varepsilon_t$  is the error term.

After unit root testing confirmed a mix of  $I(0)$  and  $I(1)$  variables, optimal lag lengths were determined using standard information criteria including the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ). Choosing appropriate lag length is especially critical in fragile contexts like Somalia, where shocks may have delayed effects, and under- or over-parameterization can distort estimates. The ARDL bounds test is then conducted to assess cointegration, with small-sample critical values from Narayan and Narayan [54] applied to ensure robustness. An additional F-test for degenerate cases is also used to confirm that the long-run relationship is not driven solely by the lagged dependent variable or the regressors.

Following confirmation of cointegration, the ARDL model is estimated to capture both short-run and long-run effects. To address potential endogeneity and dynamic bias, the study also applies the System Generalized Method of Moments (GMM) [55]. Finally, a series of diagnostic tests including tests for normality, serial correlation, heteroscedasticity, and model stability using CUSUM and CUSUMSQ—are conducted to ensure the reliability and robustness of the estimated models.

GMM effectively addresses endogeneity, which arises due to reverse causality, omitted variables, or measurement errors. By using lagged values of the dependent variable ( $AE_{t-1}$ ) and independent variables (e.g., rainfall, temperature, conflict, and agricultural production) as instruments, GMM ensures that coefficient estimates remain unbiased and consistent. This capability makes it a robust tool for analyzing complex relationships where endogeneity is a concern.

While GMM is predominantly used in panel data analysis [51], its principles are applicable in time series models when dynamic relationships and endogeneity issues need to be addressed [56]. The flexibility of GMM in accommodating such complexities makes it a valuable method for time series studies that involve highly interdependent variables, as is the case with climate, conflict, production, and employment dynamics in Somalia.

The Generalized Method of Moments (GMM) is well-suited for modeling dynamic relationships in time series data. It accounts for the influence of past values of the dependent variable, such as lagged agricultural employment ( $AE_{t-1}$ ), on its current levels ( $AE_t$ ). This is particularly important in studies where historical trends significantly impact present outcomes, as is often the case in employment and agricultural dynamics. The GMM model used in this study is specified as follows:

$$\begin{aligned} AEM_t = & \beta_0 + AE_{t-1} + \beta_1 RF_t + \beta_2 TP_t + \beta_3 CO_{2t} \\ & + \beta_4 DF_t + \beta_5 IC_t + \beta_6 EC_t + \beta_7 CP_t + \beta_8 LP_t \end{aligned}$$

The GMM model included lagged values of the dependent variable ( $AE_{t-1}$ ,  $AE_{t-1}$ ) and independent variables, such as rainfall ( $RF_{t-1}$ ), temperature ( $TP_{t-1}$ ), carbon dioxide Emissions ( $CO_{2t-1}$ ), deforestation ( $DF_{t-1}$ ), internal conflict ( $IC_{t-1}$ ), external conflict ( $EC_{t-1}$ ), crop production ( $CP_{t-1}$ ), and livestock production ( $LP_{t-1}$ ), as instruments. The instruments were chosen based on their theoretical exogeneity and relevance for addressing endogeneity in the model.

## 4 Findings and Interpretations

### 4.1 Descriptive and Correlation Analysis

Table 2 provides descriptive statistics and correlation analysis, revealing key insights into agricultural employment and its relationships with climate and conflict variables. The mean agricultural employment (AEM: 3.54) aligns with moderate levels of rainfall (RF: 280.05 mm), temperature (TP: 26.96°C), and low CO<sub>2</sub> emissions (CO<sub>2</sub>: 0.095 Mt). Internal conflict (LIC: 1.49), external conflict (LEC: 1.65), crop production (LCP: 4.58), and livestock production (LP: 95.18) show considerable variability, as reflected in their standard deviations. Skewness and kurtosis values indicate slight deviations from normality for variables like LIC and deforestation (DF: 1.69%), confirmed by the Jarque-Bera test, which identifies LIC as significantly non-normal.

