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Macro-Economic Assessment of Ethiopian Food Security: Trade, Domestic Production, and Vulnerability through the Jameel Index

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— Gregory N. Sixt,
FACT Alliance Director

Food and Climate Systems Transformation
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Macro-Economic Assessment of Ethiopian Food Security: Trade, Domestic Production, and Vulnerability through the Jameel Index

A research report submitted to the MIT J-WAFS FACT Alliance

By

Ethiopian Institute of Agricultural Research (EIAR)

Tadele Mamo, Samuel Diro, Tesfaye Solomon, Girma Mamo

Executive summary

This integrated report synthesizes findings from three sequential milestones investigating Ethiopia's food import trends, domestic production, food security status, and vulnerability to trade shocks. The study combines empirical analysis, econometric modeling, and the application of the Jameel Index to provide a comprehensive assessment of Ethiopia's food system. Key findings reveal Ethiopia's growing reliance on food imports, particularly for cereals, oils, and sugar, amidst increasing climate variability and external trade risks. Despite improvements in agricultural productivity, Ethiopia remains vulnerable to food security threats due to its dependence on global markets and fluctuating climatic conditions. The report underscores the dual role of trade as both a stabilizer and a source of risk. Strategic recommendations focusing on enhancing domestic production, improving trade diversification, and bolstering resilience through policy and infrastructure investments were drawn.

This report also explores Ethiopia's food security from a macroeconomic perspective, focusing on the country's growing vulnerability to disruptions in food imports. Using a combination of empirical data, econometric tools, and insights from the Jameel Index, the study points out a complex picture of how trade and climate factors are shaping the nation's food landscape.
Ethiopia's reliance on imported staples—particularly cereals, cooking oils, and sugar—has been increasing, despite improvements in local food production. Over the past decade, cereal imports have jumped by 14%, while domestic output has grown by just 5%. The Jameel Index offers further context, showing that between 2011 and 2022, Ethiopia consistently fell within the "Medium" vulnerability category and never crossed into the "High" resilience range.

Several indicators contribute to this pattern. The country's Food Import Foreign Exchange Ratio remains persistently high. Food Supply Reliability has sat at an "Extreme" vulnerability level for over ten years, improving only slightly in recent times. Additionally, while there was a brief uptick in Supply Chain Robustness, this too has declined, currently ranking at a "Low" level. On a more positive note, Feed Import Dependency is still "Very Low," yet critical vulnerabilities remain—especially in wheat, oil, and rice imports. Sectors like dairy, sugar, and soybeans are also struggling due to fragile supply chains.

To address these challenges, the report emphasizes the need for wide-reaching reforms. This includes boosting local production, strengthening financial capacity, improving logistics and supply systems, and adopting stronger climate adaptation strategies. Without these, Ethiopia will likely continue facing food security pressures, particularly as its population grows and climate risks intensify.

Contents

Abbreviations and Acronyms

AgSS	Agricultural Sample Survey
CSA	Central Statistical Agency
CDT	Climate Data tools
EAs	Enumeration Areas
ECA	Ethiopian Customs Services
ESPS	Ethiopia Socioeconomic Panel Survey
ESS	Ethiopian Statistical Services
EDI	Effective Drought Index
EIAR	Ethiopian Institute of Agricultural Research
EMI	Ethiopian Meteorological Institute
ENHRI	Ethiopian Nutrition and Health Research Institute
FAO	Food and Agriculture Organization
FACT	Food and Climate Systems Transformation
IPCC	Intergovernmental Panel on Climate Change
LSMS-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
MDGs	Millennium Development Goals
SPI	Standardized Precipitation Index
WHO	World Health Organization
WMO	World Meteorological Organization

1. Ethiopian Food Import, Domestic Food Production and Food security

Tesfaye Solomon, Tadele Mamo, Samuel Diro, Girma Mamo, Abu Tolcha

1.1. Introduction

1.1.1. Background and justification

Explained by the rising temperature, increased variance in rainfall pattern, and the frequency of extreme weather events, climate change is already having an impact on food and nutrition security events (IPCC, 2019; Mbow et al., 2019). Climate change affects the six dimensions of food security: availability, access, utilization, stability, agency, and sustainability directly or indirectly (FAO, 2018; HLPE, 2020; Clapp et al., 2022). These factors resulted in narrowed rural livelihood option and income, loss of marine and coastal ecosystems, and loss of terrestrial and inland water ecosystems (Gitz et al., 2015).

According to Ludwig et al. (2007), developing countries are much more vulnerable to climate change than the developed world. When paired with population growth, climate change is likely to push millions further into poverty and limit the opportunities for sustainable development. It is also likely to have a significant impact on the economies of developing countries. Without adaptation, the losses are estimated to be up to 20% of GDP. Moreover, climate change is likely to affect the attainment of many of the Sustainable Development Goals (SDGs) (Guo, Kubali & Saner, 2021; UN, 2024).

Climate change will exert pressure on trade flows and food price stability and could introduce new risks for human health (Gitz et al., 2015). Studies found that climate heterogeneity between trading partners impacts bilateral trade relationships. The larger the heterogeneity in temperatures and rainfall levels, the higher the value of bilateral exports (Bozzola et al., 2023). The result is consistent with Dallmann (2019) who found short-run impacts of weather heterogeneity on bilateral trade. Developed and developing exporters are both sensitive to climate differences but have diverse responses. For instance, higher differences in temperatures between trading partners are beneficial for exporters but detrimental for the importing country. Larger differences in rainfall levels are especially beneficial for developing exporters, although the gain in monetary terms is almost comparable between developing and developed exporters. Therefore, greatly expanded efforts to respond to climate change are needed immediately to safeguard the capacity of food systems to ensure global good security (Gitz et al., 2015).

1.1.2. Statement of the problem

The flows from food surplus to deficit areas improve the availability of food for consumers and increase the income of exporters (who charge higher prices in the market than would be possible without trade) and importers (who make purchases at lower prices) (Wacziarg and Welch, 2008). Trade may improve balanced nutrition patterns through product diversification, while stabilizing food availability, as domestic production uncertainty is higher than the total production risk across international markets (Brooks and Matthews, 2015).

International trade is also believed to have an important role in reducing the adverse effects of climate change on food security (Gitz et al., 2016; Brown et al., 2017; Gouel and Laborde, 2018). The study conducted by FAO (2005) confirms a positive relationship between market openness and food security. There is an eminent need to assess factors affecting future food security to ensure resilient food, trade, and foreign policy in a changing climate. However, there remain significant knowledge gaps regarding how different climate scenarios may affect agricultural productivity (particularly for staple food crops) and its related impact on global food supply chains, while the contribution of import to national food demand and food security was not addressed. On the other hand, the impact of climate change (drought) on domestic production and import was not observed. The aim of this study is to characterize Ethiopian food import patterns by exploring the nexus between food imports, domestic food production vis-a-vis drought, as well as between national food import and regional food security status.

In order to measure the degree of Ethiopia's reliance on international food trade and imports, better understand and analyze food security impact of climate change, and evaluate how regional-scale threats might affect the ability to trade food goods across various geographies nationally, we employed the Jameel Index, a comprehensive index that assesses countries' vulnerability to food security.

1.2. Methodology

1.2.1. Data types and sources

The data used for this report was obtained largely from secondary sources. Specifically, we obtained the import data from the Ethiopian Customs Authority, domestic production data from the Ethiopian Statistical Services (the then, Central Statistical Agency or CSA), data for information generation on food security was obtained from the World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA), a five round panel survey data. These surveys are conducted as part of the LSMS-ISA in collaboration with the Ethiopian Statistical Services. The LSMS-ISA data is also known as the Ethiopia Socioeconomic Panel Survey (ESPS), and it includes five rounds of collected data in 2011/12, 2013/14, 2015/16, 2018/19 and 2021/22. These rounds of data collection were carried out at the national level and provide detailed information on various aspects such as employment, agriculture (crop production and livestock husbandry), income, food, and nutrition security indicators.

The sampling frame for the ESPS panel survey was based on the updated pre-census cartographic database of enumeration areas by the ESS. The sampling adopted a two-stage stratified probability technique. The ESPS EAs in rural areas are the subsample of the AgSS EA sample. That means the first stage of sampling in the rural areas entailed selecting enumeration areas (i.e., the primary sampling units) using simple random sampling (SRS) from the sample of AgSS enumeration areas (EAs). The first stage of sampling for urban areas is selecting EAs directly from the urban frame of EAs within each region using systematic PPS. This is designed to automatically result in a proportional allocation of the urban sample by zone within each region. Following the selection of sample EAs, they were allocated by urban rural strata using power allocation which is happened to be closer to proportional allocation (World Bank LSMS data).

Table 1 below presents the distribution of samples in the ESS survey across the five waves conducted in Ethiopia. Initially, the first wave targeted rural areas and small towns[1]. Subsequent waves, ESS2 and ESS3, expanded to include households from both rural and urban settings, creating a panel dataset. In contrast, ESS4, conducted in 2018/19, initiated a new panel covering all regions and major cities. The most recent survey, ESPS-5 in 2021/22, continued the panel started in ESPS-4 but excluded the Tigray region due to security concerns.

Table 1. The sample distribution of the ESS surveys for all waves

Residence	Wave 1 (2011/12)	Wave 2 (2013/14)	Wave 3 (201516	Wave 4 (2018/19)	Wave 5 (2021/22)
Rural	3466	3323	3272	3115	2285
Urbans	503	1939	1682	3655	2674
Total	**3969**	**5262**	**4954**	**6770**	**4959**

Source: Compiled from WB LSMS data of five waves.

In addition, we obtained climate related data from 92 sites over an eleven year period (2010-2020). The nature of this data is presented as follows.

Meteorological stations data: The historical daily rainfall data from 2010 to 2020 for 112 meteorological stations were obtained from the Ethiopian Meteorological Institute (EMI), and from the Ethiopian Institute of Agricultural Research (EIAR). The data were analyzed using Climate Data tools (CDT v8.0) (Tufa *et al.,* 2022). The distribution and information of synoptic weather stations used in these analyses are presented in **Figure 1** while the detail of the locations along with their abbreviations is presented in appendix **Table 1.**

[1] The CSA defines small towns based on population estimates from 2007 population Census, a town with the population of less than 10,000 is a small town.

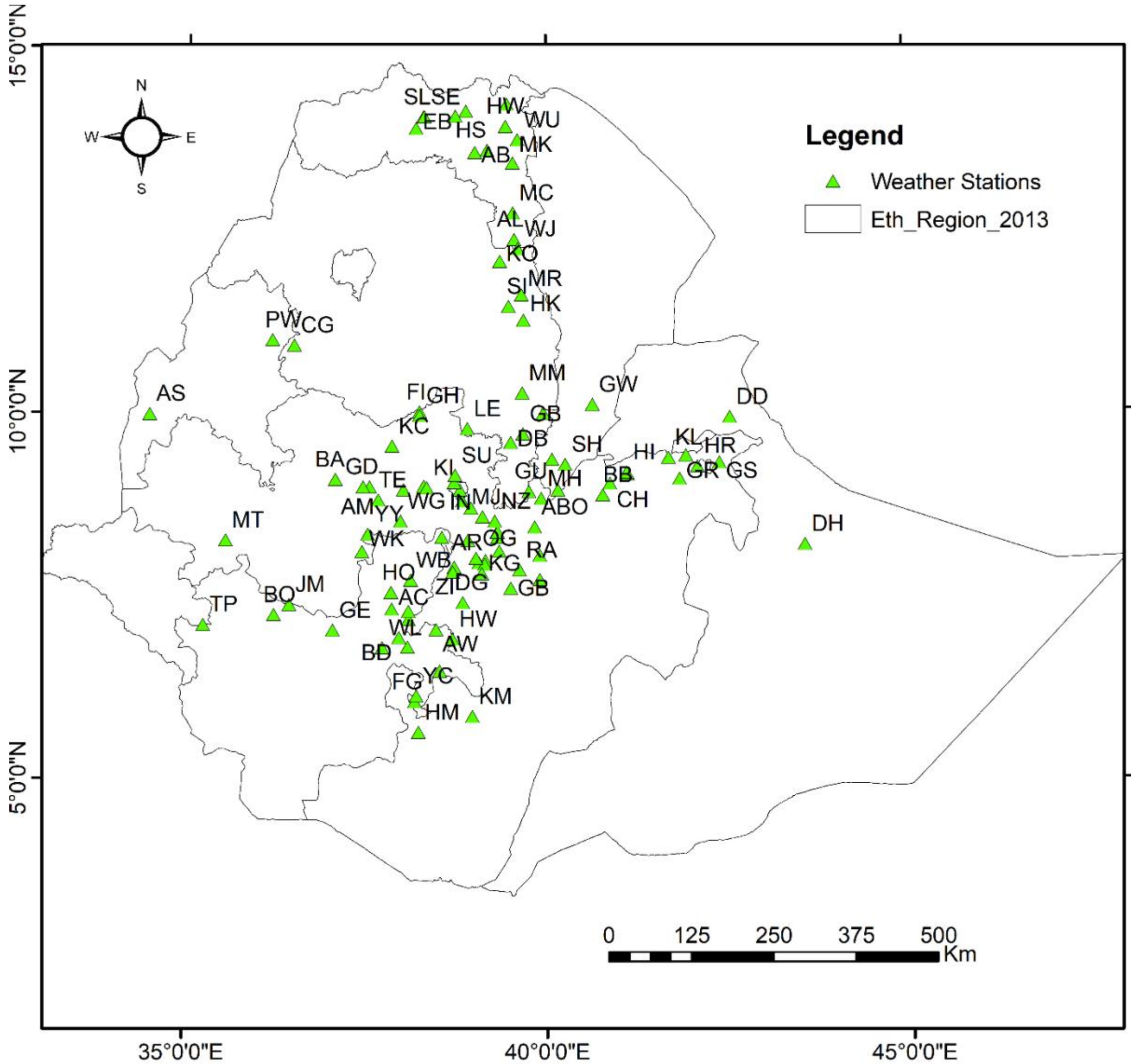


Figure 1. Distribution of weather stations used in drought analysis

Homogeneous Rainfall Regions: Rainfall over east Africa in general, and Ethiopia in particular, varies spatially both in terms of the annual cycle and the interannual variability. To account for this variability, we used 112 weather stations to divide into twelve homogeneous rainfall regions specifically for main rainy season (June, July, August and the September). Two criteria were used to identify homogeneous rainfall regions i.e., similarity of annual cycle and interannual correlations of seasonal rainfall, with the implications for the future improved agricultural technology targeting under rainfed system.

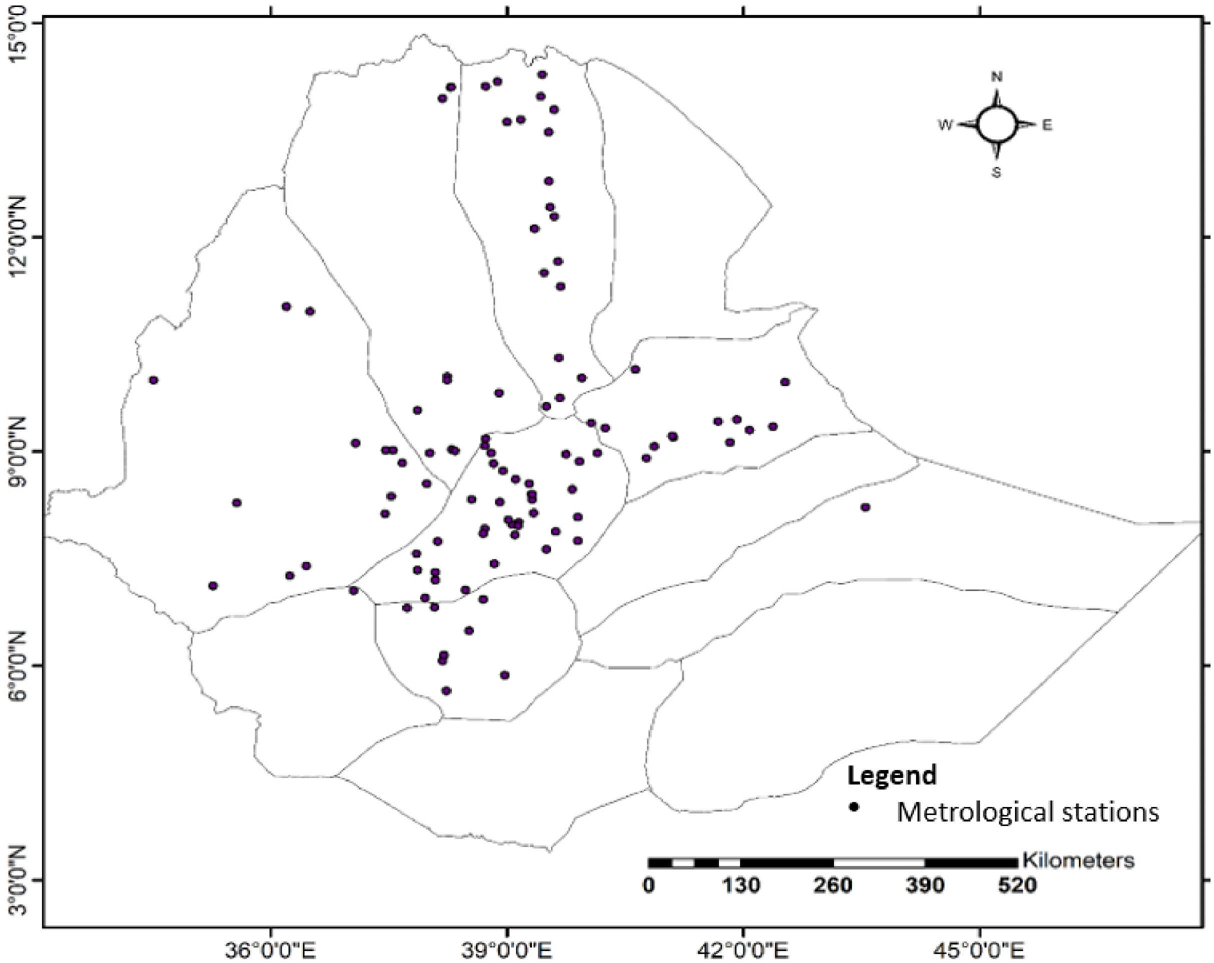


Figure 2. Homogeneous rainfall regions and station distribution

1.2.2. Data analysis methods

We used descriptive analysis to generate useful information on drought by adopting standardized Precipitation Index (SPI) tool. The SPI is a drought index that is used to investigate the intensity, and spatial pattern of drought distribution in a particular region (Wattanakij et al., 2006). Wambua et al., 2018 has compared the Effective Drought Index (EDI) and SPI and recommends SPI as a drought index because it is simple to calculate and has greater spatial consistency. The SPI was computed at different timescales (1–12 months) to identify and describe drought events. Accordingly, SPI was calculated from monthly precipitation records by first fitting the gamma probability distribution function and then transforming into a normal distribution so that the mean SPI is set to zero (McKee et al., 1993). Positive and negative SPI values indicate wet and dry conditions, respectively. The SPI values at three-, six- and twelve-months timescales (SPI3, SPI6, SPI12) were computed to determine meteorological, agricultural and hydrological droughts for the period of 2010 to 2020.

Table 2. Drought classifications based on SPI values

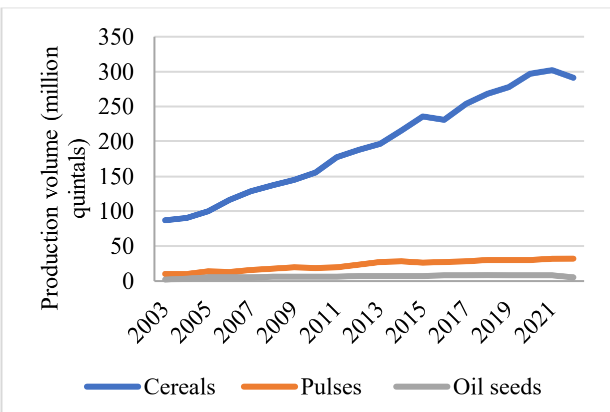
SPI	Classification
2.0+	Extremely Wet
1.5 to 1.99	Very Wet
1.00 to 1.49	Moderately Wet
-0.99 to +0.99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2.0 and less	Extremely Dry

1.3. Results and Discussion

Domestic food production and import in Ethiopia (2011–2020)

Food production trends

In Ethiopia, agricultural production is characterized by subsistence orientation and low productivity, due to low level of technology use and associated lack of modern infrastructure and market institutions, and vulnerability to extreme weather. Grain crops such as cereals, pulses, and oil seeds are the major agricultural food commodities produced in Ethiopia. In 2022, the country has produced more than 328 million quintals of grain on 12 million hectares of land. Of the total volume of grain produced, more than 291 million of quintals was cereals. Cereals dominate the land and production followed by pulses (**Figures 3 &4**) (ESS, 2023).



