Policy Research Working Paper 10999

Climate Shocks and Their Effects on Food Security, Prices, and Agricultural Wages in Afghanistan

Tosin Gbadegesin
Bo Pieter Johannes Andrée
Ademola Braimoh

WORLD BANK GROUP
Agriculture and Food Global Department &
Development Data Group
December 2024

Policy Research Working Paper 10999

Abstract

This study examines the effects of climate and weather shocks on Afghanistan's agricultural economy, with an emphasis on food security, prices, and wages. By utilizing a dynamical model and a unique data set that includes monthly global and local food prices, agricultural wages, unofficial exchange rates, and local climate data, the research provides econometric estimates of the impacts of droughts and floods. The findings reveal that both flooding and drought significantly increase food insecurity, directly and indirectly. Directly, these climatic shocks are linked to heightened risks of food insecurity in the following months, even when controlling for price and wage fluctuations. Indirectly, droughts and floods drive up food prices and depress agricultural wages, further exacerbating food insecurity. The study suggests that enhancing climate resilience in the agriculture sector could mitigate these risks, stabilize local food prices and wages, and strengthen food security and the broader agricultural economy. The results also show that price data effectively capture food security shocks from various non-economic sources, and can serve as a versatile monitoring tool in situations where detailed data on food security are unavailable.

This paper is a product of the Agriculture and Food Global Department and the Development Data Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at bandree@worldbank.org.

Climate Shocks and Their Effects on Food Security, Prices, and Agricultural Wages in Afghanistan

Tosin Gbadegesin, Bo Pieter Johannes Andrée, and Ademola Braimoh

Keywords: Food Security, Crisis, Climate Shocks, Agriculture, Food Prices
JEL: C01, C14, C25, C53, O10

Funding from the Climate Support Facility Trust Fund (TF0B9464), Afghanistan Resilience Trust Fund (TF0C3431) and Food Systems 2030 (FS2030) Multi-Donor Trust Fund program (TF0C0728) is gratefully acknowledged. This paper reflects the views of the authors and not the official views of the World Bank, its executive directors, or the countries they represent. We thank Amanullah Alamzai, Christine Heumesser, Najumuddin Najum for comments on an early draft of the paper, Vanina Daphne Forget and Zacharey Austin Carmichael for review comments and feedback. We also thank Najumuddin Najum for assistance with data collection.

1. Introduction

Afghanistan is at a critical juncture, with escalating food insecurity demanding attention as the country faces multiple crises threatening livelihoods and development. According to recent reports, hunger levels continue to rise, and progress toward the Sustainable Development Goals (SDGs) has stalled. In 2022, an estimated 12.6 million people—30.6 percent of the population—experienced severe food insecurity, according to the United Nations Food and Agriculture Organization (FAO). Of these, 2.9 million were at emergency levels (classified as Phase 4 or above by the Integrated Food Security Phase Classification, or IPC), on the brink of starvation due to economic crises and droughts, as highlighted in the latest IPC analysis (March-April 2024). The World Bank's World Food Security Outlook (Andrée 2022; 2023c) projects that Afghanistan will not achieve Sustainable Development Goal 2 (zero hunger), with severe food insecurity persisting beyond 2030.

The choice between investing in resilience or responding with humanitarian aid represents a dilemma in the development and humanitarian nexus. Investing in resilience aims to build long-term sustainability and reduce vulnerability, while aid provides immediate relief in crisis times. Striking the right balance is essential, as focusing solely on aid can perpetuate dependency, while underinvesting in resilience leaves communities exposed to future shocks. Important in this tradeoff are investment opportunities, the magnitude of preventable agricultural losses, and the role of locally produced food for food and nutrition security.

Global costs associated with natural disasters and climate extremes are rising. Newman and Noy (2023) quantify the global costs of extreme weather events attributable to climate change, highlighting economic burdens, particularly human loss of life. Addressing climate shocks can be an essential part of resilience strategies, as the agriculture sector offers opportunities for proactive adaptation and mitigation measures to reduce vulnerability (Diogo et al., 2017). Challinor et al. (2014) conducted a meta-analysis of 1,700 simulations to evaluate yield impacts of climate change and adaptation globally. Across different climate scenarios and adaptation strategies, crop-level adaptations increased simulated yields by an average of 7%–15%, a figure that aligns with the prevalence of severe food insecurity worldwide.

