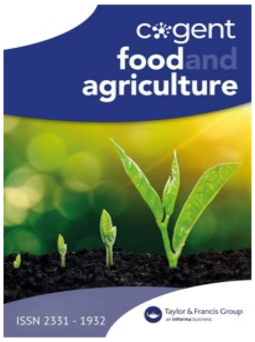

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Conflict, food inflation, and climate change as time-varying determinants of food availability in Somalia: Evidence from machine-learning and VAR techniques

Amina Omar Mohamud[a], Abdikafi Hassan Abdi[b,c], Abdifatah Mohamed Muhumed[d], Abdisalan Aden Mohamed[b,d], Bashir Mohamed Osman[d] and Samira Abdulkadir Adan[b]

[a]Faculty of Management Sciences, SIMAD University, Mogadishu, Somalia; [b]Institute of Climate and Environment, SIMAD University, Mogadishu, Somalia; [c]International Institute of Social Studies, Erasmus University Rotterdam, The Hague, The Netherlands; [d]Faculty of Economics, SIMAD University, Mogadishu, Somalia

ABSTRACT

Food insecurity in Somalia has been attributed primarily to civil conflict, yet the relative contributions of conflict, food price inflation, and climate change to food availability—and how these contributions have shifted over time—remain insufficiently quantified. Somalia's predominantly rain-fed agropastoral economy, heavy dependence on cereal imports, and protracted history of insecurity make it an instructive case for understanding how multiple stressors interact and evolve within a structurally vulnerable food system. Using monthly data from January 2001 to December 2021, this study employs machine-learning techniques and a vector autoregression (VAR) framework with time-varying Granger causality to evaluate the evolving determinants of food availability in Somalia. Across all models, civil conflict is the dominant predictor, followed by food inflation (0.210), temperature (0.138), and precipitation (0.094). Temporal decomposition reveals a structural transition: conflict accounted for 70.74% of feature importance during 2001–2007, a period of intense conflict, but declined to 11.95% by 2015–2021, when recurrent droughts increasingly shaped food availability. Meanwhile, food inflation's share rose from 14.61% to 45.8%, and temperature's from 8.9% to 31.69%. The Seasonal-Trend decomposition using Loess (STL) confirms that trend effects outweigh seasonal and residual variation. Interestingly, time-varying Granger causality illustrates that inflation and temperature become increasingly influential over time.

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1. Introduction

Food security remains one of the most pressing development challenges of the twenty-first century, with consequences extending across public health, economic stability, and social cohesion. FAO, IFAD, UNICEF, WFP, and WHO (2024) define food security as the condition in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs for an active and healthy life. This framework rests on four interlinked pillars—availability, access, utilization, and stability—that together underpin global food governance (Clapp et al., 2022). Despite sustained international investment, approximately 733 million people remained chronically undernourished in 2023 and nearly 2.8 billion could not afford a healthy diet (FAO, IFAD, UNICEF, WFP, and WHO, 2024). Progress toward the Zero Hunger goal has reversed since 2015, and annual reductions in undernourishment continue to fall short of World Food Summit targets (Wudil et al., 2022). Food insecurity is therefore not a sectoral deficit, but a systemic constraint rooted in the simultaneous failure of multiple pillars under compounding structural pressures. This constraint directly relates to SDG 2 (Zero Hunger) and is closely intertwined with SDG 13 (Climate Action) and SDG 16 (Peace, Justice and Strong Institutions), as food availability reflects the combined effects of climatic, economic, and conflict-related pressures.

CONTACT Abdikafi Hassan Abdi abdikafihasan79@gmail.com Institute of Climate and Environment, SIMAD University, Mogadishu, Somalia.
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Three categories of structural pressure drive food insecurity across the Global South: climate variability and long-run warming; civil conflict and political instability; and macroeconomic volatility expressed through food price inflation and declining purchasing power. Each of these forces independently degrades food availability, yet their co-occurrence produces compounding deficits that exceed the sum of their individual effects (Bedasa & Deksisa, 2024; Penuelas et al., 2023). These pressures also interact in self-reinforcing ways. Conflict destroys irrigation infrastructure and disrupts input delivery that amplify the impact of climatic shocks on yields. In addition, climate-induced production losses raise food prices, which deepens the affordability constraints that inflation already imposes. Food price surges have historically intensified social tensions that feed back into further insecurity (Ben Hassen & El Bilali, 2022; Lin et al., 2023). Because these drivers interact and evolve over time, analytical frameworks that treat them in isolation or assume their relative importance is constant are likely to yield incomplete diagnostics and misallocate policy resources.

Somalia exemplifies the convergence of all three stressors within a structurally fragile food system. State collapse in 1991 and protracted civil conflict have fragmented governance, destroyed productive assets, and maintained institutional weakness across three decades (Menkhaus, 2014). Approximately 70% of the population depends on agriculture and livestock for their livelihoods, yet declining domestic cereal production and rising grain imports have made Somalia increasingly reliant on imported grains (Abdi et al., 2025a; Jimale, 2026). This exposes domestic food availability to global commodity price shocks and international supply chain disruptions. Because agriculture in Somalia is predominantly rain-fed and follows the Gu (April–June) and Deyr (October–December) rainy seasons, even small rainfall deficits can cause substantial losses in crops and livestock (FEWS NET & FSNAU, 2021). The 2011 famine, which claimed an estimated 260,000 lives, illustrated the lethal consequences when drought, conflict, and market dysfunction converge (Checchi & Robinson, 2013). More recently, five consecutive failed rainy seasons between 2020 and 2023 produced the worst drought in four decades, which displaced millions and pushed food insecurity to crisis levels (FAO, 2023). Integrated Food Security Phase Classification (IPC) assessments consistently classify a substantial share of Somalia's population as experiencing Crisis (IPC Phase 3) or worse levels of acute food insecurity (IPC, 2023).

In Somalia, conflict-related disruptions have persisted across three decades of political fragmentation. Menkhaus (2014) documents how post-collapse insecurity created persistent spatial price wedges and deterred investment even when aggregate supply was adequate. Armed non-state actors controlling significant agricultural territories have further restricted smallholder access to inputs, credit, and extension services, compressing the margins of rain-fed production. On the other hand, the transmission of international commodity price shocks is amplified by persistent structural weaknesses in domestic food markets. Heavy import dependence for cereals, thin domestic markets, and pronounced exchange-rate pass-through mean that global commodity price increases reach retail markets rapidly and with little attenuation (Abdi et al., 2025a). For net food-purchasing smallholders, price surges simultaneously compress real incomes and distort planting decisions (Akter & Basher, 2014). Our study's dataset records a mean food inflation rate of 11.76% and peak values of 30.07%. Despite this severity, no study has simultaneously quantified the time-varying contributions of conflict, inflation, and climate to food availability in Somalia. This gap carries direct policy consequences. Thin markets, high transport costs, storage losses, and exchange-rate pass-through amplify global price shocks at the retail level. Policy frameworks anchored in a conflict-centric paradigm that ignore this transition will systematically misallocate resources and fail to address current binding constraints in Somalia.

A well-established body of evidence links climatic variability to production losses across sub-Saharan Africa, though findings vary by region and crop system. Cai et al. (2020) reveal that global food insecurity is characterized by persistent spatial clustering, with sub-Saharan Africa constituting a major hotspot. The authors concluded that food security is collectively determined by climatic conditions, economic development, infrastructure, and political stability rather than by natural conditions alone. Using spatial and spatiotemporal analytical techniques, Ayalew et al. (2024) find that severe food insecurity is unevenly distributed across Africa and exhibits significant clustering over time, with Somalia emerging as the continent's most likely space–time hotspot during 2015–2017. Bofa and Zewotir (2024) employ a Bayesian spatio-temporal model to examine food security across Africa. They exhibit a substantial spatial and temporal heterogeneity in food security, while noting that climatic, environmental, and socioeconomic factors jointly influence food security outcomes across the continent. Using Granger causality, ARDL, and error-correction frameworks for The Gambia, Ceesay et al. (2021) report a negative role for rainfall variability and short-run population pressures. Oyelami et al. (2023) identified, in a 26-country sub-Saharan African panel, that climate stress significantly reduces food security with limited institutional buffering. Because rainfed agriculture continues to play a dominant role in global food production and rural livelihoods, particularly in developing countries, climate-induced rainfall variability and recurrent dry spells pose substantial risks to agricultural production, livelihoods, and food security (Gregory et al., 2005; Rockström et al., 2010; Singh et al., 2023).