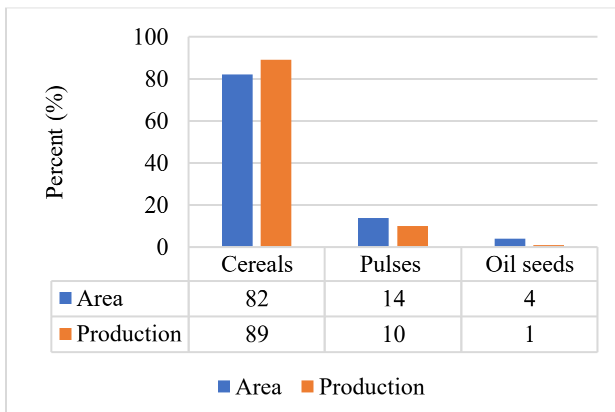


Figure 3. Grain production (millions of quintals) **Figure 4**. Percent production and land share (%)

According to ESS (2023) the share of teff, maize, sorghum, and wheat was 24%, 21%, 11%, and 15 % of the grain crop area, respectively. Similarly, maize, teff, wheat, and sorghum made up 33%, 17%, 18%, and 11% of the grain production, in that order. Faba beans, haricot beans (white), haricot beans (red), chick peas (red), chick peas (white) and field pea are also dominant grain legumes produced in the country while nug, sesame, and linseed are major oil seeds making part of the crop production system.

Characteristics of food import trends in Ethiopia

The other important contributor to Ethiopian food security is food import. Ethiopia has imported significant volume of food commodities from overseas. For instance, the country has imported food commodities which costs 3,423 million USD. **Figure 5** shows that the total food import over the last decade has increased by 20.4%.

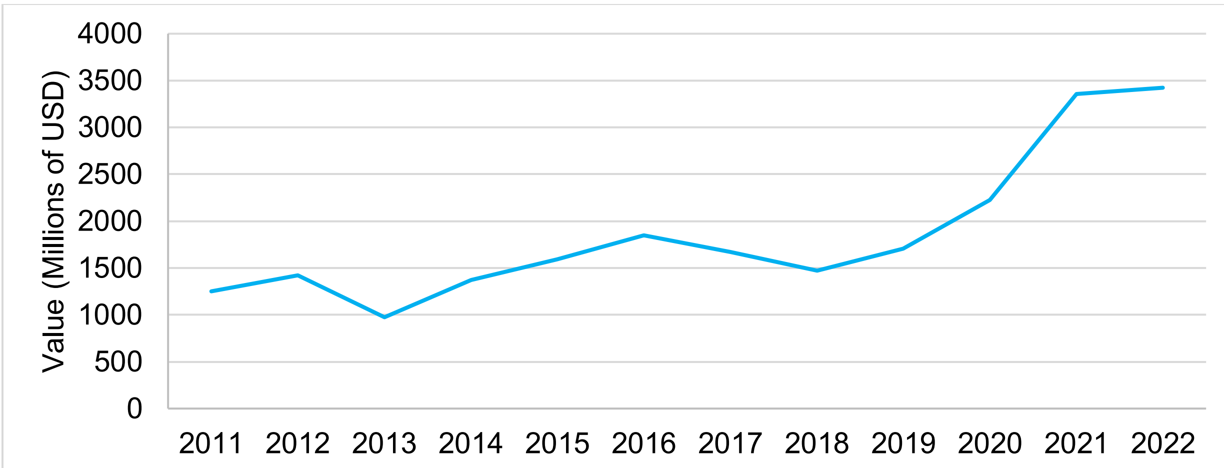


Figure 5. Ethiopian total food imports value (Millions of USD) over the past twelve years
Source: Generated from ECA (2011-2022) data

The study shows that Ethiopia's food import values have fluctuated significantly from 2011 to 2022, with cereals and animal and vegetable oils consistently representing the highest import values. Cereals saw a dramatic rise from 2019, peaking in 2021 at over 1,400 million USD before slightly declining in 2022. Animal and vegetable oils followed a similar upward trend, especially from 2019 onwards. In contrast, imports of sugar and sugar confectionery, edible vegetables, and other categories remained relatively low and stable. Overall, the data indicate a growing reliance on cereal and oil imports over the years (**Figure 6**).

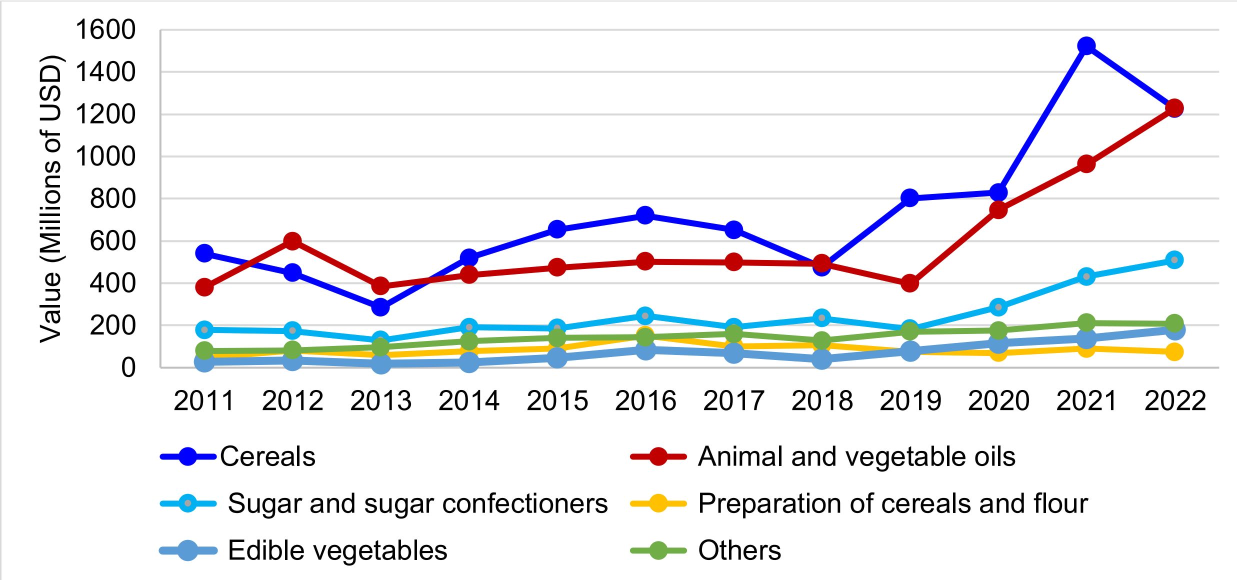


Figure 6. Ethiopian food imports value (Millions of USD)

Source: ECA, 2011–2022

The study result also shows that cereals and animal and vegetable oils have consistently accounted for the largest percentage share of Ethiopia's imported food items from 2011 to 2022. Cereals maintained the highest share for most of the period, peaking around 2019 and 2021, while animal and vegetable oils showed more fluctuation but regained prominence in 2022. The shares of other food items such as sugar and sugar confectioneries, edible vegetables, and preparations of cereals and flour remained relatively stable and lower throughout the period, with minor variations (**Figure 7**).

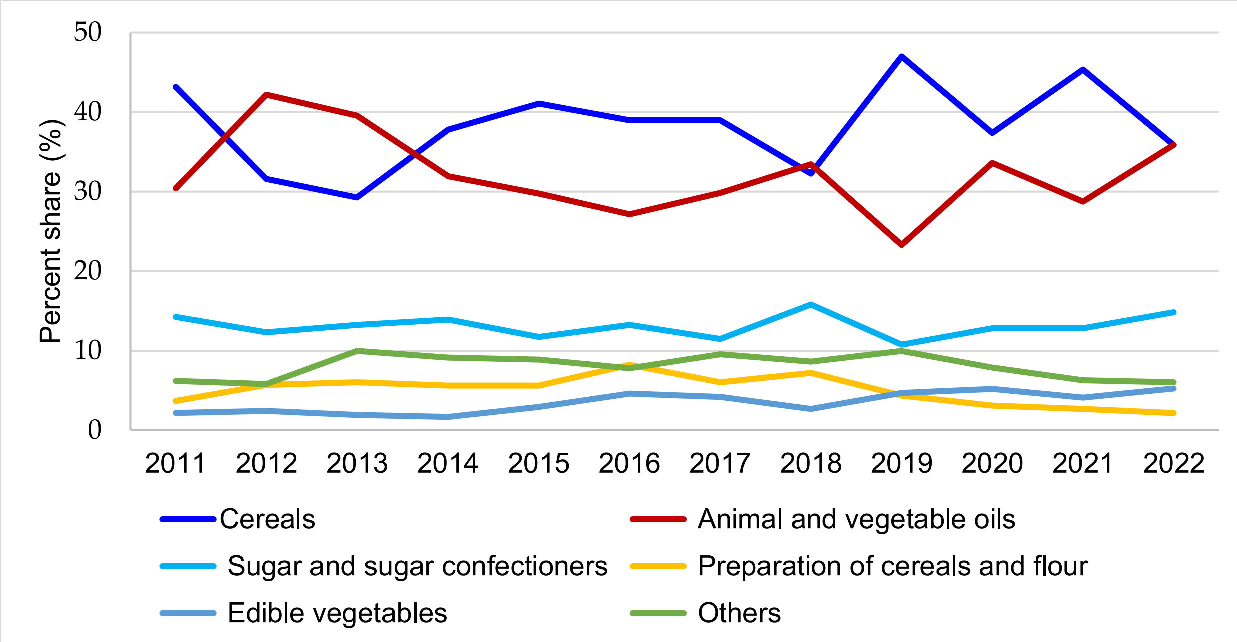


Figure 7. Percentage share of imported food items (%)

Source: ECA, 2011–2022

Sources of Food import for Ethiopia

Figure 8 below illustrates the import values of major food crop categories from various countries to Ethiopia for the period (2020–2022). It sheds valuable insights into the complex dynamics of Ethiopia's agricultural trade relationships. Remarkably, India emerges as a pivotal trade partner, showcasing substantial import values in cereals and sugar. Likewise, the United States demonstrates significant contributions across multiple food crop categories, highlighting the diversified nature of Ethiopia's trade relations and the enduring significance of key global players in Ethiopia's agricultural export market. Moreover, the inclusion of countries like Turkey, Ukraine, Argentina, and the Russian Federation highlights the diversity of Ethiopia's trade partners, reflecting the country's engagement with both traditional grain exporters and emerging agricultural powerhouses. This suggests a clear trade landscape characterized by a blend of regional and global trade dynamics (**Table 3 and 4**).

Additionally, the presence of Malaysia, Djibouti, and Indonesia among the top exporters of animal and vegetable oils to Ethiopia shows the importance of regional cooperation and economic integration within Africa and beyond. While modest export values from countries like Kenya, the United Arab Emirates, and Saudi Arabia indicate potential areas for growth and collaboration, the inclusion of countries such as Brazil, Egypt, and Vietnam emphasize the potential for expanding market diversification and enhancing Ethiopia's global agricultural trade footprint (**Figure 8**). Based on previous studies and the current findings, policymakers can formulate evidence-based strategies aimed at enhancing Ethiopia's agricultural export competitiveness, promoting sustainable economic growth and inclusive development. Such targeted interventions, including trade agreements, infrastructure investments, and capacity-building initiatives, can help unlock new market opportunities and navigate global trade dynamics more effectively, positioning Ethiopia as a key player in the global agricultural trade arena.

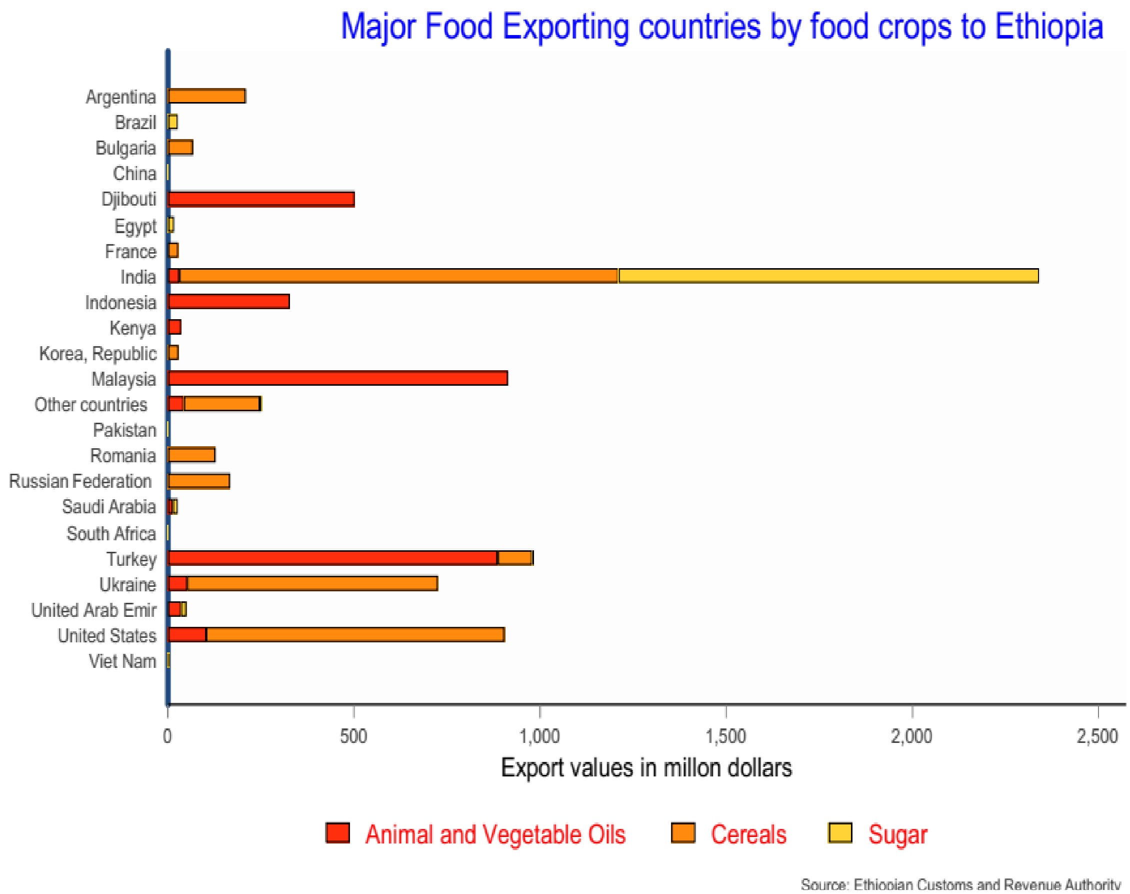


Figure 8. Major Food exporting countries to Ethiopia (2020–2022)

Table 3. Value of import in USD of cereals and flour to Ethiopia (2020–2022)

Countries	Value of export in USD	Percent share (%)
Belgium	55,000,000	23.6
United States	43,300,000	18.6
Rwanda	37,800,000	16.2
France	23,700,000	10.2
Italy	10,900,000	4.7
Turkey	9,140,312	3.9
South Africa	8,225,144	3.5
Poland	7,881,873	3.4
Kenya	6,397,402	2.8
Saudi Arabia	4,694,243	2.0
Others	25,961,026	11.1
Total	233,000,000	

Source: ECA, 2011–2022

Table 4. Top ten countries import of edible vegetables to Ethiopia (2020–2022)

Countries	Value of export in USD	Percent share (%)
United States	144,000,000	33.2
India	77,700,000	17.9
United Arab Emir	60,800,000	14.0
Ukraine	58,500,000	13.5
Turkey	29,600,000	6.8
Egypt	21,700,000	5.0
Sudan	14,300,000	3.3
Canada	11,800,000	2.7
Yemen	4,357,483	1.0
Kazakhstan	4,173,757	1.0
Others	7,068,760	1.6
Total	434,000,000	

Source: ECA, 2011–2022

Nexus between food import, domestic production, and drought in Ethiopia

Domestic food production and import

Agricultural production plays a pivotal role in ensuring food security. To enhance food security of a nation, improving agricultural production and productivity would have a paramount importance. **Figure 9** below shows that Ethiopia has experienced growth rate in cereal production. However, the percentage of increase in production and import profile is entirely different. In the last decade, the domestic cereal production has increased by 5% on average and the imported quantity increased by 14%. This could be due to high population growth, urbanization, and modernization. This may necessitate increased investment in agricultural research to generate improved technologies and injection into production system, thus boosting production and productivity and increased trade for food commodities with better comparative advantage in response to the rapidly rising population (**Figure 9**).

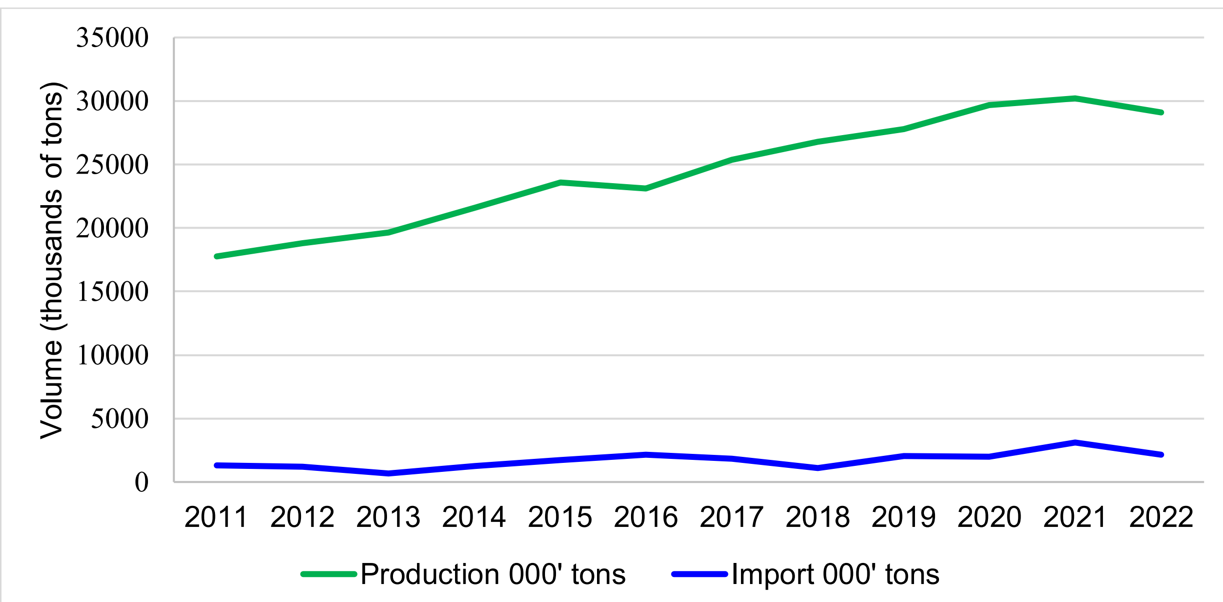


Figure 9. Local cereal production and import (000’ tons)
Source: ECA, 2011–2022

The results also showed that, though the country is highly dependent on food import, the county’s share of total demand is significant. For example, the country's domestic cereal production in 2022 accounts for 93% of overall consumption. To meet domestic demand, the country imports only 7% from overseas (**Figure 10**).