**Table 2.** Descriptive and correlation analysis

|                 | LAEM     | RF       | TP       | CO <sub>2</sub> | DF        | LIC       | LEC       | LLP       | CP        |
|-----------------|----------|----------|----------|-----------------|-----------|-----------|-----------|-----------|-----------|
| Mean            | 3.541932 | 280.0531 | 26.95719 | 0.095641        | 1.699493  | 1.485974  | 1.650873  | 4.575991  | 95.17594  |
| Median          | 3.597009 | 276.8350 | 26.92500 | 0.095200        | 1.711195  | 1.682688  | 1.748861  | 4.592591  | 97.61500  |
| Std. Dev.       | 0.141717 | 29.61526 | 0.184622 | 0.043768        | 0.060725  | 0.538264  | 0.334054  | 0.093849  | 10.30904  |
| Skewness        | -0.8524  | 0.603154 | 0.172634 | 0.201890        | -0.274732 | -1.966783 | -0.075437 | -1.451949 | -0.726106 |
| Kurtosis        | 2.254133 | 3.055318 | 2.373222 | 1.949424        | 1.700956  | 5.928798  | 3.335176  | 5.466450  | 2.665430  |
| Jarque-Bera     | 4.616468 | 1.944317 | 0.682747 | 1.688997        | 2.652568  | 32.06774  | 0.180142  | 19.35467  | 2.961139  |
| Probability     | 0.099437 | 0.378266 | 0.710793 | 0.429773        | 0.265462  | 0.000000  | 0.913866  | 0.000063  | 0.227508  |
| Sum             | 113.3418 | 8961.700 | 862.6300 | 3.060500        | 54.38376  | 47.55118  | 52.82795  | 146.4317  | 3045.630  |
| Sum Sq. Dev.    | 0.622597 | 27188.98 | 1.056647 | 0.059384        | 0.114315  | 8.981573  | 3.459344  | 0.273037  | 3294.566  |
| Observations    | 32       |          |          |                 |           |           |           |           |           |
| Correlations    |          |          |          |                 |           |           |           |           |           |
| AEM             | 1        |          |          |                 |           |           |           |           |           |
| RF              | -0.53    | 1        |          |                 |           |           |           |           |           |
| TP              | -0.55    | 0.3374   | 1        |                 |           |           |           |           |           |
| CO <sub>2</sub> | -0.93    | 0.50787  | 0.532    | 1               |           |           |           |           |           |
| DF              | -0.58    | 0.32648  | 0.52248  | 0.53278         | 1         |           |           |           |           |
| LIC             | -0.52    | 0.52452  | 0.554981 | 0.613077        | 0.5556    | 1         |           |           |           |
| LEC             | -0.12    | 0.19563  | -0.03024 | -0.08049        | 0.005878  | 0.116712  | 1         |           |           |
| LCP             | -0.52    | 0.38266  | 0.45796  | 0.6649          | 0.5975    | 0.6857    | -0.16     | 1         |           |
| LP              | -0.37    | 0.3352   | 0.4958   | 0.6008          | 0.38566   | 0.7843    | -0.19     | 0.754     | 1         |

**Table 3.** Unit root test

| ADF             |             |                   |                            |                   |
|-----------------|-------------|-------------------|----------------------------|-------------------|
| Level           |             |                   | 1 <sup>st</sup> Difference |                   |
| Variable        | Intercept   | Trend & Intercept | Intercept                  | Trend & Intercept |
| AEM             | 1.266895    | -1.562749         | -1.967212                  | -4.070408**       |
| RF              | -4.845477*  | -6.416109*        | -19.32803*                 | -18.72440*        |
| TP              | -3.620092** | -5.289612*        | -8.337898*                 | -8.198678*        |
| CO <sub>2</sub> | 0.731465    | -3.856936**       | -6.066852*                 | -6.214958**       |
| DF              | -3.353578** | -5.150729*        | -6.854120*                 | -6.720017*        |
| LIC             | -2.403951   | -2.199265         | -6.085241*                 | -6.425748*        |
| LEC             | -2.228632   | -2.249654         | -5.252684*                 | -5.172951*        |
| LCP             | -2.619789   | -3.821758**       | -8.208246*                 | -8.148399*        |
| PP              |             |                   |                            |                   |
| Level           |             |                   | 1 <sup>st</sup> Difference |                   |
| Variable        | Intercept   | Trend & Intercept | Intercept                  | Trend & Intercept |
| AEM             | 2.417878    | -1.560517         | -2.706270**                | -3.734535**       |
| RF              | -4.845477*  | -6.416109*        | -19.32803*                 | -18.72440*        |
| TP              | -3.562466** | -5.381631**       | -24.10259*                 | -26.35640*        |
| CO <sub>2</sub> | 1.632497    | -3.777543**       | -9.127294*                 | -13.22652*        |
| DF              | -2.649835   | -4.257845**       | -8.941429**                | -8.727725*        |
| LIC             | -2.403951   | -2.127599         | -6.071040*                 | -6.441657*        |
| LEC             | -2.228632   | -2.249654         | -5.247874*                 | -5.165484*        |
| LCP             | -2.520261   | -3.879271**       | -8.651665*                 | -8.853715*        |

## 4.2 Unit Root Test

Table 3 presents the results of the unit root tests (ADF and PP) for stationarity of variables at both level and first difference. The analysis reveals that most variables are non-stationary at level but become stationary at the first difference, confirming their integration of order one (I(1)). Rainfall (RF) and temperature (TP) achieve stationarity at level under the ADF test with trend and intercept, while variables such as CO<sub>2</sub> emissions (CO<sub>2</sub>), deforestation (DF), internal conflict (LIC), and external conflict (LEC) only exhibit stationarity at first difference. Similarly, agricultural employment (AEM), crop production (LCP), and livestock production (LP) show non-stationarity at level but achieve stationarity after first differencing. These results highlight the suitability of the data for ARDL modeling, which accommodates variables integrated at different orders (I(0)) or I(1)).

Given the 33-year sample period, the ARDL approach is the best option for analyzing short-run and long-run dynamics, as it is well-suited for small sample sizes and allows the inclusion of lagged variables [57]. This methodological choice ensures robust insights into the relationships among agricultural employment, climate variables, conflicts, and productivity indicators while addressing the mixed integration properties of the dataset.