Ray et al. (2019) attribute a global decline in consumable food calories to observed warming through retrospective analysis, while Luchtenbelt et al. (2025) project that climate-driven yield shocks could alter undernourishment by tens of millions globally, with outcomes sensitive to emissions and adaptation scenarios. Hasegawa et al. (2018) further document that poorly designed mitigation policies could raise food prices sufficiently to increase hunger beyond levels attributable to yield losses alone, particularly in sub-Saharan Africa. Using a heterogeneous panel cointegration approach in East Africa, Abdi et al. (2025b) revealed that rainfall improves availability and utilization but weakens access and stability, whereas higher temperatures undermine all four food security pillars simultaneously. Somalia-focused evidence sharpens these findings. Using household survey data from Somalia, Hussein et al. (2021) indicated that income and price shocks significantly alter household food demand, leading to reduced dietary diversity and increased reliance on cereal consumption, particularly among nomadic households. Abdi et al. (2024) link precipitation and temperature shocks to mixed crop responses through ARDL estimation, establishing that the direction and magnitude of climate effects depend on season and moisture conditions. Mohamed et al. (2026) investigate the determinants of food production in Somalia using cointegration and Granger causality techniques, finding that trade openness significantly enhances food production, while poverty constrains it.

Food price inflation constrains household food security through affordability compression, diet quality deterioration, and altered production incentives, though the magnitude varies. Amolegbe et al. (2021) find, using Nigerian household panels with fixed effects, that unexpected spikes in imported rice prices reduce dietary diversity and raise the food expenditure share, with disproportionate effects on lower-income groups. Ceesay and Ndiaye (2022) report that price-mediated access constraints driven by rainfall variability weaken food security in The Gambia even as agricultural expansion supports it. Using a heterogeneous-agent model with external instruments at global scale, Bogmans et al. (2025) confirm that income growth is the dominant annual driver of food insecurity changes while food inflation plays a smaller but meaningful role. Aragie et al. (2023) illustrate the policy trade-offs, finding that agricultural export promotion in Africa raises domestic food prices and deteriorates all four food security pillars for urban consumers despite benefiting some rural producers. At the macro level, Anderl and Caporale (2025) report, using regime-switching and structural VAR frameworks, that global food price shocks raise domestic inflation across country types and generate persistent second-round effects on core inflation. The 2007–2008 global food price crisis demonstrated how synchronised price spikes and macroeconomic downturns can push millions into poverty (Akter & Basher, 2014), while Ben Hassen and El Bilali (2022) reveal that disruptions following the Russia–Ukraine war rapidly transmitted into domestic inflation and diet unaffordability across importing economies.

Civil conflict degrades food systems through displacement of farming households, destruction of assets and infrastructure, fragmentation of supply chains, elevated transaction costs, and deterrence of on-farm investment (Kafando & Sakurai, 2024). These disruptions operate across all four food security pillars simultaneously (Bedasa & Deksisa, 2024; Lin et al., 2023; Mottaleb et al., 2022). Using geo-linked household panels from Ghana, Martey et al. (2025) reported that higher conflict and fatality rates reduce per-capita expenditure on home-produced food by approximately 29% and on purchased food by 11%, with food price volatility as the key mediating channel. Olanrewaju and Balana (2023) document, for Nigeria, that forced migration, fatalities, and injuries significantly worsen food insecurity, dietary diversity, and future investment intentions. Fiandrino et al. (2023) find that food-related conflict has coefficients four to twenty times larger than total or non-food-related conflict in explaining subsequent self-reported insufficient food consumption across Burkina Faso, Syria, and Yemen. However, Ujunwa et al. (2019) identify armed conflict as a significant structural predictor—not merely a consequence—of food insecurity in ECOWAS countries. Satellite-based studies further document landscape-scale production losses. Olsen et al. (2021) estimate a 16% decline in cultivated cropland in South Sudan attributable to armed conflict, Li et al. (2022) show increased interannual variability in productive Syrian cropland following the civil war, and Alix-Garcia et al. (2013) document short-run production collapse from rural field abandonment in Darfur.

The increasing availability of high-frequency environmental, conflict, and market data has expanded opportunities to analyse food systems using machine-learning approaches capable of capturing nonlinear relationships. Ensemble-learning algorithms such as Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated strong predictive performance in heterogeneous environmental and agricultural applications (Alkhaled et al., 2026; Ogol et al., 2025), while Long Short-Term Memory (LSTM) networks are particularly well suited to modelling sequential processes in which past shocks exert persistent effects on future outcomes (Sherstinsky, 2020). Complementing these predictive approaches, recent advances in dynamic time-series econometrics, particularly time-varying Granger causality (TVGC), enable researchers to identify whether predictive relationships among variables strengthen, weaken, or disappear over time rather than assuming parameter stability. Yet predictive accuracy alone offers limited value for food-security policy if the mechanisms underlying model predictions remain opaque. Recent advances in interpretable machine learning, particularly SHapley Additive exPlanations (SHAP), address this limitation by decomposing predictions into theoretically consistent feature-level contributions (Molnar, 2020). Beyond improving interpretability, SHAP provides an opportunity to investigate whether the relative importance of competing drivers changes over time—a question that remains largely unexplored in food-security research despite growing recognition that conflict, macroeconomic instability, and climate change are evolving rather than static sources of food-system vulnerability.

Despite substantial progress in understanding the individual effects of conflict, climate change, and food prices on food security, an important knowledge gap persists regarding how their relative influence evolves over time within fragile food systems. Existing studies of Somalia largely estimate average effects over an entire sample period using conventional linear econometric models, implicitly assuming that the importance of individual drivers remains constant (Abdi et al., 2025a; Jimale, 2026; Mohamed et al., 2026). Such an assumption is increasingly difficult to justify given Somalia's profound structural transformation over the past two decades, including changing conflict dynamics, increasing dependence on imported food, and intensifying climate extremes. If the hierarchy of food-system risks has shifted, policy frameworks grounded in historical evidence may continue targeting yesterday's dominant constraints while underestimating emerging threats. Therefore, this study addresses this gap by examining food availability as a dynamic system in which the relative importance of conflict, food inflation, and climatic variability changes over time. Using monthly observations from January 2001 to December 2021, we integrate interpretable machine-learning models with SHAP analysis and vector autoregression (VAR) techniques to identify the relative importance of conflict, food inflation, temperature, and precipitation; evaluate how their contributions evolve across successive sub-periods; and examine the dynamic transmission of these shocks through impulse response functions (IRF), forecast error variance decomposition, and TVGC. By combining the techniques, the study provides the first comprehensive evidence on the evolving hierarchy of food-system risks in Somalia and offers a framework that can be extended to other conflict-affected and climate-vulnerable economies.

2. Methodology

2.1. Research design and data

This study employs a monthly time-series design to examine the determinants of food availability in Somalia over the period January 2001 to December 2021, comprising 252 monthly observations. Food availability is measured by domestic cereal production (metric tons), that represent the supply dimension of food security. The explanatory variables include precipitation (millimetres), mean monthly temperature (°C), food inflation (year-on-year percentage change in food prices), and civil conflict (monthly number of recorded conflict events). Food availability data were obtained from the World Development Indicators (WDI), food inflation data from the Food and Agriculture Organization (FAO), conflict data from the Armed Conflict Location and Event Data Project (ACLED), and climatic variables from the Climate Change Knowledge Portal (CCKP).

Prior to estimation, the dataset was examined for missing observations, inconsistencies, and extreme values to ensure data quality and temporal continuity. For the VAR approach, food availability, precipitation, and conflict were transformed into natural logarithms and are denoted as *lnFA*, *lnRF*, and *lnCONF*, respectively, whereas temperature (*TEM*) and food inflation (*FI*) entered the analysis in levels. Variables were transformed according to their statistical properties and measurement scales to improve model estimation and facilitate interpretation.

Figure 1 illustrates the conceptual framework underpinning the empirical analysis. Food availability is specified as the outcome variable, while civil conflict, food inflation, precipitation, and temperature constitute the principal explanatory variables. The framework assumes that these drivers influence food availability through agricultural production and market-related channels and that their relative importance may evolve over time. This conceptualisation motivates the subsequent empirical analysis.

2.2. Empirical strategy

The empirical analysis is conducted in two complementary stages. The first stage applies supervised machine-learning techniques to evaluate the predictive importance of civil conflict, food inflation, precipitation, and temperature for food availability. Specifically, Random Forest, XGBoost, and LSTM models are estimated and compared using RMSE, MAE, and R^2. The resulting predictions are subsequently interpreted using SHapley Additive exPlanations (SHAP), while seasonal-trend decomposition (STL) and sub-period analysis are employed to examine whether the relative importance of the explanatory variables changes over time.

