Università degli Studi di Ferrara

Master's Degree course

in

Green economy and sustainability

Climate variability and food prices: an empirical investigation of African local markets

Supervisor:
Prof. Nicolò Barbieri

Student:
Fabio De Lisio

Co-supervisor:
Prof. Ugo Rizzo

Academic year 2022/2023

Contents

Abstract

In the last twenty years, climate change has worsened the consequences of climate extremes and anomalies. This has an important implication for agricultural activities, which remains the primary form of livelihood in many households in developing countries. In this Master's Thesis, we aim to explore the potential relations between climate variability and retail food prices by analyzing data on 1088 local markets in 31 African countries and using precipitations, temperature, and NDVI as a proxy of climate change. A fixed-effect model with dummy variables is used to carry out the regression analysis. The outcome indicates the existence of a relationship between environmental variability, particularly temperature, and food prices. When analyzing specific agricultural commodities, the effects are confirmed, especially for the most imported ones, highlighting the need for further detailed research regarding local household cultivations.

1 Introduction

In the decade of 2011-2020, global temperature increased of 1.1°C with respect to the 1850-1900 levels due to the greenhouse gas (GHG) emissions deriving from human activities. GHG emissions, mainly carbon dioxide (CO2) and methane (CH4), strongly influence global temperatures, leading to air, Earth's surface, and ocean warming. Unsustainable consumption patterns, extensive land use and degradation, and increased energy consumption between countries are the main source of greenhouse gases. The increase of the global temperature and the emission of pollutants have disastrous consequences on the nature: ocean level rising, extreme weather events (heavy precipitations, heatwaves, droughts, and tropical cyclones) and loss of biodiversity. At the global temperature of 1.5°C, floodings, heavy precipitations and agricultural droughts are projected to increase in Africa, Asia, North America, and Europe. Consequently, countries' economies and society are negatively affected since global warming translates in losses of people and economic activities. The communities who contributed the least to GHG emissions, with high confidence, are the ones who are experiencing disproportionate impacts (IPCC, 2023).

Efforts to reduce global emissions are undertaken by the United Nations Framework Convention for Climate Change through the formulation, and ratification by 192 countries, of the Kyoto Protocol, which entered into force in 2005. The signatory parties must had ensured an emission reduction in GHG emissions of 5% compared to 1990 levels, during the period 2008-2012 (UNFCCC, 1997).

In addition to climate friendly objectives, the United Nations' General Assembly formulated in 2015 the 17 Sustainable Development Goals (SDGs) with 169 targets to achieve by 2030 (Figure 1). The SDGs Agenda is people-centred and seeks to achieve the targets for all segments of the society. To reach the desired goals, each Government will have to decide how to incorporate the SDGs in their own peculiar economic and national planning (UN General Assembly, 2015).

Figure 1: United Nation's Sustainable Development Goals

The achievement of Sustainable Development Goals targets, unfortunately, is far from being met. In terms of climate change and climate action, extreme weather events are destroying ecosystems and damaging society in different scopes: economic, health, and social. To mitigate the magnitude of climate hazards GHG emissions must be half-cut by 2030, but current efforts are not enough to limit the rise of temperatures only seven years away from the target year. An important role is played by climate finance which is a key factor in mobilizing financial resources toward sustainable development and solutions. However, the commitment of developed countries to mobilize \$100 billion yearly in climate finance for developing countries, from 2020 to 2025, falls short: only \$83.3 billion were mobilized. Furthermore, more than 70 percent of climate financing from developed to developing countries, in the period 2016-2020, were in the form of loans.

Climate action efforts are needed not only to ensure the social and economic protection of society but also to achieve food security and food access, especially in developing countries. In 2021, nominal public spending in agriculture reached a record-high amount of $700 billion. Government spending in agriculture as a share of the GDP, however, fell from 0.50 in 2015 to 0.45 in 2021, except for North America and Europe. In the same period, agricultural aid in developing countries rose by 14.6 percent, partially because of food security concerns due to the pandemic, but returned to pre-pandemic levels in 2021 United Nations Department of Economic and Social Affairs (2023).

In this framework, there is a growing branch of literature studying the effects of climate change on food security as the review studies by Kang et al. (2009) and Vermeulen et al. (2012) suggest. Also, climate variability, proxied by environmental indicators, is being utilized in analyzing price fluctuations of specific agricultural products (Brown and Kshirsagar, 2015; Higgins et al., 2015; Salazar et al., 2023). Climate indicators, namely precipitations and temperature, are used as independent variables to analyze conflict insurgence or their impact on macroeconomic indicators (Jaramillo et al., 2023; Koren and Bagozzi, 2016; Schon and Koren, 2022).

However, none of these studies offer a complete view of how the climate crisis affects food prices. This work aims to fill this gap by employing different climate change indicators as explanatory variables, that is, average temperature, average precipitations, rainfall anomalies, and drought events. The current thesis will also contribute to the exploration of the impacts of the climate crisis on specific agricultural products, and to provide insights into possible adaptation and mitigation strategies.

2 Literature Background

Before going further, it is important to define the concept of "food security". According to the World Food Summit (1996): "Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life." Based on this definition, FAO (2008) finds the concept of food security to be a composition of four interrelated dimensions:

- Physical availability of food: it regards the supply of food, and is determined by the level of food production, stock level and net trade;
- Economic and physical access to food: adequate income levels, expenditures and food prices are important factors since they measure the affordability of food;
- Food utilization: it concerns the diversification in nutrients of the food intake, e.g., diversity of the diet, food distribution in families and good feeding practices;
- Stability of the other three dimensions over time: external factors can undermine food security even if the previous three dimensions persist over time, such as extreme weather events, conflicts, or economic factors.

When these conditions are not entirely met, food insecurity could lead to different consequences, such as malnourishment, and hence malnutrition, which is defined as an imbalance, deficiency, or excess in a person's intake of nutrients and/or energy. Undernourishment could be an additional impact of food insecurity, which happens when the habitual consumption of food is not enough to maintain a healthy and active life. Additionally, undernourishment can manifest itself in the form of nutrient deficiency (e.g. minerals and vitamins) taking the name of "hidden hunger" (Mbow et al., 2019). Studies have revealed that hidden hunger can happen in both the presence or not of undernourishment: it tends to be more present in countries where undernourishment levels are high (Muthayya et al., 2013), but it is also frequent in Western-style diets (high content of saturated fats, high amount of processed carbohydrates and excessive total calories) where calcium-deficiency is high (Aslam and Varani, 2016). Undernourishment is also used to build the PoU indicator (prevalence of undernourishment) as a measure of food security by FAO. According to FAO (2023), the PoU remained relatively unchanged from 2021 to 2022, and far above pre-pandemic levels (9.2% of the world population in 2022 versus 7.9% in 2019). This slight change, however, hides the regional and subregional differences: in Africa, Western Asia, and the Caribbeans, the hunger level is still increasing, while in Latin America and Asia, progress was made in terms of hunger reduction (FAO, 2023). The PoU is only one among all the indicators utilized to measure food security. Indeed, a broad range of them exists, and they all have shortcomings, such as the Food Insecurity Experience Scale (FIES). The FIES makes use of surveys to analyze the overall household's inability to access food, but the main shortcoming is that it does not measure if the actual diet is adequate or not concerning all the nutrition aspects (Mbow et al., 2019).

2.1 Global food system trends

During the period 1950-2010, the global food requirement increased from 2300 kcal/cap/day to 2400 kcal/cap/day, leading to an increase in food surplus from 310 kcal/cap/day to 510 kcal/cap/day. Estimates show that the CO2 emissions related to the production of food surplus increased from 130 Mt CO2eq/year to 530 Mt CO2eq/year (Hiç et al., 2016). Even if the calorie intake increased during the last six decades, hunger reduction is far from being met. In 2022, hunger increased from 22.2 to 22.5% (compared to 2021) in sub-Saharan Africa, with the largest increase in Southern Africa (1.1%). The causes of such food insecurity are found to be climate change, conflicts, the COVID-19 pandemic, and the Russia-Ukraine war, which all contributed to increased food prices. Long-term projections, which include both the COVID and the Russia-Ukraine conflict scenarios, estimate that 600 million people globally will be chronically undernourished in 2030, with a significant increase of people affected in Africa by 2030 (FAO, 2023). Food insecurity levels are heterogeneous across countries and regions, but also between urban and rural areas and genders. For example, hunger levels are lower in urban and peri-urban areas: indeed 33.3% of adults living in rural areas are food insecure, compared to 28.8% and 26% of the same group living in peri-urban and urban areas respectively (FAO, 2023). In terms of gender diversity, food insecurity affects women more than men globally. The magnitude of the gender gap on food security levels, however, differs across regions: in Europe, women are 4.7% more likely to experience some form of food insecurity compared to men, while in Sub-Saharan Africa the percentage stands at 2%. The observable drivers of the gender gap impact on food security are found to be household income, social networks, and educational attainments (Broussard, 2019).

2.2 The impact of climate change

The effects of a changing climate on crop yields are still uncertain. Different studies tried to analyze the impact of increasing GHG emissions on a variety of crops, such as maize, rice, and wheat by using statistical models to project future yields. Some of these models are the CERES-Maize (Crop Environment Resource Synthesis), CERES-Wheat, SWAP (Soil – Water – Atmosphere – Plant) and InfoCrop (Aggarwal et al., 2006; Kang et al., 2009). Studies find contrasting results on the impact of increased GHG emissions on crop yields, suggesting that a further understanding of the phenomenon is needed to improve the resilience of the food system (Anwar et al., 2007; Krishnan et al., 2007; Walker and Schulze, 2006; Akpalu et al., 2009; Yao et al., 2007). Climate variability can also affect food prices leading to price hikes that undermine the affordability of meals and staples (as described in section 2.4.4). Thus, poverty increases the risk of food insecurity, as analyzed by Iannotti et al. (2012) in Guatemala where low-income levels are correlated with low quantities of micronutrient intakes (hidden hunger). The impact of climate change extends also to the labor market. Jessoe et al. (2018) observed the variability of local employment due to increasing temperatures in rural Mexico, using a panel of 28 years on local employment. They found that the occurrence of heatwaves reduces the probability of local employment by 1.4% and increases the probability of US migration from 0.05% to 2.5%. Rising climate extremes will expand the dimension of urban poverty, leading also to increased disease transmissions (Rosenzweig et al., 2018; Bartlett, 2012).

2.3 The African context

In Africa, the achievement of the Sustainable Development Goals is far from meeting the desired targets in almost all African states. The reason behind the difficulty in pursuing sustainable development policies and projects is the multi-faceted crisis in which the African Continent is living, from climate change impacts to the scourge of armed conflicts, political instability, and migration. According to the Institute for Economics & Peace (2022), Sub-Saharian Africa hosts five of the ten least peaceful countries in the world (Central African Republic, Democratic Republic of Congo, Somalia, South Sudan, Sudan), and Mali, Burkina Faso, Niger, Nigeria, and Somalia are among the top ten countries most impacted by terrorism (Figure 2). Armed conflicts in Africa have repercussions on the economy and, in turn, on society. In 45 countries from Sub-Saharan Africa, over the period 1989-2019, armed conflicts had negative consequences on the countries' economy, by reducing revenues, increasing military expenses, and worsening the fiscal balance which resulted in higher debt levels. This involves a shift of resources from social to military spending, hampering the development (Fang et al., 2020).

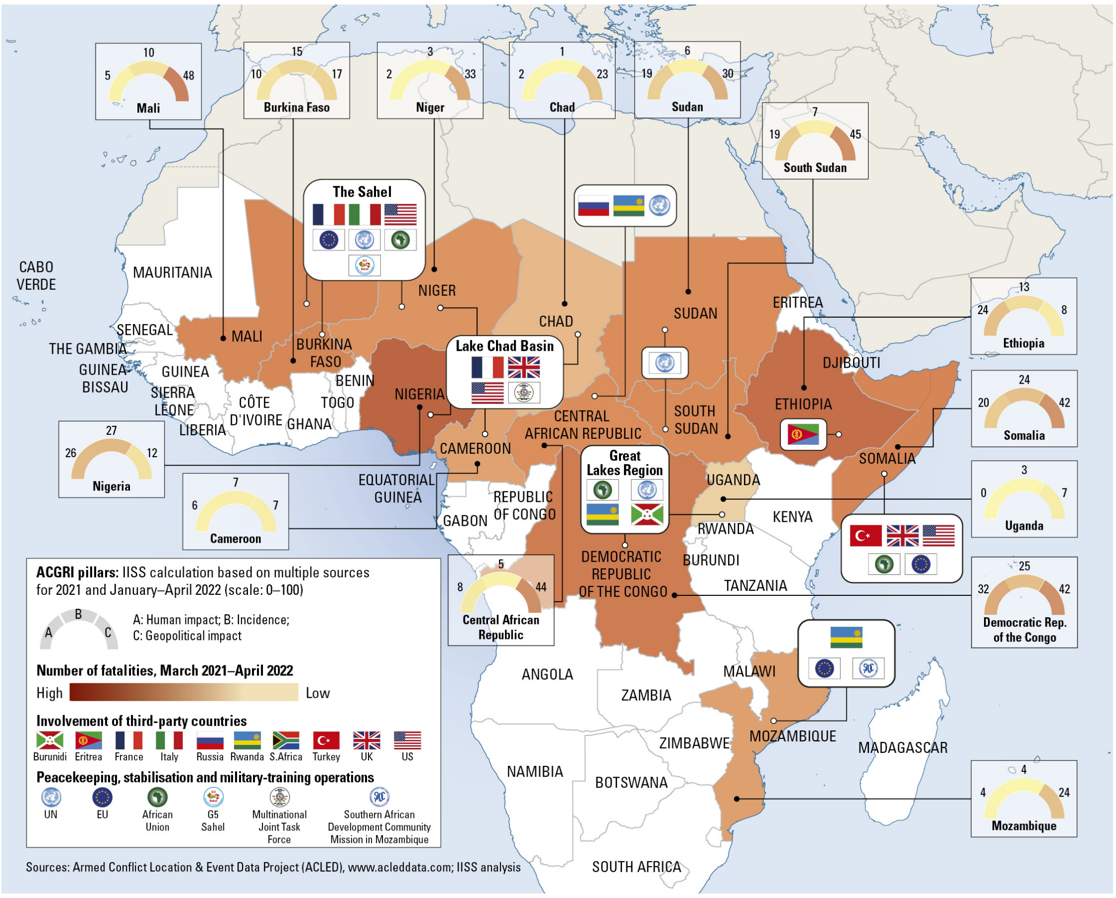


Figure 2: Armed conflicts in Africa in 2022. Source: IISS.

As we can see from Figure 3, the population in refugee settlements mostly corresponds to the countries with ongoing conflicts.