The potential for agricultural adaptation measures to strengthen food security depends on country contexts. Evidence suggests that action is particularly important in low-income settings. Vermeulen et al. (2012) highlight the complex, geographical nature of climate impacts on food systems and note that they particularly affect low-income producers and consumers. Andrée et al. (2019) assess the relationship between economic development and environmental burdens in 95 countries and show that early-stage development, associated with the greatest reduction in extreme poverty and the fastest improvements in living standards, is also linked to the highest pressure on natural resources. Eroding these resources early on can create long-term challenges to food security if local livelihoods depend on them for consumption. These contextual impacts of climate shocks call for in-depth, country-specific analysis of the climate-food security relationship.

Afghanistan faces challenges in achieving food security due to recurring climate shocks and socio-economic instability. Severe climatic events such as droughts and floods have impacted agricultural productivity and food availability. While existing studies and humanitarian reports from the World Bank and IPC document these challenges, questions remain about whether climate-induced food security shocks are sporadic or reflect deeper structural vulnerabilities, and how building agricultural resilience could provide a solution to chronic food insecurity.

This study addresses these gaps by investigating the impacts of climatic shocks on food security over a thirteen-year period in Afghanistan. Using a vector-autoregressive (VAR) model, we analyze the direct and indirect effects of weather anomalies on food insecurity, food prices, and agricultural wages. By understanding these dynamics, we provide evidence on how climatic shocks have impacted food security. Specifically, the model uses a logistic regression with two specifications to measure different levels of food insecurity: IPC levels 2 or greater (food stress) and 3 or greater (food crisis). The model evaluates the probability of these outcomes using drought and flood anomalies as primary variables, along with control variables for time-invariant vulnerabilities and economic factors including food prices and agricultural wages. In addition to the logit, food prices and agricultural wages are modeled using linear specifications. All three regressions have the same covariate structure and incorporate up to 12 time lags to account for delayed climate effects on food insecurity. The VAR setup allows analysis of both direct and indirect effects, showing how droughts impact food security directly and through price and wage effects. The model can predict at-risk populations using weighted probabilities.

Our analysis contributes to existing literature in two main ways. First, the results highlight the significant impact of climatic shocks, particularly floods, on food insecurity. A one-in-six-year flood event increases the likelihood of food stress by 23.4 percentage points and food crisis by 5.9 percentage points over 12 months. When combined with positive NDVI (Normalized Difference Vegetation Index) anomalies during the spring planting season, indicating lush natural vegetation from excessive rainfall, the impact is even greater—raising the probability of food stress by 51.2 percentage points and food crisis by 16.0 percentage points. These findings underscore the importance of resilience-building measures in flood-prone regions to mitigate food security risks.

Climatic shocks also influence food prices and wages, affecting food security. For example, floods increase food prices by 3.40% annually, while agricultural wages rise by 1.80%. These wage increases are insufficient to offset higher food prices, resulting in a net negative purchasing power shock and worsening food insecurity. Droughts similarly induce purchasing power shocks. In our model, a one-in-six-year drought leads to a 5.17% annualized increase in agricultural wages but a 6.36% increase in food prices. The model shows that climatic shocks impact food security both directly, through agricultural losses and reduced food availability, and indirectly, through price and wage dynamics. This interconnectedness highlights the need for comprehensive climate adaptation strategies that address food production and market stability to improve food security outcomes.

This paper also contributes to the literature on food security modeling. Our model's predictive accuracy—correctly classifying 69.14% of food stress cases and 87.89% of food crisis cases—provides a foundation for developing early warning systems. These systems are crucial for anticipatory humanitarian actions, allowing policy makers to monitor risks in real time and take preemptive measures before crises unfold. This work builds on research incorporating climate simulations and satellite data to account for weather impacts on crop yields, food supply chains, and food security (Lobell et al., 2008; Cartuyvels et al., 2023) and connects to studies using stochastic modeling (Wang et al., 2020; 2022), threshold modeling (Penson et al., 2024), and machine learning methods such as Random Forest (Andrée et al., 2020) and Bayesian networks (Semakula et al., 2024) for predicting food security outcomes. Our model's ability to produce accurate, population-weighted exposure probabilities at various food insecurity levels supports these types of indicators and methods that monitor food security transparently and frequently in countries like Afghanistan.

