



## OPEN ACCESS

## EDITED BY

Serdar Dindar,  
Yıldırım Beyazıt University, Türkiye

## REVIEWED BY

Dilip Khatiwada,  
Royal Institute of Technology, Sweden  
Pau Chung Leng,  
University of Technology Malaysia, Malaysia  
Zia Uddin,  
Ankara Yıldırım Beyazıt University, Türkiye

## \*CORRESPONDENCE

Ahmed Awale Ahmed  
✉ eng.ahmed@amoud.edu.so

RECEIVED 09 February 2025

ACCEPTED 19 May 2025

PUBLISHED 04 June 2025

## CITATION

Ahmed AA, Ali AA, Yousuf Duale AS, Yousuf AM and Muse AH (2025) Climate change, socioeconomic, environmental, and political drivers of road traffic fatalities in Somalia: a multivariate time series analysis. *Front. Clim.* 7:1573803. doi: 10.3389/fclim.2025.1573803

## COPYRIGHT

© 2025 Ahmed, Ali, Yousuf Duale, Yousuf and Muse. This is an open-access article distributed under the terms of the [Creative Commons Attribution License \(CC BY\)](#). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

# Climate change, socioeconomic, environmental, and political drivers of road traffic fatalities in Somalia: a multivariate time series analysis

Ahmed Awale Ahmed<sup>1\*</sup>, Abdikadir Abdi Ali<sup>1</sup>,  
Abdisalan Sh. Yousuf Duale<sup>1</sup>, Abdirashid M. Yousuf<sup>2</sup> and  
Abdisalam Hassan Muse<sup>2</sup>

<sup>1</sup>Faculty of Engineering and Technology, Amoud University, Borama, Somalia, <sup>2</sup>Research and Innovation Center, Amoud University, Borama, Somalia

**Introduction:** Road traffic fatalities (RTFs) in low-resource settings like Somalia are influenced by a complex interplay of socioeconomic, environmental, and political challenges. This study investigates the impact of climate change (temperature, rainfall), environmental degradation (CO<sub>2</sub> emissions), socioeconomic conditions (urban population, foreign aid), and political instability on RTFs in Somalia, aiming to contribute to the limited understanding of these dynamics in fragile states.

**Methods:** A multivariate time series analysis was conducted using data from 1984 to 2021. An Autoregressive Distributed Lag (ARDL) model was employed to examine the short-run and long-run effects of the selected drivers on RTFs. The robustness of the model was confirmed through a series of diagnostic tests.

**Results:** The ARDL model revealed significant long-run relationships: increased urbanization, CO<sub>2</sub> emissions, and political instability were associated with higher RTFs. Conversely, increased rainfall and foreign aid were associated with lower RTFs in the long run. In the short-run, nuanced effects were observed, with both increased temperature and rainfall exhibiting positive associations with RTFs, suggesting immediate, potentially transitory, impacts.

**Discussion/Conclusion:** These findings challenge simplistic explanations of RTF drivers and highlight the necessity of integrated road safety strategies. Such strategies should address climate change adaptation, environmental protection, socioeconomic development, and the promotion of good governance. This research provides valuable insights for evidence-based policymaking aimed at reducing RTFs and achieving Sustainable Development Goals related to health, infrastructure, and sustainable communities in Somalia and similar contexts.

## KEYWORDS

climate change, socioeconomic, environmental, road traffic accidents, low resource setting, ARDL, foreign aid received, Somalia

## 1 Introduction

Road traffic accidents (RTAs) represent a significant and pervasive global public health challenge, causing millions of fatalities and disabilities annually (Razzaghi et al., 2019, 2020). The economic burden associated with RTAs is substantial, impacting productivity, hindering sustainable development, and diverting crucial resources from other essential sectors (Ali et al., 2019; Frimpong et al., 2003). While high-income countries (HICs) have made considerable

progress in mitigating this burden, low- and middle-income countries (LMICs), particularly those in the African region, continue to experience disproportionately high rates of RTA-related mortality and morbidity (Oladeji et al., 2024; Staton et al., 2016). Elucidating the specific factors contributing to this disparity is crucial for developing effective prevention and intervention strategies tailored to the unique contexts of LMICs.

Somalia, a fragile LMIC in the Horn of Africa, faces a particularly acute RTA challenge. Its distinctive socio-economic, political, environmental, and climatic context significantly influences its road traffic accident (RTA) landscape, contributing substantially to the elevated RTA burden. This elevated RTA burden in Somalia stems from a confluence of specific, proximate factors operating at the ground level, which contribute directly to crash occurrence and severity. Key among these are severely deficient road infrastructure, characterized by widespread potholes, inadequate or absent signage and road markings, and narrow carriageways often ill-suited for mixed traffic. Compounding this is the prevalence of vehicles in poor states of repair, frequently lacking basic roadworthiness standards due to prevailing economic constraints. Furthermore, high-risk driver behaviors—including excessive speeding, vehicle overloading, and a general disregard for traffic regulations—are common, often exacerbated by the lack of robust traffic law enforcement capacity, a situation itself worsened by persistent political instability. Finally, significant challenges exist in providing timely and effective post-crash emergency response and medical care, which can tragically turn survivable injuries into fatalities. Crucially, these proximate causes do not exist in isolation; they are intrinsically linked to and often intensified by the broader climate, socioeconomic, environmental, and political factors investigated in this study. For instance, political instability (PI) directly undermines the capacity for effective law enforcement and hinders crucial investment in infrastructure maintenance and development (as also highlighted in Lines 100–104). Similarly, climate variables such as intense rainfall (RF) can accelerate the degradation of already vulnerable road surfaces, while challenging socioeconomic conditions, reflected partly by low GDP per capita, limit both public resources for safer infrastructure and private capacity to maintain vehicles to adequate safety standards. Understanding these pathways, connecting macro-level drivers to tangible, on-the-ground risks, is essential for developing comprehensive and effective RTA mitigation strategies tailored to the Somali context. Furthermore, cultural factors, driver behavior, and vehicle maintenance practices may also exert influence (Mohamed et al., 2023; Osman et al., 2022).

The deleterious impact of road traffic accidents in Somalia is frequently overlooked in global discourse. While international attention often focuses on larger nations, the human cost in this developing country remains substantial, affecting families, communities, and the overall development of the nation. This study aims to bring this critical issue to the forefront, providing empirical insights to inform targeted interventions and policy modifications. The findings from this research in Somalia can potentially benefit other low-income countries facing similar challenges.

Despite the growing global focus on RTAs, there is limited empirical research on Somalia's specific challenges. Most existing studies on African road safety overlook the unique socio-political and economic conditions prevalent in the region (Akinyemi, 2020; Alzaffin et al., 2023; Osman et al., 2022; Yusuff, 2015). This study aims to fill this gap by providing a comprehensive analysis of the factors driving RTAs in Somalia, contributing to both local and global road safety literature. This literature review highlights the multifaceted and interrelated factors influencing RTAs globally, regionally, and in Somalia. Addressing these challenges requires a holistic, evidence-based approach that considers the temperature, rainfall, health force, environmental degradation, economic growth, foreign aid investment, political stability and urban population factors in context of the region.

To address this gap, this study investigates the complex interplay of climate change, socioeconomic conditions, environmental degradation, and political instability on RTFs in Somalia. Utilizing a multivariate time series analysis with data from 1980 to 2021 and employing an Autoregressive Distributed Lag (ARDL) model, we examine the impact of climate change (temperature, rainfall), environmental degradation (CO<sub>2</sub> emissions), socioeconomic conditions (urban population, foreign aid), and political instability on RTFs. The ARDL model is particularly well-suited for time-series data with mixed integration orders (I(0) and I(1)) and can capture both short-run and long-run relationships (Abdi et al., 2024; Ageli, 2013; Li et al., 2020; Nasrullah et al., 2021; Warsame et al., 2024). This study offers a novel contribution by providing a comprehensive analysis of the factors contributing to RTAs in Somalia, thereby augmenting both local and global road safety literature.

## 2 Literature review

This literature review examines the complex interplay of climate change, socioeconomic, environmental degradation, and political drivers in shaping road traffic accidents (RTAs), with a particular focus on low-resource settings like Somalia. Extant research indicates a significant correlation between climate variables and RTA fatalities (Ali et al., 2019; Ghadi, 2025; Islam et al., 2019; Sangadah and Kartawidjaja, 2020). Extreme temperatures, both high and low, adversely affect road conditions, vehicle performance, and driver behavior (Ali et al., 2020; Ghadi, 2025; Islam et al., 2019; Mwale et al., 2023; Zurlinden et al., 2023). However, the relationship is not always straightforward, with some studies suggesting that higher temperatures can lead to more cautious driving (Ageli, 2013; Ali et al., 2020). Similarly, rainfall is a crucial environmental factor, reducing tire adhesion and visibility, but its impact on accident rates can also be nuanced, with some evidence suggesting behavioral adaptations during adverse weather (Ali et al., 2020; Jackson and Sharif, 2016; Jaroszweski and McNamara, 2014; Keay and Simmonds, 2006; Mondal, 2011; Sangkharat et al., 2021).