The rising number of conflicts coupled with the worsening of climate extremes, induce migration from the affected countries to neighbors, leading in turn to the scourge of more conflicts. However, the relationship is not linear. Reuveny (2007) argues that conflicts arise if two or more of the following factors are present, facilitated by some auxiliary conditions:

- *Competition*: displaced people arriving in the neighboring country exert pressure over the use of resources which could lead to rising tension levels and,

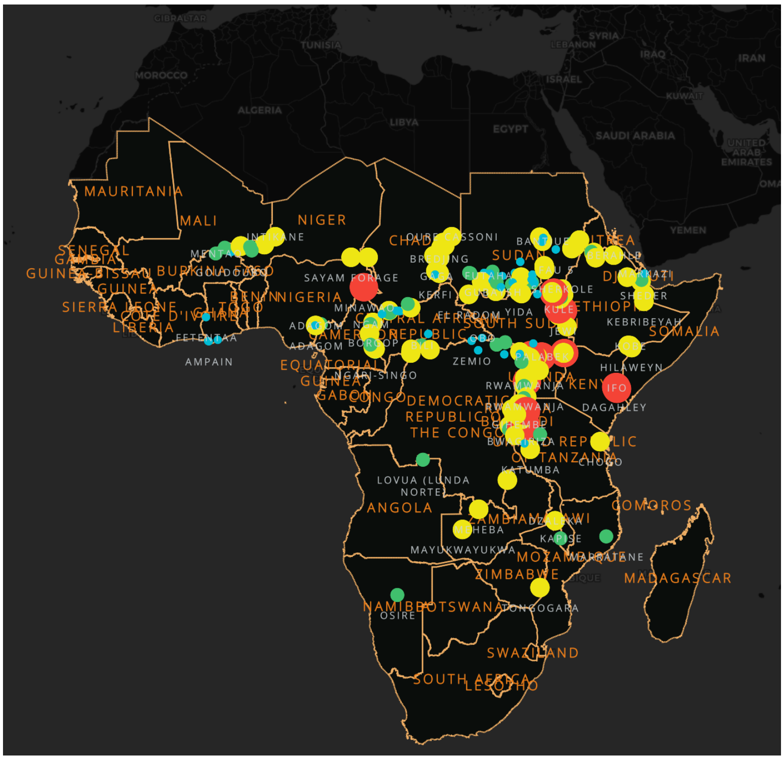


Figure 3: image showing the population in refugee settlements where blue points correspond to population between 250 and 5000 , green points from 5000 to 10'000, yellow from 10'000 to 50'000, and red from 50'000. Source: European Joint Research Center, from Baldi et al. (2022).

finally, to conflicts. Consequently, pressure can also expand beyond the country's borders leading migrants to contest neighboring resources.

- *Ethnic tensions*: it may be the case that migrants and residents belong to different ethnic groups with long-standing ethnic disputes. Residents may feel threatened as migrants try to reunite with their home country, leading to conflict and riots.

- *Distrust*: in this case, the origin country might think that the host country is accepting migrants to alter the ethnic balance of the origin country. On the other side, the receiving country might think that migration is happening intending to penetrate the host country. Displaced people in turn may resent perceived or actual mistreatment from the host.

- *Fault lines*: migrants can create socio-economic fault lines. For example, migrants and residents can start to compete over jobs, or migrant and resident farmers may start to compete over land. Political tensions may arise if rebels provoke frustrated migrants to challenge the host country.

- *Auxiliary conditions*: underdeveloped economies have more difficulty in absorbing migrants in their socio-economic sector compared to developed economies where resources are not scarce and job opportunities are often available for migrants. This aspect can induce political conflicts as environmental migrants may join rebel forces, thus intensifying violence.

Conflicts are not the only distressing events affecting the African states' economic, political, and social stability. Indeed, climate change is a factor that needs to be considered due to its global impact. Specifically, Africa's climate is continuing to experience warming trends. The mean temperature in 1991-2021 increased on average by 0.3°C per decade compared to the +0.2°C in 1961-1990. The highest temperature anomalies were registered in North Africa and West Africa, where temperatures were respectively 1,22°C and 0,91°C higher than the 1981-2010 average. In addition to temperature anomalies, Africa is also experiencing rainfall anomalies across all the states. Below-normal rainfall levels were recorded in North Africa reaching a negative average of -160mm. The rainfall season in West Africa was subject to a delayed onset and an early cessation. In Southern Africa, the rainfall deficit was over 160mm, specifically in central South Africa, western Angola, eastern Namibia, western Botswana, and northern and southern Mozambique. Since 1990, the global mean sea level has risen on average of 3,3 ± 0,4 mm per year, a trend which is accelerating due to ice melt and ocean warming. The highest sea level rise was registered on the coast of the Red Sea, followed by Tanzania and Mozambique coasts (World Meteorological Organization, 2021). The occurrence of these events leads to high food insecurity levels. In East Africa, food insecure people are projected to be 60 million by January 2024 (Figure 4), since households' stocks have been already depleted, staple food prices are abnormally high, and income-generating opportunities remain limited. Moreover, the withdrawal of Russia from the Black Sea Grain Initiative threatens the region, specifically Ethiopia and Somalia which heavily rely on Ukranian wheat imports (World Bank, 2023).

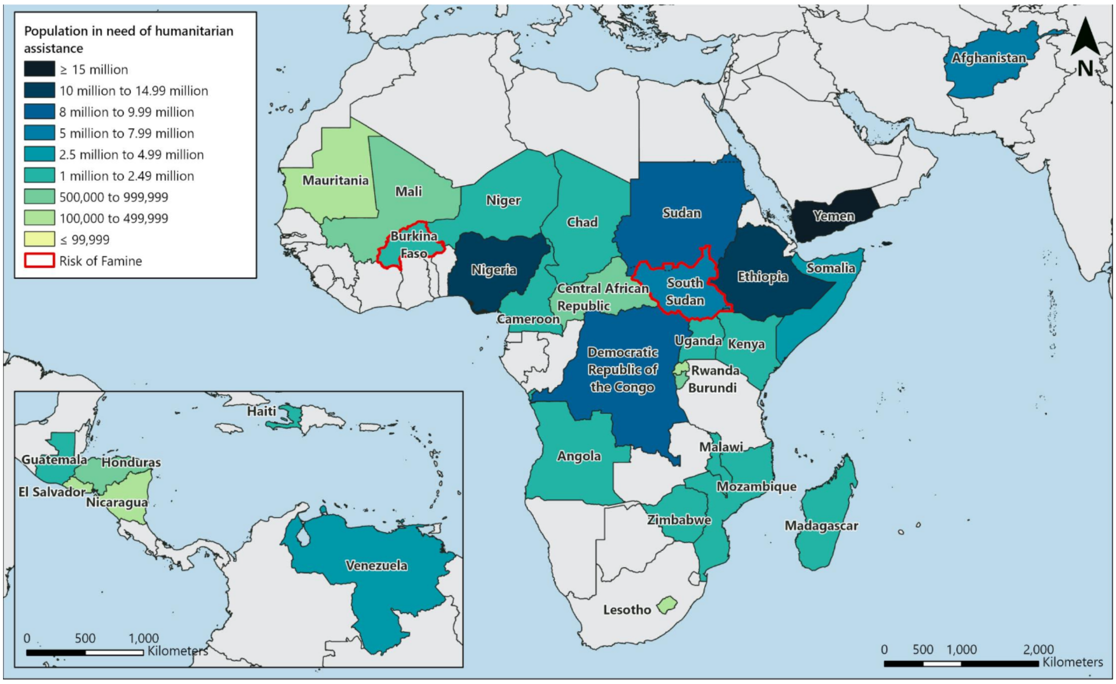


Figure 4: Famine Early Warning System projection of future population in need of food assistance in 2024. Source: FEWS NET.

2.4 The underlying causes of food price volatility

Global food prices are affected by a different number of factors, often interrelated (von Braun and Tadesse, 2012). Drawing on the Okou et al. (2022) classification, these can be grouped into four categories: supply factors, demand factors, exposure to international markets, and adverse events (climate shocks and conflicts). In the following paragraphs, the determinants of these categories are described.

2.4.1 Supply factors

In the developing world, rural areas are mostly inhabited by poor people, who find agriculture their main economic activity. In Africa, agriculture remains the most important sector in many countries, e.g. Chad, where agriculture accounts for almost 50% of the GDP and employs 75% of the population (Oxford Business Group, 2021). In the SSA's agricultural sector, increasing attention is being given to the reduction of post-harvest losses (PHL). There are no precise estimates on the exact amount of PHL since they differ from the type of crop, country-specific characteristics, and climatic factors (Kaminski and Christiaensen, 2014; Stathers et al., 2020). However, food losses limit the capacity of a country to adapt to international price shocks and supply disruption caused by conflicts or extreme weather events (Tadesse et al., 2014). Disruption in the price of intermediate inputs utilized for agricultural activity, such as fertilizers and pesticides, also indirectly affects the final price of food (Schmidhuber et al., 2020). During the COVID-19 pandemic, the increase in the transport costs of pesticides hampered the ability of East African countries to combat the locust outbreak, thus threatening food security[1]. Input and production subsidies can be used as a cushion against input price volatility, by lowering production costs and import demand. Many African countries tried to promote the use and adoption of fertilizers by implementing subsidy schemes gaining, however, scarce results (Morris et al., 2007). As Coady (2004) suggests, the efficacy of targeting intervention in developing countries is effective where economic well-being and inequalities are easier to identify. With that said input and production subsidies, if not well delivered and built, can lead to ineffective outcomes.

Related to the supply side of commodities, another factor that impacts food prices is the level of import dependence of a country. For example, COVID-19 restriction policies had an uneven short-term impact on food prices in low- and middle-income countries (LMICs). In LMICs, the increase in food prices is higher in countries in which the market is integrated and that are more dependent on trade with other markets. Moreover, the highest increase in price regarded the commodities that need to be imported (Dietrich et al., 2022).

Transport and geographical characteristics also affect food prices, by acting on the rural road connectivity, characterized by transport bottlenecks that increase food prices in rural and urban areas, and decrease market access from the rural population (Okou et al., 2022). Gebresilasse (2023) found that road networks increased the value added per worker by 18 percent, and the extension of services increased it by 24 percent. Not only that, but agricultural productivity also increased by 29.4 percent in the 2010-2016 period. The side effect is that the presence of roads increases competition between local farmers and imports of

[1] https://www.bloomberg.com/news/articles/2020-03-22/coronavirus-slowing-desert-locust-response-in-east-africa#xj4y7vzkg

crops and the access to roads changes the farmer's competitive advantage. Access to roads can lead also to a shift out from agricultural activity the area cultivated in villages with only one road decreases by 6 percent since farmers shift out from agriculture. In contrast, in villages with both roads and access to road extensions, the area cultivated increased by 4 percent due to increased specialization and engagement of farmers in agricultural activity. In addition, the construction of road infrastructure is found to influence the adoption of modern and improved agricultural inputs, the diversification of crop cultivars, the level of labour hiring, and the commercialization of farm output (Shamdasani, 2021).

Rural road connectivity and geographical characteristics play a key role in affecting food prices, thus determining market integration. To test market integration, price differentials (and then their convergence) between markets are calculated (Brenton et al., 2014; Ravallion, 1986). In the era of climate change, spatial food price transmission is being object of empirical investigations to understand how climatic shocks affect the price differential between markets. Salazar et al. (2023) analyzed how the price differential of long-shelf tomatoes and Asterix potatoes in Chile respond to drought shocks, by using the Standardized Precipitation Evapotranspiration Index (SPEI) (see Vicente-Serrano et al. (2010)). It is found that drought shocks reduce the price differentials of these two commodities, thus implying the presence of market integration. On one hand, the results cannot be generalized, while on the other hand, they offer an insight into price transmission under climatic stress. Market integration, though, has a limitation, that is, the informal trade happening between countries, as in Uganda where informal exports to its five neighbouring countries accounted for USD 231.7 million in 2006 (Lesser and Moisé-Leeman, 2009).

2.4.2 Demand factors

Overall, food demand is expected to increase from 35% to 56% in 2010-2050 (Van Dijk et al., 2021). At the core of this phenomenon, two important factors drive the demand for food upward: population growth and changes in food consumption choices. Population growth is expected to rise to 9.1 billion in 2050, and most of this growth will happen in developing countries, such as sub-Saharan Africa (+114%) and East and Southeast Asia (+13%). Estimates indicate that to be able to feed 9 billion people, food production should increase by 70 percent worldwide. For example, annual cereal production should increase by 1 billion tonnes; meat production should reach 470 million tonnes in 2050, by which 70 percent is produced by developing countries (FAO, 2009). The shift in food consumption choices also exerts an impact on the production of food and food prices, mainly determined by the rising level of income per capita. For example, China's economic growth, and per capita income growth, led to a shift in animal-based products, which will in turn increase the agricultural output needed to satisfy that demand in the future (Fukase and Martin, 2016). In Africa, the income elasticity of demand is higher for meats, fish, eggs, dairy, and beverages compared to staple foods like cereals, legumes, nuts, fruit, vegetables, tubers, fats, and oils (European Commission. Joint Research Centre., 2015), which means that the quantity of these categories of food increase as the income rises.

2.4.3 Market factors

Okou et al. (2022) analyzed cross-country differences, in terms of the quality of monetary and fiscal policies, debt-to-GDP ratio, and per capita income, finding different scales of impact on staple food prices. Monetary policy's quality, measured with the Independence, Accountability, Policy and Operational, Strategy and Communication (IAPOC) index, positively influences food prices, indicating that central banks can combat general inflation by increasing the quality of monetary policy interventions. However, commodity price shock responses should adapt to the countries' specific economic structure (De Gregorio, 2012). Also, an increase in the debt-to-GDP ratio increases food prices by 0.1 percent suggesting a weak fiscal management that could weaken the local currency. In terms of per capita income, an increase of one percent is associated with a decrease of 1.2 percent in food prices, a result in line with Engel's Law. Tadesse et al. (2014) analyzed the drivers of food price spikes in the timespan 1989-2009 finding that excessive speculative activity exerts a positive and significative impact on price spikes. Moreover, USDA supply forecasts influence prices through production expectations, and oil price spikes also impact positively prices through demand, supply channels, and increased index-fund activities. The one-way relationship between oil prices and agricultural commodity prices is often explored by observers (Dancy, 2012; Westhoff, 2012). Also in the literature, some studies explore the positive correlation existing between oil prices and food prices, suggesting that an increase in oil prices leads to an increase in the demand for agricultural inputs needed for biofuel production, thus increasing corn price (Esmaeili and Shokoohi, 2011; Taghizadeh-Hesary et al., 2019; Von Braun and Pachauri, 2006). One concern is that causality could run even in the opposite direction (from food to oil). An example is given by China's agricultural expansion which led to a higher demand for agricultural machinery, which pushed oil prices upward, invalidating the one-way relationship (Baumeister and Kilian, 2014). Another example comes from the U.S. market where oil and biofuel price shocks are found not to influence the corn price. On the opposite, corn price shocks seem to impact the short-run production costs of ethanol (Gardebroek and Hernandez, 2013). The exposure to the international food market could stabilize domestic food prices, and act as an insurance against domestic price shocks. Bradford et al. (2022) utilize the efficient risk-sharing hypothesis to analyze how much trade can insulate domestic consumption against domestic output shocks. They examined three commodity markets (maize, wheat, and rice) and found that the maize market performs as poorly as the rice market in providing insurance against domestic shocks. Instead, the wheat market performed efficiently as they expected. The reason behind the poor performance of the rice and maize markets can be that these markets have a high level of product differentiation, which leads to less protection from domestic shocks.