The paper is structured as follows: Section 2 discusses the country context and related literature. Section 3 introduces the data. Section 4 presents the modeling framework. Section 5 outlines key findings. Section 6 discusses implications, and Section 7 concludes.

2. Background and Literature Review

2.1. Food Security Challenges in Afghanistan

Afghanistan faces challenges in achieving food security due to its terrain, varied climatic conditions, and socio-economic vulnerabilities. Over the past decades, the country has experienced a series of climatic and weather shocks—including prolonged droughts, erratic rainfall, and flooding—that have impacted agricultural productivity and food availability. These disruptions have been compounded by poverty, limited market access, and ongoing conflict, creating a web of factors contributing to food insecurity and economic instability.

Research indicates that both droughts and floods are major drivers of food insecurity in Afghanistan. The World Bank (2019) reported that approximately 45% of the Afghan population was moderately food insecure in 2016, a figure that has worsened in subsequent years, now exceeding 80% (IPC, 2023), due to climatic events and the economic disruption caused by the political events of 2021. In 2018, a severe drought further intensified food insecurity, particularly in rural areas dependent on agriculture for livelihoods. This event reduced cereal yields, pushing many households to crisis levels of food insecurity and triggering large-scale humanitarian interventions. Oskorouchi et al. (2021) and Yolchi et al. (2024), using cross-sectional surveys, show that flooding also has significant negative effects on food security. Additionally, Omerkhil et al. (2020) highlight that smallholder farmers are especially vulnerable to climate change, with those in hilly regions at higher risk than those in plains, and both groups showing low adaptive capacity.

Further studies point to the increasing severity and frequency of droughts in Afghanistan, predicting more severe droughts in the future (Qutbudin et al., 2019). Khalily (2022) notes declining yields for crops such as wheat, rice, and corn due to intensified droughts linked to climate change. Jawid and Khadjavi (2019) emphasize the lack of adaptation support for Afghan farmers, while Přívara and Přívarová (2019) highlight the compounding effects of climate change on the country's environmental and socio-economic landscape, increasing vulnerability to displacement, conflicts, and food insecurity.

While the literature underscores Afghanistan’s vulnerability to climate-induced food insecurity, questions remain about whether these food security shocks are sporadic or indicative of deeper structural vulnerabilities. It is uncertain how building agricultural resilience could provide a sustainable, long-term solution to chronic food insecurity.

2.2. Direct and Indirect Effects of Climate Change on Food Security

Climate change threatens progress toward eradicating hunger through both direct agricultural productivity shocks and indirect socio-economic effects. Direct shocks limit crop productivity and food availability, impacting food systems and nutrition (Arreyndip, 2021; Mirzabaev et al., 2023; Wheeler & Von Braun, 2013).

Indirectly, climatic shocks can harm the overall economy, leading to secondary impacts on food security and extreme poverty. Climate-induced shocks pose challenges to economic stability. Cevik and Jalles (2023) show that climate shocks have varying effects on inflation and GDP growth, with differences across income groups and economic conditions. Khurshid et al. (2022) and Acevedo et al. (2020) attribute negative long-term GDP growth impacts to climate shocks, which disproportionately affect low-income countries. Droughts, in particular, add inflationary pressures by increasing food prices (Kabundi et al., 2022). Erdoğan et al. (2024) emphasize that extreme weather events exacerbated by climate change reduce crop yields, leading to product shortages and higher food prices. Temperature variations, especially in hot climates, reduce investment, suppress labor productivity, and slow agricultural output, contributing to higher food prices (Acevedo et al., 2020). Mukherjee and Ouattara (2021) highlight the persistent inflationary effects of temperature shocks, which challenge the effectiveness of monetary and fiscal policy over the long term. Coumou and Rahmstorf (2012), Coumou and Robinson (2013) and Gbadegesin (2020) point to the increasing frequency of extreme heatwaves and precipitation events due to warming, advocating for urgent adaptation measures. Blekking et al. (2022) report that climate variability in urban Sub-Saharan Africa leads to local food price increases during droughts and price hikes across urban retailers as climate impacts transmit through supply chains.