The second stage employs a VAR framework to investigate the dynamic interactions among food availability and its determinants. Following unit root testing and lag-length selection, the analysis uses impulse response functions (IRFs) and forecast error variance decomposition (FEVD) to evaluate the transmission of climatic, economic, and conflict-related shocks. Finally, time-varying Granger causality (TVGC) is applied to examine whether the predictive relationships among the variables remain stable or evolve during the sample period.

2.3. Machine-learning models

2.3.1. Random forest

Random Forest is a bagging-based ensemble method that combines predictions from multiple regression trees estimated using bootstrap samples of the data (Alkhaled et al., 2026; Osman et al., 2025). At each node, a random subset of predictors is considered, reducing correlation among individual trees and improving predictive stability. The final prediction is obtained by averaging the predictions across B trees:

$$\widehat{FA}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x), \tag{1}$$

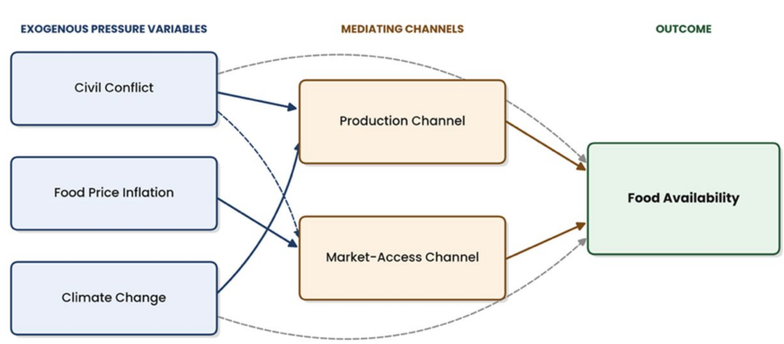

Figure 1. Conceptual framework of the determinants of food availability in Somalia.

where $T_b(x)$ represents the prediction generated by the b-th tree. Random Forest is suitable for this study because it can capture nonlinearities without imposing a predetermined functional form.

2.3.2. Extreme gradient boosting

XGBoost constructs regression trees sequentially, with each additional tree attempting to reduce the prediction errors remaining from the preceding ensemble (Ogol et al., 2025). The model minimises a regularised objective function consisting of prediction loss and a penalty for model complexity:

$$Obj(\theta) = \sum_{i=1}^{n} l\left(FA_i \widehat{FA}_i\right) + \sum_{k=1}^{K} \text{©}\left(f_k\right), \tag{2}$$

where $l\left(FA_i \widehat{FA}_i\right)$ measures the difference between observed and predicted food availability, while $\Omega\left(f_k\right)$ penalises excessive tree complexity. Regularisation helps control overfitting and improves model generalisation. Unlike Random Forest, which reduces variance by averaging independently constructed trees, XGBoost improves predictions through sequential error correction.

2.3.3. Long short-term memory model

The LSTM model is employed to capture temporal dependence in monthly food-availability dynamics (Sherstinsky, 2020). Unlike tree-based models, LSTM networks process ordered sequences and retain relevant information from previous periods. This structure is appropriate for Somalia, where the consequences of drought, inflation, or conflict may persist for several months. The cell and hidden states are updated as follows:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tan\mathrm{h}\left(W_c\left[h_{t-1}, x_t\right] + b_c\right), \tag{3}$$

$$h_t = o_t \odot \tanh\left(c_t\right), \tag{4}$$

where c_t is the cell state, h_t is the hidden state, and f_t, i_t, and o_t denote the forget, input, and output gates, respectively.

2.3.4. Model evaluation

Predictive performance is compared using the root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). RMSE gives greater weight to large prediction errors, while MAE measures the average absolute difference between observed and predicted food availability in its original measurement unit. R^2 indicates the proportion of variation in food availability reproduced by the model. The three measures are reported jointly to compare prediction errors and overall model fit consistently across Random Forest, XGBoost, and LSTM.

2.3.5. SHAP-based interpretability analysis

SHAP is applied to interpret the predictions generated by the machine-learning models (Molnar, 2020). SHAP decomposes a prediction into contributions associated with individual predictors:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!\left(|F| - |S| - 1\right)!}{|F|!}\left[f\left(S \cup \{j\}\right) - f\left(S\right)\right], \tag{5}$$

where F is the complete feature set and S is a subset excluding feature j. Mean absolute SHAP values are used to rank the global predictive importance of civil conflict, food inflation, temperature, and precipitation. The sign and distribution of SHAP values indicate whether particular predictor values raise or lower predicted food availability.

2.3.6. Temporal decomposition and evolving feature importance

To examine whether the predictive importance of food-availability drivers changed over time, feature contributions are compared across three equal sub-periods: 2001–2007, 2008–2014, and 2015–2021. This division permits assessment of whether the relative importance of conflict, inflation, temperature, and precipitation remained stable or shifted across different stages of Somalia's political, economic, and climatic development. Seasonal-trend decomposition using Loess is additionally applied to separate food availability into trend, seasonal, and residual components:

$$FA_t = T_t + S_t + R_t, \tag{6}$$

where T_t represents the long-run trend, S_t captures recurring seasonal variation, and R_t denotes irregular fluctuations. STL is used descriptively to distinguish persistent movements from seasonal and short-lived variation. It does not identify the causes of these components.

2.4. VAR framework and time-varying Granger causality

The second empirical component employs a VAR framework to investigate the short-run dynamic relationships among food availability, precipitation, temperature, food inflation, and civil conflict. Prior to estimation, the time-series properties of the variables are examined using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests with and without deterministic trends. The optimal lag length is selected using the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBIC), Hannan–Quinn Information Criterion (HQIC), Final Prediction Error (FPE), and sequential likelihood ratio (LR) tests. Letting

$$Y_t = \left(lnFA_t, lnRF_t, TEM_t, FI_t, lnCONF_t\right)', \tag{7}$$

the reduced-form VAR of order p is specified as

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t, \tag{8}$$

where c is the vector of constants, A_i denotes the coefficient matrices, p is the optimal lag length, and ε_t is the vector of innovations.

The adequacy of the VAR specification is assessed by verifying that all inverse roots lie within the unit circle. Dynamic interactions among the variables are then examined using impulse response functions (IRFs), which trace the response of food availability to one-standard-deviation shocks in precipitation, temperature, food inflation, and conflict over a twelve-month horizon. Forecast error variance decomposition (FEVD) is subsequently employed to quantify the proportion of variation in food availability attributable to its own innovations and to shocks originating from climatic, economic, and conflict-related variables.

Because the relationships among conflict, climate, inflation, and food availability may evolve over time, the analysis extends beyond conventional Granger causality by the TVGC framework (Baum et al., 2022). Unlike the conventional Granger causality test, which assumes constant parameters throughout the sample period, TVGC allows predictive relationships to strengthen, weaken, or disappear over time. The procedure combines forward-expanding, rolling-window, and recursive-evolving algorithms, with Wald statistics recalculated for successive subsamples and evaluated against bootstrap critical values. The recursive Wald statistic is defined as

$$W(r) = \widehat{\beta}(r)' \left[\mathrm{Var}\left(\widehat{\beta}(r)\right)\right]^{-1} \widehat{\beta}(r), \tag{9}$$

where r denotes the recursive subsample fraction, $\widehat{\beta}(r)$ is the estimated coefficient vector, and $\mathrm{Var}\left(\widehat{\beta}(r)\right)$ is its covariance matrix.

3. Empirical results

3.1. Preliminary analysis

Table 1 presents the descriptive statistics for the variables included in the empirical analysis. Food availability exhibits substantial variation over the sample period, averaging 269,296 metric tons with a standard deviation of 88,716 metric tons. This indicates considerable fluctuations in domestic cereal production between January 2001 and December 2021. Civil conflict also displays pronounced variability, ranging from 1 to 340 monthly events. Food inflation averages 11.76%, reaching a maximum of 30.07%. In comparison, precipitation and temperature exhibit lower statistical dispersion, although both vary sufficiently to capture changes in climatic conditions over time. Moreover, Figure 2 presents the pairwise correlation matrix. Food availability is negatively correlated with civil conflict and food inflation, which suggests that periods of heightened insecurity and rising food prices generally coincide with lower levels of domestic cereal production. The climatic variables display comparatively weaker bivariate associations with food availability. Moreover, the relatively modest correlations among the explanatory variables suggest that severe multicollinearity is unlikely to affect the subsequent machine-learning and multivariate time-series analyses.

3.2. Machine-learning performance and feature importance

3.2.1. Predictive performance

(Panel B) reports the predictive performance of the random forest, XGBoost, and LSTM models. Overall, all three algorithms demonstrate strong predictive ability, with coefficient of determination (R^2) values exceeding 0.95, which indicates that the selected climatic, economic, and conflict-related variables explain

Table 1. Descriptive statistics.