2.4.4 Adverse events: climate shocks and conflicts

The existent literature on the economic effects of climate shocks on food prices is relatively recent, which may reflect the urgent need to tackle food insecurity and adaptation/mitigation efforts in the agri-food sector towards climate change. However, the effects of climate change on agricultural productivity, and thus food security, are still unclear. World food supply simulations show that increased CO2 levels will impact developing countries more than developed countries. Precisely, results show that the increase in carbon dioxide levels would increase cereal production in developed countries while decreasing it in developing countries (Rosenzweig and Parry, 1994). The countries in which crop production is expected to decline are the same experiencing food scarcity and hunger problems (Wheeler, 2013). In line with Wheeler (2013), Shi and Tao (2014) found that an increase of 1°C in the global temperature in the period of 1961-2010 decreased maize yields by more than 10% in 8 African countries and 5 to 10% in 10 countries. A study by Kabundi et al. (2022) analyzed the impact of climate shocks (precipitations and temperature shocks) on food inflation over a wide variety of countries, utilizing local projection methods. Their sample is composed of 183 countries from 1970 to 2018 and the precipitation shocks considered are storms, floods, and droughts. They classified extreme weather events into two categories, moderate and severe, by using a disaster intensity dummy built by Becker and Mauro (2006). The authors categorized countries according to the classification proposed by the IMF in the World Economic Outlook, that is: advanced economies (AE), emerging markets (EM), and low-income and developing countries (LIDC), and by inflation targeting (IT) and non-inflation targeting (non-IT) countries (Fratzscher et al., 2020). They found that the impact of climate shocks on inflation is heterogeneous between countries, and it depends on the type of weather event, the country's economy, and the monetary regime. As a matter of fact, for AE countries, the impact of weather shocks on inflation seems to be statistically insignificant in the first year, while in the second year, it tends to decline. For EM countries, temperature shocks have a short-term impact on inflation while precipitation shocks have a persistent deflationary impact. In LIDCs, instead, the impact of temperature shocks is muted, while it is positive for negative precipitation shocks. Moreover, IT countries respond better to food inflation than non-IT countries.

From a different perspective to the previous study, climate shocks are found to impact macroeconomic outcomes in Fragile and Conflict-affected States (FCS) and non-FCS. Econometric analyses show that environmental disasters would lower cumulative GDP up to 4 percent three years after the event, and only 1 percent in non-FCS. The negative effect of droughts on GDP in the long term will act through lower crop productivity, lower food production, and decreased investments (Jaramillo et al., 2023). With regard to droughts, Schaub and Finger (2020) analyzed the impact of severe drought events on hay, feed wheat, and barley prices in two South German states. The SPEI was used as a proxy for extreme drought, and the results show that hay prices increased by 15% from month 3 to month 14 after the shock. Feed wheat and barley, instead, were not influenced by high-temperature shocks, whether the shock was regional or national. In addition to these studies, ENSO-induced climate variability is found to influence the variation of international wheat prices in Argentina, Australia, Europe and United States (Ubilava, 2017).

A novel approach to better understand the impact of climate variability on agriculture is by using satellite imagery coupled with weather and environmental indicators (usually temperature, and precipitation). A branch of literature focuses on using the Normalized Difference Vegetation Index (NDVI), which measures the greenness of a patch of land by capturing the light absorbed and reflected by leaves[2]. The index is calculated from the data obtained by the Advanced Very High Resolution Radiometer (AVHRR) which is composed of five detectors sensible to the visible and near-infrared regions of the spectrum. The NDVI is then defined by the current formula:

$$NDVI = \frac{NIR - VIS}{NIR + VIS}$$

Where NIR and VIS are the reflectances in the near-infrared spectrum (0.725

[2]https://earthobservatory.nasa.gov/features/MeasuringVegetation/measuring_vegetation_2.php

µm to 1.1 µm) and in the visible spectrum (0.58 µm to 0.68 µm) respectively. The chlorophyll density determines the degree of absorption of chlorophyll in the NIR, and the reflectance in the VIS region emitted by green leaf density both define the NDVI (Davenport and Nicholson, 1993; Tucker et al., 1985). The index can take values between -1 and +1, where negative (positive) values are associated with low (high) greenness levels. The NDVI can provide information on climate variability because of its relationship to different indicators such as CO2 emissions (Tucker et al., 1986) and rainfall (Davenport and Nicholson, 1993). Moreover, it can provide information on different scopes such as the temporal and spatial mapping of diverse types of grasslands (Reed et al., 1994) and the level of land degradation (Holm et al., 2003; Thiam, 2003), to improve crop yield predictions given its early explanatory power (K. R. Manjunath and Purohit, 2002; Wall et al., 2008), but also to improve the analysis of weather shocks and disasters on vegetation such as droughts (Ramesh P. Singh and Kogan, 2003), risks of fire (Maselli et al., 2003), the occurrence of frost (Tait and Zheng, 2003) and floods (Wang et al., 2003). NDVI measures, however, possess some shortcomings, such as: mixed pixels (a pixel encompassing both water and land), misregistration of the image taken from the satellite, comparison between NDVI pixels with no knowledge of the area of interest, cloud coverage in specific spatial locations (e.g. humid tropics) (Pettorelli et al., 2005).

Given its relevance in remote sensing for environmental studies, the NDVI is recently being used in agricultural economics as a proxy of weather variability to assess the relationship between climate change and crop yields and to assess food security levels. Brown and Kshirsagar (2015) observed the short-run impact of local weather disturbances on monthly domestic food prices in the period of

2008-2012 using NDVI anomalies as a proxy for weather disturbances. Analyzing data from 554 local commodity markets in 51 countries, they found that 19 percent of them were affected by local weather disturbances, 9 percent by international prices, and 4 percent by both previous factors. Specifically, 29 percent of the 160 markets analyzed for maize are influenced by local weather shocks (and international prices), while 15 percent of the 114 markets for rice are impacted by domestic climate shocks. Regarding rice, a striking result is that most of the markets impacted by climate change are the ones in which rice is locally cultivated. The observed relationship between NDVI anomalies and food prices is inverse, indicating the importance of precipitations in countries where crops are principally rainfed. Specifically, negative large NDVI anomalies were followed by food price shocks. Higgins et al. (2015) used NDVI data to improve millet price forecasts using monthly price data from 162 local markets during the 1992-2008 period in three African countries: Burkina Faso, Nigeria, and Mali. Findings indicate that using remote sensing data reduces forecast errors by up to 2 percent. However, the explanatory power of NDVI is low concerning millet, possibly highlighting specific commodity characteristics that interact with the environment. NDVI data was also used, coupled with maize price data, to explore the relationship between food prices and low birth weight in Kenya. The results suggest that a decrease in NDVI is associated with negative infant health outcomes. Instead, an increase in NDVI values is associated with better nutrition levels in the presence of low prices (Grace et al., 2014). Brown et al. (2012)also utilized NDVI information with local price information to build food price indices that can improve food security assessments and the delivery of humanitarian aid, differently from the FAO cereals index which only considers countries integrated with international markets. Furthermore, Jaramillo et al. (2023) mapped irrigated and rainfed agricultural lands by using NDVI-derived images to assess climate change's impact on these two different types of cultivations. The results highlight a higher vulnerability level of rainfed agricultural fields compared to irrigated lands due to their less reliance on weather patterns. Coupled with extreme weather events, conflicts negatively impact food security and societal well-being. The findings related to the effects of wars on food security and food prices are mixed, highlighting the difficulty in disentangling the multiple, and often highly localized, aspects of complex crises affecting each country (Buhaug et al., 2015). Indeed, the effects of wars on agriculture depend on the scale and the nature of the conflict, and also if the conflict is localized enough to contain the decline in production (Flores, 2004). It is found that wars exert a negative effect on food prices, more than natural disasters, by increasing staple food price level up to 4 percent (Okou et al., 2022). Conflicts have an indirect effect on food availability, and thus food prices, by wrecking irrigation schemes and displacing farmers to other places, leaving the cultivated area more vulnerable to climate shocks (Jaramillo et al., 2023). Raleigh et al. (2015) investigated the relationship between conflicts, climate variability, and food prices by using data from 113 first-level administrative unit markets from 24 African states. Their findings suggest that high conflict rates are expected in places where food prices are high and in turn violence raises the price of commodities. Additionally, unexpected dry conditions increase the frequency of conflicts, and low rainfall levels negatively affect food prices and indirectly influence the scourge of conflicts. These results can be complemented by the study of Koren and Bagozzi (2016) who found that low per capita food levels and warmer temperatures (with low precipitation levels) increase the probability of experiencing conflicts.

3 Data and Methods

The objective of the work is to explore the relationship between climate variability and retail food prices in local African markets. To proceed with the analysis, food price data were downloaded from the World Food Program (WFP)[3] database, which provides information about economic and climatic factors to complement food security analyses. Price data from WFP is collected through various methods, such as face-to-face interviews, remote calls, crowdsourcing (spontaneous contribution), and web-scraping (to find and extract price data on the web). The selection of markets to monitor is typically done by answering two major questions: how important is the market to the targeted population, and how important is the market as a hub in the domestic market system (Caccavale and Flämig, 2017).

Climate information was gathered from the AfroGrid dataset[4] (see Schon and Koren (2022)) which provides information for researchers and policymakers about climate variables (NDVI, temperature, and precipitations), conflicts and casualties, and socio-economic factors (population and nighttime light emission) from 1989 to 2020. The data is integrated into 0.5 x 0.5 resolution grid cells which correspond to 60 kM x 60 kM geographic squares at the equator and a decreasing size moving toward the poles. It is possible to integrate own data exploiting square centroid coordinates, country IDs, and correlates of war.

In addition, information about climate shocks events was downloaded from the Emergency Events Database (EM-DAT) created from a joint initiative between the Centre for Research on the Epidemiology of Disasters (CRED) of the University

[3]https://dataviz.vam.wfp.org/version2/economic/prices
[4]https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LDI5TK

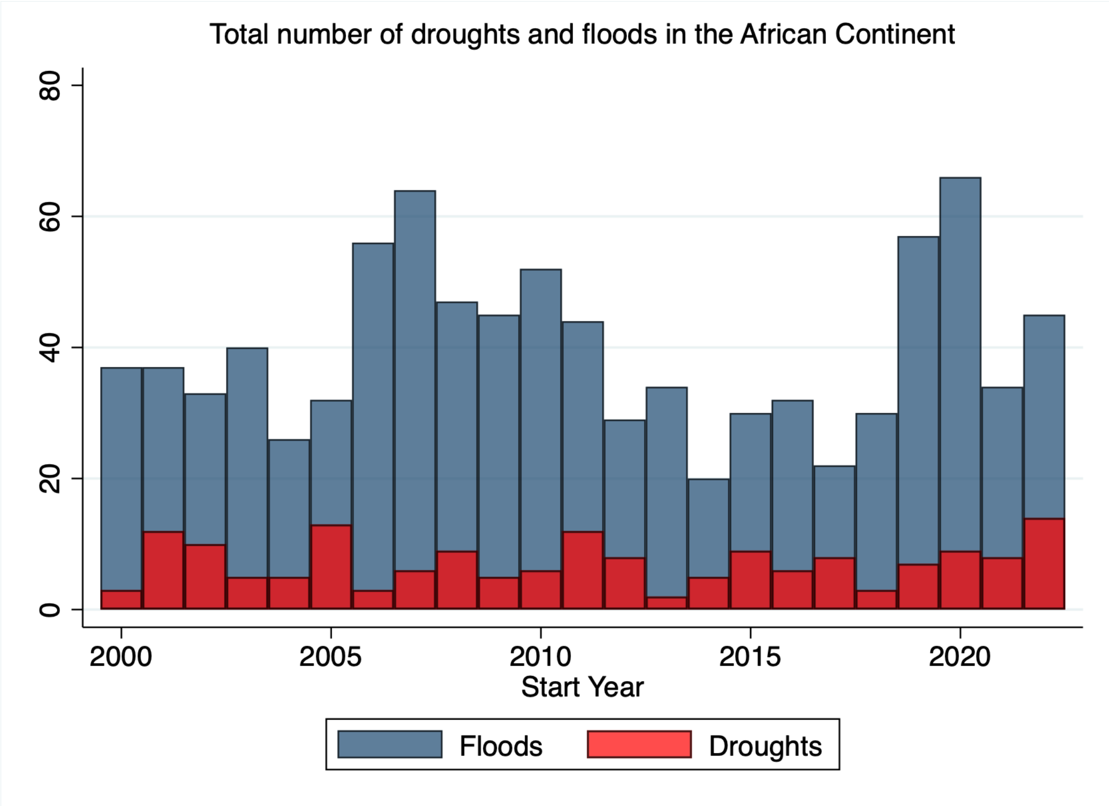


Figure 5: Bar graph showing the number of droughts and floods in the African continent from 2000 to 2022. Personal elaboration.

of Louvaine, and the World Health Organization (WHO)[5]. The database reports the happening of disasters, divided by Natural and Technological. The disasters considered for the analysis are droughts and floods. A first look at the data can start to tell something about the impact of climate extremes on society. Figure 5 below shows the occurrence of droughts and floods from 2000 to 2022.