Environmental degradation, precipitated by anthropogenic activities and natural phenomena, exerts a multifaceted influence on RTAs (Ali et al., 2019; Wang et al., 2024). Elevated carbon dioxide (CO<sub>2</sub>) emissions, primarily originating from vehicular and industrial sources, contribute to atmospheric pollution in conjunction with other contaminants, potentially affecting driver health and visibility (Bahari et al., 2023; Osman et al., 2022).

Numerous studies have established correlations between economic indicators and RTA rates (Abubakar, 2022; Akinyemi, 2020; Kopits and Cropper, 2005). Factors such as employment,

Abbreviations: AIC, Akaike Information Criterion; ARDL, Autoregressive Distributed Lag; BIC, Bayesian Information Criteria; CUSUM, Cumulative Sum; CUSUMSQ, Cumulative Sum of Squares; ECM, Error Correction Model; FAR, Foreign Aid Received; GNI, Gross National Income; LMICs, Low- and Middle-Income Countries; RTAs, Road Traffic Accidents; UP, Urban Population; VAR, Vector Autoregression; WGI, Worldwide Governance Indicators.

unemployment, highway mileage, and vehicle ownership have all been linked to RTA indicators (accidents, injuries, fatalities, economic losses) (Akinyemi, 2020). Foreign aid can also influence road traffic accidents in both negative and positive ways (Toriumi et al., 2022). Development without adequate safety measures, foreign aid may focus on expanding road networks without incorporating sufficient safety considerations, leading to increased traffic and higher accident rates. While corruption and mismanagement are poorly managed, intended safety improvements may not materialize, exacerbating existing road safety issues.

Political instability has a very significant impact on road traffic safety (Sohaee and Bohluli, 2024). Political instability can lead to neglect of infrastructure, resulting in poor road conditions, pot holes and missing signs which increase the risk of accidents (Đurić and Peek-Asa, 2008; Sohaee and Bohluli, 2024). It also results in unregulated and unsafe public transport systems such as overcrowded buses or poorly kept vehicles.

An increasing urban population directly relationship with higher road traffic accidents for more reasons likely to contribute occur to in a densely increasing populated, areas Traffic due Congestion, Pedestrian-Vehicle Interaction “There are more chances of accidents as a result of vehicle, pedestrian, and cyclist interactions in urban areas.” Public transport challenges “Overcrowding in public transport systems can lead to unsafe Inadequate practices inadequate infrastructure such development traffic as to management passengers handle hanging rapid systems” (Bauer et al., 2016; Jaroszowski and McNamara, 2014; Vasconcellos, 1999).

Researchers have employed a variety of statistical and econometric techniques to analyze the determinants of RTAs, including regression analysis, time series models (ARIMA, ARDL), and panel data analysis (Ageli, 2013; Li et al., 2020). Autoregressive Distributed Lag (ARDL) models have gained popularity in recent years for analyzing the determinants of RTAs. These models are particularly well-suited for time-series data with mixed integration orders (I(0) and I(1)) and can capture both short-run and long-run relationships (Ageli, 2013; Li et al., 2020; Nasrullah et al., 2021; Rizwanullah et al., 2020; Warsame et al., 2023, 2024). While regression analysis is a common method, it may not be appropriate for time-series data or when there are issues of endogeneity or multicollinearity. Time series models, such as ARIMA and Autoregressive Distributed Lag (ARDL) models, have been used to analyze the trends and patterns in RTA data over time. These models can capture the dynamic relationships between variables and account for autocorrelation. Panel data models, which combine cross-sectional and time-series data, have been used to examine the determinants of RTAs across multiple countries or regions. These models can control for unobserved heterogeneity and allow for more robust inferences.

Despite the growing global focus on RTAs, there is limited empirical research on Somalia's specific challenges. Most existing studies on African road safety overlook the unique socio-political and economic conditions of the region (Akinyemi, 2020; Alzaffin et al., 2023; Mohamed et al., 2023). This study aims to fill this gap by providing a comprehensive analysis of the factors driving RTAs in Somaliland, contributing to both local and global road safety literature. This literature review highlights the multifaceted and interrelated factors influencing RTAs globally, regionally, and in Somaliland. Addressing these challenges requires a holistic, evidence-based approach that considers the temperature, rainfall, health force, environmental degradation, economic growth, foreign aid investment, political stability and urban population factors in context of the region.

## 2.1 Research gap

Despite the extensive body of literature on RTA determinants, significant gaps remain, particularly concerning the complex interplay of factors in low-resource, politically unstable contexts like Somalia (Osman et al., 2022). Existing studies often focus on individual risk factors or specific interventions (Mohamed et al., 2023), neglecting the synergistic effects of climate change, socioeconomic vulnerabilities, environmental degradation, and political fragility (Hassan et al., 2024; Warsame et al., 2023, 2024). Furthermore, existing models used in other contexts may not adequately capture the complex interplay of factors unique to fragile states like Somalia, where data limitations, political instability, and specific cultural contexts present unique challenges (Ageli, 2013; Akinyemi, 2020; Li et al., 2020). This study addresses this gap by examining the combined impact of climate change, socioeconomic conditions, environmental degradation, and political instability on RTFs in Somalia, utilizing a multivariate time series analysis to provide a more comprehensive understanding of this critical issue. This study offers a novel contribution by providing a comprehensive analysis of the factors contributing to RTAs in Somalia, thereby augmenting both local and global road safety literature.

## 3 Data and methodology

### 3.1 Data description

This longitudinal study examines the impact of climate change, socioeconomic, environmental, and political factors on road traffic accidents (RTAs) in a resource-constrained setting. The analysis employs time-series data from 1980 to 2021, a period characterized by increasing concerns regarding climate variability and its societal implications. The dependent variable in this investigation is the number of road traffic fatalities in Somalia.

The key independent variables include average annual temperature (in °C); annual rainfall (in millimeters); GDP per capita; CO2 emissions; foreign aid investment, measured by the amount of foreign aid received by the setting per year; political instability, which is a dummy variable measured as 1 during periods of political instability and 0 during periods of political stability; and urbanization, measured as annual urban population.

#### 3.1.1 Criteria of variable selection

While a comprehensive understanding of RTA determinants would ideally encompass a wider range of factors, this study is constrained by data availability, particularly for a fragile state like Somalia. The selection of variables—temperature (Ali et al., 2020), rainfall (Mondal, 2011), environmental degradation (proxied by CO2 emissions) (Ali et al., 2019), economic growth (GPD per capita) (Abubakar, 2022), foreign aid investment (Đurić and Peek-Asa, 2008), political instability (Đurić and Peek-Asa, 2008), and urban population (Vasconcellos, 1999)—reflects a pragmatic approach, prioritizing variables for which reliable and consistent time-series data are available from reputable international sources. This approach acknowledges the inherent limitations of research in data-scarce environments while striving to capture the most salient and measurable influences on RTAs (Ali et al., 2024; Warsame et al., 2024).

### 3.1.2 Study variables

The research utilizes data obtained from multiple sources, including the World Bank, Climate Change Knowledge Portal (CCK), and Our World in Data. A comprehensive overview of the study variables is provided in [Table 1](#), which delineates their descriptions, measurement units, and respective data origins.

The selection of variables was predicated on evidence from pertinent literature, as well as the availability of time-series data for the specified period, which underscores a distinctive consideration to identify potential influential factors that may impact the trajectory of road traffic accident fatalities. Data will be aggregated on an annual basis and subsequently transformed to facilitate appropriate longitudinal analysis. The data is anticipated to exhibit a panel structure, with each year representing a discrete time point and each observation corresponding to the area of the low-resource setting.

## 3.2 Modelling

This study employs a methodological framework grounded in the autoregressive distributed lag (ARDL) approach, a robust econometric technique. The ARDL method is particularly well-suited for examining relationships among variables that may exhibit integration at varying orders (I(0) or I(1)), making it an ideal choice for this analysis.

### 3.2.1 Rationale for model selection

This approach, as demonstrated in [Getahun \(2021\)](#), allows for the examination of both short-run and long-run effects of climate and other factors on our dependent variable of RTA. This methodological approach was selected based on the necessity to ascertain both the immediate and sustained impact of climatic, socioeconomic, environmental and political factors on road safety. Furthermore, given the utilization of time-series data from 1980 to 2021, which is anticipated to yield a limited sample size, the ARDL method is expected to generate both short-term and long-term elasticities appropriately. The ARDL methodology is also deemed suitable when independent variables exhibit mutual cointegration. In accordance with this study, our analysis aims to elucidate how fluctuations in climate variables (Temperature and rainfall) influence RTA and to determine whether socioeconomic factors exacerbate or mitigate these effects.