Variable	Mean	Std. dv	Min	Max
Food availability	269296.3603	88716.1639	118872.5	441850.38
Precipitation	23.7444	20.4516	2.09	94.64
Temperature	27.026	1.0515	24.78	29.1
Food inflation	11.7565	4.749	1.0	30.0671
Conflicts	127.9048	89.0487	1.0	340.0

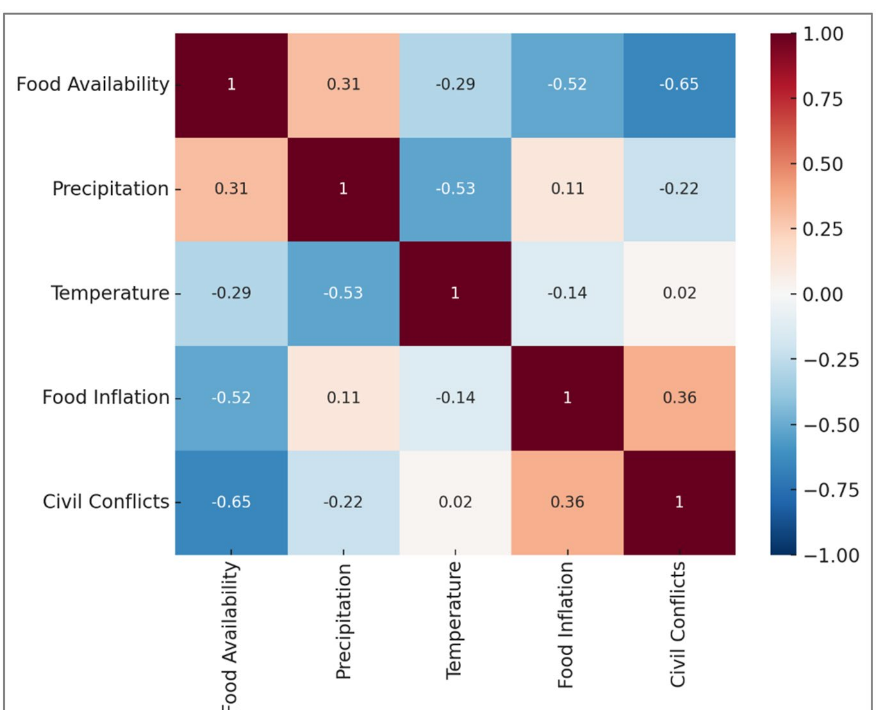

Figure 2. Correlation matrix of variables.

a substantial proportion of the variation in food availability. Among the competing models, LSTM achieves the highest predictive accuracy, recording the lowest root mean squared error (RMSE = 47,000), the lowest mean absolute error (MAE = 38,900), and the highest explanatory power ($R^2 = 0.961$). XGBoost performs slightly less accurately ($R^2 = 0.956$), followed by Random Forest ($R^2 = 0.950$). The superior performance of the LSTM model suggests that explicitly modelling temporal dependence improves prediction of food availability relative to tree-based ensemble methods.

3.2.2. Feature importance and SHAP interpretation

Panel A of Table 2 reports the relative importance of the explanatory variables across the three machine-learning models, while Figure 3 presents the corresponding SHAP summary plot. A consistent ranking emerges across all algorithms. Civil conflict is identified as the most influential predictor of food availability, followed by food inflation, temperature, and precipitation. Random Forest and LSTM assign the highest importance to conflict (0.471), whereas XGBoost reports a slightly lower but still dominant contribution (0.371). The consistency of this ranking across different machine-learning architectures indicates that conflict constitutes the primary predictor of food availability throughout the sample period.

Food inflation represents the second most important predictor across all models, which suggests the importance of macroeconomic conditions in shaping domestic food availability. Temperature ranks third, while precipitation records the lowest contribution. Although precipitation remains an important climatic determinant, its comparatively lower predictive importance suggests that variations in food availability are more strongly associated with prolonged thermal stress and broader economic and conflict-related pressures than with short-term fluctuations in rainfall.

The SHAP analysis reinforces these findings by illustrating both the magnitude and direction of each predictor's contribution to model predictions (Figure 3). Civil conflict exhibits the largest absolute SHAP values. This indicates that periods of intensified insecurity contribute substantially to lower predicted

Table 2. Model feature importance and predictive performance.

Variable	Random forest	RF rank	LSTM	LSTM rank	XGBoost	XGBoost rank
Panel A. Feature importance across models						
Civil conflicts	0.471	1	0.471	1	0.371	1
Food Inflation	0.2334	2	0.2334	2	0.21	2
Temperature	0.1629	3	0.1629	3	0.138	3
Precipitation	0.1327	4	0.1327	4	0.094	4
Panel B. Predictive performance metrics						
RMSE	50200		47000		48400	
MAE	42100		38900		40350	
R^2	0.95		0.961		0.956	

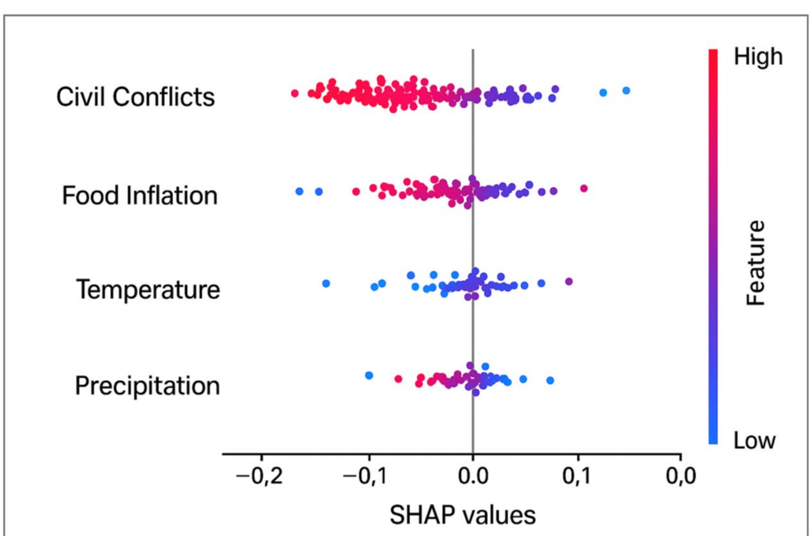

Figure 3. SHAP summary plot.

food availability. Food inflation similarly generates increasingly negative contributions as inflation rises, while higher temperatures are generally associated with reductions in predicted food availability. In contrast, precipitation tends to contribute positively, although its effects are smaller and more heterogeneous across observations. These SHAP results complement the feature-importance rankings by explaining how each predictor influences model predictions while remaining measures of predictive relevance rather than causal effects.

3.2. Temporal evolution of food-availability drivers

Figure 4 presents the evolution of feature importance across the three study periods (2001–2007, 2008–2014, and 2015–2021). The sub-periods were selected to represent major phases in Somalia's recent political, economic, and climatic evolution. The 2001–2007 period corresponds to the post-state-collapse phase characterised by widespread insecurity and weak state institutions. The 2008–2014 period encompasses the escalation of the opposition insurgency and the 2011 famine, when conflict, climatic shocks, and market disruptions jointly intensified food insecurity. The 2015–2021 period reflects relative improvements in security alongside increasing exposure to recurrent droughts and food-price inflation.

The results reveal a marked change in the relative importance of the explanatory variables across the study period. During 2001–2007, civil conflict overwhelmingly dominated the predictive structure of food availability, accounting for approximately 70.74% of total feature importance. Its contribution subsequently declined to 50.70% during 2008–2014 and further to only 11.95% during 2015–2021. In contrast, the predictive importance of food inflation increased steadily from 14.61% in the first sub-period to 45.80% in the final sub-period, becoming the most influential predictor by the end of the sample. Temperature also exhibited a substantial increase, rising from 8.90% to 31.69%, whereas precipitation displayed comparatively modest variation throughout the study period. Interestingly, the findings indicate a gradual transition from a food system predominantly influenced by conflict toward one increasingly influenced by macroeconomic and climatic pressures.