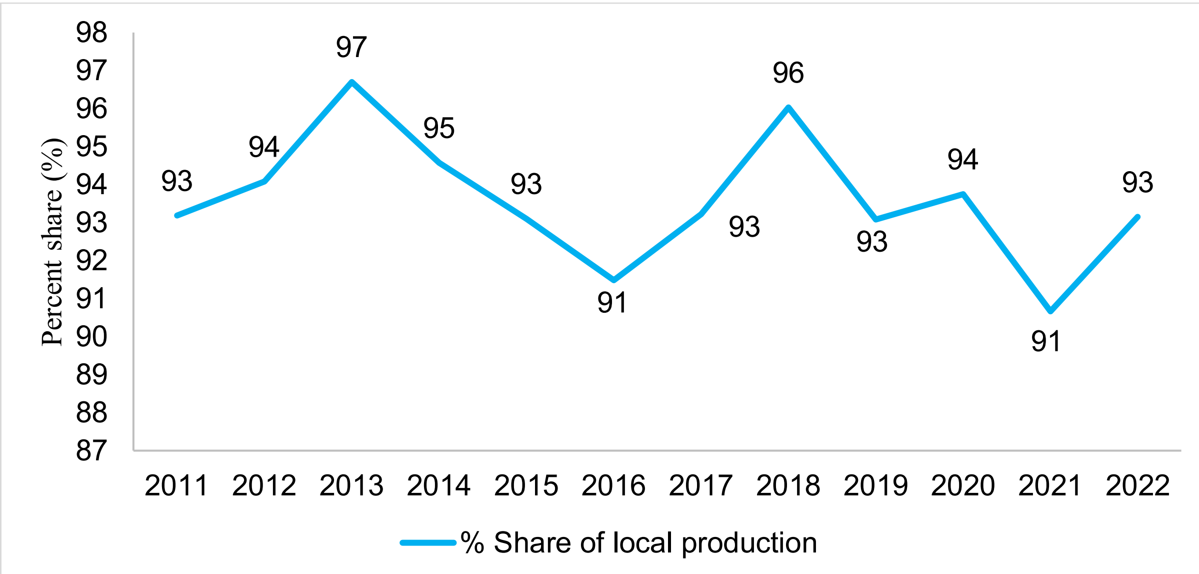


Figure 10. Time series share of local production over total consumption in %

Source: ECA, 2011–2022

Drought trends in Ethiopia

The mean SPI values at seasonal scale i.e., three months, six months, and twelve months (SPI3, SPI6, SPI12) computed for each weather station is summarized and presented in **Table 5**. The result revealed that moderate to severe drought have been experienced in Ethiopia during the period from 2010–2020. Severe droughts were identified in the years 2015 and 2016 having drought intensity of -1.54 and -1.51, respectively. On the other hand, the years 2019 and 2020 were identified as very wet years in this analysis considered normal (see **Table 2**) while the remaining years were classified as near normal.

Table 5. SPI values at different timescales

Year	SPI3	SPI6	SPI12
2010	0.04	-0.02	-0.02
2011	-0.99	-1.06	-1.04
2012	-0.62	-0.53	-0.65

2013	-0.20	-0.32	-0.28
2014	-0.99	-0.97	-0.92
2015	-0.94	-1.19	-1.54
2016	0.02	-1.67	-1.51
2017	-0.18	-0.33	-0.24
2018	-0.09	0.05	0.50
2019	0.29	-0.05	-0.45
2020	0.98	1.60	1.68

Source: Own analysis

The analyses of historical climate data revealed that the drought frequency has been highly increased during the last two decades (2000–2020). The years 2001 to 2006 were very wet years while the dry condition frequently occurred between 2007 and 2016 (**Figure 11**).

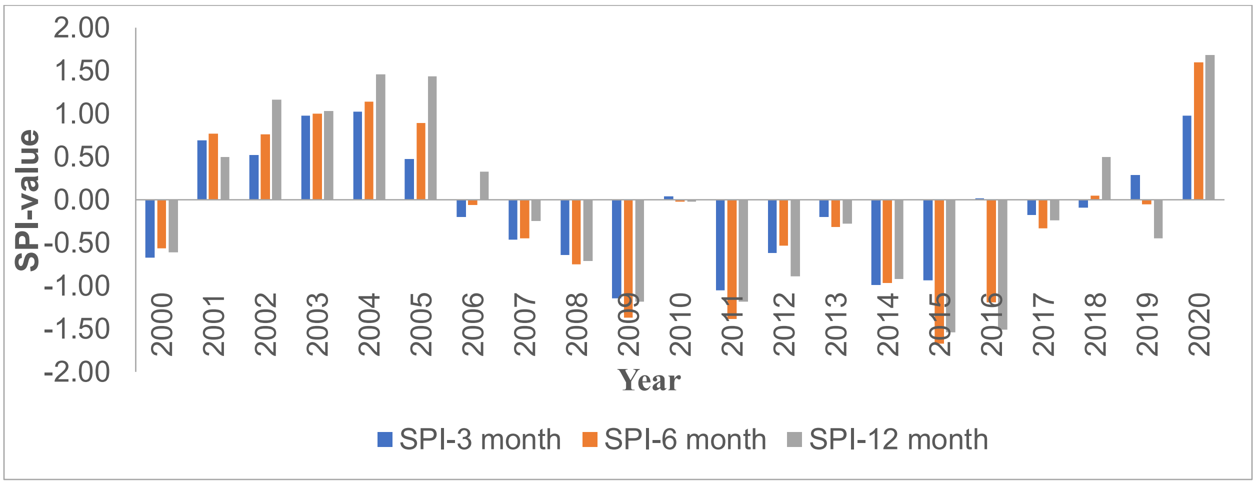


Figure 11. Standardized Precipitation Index at different time scales during 2000–2020

Domestic food production, import and drought

According to **Figure 11**, the intricate relationship among cereals import, drought incidence, and cereal production in Ethiopia from 2012 to 2022 was highlighted. Over this period, cereal food grain imports have demonstrated a consistent upward trajectory, indicative of the country's growing reliance on imported grains to meet domestic demand. This trend could be attributed to various factors such as population growth, changing consumption patterns, and challenges in domestic production, including the impact of climate-related events like drought. Indeed, the data reveals fluctuations in drought incidence, as measured by the SPI, with notable instances of negative SPI values in 2012 and 2016, signifying the presence of drought conditions. These periods of drought coincide with lower cereal production quantities, underscoring the vulnerability of Ethiopia's agricultural sector to climatic variability and extreme weather events.

Despite the challenges posed by drought, cereal production has exhibited an overall increasing trend over the years, indicating the role of improved agricultural technologies (including the short maturing and drought tolerant crop cultivars) to enhance agricultural productivity and resilience. The higher production quantities observed in later years, such as 2019 and 2022, suggesting a successful technological penetration and enhanced adoption rate of input utilization, and agronomic practices to enhance resilience to climatic shocks, and optimization of responses to a better rainfall distribution. However, the persistence of drought and the concurrent rise in cereals imports underscore the need for comprehensive strategies to bolster domestic production, mitigate the impact of climate change, and ensure food security in Ethiopia.

Further, policymakers and stakeholders need to prioritize investments in climate-smart agriculture, including irrigation development and use of drought-resistant crop varieties. In Ethiopia, the introduction and practice of climate-smart agriculture (CSA) have been ongoing for more than a decade, facilitated by concerted efforts from governmental entities and prominent non-governmental organizations (FAO, 2016). Various studies highlight the positive impacts of CSA practices on farm productivity, food security, and income levels of smallholder farmers (Tadesse and Ahmed 2023; Ahmed *et al* 2023 and Belay et al., 2023).

Additionally, efforts to promote sustainable land management practices, improve access to agricultural inputs and technologies, and strengthen market linkages are essential for supporting smallholder farmers and fostering inclusive growth. By addressing the underlying drivers of cereals imports, drought vulnerability, and cereal production trends, Ethiopia can build a more resilient and sustainable agricultural system capable of meeting the food needs of its growing population while adapting to the challenges of a changing climate.

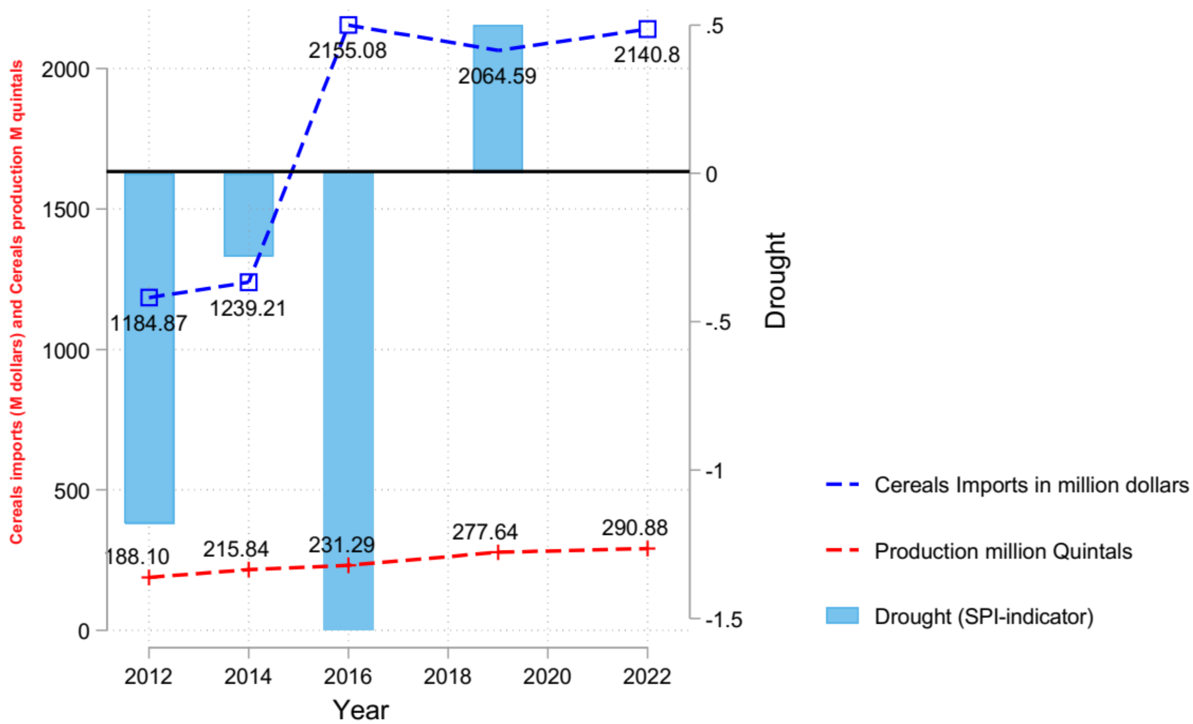


Figure 12. Nexus between food import, domestic crop production and drought in Ethiopia

Relationship between national food import and regional food security status

Food Security Status of Ethiopia

The result shows the spatial maps of household food security across regions from 2012 to 2022 in Ethiopia. From the data scrutiny, we can observe variations in food security across different regions over the years. While some regions like Addis Ababa and Dire Dawa exhibit a downward trend, others like Amhara and Gambelia show gradual improvement. The majority of regions, however, display fluctuations in food security levels, reaching a peak in 2019 followed by a slight decline. Notably, Benishangul Gumuz deviates from this pattern with a temporary peak during the analyzed period.

The regional disparities underscore the significant influence of location-specific factors on food security outcomes. This observation underscores the divergent impacts of climate change across Ethiopia's regions (Berhe et al., 2023; Kagnew et al., 2022; Tilahun et al., 2023). Regions benefiting from targeted interventions, favorable weather conditions, or improved agricultural practices may witness enhanced food security. Demsash et al. (2023) highlight that regions like Addis Ababa, SNNPR, Amhara, and Oromia have better access to food assistance programs like the Productive Safety Net Program (PSNP). Moreover, Kuse and Debeko (2023) note significant spatial variations in malnutrition among children under five, with hotspots in regions lacking adequate health facilities.

Conversely, regions in Ethiopia grappling with challenges such as drought, conflict, and limited resource access do experience notable fluctuations or declines in food security (Zhang et al., 2022; Bovienzo et al., 2023; Abay et al., 2022; Mekonen et al., 2023; Gute and Nkosi, 2021). These adversities exacerbate food insecurity, disproportionately affecting vulnerable groups including refugees, internally displaced persons, conflict-affected communities, and the urban poor. Factors such as climate change, intensified droughts, and ongoing conflicts significantly contribute to the severity of food insecurity. The civil unrest in Ethiopia has further disrupted access to essential services such as healthcare, food, and clean water, particularly impacting rural populations and households with malnourished children. Moreover, the challenges of urbanization, unemployment, and escalating food prices pose significant threats to urban food security, underscoring the urgent need for interventions to alleviate food insecurity among urban population.

These findings reinforce the need for a tailored approach to addressing food security challenges in Ethiopia. Understanding the unique constellation of factors impacting each region is crucial for crafting effective and targeted interventions (Gillespie et al., 2018). Policymakers must prioritize identifying the root causes of fluctuating or declining food security in specific regions and enforce evidence-based solutions tailored to their unique contexts. This region-specific approach holds the potential to enhance the long-term effectiveness and sustainability of food security interventions across all Ethiopian regions.

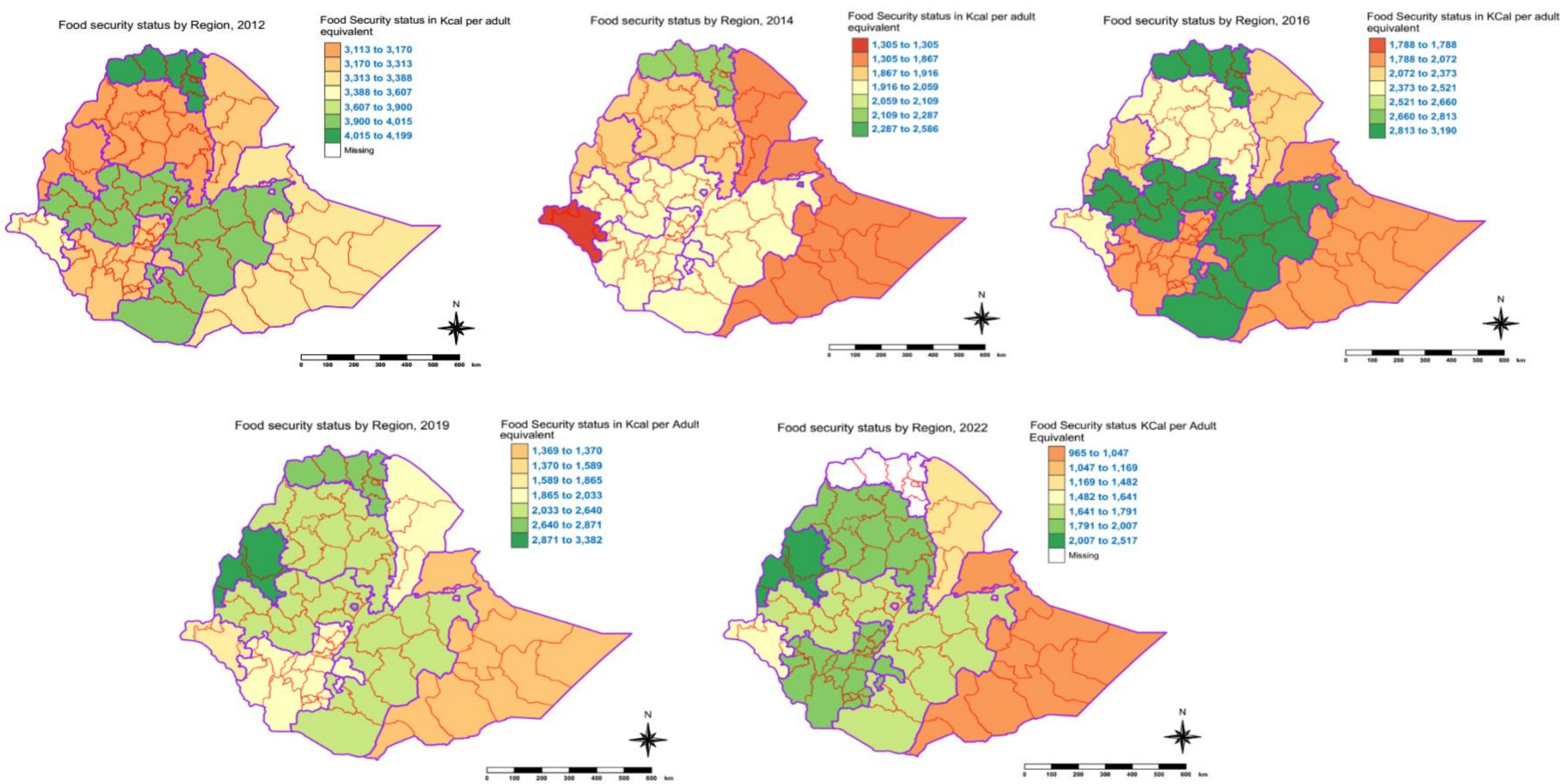


Figure 13. Dynamic food security status by regions

The national food import and food security status nexus

Ethiopia faces significant challenges regarding food security, with a substantial portion of its population vulnerable to food insecurity and malnutrition (World Food Programme, 2023). The country's reliance on food imports adds another layer of complexity to this issue, as it impacts both the economy and the ability to ensure adequate food availability for its citizens. Understanding the relationship between food import and food security is crucial for formulating effective policies and interventions to address these challenges.

Ethiopia's dependence on food imports has been a subject of concern due to its implications for food security (World Food Programme, 2023). Despite being an agrarian economy with vast natural resource potential, the country still relies on imports to meet its food requirements, especially during periods of production deficits or shocks such as droughts or conflicts (World Bank, 2022). The extent of this dependency varies across different food commodities and regions within the country.

Figure 13 illustrates the relationship between food security and food import in Ethiopia from 2012 to 2022. Over this period, both food security and food import levels exhibit noticeable fluctuations, suggesting a dynamic interplay between these two variables. The fluctuations observed in food import levels might be a reflective of changes in domestic production, global market conditions, and government policies influencing trade and agricultural development strategies. Similarly, the variations in food security levels could be attributed to factors such as climate variability, population growth, income distribution, and access to resources and infrastructure.

The positive correlation between food security and food import is observed during the period (2014–2019), implying that increases in food import levels are associated with improved food security outcomes, at least to some extent. This positive correlation aligns with observations made by Jemal et al. (2018) who found that food imports played a role in addressing food insecurity in Ethiopia's dryland regions. However, it is essential to note that while food imports can temporarily alleviate food insecurity, overreliance on imports may pose long-term challenges to food sovereignty and domestic agricultural development.

The deviations from the overall trend in certain years, particularly in food import levels, could be indicative of various factors impacting Ethiopia's food security landscape. For instance, the sharp decline in food import levels in 2019 might be attributed to better rainfall distribution, and improved domestic production or changes in trade policies aimed at promoting self-sufficiency. Conversely, the subsequent increase in food imports in 2022 might be linked to adverse weather conditions or disruptions in domestic production, necessitating higher reliance on external sources to meet food demand (FAO, 2021).

Therefore, the graph provides valuable insights into the complex relationship between food security and food import dynamics in Ethiopia. Food imports play a crucial role in enhancing short-term food security, efforts to strengthen domestic agricultural productivity, promote sustainable farming practices, and improve market access remain essential for achieving long-term food security and resilience in the country. Policymakers and stakeholders need to consider these insights when formulating strategies and interventions to address Ethiopia's evolving food security challenges in the context of broader socio-economic and environmental dynamics.