### 3.2.2 Model estimation

To investigate the complex relationships between the dependent variable and covariates of this study, we employed a baseline model

that specifies road traffic accidents as a function of all the variables and incorporates lagged terms in the ARDL as follows:

$$RTA_t = \alpha_0 + \alpha_1 TP_t + \alpha_2 RF_t + \alpha_3 CO_2_t + \alpha_4 GDP_t + \alpha_5 FAR_t + \alpha_6 UP_t + \alpha_7 PI_t + \varepsilon_t \quad (1)$$

By transforming all variables of [Equation 1](#), with the exception of the dummy variable, into natural logarithms, the model is formulated as follows:

$$\ln RTA_t = \alpha_0 + \alpha_1 \ln TP_t + \alpha_2 \ln RF_t + \alpha_3 \ln CO_2_t + \alpha_4 \ln GDP_t + \alpha_5 \ln FAR_t + \alpha_6 \ln UP_t + \alpha_7 PI_t + \varepsilon_t \quad (2)$$

[Equation 2](#) represents an Autoregressive Distributed Lag (ARDL) model designed to investigate the determinants of logarithms of road traffic accidents ( $\ln RTA_t$ ). The model posits that road traffic accidents in a given period (t) are influenced by a combination of factors, including: log of average annual temperature ( $\ln TP_t$ ), log average annual rainfall ( $\ln RF_t$ ), log average annual carbon dioxide emissions ( $\ln CO_2_t$ ), log of Gross Domestic Product ( $\ln GDP_t$ ), log of foreign aid received ( $\ln FAR_t$ ), log of urban population ( $\ln UP_t$ ), and a political instability index ( $PI_t$ ). The coefficients ( $\alpha_1$  through  $\alpha_6$ ) associated with each explanatory variable quantify the magnitude and direction of their respective impacts on road traffic accidents. Finally,  $\varepsilon_t$  represents the error term, encompassing any unobserved or unexplained factors that may contribute to variations in road traffic accidents.

Consistent with the methodology used by [Nasrullah et al. \(2021\)](#), all variables will undergo a natural logarithmic transformation to linearize the model and obtain elasticity interpretations. The ARDL representation of our model is:

$$\begin{aligned} \Delta \ln RTA_t = & \alpha_0 + \sum_{k=1}^n \alpha_1 \Delta \ln RTA_{t-k} + \sum_{k=1}^n \alpha_2 \Delta \ln TP_{t-k} + \\ & \sum_{k=1}^n \alpha_3 \Delta \ln RF_{t-k} + \sum_{k=1}^n \alpha_4 \Delta \ln CO_2_{t-k} + \\ & \sum_{k=1}^n \alpha_5 \Delta \ln GDP_{t-k} + \sum_{k=1}^n \alpha_6 \Delta \ln FAR_{t-k} + \\ & \sum_{k=1}^n \alpha_7 \Delta \ln UP_{t-k} + \sum_{k=1}^n \alpha_8 \Delta PI_{t-k} + \\ & \lambda_1 \ln RTA_{t-1} + \lambda_2 \ln TP_{t-1} + \lambda_3 \ln RF_{t-1} + \\ & \lambda_4 \ln CO_2_t + \lambda_5 \ln GDP_t + \lambda_6 \ln FAR_t + \\ & \lambda_7 \ln UP_t + \lambda_8 PI_t + \varepsilon_t \end{aligned} \quad (3)$$

TABLE 1 Variable description and data source.

| Variable | Description            | Unit measurement                                                                                                         | Source               |
|----------|------------------------|--------------------------------------------------------------------------------------------------------------------------|----------------------|
| RTA      | Road traffic accidents | Death rate from road injuries (per 100,000 people)                                                                       | Our World in Data    |
| Urban    | Urban population       | Percentage of urban population to the total population                                                                   | World Bank           |
| Temp     | Temperature            | Average annual temperature (°C)                                                                                          | World Bank           |
| Rainfall | Rainfall               | Average annual precipitation (mm)                                                                                        | World Bank           |
| Co2      | Carbon dioxide         | Thousands of tons                                                                                                        | World Bank           |
| FAR      | Foreign aid received   | Net Official Development assistance in US Dollars                                                                        | Our World in Data    |
| GDP      | Gross domestic product | GDP per capita in US Dollars                                                                                             | World Bank           |
| PI       | Political instability  | It is a dummy variable measured as 1 during periods of political instability and 0 during periods of political stability | Author's Computation |

Where  $\alpha_0$  represents the drift component,  $\Delta$  denotes the first difference, and  $\varepsilon_t$  represents the white noise. The study utilizes the AIC (Akaike Information Criterion) for selecting the optimal lag length. The inclusion of the lagged dependent variable ( $\ln RTA_{t-1}$ ) captures the autoregressive nature of the model, accounting for the influence of past road traffic accident levels on current levels. After establishing the long-run association between variables, the study employs the error correction model (ECM) to determine the short-run dynamics. The general form of the ECM Equation 3 is formulated below in Equation 4.

For evaluating short-run dynamics, an error correction model (ECM) is incorporated:

$$\begin{aligned} \Delta \ln RTA_t = & \alpha_0 + \sum_{k=1}^n \alpha_1 \Delta \ln RTA_{t-k} + \sum_{k=1}^n \alpha_2 \Delta \ln TP_{t-k} + \\ & \sum_{k=1}^n \alpha_3 \Delta \ln RF_{t-k} + \sum_{k=1}^n \alpha_4 \Delta \ln CO2_{t-k} + \\ & \sum_{k=1}^n \alpha_5 \Delta \ln GDP_{t-k} + \sum_{k=1}^n \alpha_6 \Delta \ln FAR_{t-k} + \\ & \sum_{k=1}^n \alpha_7 \Delta \ln UP_{t-k} + \sum_{k=1}^n \alpha_8 \Delta PI_{t-k} + \\ & \odot ECM_{t-1} + \varepsilon_t \end{aligned} \quad (4)$$

Where  $\odot$  represents the coefficients of ECM for short-run dynamics. ECM denotes the rate of adjustment to long-run equilibrium following a short-run shock.

### 3.2.3 Model checking

To ensure the reliability and accuracy of the ARDL model, a series of diagnostic tests were conducted. These included: (1) unit root tests to confirm the stationarity properties of the variables, (2) lag selection criteria to determine the optimal model structure, (3) cointegration tests to verify the existence of a long-run relationship among the variables, and (4) stability tests to assess the consistency of the model parameters over time. By performing these tests, we aimed to validate the appropriateness of the ARDL model for the data and ensure the robustness of the findings.

#### 3.2.3.1 Unit root tests

The ARDL approach necessitates stationarity assessment; consequently, we employed the augmented Dickey-Fuller and Phillips-Perron (PP) tests to ascertain whether variables are integrated of order zero (I(0)) or one (I(1)), consistent with previous studies (Nasrullah et al., 2021; Rizwanullah et al., 2020).

#### 3.2.3.2 Lag selection criteria

The optimal lag structure for the ARDL model was determined based on the Akaike Information Criterion (AIC) or Bayesian Information Criteria (BIC). The long-run relationship among the variables was examined using the Wald test, by comparing its calculated F-statistics with the upper and lower bound values of critical values by Pesaran and Shin (1995).

#### 3.2.3.3 Cointegration tests

To determine the presence of a long-run relationship among the variables, the study employs the Autoregressive Distributed Lag

(ARDL) bounds testing approach to cointegration. This methodology offers several advantages, including its applicability irrespective of whether the underlying variables are I(0) or I(1), and its capacity to estimate the long-run and short-run coefficients simultaneously. The bounds test involves conducting an F-test to assess the joint significance of the lagged levels of the variables in the error correction form of the ARDL model. If the calculated F-statistic exceeds the upper critical bound, the null hypothesis of no cointegration is rejected, indicating the existence of a stable long-run relationship among road traffic accidents, temperature, rainfall, CO2 emissions, GDP, foreign aid, urban population, and political instability. Conversely, if the F-statistic falls below the lower critical bound, the null hypothesis cannot be rejected, suggesting the absence of cointegration.

#### 3.2.3.4 Stability tests

To assess the stability of the estimated ARDL model parameters over the sample period, the study employs the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUM Square) tests. These tests, based on the recursive residuals of the model, provide a visual assessment of parameter constancy. The CUSUM test detects systematic deviations from the null hypothesis of parameter stability, while the CUSUM Square test exhibits greater sensitivity to sudden or abrupt changes in the model's coefficients. If the plots of the CUSUM and CUSUM Square statistics remain within the critical bounds at a specified significance level (typically 5%), the null hypothesis of parameter stability is accepted, indicating that the model's coefficients are stable over time and that the model is suitable for forecasting. Conversely, if the plots cross the critical bounds, it suggests that the model parameters are unstable and that the model may not be reliable for long-term predictions (Brown et al., 1975).