## 4.3 Lag Length Criteria

Table 4 presents the VAR lag selection criteria used to determine the optimal lag length for the model. The lag order of 2 is selected as optimal based on the lowest values of key information criteria, including Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ). The significant LR statistic further supports the selection of lag 2, indicating that including this lag improves the model fit and better captures the data dynamics.

**Table 4.** Lag length criteria

| Lag | LogL      | LR        | FPE       | AIC       | SC        | HQ        |
|-----|-----------|-----------|-----------|-----------|-----------|-----------|
| 0   | -115.9121 | NA        | 3.35e-08  | 8.327471  | 8.747830  | 8.461948  |
| 1   | 48.61177  | 219.3651* | 1.62e-10  | 2.759215  | 6.962807* | 4.103980  |
| 2   | 170.9888  | 89.74316  | 6.26e-11* | 0.000746* | 7.987571  | 2.555800* |

## 4.4 Cointegration Test

To determine the existence of a long-run equilibrium relationship among the study variables, this research employed the ARDL bounds testing approach to cointegration. The results, presented in Table 5, show that the calculated F-statistic for the standard ARDL bounds test is 7.883099. This value exceeds the upper bound critical values reported by Pesaran et al. [51] at the 10% (2.85), 5% (3.15), 2.5% (3.42), and 1% (3.77) significance levels, leading to the rejection of the null hypothesis of no cointegration. Thus, the results provide robust evidence of a long-run relationship among the variables, including agricultural employment, CO<sub>2</sub> emissions, rainfall, temperature, deforestation, and conflict indicators.

However, since the bounds critical values in the study [51] are based on asymptotic distributions and may not fully account for small-sample properties, the analysis further draws on the recommendations of Narayan and Narayan [54], who provide bounds critical values more appropriate for smaller samples. The robustness of the conclusion remains unchanged, as the F-statistic far exceeds the corresponding upper bounds, confirming a reliable long-run association even in the small-sample context.

To ensure that the cointegration result is not a degenerate case where the long-run significance is driven solely by either the lagged dependent variable (degenerate case I) or only the regressors (degenerate case II) an additional F-test for degenerate cases was conducted. The F-statistic for this test is 7.739649, which also exceeds the upper bound critical values across all significance levels. This eliminates the possibility of degenerate cointegration and reinforces the validity of the long-run relationship.

**Table 5.** Cointegration test

| Standard ARDL Bounds F-test |          |         |      |      | F-test for Degenerate Cases |          |         |      |      |
|-----------------------------|----------|---------|------|------|-----------------------------|----------|---------|------|------|
| Test Statistic              | Value    | Signif. | I(0) | I(1) | Test Statistic              | Value    | Signif. | I(0) | I(1) |
| F-statistic                 | 7.883099 | 10%     | 1.85 | 2.85 | F-statistic                 | 7.739649 | 10%     | 1.85 | 2.85 |
|                             |          | 5%      | 2.11 | 3.15 |                             |          | 5%      | 2.11 | 3.15 |
|                             |          | 2.5%    | 2.33 | 3.42 |                             |          | 2.5%    | 2.33 | 3.42 |
| k                           | 8        | 1%      | 2.62 | 3.77 | k                           | 8        | 1%      | 2.62 | 3.77 |

The strong results from both the standard ARDL bounds test and the degenerate case test validate the use of the ARDL model in this context. These findings support the model's suitability for capturing both short-run adjustments



and long-run dynamics in the relationship between climate and conflict variables and agricultural employment in Somalia. The outcome further justifies the complementary use of ARDL with GMM to address endogeneity, lag effects, and structural interdependence, offering a more comprehensive understanding of how environmental and socio-political factors influence agricultural labor outcomes in fragile settings.

#### 4.5 Long-Run Analysis

After confirming the presence of long-run cointegration, the long-run coefficients between climate variables, conflict indicators, agricultural productivity measures, and agricultural employment are analyzed. Table 6 presents these coefficients, revealing the nuanced effects of both environmental and socio-economic factors on agricultural employment.

**Table 6.** Long-run results

| Variable        | Coefficient | Prob.  |
|-----------------|-------------|--------|
| RF              | -0.000685   | 0.2499 |
| TP              | -0.199306   | 0.0901 |
| CO <sub>2</sub> | -3.086375   | 0.0002 |
| DF              | -0.423441   | 0.2046 |
| LIC             | 0.099277    | 0.0851 |
| LEC             | -0.094323   | 0.0221 |
| LCP             | -0.236952   | 0.1627 |
| LP              | 0.004412    | 0.0625 |
| C               | 10.75545    | 0.0118 |

Rainfall (RF) has a negative but statistically insignificant effect on agricultural employment (-0.000685,  $p = 0.2499$ ). In the fragile context of Somalia, this could indicate that while rainfall variability influences seasonal agricultural activities, its long-term effects on employment may be muted due to the absence of advanced irrigation systems or climate-resilient practices that would otherwise create stability in agricultural labor demand. Temperature (TP) demonstrates a significant negative relationship with agricultural employment (-0.199,  $p = 0.0901$ ), highlighting the detrimental effects of rising temperatures on agricultural labor demand. Carbon dioxide emissions (CO<sub>2</sub>) have a strong and highly significant negative effect on agricultural employment (-3.086,  $p = 0.0002$ ). In Somalia's context, this finding underscores the compounded challenges of climate change, as the country lacks the technological capacity and infrastructure to mitigate the effects of rising emissions. Deforestation (DF) also negatively affects agricultural employment (-0.423,  $p = 0.2046$ ), though the relationship is statistically insignificant. The negative but insignificant coefficient may reflect the localized impacts of deforestation, which disproportionately affect rural areas reliant on forest ecosystems for agricultural livelihoods.