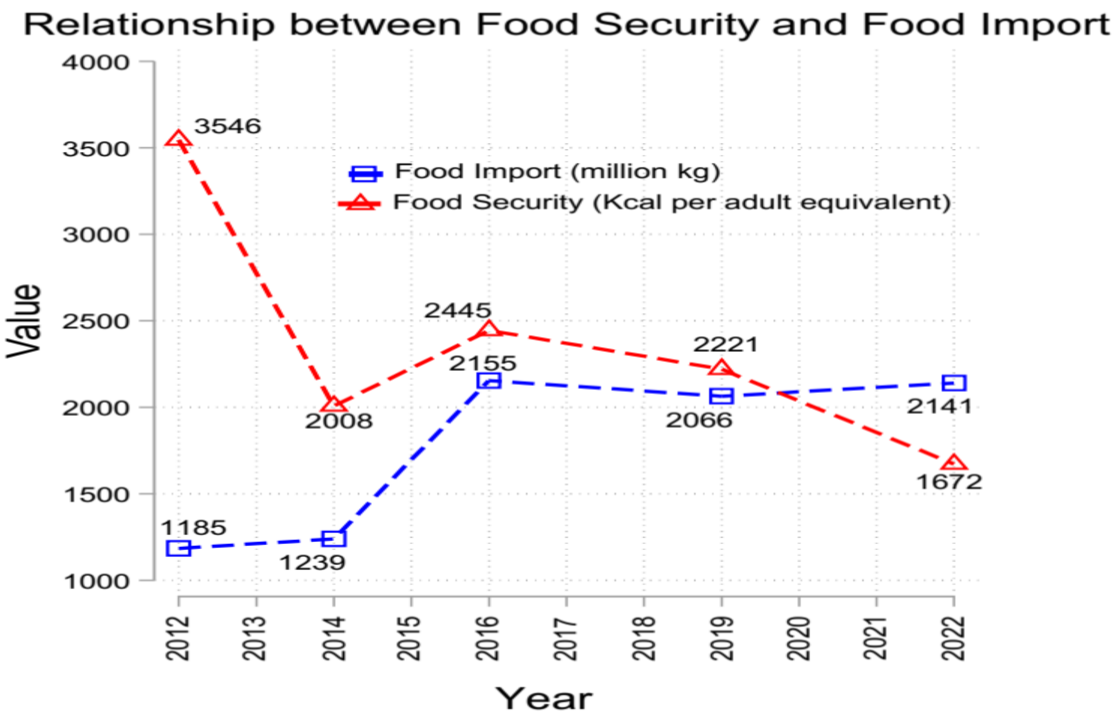


Figure 14: Food Security and Food Import trends (2012–2022)

1.4. Conclusion and take-home message

In this section, a comprehensive analysis of the Ethiopia's food sector encompassing food import patterns, domestic food production trends, and food security status over the past decade. The key finding reveals a multifaceted challenge resulted from climatic variability, demographic pressure, and structural limitations in agriculture. Despite several efforts made by the country towards increasing domestic cereal production through improved agronomic practices, technology adoption, and public investments, the food import trends (particularly cereals and vegetable oils) is moving upward disproportionately. This rising dependence on imports, especially during periods of drought or conflict, reflects vulnerabilities in Ethiopia's food system, which are further amplified by global market volatility and supply chain disruptions.

Ethiopian food sector vulnerability to climate variabilities: This is explained by the observed moderate-to-severe drought episodes in 2015 and 2016 which significantly impacted agricultural productivity and underlined the sensitivity of Ethiopia's food system to climate extremes. Cereal production exhibited an upward trend post-2016. However, imports continued to rise suggesting to a structural gap between food demand and supply which is hard to close by domestic efforts alone under the current pace of growth.

More importantly, the panel data analysis shows regional disparities in food security which emphasizes the need for spatially differentiated and targeted interventions. The positive relationship between increased food imports and improved national food security in certain periods indicates the temporary buffer role that food imports can play. Nevertheless, depending on food import and following this strategy could negatively affect long-term food sovereignty, rural livelihoods, and resilience.

In conclusion, Ethiopia's food security landscape is explained by a complex nexus of climate change, production capacity, trade dependency, and socio-political factors. Therefore, a strategy that combines strengthening domestic food systems through climate-smart agriculture with leveraging strategic imports to address short-term gaps would work better for sustainable and inclusive food security.

Recommendations

Based on the analytical results drawn from our report, the following major recommendations and policy directions are suggested to enhance Ethiopia's food security to reduce vulnerability to the adverse external shocks:

The need for adopting and investing in climate-smart agriculture (CSA): Generating or adapting proven CSA, such as drought-resistant crop varieties, diseases resistant crop varieties and animal breeds, conservation agriculture, rainwater harvesting for supplemental irrigation and scaling, would be an important policy direction. To increase the acceptance of such technologies, strengthen institutional support and capacitating farmers for response to adopt improved agricultural technologies is also an important action point. Promoting agroecological zones specific technologies and aligning crop choice with rainfall patterns and associated risk levels is also an important action point.

Strengthen Agricultural Research and Extension Services: To avail proven CSA technologies that afford the ongoing climate change, the need for intensifying digitalization of data collection from the research fields is becoming critical. In practice, generation of climate-resilient and high-yielding crop varieties and livestock technologies enable big data analytics and its translation into informed decisions require digitalization of agricultural research. Following the generation of such technologies, digitalization of technology services extension also enhances the role of agricultural extension in food system transformation and nutrition initiative in an end-to-end manner.

Enhance strategic food reserves and import management: To achieve this, developing and maintaining strategic grain reserves (buffer stock) to stabilize food availability and accessibility during climatic and market shocks, promoting regional and international trade agreements that ensure stable and affordable food imports, and monitoring global commodity markets and use of early warning systems to guide import decisions, among others.

Build resilient food supply chains: This could be achieved through a number of means including investing in rural digital infrastructure (e.g., storage, roads, market access, and connectivity) to reduce post-harvest losses and enhance market linkages, supporting agro-processing industries to increase value addition and reduce dependence on imported processed food items, and strengthening food logistics and supply networks for better regional food distribution. This requires establishing a value chain of partners.

Reducing regional food security disparities: Ethiopia is a country with wide agroecological zones with different agricultural potential. Therefore, prioritizing interventions in drought-prone, conflict-affected, and under-served regions, integrating food assistance programs with development initiatives to build long-term resilience, and customizing safety net and nutrition programs to address specific regional vulnerabilities would be important. In addition, addressing problems related to road infrastructure would help in transferring food from high to low potential areas would help to reduce regional food security differences, provided that people in low potential area are supported by income generating activities to purchase food.

Promote Integrated Food Security and Trade Policy: This could be achieved through aligning national food security objectives with trade and agricultural policies, facilitating inter-ministerial coordination to ensure coherent strategies for production, trade, and emergency response, and fostering partnerships with international organizations for technical and financial support, among others.

Leverage Data for Evidence-Based Planning: Pertinent real-time data is important to improve food security, especially during the drought and food crisis. To this end, institutionalizing the use of tools like the Jameel Index for ongoing food system monitoring and policy formulation; investing in climate and agricultural data infrastructure to enhance scenario planning and risk assessment; and promoting open-access data sharing to support research, planning, and private sector innovation would be an important recommendations to improve the national food security and contribute to the Ethiopian Food System Transformation and Nutrition (EFST&N) Initiative.

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2. Role of Trade on Food Security in Ethiopia: A Macro-Economic Analysis

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2.1. Introduction

The problem of food security continues to receive particular attention in both developing and developed countries (Sun & Zhang, 2021). Food security highly affects a country's social stability and ultimately its course of economic development (Zhou, 2010). Moreover, food insecurity and malnutrition have direct consequences on human health and development (FAO, 2022). This in turn contributes to low individual productivity and therefore a delay in economic development (Alderman & Garcia, 1994).

Food security is a situation that exists when all people at all times have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life (FAO, 2001; Pinstrup-Andersen, 2009). Based on this definition, the four dimensions of food security are defined as: food availability, economic and physical access to food, food utilization, and stability of access to food over time.

Food security in vulnerable countries can be achieved only through a balanced approach between domestic production and international trade (Beckford and Bailey, 2009; Beckford et al., 2013). However, the debate over the trade and food security relationship has been heated and complex due to two fundamentally divergent views. The two perspectives are "trade as a threat" and "trade as an opportunity" to food security.

Trade from the threat perspective considers international food trade as a threat to food security, particularly of countries that rely on import of food. This viewpoint has gained popularity after the 2008 food crisis when global food price increased and created significant barrier to food access. The supporters of this perspective advocate for domestic food production and decreased reliance on food import. In addition to providing a critique, it also maps out an alternative vision for food security built on a fundamentally different way of organizing the food and agriculture sector, one that focuses on smallholder farmers, bio-diverse farming systems, and a radical reduction in the reliance on international trade for meeting food security needs (Clapp, 2015).

In contrary, trade from the opportunity perspective stresses the importance of trade in boosting food security in two key argumentations. The first is the theory of comparative advantage outlined by David Ricardo in 1817. The theory supports the idea that countries should specialize in producing goods for which they have the lowest opportunity cost. This specialization leads to increased efficiency and higher global and national food availability and access. The theory has remained a dominant rationale for trade liberalization and is often cited by those who argue that trade liberalization enhances food security (World Bank, 2012; Lamy, 2013; Zorya et al., 2015). A second common argument for why international trade enhances food security is that it acts as a transmission belt due to its ability to transfer food from areas of abundance to areas of scarcity caused by natural resource differences, climate change and variability, and technology and productivity difference. This food availability and access balancing role of trade holds true at the local, regional, and international levels (Kerr, 2011; Lamy, 2012; OECD, 2013). By redistributing food, trade not only ensures availability but also contributes to price stabilization, which is critical for food security.

The advocates of trade liberalization have seen trade as a way to increase food security through the free movement of food across borders to enhance availability, access, nutrition, and stability; the counter narrative prioritizes locally produced foods to meet these needs. This alternative viewpoint has been critical of more recent interpretations of the concept of food security precisely because these definitions do not specify where food should come from, nor how that food should be produced, and this silence on these issues is assumed to mean that it advocates free trade and industrial food systems (Patel, 2009; Fairbairn, 2010; Jarosz, 2011; Lee, 2013).

Contribution of food import to Ethiopian food security is immense despite efforts at domestic production. This study was aimed to provide a macroeconomic analysis of how trade affects food availability, access, and stability in Ethiopia, evaluating the impact of trade liberalization on the country's selected food security outcomes. By examining these relationships, the study seeks to contribute to ongoing debates and provide insights for policy measures that could enhance food security in vulnerable contexts like Ethiopia. The general objective of the study is to investigate the role of trade in enhancing food availability, access, and stability in Ethiopia. The specific objectives are to evaluate the impact of trade on food availability, and analyze the relationship between key macroeconomic variables and food security in Ethiopia.

2.2. Methodology

2.2.1. Data sources and description

A secondary source of data is employed for the econometric regression. The main source of data for this study is Food and Agricultural Organization (FAO), Ethiopian Statistical Services (ESS), and National Bank of Ethiopia (NBE) from 2000 to 2022. In addition, we used data from the World Bank database. This study is limited to assessing two variables with suitable lag length due to the lack of long-term data.

Variables	**Measurement and definition**	**Category**
Per capita food supply [lnpcfoodsupply]	Per capita food supply measured in kilo calorie per capita per day is the average daily caloric intake available per person. It indicates the quantity of food that is accessible to individuals within a country or region. A higher per capita food supply implies better food security.	
Prevalence of undernourishment [lnundernourshiment]	The proportion (%) of a population whose caloric consumption falls short of the minimum daily energy requirements essential for maintaining a healthy lifestyle. A high rate of undernourishment indicates considerable food insecurity, whereas a lower rate signifies improved access to food resources.	Target variable (proxy variables for food security)
Food production index [Foodpdnindex]	The overall agricultural production of a nation, encompassing both crop yields and livestock, in relation to a designated base year. It monitors fluctuations in food production over time, offering valuable insights into a nation's ability to support its population through domestically sourced food expressed as a percentage.	
Food import as a percentage of merchandise import [lnfoodimport]	The proportion (%) of imported food items relative to the total value of all imported goods (merchandise) within a country. It reflects how much of a country's import spending is allocated to food products.	
Total export measured in value of trade in USD [lnexport]	The sale and shipment of goods or services from one country to another. Exports can affect the domestic availability of food and influence the balance of payments.	Explanatory variables

Thus, food security (y_t) measured in per capita food supply, undernourishment, and food production index, and independent variables export (x_1), and import (x_2) was used in modeling the equation (1) to examine the causal relationship among the variables in Ethiopia.

$$y_t = \beta_1 x_1 + \beta_2 x_2 + u_t \text{ ……… (1)}$$

2.2.2. Econometric model

This study employed the Auto Distributed Lag (ARDL) model to examine the relationship between food security and macroeconomic variables. The choice of the ARDL model is justified by several advantages, particularly its suitability in scenarios where data for many explanatory variables is limited (Nkoro & Uko, 2016; Osakede & Sanusi, 2018; Stoian & Iorgulescu, 2020). This model effectively identifies co-integrating relationships even in cases with small sample sizes (Ghatak and Siddiki, 2001; Tang, 2003). Furthermore, it is favored for its ability to derive a parsimonious equation from an over-parameterized model. The temporal responses of variables may vary, suggesting that different variables may have distinct optimal lags. The ARDL model accommodates such variations in optimal lags across different variables. Additionally, it does not impose a stringent requirement that all variables must be integrated of the same order. It can be utilized regardless of whether the regressors are integrated of order one, I(1), or order zero, I(0), or even if they are mutually co-integrated. However, it is essential that the integration order of the variables does not exceed one (Pesaran et al., 2001; Acaravci and Ozturk, 2012; Orhunbilge, 2014). In instances where the stationarity of the data remains ambiguous, the application of the ARDL bounds test is deemed suitable (Pesaran et al., 2001; Fuinhas and Marques, 2012; Hoque and Yusop, 2010).

The ARDL model employs an ordinary least squares (OLS) estimation approach, necessitating adherence to the fundamental assumptions of OLS to ensure the attainment of the best linear unbiased estimates. Consequently, we conducted assessments for the assumptions of normality, homoscedasticity, linearity, and serial correlation (Gujarati, 2004).

In our model, we identified three variables related to food security indicators as the dependent variable: per capita food supply, prevalence of undernourishment, and the food production index. As outlined by Pesaran *et al.* (2001), the specification of the ARDL model is presented as follows:

$$\emptyset(L,p)y_t = c_0 + \sum_{i=1}^{k} \beta_i(L,q_i)x_{it} + \delta w_t + u_t \text{ .... (2)}$$

where, y_t is the dependent variable, c_0 is the constant term, x_{it} are the independent variables, L is the lag operator, p is the number of lags for the dependent variable y_t and w_t is the *s* x 1 vector of deterministic variables including intercept terms, dummy variables, time trends and other exogenous variables with fixed lags.

Considering per capita food supply (lnpcfoodsupply), prevalence of undernourishment (lnundernourshiment), and food production index (Foodpdnindex) as target variables and food import (lnfoodimport) and export (lnexport) as explanatory variables, the general form of the model specification used in the study is stated as:

$$ln\text{pcfoodsupply}_t = \beta_0 + \beta_1 t + \beta_2 \text{lnexport}_t + \beta_2 \text{lnfoodimport}_t + \epsilon_t \text{ .... (3)}$$

$$ln\text{undernourshiment}_t = \emptyset_0 + \emptyset_1 t + \emptyset_2 \text{lnexport}_t + \emptyset_2 \text{lnfoodimport}_t + u_t \text{...... (4)}$$

$$\text{Foodpdnindex}_t = \rho_0 + \rho_1 t + \rho_2 \text{lnexport}_t + \rho_2 \text{lnfoodimport}_t + \nu_t \text{ .... (5)}$$

Where β_0, $\emptyset_0$ and ρ_0 are the intercepts, *t* the trends, *Ln* is the natural logarithm, ϵ_t, u_t and ν_t are the disturbance terms assuming white noise and normal distribution. The natural logarithm specification enables interpretation of findings as percentages or elasticities of the variables by their associated coefficients. Equations above equations can be converted into an unrestricted ARDL form as:

$$\Delta ln\text{pcfoodsupply}_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p-1} \beta_{2i}\, \Delta ln\text{pcfoodsupply}_{t-1} + \sum_{i=0}^{p-1} \beta_{3i}\, \Delta\text{lnexport}_{t-1} + \sum_{i=0}^{p-1} \beta_{4i}\, \Delta\text{lnfoodimport}_{t-1} + \beta_5 \text{lnexport}_t + \beta_6 \text{lnfoodimport}_t + \omega_t \text{ .... (6)}$$

$$\Delta ln\text{undernourshiment}_t = \emptyset_0 + \emptyset_1 t + \sum_{i=1}^{p-1} \emptyset_{2i}\, \Delta ln\text{undernourshiment}_{t-i} + \sum_{i=0}^{p-1} \emptyset_{3i}\, \Delta\text{lnexport}_{t-1} + \sum_{i=0}^{p-1} \emptyset_{4i}\, \Delta\text{lnfoodimport}_{t-1} + \emptyset_5 \text{lnexport}_t + \emptyset_6 \text{lnfoodimport}_t + \sigma_t \text{ ... (7)}$$

$$\Delta \text{Foodpdnindex}_t = \rho_0 + \rho_1 t + \sum_{i=1}^{p-1} \rho_{2i}\, \Delta \text{Foodpdnindex}_{t-1} + \sum_{i=1}^{p-1} \rho_{3i}\, \Delta \text{lnexport}_{t-1} + \sum_{i=1}^{p-1} \rho_{4i}\, \Delta \text{lnfoodimport}_{t-1} + \rho_5 \text{lnexport}_t + \rho_6 \text{lnfoodimport}_t + \Upsilon_t \ldots\ldots\ldots (8)$$

Where, Δ denotes the first difference operator and is the maximum lag length. The parameters $\beta_2 - \beta_4$, $\emptyset_2 - \emptyset_4$ and $\rho_2 - \rho_4$ explain the short run dynamic coefficients, while $\beta_5 - \beta_6$, $\emptyset_5 - \emptyset_6$ and $\rho_5 - \rho_6$ explain the long run multipliers of the equation when there is co-integration. With no co-integration, only the short run parameters of the variables are shown. The presence of a co-integrating relationship suggests that the connection between food security and the predictor variables remains consistent throughout the sample period. Consequently, the findings presented pertain to both the short-term and long-term dynamics.

Pre and post estimation tests

To establish the robustness and validity of the ARDL model, a comprehensive set of diagnostic tests was conducted. These initial assessments are crucial for verifying that the series incorporated in the model meet the fundamental assumptions necessary for dependable estimation, thereby facilitating both short- and long-term dynamic analyses of the variables.

Unit Root Test: Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests were used to assess the stationarity and unit-root characteristics of variables. The Dickey-Fuller (DF) test might seem reasonable to test the existence of a unit root in the series using the most general form of model (Dickey and Fuller, 1979; 1981). The Phillips-Perron test is similar to the ADF test, but it is a bit more advanced. It helps to check if the data points are changing in a predictable way. If the data points are changing in a predictable way, then the time series is stationary. If the data points are changing in an unpredictable way, then the time series is non-stationary (Phillips and Perron, 1988).

The Augmented Dickey-Fuller (ADF) test is a unit root test where lagged terms are added to the Y variable to remove possible autocorrelation. The number of lags is determined by the Akaike information criterion (AIC) or Bayesian information criterion (BIC). The test has the following form

$$\Delta Y_t = \alpha_0 + \beta_1 t + \emptyset Y_{t-j} + \sum_{j=1}^{m} \mu_j\, \Delta Y_{t-j} + \epsilon_t \ldots\ldots\ldots\ldots (9)$$

Where t=m+1 …. t, α is a constant and β is the coefficient of time trend. $\sum_{j=1}^{m} \mu_j \, \Delta Y_{t-j}$ is the sum of the differentiated lagged Ys together with their coefficient, m lags of ΔY_{t-j} are added to remove serial correlation in the residuals. The null hypothesis of the test is, ϕ = 0 and the alternative hypothesis ϕ < 1. When the null hypothesis is being rejected indicates Yt does not exhibit a unit root and therefore is stationary otherwise not stationary. The hypothesis is tested on the basic principle of t-statistic of the coefficient ϕ. This is obtained by comparing the ADF test statistic with a critical value at a given significance level.

Optimum Lag Selection: The determination of the number of lags (orders) to be used in the Vector Autoregression (VAR) model can be determined based on the criteria of Akaike Information Criteria (AIC), Schwarz Information Criteria (SC), or Hannan Quinn (HQ). The lag to be chosen in this research model is the model with the smallest HQ value. In this stage, we also tested the stability of the VAR model.