[5]https://www.emdat.be

It can be observed that the number of flood events is higher compared to droughts. But the impact scale is different: flooding events tend to be more localized in coastal regions, river basins, and lakes, while droughts tend to cover a wider area of land. This phenomenon can be observed in Figure 6 which displays the total number of people affected by the two climate extremes. It is clear from the graph

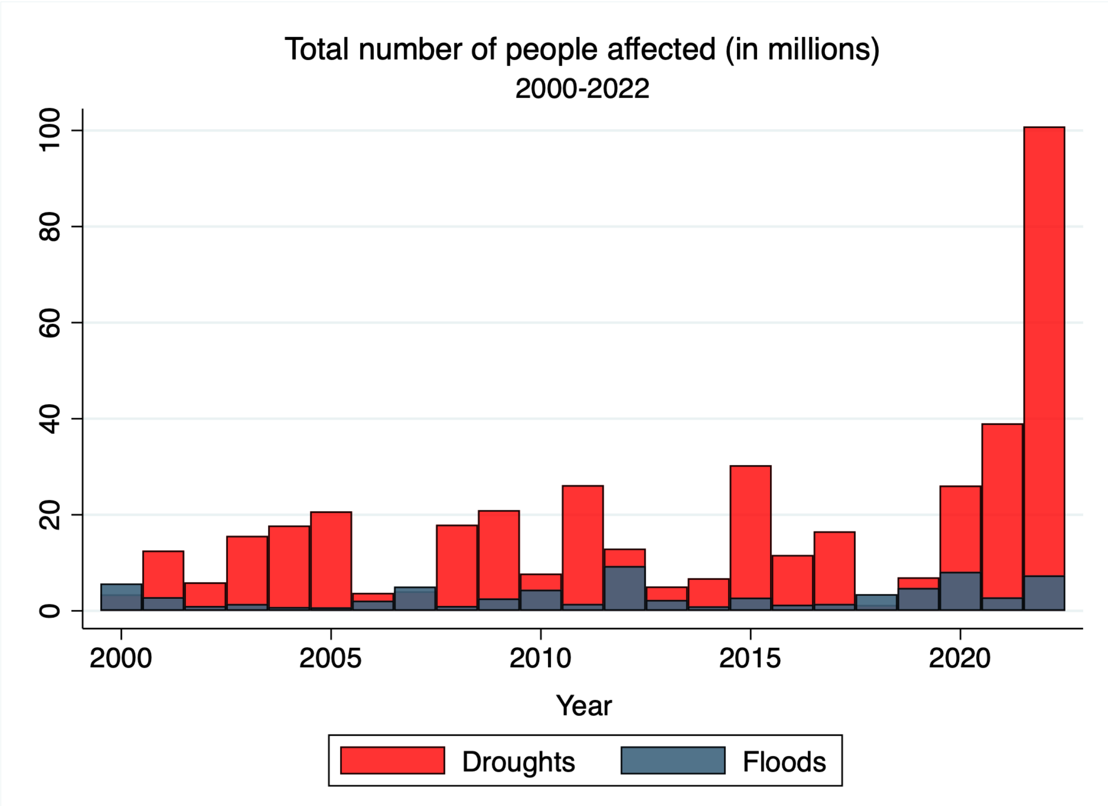


Figure 6: Bar graph showing the total number of people affected (in millions). Personal elaboration.

that droughts tend to affect a higher number of people relative to floods. Moving to the data management process, the price information dataset was analyzed to inspect for missing data and irrelevant information. To overcome the problem of missing information, price data regarding a common commodity were aggregated, e.g., all the prices for small-shelled and large-shelled groundnuts were merged into the general category of "Groundnuts". Food products having a high frequency of missing data were dropped out of the analysis, along with all non-commodity price information. The next step was to convert price information into a common currency: the international dollar. The conversion was carried out by using Purchasing Power Parity (PPP) implied conversion rates downloaded from the World Bank database[6] and then dividing commodity prices by the rate. The rationale behind the use of PPP conversion rates rather than market exchange rates is that PPP measures the quantity of foreign currency needed to buy the same amount of goods in the analyzed country. PPP rates are collected and calculated by the International Comparison Program (ICP) by issuing surveys to countries to collect price information (ICP, 2013). Surveys, however, are issued in different reference periods, leading to one of the biggest drawbacks of PPP: since data is available only in specific time intervals, missing data must be estimated, which can lead to inaccuracies[7]. Previous ICP rounds were carried out in 2005, 2011 and 2017. The data in between rounds is interpolated. Indeed, the PPP conversion rate used for the transformation is estimated.

In parallel with this process, the AfroGrid dataset was cleaned of unnecessary information, keeping only climatic variables, that is average temperature, average precipitation, temperature and precipitation anomalies, the Standardized Precipitation Evapotranspiration Index (SPEI), average NDVI levels, minimum and maxim NDVI, and the sum of nighttime light data. The dataset was cleaned of not available NDVI information since, in some grids, the presence of water cannot be used to calculate the index. After, mean, maximum, and minimum val-

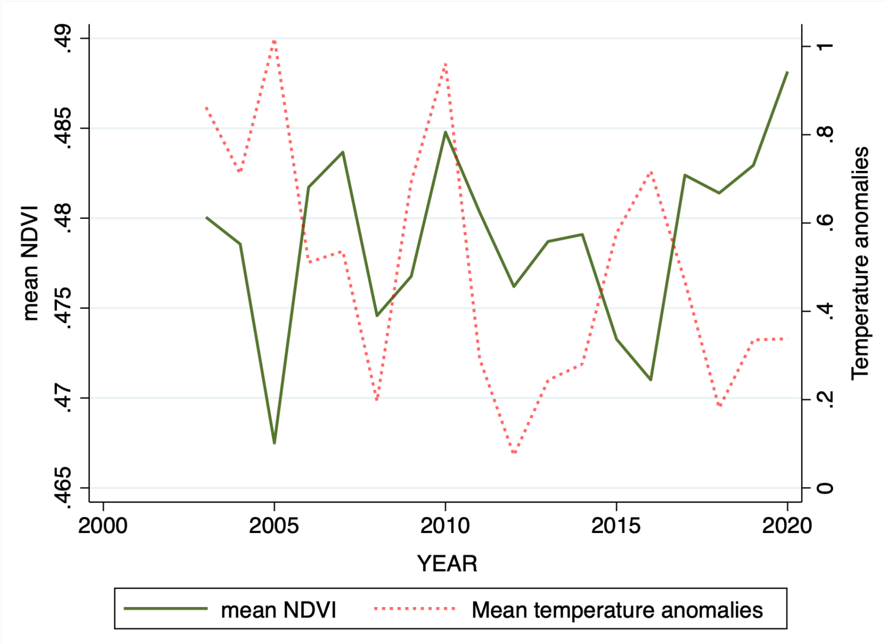
[6]https://databank.worldbank.org/source/world-development-indicators

[7]https://www.imf.org/en/Publications/fandd/issues/Series/Back-to-Basics/Purchasing-Power-Parity-PPP

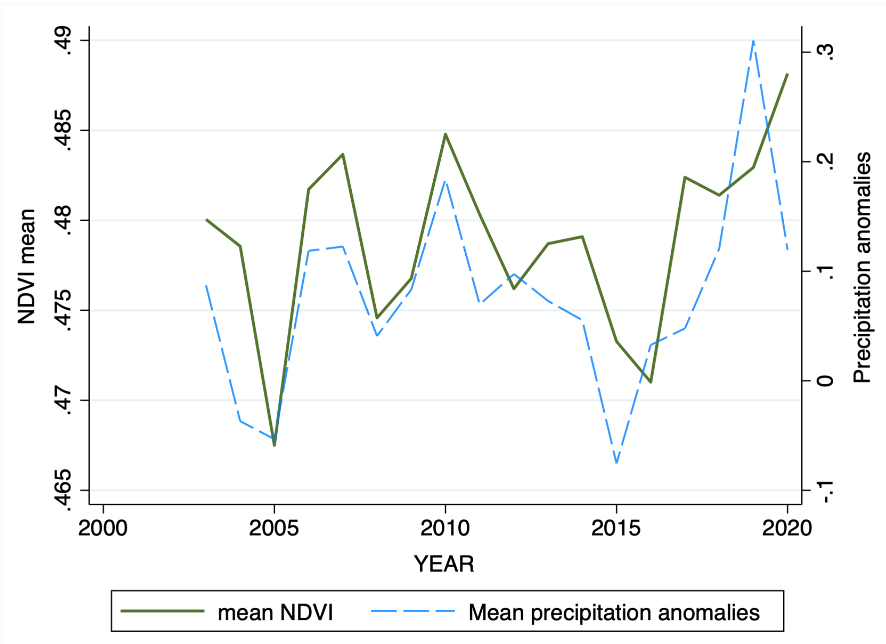
ues of NDVI were extracted from the dataset, and also temperature and rainfall anomalies. The trend of climate anomalies and NDVI values is explored in the plots below, which suggest an intuitive relationship between the variables. Such a relationship, indeed, is confirmed in the literature and exploited, for example, to improve the analysis of the impacts of massive-scale events, such as the El-Niño Southern Oscillation (ENSO)(Anyamba and Eastman, 1996). Graph a shows that positive temperature anomalies and negative precipitation anomalies are followed by negative NDVI values, specifically during 2005, 2016, and 2017. This means that a lack of rainfall and an increase in temperature leads to a decrease in vegetation levels. The inverse can be observed graph b in which increasing rainfall and decreasing temperature anomalies lead to higher NDVI values.

After preparing both price data and the AfroGrid dataset, each market location in terms of latitude and longitude was found using Python. Coordinate research was characterized by a low degree of error since some markets were located in unnamed areas or cities with the same name as other locations, leading Python to assign a wrong coordinate. Therefore, a few market coordinates needed a manual correction. The next step of the creation of the dataset was to merge the market coordinates dataset with the price information dataset on STATA, and then merge it with the AfroGrid information. Table 1 shows the structure of the merged datasets.

Successively, retail price data relative to the selected commodities was analyzed to see the frequency of missing data. Since price information is heterogeneous in terms of years, it was important to choose a starting year for the analysis. By an-



(a)



(b)

Figure 7: Line plots showing the trend of average NDVI values against average temperature and precipitation anomalies in the period 2003-2020. Personal elaboration.

DATASET STRUCTURE					
VARIABLES	OBSERVATIONS	Unique values	Mean	Min	Max
Country	376'733	31	.	.	.
Administrative Units	376'733	303	.	.	.
Markets	376'733	1088	.	.	.
Price (in PPP)	276'400	97'663	62.56097	0.0017524	20034.44
Average total precipitations	369'837	4575	1038.376	11.6	3155.65
Average temperature	369'837	5167	24.06258	4.85	37.34
Rainfall anomalies (maximum)	337'903	4982	.1952666	-3.6	5.03
Commodities	376'733	103	.	.	.
Sum of nighttime lights	369'837	4468	8414.886	0	52060

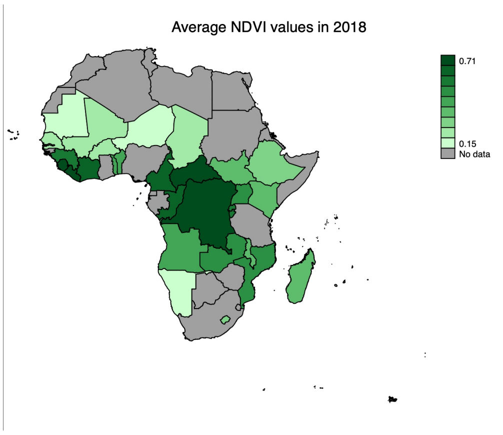
Table 1: The table shows the structure of the dataset in STATA using the `codebook` command.

alyzing missing prices per country, it was possible to discard the countries where there was no observation. Ultimately, after leaving out from the sample Algeria, Eritrea, Eswatini, Nigeria, United Republic of Tanzania, Zimbabwe, Guinea-Bissau, and Gabon, the sample resulted in 31 countries starting from 2012 to 2018. The choice of keeping the timespan up to 2018 is motivated by the presence of global shocks that could distort the analysis (the COVID-19 pandemic and the Russia-Ukraine war). Table 2 shows the top 10 countries from the sample with the highest prices in logarithm. Sierra Leone and Liberia are the two countries whose values are far higher than other countries. The reasons might be that both countries are characterized by a very hot and very wet climate, making them highly subject to floods, heavy rains, droughts, coastal erosion, and landslides which negatively impact the population (Ishizawa et al., 2020; The World Bank Group, 2021). Regarding Sierra Leone, the high price levels can be explained by the price-setting behavior of entrepreneurs who tend to adjust their prices in response to

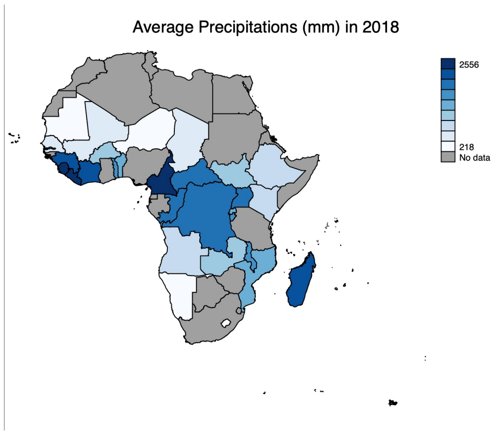
COUNTRIES	PRICES IN LOG
Sierra Leone	7.616809
Liberia	7.450596
Ethiopia	1.776684
South Sudan	1.608364
Lesotho	1.606025
Angola	1.542138
Madagascar	0.9833402
Congo	0.8726164
Mauritania	0.7656989
Gambia	0.7652534
Guinea	0.707812

Table 2: Ranking of the top 10 African countries with the highest prices.

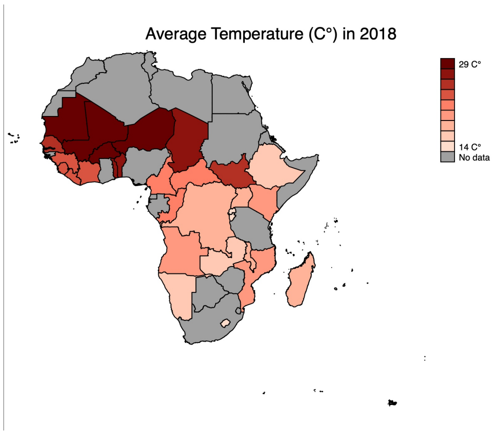
specific events (Kovanen, 2007). Figure 8 show the average NDVI, temperature, and precipitation values in 2018 for the final sample. It is possible to observe in (a) that high average NDVI values are registered in countries where average precipitation levels are higher, thus indicating a high presence of vegetation. Contrarily, high average temperature levels (c) are registered in the Saharan-Sahelian desert regions. The maps also show an important factor that needs to be accounted for in the analysis, that is, geographical characteristics. As explained before (with Sierra Leone and Liberia) each country is peculiar in terms of biodiversity, natural capital, and morphological characteristics, which imply different land use for agriculture and crops cultivated. In this context, each country experiences climatic events differently from others, and that could have an impact on local agriculture.