These climate-induced economic shocks can lead to further indirect and potentially long-lasting consequences for food security and nutrition outcomes. The literature indicates that these outcomes disproportionately affect low-income countries and vulnerable groups such as women and children. Gatti et al. (2023), for example, highlight the long-term harmful effects of short-lived food price spikes on food security and health in the Middle East and North Africa, emphasizing the disproportionate impact on vulnerable populations.

2.3 Application of VAR Models in Dynamical Climate Impact Studies

Statistical models using historical data to calibrate regression equations against future responses can process time series data from a single location (univariate time series methods) or multiple (panel methods extending across time and space). Univariate time-series models capture behavior specific to a given area, while panel methods assume common parameter values for all locations, differentiating between locations using cross-sectional variables that vary spatially. Panel and univariate time series methods have been used to estimate the impacts of climatic factors (e.g., temperature, precipitation, extreme weather events) on agricultural output and food security (Lobell & Burke, 2010) but are limited by their focus on unidirectional causal pathways.

VAR models can handle dynamic dependencies among multiple univariate time series. These methods can be extended to model dynamic relationships in panel data over time. For example, studies by Andrée (2020) and Gheasi et al. (2023) applied VAR frameworks to spatial time series data to explore macroeconomic shocks on regional economies, while Wang et al. (2020; 2022) used panel VAR approaches to assess food security responses to climatic events.

In this study, we adopt a VAR approach to analyze how climate shocks affect food security and propagate through domestic food prices and wages. The VAR setup estimates the direct and indirect effects of climatic shocks on food security by incorporating variables such as food prices and agricultural wages. This approach allows the model to capture how droughts and floods impact food security directly and through economic channels, providing a comprehensive understanding for policy. We examine three main pathways: (1) the direct impact of weather and climate shocks on food insecurity, (2) the relationship between these shocks and domestic food prices, and (3) the effect on agricultural wages. Additionally, we assess the impacts of inflation and wage changes on food security outcomes, highlighting the indirect effects of climatic shocks through the destabilization of the agricultural economy.

3. Data

The variables used in the study cover climatic, economic, and structural factors relevant for understanding food security outcomes, agricultural wages, and food prices. Table 1 provides an overview. The following sections discuss the target variables and covariates in more detail.

Table 1: summary statistics of the data

The table presents summary statistics for the variables used in the analysis. The values are based on the original units and summarize key indicators across the sample. For each variable, the table shows the mean, standard deviation (Std), minimum (Min), and maximum (Max) values, providing insights into the variability and range of the data.

Variables	Mean	Std	Min	Max	Unit
IPC Rating	1.754	0.703	1.000	4.000	IPC phase
Rainfall	10.788	11.919	0.000	116.158	mm/m
NDVI	0.167	0.096	-0.049	0.756	Index
Agricultural Wages (Qualified Labor)	670.694	87.250	292.503	1034.540	AFN
Food Prices	39.839	9.452	20.858	84.432	AFN
Fuel Prices	51.319	13.234	27.125	119.068	AFN
Global Food Price	672.849	139.588	494.273	1121.430	USD
Exchange Rate	66.307	13.864	45.088	100.088	AFN/USD
Cropland	7.973	8.460	0.030	33.186	Percentage
Terrain Ruggedness	349552.026	198149.660	26754.030	776683.500	Index
Population Density	114.822	173.223	4.239	1243.665	People/m2
Pastureland	47.326	17.770	1.741	82.399	Percentage

In Table 1, the IPC rating reflects the phases of food insecurity, from minimal (IPC phase 1) to humanitarian emergency (IPC phase 4). Climatic variables such as rainfall and NDVI capture environmental conditions, with rainfall measured in millimeters per month and NDVI indicating vegetation health on a scale from -1 (water) to 1 (dense, healthy vegetation). Economic variables include agricultural wages and food prices along with fuel prices, measured in Afghanis (AFN). The global food price index, in USD, indicates international food price trends. The exchange rate reflects the value of the Afghan afghani relative to the US dollar.

Structural variables such as cropland, terrain ruggedness, population density, and pastureland provide insights into the geographic and demographic context. Cropland and pastureland are expressed as percentages of total land area, while terrain ruggedness is an index indicating the difficulty of the terrain. Population density measures the number of people per square kilometer, capturing human activity concentration in the region.