Granger Causality Test: Granger causality tests are widely used to investigate causal relationships between variables. The Granger causality test is a statistical hypothesis test for determining whether one variable affects another. Granger (1969) approached the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. A general specification of the Granger causality test in a bivariate (x, y) context can be expressed as:

$$y_t = \sum_{i=1}^{a} \alpha_i x_{t-i} + \sum_{i=1}^{b} \beta_j y_{t-j} + \varepsilon_{1t} \quad \ldots\ldots\ldots\ldots (10)$$

$$x_t = \sum_{i=1}^{a} \delta_i x_{t-i} + \sum_{i=1}^{b} \varphi_j y_{t-j} + \varepsilon_{2t} \quad \ldots\ldots\ldots\ldots. (11)$$

where a is the maximum number of lagged observations included in the model. The significance of the coefficients $\alpha, \beta, \delta \; and \; \varphi$ determine the direction of causality and the coefficients are jointly tested for their significance. Two different causality tests can be obtained from the analysis in equation 3 and 4 above; the first scenario examines the null hypothesis that the x does not Granger-cause y while the second scenario examines the null hypothesis that the y does not Granger-cause x. If there is acceptance of the former null hypothesis and reject the latter, then there will be conclusion of x changes are Granger-caused by a change in y. Unidirectional causality occurs between two variables when either null hypothesis of equation 3 or 4 is rejected. Bidirectional causality occurs when there is rejection of both null hypotheses and no causality exists if neither null hypothesis of equation 3 nor 4 is rejected.

Co-integration Test: The concept of co-integration is basically to see the long-term balance among the observed variables. Thus, after the evaluation of the univariate properties of the time series, the next step is to determine the level of co-integration between variables. Two or more integrated one variable are said to be co-integrated if there exists a linear combination of them that is stationary (Engle and Granger, 1987). This study used the Johanson co-integration technique. Unlike the Engle-Granger methodology, the Johanson methodology allows for testing the presence of more than one co-integration vector. In addition to this, it allows one to estimate the model without restricting the variables to endogenous and exogenous a priori (Johansen and Juselius, 1992).

Post Estimation Tests: Major post estimations tests such as normal distribution of disturbances (Jarque-Bera test), residual autocorrelation (Lagrange- multiplier test) and stability condition (eigenvalue stability condition) were undertaken.

2.3. Result and Discussion on Food Security and Trade

Among the four food security dimensions, we included three: undernourishment measured by the proportion of population under nourishment, food production index, and per capital food supply measured in kilo calorie per capita. These variables entered in the ARDL model as target (dependent) variables. In addition, two international trade variables, namely total export measured in value of trade in USD and food import as a percentage of merchandise import, were included as explanatory variables.

To evaluate whether the data are stationary or not, we used both Augmented Dickey-Fuller (ADF) and Phillip-Perron tests. **Table 1** presents the test result. The result indicated that one of the variables (food import) is stationary at level (has no trend that misleads the model results and no need of differencing) while most of the variables are non-stationary at level but become stationary at the first difference using both methods. When the variables become stationary at different order, the appropriate model is the Autoregressive Distributed Lag (ARDL). Therefore, we used the ARDL model for the analysis.

Table 1. Unit root test result

Tests	**Level**		**1st difference**		
	Intercept	Intercept and trend	Intercept	Intercept and trend	Outcome
Augmented Dickey-Fuller					
lnundernourshiment	-1.939	0.427	-1.224	-1.521	I(2)
Foodpdnindex	-2.434	-0.677	-4.86***	-6.840***	I(1)
lnpcfoodsupply	-1.655	-2.242	-4.780***	-4.586***	I(1)
lnexport	0.589	-1.579	-2.234	-2.199	I(2)
lnfoodimport	-2.90**	-3.163*	-7.50***	-7.566***	I(0)/I(1)
Phillip-Perron					
lnundernourshiment	-1.658	-0.273	-1.655	-1.997	I(2)
Foodpdnindex	-3.61***	0.129	-4.868***	-7.984***	I(0)/I(1)
lnpcfoodsupply	-1.784	-2.312	-4.907***	-4.674***	I(1)
lnexport	0.348	-1.979	-2.207	-2.193	I(2)
lnfoodimport	-3.028**	-3.301*	-7.596***	-8.003***	I(0)/I(1)

Once the appropriate model is selected, the next stage is to search for the optimum lag length. **Table 2** presents the lag length selection criteria and the optimum lag length. The result shows that the optimum lag length for all the three models (the three target variables) is four (as indicated in asterisk in the fourth lag length based on LR, AIC, HQIC). Therefore, the optimum lag length in this model is four.

Table 2. Lag length selection

Target variable	**Lag**	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
lnundernourshiment	0	-20.37				0.00235	2.45994	2.48518	2.60906
	1	43.96	128.7	9	0	7.1E-06	-3.36374	-3.26279	-2.76726
	2	73.36	58.80	9	0	9.0e-07*	-5.51128	-5.33462	-4.46743*
	3	81.36	16.00	9	0.067	1.3E-06	-5.40617	-5.1538	-3.91495
	4	98.72	34.73*	9	0	9.3E-07	-6.2868*	-5.9587*	-4.34822
Lnpcfoodsupply	0	-36.50				0.0128	4.15803	4.18327	4.30715
	1	17.24	107.48	9	0	0.0001	-0.55136	-0.45041	0.045132
	2	24.08	13.677	9	0.134	0.0002	-0.32381	-0.14715	0.720042
	3	28.700	9.25	9	0.415	0.0003	0.136833	0.389206	1.62805
	4	70.18	82.97*	9	0	0.0002*	-3.2824*	-2.9543*	-1.34379*
lnfoodpdnindex	0	1.99				0.0002	0.105903	0.13114	0.255025
	1	60.12	116.3	9	0	1.3E-06	-5.06525	-4.9643	-4.46876

2	69.12	17.99	9	0.035	1.4E-06	-5.06489	-4.88823	-4.02104
3	76.11	13.99	9	0.123	2.2E-06	-4.85358	-4.60121	-3.36236
4	101.85	51.49*	9	0	6.7e-07*	-6.616*	-6.2879*	-4.67739*

Following the optimum lag length selection, the next step is to evaluate if there is a long run cointegration among two or more variables. If the variables considered in the analysis are integrated of the same order, the Johansen test of co-integration can be used to test for the cointegration. However, when the variables are not at the same order of cointegration, the Pesaran/Shin/Smith (2001) ARDL Bounds Test of cointegration is an appropriate. In this study, we used the ARDL Bounds Test of cointegration because the variables at hand are stationary at different orders. **Table 3** presents the result of the ARDL bound test. The result reveals that there are cointegration between the variables when undernourishment and per capita food supply are considered as target variables. However, when food production index is considered as a target variable, there is no long term cointegration among the variables. As a result, the model results of the models are presented and discussed here while a model with no long term cointegration (food production index) is annexed for the reference purpose.

Table 3. Pesaran/Shin/Smith (2001) ARDL Bounds Test

Target variable	F-statistic/t-statistic	Cointegration	Decision
Lnundernourshiment	F=36.787 t-=-7.384	Yes	Estimate both short and long term
Lnpcfoodsupply	F = 19.453 t = -4.114	Yes	Estimate both short and long term
Lnfoodpdnindex	F = 3.910 t = -1.196	No	Estimate short term

The result in **Table 4** reveals that total export is negatively associated with undernourishment at 1% level of significance in the long run. As total export increases by one million USD, the percentage of population undernourishment decreases 0.3, ceteris paribus. On the other hand, food import as a percentage of merchandise import is positively associated with the prevalence of undernourishment at 1% in the long run. As the percentage of food import to merchandise import increases by one unit, the percentage of population undernourishment increases by 0.45, keeping other variables constant. In the short term, past year level of prevalence of undernourishment is positively associated with the current level of prevalence of undernourishment. This means, undernourishment problem cannot be solved overnight but needs adequate time. Results further reveal that total export is positively associated with undernourishment in the short run at 1% whereas food import negatively associated with it in the short run at 5%. Similar results have been reported in previous studies in Azerbaijan by Huseynov (2019) also found a negative impact of food import on domestic food supply in the long term and positive impact in the short term in Azerbaijan. The empirical result call for Ethiopia to follow more inward looking policies to reduce the prevalence of undernourishment in the long term rather than solving the problem through food import although it could be a solution in the short term. In contrast, improving export status would solve a long-term problem of prevalence of undernourishment but would have an adverse effect on the prevalence of undernourishment in the short-term.

The value of Error Correction model (ECM) term is negative and significant falling between 0 to -1 which confirms the short-term existence of long term established cointegration. In this study, the value of ECM is 0.356 and significant at 1% implying that the convergence from the equilibrium level of prevalence of undernourishment of the current year will be adjusted by 35.6% in coming years. It can also be interpreted as the convergence from the equilibrium level of prevalence of undernourishment of the previous period is corrected in the current period by an adjustment speed of 35.6% meaning within a three years' period of time.

Table 4. ARDL (2, 1, 4) model result on the role of total export and food import on undernourishment

Equations	Coefficient	Std.err.	T	P>t
Long run equation				
Lnexport	-0.312	0.016	-19.14	0.000
Lnfoodimport	0.452	0.128	3.54	0.006
Short run equation				
D(lnundernourshiment (-1))	1.183	0.067	17.58	0.000
D(lnexport)	0.197	0.050	3.93	0.003
D(lnfoodimport)	-0.126	0.049	-2.59	0.029
D(lnfoodimport (-1))	-0.091	0.041	-2.22	0.054
D(lnfoodimport(-2)	-0.074	0.035	-2.1	0.065
D(lnfoodimport(-3)	-0.072	0.022	-3.29	0.009
Constant	1.930	0.214	9.02	0.000
ADJ or ECM (-1)	-0.356	0.048	-7.38	0.000
R-squared = 0.9835				
Adj R-squared = 0.9669				

Log likelihood = 58.151334
Root MSE = 0.0165

As seen in the **Table 5** below, the proportion of food import to merchandise import has a significant and positive impact on per capita food supply measured in kilo calorie per person per day in the long term, keeping other things constant. As proportion of food import increases by one percent, per capita food supply increases by about 2.6%.

In the short term, per capita food supply is positively associated with total export and the second lag of the export but the result is insignificant in the long run. In contrast, the per capita food supply is negatively associated with its second lag, first and third lags of export, food import and lags (1-3) of the food import all at 1% level of significance. Therefore, policies promote food import cannot be a short-term solution to improve food supply in Ethiopia while it can be adopted as a long-term solution.

The value of Error Correction model (ECM) term in the food supply model is negative and significant. In this model, the value of ECM is -1.239 and significant at 5% implying that the convergence from the equilibrium level of per capita food supply of the current year will be adjusted by 123.9% in coming years which means it takes less than a year to converge to the equilibrium position.

Table 5. ARDL (4, 4, 4) model result on the role of total export and food import on per capita food supply

Lnpcfoodsupply	Coefficient	Std. err.	T	P>t
Long Run equation				
Lnexport	0.100	0.050	2.02	0.113
Lnfoodimport	2.575	0.484	5.32	0.006
Short Run equation				
D(lnpercapitafoodsupply(-1)	0.193	0.255	0.76	0.491
D(lnpercapitafoodsupply(-2)	-0.767	0.179	-4.30	0.013
D(lnpercapitafoodsupply(-3)	0.146	0.176	0.83	0.453
D (lnexport)	3.274	0.759	4.31	0.013
D (lnexport(-1)	-2.946	0.582	-5.06	0.007
D (lnexport(-2)	1.859	0.543	3.42	0.027
D (lnexport(-3)	-2.944	0.480	-6.13	0.004
D(lnfoodimport)	-2.759	0.388	-7.11	0.002
D(lnfoodimport(-1)	-2.622	0.341	-7.69	0.002

D(lnfoodimport (-2)	-2.701	0.415	-6.51	0.003
D(lnfoodimport(-3)	-1.693	0.293	-5.78	0.004
Constant	-5.419	0.998	-5.43	0.006
ADJ or ECM (-1)	-1.239	0.301	-4.11	0.015
R-squared = 0.9665				
Adj R-squared = 0.8494				
Log likelihood = 26.430189				
Root MSE = 0.1312				

2.4. Conclusion and Recommendation

International trade (total export and food import) had a significant impact on some components of food security, such as undernourishment and food supply. Food import would have an adverse impact on undernourishment in the long run, but improves undernourishment in the short run. However, the result is opposite in the case of total export. Therefore, it can be recommended that inward looking instead of depending on food import would be a sustainable policy direction for Ethiopia while encouraging the export component is important in the long run. Regarding the food supply component of the food security, food import would be a long-term policy direction.

It is important to design specific policies and strategies to different food security dimensions as a single policy could not work to bring a positive impact on all components of food security in Ethiopia. This calls for prioritizing the issues and design and implement multiple policies and strategies to improve food security through international trade.

The main limitation of this work is that it lacks to incorporate other variables relevant to food security, such as availability of agricultural inputs, climate-related factors, and others. This is mainly due to short time span of the available data which leads to few observations which is insufficient to model other time series econometric models and difficulties of modeling the ARDL model when more variables are included. Therefore, one of the future research directions would be to gather enough observation or use alternative models such as CGE and related economy wide model.

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3. Ethiopian Food Trade and Vulnerability Analysis: Application of Full Jameel Index

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3.1. Background and justification

Food security in vulnerable countries can be achieved only through a balanced approach between domestic production and international trade (Beckford & Bailey, 2009; Beckford et al., 2013). Despite ongoing domestic production efforts, Ethiopia continues to depend significantly on food imports to meet national food needs. Trade plays a vital role in ensuring food availability, accessibility, and price stability in the country. As such, a macroeconomic analysis of the relationship between trade liberalization and food security is essential. This study aims to evaluate how international trade influences key food security outcomes in Ethiopia and to contribute empirical insights to ongoing policy debates.

Specifically, the research will investigate how trade affects the three pillars of food security—availability, access, and stability—and analyze the role of macroeconomic factors in shaping food security dynamics. In the context of rising population pressures and economic challenges, understanding this trade–food security nexus is increasingly vital for policy interventions in Ethiopia.

Climate change poses a growing threat to global food and nutritional security by disrupting the four pillars of food security: availability, access, utilization, and stability. Temperature and precipitation variability are key climate drivers affecting food production and distribution (FAO, 2018). The Intergovernmental Panel on Climate Change (IPCC) identifies four major food-related risks: loss of rural livelihoods and income; degradation of marine and coastal ecosystems and livelihoods; degradation of terrestrial and freshwater ecosystems and livelihoods; and the collapse of food systems (Gitz et al., 2015).

Developing countries, including Ethiopia, are especially vulnerable to climate change. The compounding effects of poverty, rapid urbanization, and limited adaptive capacity increase the risk of food insecurity. Moreover, climate change impacts extend beyond local production, influencing trade flows, food market stability, and health risks.

Recent studies show that climate heterogeneity between trading partners affects bilateral trade. For example, such heterogeneity benefits developed exporters but may disadvantage developing exporters. Differences in rainfall, however, are particularly beneficial for developing exporters (Bozzola et al., 2023; Dallmann, 2019). These findings suggest that climate factors shape trade dynamics and, in the long run, food security outcomes.

Trade plays a stabilizing role in food systems under climate stress by shifting food from regions of surplus to regions facing scarcity. It improves not only food availability but also market efficiency and resilience. Furthermore, diversified international trade contributes to more stable food prices and nutrition patterns by compensating for domestic production variability (Brooks & Matthews, 2015; Wacziarg & Welch, 2008). These dynamics underscore the critical link between trade, climate resilience, and food security.

In light of the challenges posed by trade dependence, climate vulnerability, and food system fragility, there is a pressing need for robust tools to assess national food security in an integrated way. The Full Jameel Index offers a comprehensive framework to evaluate a country's exposure and resilience to food trade risks. In the Jameel Index, individual indicators are compiled into a single index (Greco et al., 2019) to a recursive framework where meta-indicators are assimilated into a single index. By analyzing key indicators such as import dependency, supply chain robustness, exporter reliability, and macroeconomic trade variables, the index enables systematic vulnerability assessments.

In the Ethiopia context, applying the Full Jameel Index provides critical insights into how international trade affects food security in a climate-vulnerable context. It informs strategies to strengthen resilience, reduce import dependency risks, and guide trade policy in ways that support long-term food stability and availability.

Moreover, this study aligns with broader efforts such as the MIT J-WAFS Food and Climate Systems Transformation (FACT) Alliance, which aims to catalyze collaborative, transdisciplinary research for sustainable food systems. By focusing on Ethiopia as a case study, this research contributes foundational knowledge to the FACT Alliance's mission of addressing climate-driven food security threats and shaping adaptive trade and food policies in developing countries.

3.2. Methodology

3.2.1. Data and data generation

The primary data sources for the indicators are FAOSTAT and the National Bank of Ethiopia. The indicators for each of the eight commodities included in the Jameel Index, namely wheat, maize, soybean, rice, meat, dairy, oil, and sugar, are calculated using raw data. A time series from 2011 to 2022 is used to illustrate the trends and dynamics of the country's vulnerability status and index.

3.2.2. Performance metrics analysis

We used a composite index approach to evaluate national vulnerability to food import disruptions across eight essential commodities: wheat, maize, rice, soy, dairy, meat, sugar, and oils for Ethiopia. The Jameel Index integrates both biophysical and socioeconomic dimensions by aggregating five selected meta-indicators that reflect different aspects of vulnerability in food trade systems, namely food import dependency ratio, feed import dependency ratio, food import to foreign exchange ratio, export reliability, and supply chain robustness. The detail of the analysis method for each indicator is elaborated below.

Food import dependency

The food import dependency meta-indicator is the ratio of the nation's commodity demand that is imported to the total commodity demand. It is a measure of how dependent a nation's food supply across all commodities is on imports.

$$FIDR = \frac{Food\ imports}{Food\ imports + Domestic\ food\ production} x100 \ \ldots\ldots\ldots (1)$$

Where FIDR is the food import dependency ratio, food imports are the quantity of food imported, domestic production is the quantity of food produced domestically. The higher FIDR indicates greater dependence on food imports, and the lower FIDR indicates greater self-sufficiency. The food commodities are weighted or converted into kilocalories to measure and compare their contribution to food security. The raw food import dependency score (RIDS) is calculated by summing the weighted food supply import dependency indicator over all commodities. Using rules developed to map RIDS to vulnerability[2], the scores were categorized from very low to extreme.

Feed import dependency ratio

The feed supply dependency ratio reflects the concept of food supply dependency. The feed import dependency indicator measures how reliant a country's livestock feed supply is on imported grain commodities. It quantifies the proportion of feed demand met by imports for these key crops. The feed import dependency ratio is calculated using two key indicators. The first is import dependency ratio, which is the share of a grain commodity's total demand met by imports, and the second is feed ratio, which is the proportion of a grain commodity's total demand used for feed. By combining these two metrics, the ratio quantifies a country's reliance on imported grains for livestock feed.

$$IDR_{gc} = \frac{IM_{gc}}{TD_{gc}} \ldots\ldots\ldots\ldots (2)$$

Where IDR_{gc} is the import dependency ratio of grain commodity, IM_{gc} is imports of grain commodity, TD_{gc} is total demand for grain commodity.

$$FR_{gc} = \frac{FU_{gc}}{TD_{gc}} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where FR_{gc} is the feed ratio of grain commodity that represents the fraction of total demand used for feed, FU_{gc} is the feed use of grain commodity. The feed import dependency ratio of a specific grain commodity ($FIDR_{gc}$) is given by

$$FIDR_{gc} = IDR_{gc} \; X \; FR_{gc} \ldots\ldots\ldots\ldots (4)$$

For this sub-indicator, each commodity is weighted by the percentage of feed calories supplied by each grain commodity of total feed calories. The raw continuous value meta-indicator is calculated

[2] The mapping from RIDS (Food Import Dependency) to vulnerability levels follows threshold-based classification developed under the Jameel Index methodology (Strzepek et al., 2025). The raw scores are mapped as follows: VERY LOW: < 0.15, LOW: 0.15 - < 0.3, MEDIUM: 0.3 - < 0.75, HIGH: 0.75 - < 0.875, and EXTREME: ≥ 0.875. These thresholds were established through expert consultation and empirical calibration using historical food security and trade data.

by summing the weighted feed supply import dependency indicator over all grain commodities. To evaluate the vulnerability level[3], the scores were categorized from very low to extreme.