(a)



(b)



(c)

Figure 8: Maps showing environmental data for 31 countries in 2018. Personal elaboration on STATA using `grmap` command

A first exploration of the relationship between food prices and climatic factors (precipitations, temperature, and NDVI) can be made by plotting price data with average rainfall levels, average registered temperature, and average NDVI. Plot a shows how a drop in NDVI in 2015 was followed by an increase in prices up to 2017, while NDVI values were increasing. A comparison with plot b shows also the increase in precipitation levels in the same year, confirming the established relationship between vegetation greenness and rainfall. In plot b, it can be seen how a drop in average yearly precipitations corresponds to an increase in prices. Plot c show the trend of temperature with price. It is interesting to note that a temperature increase goes hand-in-hand with a price increase, and an initial reduction in average temperature is also associated with a decrease in prices. By comparing the second and third graphs, we can see the inverse trend between average temperature and rainfall: increasing temperature corresponds to decreasing precipitations. However, the relationship cannot be only assessed by the plots, and further investigation is needed to explore the interconnection.

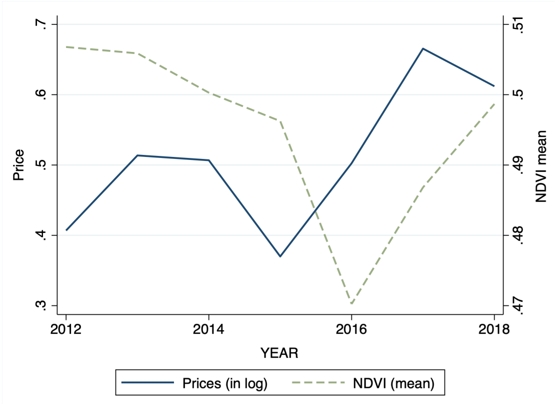
Since the aim of the work is to explore the potential relationship between climate variability and food prices, the econometric model selected for this end is a fixed effect model with dummy variables. This particular technique allows researchers to make conditional inferences, that is, to draw conclusions on the population parameters that are the object of study, and to not generalize as in random-effects models (Hedges and Vevea, 1998). The sample object of study is non-random, so the appropriate model is the fixed-effect. A model with fixed effects assumes that there are unobserved and time-invariant characteristics that can lead to the "omitted variable bias", which undermines the reliability of estimations. To account for the unobserved characteristics, two mathematical methods are available: time de-meaning and inclusion of dummy variables. The first method eliminates the unobserved time-fixed effect by differentiating the mean of the variables on both sides of the equation. Since the unknown parameter is time-fixed, its mean is equal to its value, thus it gets eliminated from the equation. The second method makes use of the inclusion of dummy variables to "absorb" the unobserved parameter. Both methods yield the same estimation of the beta coefficient. One characteristic of the dummy variable model is that its R^2 tends to be higher with respect to the de-meaned model because of the inclusion of additional variables. The classical fixed effect model is described as follows:

$$Y_{it} = \beta_1\ x_{it1} + \beta_2\ x_{it2} + \ldots + \beta_k\ x_{itk} + \alpha_i + \varepsilon_{it} \tag{1}$$

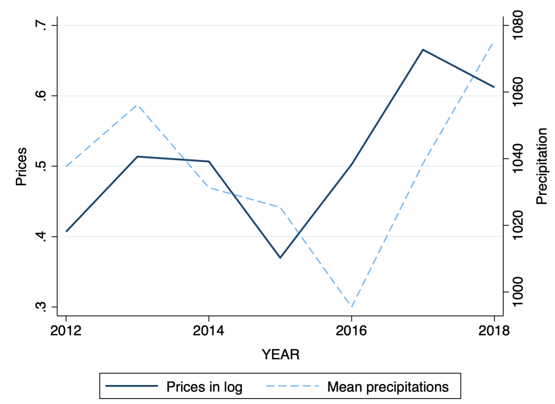
Where:

- Y_{it}: is the dependent variable (of individual i at time t);
- x_{itk}:are the independent variables of individual i at time tt for the *k-th* observation;
- β_k: are the coefficients of the independent variables;
- α_i: is the unobserved time-fixed error term;
- $\varepsilon_i t$: is the error term for individual i at time t.

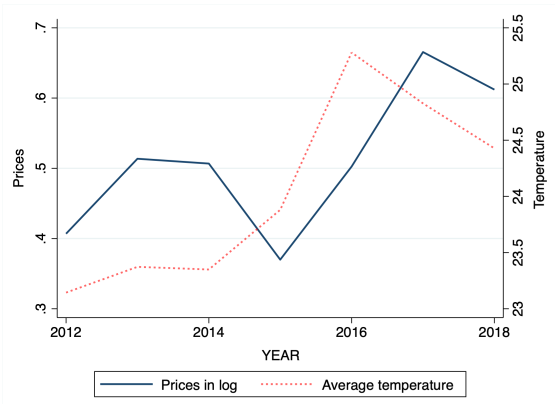
With respect to the analysis to carry out, the dummy variable method was chosen to account for α_i because the inclusion of dichotomic variables allows to explicitly capture the unobserved heterogeneity of α_i.



(a)



(b)



(c)

Figure 9: Line plots showing the time trend between environmental variables and prices during the period 2012-2018. Personal elaboration.

The fixed effect model with dummy variables is then described as follows:

$$Y_{it} = \beta_1\ x_{it1} + \beta_2\ x_{it2} + \ldots + \beta_k\ x_{itk} + d_{it1}\mu_i + \ldots + d_{itk}\mu_i + \varepsilon_{it} \quad (2)$$

Where d_{itk} corresponds to the dichotomic variables which take a value equal to 1 if a specific condition is satisfied, and 0 otherwise.

Two models were constructed to explore the relationship between climate variability and prices, and different independent variables were selected: the first model uses average yearly precipitations and average yearly temperature; and the second one with dummy variables that take into account climate anomalies, droughts, and precipitation anomalies. A question that might arise is why not measure floods instead of rainfall anomalies. The answer is based on what was said in the previous paragraphs of this section: floods tend to be more localized in specific areas, and rainfall anomalies allow us to broaden the scope to the different countries of the sample. Finally, the sum of nighttime light emissions is added to the model to account for distance to markets, road density, and socio-economic development. What follows is the description of how the independent variables are calculated in the original dataset (Schon and Koren, 2022) and by personal elaboration:

1. Average NDVI: this variable is the average monthly NDVI value across all 0.08° pixels within a given cell. The values are obtained from the MODIStsp R package;

2. Average temperature: is the average monthly registered temperature across all 0.08° pixels within a given cell, from the CRU Time Series dataset (Harris et al., 2020);

3. Average precipitation: is the average monthly registered rainfall across all 0.08° pixels within a given cell, obtained from Harris et al. (2020);

4. Rainfall anomaly dummy: is the Z-scored deviation from the mean of the 30-year rolling precipitation average for all 0.08° pixels within a given cell, from Harris et al. (2020). The dummy variable is equal to 1 when the deviation is positive.

5. Drought event dummy: is a dummy variable that takes a value equal to 1 when a drought event happened in the 2012-2018 period. The data about climate extremes is obtained from the EM-DAT dataset.

All the variables that are not dichotomic are transformed in natural logarithm to normalize the distribution. As explained before, the NDVI can take a negative value up to -1, and the natural log of a negative number is undefined in the real number set. In this case, the average NDVI values in the dataset are all positive, so the transformation can be carried out.

The resulting models take the following form:

$$logPrice_{ict} = \beta_1 logNDVI_{it} + \beta_2 logC^{\circ}_{it} + \beta_3 logPrecip_{it} + \beta_4 logNL_{it} + \delta_c + \gamma_i + \theta_t + \varepsilon_{it} \tag{3}$$

Where:

- *Price*: is the logged price of commodity c in market i at time t;
- *NDVI*: are the logged average monthly NDVI values for market i at time t;
- C°_{it}: is the logged average monthly temperature for market i at time t;

- NL: is the logged sum of nighttime light emissions;
- δ_c: is a commodity-specific dummy variable for commodity c;
- γ_i: is a market-specific dummy variable;
- θ_t: is a monthly dummy;
- ε_{it}: is the error term for market i at time t.

The second model, instead, differs from the first one for the independent variables:

$$logPrice_{ict} = \beta_1 logNDVI_{it} + \beta_2 drought_{it} + \beta_3 RH_{it} + \beta_4 logNL_{it} + \delta_c + \gamma_i + \theta_t + \varepsilon_{it} \quad (4)$$

Where *drought* is a dummy variable that takes a value equal to 1 if a drought event happened in country i at time t; and RH is a dummy variable that equals 1 if the registered anomaly in rainfall is higher than 0.

A note on fixed-effects dummy variables: the monthly dummies need to be included in the model to account for time-fixed effects that are not observable in the analysis, such as macroeconomic shocks. In this specific case, they also might absorb the seasonal crop change. This should not be a concern since the potential harvest failure due to a seasonal anomaly change (and thus climate variability) is already explained by the environmental variables. The commodity dummy, instead, is an addition that permits the elimination of the intrinsic commodity-specific characteristics that could distort the estimation. Finally, market dummies account for potential market shocks, specific consumption patterns, and geographical characteristics.

4 Results and Discussion

The first model to be estimated is 3, that is, with precipitations, temperature, and NDVI as climatic factors, and nighttime lights as the "economic variable". The table below shows the results of the first regression which was run on all the categories of commodities. Overall, the regression model seems to explain the

VARIABLES	COEFFICIENTS
Log NDVI	-0.280***
Log Precipitations	-0.119***
Log Temperature	0.159***
Log Nighttime lights (sum)	0.00181
Constant	2.021***
OBSERVATIONS	314'603

Table 3: The table shows the coefficients of the independent variables and their significance level where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

potential relationship between the variables. Indeed, The R^2 of the model is equal to 0.8557 (which represents the proportion of variance explained by the model) and the Root Mean Square Error (RMSE) is equal to 0.47542 (which measures the difference between the actual and predicted values). The table shows the coefficients of the independent variables and their significance levels. All of them are significant at p-value $p < 0.001$. This means that there exists a relationship between climate variability and food prices. Since the model is in log-log form, the interpretation is in percentage change: a 1% change in X causes a relative percentage change in Y (Benoit, 2011).

Following this framework, a 1% increase in average precipitation levels and temperature registered causes a - 0.119 and + 0.159 percentage change respectively in prices. This type of relationship is intuitive as increased rainfall levels can benefit agricultural fields permitting crop development and harvest, thus increasing the production of food products and reducing their relative price. On the contrary, an increase in temperature levels might negatively affect yields as warmer periods could let the harvest fail, which would cause an increase in price levels due to the lack of supply. This suggests that farmers will try to recover the missing profits from climate change by increasing prices. With regard to rainfall and temperature, the results obtained are in line with the explored literature concerning the effects of climate change on the economy. Going further with the results, it is interesting to note the coefficient of NDVI: a 1% increase in average NDVI causes a - 0. 280 percentage change in prices. This inverse relationship is in line with (Brown and Kshirsagar, 2015) and highlights its explanatory power relative to food prices. Increasing NDVI values indicate higher levels of vegetation greenness which could in turn outline the importance of crop wellbeing on agricultural productivity, and then food security. Finally, we can observe that the coefficient of the nighttime lights sum is not significant meaning that it does not exert any impact on price levels.

The analysis went on by running model 4 with rainfall anomalies and drought shock dummies as explanatory variables, with average NDVI as a control variable and nighttime light sum as the economic variable. The regression model has a

VARIABLES	COEFFICIENTS
Log NDVI	-0.334***
Drought shocks	0.0340***
Rainfall anomalies	0.00625***
Log Nighttime lights (sum)	0.000877
Constant	1.726***
OBSERVATIONS	314’603

Table 4: The table shows the coefficients of the independent variables and their significance level where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

R^2 of 0.8555 and a RMSE of 0.47566 which is slightly higher than model 3. The table shows that all the coefficients, except for nighttime lights, are significant at p¡0.001. In this case, the coefficient of the average NDVI is higher than in model 3. Specifically, a 1-point percentage increase in NDVI leads to a decrease in prices of 0.334%. This increased coefficient might indicate the importance of vegetation status under climatic stresses. The effect of rainfall anomalies on prices is positive: the occurrence of a higher than zero precipitation anomaly event leads to an increase in food prices by 0.00625%. Even if the marginal change is smaller than in model 3, the existing relationship is negative, indicating that higher than average precipitation levels could damage crop cultivation through soil inundations (Chau et al., 2013). Moreover, heavy rains can also damage food reserves and lead to Post Harvest Losses (PHL) due to poor storage technologies and mold formation (with poor dry conditions) (Hell et al., 2000; Mwangi et al., 2017). The effect of droughts on food prices is positive: the occurrence of a drought event leads to an increase in prices of 0.0340%, as opposed to when there is no drought. The magnitude of the effect is lower than the one exerted by the marginal increase in average temperature in the first model, but the sign of the coefficient is still positive. In this case, the regression model is different because climate shocks are expressed as dichotomic variables, thus potentially influencing the estimation of the coefficients. In any case, the effects are positive for both climate shocks, which highlights how droughts and potential floods negatively affect food prices.

To deepen the understanding of how climate change impacts food prices, both regression models were tested on two types of crops which were divided in: 1) most imported and 2) locally produced. This distinction is useful to assess the sensitivity of the price of mostly imported crops on climate variability, and the magnitude of such a relationship. Wheat, rice, and maize were chosen as the most imported commodities since Africa is a historic importer of such products (Johnson et al., 2022). With regard to the locally produced crops, cassava, onions, tomatoes, sugar, sorghum, and groundnuts were chosen due to their high adoption as main cash crops[8].

Starting from the most imported crops, model 3 was estimated for the three commodities. Table 5 shows the R2 and the RMSE for each crop. The R-squared for the three models is high meaning that they explain at least 80% of the variance. Moreover, the root MSE is low for each of the three crops.

[8]https://www.fao.org/family-farming/detail/en/c/1507024/

	Wheat	Maize	Rice
R-squared	0.8907	0.8505	0.9875
Root MSE	0.26647	0.32584	0.16918
Observations	11'075	71'949	35'671

Table 5: table showing R-squared, Root mean squared error and sample size for the three most imported commodities.

	Wheat	Maize	Rice
Log NDVI	-0.0208	-0.658***	-0.0933**
Log Precipitations	0.0641*	-0.149***	-0.0495***
Log Temperature	-0.000888	0.243***	0.0366***
Log Nighttime lights	-0.0370***	0.00619**	-0.0153***

Table 6: regression table showing the coefficients with climate variability as independent variables, for wheat, rice and maize (model 3).