Internal conflict (LIC) positively and significantly influences agricultural employment (0.0990,  $p = 0.0851$ ), suggesting that localized labor retention amidst conflict may stabilize rural employment. On the other hand, external conflict (LEC) significantly reduces agricultural employment (-0.094,  $p = 0.0221$ ). For Somalia, frequent external conflicts with cross-border implications exacerbate displacement and disrupt the fragile agricultural supply chains, leading to further declines in employment. Crop production (LCP) has a negative but statistically insignificant impact on agricultural employment (-0.236,  $p = 0.1627$ ). This result may reflect the increasing mechanization and less labor-intensive practices in agriculture. Livestock production (LP), however, positively and significantly affects agricultural employment (0.00440,  $p = 0.0625$ ).

#### 4.6 Short-Run Analysis

After confirming the existence of a long-run relationship, the short-run dynamics are analyzed using ECM regression. Table 7 presents the short-run results, capturing the immediate effects of climate variables, conflict indicators, and productivity measures on agricultural employment.

The lagged dependent variable (D(AEM(-1))) has a positive and significant coefficient (0.2960,  $p = 0.0124$ ), indicating that agricultural employment is moderately persistent over time, with current levels influenced by past employment trends. Rainfall (D(RF)) has a positive but marginally significant effect (9.47E-05,  $p = 0.0537$ ), and its lagged value (D(RF(-1))) shows a strongly significant positive effect (0.0002030,  $p = 0.0088$ ). These results suggest that rainfall variability in the short run positively impacts agricultural employment, likely due to increased labor demand during favorable rainfall periods for planting and harvesting. Temperature (D(TP)) has a significant negative coefficient (-0.022,  $p = 0.0300$ ), indicating that rising temperatures reduce agricultural employment in the short term, likely due to heat stress and its detrimental effects on crop productivity. The lagged temperature (D(TP(-1))) displays a positive and highly significant coefficient (0.0420,  $p = 0.0036$ ), suggesting that the labor market may adapt

temporarily, possibly through resilience mechanisms like staggered planting cycles or alternative crop choices. CO<sub>2</sub> emissions (D(CO<sub>2</sub>)) show a strong and significant negative effect on agricultural employment (-0.639,  $p = 0.0049$ ). This underscores the immediate adverse impacts of environmental degradation on labor demand. Deforestation (D(DF)) has a negative coefficient (-0.0588,  $p = 0.0587$ ) that is marginally significant, while its lagged value (D(DF(-1))) shows a significant positive effect (0.0620,  $p = 0.0345$ ). These results suggest that while deforestation initially reduces employment, it may create temporary labor demand in related activities like logging or land clearing. Internal conflict (D(LIC)) and its lag (D(LIC(-1))) show insignificant and significant negative coefficients (-0.028,  $p = 0.005$ ), respectively. This reflects the disruptive nature of internal conflicts, which reduce labor supply by displacing workers and destabilizing rural communities. External conflict (D(LEC(-1))) has a positive and significant effect (0.0240,  $p = 0.0059$ ), indicating that external conflicts may temporarily shift labor back to agriculture, possibly as displaced populations return to rural areas. Crop production (D(LCP)) and its lag (D(LCP(-1))) show consistently negative and significant effects (-0.095,  $p = 0.0087$ ; -0.046,  $p = 0.0545$ ), suggesting that stagnation or decline in crop production limits labor demand. Livestock production (D(LP)) shows a positive and significant short-term effect (0.00280,  $p = 0.0003$ ), reinforcing its stabilizing role in rural employment during climatic and socio-political shocks. The error correction term (CointEq(-1)) is negative and highly significant (-0.433,  $p = 0.0008$ ), confirming the model's convergence to the long-run equilibrium. This coefficient indicates that about 43% of deviations from the long-run relationship are corrected in the short run, emphasizing a relatively fast adjustment process in Somalia's agricultural labor market.