Food import foreign exchange ratio

The food import foreign exchange ratio is an original indicator developed for the Jameel Index. The meta-indicator is the ratio of the value of all food imports to the total value of all exports, including agricultural, minerals, industrial products, etc. The lower the ratio, the less vulnerable a nation will be to economic shocks and the internal competition for foreign to pay for food imports.

$$FIXR_c = \frac{FIM_c}{EX} \ldots\ldots\ldots. (5)$$

Where $FIXR_c$ is the food import to foreign exchange ratio, FIM_c is the value of food imports for commodity c; and EX is the total value of national exports. Since the indicator is a monetary value, there is no weighting by commodity. The raw continuous value meta-indicator is calculated by summing the food import foreign exchange indicator over all commodities. Using rules[4] developed to map RIDS to vulnerability, the scores were categorized from very low to extreme.

Supply chain reliability

Food Supply Chain Reliability is an original indicator developed for the Jameel Index using data from the Oxford Programme for Sustainable Infrastructure Systems. The Food Supply Chain Reliability meta-indicator is designed to measure the reliability in commodity production due to climate variability in the exporting nations that make up 80 percent of a nation's imports of commodity C. High variability is likely to make export supplies vulnerable in low production years thus reducing the reliability of supply from the exporting nation. The Food Supply Chain Reliability Indicator for each commodity C is calculated as a weighted sum of the Coefficients of Variation, where the weights are the share of imports from each exporter:

$$COV_C = \sum_{x \in X} P_{CX}.COV_{CX} \ldots\ldots\ldots\ldots. (6)$$

Where COV_C is the overall reliability indicator for commodity C; The proportion of imports of commodity C that comes from exporter X, X is the set of exporting countries that together account

[3] The mapping from RIDS (Feed Import Dependency) to vulnerability levels follows threshold-based classification developed under the Jameel Index methodology (Strzepek et al., 2025). The raw scores are mapped as follows: VERY LOW: < 0.15, LOW: 0.15 - < 0.3, MEDIUM: 0.3 - < 0.75, HIGH: 0.75 - < 0.875, and EXTREME: ≥ 0.875. These thresholds were established through expert consultation and empirical calibration using historical food security and trade data.

[4] For Food Import Foreign Exchange Ratio, the raw continuous value meta-indicator (RFXR) is mapped to vulnerability categories as follows: VERY LOW: < 0.01, LOW: 0.01 - < 0.035, MEDIUM: 0.035 - < 0.25, HIGH: 0.25 - < 0.575, and EXTREME: ≥ 0.575. These thresholds are defined in "The Jameel Index for Food Trade and Vulnerability: Methodological Framework."

for 80% of the nation's importing of commodity C, and COV_{CX} is production variability (coefficient of variation) for exporter X and commodity C. A higher COV_C value indicates greater variability or lower reliability in the supply of the commodity due to climate-induced risks in key exporting countries. Lower COV_C implies more stable and reliable import sources for that commodity.

For this sub-index, we weight each commodity by two multiplicative weights of percent of total calories (PC) in the diet and food consumption score (FCS), which was developed by the World Food Program (WFP, 2008). The FCS provides a gauge of the relative nutritional value of the consumed food groups. The calculation for weighted representation by the W food supply import dependency indicator is then given by:

$$WCOV_C = COV_C * PC_C * FCS_C \text{ .... (7)}$$

The raw continuous value meta-indicator is calculated by summing the weighted food supply chain reliability indicator over all commodities.

$$RCOV = \sum_C WCOVP_C \text{ .... (8)}$$

Using rules[5] developed to map raw food supply chain reliability scores (RFSCR) to vulnerability, the scores were categorized from very low to extreme.

Food supply chain robustness

Food supply chain robustness is an original indicator developed for the Jameel Index. The supply chain robustness meta-indicator is the number of exporting nations that make up 80 percent of a nation's imports by commodity C. The higher the number, the less vulnerable a nation will be to shocks in the supply chain, from drought, shipping bottlenecks, geopolitics, or other conflicts.

We weight each commodity by two multiplicative weights of percent of total calories (PC) in the diet and food consumption score (FCS), which was developed by the World Food Program (WFP, 2008).

$$WNP_C = NP_C \; X \; PC_C \; X \; FCS_C \text{ .... (9)}$$

Where WNP_C is the weighted food supply chain robustness indicator for a commodity C, NP_C raw indicator for a commodity C, PC_C is the proportion of total calorie intake from commodity C, and FCS_C is the food consumption score for a commodity C. The final meta-indicator is computed by summing the weighted indicators across all commodities.

[5] The Raw Food Supply Chain Reliability (RFSCR) score is translated into vulnerability categories using upper-bound thresholds: Very Low (<0.025), Low (<0.05), Medium (<0.075), High (<0.15), and Extreme (<0.50). These categories are derived from expert-defined thresholds calibrated through the Jameel Index for Food Trade and Vulnerability to reflect increasing systemic food supply risk.

$$RFSCR = \sum_{c \in C} WNP_C = \sum_{c \in C} (NP_C \ X \ PC_C \ X \ FCS_C \ \ldots\ldots\ldots\ldots\ldots (10)$$

Where RSCR is a raw meta-indicator of food supply chain robustness, and C is set of all food commodities considered. Using rules[6] developed to map RSCR to vulnerability, the scores were classified from very low to extreme.

The Jameel Index for Food Trade and Vulnerability

With the five meta-indicators defined and evaluated for the country, the composite index that comprises the Jameel Index for Food Trade and Vulnerability was developed. A linear multi-criterion weighting model was used to combine the five meta-indicators into the . There are five meta-indicators developed: food import dependency, feed import dependency, foreign exchange, supply chain reliability, and supply chain robustness. To perform the multi-criterion aggregation to a single index, each of the normalized vulnerabilities was mapped to an intermediate value and is stored in the single variable - vulnerability of meta-indicator M (VUL_M) classified from very low (1) to extreme (5) (Strzepek et al., 2025). The raw composite index (RAWJx) was calculated using the formula:

$$RAWJ_X = (\Pi_M WM_M * VUL_M)^{1/M} \ \ldots\ldots\ldots\ldots\ldots (12)$$

Where WM_M is the user-assigned weight for each meta-indicator, and VUL_M is its corresponding ordinal vulnerability score. We used a normalization step to scale the raw index values to a 0 -100 range for ease of interpretation. The normalized Jameel Index (JX) is calculated as:

$$JX = \frac{RawJX - 1}{RangeJX} * 100 \ \ldots\ldots\ldots\ldots (13)$$

In the case of equal weighting, MinJX=1.0, MaxJX=5.0, and RangeJX=4.0. This approach ensures comparability across nations and facilitates communication of the results as a percentage of the maximum possible vulnerability. Finally, Jameel Index was classified based on <15.8 very low, 15.8-25.1 low, 25.1-39.8 medium, 39.8-63.1 high, and ≥63.1 extreme.

[6] The Raw Supply Chain Robustness Score (RSCR) is mapped to vulnerability classifications using predefined thresholds: Very Low (<7.5), Low (<5.0), Medium (<3.0), High (<1.5), and Extreme (=0). This rules-based mapping reflects diminishing supply chain resilience as the robustness score declines, and was established in accordance with the Jameel Index for Food Trade and Vulnerability framework.

3.3. Major findings

Results of meta-indicators for Ethiopia

Under this subtitle, we present the results of our analysis on Ethiopia's meta-indicator estimation. All five meta-indicators were carefully evaluated, with a focus on eight major commodities (dairy, oil, meat, sugar, wheat, rice, maize, and soybean) over the period from 2011 to 2022. This time frame was chosen to capture the trends and dynamics influencing the country's food production and trade performance across key sectors.

Food import dependency

The study results showed notable fluctuations in food import dependency across various commodities from 2011 to 2022. Oil, rice, and soybeans consistently exhibited high dependency, with oil peaking at 1.0998 in 2021 and rice surpassing 1.5 in 2020. Soybean showed full dependency (1.0000) from 2014 to 2018, then dropped sharply to zero by 2022 (**Table 1**).

Sugar and wheat showed moderate but rising dependency over time, with sugar increasing significantly to 0.9553 in 2022. Dairy and maize remained low throughout, though dairy saw a gradual increase. Meat dependency was negligible across all years, indicating domestic self-sufficiency in this category. Generally, the data points to a growing reliance on imports for key staples, especially rice, oil, and sugar, raising potential concerns for food security and resilience.

Table 1: Trends of food import dependency ratio by commodity

Year	Dairy	Mize	Meat	Oil	Rice	Soybean	Sugar	Wheat
2011	0.0051	0.0046	0.0000	0.7158	0.4678	1.7500	0.1806	0.3745
2012	0.0041	0.0013	0.0000	0.7011	0.5278	0.6667	0.1991	0.2175
2013	0.0044	0.0011	0.0000	0.7446	0.4891	0.6667	0.1083	0.1845
2014	0.0059	0.0008	0.0012	0.7794	0.6802	1.0000	0.1635	0.1997
2015	0.0071	0.0008	0.0000	0.8626	0.7543	1.0000	0.2084	0.2284
2016	0.0082	0.0009	0.0000	0.8162	0.9409	1.0000	0.2083	0.4233
2017	0.0108	0.0037	0.0000	0.8029	0.7946	1.0000	0.1937	0.2036

2018	0.0094	0.0016	0.0000	0.8342	0.8486	1.0000	0.3102	0.2173
2019	0.0149	0.0082	0.0021	0.6728	0.8240	0.6000	0.1868	0.2212
2020	0.0200	0.0080	0.0000	0.9084	1.5041	0.7500	0.4937	0.1809
2021	0.0247	0.0007	0.0010	1.0998	1.4744	0.2000	0.7790	0.2859
2022	0.0146	0.0011	0.0000	0.9162	1.0164	0.0000	0.9553	0.2019

The study results showed that wheat consistently contributed the most to the overall food import dependency score from 2011 to 2022, despite some fluctuations. Oil and rice followed as significant contributors, with rice peaking sharply in 2020 and 2021. Sugar's contribution gradually increased, becoming more prominent in later years. Dairy, maize, and soybean had minor impacts throughout the period, while meat showed no import dependency at all. The total dependency score peaked in 2021 (0.434), aligning with heightened vulnerability during the COVID-19 period, and then slightly declined in 2022 (**Table 2**).Overall, the trend reflects a reliance on key staples, particularly wheat, oil, and rice, indicating potential pressure points in the national food supply chain.

Table 2: Trends of food import dependency score by commodity

Year	Dairy	Maize	Meat	Oil	Rice	Soybean	Sugar	Wheat	Total
2011	0.001	0.004	0.000	0.020	0.012	0.005	0.005	0.260	0.307
2012	0.001	0.001	0.000	0.021	0.014	0.001	0.005	0.149	0.194
2013	0.001	0.001	0.000	0.024	0.015	0.002	0.003	0.126	0.171
2014	0.002	0.001	0.000	0.027	0.030	0.002	0.005	0.143	0.210
2015	0.002	0.001	0.000	0.047	0.044	0.006	0.006	0.152	0.257
2016	0.002	0.001	0.000	0.032	0.045	0.004	0.007	0.290	0.381
2017	0.002	0.003	0.000	0.033	0.054	0.002	0.006	0.118	0.219
2018	0.002	0.001	0.000	0.038	0.086	0.002	0.011	0.124	0.265
2019	0.004	0.007	0.000	0.020	0.072	0.002	0.005	0.146	0.255
2020	0.006	0.006	0.000	0.046	0.167	0.006	0.015	0.098	0.346
2021	0.005	0.000	0.000	0.073	0.168	0.001	0.025	0.161	0.434
2022	0.003	0.001	0.000	0.064	0.096	0.000	0.029	0.116	0.309

The study result showed that between 2011 and 2022, the food import vulnerability score fluctuated, indicating shifts in the country's reliance on external food sources and its exposure to associated risks. Over this year, the dependency score mostly remained in the low vulnerability range, with intermittent increases into the medium range. In the early years (2011–2015), the vulnerability level dropped from medium in 2011 (0.3068) to low in subsequent years, reaching a minimum in 2013 (0.1713). This suggests an improvement in food import resilience during that time.

However, starting in 2016, the score saw periodic spikes into the medium range: 2016 (0.3806), 2020 (0.3455), 2021 (0.4344), and 2022 (0.3090). These peaks suggest growing sensitivity to global food supply chain disruptions, possibly due to factors like economic shocks, trade restrictions, or geopolitical tensions during those years, especially 2020–2021, which aligns with the COVID-19 pandemic and internal conflicts (**Table 3**).

Despite these medium-risk periods, most years maintained a low vulnerability level, indicating relatively stable food import conditions. Nonetheless, the increasing scores toward the end of the period may reflect a trend toward rising risk, warranting attention to food security strategies.

Table 3: Trend and summary of food import dependency score and vulnerability level

Year	Dependency score	Vulnerability level
2011	0.3068	Medium
2012	0.1935	Low
2013	0.1713	Low
2014	0.2095	Low
2015	0.2566	Low
2016	0.3806	Medium
2017	0.2188	Low
2018	0.2650	Low
2019	0.2554	Low
2020	0.3455	Medium
2021	0.4344	Medium
2022	0.3090	Medium

Note: Vulnerability level: <0.15 very low; 0.16-0.30 low; 0.31-0.75 medium; 0.76-0.875 high; >0.875 extreme

Animal feed import dependency

We also estimated the import dependency ratio for various animal feed components from 2011 to 2022. Overall, most categories exhibit low dependency, typically near or below 0.01, indicating minimal reliance on imports. Notable exceptions include oil, which consistently has the highest relative dependency, peaking at 0.1199 in 2021, showing a strong reliance on imported oil byproducts for animal feed. Soybean also shows intermittent spikes, especially in 2016 (0.019) and 2017 (0.0058), suggesting occasional surges in import reliance. This could be due to high demand for soybean and oilseed cake by feed processing industries due to the establishment of huge feed processing industries and security problems in the Amhara region, where more than 95% of soybeans are produced and distributed to oil and feed processing companies. Sugar and rice show fluctuating import dependency, with rice sharply rising in 2019 and sugar peaking in 2014 and 2022. However, dairy remains negligible until 2021, when it surges to 0.0504, indicating a one-time spike in dependency. Maize, meat, and wheat show consistently low ratios with minor fluctuations, reflecting relatively stable and low import reliance for these feed types (**Table 4**).

Table 4: Trend of animal feed import dependency ratio

Year	Dairy	Wheat	Sugar	Rice	Oil	Maize	Meat	Soybean
2011	0.000011	0.004007	0.008446	0.001406	0.058386	0.000180	0.000005	0.000461
2012	0.000009	0.002589	0.016887	0.002482	0.010022	0.000047	0.000883	0.000058
2013	0.000127	0.001580	0.005412	0.002985	0.056427	0.000042	0.000005	0.000063
2014	0.000015	0.001783	0.028792	0.004000	0.000022	0.000033	0.000001	0.000081
2015	0.000022	0.001961	0.006656	0.004545	0.063623	0.000038	0.000020	0.001677
2016	0.000014	0.004049	0.008197	0.005001	0.063897	0.000039	0.000016	0.019554
2017	0.000018	0.001771	0.010876	0.006698	0.066964	0.000163	0.000008	0.005823
2018	0.000017	0.001862	0.021731	0.008275	0.067074	0.000076	0.000014	0.002365
2019	0.000015	0.001938	0.010622	0.046035	0.064354	0.000368	0.000061	0.001523
2020	0.000033	0.001874	0.016357	0.000960	0.000422	0.000371	0.000001	0.006690
2021	0.050366	0.002868	0.018187	0.015857	0.119992	0.000042	0.000027	0.000379
2022	0.000019	0.006877	0.027746	0.034216	0.114071	0.000050	0.000004	0.000642

From 2011 to 2022, feed import dependency ratios (FIDR) reveal varying reliance across key commodities. Wheat shows the highest and gradually increasing FIDR, indicating moderate and growing vulnerability to import disruptions. Rice exhibits a rising trend, peaking in 2021, suggesting an emerging reliance that may require attention. In contrast, maize and soybeans maintain consistently low FIDRs, reflecting strong domestic supply and low import risk. Overall, the feed system demonstrates very low vulnerability (**Table 5**).

Table 5: Trend of animal feed import dependency score by major feed commodity

Year	Wheat	Rice	Maize	Soybean	Total	Vulnerability level
2011	0.03414	0.00036	0.00216	0.00003	0.03668	Very low
2012	0.02110	0.00073	0.00056	0.00011	0.02249	Very low
2013	0.01363	0.00075	0.00053	0.00001	0.01491	Very low
2014	0.01470	0.00151	0.00037	0.00001	0.01659	Very low
2015	0.01665	0.00205	0.00044	0.00019	0.01932	Very low
2016	0.03665	0.00219	0.00046	0.00175	0.04104	Very low
2017	0.01218	0.00312	0.00204	0.00049	0.01782	Very low
2018	0.01280	0.00542	0.00089	0.00033	0.01944	Very low
2019	0.01593	0.01387	0.00440	0.00020	0.03440	Very low
2020	0.01382	0.00092	0.00441	0.00137	0.02052	Very low
2021	0.03079	0.02535	0.00041	0.00009	0.05665	Very low
2022	0.03714	0.01962	0.00038	0.00007	0.05721	Very low

Note: Vulnerability level: <0.15 very low; 0.16-0.30 low; 0.31-0.75 medium; 0.76-0.85 high; >0.85 extreme

Animal feed import dependency fluctuated over the years, with a noticeable peak in 2016 (0.041) and a sharp rise again in 2021 and 2022, both reaching the highest score of 0.057. This suggests increasing reliance on imported feed components in recent years, with 2022 matching the highest recorded dependency, potentially signaling growing vulnerability in feed supply chains (**Figure 1**).

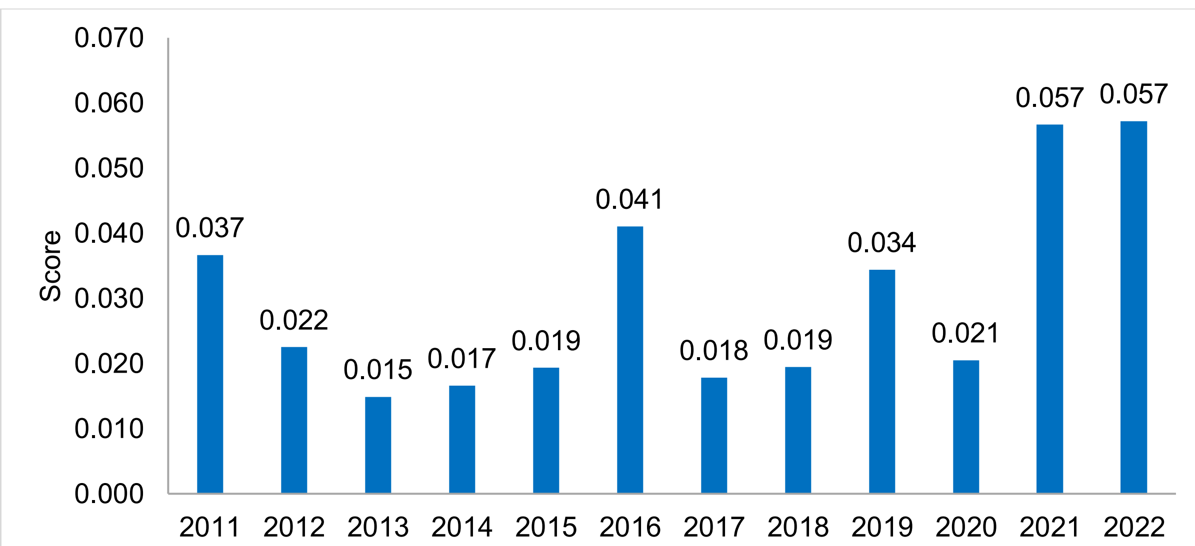

Figure 1: Trend of animal feed import dependency score

Food import foreign exchange ratio

Ethiopia's Food Import Foreign Exchange Indicator from 2011 to 2022 reflects persistent vulnerability in its food import system, with high vulnerability recorded in eight out of twelve years. The total indicator values generally range between 0.1939 (2019) and a peak of 0.4437 (2021), indicating significant pressure on foreign exchange reserves due to food imports.