Table 6 shows the specific results for wheat, rice, and maize. It can be seen that the coefficients of the environmental variables for maize are higher than rice and statistically significant at $p < 0.001$. The log of average NDVI is significant for maize at $p < 0.001$ and for rice at $p < 0.01$, while not significant for wheat. The signs of the coefficients are negative confirming the inverse relationship between vegetation greenness and food prices. Precisely, the coefficient of maize is higher than the coefficient of rice, probably showing that maize is more sensitive to changes in prices due to vegetation abundance than rice. The coefficients for the log precipitations are all statistically significant for the three commodities: at $p < 0.05$ for wheat, and $p < 0.001$ for both maize and rice. The sign of the coefficient for wheat is positive, while negative for maize and rice highlighting the beneficial effect of increasing marginal rainfall levels on crop cultivations. Concerning log average temperatures, the coefficients for maize and rice are statistically significant at $p < 0.001$ and of positive sign, while not significant for wheat. Overall, the type of relationships showed with the aggregate regression between climate variability and food prices is confirmed in this case: an inverse-type relationship between NDVI, rainfall, and prices, and a positive relationship between average temperature and food prices. The nighttime lights coefficients are statistically significant and of negative sign at p¡0.001 for wheat and rice, while of positive sign and significant at $p < 0.01$ for maize. The negative sign potentially highlights the positive effect of road infrastructure and market connection on food prices.

Model 4 with climate shocks variables was estimated to check for potential differences between the type of relationship.

	Wheat	Maize	Rice
Log NDVI	0.138	-0.706***	-0.0636
Droughts	0.0276*	0.0499***	0.0450***
Rainfall anomalies	-0.00712	0.00283	0.00875***
Log Nighttime lights	-0.0392***	0.00499*	-0.0175***

Table 7: regression table showing the coefficients with climate shocks as independent variables, for wheat, rice and maize (model 4).

In this case the average NDVI is statistically significant at $p < 0.001$ only for maize, thus indicating that it is a good predictor only for that commodity. It is interesting to notice that droughts exert a negative effect on food prices, confirming the potential relationship showed by the aggregate regression model. The coefficients for drought shocks are all statistically significant: for maize and rice at $p < 0.001$ and for wheat at $p < 0.05$. The sign is positive and the probable impact of drought events on food prices is detrimental. Moving to rainfall anomalies, the coefficient is positive and significant at $p < 0.001$ only for rice. Even in this case the nighttime lights coefficients are statistically significant for all the different crops: at $p < 0.001$ for wheat and rice, and at $p < 0.05$ for maize. An interesting detail to observe is that in both regression models, the nighttime lights coefficient is positive for maize while negative for wheat and rice. Moreover, an important consideration has to be made: the observations for wheat are lower than maize and rice. This potentially influence the estimation process since increasing the sample size can increase the significance of the results, and thus reflect the behavior of the whole category under analysis. Now model 3 is estimated for the cash crops selected before. Table 8 shows the R^2, the root MSE, and the number of observations for each crop.

	Groundnuts	Onions	Tomatoes	Sorghum	Sugar	Cassava
R-squared	0.9665	0.5921	0.5676	0.8184	0.6731	0.9731
Root MSE	0.24566	0.24015	0.31095	0.18965	0.14703	0.28581
Observations	19'778	7'009	6'237	29'849	6'926	23'567

Table 8: table showing R-squared, root MSE and sample size for the selected cash crops.

The R-squared for onions, tomatoes, and sugar is low showing that the regression model 3 explains only 59, 56, and 67 percent of the total variance respectively. Instead, for groundnuts, sorghum, and cassava the R-squared is high. It is also evident that the crops with the highest R-squared are the ones with the highest sample size. Overall, the RMSE is low for all the six commodities.

Moving to the regression, the table below shows the results of the estimation of model 3. The log of average NDVI is significant $p < 0.001$ only for sugar and

	Groundnuts	Onions	Tomatoes	Sorghum	Sugar	Cassava
NDVI	0.184*	-0.312	0.536	-0.0249	0.483***	-1.713***
Precipitations	-0.00935	0.731***	-0.336	0.00711	-0.0404*	-0.108**
Temperature	0.178***	-0.782***	-0.816***	0.114***	0.00199	-0.139**
Nighttime lights	-0.00298	-0.0242*	0.0547*	-0.181	-0.0631***	-0.00985*

Table 9: regression table showing the estimates of model 3 of main cash crops.

cassava, and at $p < 0.05$ for groundnuts. The sign of the coefficients for groundnuts and sugar, however, does not reflect the inverse relationship checked in the previous paragraphs; it does so only for cassava. The log of average precipitations is significant at $p < 0.001$ for onions, at $p < 0.05$ for sugar, and at $p < 0.01$ for cassava. Even in this case, the inverse relationship found before is not present for the most significant crop. The negative sign is present only for sugar and cassava. Shifting to the log of average temperature, coefficients are significant at $p < 0.001$ for groundnuts, onions, tomatoes and sorghum, and at $p < 0.01$ for cassava. The signs of the coefficients are positive for groundnuts and sorghum while negative for onions, tomatoes, and cassava. As for nighttime lights, coefficients are significant only for sugar at $p < 0.001$ and cassava at $p < 0.05$.

By utilizing model 4 we can see slight differences in coefficients compared to model 3. For example, the NDVI coefficient is significant at the same p-value levels for the same three commodities of the table before, but the magnitude has changed. As for rainfall anomalies, groundnuts and tomatoes coefficients are

	Groundnuts	Onions	Tomatoes	Sorghum	Sugar	Cassava
NDVI	0.239**	-0.346	0.588	-0.0249	0.747***	-1.644***
Rainfall anom.	0.0189***	-0.00746	-0.816***	0.00827**	0.00401	-0.0125**
Droughts	0.171***	-0.115***	-0.336	-0.0548***	0.109***	-0.0256
Nighttime lights	-0.00363	-0.0166	0.0547*	0.00234	-0.0702***	-0.00953*

Table 10: regression table showing the coefficients for the cash crops with climate shocks as independent variables.

significant at $p < 0.001$, while for sorghum and cassava at $p < 0.01$. In this case, the difference is that the onions and sugar coefficients are not significant. The interpretation of the sign is also important: rainfall anomalies seem to benefit tomatoes and cassava prices but exacerbate those of groundnuts and sorghum. Moving to drought shocks, groundnuts, and sugar seem to be negatively affected by water scarcity, with positive coefficients significant at $p < 0.001$. Instead, onions and sorghum seem to react oppositely with negative values with $p < 0.001$. Finally, nighttime light coefficients are significant at $p < 0.001$ for sugar, and for cassava at $p < 0.05$.

Looking at the results of both most imported commodities and locally produced crops, it can be noticed that temperature (intended also as drought shock) is a good predictor of retail food prices having most of the coefficient significant. Precipitation levels also are a good predictor of climate stress on wheat, rice, and maize. Rainfall anomalies, on the contrary, seem to be significant mostly on locally produced crops, thus highlighting the probable lower reliance on imports (Table 9). Concerning the coefficients' sign of both models 3 and 4, this discrepancy in results might hide the complexity of explaining single commodity prices due to good farming practices and the capability of the specific crop to adapt to climate stresses. For example, the coefficient for tomatoes when climate shocks are included is negative, which intuitively can be interpreted as "a 1% increase in temperature leads to a 0.816% decrease in its price". It has to be considered that different tomato genotypes adapt in different ways to heat stress, highlighting, thus, the probable presence of diversification in crop cultivars among farmers (Kugblenu et al., 2013). Also, cassava is highly adopted in sub-Saharan Africa as a strategic crop due to its high adaptability to marginal environments and its capability to produce well in arid and semi-arid temperatures (Brown et al., 2016; Okogbenin et al., 2013). This essential attribute could partially explain the negative, and significant, cassava coefficient under marginal increasing temperatures.

5 Conclusions

This work aimed to answer the question of how climate change impacts local food prices by using a regression fixed effect model with dummy variables to explicitly capture the unobserved time-fixed effects. The results yielded by the econometric model show an inverse relationship between marginally increasing average precipitations, average NDVI, and retail food prices, suggesting that water availability benefits crop yields and plant status. While marginally increasing temperature levels exacerbate prices by increasing soil aridity, thus reducing crop yields and vegetation greenness.

A deepening of the effect of climate extremes on food prices was made by considering the happening of drought events and rainfall anomalies in a second regression model. The outcomes confirm the negative effect of environmental shocks and the positive effect of vegetation on retail food prices. To have a broader, and more specific, understanding of how environmental variability affects food prices, mostly imported commodities and locally produced crops were considered for the analysis. The estimation of models 3 and 4 on the two categories of commodities produced mixed results: for the highly imported commodities temperature is found to be most significant in terms of negative impacts. For locally produced commodities, instead, the results underline the difficulty of assessing the influence of climate change.

An important detail that needs to be considered is that highly imported commodities are richer in terms of observations than locally produced crops, which has an impact on regression outcomes. Missing information, indeed, is one of the limitations of the current work. Further, aggregating different commodities into a single category has the shortcoming of generalizing the results for different crop types, which might react differently to climate change.

The previously stated limitations lead us to the first consideration: it is important for policymaking and risk assessment to gather more data in order to produce information and make precise and reliable inferences. In the context of this research, data for some commodities was missing for consecutive months, even years. Also, understanding why observations are missing could be a step forward in causal inference analysis: for example, if a market does not have observation because of displacement due to climate change or ongoing conflicts, research outputs can take different turns in causality assessment. Indeed, the current work does not aim at offering certainties and stating causality about climate change and food prices, but rather to discover further *uncertainties* to be explored that could develop into interesting insights and new research questions.

The uncertainty with which I am speaking concerns the complexity of the climate change phenomena, and more broadly, the complexity of nature itself. As humans, we still know little about the interaction between the environment as a whole (including us) and climate extremes, because the time we are living in is unique. In the context of this work, it is important to study how crops react to environmental variability in order to develop adaptation and mitigation innovations (climate change resistant crops or new farming technologies), and thus build a more resilient agricultural sector. Precision farming technologies as an alternative to satellite-based imagery, for example, can serve as a useful tool for agronomists to precisely map fertility areas, thus bypassing NDVI pitfalls (Ghosh et al., 2023). As showed in the introduction, weather extremes are happening at a highly frequent rate, especially in developing countries. Therefore it is crucial for a country's economy to adapt the size of financial resources destined for disaster reconstruction in relation to the level of risks of such events (Hallegatte and Dumas, 2009).

Starting from the study's limitations, possible developments of this work are different. Given that the widest climate anomalies are concentrated during ENSO years (2005 and 2015), to better understand the impact of this disrupting climatic event a synthetic control method could be utilized on affected countries. In this case, a Difference-in-Difference model could also be used. However, environmental shocks are increasingly occurring making the impact of a single event difficult to disentangle from the previous one. Thus, the synthetic control method would permit to build a fictional country where environmental disasters are not present, enhancing comparability. Moreover, a deeper knowledge of droughts and floods' impacts on food prices could be achieved by considering market integration, which would allow researchers to determine, in spatial terms, how far extreme event consequences are transmitted.

References

P. Aggarwal, N. Kalra, S. Chander, and H. Pathak. InfoCrop: A dynamic simulation model for the assessment of crop yields, losses due to pests, and environmental impact of agro-ecosystems in tropical environments. I. Model description. *Agricultural Systems*, 89(1):1–25, July 2006. ISSN 0308521X. doi: 10.1016/j.agsy.2005.08.001. URL `https://linkinghub.elsevier.com/retrieve/pii/S0308521X05001459`.

W. Akpalu, R. M. Hassan, et al. *Climate variability and maize yield in South Africa: results from GME and MELE methods*. Intl Food Policy Res Inst, 2009.

M. R. Anwar, G. O'Leary, D. McNeil, H. Hossain, and R. Nelson. Climate change impact on rainfed wheat in south-eastern Australia. *Field Crops Research*, 104 (1-3):139–147, Oct. 2007. ISSN 03784290. doi: 10.1016/j.fcr.2007.03.020. URL `https://linkinghub.elsevier.com/retrieve/pii/S0378429007001219`.

A. Anyamba and J. R. Eastman. Interannual variability of NDVI over Africa and its relation to El Niño/Southern Oscillation. *International Journal of Remote Sensing*, 17(13):2533–2548, Sept. 1996. ISSN 0143-1161, 1366-5901. doi: 10.1080/01431169608949091. URL `https://www.tandfonline.com/doi/full/10.1080/01431169608949091`.

M. Aslam and J. Varani. The Western-Style Diet, Calcium Deficiency and Chronic Disease. *Journal of Nutrition & Food Sciences*, 06(03), 2016. ISSN 21559600. doi: 10.4172/2155-9600.1000496. URL `https://www.omicsonline.org/open-access/the-westernstyle-diet-calcium-deficiency-and-chronic-disease-2155-9600-1000496.php?aid=72703`.

D. Baldi, M. Moner-Girona, E. Fumagalli, and F. Fahl. Planning sustainable electricity solutions for refugee settlements in sub-Saharan Africa. *Nature Energy*, 7(4):369–379, Apr. 2022. ISSN 2058-7546. doi: 10.1038/s41560-022-01006-9. URL https://www.nature.com/articles/s41560-022-01006-9.

S. Bartlett. Climate change and urban children: impacts and implications for adaptation in low-and middle-income countries. In *Adapting Cities to Climate Change*, pages 175–199. Routledge, 2012.

C. Baumeister and L. Kilian. Do oil price increases cause higher food prices? *Economic Policy*, 29(80):691–747, Oct. 2014. ISSN 02664658. doi: 10.1111/1468-0327.12039. URL https://academic.oup.com/economicpolicy/article-lookup/doi/10.1111/1468-0327.12039.

T. Becker and P. Mauro. Output Drops and the Shocks That Matter. *IMF Working Papers*, (172), 2006.

K. Benoit. Linear Regression Models with Logarithmic Transformations. *London School of Economics*, 1(22):23–36, 2011.

S. C. Bradford, D. S. Negi, and B. Ramaswami. International risk sharing for food staples. *Journal of Development Economics*, 158:102894, Sept. 2022. ISSN 03043878. doi: 10.1016/j.jdeveco.2022.102894. URL https://linkinghub.elsevier.com/retrieve/pii/S0304387822000578.

P. Brenton, A. Portugal-Perez, and J. Régolo. *Food Prices, Road Infrastructure, and Market Integration in Central and Eastern Africa*. Policy Research Working Papers. The World Bank, Aug. 2014. doi: 10.1596/1813-9450-7003. URL http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-7003.

N. H. Broussard. What explains gender differences in food insecurity? *Food Policy*, 83:180–194, Feb. 2019. ISSN 03069192. doi: 10.1016/j.foodpol.2019.01.003. URL https://linkinghub.elsevier.com/retrieve/pii/S0306919218300824.

A. L. Brown, T. R. Cavagnaro, R. Gleadow, and R. E. Miller. Interactive effects of temperature and drought on cassava growth and toxicity: implications for food security? *Global Change Biology*, 22(10):3461–3473, Oct. 2016. ISSN 1354-1013, 1365-2486. doi: 10.1111/gcb.13380. URL https://onlinelibrary.wiley.com/doi/10.1111/gcb.13380.