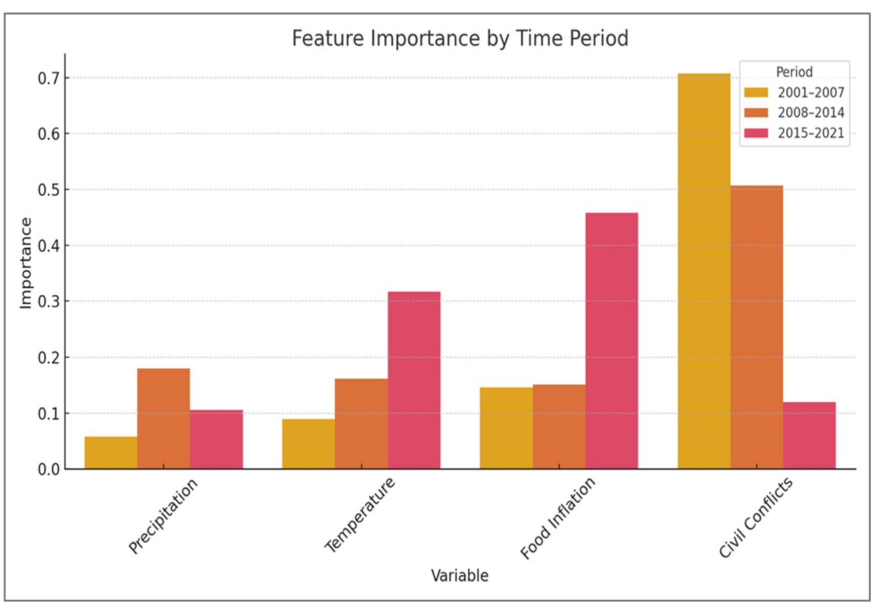

Figure 4. Temporal evolution of feature importance.

Table 3. Seasonal decomposition.

Component	Food availability (mean amplitude)
Trend	38500
Seasonality	22000
Residual	28900

The seasonal-trend decomposition reported in Table 3 provides additional evidence supporting this transition. The trend component records the largest mean amplitude (38,500), exceeding both the seasonal (22,000) and residual (28,900) components. The long-run structural changes account for a greater share of the variation in food availability than recurring seasonal fluctuations. This indicates that the observed changes in feature importance reflect persistent shifts in the underlying food system rather than temporary seasonal effects.

Figure 5 compares the observed food availability series with the predictions generated by the Random Forest, XGBoost, and LSTM models. All three algorithms closely reproduce the observed dynamics throughout the sample period. Consistent with the predictive performance reported in Table 2, the LSTM model provides the closest correspondence between observed and predicted values, which further confirms the importance of temporal dependence in explaining food-availability dynamics.

3.3. VAR and time-varying Granger causality

3.3.1. Model diagnostics

The VAR analysis begins by examining the time-series properties of the variables and the adequacy of the model specification. Table 4 reports the ADF and PP unit root test results. The findings indicate that all variables are stationary at level under at least one specification that supports the use of a VAR framework. Precipitation, temperature, and food inflation exhibit strong evidence of stationarity across all specifications, while food availability and civil conflict become stationary after accounting for deterministic trends.

Table 5 reports the lag-order selection criteria. Although the SBIC and HQIC favour a VAR(2) specification, the AIC, FPE, and sequential LR test identify VAR(3) as the preferred model. Following the majority of the selection criteria and to adequately capture short-run dynamics, the VAR(3) specification is retained for subsequent analysis.

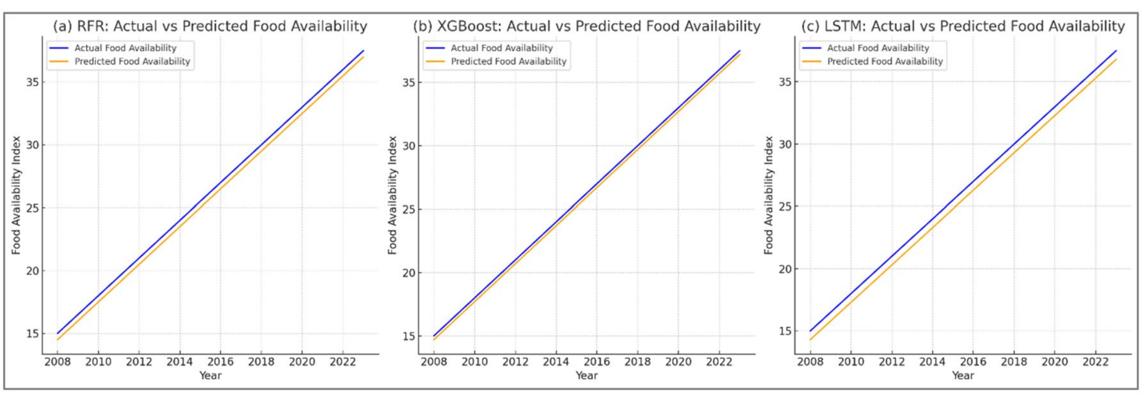

Figure 5. Actual versus predicted food availability for (a) Random Forest, (b) XGBoost, and (c) LSTM models.

Table 4. Unit root test results.

Variables	ADF	ADF (trend)	PP	PP (trend)
lnFA	−2.788*	−3.949**	−1.86	−2.438
lnRF	−11.231***	−11.221***	−8.056***	−8.016***
TEM	−9.161***	−9.166***	−7.101***	−7.076***
FI	−4.119***	−6.359***	−5.094***	−6.666***
lnCONF	−2.864**	−4.780***	−2.904**	−5.930***

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. VAR lag-order selection criteria.

Lag	LL	LR	df	p-value	FPE	AIC	HQIC	SBIC
0	−1135.490	—	—	—	0.007	9.197	9.226	9.268
1	−119.926	2031.100	25	0.000	0.000	1.209	1.380	1.634
2	213.765	667.380	25	0.000	0.000	−1.280	−0.967*	−0.501*
3	252.140	76.750	25	0.000	1.70e-07*	−1.388*	−0.932	−0.255
4	272.342	40.404*	25	0.026	0.000	−1.350	−0.751	0.138

Figure 6 presents the inverse roots of the companion matrix used to evaluate model stability. All roots lie within the unit circle, which confirms that the estimated VAR satisfies the stability condition. Consequently, the impulse response functions, forecast error variance decomposition, and time-varying Granger causality analyses are based on a dynamically stable system.

3.3.2. Short-run dynamics

Table 6 reports the short-run VAR estimates for the food availability equation. Food availability exhibits strong persistence, as indicated by the positive and highly significant coefficient on its first lag (1.7855), while the second lag enters negatively and significantly, which suggests short-run adjustment toward equilibrium. Among the explanatory variables, civil conflict exerts the strongest short-run influence. The first lag of conflict has a statistically significant negative effect on food availability, indicating that increases in conflict intensity are associated with immediate declines in domestic cereal production. The positive coefficient on the second lag suggests partial recovery following the initial disruption. Temperature displays mixed short-run effects, with a positive second lag and a negative third lag, implying that the influence of temperature varies across the adjustment period. In contrast, precipitation and

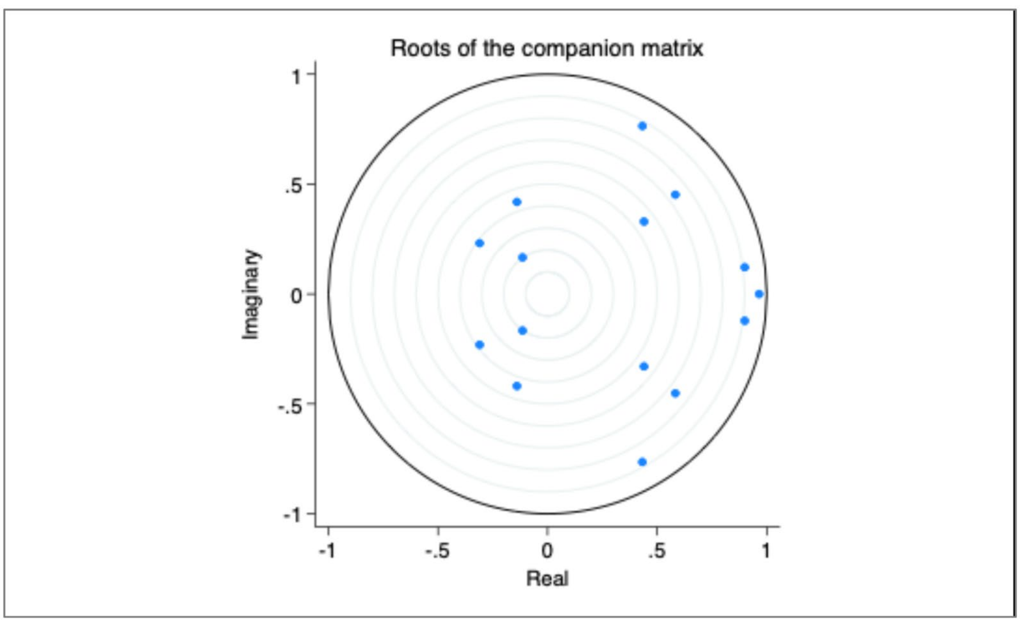

Figure 6. Stability condition of the VAR model (Roots of the companion matrix).