Oil consistently registers the highest individual burden, peaking at 0.1639 in 2021, making it the most financially demanding import item. Wheat also contributes heavily across all years, particularly in 2016 (0.1231) and 2021 (0.1153), emphasizing its critical role and import reliance. Meanwhile, rice shows a steady rise in financial impact, increasing from 0.0188 in 2011 to 0.0908 in 2021, indicating growing dependency.

Less financially burdensome items like meat, dairy, maize, and soy remain relatively stable and low in value, reflecting minimal strain on foreign exchange from these commodities.

Despite brief improvements to a medium vulnerability level in years including 2012, 2014, 2017, and 2019, the general trend points toward rising import costs and increasing reliance on foreign markets for key food items. The elevated values in 2021 and 2022 signal mounting exposure to external shocks and emphasize the need for strengthened domestic production and diversification to ensure food and financial security (**Table 6**).

Table 6: Food Import Foreign Exchange Indicator for Ethiopia

Year	Dairy	Sugar	Oil	Meat	Rice	Maize	Wheat	Soybean	Total	Vulnerability level
2011	0.0019	0.0338	0.0730	0.0001	0.0188	0.0064	0.1191	0.0027	0.2558	High
2012	0.0016	0.0242	0.0690	0.0001	0.0223	0.0038	0.0905	0.0006	0.2122	Medium
2013	0.0017	0.0397	0.0775	0.0006	0.0341	0.0020	0.1088	0.0016	0.2661	High
2014	0.0021	0.0323	0.0834	0.0009	0.0377	0.0009	0.0625	0.0007	0.2207	Medium
2015	0.0027	0.0359	0.0894	0.0005	0.0632	0.0015	0.0756	0.0034	0.2723	High
2016	0.0018	0.0410	0.0894	0.0003	0.0568	0.0014	0.1231	0.0013	0.3150	High
2017	0.0021	0.0332	0.0866	0.0002	0.0599	0.0036	0.0552	0.0008	0.2416	Medium
2018	0.0019	0.0477	0.0800	0.0002	0.0759	0.0021	0.0610	0.0006	0.2694	High
2019	0.0018	0.0254	0.0421	0.0002	0.0528	0.0063	0.0649	0.0005	0.1939	Medium
2020	0.0038	0.0448	0.0712	0.0001	0.0823	0.0042	0.0585	0.0011	0.2661	High
2021	0.0028	0.0692	0.1639	0.0002	0.0908	0.0007	0.1153	0.0006	0.4437	High
2022	0.0019	0.0558	0.1362	0.0001	0.0869	0.0009	0.0858	0.0002	0.3677	High

Note: Vulnerability level: ≤0.01 very low; 0.012-0.035 low; 0.036-0.25 medium; 0.26-0.575 high; >0.575 extreme

Supply chain reliability

The table below outlines the supply chain reliability scores for various commodities in Ethiopia from 2011 to 2022, highlighting notable trends and sector-specific challenges. Wheat shows fluctuating reliability, peaking modestly in 2014 (0.101) before declining, suggesting an ongoing instability. Dairy remains consistently low throughout, with a slight improvement in 2022 (0.010), indicating persistent structural issues. Maize demonstrates intermittent reliability, with peaks in 2012 (0.184) and 2017 (0.160), followed by a decline, reflecting sensitivity to production and supply disruptions. Soybean consistently records near-zero scores, pointing to a chronically weak and unreliable supply chain. Meat exhibits sporadic reliability, with a notable rise in 2018 (0.017) but inconsistent performance overall. Oil and rice show gradual improvement over time, particularly rice, which increased from 0.003 in 2012 to a high of 0.017 in 2021, suggesting the impact of policy support and localized production efforts. Sugar maintains low but slightly rising scores, signaling ongoing vulnerabilities (**Table 7**).

Table 7: Trends of supply chain reliability score by commodity

Year	Wheat	Dairy	Maize	Soybean	Meat	Oil	Rice	Sugar
2011	0.045	0.005	0.043	0.001	0.003	0.003	0.518	0.002
2012	0.028	0.004	0.184	0.001	0.003	0.005	0.003	0.004
2013	0.057	0.015	0.104	0.001	0.007	0.007	0.004	0.004
2014	0.101	0.009	0.080	0.000	0.012	0.007	0.006	0.003
2015	0.035	0.004	0.153	0.001	0.003	0.012	0.008	0.002
2016	0.071	0.003	0.104	0.001	0.004	0.006	0.007	0.005
2017	0.071	0.002	0.160	0.000	0.005	0.005	0.010	0.003
2018	0.059	0.003	0.157	0.000	0.017	0.005	0.015	0.002
2019	0.062	0.003	0.164	0.000	0.003	0.003	0.011	0.005
2020	0.031	0.005	0.115	0.001	0.004	0.005	0.015	0.005
2021	0.024	0.006	0.035	0.005	0.004	0.006	0.017	0.006
2022	0.038	0.010	0.069	0.001	0.001	0.005	0.013	0.004

The table below on supply chain reliability in Ethiopia from 2011 to 2022 highlights the varying degrees of stability across different agricultural and food commodities. Among all the commodities, rice stood out in 2011 with a notably high reliability score of 0.518, indicating a robust supply chain at the time, possibly due to favorable import arrangements or stable domestic conditions. However, this reliability dropped sharply in 2012 and remained relatively low in subsequent years, showing only a gradual improvement, peaking at 0.017 in 2021. This pattern suggests that while rice experienced a significant disruption, there have been efforts to restore its supply chain gradually.

Maize, another staple crop, demonstrated relatively consistent and moderate-to-high reliability scores across most years, with a peak in 2012 (0.184). This indicates a comparatively resilient supply chain, likely supported by strong domestic production and investment. In contrast, wheat showed fluctuating reliability over the period, with the highest score in 2014 (0.101), followed by a general decline, suggesting vulnerability to external shocks and inconsistencies in production and imports.

Dairy products consistently recorded very low reliability scores, ranging from 0.002 to 0.015, reflecting a fragile supply chain possibly constrained by underdeveloped cold chain infrastructure, informal marketing systems, and limited processing capabilities. Similarly, soybeans maintained extremely low scores throughout the period, indicating an emerging or poorly developed sector with minimal supply chain maturity.

The meat sector showed some modest improvement, with a slight uptick in reliability in recent years (0.017 in 2018), pointing to incremental progress likely driven by sectoral reforms or infrastructure investments. Edible oil showed low but relatively stable scores, suggesting some improvement in local oilseed processing, though challenges remain due to import dependence and limited capacity. Sugar, on the other hand, remained consistently unreliable, with scores rarely exceeding 0.006. This points to persistent inefficiencies in the sugar supply chain, exacerbated by delays and failures in government-run projects.

Overall, the data reveal that Ethiopia's agricultural supply chains have generally low reliability, with few commodities showing signs of consistent improvement. These trends underscore the impact of systemic challenges such as weather shocks, logistical constraints, political instability, and external market disruptions. Commodities with stronger domestic production bases, like maize, tend to exhibit better reliability. This analysis highlights the need for targeted policy interventions to strengthen supply chains, including investments in infrastructure, import substitution strategies, and support for agro-processing. Building more resilient and efficient supply chains will be essential to enhancing food security and economic stability in Ethiopia (**Table 8**).

Table 8: Supply chain reliability score by summary and vulnerability classification

Year	Supply chain reliability score	Level
2011	0.619	Extreme
2012	0.232	Extreme
2013	0.199	Extreme
2014	0.219	Extreme
2015	0.218	Extreme
2016	0.200	Extreme
2017	0.257	Extreme
2018	0.259	Extreme
2019	0.250	Extreme
2020	0.181	Extreme
2021	0.103	High
2022	0.142	High

Note: Vulnerability level: <0.025 very low; 0.026-0.05 low; 0.051-0.075 medium; 0.076-0.15 high; >0.15 extreme

The figure below also shows Ethiopia's supply chain reliability scores from 2011 to 2022. Each point on the graph represents the annual score, with labels indicating the vulnerability level "extreme" or "high". The horizontal dashed lines represent the thresholds for the vulnerability classifications (**Figure 2**).

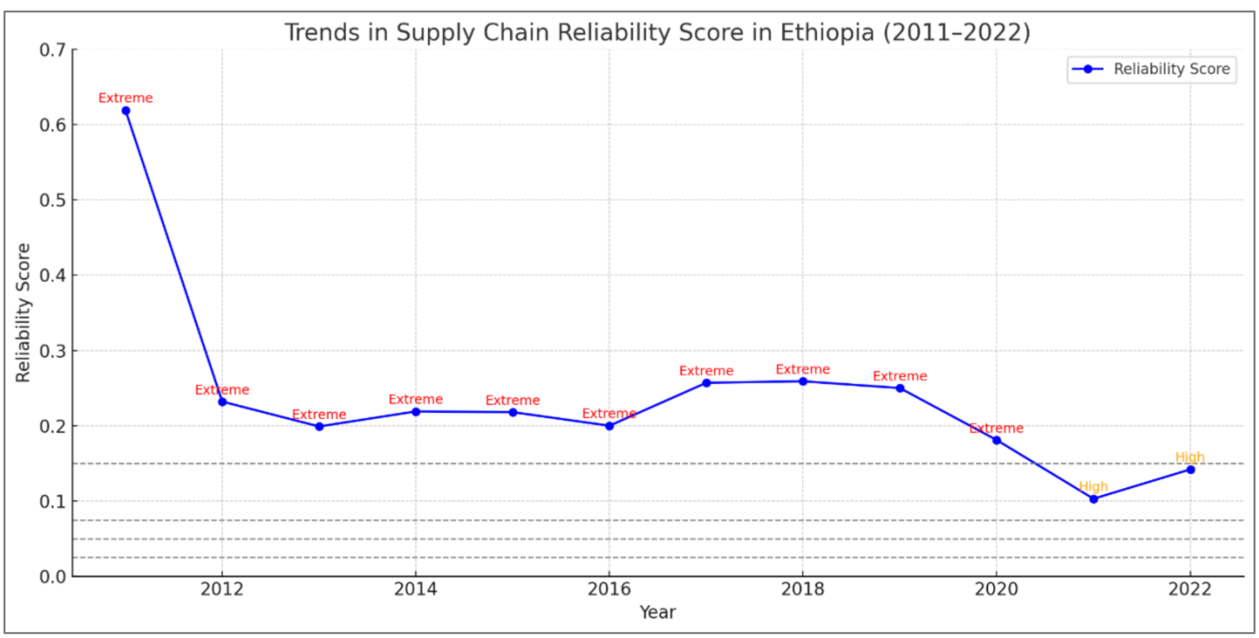

Figure 2: Trends of supply chain reliability score in Ethiopia

Supply chain robustness

The presented data reflect the robustness of Ethiopia's supply chains across several key agricultural and food commodities, namely dairy, maize, meat, oil, rice, soybean, sugar, and wheat, summarized annually. The values represent an index of supply chain robustness, where higher values indicate more robust and reliable supply systems. Overall, the composite supply chain robustness score demonstrates a significant fluctuation over the 12 years. Starting at a high of 9.19 in 2011, the index dropped sharply to 3.352 in 2013, signaling systemic vulnerability across sectors during that period. A modest recovery was observed in subsequent years, with values oscillating before climbing again from 2019 onward, reaching 5.762 in 2022. This trajectory reflects external pressures (such as climate shocks, market disruptions, or policy gaps) as well as potential improvements in certain sectors during later years.

The commodity-level analysis reveals varying trends in robustness across sectors from 2011 to 2022. Dairy and maize show signs of recovery and strengthening after early volatility, likely due to improved production and policy support. Meat and wheat remain volatile, impacted by diseases, logistical issues, and import dependence. Rice and oil exhibit gradual improvement, reflecting investment in local processing and import substitution. However, soybeans and sugar persistently show low robustness, indicating ongoing supply vulnerabilities. Overall, while early years were marked by instability and mid-period volatility, recent trends suggest modest stabilization (**Table 9**).

Table 9: Trends of supply chain robustness by commodity

Year	Dairy	Maize	Meat	Oil	Rice	Soybean	Sugar	Wheat	Total reliability	Level
2011	2.181	4.301	0.564	0.005	0.027	0.027	0.005	2.080	9.190	Very low
2012	2.046	1.708	0.480	0.006	0.055	0.055	0.005	3.435	7.790	Very low
2013	0.802	0.855	0.255	0.006	0.030	0.030	0.005	1.369	3.352	Medium
2014	1.015	1.563	0.266	0.007	0.045	0.045	0.006	2.148	5.094	Low
2015	0.929	1.528	0.506	0.011	0.058	0.058	0.006	0.665	3.760	Medium
2016	1.501	1.605	0.260	0.008	0.048	0.048	0.003	0.685	4.158	Medium
2017	1.643	1.796	0.475	0.008	0.068	0.068	0.006	0.580	4.644	Medium
2018	1.437	1.673	0.117	0.009	0.101	0.101	0.011	0.570	4.020	Medium
2019	1.990	0.832	0.399	0.009	0.088	0.088	0.003	1.316	4.725	Medium
2020	1.705	1.612	0.529	0.015	0.111	0.111	0.003	2.164	6.250	Low

2021	1.082	3.027	0.233	0.013	0.114	0.114	0.003	1.128	5.714	Low
2022	1.143	3.027	0.231	0.021	0.095	0.095	0.003	1.148	5.762	Low

Note: Vulnerability level: >7.5 very low; 5.1-7.5 low; 3.1-5.0 medium; 1.5-3.0 high; 0-1.5 extreme

This graph illustrates the robustness trends of Ethiopia's supply chains from 2011 to 2022 across key agricultural commodities, including dairy, maize, meat, oil, rice, soybean, sugar, and wheat. The composite score, shown by the dashed black line, indicates overall systemic resilience. Fluctuations in individual commodities highlight the varying vulnerabilities and strengths across the sector, underscoring areas for policy intervention and investment.

The line graph depicting supply chain robustness trends in Ethiopia from 2011 to 2022 reveals notable patterns across key commodities and the overall system. The composite score, represented by a black dashed line, highlights a sharp decline in 2013, followed by a gradual recovery starting in 2018, indicating system-level stress and subsequent stabilization. Maize, shown by the orange line, experienced significant volatility with a steep drop post-2011 but rebounded strongly by 2021 and remained stable through 2022. Dairy and wheat display moderate robustness with noticeable fluctuations, suggesting sensitivity to external shocks but relatively better resilience. Meanwhile, meat, oil, and rice show a pattern of gradual strengthening, particularly oil and rice, which may reflect the positive impact of strategic policy measures. In contrast, soybean and sugar consistently exhibit low robustness throughout the period, underscoring structural weaknesses and the urgent need for focused policy interventions (**Figure 3**).

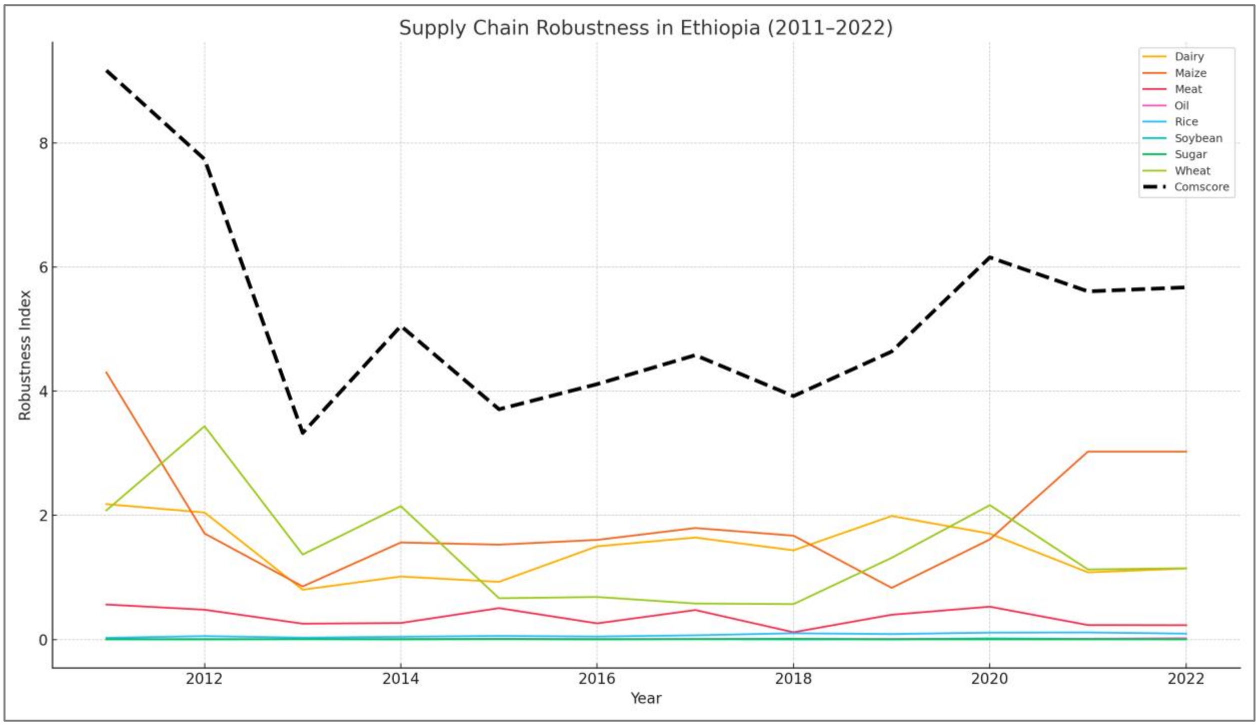

Figure 3: Supply chain robustness in Ethiopia (2011–2022)

Assessment of Ethiopia's performance in the Jameel Index

The table below reveals several striking patterns in Ethiopia's food system vulnerabilities between 2011 and 2022. Notably, food supply reliability remained at an "Extreme" vulnerability level for a full decade (2011–2020), underscoring persistent instability and systemic fragility in ensuring consistent food availability. In contrast, feed import dependency consistently stayed at a "Very low" vulnerability level throughout the period, suggesting strong domestic production capacity or minimal reliance on external sources for animal feed. Despite some improvements in food supply reliability after 2020, the vulnerability associated with food import foreign exchange remained consistently "High," reflecting sustained pressure on Ethiopia's financial capacity to cover food imports. Meanwhile, food supply chain robustness showed gradual improvement from "Very low" to "Medium" during the mid-2010s, but regressed to "Low" in the final years, indicating unresolved structural weaknesses in maintaining a resilient food distribution and logistics network (**Table 10**).

Table 10: Vulnerability classification (level) of meta-indicators

Year	Food import dependency	Feed import dependency	Food import foreign exchange	Food supply reliability	Food supply chain robustness
2011	Medium	Very low	High	Extreme	Very low
2012	Low	Very low	Medium	Extreme	Very low
2013	Low	Very low	High	Extreme	Medium
2014	Low	Very low	Medium	Extreme	Low
2015	Low	Very low	High	Extreme	Medium
2016	Medium	Very low	High	Extreme	Medium
2017	Low	Very low	Medium	Extreme	Medium
2018	Low	Very low	High	Extreme	Medium
2019	Low	Very low	Medium	Extreme	Medium
2020	Medium	Very low	High	Extreme	Low
2021	Medium	Very low	High	High	Low
2022	Medium	Very low	High	High	Low

The Jameel Index results for Ethiopia from 2011 to 2022 indicate a consistent pattern of moderate performance in food system resilience. The Jameel Index (JX) percentage values ranged between 24.4% and 33.8%, placing Ethiopia mostly in the "Medium" classification throughout the period. The only exception was in 2012, when the JX dropped to 24.4%, corresponding to a "Low" classification, suggesting a temporary weakening in system robustness that year.

From 2013 onward, the Jameel Index improved and stabilized within the medium range (26.2% to 33.8%), peaking in 2016 at 33.8%. This indicates gradual enhancements in certain dimensions of food system resilience, such as access, availability, and reliability. However, the failure to reach a "High" classification (above 40%) throughout the entire period highlights enduring structural limitations and vulnerabilities in Ethiopia's food systems (**Table 11**).