M. Brown, F. Tondel, T. Essam, J. Thorne, B. Mann, K. Leonard, B. Stabler, and G. Eilerts. Country and regional staple food price indices for improved identification of food insecurity. *Global Environmental Change*, 22(3):784–794, Aug. 2012. ISSN 09593780. doi: 10.1016/j.gloenvcha.2012.03.005. URL https://linkinghub.elsevier.com/retrieve/pii/S0959378012000295.

M. E. Brown and V. Kshirsagar. Weather and international price shocks on food prices in the developing world. *Global Environmental Change*, 35:31–40, Nov. 2015. ISSN 09593780. doi: 10.1016/j.gloenvcha.2015.08.003. URL https://linkinghub.elsevier.com/retrieve/pii/S0959378015300248.

H. Buhaug, T. A. Benjaminsen, E. Sjaastad, and O. Magnus Theisen. Climate variability, food production shocks, and violent conflict in Sub-Saharan Africa. *Environmental Research Letters*, 10(12):125015, Dec. 2015. ISSN 1748-9326. doi: 10.1088/1748-9326/10/12/125015. URL https://iopscience.iop.org/article/10.1088/1748-9326/10/12/125015.

O. M. Caccavale and T. Flämig. Collecting prices for food security programming.

The how and why of price data collection at WFP., 2017. URL https://www.wfp.org/publications/collecting-prices-food-security-programming-how-why-price-data-collection-wfp-march-2017.

V. N. Chau, J. Holland, S. Cassells, and M. Tuohy. Using GIS to map impacts upon agriculture from extreme floods in Vietnam. *Applied Geography*, 41:65–74, 2013. ISSN 0143-6228. doi: https://doi.org/10.1016/j.apgeog.2013.03.014. URL https://www.sciencedirect.com/science/article/pii/S0143622813000805.

D. Coady. Targeting Outcomes Redux. *The World Bank Research Observer*, 19(1):61–85, Mar. 2004. ISSN 1564-6971. doi: 10.1093/wbro/lkh016. URL https://academic.oup.com/wbro/article-lookup/doi/10.1093/wbro/lkh016.

J. Dancy. Food Prices Mirror Oil Prices: The Crude Oil - FAO Food Price Index Price Correlation, 2012. URL https://www.financialsense.com/contributors/joseph-dancy/food-prices-mirror-oil-prices-the-crude-oil-fao-food-price-index-price-correlation#:~:text=The%20coefficient%20of%20determination%20(%27r,of%20oil%20during%20this%20period.

M. L. Davenport and S. E. Nicholson. On the relation between rainfall and the Normalized Difference Vegetation Index for diverse vegetation types in East Africa. *International Journal of Remote Sensing*, 14(12):2369–2389, Aug. 1993. ISSN 0143-1161, 1366-5901. doi: 10.1080/01431169308954042. URL https://www.tandfonline.com/doi/full/10.1080/01431169308954042.

J. De Gregorio. Commodity Prices, Monetary Policy, and Inflation. *IMF Economic*

Review, 60(4):600–633, Dec. 2012. ISSN 2041-4161, 2041-417X. doi: 10.1057/imfer.2012.15. URL `http://link.springer.com/10.1057/imfer.2012.15`.

S. Dietrich, V. Giuffrida, B. Martorano, and G. Schmerzeck. COVID -19 policy responses, mobility, and food prices. *American Journal of Agricultural Economics*, 104(2):569–588, Mar. 2022. ISSN 0002-9092, 1467-8276. doi: 10.1111/ajae.12278. URL `https://onlinelibrary.wiley.com/doi/10.1111/ajae.12278`.

A. Esmaeili and Z. Shokoohi. Assessing the effect of oil price on world food prices: Application of principal component analysis. *Energy Policy*, 39(2):1022–1025, Feb. 2011. ISSN 03014215. doi: 10.1016/j.enpol.2010.11.004. URL `https://linkinghub.elsevier.com/retrieve/pii/S0301421510008104`.

European Commission. Joint Research Centre. *Income elasticities of food demand in Africa: a meta analysis.* Publications Office, LU, 2015. URL `https://data.europa.eu/doi/10.2791/661366`.

X. Fang, K. Siddarth, C. McLoughlin, and M. Yenice. The Economic Consequences of Conflict in Sub-Saharan Africa. *IMF Working Papers*, 221, 2020. doi: https://doi.org/10.5089/9781513559667.001.

FAO. An Introduction to the Basic Concepts of Food Security, 2008. URL `https://www.fao.org/3/al936e/al936e00.pdf`.

FAO. How to feed the world in 2050. Technical report, 2009.

FAO. *The State of Food Security and Nutrition in the World.* FAO; IFAD; UNICEF; WFP; WHO;, July 2023. ISBN 978-92-5-137226-5. doi: 10.4060/cc3017en. URL `http://www.fao.org/documents/card/en/c/cc3017en`.

M. Flores. Conflicts, Rural Development and Food Security in West Africa. *Research in Agricultural & Applied Economics*, page 21, 2004. doi: http://dx.doi.org/10.22004/ag.econ.23811.

M. Fratzscher, C. Grosse-Steffen, and M. Rieth. Inflation targeting as a shock absorber. *Journal of International Economics*, 123:103308, Mar. 2020. ISSN 00221996. doi: 10.1016/j.jinteco.2020.103308. URL https://linkinghub.elsevier.com/retrieve/pii/S0022199620300271.

E. Fukase and W. Martin. Who Will Feed China in the 21st Century? Income Growth and Food Demand and Supply in China. *Journal of Agricultural Economics*, 67(1):3–23, Feb. 2016. ISSN 0021-857X, 1477-9552. doi: 10.1111/1477-9552.12117. URL https://onlinelibrary.wiley.com/doi/10.1111/1477-9552.12117.

C. Gardebroek and M. A. Hernandez. Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics*, 40:119–129, Nov. 2013. ISSN 01409883. doi: 10.1016/j.eneco.2013.06.013. URL https://linkinghub.elsevier.com/retrieve/pii/S0140988313001266.

M. Gebresilasse. Rural roads, agricultural extension, and productivity. *Journal of Development Economics*, 162:103048, May 2023. ISSN 03043878. doi: 10.1016/j.jdeveco.2023.103048. URL https://linkinghub.elsevier.com/retrieve/pii/S0304387823000032.

S. B. Ghosh, H. P. G. Rao, H. Agrahari, R. P. Yadav, and R. P. Yadav. Design of uav-based rf transceiver for detecting land fertility. In S. N. Singh, S. Mahanta, and Y. J. Singh, editors, *Proceedings of the NIELIT's International Conference on Communication, Electronics and Digital Technology*, pages 353–366, Singapore, 2023. Springer Nature Singapore. ISBN 978-981-99-1699-3.

K. Grace, M. Brown, and A. McNally. Examining the link between food prices and food insecurity: A multi-level analysis of maize price and birthweight in Kenya. *Food Policy*, 46:56–65, June 2014. ISSN 03069192. doi: 10.1016/j.foodpol.2014.01.010. URL `https://linkinghub.elsevier.com/retrieve/pii/S0306919214000244`.

S. Hallegatte and P. Dumas. Can natural disasters have positive consequences? Investigating the role of embodied technical change. *Ecological Economics*, 68(3): 777–786, Jan. 2009. ISSN 09218009. doi: 10.1016/j.ecolecon.2008.06.011. URL `https://linkinghub.elsevier.com/retrieve/pii/S0921800908002863`.

I. Harris, T. J. Osborn, P. Jones, and D. Lister. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, 7(1):109, Apr. 2020. ISSN 2052-4463. doi: 10.1038/s41597-020-0453-3. URL `https://doi.org/10.1038/s41597-020-0453-3`.

L. V. Hedges and J. L. Vevea. Fixed- and Random-Effects Models in Meta-Analysis. *Psychological Methods*, 3(4):486–504, 1998. doi: https://psycnet.apa.org/doi/10.1037/1082-989X.3.4.486.

K. Hell, K. F. Cardwell, and M. Setamou. The influence of storage practices on aflatoxin contamination in maize in four agroecological zones of Benin, west Africa. *Journal of Stored Products Research*, 2000.

N. Higgins, B. Hintermann, and M. E. Brown. A model of West African millet prices in rural markets. *Food Policy*, 52:33–43, Apr. 2015. ISSN 03069192. doi: 10.1016/j.foodpol.2014.09.011. URL https://linkinghub.elsevier.com/retrieve/pii/S0306919214001420.

C. Hiç, P. Pradhan, D. Rybski, and J. P. Kropp. Food Surplus and Its Climate Burdens. *Environmental Science & Technology*, 50(8):4269–4277, Apr. 2016. ISSN 0013-936X, 1520-5851. doi: 10.1021/acs.est.5b05088. URL https://pubs.acs.org/doi/10.1021/acs.est.5b05088.

A. M. Holm, S. W. Cridland, and M. L. Roderick. The use of time-integrated NOAA NDVI data and rainfall to assess landscape degradation in the arid shrubland of Western Australia. *Remote Sensing of Environment*, 85(2):145–158, 2003. ISSN 0034-4257. doi: https://doi.org/10.1016/S0034-4257(02)00199-2. URL https://www.sciencedirect.com/science/article/pii/S0034425702001992.

L. L. Iannotti, M. Robles, H. Pachón, and C. Chiarella. Food Prices and Poverty Negatively Affect Micronutrient Intakes in Guatemala. *The Journal of Nutrition*, 142(8):1568–1576, Aug. 2012. ISSN 00223166. doi: 10.3945/jn.111.157321. URL https://linkinghub.elsevier.com/retrieve/pii/S0022316622027055.

ICP. *Measuring the Real Size of the World Economy*. The World Bank, 2013. ISBN 978-0-8213-9728-2. doi: 10.1596/978-0-8213-9728-2. URL https://elibrary.worldbank.org/doi/abs/10.1596/978-0-8213-9728-2. _eprint: https://elibrary.worldbank.org/doi/pdf/10.1596/978-0-8213-9728-2.

Institute for Economics & Peace. Global Peace Index 2022: Measuring Peace in a

Complex World. Technical report, June 2022. URL http://visionofhumanity.org/resources.

IPCC. IPCC Sixth Assessment Report. Technical report, 2023.

O. A. Ishizawa, L. Bonnafous, M. Gaspari, A. G. Gordillo, J. M. Díaz, A. Pomonis, and N. Wandel. Disaster Risk Management Diagnostic Note, 2020.

L. Jaramillo, A. Cebotari, Y. Diallo, R. Gupta, Y. Koshima, C. Kularatne, J. D. Lee, S. Rehman, K. I. Tintchev, and F. Yang. Climate Challenges in Fragile and Conflict-Affected States. *Staff Climate Notes*, 2023(001):A001, 2023. doi: 10.5089/9798400252082.066.A001. URL https://www.elibrary.imf.org/view/journals/066/2023/001/article-A001-en.xml. ISBN: 9798400252082 Place: USA Publisher: International Monetary Fund.

K. Jessoe, D. T. Manning, and J. E. Taylor. Climate Change and Labour Allocation in Rural Mexico: Evidence from Annual Fluctuations in Weather. *The Economic Journal*, 128(608):230–261, Feb. 2018. ISSN 00130133. doi: 10.1111/ecoj.12448. URL https://academic.oup.com/ej/article/128/608/230-261/5068979.

M. E. Johnson, J. Farris, S. Morgan, J. R. Bloem, K. Ajewole, and J. Beckman. Africa's Agricultural Trade: Recent Trends Leading up to the African Continental Free Trade Area. *USDA*, 2022. URL https://www.ers.usda.gov/publications/pub-details/?pubid=105223.

M. B. P. K. R. Manjunath and N. L. Purohit. Large area operational wheat yield model development and validation based on spectral and meteorological data. *International Journal of Remote Sensing*, 23(15):3023–3038,

2002. doi: 10.1080/01431160110104692. URL https://doi.org/10.1080/01431160110104692. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01431160110104692.

A. Kabundi, J. Yao, and M. Mlachila. How Persistent are Climate-Related Price Shocks? Implications for Monetary Policy. *IMF Working Papers*, 2022(207):1, Oct. 2022. ISSN 1018-5941. doi: 10.5089/9798400223556.001. URL https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2022&issue=207.

J. Kaminski and L. Christiaensen. Post-harvest loss in sub-Saharan Africa—what do farmers say? *Global Food Security*, 3(3-4):149–158, Nov. 2014. ISSN 22119124. doi: 10.1016/j.gfs.2014.10.002. URL https://linkinghub.elsevier.com/retrieve/pii/S221191241400042X.

Y. Kang, S. Khan, and X. Ma. Climate change impacts on crop yield, crop water productivity and food security – A review. *Progress in Natural Science*, 19(12): 1665–1674, Dec. 2009. ISSN 10020071. doi: 10.1016/j.pnsc.2009.08.001. URL https://linkinghub.elsevier.com/retrieve/pii/S1002007109002810.

O. Koren and B. E. Bagozzi. From global to local, food insecurity is associated with contemporary armed conflicts. *Food Security*, 8(5):999–1010, Oct. 2016. ISSN 1876-4517, 1876-4525. doi: 10.1007/s12571-016-0610-x. URL http://link.springer.com/10.1007/s12571-016-0610-x.

A. Kovanen. Price Variability Under Price Level Stability—A Study of Sierra Leone's Price Dynamics Using Micro-Level Price Data. *IMF Staff Papers*, 54

(4):701–726, Nov. 2007. ISSN 1564-5150. doi: 10.1057/palgrave.imfsp.9450021. URL https://doi.org/10.1057/palgrave.imfsp.9450021.

P. Krishnan, D. Swain, B. Chandra Bhaskar, S. Nayak, and R. Dash. Impact of elevated CO2 and temperature on rice yield and methods of adaptation as evaluated by crop simulation studies. *Agriculture, Ecosystems & Environment*, 122(2):233–242, Oct. 2007. ISSN 01678809. doi: 10.1016/j.agee.2007.01.019. URL https://linkinghub.elsevier.com/retrieve/pii/S016788090700045X.

Y. O. Kugblenu, E. Oppong Danso, K. Ofori, M. N. Andersen, S. Abenney-Mickson, E. B. Sabi, F. Plauborg, M. K. Abekoe, J. Ofosu-Anim, R. Ortiz, and S. T. Jørgensen. Screening tomato genotypes for adaptation to high temperature in West Africa. *Acta Agriculturae Scandinavica, Section B - Soil & Plant Science*, 63(6):516–522, Sept. 2013. ISSN 0906-4710, 1651-1913. doi: 10.1080/09064710.2013.813062. URL http://www.tandfonline.com/doi/abs/10.1080/09064710.2013.813062.