## 4 Empirical results and discussion

### 4.1 Descriptive statistics

Table 2 presents descriptive statistics for the variables used in the analysis. The mean logarithmic urban population (lnUP) was 14.99 (SD = 0.50), while the mean political instability index (PI) was 0.24 (SD = 0.43), indicating that the political context in Somalia was slightly unstable. The mean logarithm road traffic accidents (lnRTA) was 7.25 (SD = 0.20) while the mean of logarithm rainfall was 5.62 (SD = 0.14) indicating that the sample was skewed to road traffic accidents and rainfall level, respectively.

### 4.2 Correlation matrix

The correlation matrix in Table 3 reveals several notable relationships between the variables. Logarithmic urban population (lnUP) exhibits a strong positive correlation with logarithmic gross domestic product (lnGDP) at 0.878, suggesting that economic activity tends to concentrate in urban areas. Conversely, lnUP shows a strong negative correlation with logarithmic road traffic accidents (lnRTA) at  $-0.792$ , indicating that increased urbanization is associated with decreased road traffic accidents. Logarithmic temperature (lnTP) and logarithmic rainfall (lnRF) show positive correlations with lnUP, but negative correlations with lnRTA. Logarithmic carbon dioxide

TABLE 2 Description statistics of the variable used.

| Variables   | lnUP   | lnTP  | lnRA   | lnCO2  | lnFAR  | lnRTA | lnGDP  | PI    |
|-------------|--------|-------|--------|--------|--------|-------|--------|-------|
| Mean        | 14.986 | 3.292 | 5.615  | 13.361 | 20.303 | 7.248 | 5.531  | 0.238 |
| Std. Dev.   | 0.502  | 0.008 | 0.136  | 0.232  | 0.853  | 0.2   | 0.595  | 0.431 |
| Min         | 14.278 | 3.276 | 5.231  | 12.524 | 18.598 | 6.877 | 4.572  | 0.000 |
| Max         | 15.904 | 3.308 | 5.867  | 13.819 | 21.876 | 7.806 | 6.376  | 1.000 |
| p1          | 14.278 | 3.276 | 5.231  | 12.524 | 18.598 | 6.877 | 4.572  | 0.000 |
| p99         | 15.904 | 3.308 | 5.867  | 13.819 | 21.876 | 7.806 | 6.376  | 1.000 |
| Skew.       | 0.294  | 0.078 | −0.279 | −0.498 | −0.485 | 0.031 | −0.158 | 1.230 |
| Kurt.       | 1.757  | 2.691 | 3.414  | 5.861  | 2.257  | 2.946 | 1.618  | 2.512 |
| Jarque-Bera | 9.51   | 0.06  | 1.81   | 8.39   | 3.47   | 0.14  | 14.35  | 0.001 |
| Prob        | 0.009  | 0.97  | 0.405  | 0.015  | 0.176  | 0.931 | 8.54   | 0.014 |
| Obs         | 42     | 42    | 42     | 42     | 42     | 42    | 42     | 42    |

TABLE 3 Matrix of correlations.

| Variables | lnUP   | lnTP   | lnTP   | lnCO2  | lnFAR  | lnRTA  | lnGDP  | PI    |
|-----------|--------|--------|--------|--------|--------|--------|--------|-------|
| lnUP      | 1.000  |        |        |        |        |        |        |       |
| lnTP      | 0.640  | 1.000  |        |        |        |        |        |       |
| lnRF      | 0.378  | 0.087  | 1.000  |        |        |        |        |       |
| lnCO2     | −0.227 | −0.100 | −0.265 | 1.000  |        |        |        |       |
| lnFAR     | 0.300  | 0.045  | 0.145  | 0.346  | 1.000  |        |        |       |
| lnRTA     | −0.792 | −0.557 | −0.326 | 0.229  | −0.226 | 1.000  |        |       |
| lnGDP     | 0.878  | 0.519  | 0.429  | −0.393 | 0.018  | −0.818 | 1.000  |       |
| PI        | −0.288 | −0.195 | −0.148 | −0.187 | −0.400 | 0.397  | −0.160 | 1.000 |

(lnCO2) and political instability (PI) show weak correlations with most variables, except for a moderate negative correlation between PI and logarithmic foreign aid (lnFAR) at  $-0.400$ , suggesting that political instability may hinder the effective distribution or utilization of foreign aid.

### 4.3 Multicollinearity test

To assess the potential issue of multicollinearity among the predictor variables (lnUP, lnFAR, PI, lnTP, lnCO2, lnRF), a Variance Inflation Factor (VIF) analysis was conducted. The results, presented in Table 4, show that the individual VIF values range from 1.29 (lnRF) to 2.54 (lnUP). All individual VIF values are substantially below the commonly accepted threshold of 10, and also below the more conservative threshold of 5. Furthermore, the mean VIF is 1.96, which is also very low. These findings indicate that multicollinearity is not a significant concern in this model, suggesting that the estimated regression coefficients are unlikely to be substantially inflated or unreliable due to correlations among the predictor variables.

### 4.4 Unit root tests

Table 5 reports the results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests conducted to assess the stationarity of the variables. The analysis reveals that both lnRTA,

TABLE 4 Variance inflation factor (VIF) results for multicollinearity assessment.

| Variable | VIF  |
|----------|------|
| lnUP     | 2.54 |
| lnFAR    | 2.34 |
| PI       | 2.23 |
| lnTP     | 1.88 |
| lnCO2    | 1.49 |
| lnRF     | 1.29 |

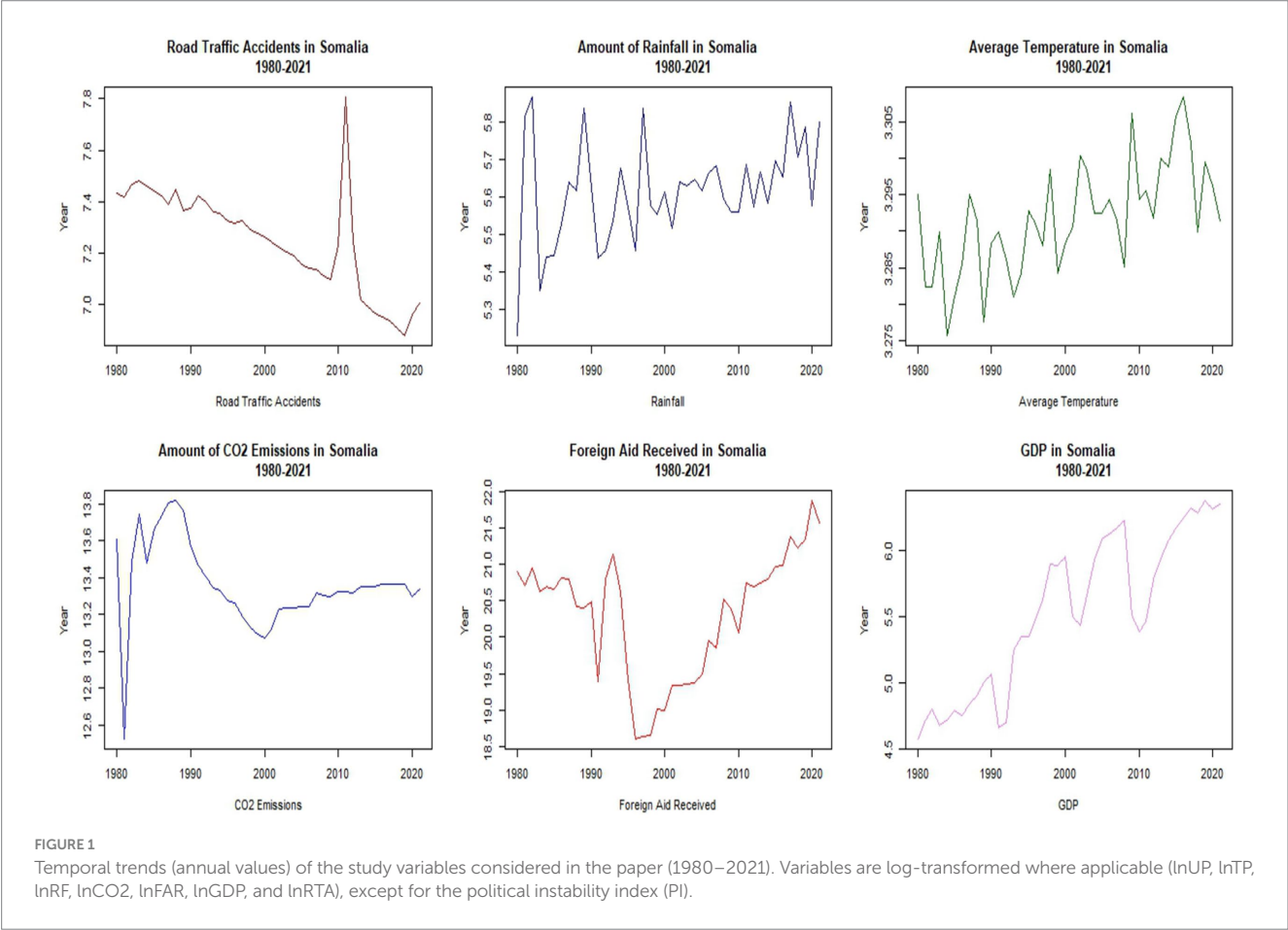
VIF, Variance Inflation Factor. A common threshold suggests VIF values below 10 indicate an absence of serious multicollinearity. The Mean VIF for these variables is 1.96.

lnUP, lnFAR, and lnGDP were non-stationary at their levels but became stationary after first differencing. The null hypotheses, in general, that the variables contain a unit root, meaning they are non-stationary, is rejected. The results indicated that the logarithmic temperature (lnTP), logarithmic rainfall (lnRF), and logarithmic carbon dioxide (lnCO2) were stationary at their levels. The political instability variable (PI), being a dummy variable, was tested in its original form (not log-transformed) and found to be integrated of order one,  $I(1)$ . These findings led to the selection of an ARDL model, suitable for handling variables integrated at different orders. Figure 1 illustrates the RTA at first differencing.