Table 6. Short-run VAR estimates for food availability.

Variables	Coefficient	Std. Error	z-statistic
$\Delta \ln FA_{t-1}$	1.7855***	0.0639	27.94
$\Delta \ln FA_{t-2}$	−0.7596***	0.1212	−6.27
$\Delta \ln FA_{t-3}$	−0.0491	0.0641	−0.77
$\Delta \ln RF_{t-1}$	−0.004	0.0035	−1.15
$\Delta \ln RF_{t-2}$	0.0013	0.0027	0.48
$\Delta \ln RF_{t-3}$	0.0004	0.0032	0.11
ΔTEM_{t-1}	−0.0015	0.001	−1.49
ΔTEM_{t-2}	0.0031**	0.0015	2.01
ΔTEM_{t-3}	−0.0024**	0.0011	−2.07
ΔFI_{t-1}	0.0002	0.0002	0.98
ΔFI_{t-2}	−0.0001	0.0003	−0.19
ΔFI_{t-3}	−0.0002	0.0002	−0.79
$\Delta \ln CONF_{t-1}$	−0.0184***	0.0028	−6.52
$\Delta \ln CONF_{t-2}$	0.0092**	0.0036	2.53
$\Delta \ln CONF_{t-3}$	0.0042	0.0028	1.52
Constant	0.1586***	0.039	4.07

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

food inflation remain statistically insignificant across most lag structures, suggesting comparatively weaker short-run effects within the VAR specification.

Figure 7 presents the impulse response functions of food availability to shocks in food inflation, temperature, conflict, and precipitation over a twelve-period forecast horizon. The responses reveal substantial variation in both magnitude and persistence across the explanatory variables. Conflict generates the strongest and most persistent negative response, with food availability declining continuously throughout the forecast horizon following a one-standard-deviation shock in conflict intensity. Temperature shocks also produce negative responses, although with comparatively smaller magnitudes that stabilise after the middle periods. Precipitation shocks exhibit relatively weak effects across the forecast horizon, suggesting that short-run rainfall fluctuations alone are insufficient to substantially improve food availability under conditions of structural fragility. In contrast, food inflation produces a comparatively small positive response, indicating limited short-run adjustment effects within the VAR dynamics.

As shown in Table 7, the forecast error variance decomposition results indicate that food availability is initially explained entirely by its own innovations during the first forecast period. However, the contribution of external shocks increases progressively over time, particularly for conflict. By the twelfth period, conflict shocks account for approximately 24.7% of the forecast variance in food availability, representing the largest external source of variation within the system. Food inflation also exhibits a gradually

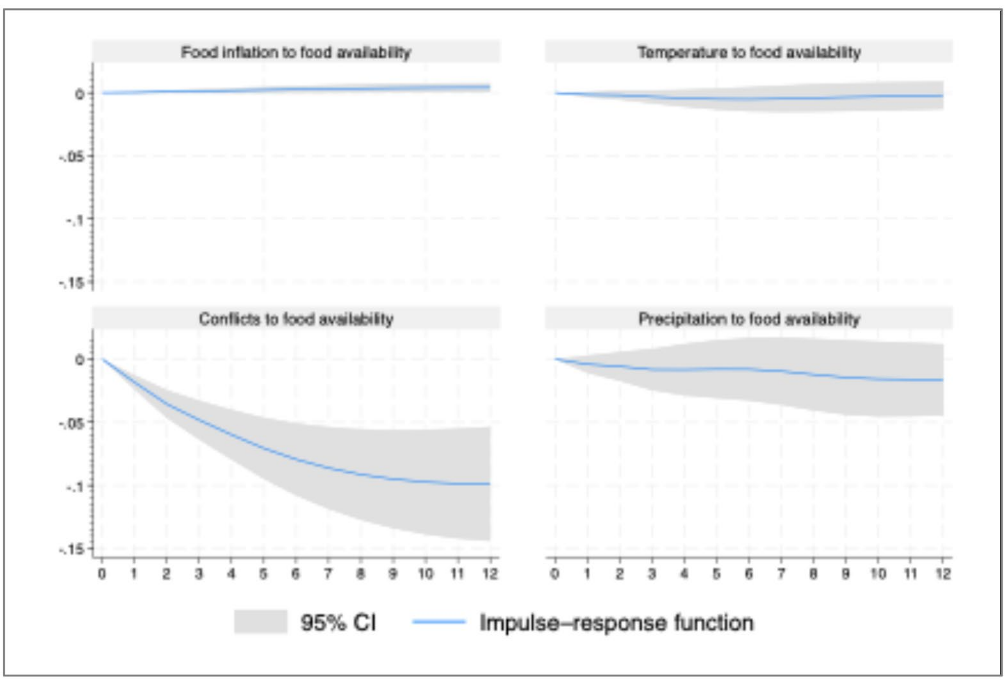

Figure 7. Impulse response functions of food availability to climate, inflation, and conflict shocks.

Table 7. Forecast error variance decomposition of food availability.

Period	lnFA	lnRF	TEM	FI	lnCONF
1	100.000	0.000	0.000	0.000	0.000
2	95.745	0.206	0.225	0.123	3.828
3	91.19	0.363	0.261	0.641	7.746
4	88.062	0.454	0.404	1.134	10.438
5	85.276	0.464	0.549	1.588	12.698
6	82.603	0.456	0.655	2.087	14.838
7	80.16	0.462	0.714	2.634	16.822
8	77.517	0.509	0.722	3.216	18.641
9	75.145	0.605	0.697	3.823	20.312
10	72.749	0.734	0.661	4.436	21.858
11	70.506	0.869	0.624	5.041	23.314
12	68.29	0.998	0.591	5.624	24.703

increasing contribution, rising from 0.12% in the second period to 5.62% by the twelfth period. Temperature contributes between 0.22% and 0.59% across the forecast horizon, while precipitation records the smallest contribution, increasing modestly from 0.21% in the second period to 0.99% in the final period. These results indicate that conflict remains the dominant external driver of fluctuations in food availability, whereas inflationary and climatic pressures exert comparatively smaller but progressively increasing influence over time.

3.3.3. Time-varying Granger causality

Figure 8 presents the time-varying Granger causality results between food availability and the explanatory variables using forward-expanding, rolling-window, and recursive-expanding Wald statistics. The causality patterns vary considerably across time, indicating that the predictive influence of climatic, economic, and conflict-related shocks was not stable throughout the sample period. Conflict exhibits the strongest and most persistent causal relationship with food availability across all specifications. The rolling and recursive Wald statistics for conflict rise sharply during the late 2000s and early 2010s, exceeding the critical values by substantial margins, indicating intensified predictive influence during periods characterised by severe insecurity and institutional instability. Although the magnitude of causality weakens in