**Table 7.** Short-run results

| Variable            | Coefficient | Prob.  |
|---------------------|-------------|--------|
| D(LAEM(-1))         | 0.296448    | 0.0124 |
| D(RF)               | 9.47E-05    | 0.0537 |
| D(RF(-1))           | 0.000203    | 0.0088 |
| D(TP)               | -0.022384   | 0.0300 |
| D(TP(-1))           | 0.042007    | 0.0036 |
| D(CO <sub>2</sub> ) | -0.639969   | 0.0049 |
| D(DF)               | -0.058801   | 0.0587 |
| D(DF(-1))           | 0.062572    | 0.0345 |
| D(LIC)              | -0.000361   | 0.9564 |
| D(LIC(-1))          | -0.028931   | 0.0054 |
| D(LEC)              | 0.008564    | 0.1323 |
| D(LEC(-1))          | 0.024574    | 0.0059 |
| D(LCP)              | -0.095404   | 0.0087 |
| D(LCP(-1))          | -0.046043   | 0.0545 |
| D(LP)               | 0.002858    | 0.0016 |
| D(LP(-1))           | 0.001504    | 0.0093 |
| CointEq(-1)*        | -0.433490   | 0.0008 |

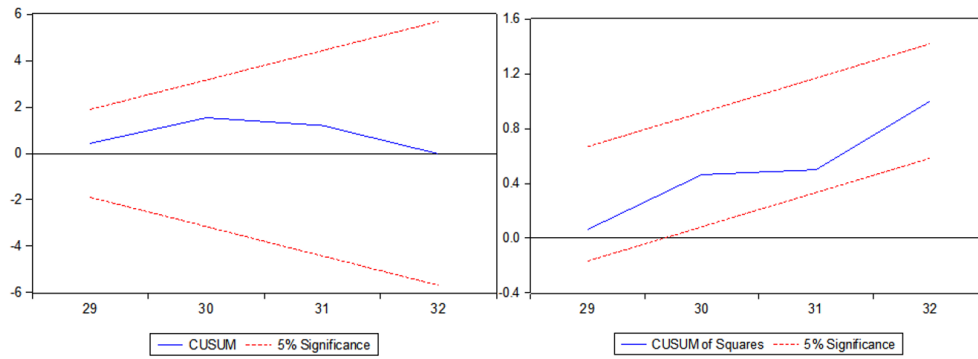
#### 4.7 Stability of the Model

The stability of the model is confirmed by the diagnostic tests presented in Table 8 and Figure 2. The results indicate no evidence of heteroskedasticity, serial correlation, or deviations from normality, ensuring that the residuals are well-behaved and the model is correctly specified.

**Table 8.** Model stability test

| Stability Test          | F-statistic | Prob. F(10,20) |
|-------------------------|-------------|----------------|
| Heteroskedasticity Test | 0.326326    | 0.965100       |
| Serial Correlation      | 6.503979    | 0.133300       |
| Normality test          | 92.10005    | 0.592936       |

Additionally, the CUSUM and CUSUM of Squares plots show that the model remains stable over time, with all test statistics staying within the acceptable significance bounds. These findings validate the robustness and reliability of the model in capturing the relationships between agricultural employment and its determinants.



**Figure 2.** Recursive estimation

#### 4.8 Generalized Method of Moments

The GMM estimation, as shown in Table 9, provides valuable insights into the determinants of agricultural employment, considering the dynamic nature of relationships and addressing potential endogeneity issues. The results indicate that rainfall does not have a statistically significant effect on agricultural employment, suggesting its immediate impact on labor demand may be limited compared to other climatic factors. Conversely, temperature demonstrates a significant and negative effect, underscoring the detrimental influence of rising temperatures on agricultural labor. This finding aligns with prior studies highlighting the adverse effects of heat stress on productivity and crop yields. Similarly, carbon dioxide emissions are found to negatively and significantly affect agricultural employment, reflecting their contribution to climate change, which ultimately reduces agricultural output and labor demand.

**Table 9.** GMM

| Variable             | Coefficient | Std. Error         | t-Statistic | Prob.    |
|----------------------|-------------|--------------------|-------------|----------|
| C                    | 136.4764    | 32.05705           | 4.257297    | 0.0004   |
| RF(-1)               | -0.006446   | 0.006001           | -1.074254   | 0.2955   |
| TP(-1)               | -3.182025   | 0.837522           | -3.799331   | 0.0011   |
| CO <sub>2</sub> (-1) | -116.9465   | 4.615167           | -25.33960   | 0.0000   |
| DF(-1)               | -9.050066   | 3.916803           | -2.310575   | 0.0316   |
| LIC(-1)              | 0.135813    | 1.042054           | 0.130332    | 0.8976   |
| LEC(-1)              | -2.237297   | 0.731081           | -3.060259   | 0.0062   |
| LCP(-1)              | 0.655238    | 4.183653           | 0.156619    | 0.8771   |
| LP(-1)               | 0.125095    | 0.052632           | 2.376771    | 0.0276   |
| R-squared            | 0.951534    | Mean dependent var |             | 34.45771 |
| Adjusted R-squared   | 0.932147    | S.D. dependent var |             | 4.701287 |
| S.E. of regression   | 1.224619    | Sum squared resid  |             | 29.99384 |
| Durbin-Watson stat   | 1.606215    | J-statistic        |             | 5.332855 |
| Instrument rank      | 11          | Prob(J-statistic)  |             | 0.069500 |