TABLE 5 Unit root tests.

| Variable | ADF       |                 | PP         |                 | Order of integration |
|----------|-----------|-----------------|------------|-----------------|----------------------|
|          | Levels    | 1st differences | Levels     | 1st differences |                      |
| lnRTA    | −2.212    | −7.233*         | −7.821     | −37.816*        | I (1)                |
| lnUP     | 2.009     | −4.418*         | 0.671      | −24.431*        | I (1)                |
| lnTP     | −3.869*** | −9.150*         | −23.103*** | −44.098*        | I (0)                |
| lnRF     | −6.588*** | −9.417*         | −42.180*** | −43.959*        | I (0)                |
| lnCO2    | −3.941*** | −13.512*        | −25.942*** | −58.960*        | I (0)                |
| lnFAR    | −1.452    | −6.487*         | −4.903     | −39.107*        | I (1)                |
| lnGDP    | −1.284    | −5.224*         | −2.864     | −28.522*        | I (1)                |
| lnPI     | −2.438    | −7.958*         | −10.584    | −48.281*        | I (1)                |

\*indicates significance at the 1% level ( $p < 0.01$ ). \*\*\* indicates significance at the 1% level ( $p < 0.01$ ).



4.5 Lag selection criteria

Table 6 presents the criteria for selecting an appropriate lag order using Vector Autoregression model (VAR), showing that a lag order of 3 was optimal, as indicated by the lowest AIC (−22.8253) and SBIC (−14.2064), marked by the asterisk (\*). This lag length was chosen as it represents an optimal balance, according to the information criteria, capturing sufficient dynamic interrelationships within the time series while mitigating the risks of model overfitting and excessive loss of

degrees of freedom given the sample size. This lag length will ensure the parameters are robust and can take the most of available information to fit for time-series.

4.6 ARDL bound test for cointegration

Table 7 shows the results of the ARDL bounds test for cointegration, indicating a statistically significant long-run

TABLE 6 Lag order criteria by using VAR (vector autoregression).

| Lag | LL      | LR      | df | <i>p</i> | FPE                   | AIC       | HQIC      | SBIC      |
|-----|---------|---------|----|----------|-----------------------|-----------|-----------|-----------|
| 0   | 170.350 | NA      | NA | NA       | $2.7 \times 10^{-14}$ | −8.545472 | −8.42206  | −8.19997  |
| 1   | 381.189 | 421.680 | 64 | 0.000    | $1.3 \times 10^{-17}$ | −16.2731  | −15.1692  | −13.1703  |
| 2   | 468.335 | 174.290 | 64 | 0.000    | $6.0 \times 10^{-18}$ | −17.4913  | −15.4061  | −11.6305  |
| 3   | 633.681 | 330.69* | 64 | 0.000    | $1.4 \times 10^{-19}$ | −22.8253* | −19.7588* | −14.2064* |

TABLE 7 ARDL bound test for cointegration.

| Equation                                               | Lag               | F-statistics | <i>P</i> -value |
|--------------------------------------------------------|-------------------|--------------|-----------------|
| Rta = f(Urban, Tp, RF, CO <sub>2</sub> , Fia, Gdp, Pi) | (1,1,0,0,0,1,1,1) | 11.910*      | 0.000           |
| Critical value                                         | 1%                | 5%           | 10%             |
| Lower bound I (0)                                      | 3.150             | 2.450        | 2.120           |
| Upper bound I (1)                                      | 4.43              | 3.610        | 3.230           |

\*Represents the 1% significance level.

TABLE 8 Long-run estimation of parameters from ARDL models.

| Variables | Coefficients | Std. error | T-statistics | Prob. |
|-----------|--------------|------------|--------------|-------|
| LUrban    | 0.273        | 0.032      | 8.420        | 0.000 |
| LTemp     | −5.820       | 1.128      | −5.160       | 0.002 |
| LRainfall | −2.491       | 0.149      | −16.720      | 0.000 |
| LCo2      | 0.781        | 0.085      | 9.240        | 0.000 |
| LFia      | −0.146       | 0.017      | −8.820       | 0.000 |
| LPi       | 0.178        | 0.027      | 6.590        | 0.001 |
| C         | 72.941       | 14.876     | 4.900        | 0.003 |

relationship among the variables (F-statistic = 11.910,  $p < 0.01$ ). The F-statistic is greater than the upper bound critical value at the 1% significance level (4.43), leading to the rejection of the null hypothesis of no cointegration. This suggests that the selected variables exhibit a stable long-run relationship with road traffic accidents.

## 4.7 Long run results

Table 8 presents the long-run results from the ARDL model (ARDL(1,1,0,0,0,1,1,1)), revealing significant coefficients for several variables. Logarithmic urban population (LnUP) had a positive and statistically significant coefficient (0.273, SE = 0.032,  $t = 8.420$ ,  $p < 0.001$ ), indicating that a 1% increase in urban population is associated with a 0.273% increase in road traffic accidents in the long run. In contrast, logarithmic rainfall (LnRF) was negative and statistically significant (−2.491, SE = 0.149,  $t = -16.720$ ,  $p < 0.001$ ), suggesting that a 1% increase in rainfall is associated with a 2.491% decrease in road traffic accidents in the long run. Logarithmic temperature (LnTP) had a negative and statistically significant coefficient (−5.820, SE = 1.128,  $t = -5.160$ ,  $p = 0.002$ ), indicating that a 1% increase in temperature is associated with a 5.820% decrease in road traffic accidents in the long run. Logarithmic carbon dioxide (LnCO<sub>2</sub>) had a positive and statistically significant coefficient (0.781,

SE = 0.085,  $t = 9.240$ ,  $p < 0.001$ ), indicating that a 1% increase in carbon dioxide is associated with a 0.781% increase in road traffic accidents in the long run. Logarithmic foreign aid (LnFAR) had a negative and statistically significant coefficient (−0.146, SE = 0.017,  $t = -8.820$ ,  $p < 0.001$ ), indicating that a 1% increase in foreign aid is associated with a 0.146% decrease in road traffic accidents in the long run. Logarithmic political instability (LnPI) had a positive and statistically significant coefficient (0.178, SE = 0.027,  $t = 6.590$ ,  $p < 0.001$ ), indicating that a 1% increase in political instability is associated with a 0.178% increase in road traffic accidents in the long run.

## 4.8 Short run results

Table 9 presents the short-run results from the ARDL model (ARDL(1,1,0,0,0,1,1,1)), showing the coefficients of the differenced variables. The change in logarithmic urban population (D.lurban) had a negative and statistically significant coefficient (−2.606, SE = 0.551,  $t = -4.730$ ,  $p = 0.003$ ), indicating that a 1% increase in the change of urban population is associated with a 2.606% decrease in road traffic accidents in the short run. The change in logarithmic temperature (D.ltemp) had a positive and statistically significant coefficient (6.258, SE = 2.128,  $t = 2.940$ ,  $p = 0.026$ ), indicating that a 1% increase in the change of temperature is associated with a 6.258% increase in road traffic accidents in the short run. The change in logarithmic rainfall (D.lrainfall) had a positive and statistically significant coefficient (5.108, SE = 0.786,  $t = 6.490$ ,  $p = 0.001$ ), indicating that a 1% increase in the change of rainfall is associated with a 5.108% increase in road traffic accidents in the short run. The change in logarithmic carbon dioxide (D.lco2) had a negative and statistically significant coefficient (−4.341, SE = 0.412,  $t = -10.520$ ,  $p < 0.001$ ), indicating that a 1% increase in the change of carbon dioxide is associated with a 4.341% decrease in road traffic accidents in the short run. The change in logarithmic foreign aid (D.lfia) had a positive and statistically significant coefficient (0.241, SE = 0.030,  $t = 8.040$ ,  $p < 0.001$ ), indicating that a 1% increase in the change of foreign aid is associated with a 0.241% increase in road traffic accidents in the short run. The change in logarithmic political instability (D.lpi) had a negative and statistically significant coefficient (−0.201, SE = 0.055,  $t = -3.680$ ,  $p = 0.010$ ), indicating that a 1% increase in the change of political instability is associated with a 0.201% decrease in road traffic accidents in the short run.