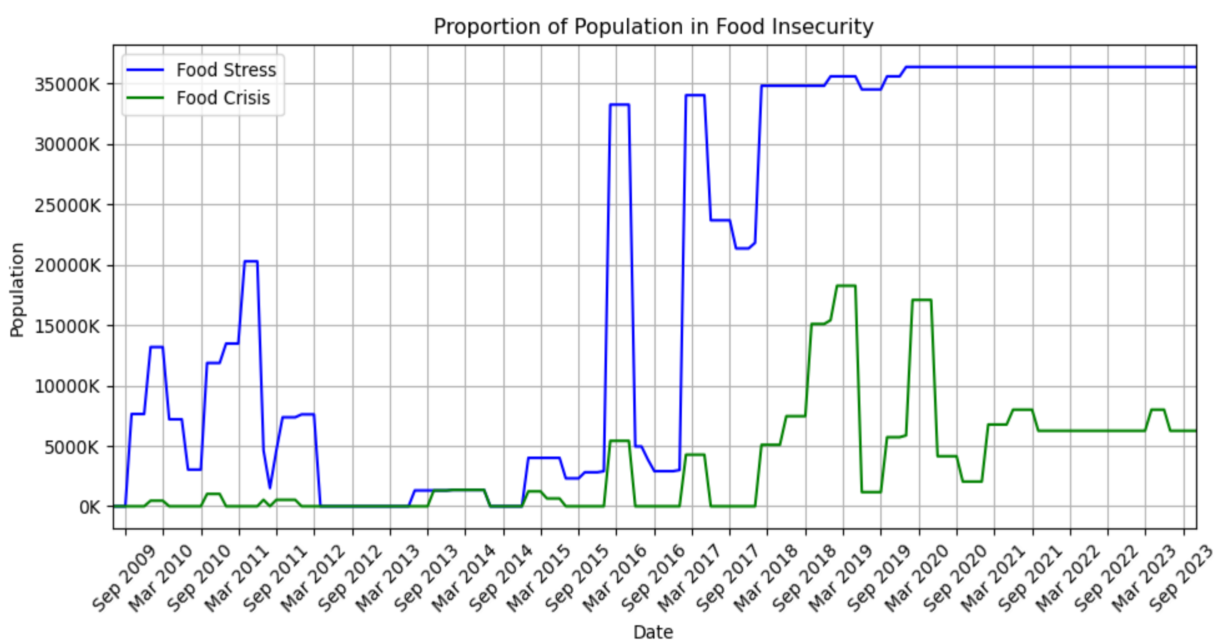
3.1 Target Variable: Food Insecurity, Food Prices, and Agricultural Wages

We obtained historical data on food insecurity from periodic assessments conducted by the Famine Early Warning Systems Network (FEWS NET) across 40 districts in Afghanistan from 2009 to 2023. FEWS NET aligns with the IPC system to assess and standardize acute food insecurity outcomes into five phases: Minimal (Phase 1), Stressed (Phase 2), Crisis (Phase 3), Emergency (Phase 4), and Famine (Phase 5). Since 2012, FEWS NET data identify areas where humanitarian assistance reduced the IPC phase by one level. Following the methodology of Andrée et al. (2020) and Penson et al. (2024), we derived IPC phases adjusted for aid effects by combining IPC phase data with a binary indicator representing the presence of humanitarian aid, focusing on inherent food insecurity rather than the impact of humanitarian response.

We then created two binary food insecurity outcomes: the first equals 1 when the adjusted IPC rating is 2 or greater (food stress), and the second equals 1 when the IPC rating is 3 or greater (food crisis). Figure 1 shows the resulting proportion of the population experiencing food stress (IPC ≥ 2) and food crisis (IPC ≥ 3) from July 2009 to November 2023. The population facing food stress fluctuated, peaking above 1 million during several periods, particularly after 2015 while the incidence of food crisis increased notably after 2015, indicating worsening food security conditions in recent years.