C. Lesser and E. Moisé-Leeman. Informal Cross-Border Trade and Trade Facilitation Reform in Sub-Saharan Africa. (86), 2009. doi: https://doi.org/https://doi.org/10.1787/225770164564. URL https://www.oecd-ilibrary.org/content/paper/225770164564.

F. Maselli, S. Romanelli, L. Bottai, and G. Zipoli. Use of NOAA-AVHRR NDVI images for the estimation of dynamic fire risk in Mediterranean areas. *Remote Sensing of Environment*, 86(2):187–197, 2003. ISSN 0034-4257. doi: https:

//doi.org/10.1016/S0034-4257(03)00099-3. URL https://www.sciencedirect.com/science/article/pii/S0034425703000993.

C. Mbow, C. Rosenzweig, L. G. Barioni, T. G. Benton, M. Herrero, M. Krishnapillai, E. Liwenga, P. Pradhan, M. G. Rivera-Ferre, T. Sapkota, F. N. Tubiello, and Y. Xu. Food security. In P. R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, and J. Malley, editors, *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*. Intergovernmental Panel on Climate Change, 2019.

M. Morris, V. A. Kelly, R. J. Kopicki, and D. Byerlee. *Fertilizer Use in African Agriculture: Lessons Learned and Good Practice Guidelines*. The World Bank, Mar. 2007. ISBN 978-0-8213-6880-0 978-0-8213-6881-7. doi: 10.1596/978-0-8213-6880-0. URL http://elibrary.worldbank.org/doi/book/10.1596/978-0-8213-6880-0.

S. Muthayya, J. H. Rah, J. D. Sugimoto, F. F. Roos, K. Kraemer, and R. E. Black. The Global Hidden Hunger Indices and Maps: An Advocacy Tool for Action. *PLoS ONE*, 8(6):e67860, June 2013. ISSN 1932-6203. doi: 10.1371/journal.pone.0067860. URL https://dx.plos.org/10.1371/journal.pone.0067860.

J. K. Mwangi, C. M. Mutungi, S.-K. G. Midingoyi, A. K. Faraj, and H. D. Affognon. An assessment of the magnitudes and factors associated with postharvest losses in off-farm grain stores in Kenya. *Journal of Stored Products Research*, 73:7–20, 2017. ISSN 0022-474X. doi: https://doi.org/10.1016/j.jspr.2017.05.006. URL https://www.sciencedirect.com/science/article/pii/S0022474X17300607.

E. Okogbenin, T. Setter, M. Ferguson, R. Mutegi, H. Ceballos, B. Olasanmi, and M. Fregene. Phenotypic approaches to drought in cassava: review. *Frontiers in Physiology*, 4, 2013. ISSN 1664-042X. doi: 10.3389/fphys.2013.00093. URL https://www.frontiersin.org/articles/10.3389/fphys.2013.00093.

C. Okou, J. Spray, and F. D. Unsal. Staple Food Prices in Sub-Saharan Africa: An Empirical Assessment. *IMF Working Papers*, 2022(135):1, July 2022. ISSN 1018-5941. doi: 10.5089/9798400216190.001. URL https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2022&issue=135.

Oxford Business Group. Agriculture in Africa. Technical report, 2021. URL https://oxfordbusinessgroup.com/wp-content/uploads/files/blog/specialreports/960469/OCP_Agriculture_Africa_Report_2021.pdf.

N. Pettorelli, J. O. Vik, A. Mysterud, J.-M. Gaillard, C. J. Tucker, and N. C. Stenseth. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, 20(9):503–510, Sept. 2005. ISSN 01695347. doi: 10.1016/j.tree.2005.05.011. URL https://linkinghub.elsevier.com/retrieve/pii/S016953470500162X.

C. Raleigh, H. J. Choi, and D. Kniveton. The devil is in the details: An investigation of the relationships between conflict, food price and climate across Africa. *Global Environmental Change*, 32:187–199, May 2015. ISSN 09593780.

doi: 10.1016/j.gloenvcha.2015.03.005. URL https://linkinghub.elsevier.com/retrieve/pii/S0959378015000357.

S. R. Ramesh P. Singh and F. Kogan. Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. *International Journal of Remote Sensing*, 24(22):4393–4402, 2003. doi: 10.1080/0143116031000084323. URL https://doi.org/10.1080/0143116031000084323. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/0143116031000084323.

M. Ravallion. Testing Market Integration. *American Journal of Agricultural Economics*, 68(1):102–109, Feb. 1986. ISSN 0002-9092, 1467-8276. doi: 10.2307/1241654. URL https://onlinelibrary.wiley.com/doi/10.2307/1241654.

B. C. Reed, J. F. Brown, D. VanderZee, T. R. Loveland, J. W. Merchant, and D. O. Ohlen. Measuring phenological variability from satellite imagery. *Journal of Vegetation Science*, 5(5):703–714, 1994. doi: https://doi.org/10.2307/3235884. URL https://onlinelibrary.wiley.com/doi/abs/10.2307/3235884. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2307/3235884.

R. Reuveny. Climate change-induced migration and violent conflict. *Political Geography*, 26(6):656–673, Aug. 2007. ISSN 09626298. doi: 10.1016/j.polgeo.2007.05.001. URL https://linkinghub.elsevier.com/retrieve/pii/S0962629807000601.

C. Rosenzweig and M. L. Parry. Potential impact of climate change on world food supply. *Nature*, 367:133–138, 1994. doi: 10.1038/367133a0.

C. Rosenzweig, W. D. Solecki, P. Romero-Lankao, S. Mehrotra, S. Dhakal, and

S. A. Ibrahim. *Climate change and cities: Second assessment report of the urban climate change research network*. Cambridge University Press, 2018.

C. Salazar, A. Acuña-Duarte, and J. M. Gil. Drought shocks and price adjustments in local food markets in Chile: Do product quality and marketing channel matter? *Agricultural Economics*, 54(3):349–363, May 2023. ISSN 0169-5150, 1574-0862. doi: 10.1111/agec.12760. URL https://onlinelibrary.wiley.com/doi/10.1111/agec.12760.

S. Schaub and R. Finger. Effects of drought on hay and feed grain prices. *Environmental Research Letters*, 15(3):034014, Mar. 2020. ISSN 1748-9326. doi: 10.1088/1748-9326/ab68ab. URL https://iopscience.iop.org/article/10.1088/1748-9326/ab68ab.

J. Schmidhuber, J. Pound, and B. Qiao. *COVID-19: Channels of transmission to food and agriculture*. FAO, 2020. ISBN 978-92-5-132354-0. doi: 10.4060/ca8430en. URL http://www.fao.org/documents/card/en/c/ca8430en.

J. Schon and O. Koren. Introducing AfroGrid, a unified framework for environmental conflict research in Africa. *Scientific Data*, 9(1):116, Mar. 2022. ISSN 2052-4463. doi: 10.1038/s41597-022-01198-5. URL https://www.nature.com/articles/s41597-022-01198-5.

Y. Shamdasani. Rural road infrastructure & agricultural production: Evidence from India. *Journal of Development Economics*, 152:102686, Sept. 2021. ISSN 03043878. doi: 10.1016/j.jdeveco.2021.102686. URL https://linkinghub.elsevier.com/retrieve/pii/S0304387821000638.

W. Shi and F. Tao. Vulnerability of African maize yield to climate change and variability during 1961–2010. *Food Security*, 6(4):471–481, Aug. 2014. ISSN 1876-4517, 1876-4525. doi: 10.1007/s12571-014-0370-4. URL http://link.springer.com/10.1007/s12571-014-0370-4.

T. Stathers, D. Holcroft, L. Kitinoja, B. M. Mvumi, A. English, O. Omotilewa, M. Kocher, J. Ault, and M. Torero. A scoping review of interventions for crop postharvest loss reduction in sub-Saharan Africa and South Asia. *Nature Sustainability*, 3(10):821–835, Oct. 2020. ISSN 2398-9629. doi: 10.1038/s41893-020-00622-1. URL https://www.nature.com/articles/s41893-020-00622-1.

G. Tadesse, B. Algieri, M. Kalkuhl, and J. Von Braun. Drivers and triggers of international food price spikes and volatility. *Food Policy*, 47:117–128, Aug. 2014. ISSN 03069192. doi: 10.1016/j.foodpol.2013.08.014. URL https://linkinghub.elsevier.com/retrieve/pii/S0306919213001188.

F. Taghizadeh-Hesary, E. Rasoulinezhad, and N. Yoshino. Energy and Food Security: Linkages through Price Volatility. *Energy Policy*, 128:796–806, May 2019. ISSN 03014215. doi: 10.1016/j.enpol.2018.12.043. URL https://linkinghub.elsevier.com/retrieve/pii/S0301421518308486.

A. Tait and X. Zheng. Mapping Frost Occurrence Using Satellite Data. *Journal of Applied Meteorology*, 42(2):193 – 203, 2003. doi: https://doi.org/10.1175/1520-0450(2003)042⟨0193:MFOUSD⟩2.0.CO;2. URL https://journals.ametsoc.org/view/journals/apme/42/2/1520-0450_2003_042_0193_mfousd_2.0.co_2.xml. Place: Boston MA, USA Publisher: American Meteorological Society.

The World Bank Group. Climate Risk Country Profile: Liberia, 2021.

A. K. Thiam. The causes and spatial pattern of land degradation risk in southern Mauritania using multitemporal AVHRR-NDVI imagery and field data. *Land Degradation & Development*, 14(1):133–142, 2003. doi: https://doi.org/10.1002/ldr.533. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/ldr.533`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ldr.533.

C. Tucker, C. Vanpraet, M. Sharman, and G. Van Ittersum. Satellite remote sensing of total herbaceous biomass production in the senegalese sahel: 1980–1984. *Remote Sensing of Environment*, 17(3):233–249, June 1985. ISSN 00344257. doi: 10.1016/0034-4257(85)90097-5. URL `https://linkinghub.elsevier.com/retrieve/pii/0034425785900975`.

C. Tucker, I. Fung, C. Keeling, and R. Gammon. Relationship between atmospheric CO2 variations and a satellite-derived vegetation index. *Nature*, 319: 195–199, 1986. doi: https://dx.doi.org/doi:10.1038/319195a0.

D. Ubilava. The enso effect and asymmetries in wheat price dynamics. *World Development*, 96:490–502, 2017. ISSN 0305-750X. doi: https://doi.org/10.1016/j.worlddev.2017.03.031. URL `https://www.sciencedirect.com/science/article/pii/S0305750X15310172`.

UN General Assembly. Transforming our world: the 2030 Agenda for Sustainable Development, 2015.

UNFCCC. Kyoto Protocol to the United Nations Framework Convention on Climate Change, 1997.

United Nations Department of Economic and Social Affairs. *The Sustainable Development Goals Report 2023: Special Edition*. The Sustainable Development Goals Report. United Nations, July 2023. ISBN 978-92-1-002491-4. doi: 10.18356/9789210024914. URL https://www.un-ilibrary.org/content/books/9789210024914.

M. Van Dijk, T. Morley, M. L. Rau, and Y. Saghai. A meta-analysis of projected global food demand and population at risk of hunger for the period 2010–2050. *Nature Food*, 2(7):494–501, July 2021. ISSN 2662-1355. doi: 10.1038/s43016-021-00322-9. URL https://www.nature.com/articles/s43016-021-00322-9.

S. J. Vermeulen, B. M. Campbell, and J. S. Ingram. Climate Change and Food Systems. *Annual Review of Environment and Resources*, 37(1):195–222, 2012. doi: 10.1146/annurev-environ-020411-130608. URL https://doi.org/10.1146/annurev-environ-020411-130608. _eprint: https://doi.org/10.1146/annurev-environ-020411-130608.

S. M. Vicente-Serrano, S. Beguería, and J. I. López-Moreno. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23(7):1696 – 1718, 2010. doi: https://doi.org/10.1175/2009JCLI2909.1. URL https://journals.ametsoc.org/view/journals/clim/23/7/2009jcli2909.1.xml. Place: Boston MA, USA Publisher: American Meteorological Society.

J. Von Braun and R. K. Pachauri. The promises and challenges of biofuels for the poor in developing countries. Annual, International Food Policy Research Institute, Washington D.C., 2006. URL http://dx.doi.org/10.2499/0896299147.

J. von Braun and G. Tadesse. Global Food Price Volatility and Spikes: An

Overview of Costs, Causes, and Solutions. *ZEF-Discussion Papers on Development Policy*, 161, 2012. ISSN 1436-9931.

N. Walker and R. Schulze. An assessment of sustainable maize production under different management and climate scenarios for smallholder agro-ecosystems in KwaZulu-Natal, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C*, 31(15-16):995–1002, Jan. 2006. ISSN 14747065. doi: 10.1016/j.pce.2006.08.012. URL https://linkinghub.elsevier.com/retrieve/pii/S1474706506001744.

L. Wall, D. Larocque, and P. Léger. The early explanatory power of NDVI in crop yield modelling. *International Journal of Remote Sensing*, 29(8):2211–2225, Apr. 2008. ISSN 0143-1161, 1366-5901. doi: 10.1080/01431160701395252. URL https://www.tandfonline.com/doi/full/10.1080/01431160701395252.

J. Wang, P. M. Rich, and K. P. Price. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. *International Journal of Remote Sensing*, 24(11):2345–2364, Jan. 2003. ISSN 0143-1161, 1366-5901. doi: 10.1080/01431160210154812. URL https://www.tandfonline.com/doi/full/10.1080/01431160210154812.

P. Westhoff. Oil prices affect the cost of food in many ways., 2012. URL https://eu.columbiatribune.com/story/business/2012/03/03/oil-prices-affect-cost-food/21631694007/.

T. Wheeler. Climate Change Impacts on Global Food Security. 341, 2013.

World Bank. Food Security Update. Technical report, July 2023. URL https:

`//thedocs.worldbank.org/en/doc/40ebbf38f5a6b68bfc11e5273e1405d4-0090012022/related/Food-Security-Update-XC-July-27-2023.pdf`.

World Meteorological Organization. *State of the climate in Africa*. 2021. ISBN 978-92-63-11300-9.

F. Yao, Y. Xu, E. Lin, M. Yokozawa, and J. Zhang. Assessing the impacts of climate change on rice yields in the main rice areas of china. *Climatic Change*, 80:395–409, 2007.

Acknowledgements

As a last part of this work, I would like to dedicate a few words to the people who accompanied me during this academic period. Firstly, I want to thank Prof. Nicoló Barbieri for the precious opportunity and the flawless suggestions given for developing this thesis, and beyond. I want to thank my whole family who supported me in every aspect of my student, and human, life. I thank my close friends, Nicola, Maria Vittoria, Adarsh, and Gabriele, with whom I shared a big part of the university life, and the life outside the academia. I also thank Andrea who supported me, especially during the last months of our thesis writing. Finally, I thank all the people who are, and have been, part of my life.