## 4.9 Diagnostic tests

Table 10 presents the diagnostic test results for the ARDL model, assessing its overall fit and validity. The model exhibits a high R-squared value of 0.995 and an adjusted R-squared of 0.960, indicating that the model explains a large proportion of the variance in road traffic

TABLE 9 Short-run estimation of parameters from ARDL models.

| Variables | Coefficients | Std. error | T-statistics | Prob. |
|-----------|--------------|------------|--------------|-------|
| D.lnUP    | −2.606       | 0.551      | −4.730       | 0.003 |
| D.lnTP    | 6.258        | 2.128      | 2.940        | 0.026 |
| D.lnRF    | 5.108        | 0.786      | 6.490        | 0.001 |
| D.lnCO2   | −4.341       | 0.412      | −10.520      | 0.000 |
| D.lnFAR   | 0.241        | 0.030      | 8.040        | 0.000 |
| D. PI     | −0.201       | 0.055      | −3.680       | 0.010 |

TABLE 10 Diagnostic tests.

| Diagnostic test             | Chi-square (p-value) |
|-----------------------------|----------------------|
| R-square                    | 0.995                |
| Adjusted R-square           | 0.960                |
| Durbin-Watson statistics    | 2.465                |
| X <sup>2</sup> Ramsey reset | 1.82 (0.3743)        |
| X <sup>2</sup> ARCH         | 0.11 (0.7434)        |
| X <sup>2</sup> B-G          | 0.1 (0.35)           |
| X <sup>2</sup> Normality    | 0.02 (0.991)         |

accidents. The Durbin-Watson statistic is 2.465, suggesting no significant autocorrelation in the residuals. The Ramsey RESET test ( $X^2 = 1.82$ ,  $p = 0.3743$ ), ARCH test ( $X^2 = 0.11$ ,  $p = 0.7434$ ), Breusch-Godfrey test ( $X^2 = 0.1$ ,  $p = 0.35$ ), and Normality test ( $X^2 = 0.02$ ,  $p = 0.991$ ) all have  $p$ -values greater than 0.05, indicating that the model passes these diagnostic tests and does not suffer from misspecification, heteroscedasticity, serial correlation, or non-normal residuals.

## 4.10 Stability checks

As standard diagnostic procedures for assessing parameter consistency in ARDL models, the CUSUM and CUSUM of Squares tests for model stability indicate that the model parameters are stable over the sample period.

The CUSUM and CUSUM of Squares tests for model stability indicate that the model parameters are stable over the sample period. The CUSUM plot in Figure 2 shows the cumulative sum of residuals over time, and it remains within the 5% significance boundaries, indicating that the model parameters are stable. Similarly, the CUSUM of Squares plot also stays within the 5% critical bounds, reinforcing the stability of the model. Together, these diagnostic tests and stability checks confirm that the model is well-specified, with no issues related to heteroskedasticity, serial correlation, or parameter instability, which is crucial for making accurate inferences from the model's results.

## 5 Discussions

This study provides a comprehensive analysis of the factors influencing road traffic fatalities (RTFs) in Somalia, a low-resource setting facing complex challenges. The ARDL model results reveal significant relationships between climate change, socioeconomic

conditions, environmental factors, political instability, and RTFs, offering valuable insights for evidence-based policymaking.

The positive and statistically significant long-run coefficient for logarithmic urban population (0.273,  $p < 0.001$ ) indicates that increased urbanization is associated with higher RTFs in Somalia. This finding aligns with previous research suggesting that urban areas often experience higher traffic density, congestion, and pedestrian-vehicle interactions, leading to increased accident risk (Cabrera-Arnau and Bishop, 2021). However, the negative short-run coefficient (−2.606,  $p = 0.003$ ) suggests that immediate increases in urbanization may initially result in decreased RTFs, potentially reflecting focused infrastructure improvements or heightened safety awareness campaigns in newly developing urban areas before the negative impacts of congestion and density fully manifest.

The negative and statistically significant long-run coefficient for logarithmic temperature (−5.820,  $p = 0.002$ ) indicates that higher temperatures are associated with lower RTFs in Somalia. This finding contradicts some studies that suggest higher temperatures increase RTFs due to driver fatigue and vehicle malfunctions (Ali et al., 2019). However, it aligns with research indicating that drivers may adopt more cautious behavior during extreme heat (the safety offset hypothesis) (Ali et al., 2019). The positive short-run coefficient (6.258,  $p = 0.026$ ) suggests that immediate temperature increases may lead to higher RTFs, potentially due to sudden physiological impacts on driver alertness and fatigue, or temporary adverse effects on vehicle performance (e.g., tire pressure) and road surface conditions before behavioral adaptations take hold.

The negative and statistically significant long-run coefficient for logarithmic rainfall (−2.491,  $p < 0.001$ ) suggests that higher rainfall is associated with lower RTFs in Somalia. This finding contradicts some studies that suggest higher rainfall increases RTFs due to reduced visibility and tire grip (Abu el-Hassan et al., 2024). However, it aligns with research indicating that drivers may adjust their behavior during adverse weather conditions (Torre-Pascual et al., 2024). The positive short-run coefficient (5.108,  $p = 0.001$ ) suggests that immediate increases in rainfall may lead to higher RTFs, consistent with the well-documented immediate hazards of reduced visibility and decreased tire friction during precipitation events, potentially occurring before drivers significantly alter their travel plans or driving behavior.

The positive and statistically significant long-run coefficient for logarithmic carbon dioxide (0.781,  $p < 0.001$ ) indicates that elevated CO<sub>2</sub> emissions are associated with higher RTFs in Somalia. This finding is consistent with research demonstrating that air pollution and environmental degradation can adversely affect driver health and visibility, thereby increasing accident risk (Ali et al., 2019). The negative short-run coefficient (−4.341,  $p < 0.001$ ) suggests that immediate increases in CO<sub>2</sub> emissions may result in lower RTFs, potentially due to temporary reductions in traffic volume or enhanced awareness campaigns.

The negative and statistically significant long-run coefficient for logarithmic foreign aid (−0.146,  $p < 0.001$ ) indicates that increased foreign aid is associated with lower RTFs in Somalia. This finding is consistent with research demonstrating that foreign aid can enhance infrastructure, healthcare, and road safety, thereby reducing accident risk (Torre-Pascual et al., 2024). The positive short-run coefficient (0.241,  $p < 0.001$ ) suggests that immediate increases in foreign aid may result in higher RTFs, potentially due to increased traffic volume or inadequately planned infrastructure projects.

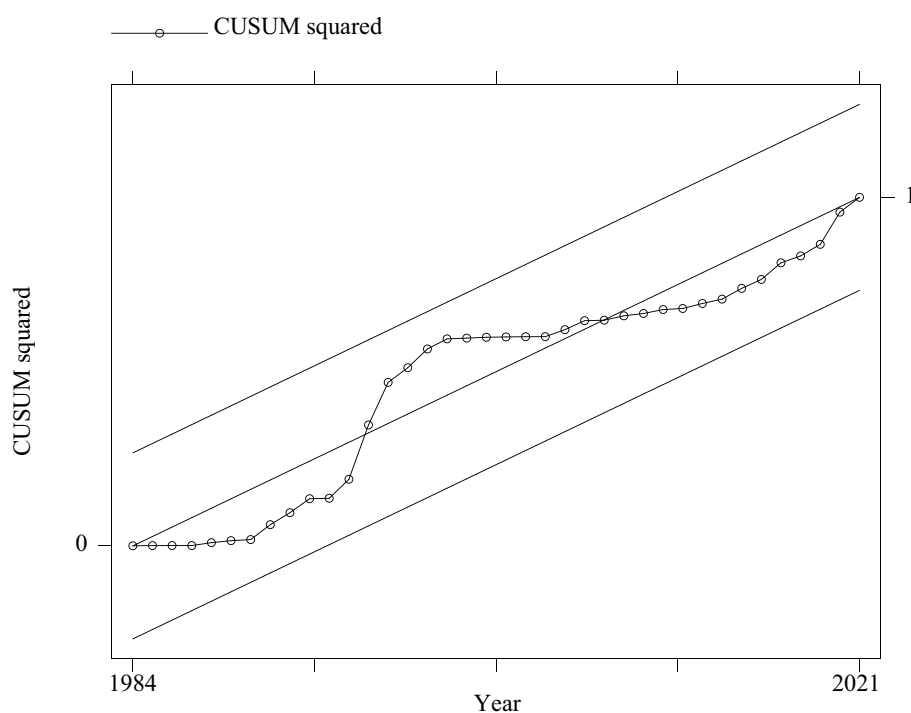


FIGURE 2  
CUSUM square test.