Figure 1: Proportion of Population with Integrated Food Security Classification ≥ 2 and ≥ 3

Figure 1 is a line plot depicting the proportion of the population in food insecurity over time. The plot includes two lines: one for the proportion of the population experiencing food stress (IPC ≥ 2), shown in blue, and another for the proportion experiencing a food crisis (IPC ≥ 3), shown in green. The figure shows significant fluctuations, with notable peaks in food stress around 2011, 2015, and 2016, reaching more than 1 million individuals during certain periods. Similarly, food crisis incidence, while generally lower, spiked particularly in 2016, 2017, and 2018. Note that the data follows a 4-month interval and has been interpolated. No assessments were caried out between June 2021 and February 2023.

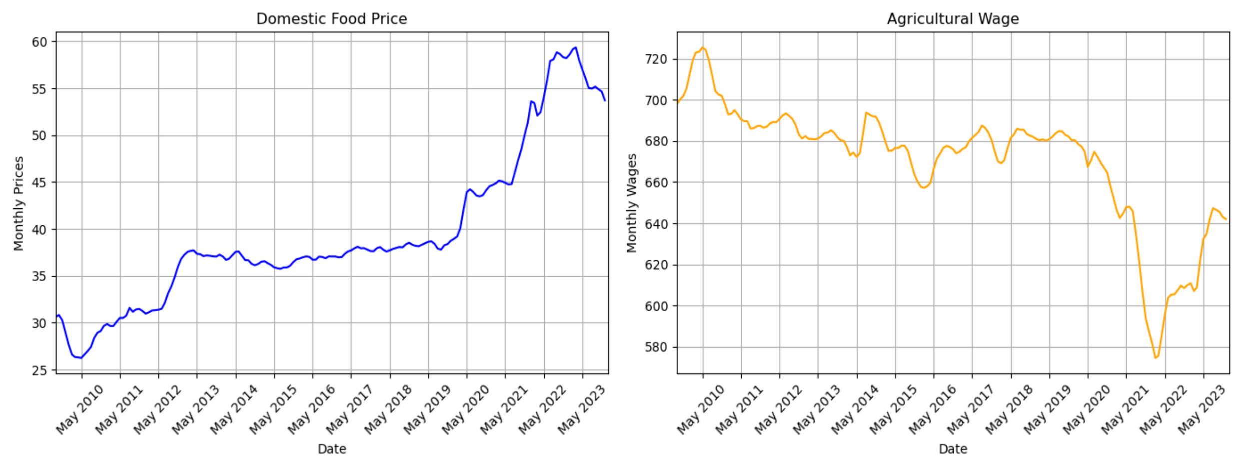


To analyze the relationship between weather and climate shocks and economic variables, we used domestic food prices and local agricultural wages as dependent variables. These data were obtained from Andrée (2021b, 2023b), prepared using surveys from the World Food Programme following the methods of Andrée (2021a) and Andrée and Pape (2023) (see also Adewopo et al. (2024)).

Figure 2 shows trends in average monthly domestic food prices and agricultural wages in Afghanistan from 2009 to 2023. Domestic food prices rose steadily, peaking above 55 afghanis in 2022 after climbing from around 30 afghanis in 2016. In contrast, agricultural wages fell from around 1,300 afghanis in 2010 to below 700 afghanis by 2022, reflecting worsening economic conditions for agricultural workers. The data indicate growing challenges with food affordability as wages have fallen over a period during which prices rose sharply.

Figure 2: Average Monthly Agricultural Wages and Food Prices

Figure 2 is a comparative analysis of domestic food prices and agricultural wages in Afghanistan from 2009 to 2023. The left subplot illustrates the trend in domestic food prices, showing a gradual increase over the years, with notable spikes in 2012 and a significant rise starting in 2020, peaking in 2022 before a slight decline. The right subplot depicts the trend in agricultural wages, which declined sharply in 2011, followed by fluctuations and a gradual downward trend, stabilizing at lower levels from 2017 on.