Deforestation also shows a significant negative impact on agricultural employment, pointing to the harmful consequences of environmental degradation and loss of arable land on the agricultural labor market. While internal conflict does not exhibit a significant direct effect, external conflict significantly reduces agricultural employment, emphasizing its destabilizing influence on economic activities and labor markets. Livestock production, on the other hand, positively and significantly affects agricultural employment, highlighting its role as a crucial source of livelihood and job opportunities in rural areas. Crop production, however, does not show a statistically significant relationship, suggesting that its short-term fluctuations may not directly influence employment dynamics. The diagnostic measures in Table 9 support the robustness of the model. The high R-squared value indicates that the model captures a substantial portion of the variability in agricultural employment, while the J-statistic confirms the validity of the instruments used, addressing concerns about over-identification. The Durbin-Watson statistic further suggests the absence of significant autocorrelation, enhancing the reliability of the results. Overall, the findings from the GMM estimation align with those from the ARDL analysis, particularly in identifying temperature, carbon dioxide emissions, and conflict as critical drivers of agricultural employment. However, the GMM approach adds robustness by addressing endogeneity and providing dynamic insights, making it a complementary and valuable addition to the analysis.

## 5 Discussions

The results of the ARDL model reveal a complex and nuanced relationship between climate change, conflict, agricultural productivity, and employment in Somalia. These findings reflect not only the physical effects of environmental change but also the structural vulnerabilities and coping mechanisms of Somalia's rural economy. In both the short and long run, the interactions between climate stressors and employment show evidence of nonlinear responses, lagged effects, and context-specific dynamics shaped by the country's fragile institutional and ecological conditions.

Rainfall emerges as a variable with contrasting temporal effects. In the short run, rainfall has a positive and marginally significant effect on agricultural employment, and its lagged value is strongly significant. This suggests that during seasons with adequate rainfall, agricultural labor demand increases due to expanded farming activities such as land preparation, planting, and harvesting. This finding aligns with Wang et al. [58] and Piya et al. [21], this seasonal employment response to rainfall shocks is consistent with patterns observed in other developing countries. However, in the long run, the effect of rainfall becomes negative and statistically insignificant, which may reflect Somalia's limited capacity to convert rainfall into sustainable productivity. The country lacks widespread irrigation infrastructure, water storage systems, and climate-resilient agricultural techniques. As a result, rainfall contributes to short-term employment spikes but fails to provide consistent support for labor absorption over time.

Temperature shows a more consistent and detrimental effect across both timeframes. In the short term, rising temperatures significantly reduce agricultural employment, likely due to heat stress affecting both crops and laborers. High temperatures can lower working capacity in open fields and increase crop failure rates, especially in subsistence-based systems. Interestingly, the lagged temperature variable in the short run is positive and significant, suggesting a delayed adaptation effect, such as switching to heat-tolerant crops or adjusting labor schedules. However, in the long run, the negative relationship persists and becomes statistically significant, indicating that any short-term adaptations are insufficient to counterbalance the cumulative damage caused by rising temperatures. This is consistent with findings by Ozdemir [25] and Jiang and Guo [17], who emphasize the long-term erosion of agricultural labor markets under sustained heat exposure, especially in fragile ecosystems like Somalia's.

Carbon dioxide emissions ( $\text{CO}_2$ ) present the strongest and most consistent negative effect on agricultural employment, with highly significant coefficients in both short- and long-run estimations. In the short term, emissions reduce employment likely through impacts on air quality, soil degradation, and heat intensification, while in the long run, the degradation of natural ecosystems becomes more pronounced. The long-run coefficient of -3.086 is particularly noteworthy, underscoring the unsustainable environmental trajectory facing Somalia. These results echo Rehman et al. [24] and Hassan and Mohamed [12], who found that emissions contribute to land degradation, reduced yields, and displacement from agricultural livelihoods. Somalia's inability to invest in emission mitigation or green technology worsens the situation, as environmental degradation accelerates without institutional countermeasures.

The impact of deforestation on agricultural employment reveals a time-sensitive dynamic rooted in both environmental and livelihood transitions. In the long run, deforestation negatively affects agricultural employment, though the result is statistically insignificant. This likely reflects the gradual degradation of soil fertility, water regulation, and land productivity that reduces the sector's capacity to absorb labor over time.

In the short term, the immediate effect of deforestation is also negative and marginally significant, consistent with the disruption of natural growing conditions and the loss of microclimatic stability following forest clearance. However, the lagged short-run effect is positive and statistically significant, suggesting that deforestation initially generates temporary employment through activities such as charcoal production, manual land clearing, and firewood collection. In Somalia, where charcoal production is widely used as a coping strategy by displaced and resource-insecure populations, these short-term labor responses are common. Yet, they are embedded in an unsustainable cycle that contributes to long-term ecological decline and economic vulnerability.

This pattern highlights the dual role of deforestation: as a short-term income source under crisis conditions and as a driver of declining agricultural employment potential due to environmental degradation.

The influence of internal conflict (LIC) is another case of temporal contradiction. In the short run, internal conflict significantly reduces agricultural employment, reflecting the immediate disruptions to farming activity, displacement of labor, and breakdown of rural economies. However, in the long run, internal conflict shows a statistically significant positive association with employment. This may appear counterintuitive, but it is consistent with the "conflict entrapment" hypothesis suggested by Ronzani et al. [59], where limited mobility and lack of alternative jobs force rural populations to remain engaged in low-productivity agricultural work even amid insecurity. In Somalia, internal conflict may effectively trap labor within subsistence agriculture, raising employment figures without improving well-being or output.