Similarly, the contrasting signs for foreign aid ( $\text{LnFAR}$ ) warrant discussion. The positive short-run coefficient ( $0.241, p < 0.001$ ) might suggest that immediate aid inflows, perhaps leading to rapid but poorly integrated infrastructure projects or an abrupt increase in vehicle imports and traffic volume, initially elevate RTF risk. Conversely, the negative and significant long-run coefficient ( $-0.146, p < 0.001$ ) aligns with the expectation that sustained foreign aid, when effectively utilized, eventually contributes to better overall infrastructure, improved healthcare access for injury treatment, and potentially enhanced road safety regulations and enforcement, thereby reducing RTFs over time.

The positive and statistically significant long-run coefficient for logarithmic political instability ( $0.178, p < 0.001$ ) indicates that higher political instability is associated with higher RTFs in Somalia. This finding is consistent with research suggesting that political instability can result in neglected infrastructure, inadequate enforcement of traffic laws, and increased risk-taking behavior among drivers, thereby elevating accident risk (Alzaffin et al., 2023). The negative short-run coefficient ( $-0.201, p = 0.010$ ) implies that immediate increases in political instability may lead to lower RTFs, potentially due to reduced traffic volume or heightened caution among drivers.

This study's strength lies in its utilization of the ARDL model, which facilitates the examination of both short- and long-run effects of climate change, socioeconomic conditions, environmental factors, and political instability on RTFs. The use of time-series data spanning 38 years provides a robust analysis of RTF dynamics in Somalia. Furthermore, the study's focus on Somalia, a low-resource setting facing complex challenges, addresses a gap in the existing literature. The diagnostic tests (Table 9) confirm the validity and robustness of the model.

The study is not without limitations. The reliance on secondary data may not fully capture the nuances of local RTF drivers, particularly in the context of data scarcity and reporting challenges. Furthermore,

while this study incorporated key variables guided by data availability within Somalia's challenging context, we acknowledge that other potentially significant factors influencing RTFs could not be included in the quantitative model. Specifically, variables such as income inequality (often measured by the Gini coefficient), granular metrics of corruption (particularly those related to infrastructure procurement and oversight), and objective data on road construction quality, standards, and potential malpractices, while highly relevant, were omitted. The primary constraint was the lack of consistent, reliable, and publicly available time-series data for these specific indicators covering the extensive 1980–2021 study period for Somalia. Such data scarcity is a common and significant hurdle in conducting longitudinal quantitative research in fragile state environments. While our model includes GDP per capita as a broad indicator of socioeconomic conditions, it cannot capture the nuances represented by these omitted variables. Therefore, investigating the specific impact of income inequality, corruption, and road quality on RTFs in Somalia remains a critical area for future research, contingent upon improvements in data collection and availability within the country.

The primary contribution of this paper is its comprehensive analysis of the factors influencing RTFs in Somalia, elucidating the complex interplay between climate change, socioeconomic conditions, environmental factors, and political instability. The study's findings challenge linear narratives that position any single factor as the primary driver of RTFs, instead emphasizing the importance of understanding how multiple factors interact to shape RTF outcomes. The study also provides valuable insights for evidence-based policymaking in Somalia and other low-resource settings facing similar challenges.

The findings of this study align with several Sustainable Development Goals (SDGs). The negative relationship between foreign aid and RTFs underscores the importance of SDG 3 (Good

Health and Well-being) and SDG 9 (Industry, Innovation, and Infrastructure) in improving road safety. The positive relationship between political instability and RTFs highlights the need for SDG 16 (Peace, Justice, and Strong Institutions) to promote stability and good governance. The positive relationship between CO<sub>2</sub> emissions and RTFs emphasizes the importance of SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action) in reducing environmental degradation and its impact on road safety.

## 6 Conclusion and policy implications

This study presents a comprehensive analysis of the factors influencing road traffic fatalities in Somalia, elucidating the complex interplay between climate change, socioeconomic conditions, environmental factors, and political instability. The ARDL model results reveal significant relationships between these factors and RTFs, providing valuable insights for evidence-based policymaking. Key findings include. Increased urbanization, CO<sub>2</sub> emissions, and political instability are associated with higher RTFs in the long run. Increased rainfall and foreign aid are associated with lower RTFs in the long run. Short-run dynamics reveal nuanced effects, with temperature and rainfall exhibiting positive associations with RTFs.

These findings challenge simplistic explanations of RTF drivers, highlighting the need for integrated road safety strategies. Therefore, we recommend the following policy implications for Somalia and other low-resource settings seeking to reduce road traffic fatalities:

- *Comprehensive Strategies:* Policymakers should adopt comprehensive road safety strategies that address the complex interplay between climate change, socioeconomic conditions, environmental factors, and political instability. These strategies should encompass investments in infrastructure, healthcare, education, and law enforcement.
- *Climate Change Adaptation:* Policymakers should prioritize climate change adaptation measures to mitigate the impact of climate variability on road safety. These measures should include improving road infrastructure to withstand extreme weather events, promoting sustainable transportation options, and enhancing public awareness regarding safe driving practices during adverse weather conditions.
- *Environmental Protection:* Policymakers should implement policies to reduce CO<sub>2</sub> emissions and environmental degradation, such as promoting renewable energy sources, improving vehicle fuel efficiency, and enforcing environmental regulations.
- *Socioeconomic Development:* Policymakers should invest in socioeconomic development to reduce poverty, improve healthcare access, and promote education. These investments can enhance road safety by increasing access to safe vehicles, healthcare services, and driver education programs.
- *Good Governance and Political Stability:* Policymakers should prioritize good governance and political stability to create a secure and predictable environment for road users. This includes strengthening law enforcement, improving infrastructure, and promoting transparency and accountability.
- *Targeted Interventions:* Policymakers should implement targeted interventions to address specific risk factors for RTFs, such as promoting seatbelt use through awareness campaigns and stricter enforcement, reducing drunk driving via measures like random

breath testing and appropriate penalties, and improving vehicle maintenance practices through basic roadworthiness checks or educational initiatives for drivers and mechanics.

This study contributes to the limited literature on RTFs in fragile states and provides valuable insights for evidence-based policymaking aimed at achieving Sustainable Development Goals related to health, infrastructure, and sustainable communities. Future research should focus on exploring regional variations in RTF dynamics, assessing the efficacy of specific policy interventions, and incorporating qualitative methods to gain a more profound understanding of the lived experiences of road users.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Author contributions

AhA: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. AbA: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. ASY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. AMY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. AM: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

## Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

## Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated

organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

## References

- Abdi, A. H., Warsame, A. A., and Sheik-ali, I. A. (2024). Testing the non-linearities of exchange rate pass-through in Somalia: does dollarization affect consumer prices? *Cogent Econ. Finance* 12:2344720. doi: 10.1080/23322039.2024.2344720
- Abu el-Hassan, K., Hakeem, I. Y., Amin, M., Tayeh, B. A., Zeyad, A. M., Agwa, I. S., et al. (2024). Effects of nano titanium and nano silica on high-strength concrete properties incorporating heavyweight aggregate. *Struct. Concr.* 25, 239–264. doi: 10.1002/suco.202300232
- Abubakar, M. A. (2022). *Road traffic accidents and their effects on economic growth: a case study of Mogadishu*.
- Ageli, M. M., (2013) *Road traffic accidents in Saudi Arabia: an ardl approach and multivariate granger causality*.
- Akinyemi, Y. (2020). Relationship between economic development and road traffic crashes and casualties: empirical evidence from Nigeria. *Transp. Res. Procedia* 48, 218–232. doi: 10.1016/j.trpro.2020.08.017
- Ali, A., Mohamed, J., and Asumadu, S. (2024). Heliyon natural disasters, deforestation, and emissions affect economic growth in Somalia. *Heliyon* 10:e28214. doi: 10.1016/j.heliyon.2024.e28214
- Ali, Q., Yaseen, M. R., and Khan, M. T. I. (2019). Road traffic fatalities and its determinants in high-income countries: a continent-wise comparison. *Environ. Sci. Pollut. Res.* 26, 19915–19929. doi: 10.1007/s11356-019-05410-9
- Ali, Q., Yaseen, M. R., and Khan, M. T. I. (2020). The impact of temperature, rainfall, and health worker density index on road traffic fatalities in Pakistan. *Environ. Sci. Pollut. Res.* 27, 19510–19529. doi: 10.1007/s11356-020-08233-1
- Alzaffin, K., Kaye, S.-A., Watson, A., and Haque, M. M. (2023). Modelling the continuum of serious traffic injuries in police-hospital linked data by applying the random parameters hazard-based duration model. *Anal. Methods Accid. Res.* 40:100291. doi: 10.1016/j.amar.2023.100291
- Bahari, N. A. Z., Mohd Nusa, F. N., Tarudin, N. F., Mohamad, N. D., and Md Murozi, A.-F. (2023). Factors contributing to road accidents: case study of Jalan Seremban-Tampin/Nur Amalia Zulaikha...[et al.]. *Malays. J. Comput. (MJoC)* 8, 1436–1448.
- Bauer, R., Machata, K., Brandstaetter, C., Yannis, G., Laiou, A., and Folla, K. (2016). Road traffic accidents in European urban areas. Proceedings of the 1st European road infrastructure congress, Leeds, UK, 18–20.
- Brown, R. L., Durbin, J., and Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *J. R. Stat. Soc. Ser. B Stat Methodol.* 37, 149–163. doi: 10.1111/j.2517-6161.1975.tb01532.x
- Cabrera-Arnau, C., and Bishop, S. R. (2021). Urban population size and road traffic collisions in Europe. *PLoS one*. 16, e0256485.
- Đurić, P., and Peek-Asa, C. (2008). Economic sanctions, military activity, and road traffic crashes in Vojvodina, Serbia *Inj. Prev.* 14, 372–376, doi: 10.1136/ip.2008.019240, PMID: PMC2666017
- Frimpong, Y., Oluwoye, J., and Crawford, L. (2003). Causes of delay and cost overruns in construction of groundwater projects in a developing country: Ghana as a case study. *Int. J. Proj. Manag.* 21, 321–326. doi: 10.1016/S0263-7863(02)00055-8
- Getahun, K. A. (2021). Time series modeling of road traffic accidents in Amhara region. *J. Big Data* 8:102. doi: 10.1186/s40537-021-00493-z
- Ghadi, M. Q. (2025). Investigating the impact of climate change on traffic accidents in Jordan. *Sustainability* 17:2161. doi: 10.3390/su17052161
- Hassan, A. A., Muse, A. H., and Chesneau, C. (2024). Machine learning study using 2020 SDHS data to determine poverty determinants in Somalia. *Sci. Rep.* 14:5956. doi: 10.1038/s41598-024-56466-8
- Islam, M. M., Alharthi, M., and Alam, M. M. (2019). The impacts of climate change on road traffic accidents in Saudi Arabia. *Climate* 7:103. doi: 10.3390/cli7090103
- Jackson, T. L., and Sharif, H. O. (2016). Rainfall impacts on traffic safety: rain-related fatal crashes in Texas. *Geomat. Nat. Hazards Risk* 7, 843–860. doi: 10.1080/19475705.2014.984246
- Jaroszweski, D., and McNamara, T. (2014). The influence of rainfall on road accidents in urban areas: a weather radar approach. *Travel Behav. Soc.* 1, 15–21. doi: 10.1016/j.tbs.2013.10.005
- Keay, K., and Simmonds, I. (2006). Road accidents and rainfall in a large Australian city. *Accid. Anal. Prev.* 38, 445–454. doi: 10.1016/j.aap.2005.06.025
- Kopits, E., and Cropper, M. (2005). Traffic fatalities and economic growth. *Accid. Anal. Prev.* 37, 169–178. doi: 10.1016/j.aap.2004.04.006
- Li, X., Liu, J., Zhou, J., Liu, X., Zhou, L., and Wei, W. (2020). The effects of macroeconomic factors on road traffic safety: a study based on the ARDL-ECM model. *Sustainability* 12:10262. doi: 10.3390/su122410262
- Mohamed, J., Mohamed, A. I., Ali, D. A., and Gebremariam, T. T. (2023). Prevalence and factors associated with ever had road traffic accidents among drivers in Hargeisa city, Somaliland, 2022. *Heliyon* 9:e18631. doi: 10.1016/j.heliyon.2023.e18631
- Mondal, P. (2011). Are road accidents affected by rainfall? A case study from a large Indian metropolitan city. *Br. J. Appl. Sci. Technol.* 1, 16–26. doi: 10.9734/BJAST/2011/106
- Mwale, M., Mwangelwa, K., Kakoma, E., and Jaych, K. (2023). Estimation of the completeness of road traffic mortality data in Zambia using a three source capture recapture method. *Accid. Anal. Prev.* 186:107048. doi: 10.1016/j.aap.2023.107048
- Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T., and Liang, L. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *J. Water Clim. Change* 12, 2256–2270. doi: 10.2166/wcc.2021.030
- Oladeji, E. O., Ezeme, C., Baiyewu, L. A., Okunola, M. O., and Ogunlade, S. O. (2024). The catastrophic cost of motorcycle road traffic injuries: experience from a major reference Centre in a lower-middle income country. *Injury* 55:111314. doi: 10.1016/j.injury.2024.111314
- Osman, H. M., Hassan, I. A., Kasim, A. M., and Omar, O. A. (2022). Empirical research on factors contributing road accident among Bajaj drivers in Banadir region, Mogadishu, Somalia. *East Afr. J. Interdiscip. Stud.* 5, 133–139. doi: 10.37284/eajis.5.1.754
- Pesaran, M. H., and Shin, Y. (1995). *An autoregressive distributed lag modelling approach to cointegration analysis* (Vol. 9514). Cambridge, UK: Department of Applied Economics, University of Cambridge.
- Razzaghi, A., Soori, H., Abadi, A., and Khosravi, A. (2020). World health organization's estimates of death related to road traffic crashes and their discrepancy with other countries' national report. *J. Inj. Violence Res.* 12:39. doi: 10.5249/jivr.v12i3.1425
- Razzaghi, A., Soori, H., Kavousi, A., Abadi, A., Khosravi, A. K., and Alipour, A. (2019). Risk factors of deaths related to road traffic crashes in World Health Organization regions: a systematic review. *Arch. Trauma Res.* 8, 57–86. doi: 10.4103/atrr.59\_19
- Rizwanullah, M., Liang, L., Yu, X., Zhou, J., Nasrullah, M., and Ali, M. U. (2020). Exploring the cointegration relation among top eight Asian stock markets. *Open J. Bus. Manag.* 08, 1076–1088. doi: 10.4236/ojbm.2020.83068
- Sangadah, K., and Kartawidjaja, J. (2020). 主観的健康感を中心とした在宅高齢者における健康関連指標に関する共分散構造分析. *Orphanet J. Rare Dis.* 21, 1–9. Covariance structure analysis of health-related indicators in elderly people living at home, focusing on subjective health.
- Sangkharat, K., Thornes, J. E., Wachiradilok, P., and Pope, F. D. (2021). Determination of the impact of rainfall on road accidents in Thailand. *Heliyon* 7:e06061. doi: 10.1016/j.heliyon.2021.e06061
- Sohaee, N., and Bohluli, S. (2024). Nonlinear analysis of the effects of socioeconomic, demographic, and technological factors on the number of fatal traffic accidents. *Safety* 10:11. doi: 10.3390/safety10010011
- Staton, C., Vissoci, J., Gong, E., Toomey, N., Wafula, R., Abdelgadir, J., et al. (2016). Road traffic injury prevention initiatives: a systematic review and metasummary of effectiveness in low and middle income countries. *PLoS One* 11:e0144971. doi: 10.1371/journal.pone.0144971
- Toriumi, A., Abu-Lebdeh, G., Alhajjaseen, W., Christie, N., Gehlert, T., Mehran, B., et al. (2022). A multi-country survey for collecting and analyzing facts related to road traffic safety: legislation, enforcement, and education for safer drivers. *IATSS Res.* 46, 14–25. doi: 10.1016/j.iatssr.2022.01.004
- Torre-Pascual, E., Gangoiti, G., Rodríguez-García, A., Sáez de Cámara, E., Ferreira, J., Gama, C., et al. (2024). Analysis of an intense O<sub>3</sub> pollution episode on the Atlantic coast of the Iberian Peninsula using photochemical modeling: characterization of transport pathways and accumulation processes. *Atmos. Chem. Phys.* 24, 4305–4329. doi: 10.5194/acp-24-4305-2024
- Vasconcellos, E. A. (1999). Urban development and traffic accidents in Brazil. *Accid. Anal. Prev.* 31, 319–328. doi: 10.1016/S0001-4575(98)00065-7
- Wang, C., Wang, F., Mahmood, M. A., and Ali, Q. (2024). The impact of climate change, environment, and health worker density index on road accident fatalities: evidence from top ten pollution emitting countries. *Pol. J. Environ. Stud.* 33, 3887–3902. doi: 10.15244/pjoes/175305
- Warsame, A. A., Abdukadir, I., Hassan, A., and Sarkodie, S. A. (2024). The nexus between climate change, conflicts and food security in Somalia: empirical evidence from time-varying granger causality. *Cogent Food Agric.* 10:2347713. doi: 10.1080/23311932.2024.2347713
- Warsame, A. A., Sheik-Ali, I. A., Barre, G. M., and Ahmed, A. (2023). Examining the effects of climate change and political instability on maize production in Somalia. *Environ. Sci. Pollut. Res.* 30, 3293–3306. doi: 10.1007/s11356-022-22227-1
- Yusuff, M. A. (2015). Impact assessment of road traffic accidents on Nigerian economy. *J. Res. Humanit. Soc. Sci.* 3, 8–16.
- Zurlinden, H., Gaffney, J., and Hovenden, E. (2023). Can I stop?: considering opportunities to influence multidisciplinary factors that result in crashes. *J. Road Saf.* 34, 57–69. doi: 10.33492/JRS-D-22/00008