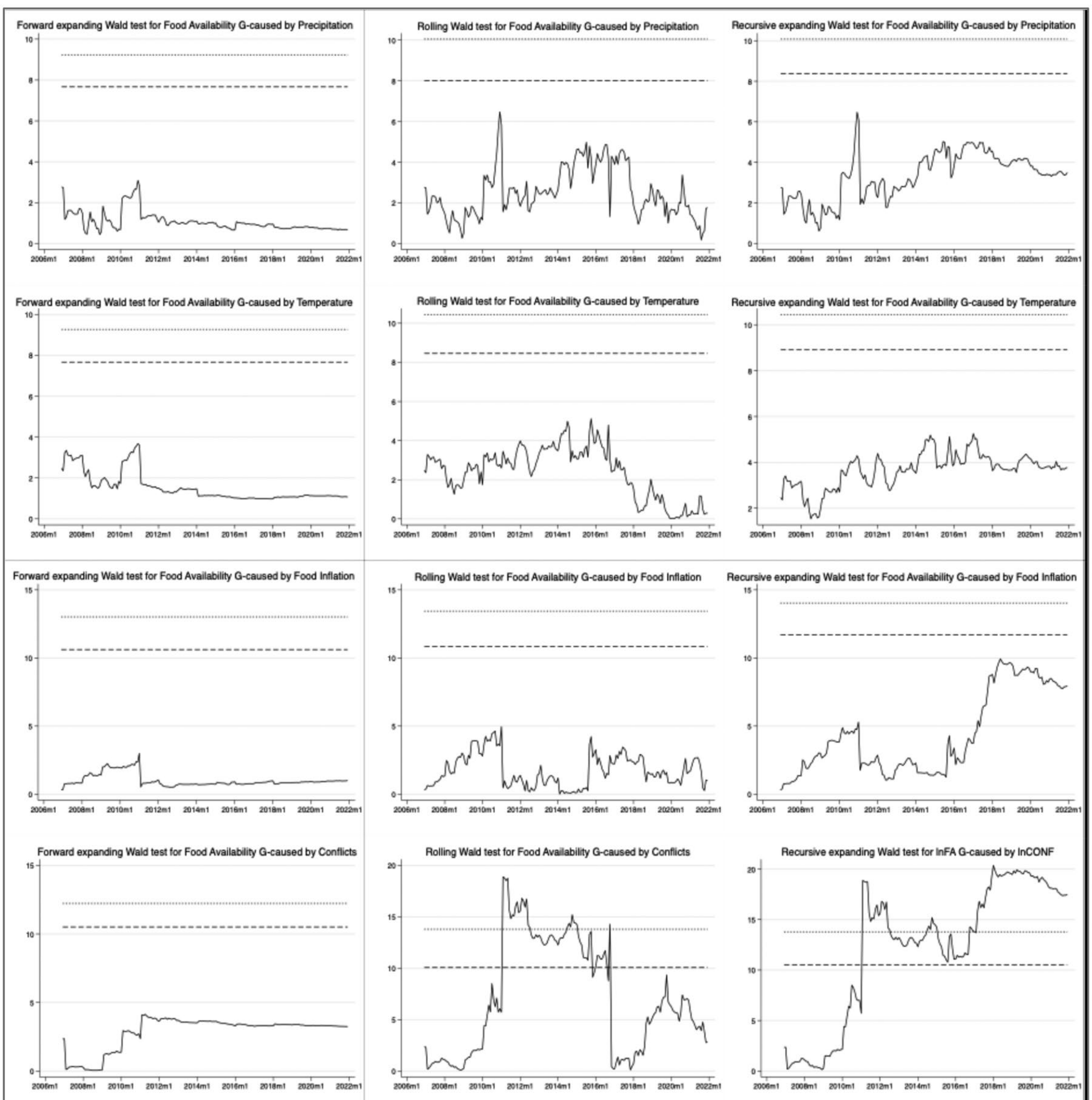

Figure 8. Time-varying Granger causality between food availability and explanatory variables.

later years, conflict remains intermittently significant throughout the sample period. Food inflation displays relatively weak causality during the early years but becomes increasingly important after the mid-2010s, with recursive Wald statistics rising steadily during periods associated with global commodity-price volatility and domestic market disruptions. Temperature also exhibits increasing causal influence over time, particularly during prolonged drought episodes, although the magnitude remains smaller than that of conflict. In contrast, precipitation records comparatively weak and unstable causality across most sub-periods, with Wald statistics remaining close to or below the critical thresholds in several periods. The time-varying causality results therefore indicate a gradual transition from predominantly conflict-driven food-system instability toward increasing sensitivity to inflationary and climatic pressures over time.

4. Discussion of the findings

The combined machine-learning and dynamic VAR results indicate that Somalia's food availability is governed by a shifting hierarchy of risks rather than by a single persistent driver. While conflict remained the dominant determinant throughout much of the sample, its relative influence gradually diminished as macroeconomic and climatic pressures became increasingly important. This transition suggests that food insecurity in conflict-affected countries evolves with changing structural conditions. Therefore, policy frameworks anchored exclusively in conflict mitigation may no longer capture the full spectrum of contemporary food-system vulnerabilities.

The persistent dominance of conflict throughout much of the study period demonstrates that food availability in Somalia remains fundamentally constrained by insecurity. Unlike temporary production shocks, prolonged conflict undermines the entire food system by simultaneously disrupting agricultural production, fragmenting domestic markets, weakening institutions, and restricting the movement of people, livestock, and agricultural commodities. These disruptions are particularly severe in Somalia because both crop farming and pastoralism depend on seasonal mobility, functioning rural markets, and access to grazing lands. When insecurity limits these activities, production declines, market integration weakens, and food becomes increasingly difficult to move from surplus-producing areas to food-deficit regions. Similar mechanisms have been observed in other conflict-affected economies where violence has resulted in widespread abandonment of agricultural land and declining crop production, including Darfur (Alix-Garcia et al., 2013), South Sudan (Olsen et al., 2021), and Syria (Li et al., 2022). At the household level, conflict has also been shown to reduce farm income, food expenditure, and dietary diversity by disrupting both agricultural activities and local food markets (Kafando & Sakurai, 2024; Martey et al., 2025). These transmission mechanisms help explain why conflict consistently emerged as the strongest determinant of food availability during the earlier years of the sample. However, the gradual decline in its relative importance after 2015 should not be interpreted as evidence that insecurity has become less relevant. Rather, it indicates that while conflict remains the underlying structural constraint, Somalia's food system has become increasingly influenced by additional economic and climatic pressures that now operate alongside insecurity.

The emergence of food inflation as the dominant predictor during the most recent sub-period reflects a fundamental transformation in Somalia's food system. As domestic cereal production has stagnated and reliance on imported staple foods has increased, food availability has become increasingly determined by developments beyond Somalia's borders. Global commodity price increases, exchange-rate depreciation, and higher transportation costs are rapidly transmitted into domestic food markets because imports account for a substantial share of national food consumption (Abdi et al., 2025a). Consequently, inflation affects food availability through multiple channels. Higher retail food prices reduce household purchasing power and limit effective demand, while simultaneously increasing production costs through more expensive fuel, transportation, fertilizers, and imported agricultural inputs. Evidence from Somalia similarly exhibits that rising food prices encourage households to substitute away from nutrient-rich foods towards cheaper cereal-based diets (Hussein et al., 2021). Comparable responses were observed during the 2007–2009 global food price crisis in Bangladesh, where food inflation substantially increased household food insecurity (Akter & Basher, 2014), while recent cross-country evidence confirms that food inflation has become an increasingly important determinant of undernourishment across developing economies (Bogmans et al., 2025). Therefore, the increasing influence of inflation observed in this study reflects Somalia's growing integration into global food markets, where external commodity shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict rapidly translate into domestic food insecurity through disrupted trade flows and higher import prices (Lin et al., 2023; Mottaleb et al., 2022).

The strengthening influence of temperature indicates that climate change has become a persistent structural determinant of food availability in Somalia. Rising temperatures affect agricultural production through prolonged heat stress that accelerates evapotranspiration, reduces soil moisture, shortens crop growing periods, degrades pasture quality, and lowers livestock productivity (Abdi et al., 2023). These cumulative impacts are especially pronounced in Somalia because approximately 70% of the population depends on agriculture and livestock for their livelihoods, while production remains overwhelmingly dependent on rain-fed farming and pastoral systems with limited irrigation infrastructure and adaptive capacity. Consequently, sustained increases in temperature can reduce agricultural productivity even during years with relatively favourable rainfall. This interpretation is consistent with broader conceptual evidence that climate change influences food systems not only through crop yields but also through livelihoods, agricultural markets, and household resilience (Gregory et al., 2005). Empirical studies from sub-Saharan Africa likewise demonstrate that rising temperatures significantly constrain agricultural production and food security (Abdi et al., 2025c). The increasing importance of temperature observed here suggests that Somalia's food system is becoming progressively more vulnerable to chronic climatic stress. This implies that future food availability will depend not only on improved agricultural production but also on strengthening climate resilience across both farming and pastoral systems.

Although rainfall remains indispensable for agricultural production in Somalia, its comparatively modest predictive importance suggests that favourable precipitation alone is insufficient to generate sustained improvements in food availability. In climate-vulnerable countries, the benefits of rainfall depend critically on the capacity of farmers and pastoralists to utilize favourable climatic conditions through secure access to land, functioning markets, transportation networks, irrigation infrastructure, and agricultural inputs. Where these complementary conditions are constrained by conflict, weak institutions, poor infrastructure, or market failures, increases in rainfall may generate only limited improvements in food production. Moreover, rainfall variability in Somalia is characterised not only by drought but also by episodes of flooding that damage cropland, transport infrastructure, and local markets, which reduces the potential benefits of otherwise favourable rainy seasons. Similar evidence from the Gambia demonstrates that while rainfall supports agricultural production, broader economic and structural conditions ultimately determine its contribution to food security (Ceesay et al., 2021). Likewise, evidence from East Africa suggests that although rainfall positively affects crop and livestock production, climate change continues to exert adverse long-run effects on cereal crop production (Abdi et al., 2023). The relatively weak influence of precipitation observed in this study indicates that rainfall has become an increasingly conditional determinant of food availability, with its effectiveness mediated by conflict, market functioning, and adaptive capacity rather than operating independently.