In summary, the Jameel Index underscores moderate and stagnant resilience, with no sustained movement toward a high-performing system, pointing to the need for transformative interventions across food production, logistics, and policy frameworks.

Table 11: Jameel Index result of Ethiopia

Year	Score	Product	RAWJx	Jameel Index (JX) in (%)	Classification
2011	3, 1, 4, 5, 1	60	2.047	26.2	Medium
2012	2, 1, 3, 5, 1	30	1.974	24.4	Low
2013	2, 1, 4, 5, 3	120	2.297	32.4	Medium
2014	2, 1, 3, 5, 2	60	2.047	26.2	Medium

2015	2, 1, 4, 5, 3	120	2.297	32.4	Medium
2016	3, 1, 4, 5, 3	180	2.353	33.8	Medium
2017	2, 1, 3, 5, 3	90	2.186	29.7	Medium
2018	2, 1, 4, 5, 3	120	2.297	32.4	Medium
2019	2, 1, 3, 5, 3	90	2.186	29.7	Medium
2020	3, 1, 4, 5, 2	120	2.297	32.4	Medium
2021	3, 1, 4, 4, 2	96	2.212	30.3	Medium
2022	3, 1, 4, 4, 2	96	2.212	30.3	Medium

3.4. Conclusion and recommendation

Between 2011 and 2022, Ethiopia's food system exhibited persistent vulnerabilities and only modest improvements in resilience, as reflected both in meta-indicator trends and the Jameel Index outcomes. Food supply reliability remained at an "Extreme" vulnerability level for a decade, with only marginal improvement in recent years, highlighting chronic instability in ensuring consistent food access. The consistently "High" vulnerability in food import foreign exchange emphasizes the country's ongoing financial strain to secure essential food imports. While feed import dependency remained "Very low," indicating strong domestic self-sufficiency in this area, food supply chain robustness showed a temporary recovery before declining again to "Low," reflecting structural weaknesses in logistics and infrastructure.

The Jameel Index consistently placed Ethiopia in the "Medium" category, with no year surpassing the 40% threshold required for "High" resilience. This plateau in performance underlines a stagnation in progress and a failure to achieve substantial, sustained system improvements. Commodity-level analysis revealed that wheat, oil, and rice are particularly critical points of dependency and foreign exchange pressure, while sectors like dairy, sugar, and soybean suffer from weak supply chains and limited robustness.

Recommendations:

1. **Diversify and strengthen domestic production** of high-dependency commodities such as oil, rice, and wheat through targeted investments, improved input access, and extension services to reduce import reliance and foreign exchange burden.

2. **Enhance supply chain infrastructure**, including cold storage, transportation, and market access systems, to improve the robustness and reliability of distribution, particularly for dairy, sugar, and perishable goods.

3. **Promote import substitution strategies** by supporting agro-processing industries and encouraging local value addition to reduce vulnerability from global market fluctuations.

4. **Build foreign exchange resilience** through strategic reserves, trade diversification, and support for export-generating agricultural sectors to buffer against global shocks.

5. **Invest in data systems and early warning mechanisms** to monitor vulnerabilities in real-time and enable proactive policy responses, especially in response to external disruptions like pandemics, climate change, and conflicts.

In summary, Ethiopia's food system requires systemic, multi-sectoral reform to transition from stagnation to resilience. Without targeted, coordinated interventions, the nation risks continued exposure to food insecurity and external shocks. Enhancing the Ethiopian Food System Transformation (EFST) and Nutrition Initiative may provide the best way solution.

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Appendix

Appendix **Table 1**. Top countries export cereals to Ethiopia (2020–2022)

Countries	Value of export in USD	Percent share (%)
India	1,180,000,000	33.1
United States	801,000,000	22.5
Ukraine	674,000,000	19.1
Argentina	210,000,000	5.5
Russian Federation	167,000,000	4.7
Romania	128,000,000	3.6
Turkey	92,700,000	2.6
Bulgaria	67,400,000	1.9
Korea, Republic	28,400,000	0.7
France	27,500,000	0.7
Others	204,000,000	5.6
Total	3,580,000,000	

Source: ECA, 2011–2022

Appendix **Table 2**. Top countries export animal and vegetable oils to Ethiopia (2020–2022)

Countries	Value of export in USD	Percent share (%)
Malaysia	914,000,000	31.1
Turkey	886,000,000	30.1
Djibouti	502,000,000	17.1
Indonesia	327,000,000	11.1
United States	103,000,000	3.5
Ukraine	51,600,000	1.7
Kenya	35,000,000	1.2
United Arab Emir	34,800,000	1.2
India	30,600,000	1.0

Saudi Arabia	13,400,000	0.5
Others	42,600,000	1.5
Total	2,940,000,000	

Source: ECA, 2011–2022

Appendix **Table 3**. Top countries export sugar and sugar confectioners to Ethiopia (2020–2022)

Countries	Value of export in USD	Percent share (%)
India	1,130,000,000	92.6
Brazil	26,000,000	2.1
Egypt	17,000,000	1.4
United Arab Emir	14,400,000	1.2
Saudi Arabia	13,100,000	1.1
Turkey	4,013,855	0.3
Viet Nam	3,754,712	0.3
Pakistan	2,729,349	0.2
China	2,109,339	0.2
South Africa	2,007,163	0.2
Others	4,885,582	0.4
Total	1,220,000,000	

Source: ECA, 2011–2022

Appendix **Table 5**. Top countries import cereals by year (Millions of USD)

Year	Description	Rank of top source countries										
2022	Country	Total	India	USA	Ukraine	Argentina	Bulgaria	Russia	Romania	Turkey	Korea, Republic	Others
	Value (Mill. USD)	1,226.18	402.31	377.29	194.42	114.92	34.26	29.45	24.64	9.14	8.78	30.97
2021	Country	Total	India	Ukraine	USA	Russia	Romania	Turkey	Bulgaria	Italy	Serbia	Others
	Value (Mill. USD)	1,521.52	527.07	374.72	226.48	115.09	77.00	74.53	24.29	20.36	16.70	65.27
2020	Country	Total	India	USA	Ukraine	Argentina	Romania	Russia	South Africa	France	Pakistan	Others
	Value (Mill. USD)	830.77	248.46	196.92	104.62	94.10	26.41	22.72	22.49	15.51	14.62	84.92
2019	Country	Total	Ukraine	USA	India	Romania	Russia	South Africa	Bulgaria	France	Korea, Democratic	Others
	Value (Mill. USD)	801.92	153.99	149.20	148.24	83.07	60.70	36.10	34.82	21.60	13.99	100.19
2018	Country	Total	India	USA	Romania	Russia	Ukraine	Egypt	France	Korea, Republic	Bulgaria	Others
	Value (Mill. USD)	793.59	232.74	147.33	111.74	87.90	43.42	29.00	22.38	18.65	15.87	84.56
2017	Country	Total	India	USA	Romania	Italy	Bulgaria	Ukraine	Russia	Egypt	China	Others
	Value (Mill. USD)	651.34	166.28	149.81	81.99	75.48	30.65	25.98	23.22	14.41	8.20	75.33
2016	Country	Total	Romania	India	Italy	USA	Russia	Ukraine	Germany	Latvia	Serbia	Others
	Value (Mill. USD)	718.75	160.71	154.02	64.29	55.80	50.89	46.43	43.17	24.64	22.46	96.34
2015	Country	Total	USA	India	Ukraine	Bulgaria	Germany	Russia	France	Egypt	Romania	Others
	Value (Mill. USD)	654.03	151.18	142.65	95.26	66.35	44.79	42.09	19.76	18.10	16.87	56.97
2014	Country	Total	India	USA	Romania	Ukraine	Denmark	Italy	Pakistan	Belgium	Russia	Others
	Value (Mill. USD)	517.41	158.71	102.99	76.62	73.13	19.50	13.73	11.34	10.85	10.70	39.85
2013	Country	Total	Ukraine	USA	India	Russia	France	Bulgaria	Netherlands	Pakistan	Egypt	Others
	Value (Mill. of USD)	285.3	76.44	73.30	35.60	33.5	16.60	10.94	6.81	6.49	6.39	19.3
2012	Country	Total	USA	India	Argentina	Italy	Brazil	Russia	Belize	Denmark	Pakistan	Others
	Value (Mill. USD)	448.09	103.83	94.54	61.75	41.97	29.29	29.18	18.25	14.26	10.16	44.86
2011	Country	Total	Russia	USA	Pakistan	Italy	China	Oman	Bulgaria	Sudan	Brazil	Others
	Value (Mill. USD)	539.31	191.33	143.35	45.78	30.06	23.82	14.62	13.24	10.17	9.88	57.05

Source: ECA, 2011–2022

Appendix **Table 6.** Top countries import animal and vegetable oils by year (Millions of USD)

Year	Description	Rank of top source countries										
2022	Country	Total	Malaysia	Turkey	Djibouti	Indonesia	USA	Kenya	India	UAE	Saudi Arabia	Others

	Value (Mill. USD)	1,228.10	373.44	348.41	306.06	65.06	39.27	34.46	20.60	18.13	7.49	15.19
2021	Country	Total	Malaysia	Turkey	Djibouti	Indonesia	USA	Ukraine	UAE	India	Saudi Arabia	Others
	Value (Mill. USD)	963.56	366.48	253.24	151.12	80.50	41.59	28.41	16.10	8.67	4.14	13.30
2020	Country	Total	Turkey	Indonesia	Malaysia	Djibouti	USA	Ukraine	Moldova	Egypt	Saudi Arabia	Others
	Value (Mill. USD)	746.15	284.62	181.54	174.10	44.87	22.46	16.10	5.33	5.23	1.77	10.12
2019	Country	Total	Malaysia	Turkey	Indonesia	Djibouti	Ukraine	USA	Egypt	UAE	Singapore	Others
	Value (Mill. USD)	396.17	130.35	106.07	90.42	21.69	14.57	12.30	7.25	4.79	1.86	6.87
2018	Country	Total	Malaysia	Indonesia	Turkey	UAE	USA	Ukraine	Egypt	India	Yemen	Others
	Value (Mill. USD)	395.02	183.27	103.56	52.67	21.78	17.30	4.91	3.25	1.91	1.15	5.23
2017	Country	Total	Malaysia	Indonesia	Turkey	UAE	USA	Egypt	Italy	Ukraine	Yemen	Others
	Value (Mill. USD)	498.08	263.98	128.35	39.85	24.21	14.41	10.61	4.18	2.74	2.73	7.03
2016	Country	Total	Malaysia	Indonesia	UAE	USA	Turkey	Saudi Arabia	Egypt	Italy	Yemen	Others
	Value (Mill. USD)	500.00	223.21	179.91	34.96	21.65	13.44	7.10	6.56	3.57	2.41	7.19
2015	Country	Total	Indonesia	Malaysia	UAE	USA	Egypt	Turkey	Yemen	Spain	Netherlands	Others
	Value (Mill. USD)	473.46	274.41	123.70	26.26	15.83	12.61	9.76	2.92	1.64	1.39	4.94
2014	Country	Total	Indonesia	Malaysia	UAE	USA	Italy	Yemen	Turkey	Egypt	India	Others
	Value (Mill. USD)	438.31	304.98	85.57	16.22	14.28	4.54	4.11	3.26	1.81	1.13	2.41
2013	Country	Total	Indonesia	Malaysia	USA	Yemen	Egypt	Turkey	UAE	India	Italy	Others
	Value (Mill. USD)	385.34	244.50	110.99	12.41	4.43	3.73	3.40	3.15	0.74	0.66	1.33
2012	Country	Indonesia	Malaysia	USA	Italy	UAE	Yemen	Turkey	India	Egypt	Spain	Others
	Value (Mill. USD)	349.73	187.98	19.67	12.84	12.35	6.12	3.25	3.07	1.96	0.52	101.96
2011	Country	Malaysia	Indonesia	Egypt	USA	UAE	Yemen	Turkey	Italy	India	Kenya	Others
	Value (Mill. USD)	214.45	97.11	21.56	19.71	13.76	5.55	3.83	2.34	0.78	0.39	49.42

Source: ECA, 2011–2022

Appendix **Table 7**. Top countries import sugar and sugar confectionaries by year (Millions of USD)

Year	Description	Rank of top source countries										
2022	Country	Total	India	Egypt	Brazil	UAE	Saudi Arabia	Turkey	USA	Mauritius	Viet Nam	Others
	Value (Mill. USD)	508.18	461.98	13.53	9.89	9.01	6.58	2.21	1.30	0.95	0.72	1.99
2021	Country	Total	India	Brazil	Egypt	Saudi Arabia	Viet Nam	Turkey	Pakistan	China	Malaysia	Others
	Value (Mill. USD)	430.31	417.95	3.19	2.53	2.16	1.16	1.02	0.91	0.42	0.33	0.63

2020	Country	Total	India	Brazil	UAE	Saudi Arabia	Viet Nam	South Africa	China	Pakistan	Belize	Others
	Value (Mill. USD)	284.62	252.05	12.95	5.18	4.31	1.88	1.60	1.46	1.45	1.40	2.35
2019	Country	Total	India	Brazil	Egypt	Pakistan	Saudi Arabia	China	South Africa	Turkey	Viet Nam	Others
	Value (Mill. USD)	183.71	165.50	3.74	3.19	2.83	2.26	1.92	0.97	0.73	0.69	1.88
2018	Country	Total	India	Pakistan	UAE	Thailand	Brazil	Egypt	France	Saudi Arabia	Denmark	Others
	Value (Mill. USD)	327.76	114.95	69.40	64.77	41.28	23.81	3.70	1.97	1.86	1.26	4.77
2017	Country	Total	Brazil	India	Algeria	Thailand	Pakistan	UAE	Egypt	Saudi Arabia	Viet Nam	Others
	Value (Mill. USD)	191.57	65.52	50.19	19.69	18.08	13.68	7.16	4.75	4.41	1.73	6.36
2016	Country	Total	India	Brazil	Pakistan	UAE	Saudi Arabia	Ukraine	Viet Nam	Turkey	China	Others
	Value (Mill. USD)	245.09	185.27	34.38	4.51	4.46	4.21	2.75	2.14	1.60	1.35	4.42
2015	Country	Total	India	UAE	Brazil	Pakistan	Saudi Arabia	Morocco	Singapore	Egypt	Viet Nam	Others
	Value (Mill. USD)	186.73	92.42	57.35	11.09	8.96	3.31	2.17	2.17	1.93	1.65	5.69
2014	Country	Total	Thailand	India	UAE	Pakistan	Saudi Arabia	Brazil	Egypt	China	USA	Others
	Value (Mill. USD)	190.55	61.69	44.78	31.64	24.58	7.76	7.46	3.70	1.44	1.42	6.07
2013	Country	Total	Thailand	UAE	India	Pakistan	Saudi Arabia	China	Viet Nam	Belgium	USA	Others
	Value (Mill. USD)	217.80	83.25	64.40	41.07	18.27	1.93	1.24	1.20	0.85	0.66	4.94
2012	Country	Total	India	UAE	Thailand	Brazil	Pakistan	Saudi Arabia	Viet Nam	China	Italy	Others
	Value (Mill. USD)	174.32	75.41	53.28	11.75	11.31	8.03	7.70	1.85	1.58	1.29	2.10
	Country	Total	India	Brazil	Thailand	Saudi Arabia	Guatemala	China	Viet Nam	Algeria	Italy	Others
	Value (Mill. USD)	178.6	130.06	14.45	12.77	8.61	5.60	2.12	1.61	1.05	0.60	1.75

Source: ECA, 2011–2022

Appendix **Table 8**. Conversion factors used in food consumption estimation

Food item	kcal/100 gram
Teff	341
Barley	354
Wheat	351
Karka'eta*	352
Maize	362
Sorghum	347
Lentil	353
Bean	344
Fieldpeas	341
Chickpeas	364
guaya	347
Finger milet	312
Coffee	2
Sugar	400
Berbere	318
Salt	0
Oil	884
Onion	42
Garlic	149
Potato	87
Tomato	18
Milk	39
chease	132
Beef	235
chicken	140
Egg	68

**note for karka 'eta (a mix of wheat and barley)we used average of calorie content of the two*

Source: Ethiopian Nutrition and Health Research Institute (ENHRI) and world health organization (WHO)

Appendix **Table 9**. Meteorological stations used in drought index analysis

Station Name	Station ID	Station Name	Station ID	Station Name	Station ID	Station Name	Station ID	Station Name	Station ID
Awassa	AW	Waja	WJ	Awash 7 killo	AW7	Wolkite	WK	Babile	BB
Ziway	ZI	Arsinegele	AN	Bui	BU	Wulbareg	WB	Degahabur	DH
Adamitulu	AD	Pawe	PW	Debre Berhan	DB	Yaya	YY	Dengego	DGG
Melkassa	ML	Chagni	CG	Efeson	EF	Billate	BL	Diredawa	DD
Dhera	DE	Ambo	AM	Filiklik	FI	Boditi	BD	Gewane	GW
Miesso	MI	Asgori	AG	Gedo	GD	Fiseha Genet	FG	Girawa	GR
Chiro	CH	Akaki	AK	Gohatsion	GH	Hagere Mariam	HM	Gursum	GS
Alemtena	AT	Gera	GE	Guder	GU	Hagere Selam	HS	Harar School	HR
Worer	WO	Abi_Adi	AB	Gudoberet	GB	Haisawita	HW	Hirna	HI
Assosa	AS	Adigrat	AG	Hosana	HO	Kibre Mengist	KM	Kulibi	KL
Baco	BA	Adwa	AD	Intoto	IN	Wolaita	WL	Asasa	ASS
Bonga	BO	Axum	AX	Kachis	KC	Abomsa	ABO	Bekoji	BK
DZeit	DZ	Endabaguna	EB	Kimoye	KI	Adele	ADE	Kofele	KF
Holleta	HO	Hagere.Selam	HS	Lemi	LE	Arata	AR	Adaba	ADB
Jimma	JM	Hawzen	HW	Melkasa	ML	Assela	ASL	Dinsho	DI
Kulumsa	KU	Maichew	MC	Metehara	MH	Dagaga	DG	Bale Robe	BR
Metu	MT	Mekele	MK	Mojo	MJ	Gobessa	GB	Sinana	SN
Teppi	TP	Shire.Endasilasse	SE	Nazeret	NZ	Huruta	HU	Goro	GO
Sirinka	SI	Wukro	WU	Nuraera	NU	Ketera Genet	KG	Guna	GN
Haik	HK	Addis Ababa	AA	Sululta	SU	Yirga Chefe	YC	Sagure	SG
Kobo	KO	Alaba Kulito	LK	Mehal Meda	MM	Ogolcho	OG		
Alamata	AL	Selehelehe	SL	Tikur Enchine	TE	Arsi Robe	RA		
Mersa	MR	Angacha	AC	Woliso Giyon	WG	Awash Shelko	SH		

Appendix **Table 2.1**. ARDL (4, 3, 4) model result on the role of total export and food import on food production index

lnfoodpdnindex	**Coefficient**	**Std. err.**	**T**	**P>t**
Lnfoodpdnindex				
L1.	0.117	0.423	0.280	0.793
L2.	0.389	0.475	0.820	0.449
L3.	-0.718	0.541	-1.330	0.242
L4.	0.815	0.399	2.040	0.096
Lnexport				
--.	0.032	0.086	0.380	0.722
L1.	-0.092	0.142	-0.650	0.544
L2.	0.235	0.140	1.680	0.154
L3.	-0.110	0.086	-1.290	0.255
Lnfoodimport				
--.	0.010	0.047	0.200	0.847
L1.	-0.087	0.060	-1.450	0.208
L2.	0.070	0.043	1.610	0.169
L3.	-0.108	0.039	-2.750	0.040
L4.	-0.039	0.034	-1.140	0.305
Constant	1.518	0.665	2.280	0.071

Observations 19
F(13, 5) = 126.03
Prob > F = 0.0000
R-squared = 0.9970
Adj R-squared = 0.9890
Log likelihood = 54.112705
Root MSE = 0.0273