External conflict (LEC) shows a more consistent pattern. In the long run, it significantly reduces agricultural employment, confirming that cross-border violence and political instability reduce labor availability, restrict trade access, and damage market infrastructure. These results are consistent with Adelaja and George [60], who found that external conflicts have more damaging and far-reaching consequences than internal unrest. However, in the short

run, the lagged external conflict variable has a positive and significant coefficient. This may reflect the tendency of displaced populations to return to rural areas and re-engage in farming activities after external violence subsides, even if conditions remain suboptimal.

Crop production (LCP) has a statistically significant negative effect in the short run and an insignificant negative effect in the long run. This suggests that declines in crop yields or stagnation in crop-based agriculture may reduce labor demand, especially where mechanization is minimal but investment is also lacking. This finding is echoed in Charlton [31], who observed that low crop profitability leads to labor withdrawal, particularly among youth and women. In Somalia, factors such as poor irrigation, lack of inputs, and climate risks have severely limited crop sector growth, diminishing its potential as a labor-absorbing activity.

In contrast, livestock production (LP) demonstrates a statistically significant and positive effect on employment in both short- and long-term estimations. This confirms its role as a key stabilizer of rural livelihoods in Somalia. As found by Mehra et al. [28] and Syahputri et al. [35], livestock rearing offers more resilience against climate variability due to its mobility and lower dependence on rainfall. In Somalia's pastoral economy, livestock are not only a source of food and income but also a form of savings and social capital. The sector continues to offer employment opportunities across value chains, including herding, veterinary services, milk processing, and local trade.

Finally, the error correction term is negative and highly significant ( $-0.433$ ), indicating a relatively quick speed of adjustment toward long-run equilibrium. About 43% of the deviation from equilibrium is corrected each year. This suggests that while Somalia's agricultural employment system is fragile, it is also reactive. Workers quickly return to agriculture following shocks, not necessarily due to improved conditions, but because there are few alternative income sources outside the sector. This structural dependency underscores the urgent need for diversification and investment in rural employment beyond farming.

In summary, the results highlight the multifaceted vulnerabilities of Somalia's agricultural labor market. Climate variables, particularly temperature and emissions, consistently undermine employment. Rainfall and deforestation show short-term gains but lack sustainability. Internal and external conflicts have asymmetric effects, with internal strife entrenching labor in agriculture and external tensions driving people out. The livestock sector remains a cornerstone of rural employment, while crop production continues to underperform. Together, these insights call for urgent investment in adaptive agriculture, livestock development, and climate-resilient employment strategies to safeguard livelihoods in one of the world's most climate- and conflict-vulnerable regions.

## 6 Conclusion

This study investigated the interrelated impacts of climate change and armed conflict on agricultural employment in Somalia, applying dynamic econometric models to disentangle the short- and long-term effects of climatic and socio-political stressors. The findings reveal that climate change and conflict are distinct but interconnected forces that jointly shape rural labor markets in fragile states. Climate change—reflected through variables such as rainfall variability, rising temperatures, CO<sub>2</sub> emissions, and deforestation—alters the structure of agricultural labor demand by undermining productivity, degrading natural resources, and increasing environmental uncertainty. Armed conflict, on the other hand, disrupts access to land and inputs, displaces rural populations, and weakens institutions that support agricultural development. Yet, the two are not mutually exclusive. In fragile environments like Somalia, where institutional resilience is weak, climate shocks often exacerbate underlying tensions over land, water, and political control, reinforcing cycles of violence and livelihood disruption.

This study contributes to knowledge by offering a comprehensive, Somalia-specific framework that integrates climate and conflict dimensions into one dynamic empirical model. The results show that rising temperatures and CO<sub>2</sub> emissions are consistent and significant deterrents to agricultural employment, highlighting Somalia's exposure to global environmental changes and its limited adaptive capacity. Meanwhile, deforestation appears to provide temporary labor opportunities but leads to long-term degradation and job loss, particularly in regions reliant on agro-forestry or livestock. Internal conflict reveals a paradoxical stabilizing effect in the long run, suggesting that immobile rural populations are often trapped in subsistence agriculture during conflict episodes due to a lack of alternative employment. Conversely, external conflict significantly disrupts labor markets by displacing communities and limiting access to cross-border trade and inputs. Crop production does not significantly contribute to employment, reflecting the sector's stagnation, while livestock production consistently supports rural labor, reinforcing its strategic importance in Somalia's agrarian economy.

The short-run dynamics offer additional insights into the responsiveness of agricultural labor markets to climatic variability. For example, rainfall has a positive short-run effect on employment, indicating that favorable weather temporarily boosts labor demand during planting and harvesting periods. However, this benefit is not sustained in the long run due to Somalia's lack of irrigation infrastructure and adaptive agricultural systems. Temperature shocks, meanwhile, exhibit immediate negative effects, but are followed by short-term adaptation responses—suggesting that farmers may temporarily adjust planting cycles or labor practices. These temporal patterns emphasize the



importance of distinguishing between immediate coping mechanisms and long-term structural challenges when designing interventions.