3.2 Covariates

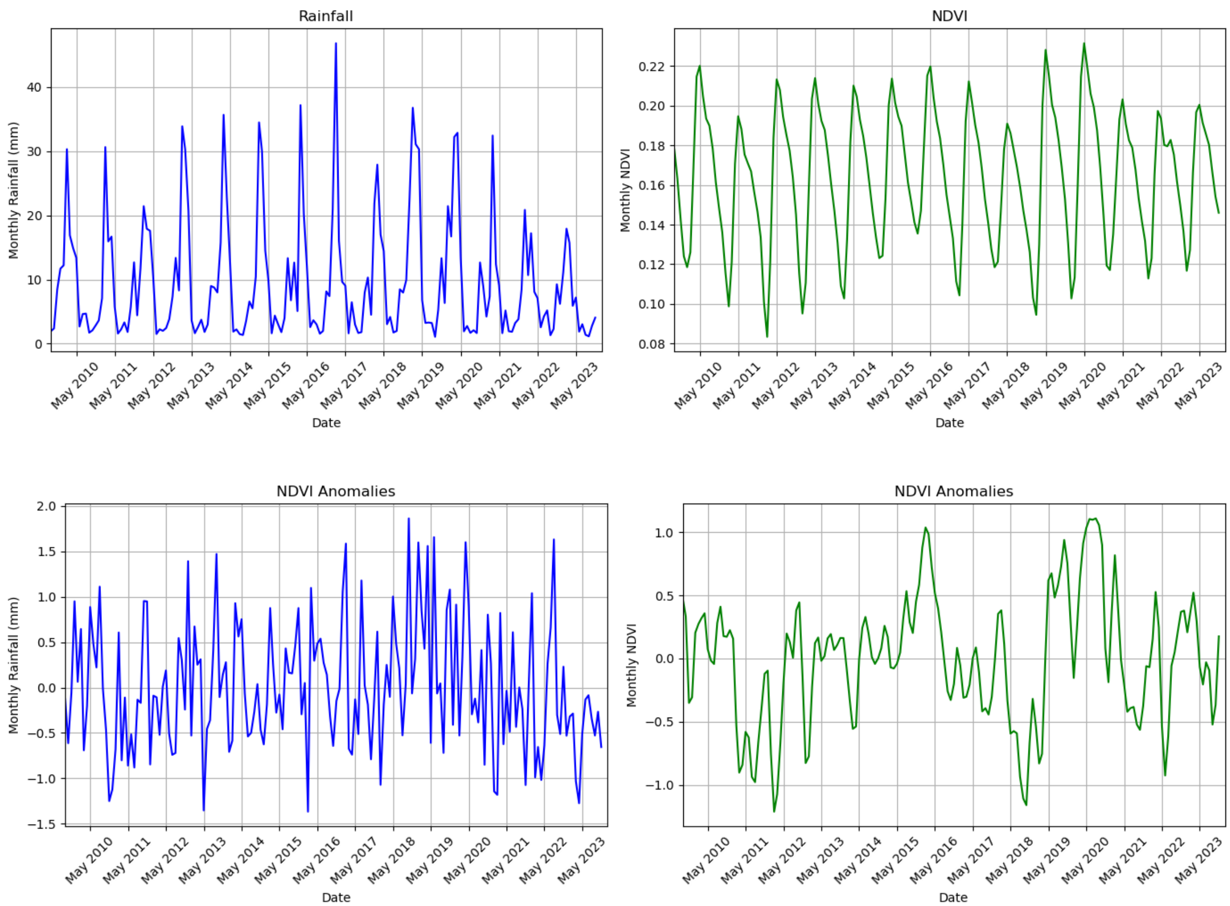
Climate Variable of Interest: Rainfall and NDVI

We used rainfall and NDVI data from the Humanitarian Data Exchange (HDX) as key climate variables. Rainfall is crucial for crop growth, providing the moisture needed for germination and development (Almouctar et al., 2024). Studies such as Hou et al. (2022) show the positive correlation between rainfall and vegetation health, affecting water availability and soil moisture. The NDVI, derived from satellite imagery, reflects vegetation density and health; higher values indicate better crop growth and yields (Pei et al., 2021). Mehmood et al. (2024) note the NDVI's sensitivity to climatic conditions, highlighting its role as a proxy for ecosystem functioning and environmental health.

Figure 3 shows the trends in average monthly rainfall and NDVI from July 2009 to December 2023. The rainfall data exhibit fluctuations with periodic peaks and troughs, indicating variability in water availability. Notable spikes are seen in 2015 and 2016, with an overall downward trend in recent years. The NDVI shows more consistent seasonal fluctuations, with peaks around 0.22 and troughs around 0.12, suggesting regular growth cycles but no long-term improvement in vegetation health.