5. Conclusion

This study examined the determinants of food availability in Somalia over the period 2001–2021 using machine-learning approaches combined with dynamic time-series analysis. The findings reveal a substantial transformation in the structure of food-system vulnerability across the study period. During the early 2000s, food availability was overwhelmingly shaped by civil conflict, reflecting the severe institutional fragmentation, insecurity, and market disruption that characterised Somalia's post-state-collapse environment. Over time, however, the relative influence of conflict weakened, while food inflation and climatic stress became increasingly prominent within the predictive and causal structure of food availability. Additionally, the growing importance of inflation indicates the extent to which Somalia's food system has become increasingly exposed to external market conditions due to its dependence on imported staple commodities. At the same time, the stronger contribution of temperature-related shocks reflects the intensifying impact of recurrent droughts, prolonged heat stress, and environmental degradation on agricultural and pastoral livelihoods. Nevertheless, conflict remains a major destabilising force, particularly through its persistent disruption of production systems, market integration, and mobility. The results also demonstrate the usefulness of combining machine-learning algorithms with dynamic econometric techniques in analysing food-system vulnerability. Furthermore, the time-varying Granger causality analysis further reveals that the influence of these determinants evolved considerably over time.

The findings of this study provide several important policy implications for strengthening food availability and food-system resilience in Somalia. Firstly, the persistent influence of conflict highlights the need to strengthen peacebuilding initiatives, local security coordination, and institutional stability, particularly in agricultural and pastoral regions where insecurity continues to disrupt production, market access, and livestock mobility. Secondly, the growing importance of food inflation suggests the necessity of reducing excessive dependence on imported staple commodities through policies that support domestic agricultural production, strategic food reserves, and market stabilization mechanisms. Thirdly, the increasing role of temperature-related shocks indicates the urgency of expanding climate adaptation strategies, including drought-resilient crops, sustainable water management systems, rangeland restoration, and climate-smart agricultural practices tailored to arid and semi-arid environments. Fourthly, the relatively weak influence of precipitation compared with temperature suggests that improving rainfall alone may not substantially enhance food availability without parallel investments in irrigation infrastructure, storage systems, and rural transport networks capable of reducing structural production constraints. Fifthly, the strong temporal persistence observed in the LSTM and VAR analyses underscores the importance of establishing early warning and rapid response systems that can identify emerging climatic, conflict-related, and inflationary pressures before they escalate into severe food crises. Finally, the evolving transition from conflict-driven vulnerability toward multidimensional economic and environmental pressures indicates that food security policies in Somalia should move beyond isolated sectoral interventions and instead adopt integrated approaches linking climate adaptation, macroeconomic stability, agricultural development, and institutional resilience within a coordinated national food-system strategy.

Several limitations warrant consideration. First, the study is confined to Somalia over the period 2001–2021. Accordingly, the generalizability of the findings to countries with different institutional levels, food systems, or agroecological conditions may be limited. Second, food availability is proxied by cereal production, which captures the domestic production component of food availability but does not account for other important sources of food supply, such as food imports, humanitarian food assistance, post-harvest losses, and informal cross-border trade, all of which play an important role in Somalia's food system. Third, while the study focuses on the time-varying effects of conflict, food inflation, and climate variability, other potentially important determinants—including exchange-rate fluctuations, transport costs, infrastructure development, market integration, institutional quality, and government policy interventions—were not incorporated into the empirical analysis and may also influence food availability. Fourth, the machine-learning models were included to enhance predictive assessment, and the SHAP values and feature importance measures should be interpreted as indicators of predictive relevance rather than causal effects. Fifth, the VAR impulse responses and time-varying Granger causality analyses are reduced-form approaches that depend on model specification, including lag selection, stationarity transformations, and identification assumptions, and therefore should not be interpreted as structural causal relationships. Finally, the conflict and climate datasets may contain measurement errors arising from reporting bias, spatial aggregation, and data limitations. Future research could incorporate additional structural, institutional, and trade-related variables, together with broader measures of food availability.

Author contributions

- Amina Omar Mohamud: Conceptualization, Data Collection, Writing – Original Draft.
- Abdikafi Hassan Abdi: Conceptualization, Formal Analysis, Visualization, Writing – Original Draft, Writing – Review & Editing, Supervision.
- Abdifatah Mohamed Muhumed: Literature Review, Methodology, Validation.
- Abdisalan Aden Mohamed: Data Curation, Formal Analysis.
- Bashir Mohamed Osman: Methodology, Visualization, Writing – Discussion Section, Review & Editing.
- Samira Abdulkadir Adan: Manuscript Editing, Proofreading, Review & Validation.

Consent for publication

Not applicable.

Consent to participate

Not applicable.

Data availability

The data supporting the findings of this study are publicly available in Zenodo at https://doi.org/10.5281/zenodo.20450896. The repository contains the Excel dataset used in the analysis, including all variables employed in the machine-learning and econometric estimations. The original data were obtained from the World Development Indicators (WDI), the Food and Agriculture Organization (FAO), the Armed Conflict Location and Event Data Project (ACLED), and the Climate Change Knowledge Portal (CCKP).

Disclosure statement

The authors declare that they have no known competing financial or non-financial interests that could have influenced the work reported in this paper.

Ethical approval

This study adhered to internationally accepted ethical standards in academic research and scientific writing. The authors confirm that the manuscript is original, has not been published previously, and is not currently under consideration for publication elsewhere.

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About the authors

Amina Omar Mohamud is the Deputy Rector for Planning and Development at SIMAD University, Somalia. She holds a PhD in Islamic Finance from INCEIF University, Malaysia. During her academic career at SIMAD University, she has served in several leadership and academic positions, including lecturer, Dean of the Graduate Studies Center, and Acting Rector. Her research interests include Islamic banking and finance, financial technology (FinTech), sustainable development, entrepreneurship, and climate finance. She is also actively involved in institutional strategy, digital transformation, capacity building, and initiatives supporting educational innovation and women's empowerment in Somalia.

Abdikafi Hassan Abdi is a PhD researcher in development economics at the International Institute of Social Studies (ISS), Erasmus University Rotterdam, and a lecturer in the Faculty of Economics at SIMAD University, Somalia, where he also serves as Head of Research at the Institute of Climate and Environment (ICE). His research interests include development economics, regional economic integration, structural transformation, export diversification, and sustainable development, with a particular focus on Somalia and sub-Saharan Africa. He has authored more than 40 peer-reviewed articles published in SCI/SSCI- and Scopus-indexed journals.

Abdifatah Mohamed Muhumed is a researcher in the Faculty of Economics at SIMAD University, Somalia, and a public finance professional in the Research and Policy Support Unit of the Revenue Directorate at the Ministry of Finance, Federal Government of Somalia. He holds a bachelor's degree in Economics from SIMAD University and a bachelor's degree in Education, specializing in Mathematics and Physics, from Mogadishu University. His research interests include applied econometrics, public finance, fiscal policy, taxation, macroeconomics, and quantitative economic analysis in Somalia.

Abdisalan Aden Mohamed is a researcher and lecturer in the Faculty of Economics at SIMAD University, Somalia. He is also affiliated with the Institute of Climate and Environment (ICE) in Somalia. His academic work is grounded in applied economic analysis, with a particular emphasis on environmental and development economics, quantitative econometric methods (time-series and panel frameworks), and the dynamics of structural change and long-term growth. His research also addresses sustainability and international trade issues, drawing extensively on empirical evidence from Somalia and the wider sub-Saharan African region. He has published peer-reviewed studies in SCIE- and Scopus-indexed journals.

Bashir Mohamed Osman is a lecturer in statistics at SIMAD University in Mogadishu, Somalia, and a PhD candidate in statistics at Ondokuz Mayıs University, Türkiye. His research interests encompass a broad range of applied quantitative methods, including machine learning, econometrics, time-series analysis, and statistical modeling, with a particular focus on food security. His work seeks to leverage advanced statistical and computational tools to address pressing developmental challenges.

Samira Abdulkadir Adan is an academic administrator at SIMAD University, Somalia, where she serves as Head of Engagement and Development at the Executive Leadership Institute (ELI). She holds a bachelor's degree in Banking and Finance from SIMAD University. Her professional and academic interests include institutional development, stakeholder engagement, leadership, entrepreneurship, and organizational capacity building. She has previously led the engagement and operational activities at the Institute of Climate and Environment and has participated in the coordination of academic and regional initiatives.

ORCID

Abdikafi Hassan Abdi http://orcid.org/0000-0002-3714-7546
Abdisalan Aden Mohamed http://orcid.org/0000-0002-3462-8408
Bashir Mohamed Osman http://orcid.org/0009-0003-2003-972X

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