To address the multidimensional challenges facing Somalia's agricultural labor market, a comprehensive policy approach is required one that simultaneously tackles environmental degradation, conflict, and structural weaknesses in the rural economy.

## 7 Policy Recommendations

Climate-resilient agriculture must be promoted through the adoption of drought-tolerant crops such as sorghum, millet, and cowpea, alongside small-scale drip irrigation systems and contour farming to improve water retention and reduce erosion. These practices buffer the impacts of variable rainfall and rising temperatures, reducing volatility in labor demand and enhancing long-term productivity. Expanding climate-smart agriculture would also help transition Somalia's farming sector away from its high sensitivity to climatic shocks.

Given the significant and positive role of livestock in sustaining rural employment, greater investment in this sub-sector is crucial. Strengthening mobile veterinary clinics, improving access to seasonal grazing corridors and water catchments, and supporting pastoral markets and early-warning systems for animal diseases would enhance resilience against both climate-related and conflict-driven disruptions.

Efforts to combat deforestation must also be prioritized. This includes enforcing regulations on charcoal production, introducing cash-for-work reforestation programs for displaced populations, and planting indigenous, drought-resistant tree species such as *Acacia senegal* or *Ziziphus mauritiana*, which are suited to Somalia's semi-arid climate. Reducing land degradation will ultimately support both environmental sustainability and employment generation.

To limit the adverse effects of CO<sub>2</sub> emissions and biomass energy use, solar-powered irrigation pumps, portable solar lighting systems, and small-scale biogas digesters should be scaled up in rural farming communities. These technologies offer decentralized, low-cost solutions that reduce dependence on firewood and charcoal while enhancing agricultural productivity.

Conflict-sensitive agricultural development policies must also be implemented to stabilize labor markets in fragile areas. This includes rebuilding rural feeder roads, protecting input supply chains, and fostering community-based peacebuilding through inclusive farmer cooperatives. These actions support recovery and labor absorption in conflict-affected zones.

Preparedness and early warning systems should be strengthened to monitor both climate risks and emerging conflict dynamics. These systems can draw on community-led data collection, mobile alerts, and partnerships with regional climate networks to enable rapid responses to crises, thereby minimizing employment shocks.

Finally, Somalia's labor market would benefit from the expansion of integrated farming systems, particularly in areas with access to irrigation or agro-pastoral zones. These systems combine livestock and crop activities, diversify income sources, reduce climate vulnerability, and enhance employment absorption. Public-private investments in agricultural extension services, youth-focused training programs, and labor-saving technologies such as threshers and plows would further support the transition to a more resilient agricultural sector.

## 8 Limitations and Future Research

While the study makes important contributions, it is not without limitations. The analysis relies on national-level annual data, which may mask important spatial and seasonal variations in climate, conflict, and employment patterns. Sub-regional analysis using higher-frequency or geospatial data could provide a more nuanced understanding of labor market dynamics, particularly in regions repeatedly affected by climate shocks or local conflicts.

Similarly, the study does not disaggregate employment outcomes by gender or age, despite strong evidence that women and youth are disproportionately affected by both environmental and political disruptions. Future research should explore these intersectional dimensions to inform more inclusive employment strategies and rural development interventions.

Methodologically, while ARDL and GMM models are well-suited to this context, they also have limitations. The ARDL model may be sensitive to structural breaks—common in fragile states like Somalia potentially affecting the stability of long-run relationships. Likewise, the GMM approach, while useful for addressing endogeneity, can suffer from instrument proliferation or weak instruments if not carefully specified. Although diagnostic tests were used to mitigate these risks, caution is warranted in interpreting the results, especially in light of Somalia's political and economic volatility.

Despite their strengths, both ARDL and GMM have limitations in fragile state contexts. ARDL may be sensitive to structural breaks that are common in conflict-affected regions, while GMM can be affected by instrument proliferation or weak instrument bias. These risks were mitigated by using diagnostic checks and a carefully selected instrument set, but results should still be interpreted with attention to Somalia's political and economic volatility.

In terms of scope, the study focuses exclusively on Somalia, limiting the generalizability of findings to other fragile states. Comparative studies involving countries with similar agro-ecological and political conditions such as South Sudan, Chad, or the Central African Republic could help validate the model and extend its policy relevance. Finally, integrating qualitative data such as household surveys, focus group discussions, or local narratives could complement the quantitative findings by capturing perceptions of vulnerability, resilience, and adaptation strategies among rural communities.

### Author Contributions

Conceptualization, A.A.M.; methodology, A.A.M.; validation, A.M.A.; formal analysis, A.A.M.; writing—original draft preparation, A.A.M. and A.M.A.; data curation, A.A.M. and A.M.Y.I.; writing—review and editing, A.A.M., A.M.Y.I., A.M.A. and G.M.B; supervision, G.M.B. All authors have read and agreed to the published version of the manuscript.

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### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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