Figure 3: Average Monthly Rainfall and NDVI

These figures are a visual representation of country-average trends in rainfall and the NDVI from July 2009 to December 2023. The left subplot depicts monthly rainfall, characterized by significant fluctuations, with peaks occurring monthly, indicating the seasonal nature of rainfall patterns. Notable spikes are observed in 2015 and 2016, with an overall downward trend in recent years. The right subplot shows the NDVI, which measures vegetation health, displaying a consistent seasonal pattern with peaks typically occurring mid-year, reflecting the cyclical growth phases of vegetation. The data are from the Humanitarian Data Exchange. The bottom plots indicate the national averages of the corresponding z-score anomalies.



Control Variables

In addition to our primary variables, we included control variables known to affect food security. We collected fuel price data from Andrée (2023a) and global food prices from the World Bank Pink Sheet. Changes in global food prices influence the cost of imported and exported food commodities, while fuel price fluctuations impact transportation and production costs throughout the food supply chain, affecting domestic food availability and prices.

We also included time-invariant variables such as population density, terrain ruggedness, cropland, and pastureland, accessed from the Predicting Food Crises dataset (Andrée et al., 2020). These factors influence agricultural productivity and market access, thereby affecting food security (Jawid & Khadjavi, 2019).

Seasonality affects agricultural productivity and food security (Aweke et al., 2022; Tay et al., 2023). Harsh winter weather often decreases agricultural productivity, leading to food shortages. While food availability generally increases during the summer, extreme heatwaves and droughts can reduce crop yields. Spring is important for planting, with favorable weather boosting productivity, whereas fall marks the harvest season, but unpredictable weather can impact crop quality and yield. To account for seasonal variations, we included three seasonal dummy variables as additional controls in our analysis.

3.3 Data Preparation

The rainfall and NDVI data were initially divided into 401 administrative codes and aggregated at the administrative division level. Each month included three data points corresponding to the 1st, 11th, and 21st days. For rainfall, we aggregated these data points using sum and mean operations to calculate average and total rainfall per month. We then standardized the monthly rainfall values using Z-scores within each market to create a rainfall anomaly variable, representing long-term rainfall variability. This approach aligns with methodologies used by Ngoma et al. (2023) and Penson et al. (2024) to capture deviations from normal rainfall patterns. A similar procedure was applied to the NDVI data. We aggregated NDVI data to obtain average NDVI per month and calculated NDVI anomalies by standardizing the average NDVI values as Z-scores within each administrative division.

To account for extreme weather events such as droughts and floods, we modeled anomalies asymmetrically. Excessive rainfall increases flood risk, while rainfall shortages increase drought risk; both conditions can exacerbate food insecurity (Coumou & Rahmstorf, 2012). We created two dummy variables for anomaly types—one indicating positive anomalies (flood anomalies) and the other indicating negative anomalies (drought anomalies). We then generated interaction terms by multiplying these dummies with the anomaly variable, allowing us to separately assess the impacts of floods and droughts.

Data on agricultural wages, exchange rates, domestic food prices, and fuel prices were organized according to administrative levels and market names. These datasets included monthly open, close, high, and low values, which we aggregated using mean operations to obtain typical monthly averages. To capture the dynamic interrelations among these economic factors, we used their percentage changes in our analysis.

Time-invariant variables such as population density, terrain ruggedness, cropland, and pastureland were available up to 2020. Due to their static nature, we extended these variables to 2023 using forward-filling techniques and applied logarithmic transformations to normalize their distributions.

4. Methods

4.1 Conceptual Model

To develop a model to investigate the influence of climate and weather shocks on domestic food prices and local agricultural wages, we start with a general form of the K-variable VAR:

$$Y_t = c + AY_{t-1} + BX_{t-1} + \varepsilon_t \tag{4}$$

where:

- Y_t is a $K \times 1$ vector of observations of the endogenous variables at time t, where K is the number of endogenous variables.
- X_t is a $M \times 1$ vector of observations of the exogenous variables at time t, where M is the number of exogenous variables.
- c is a $K \times 1$ vector of constants.
- A is a $K \times K$ matrix of coefficients capturing the influence of lagged endogenous variables.
- B is a $K \times M$ matrix of coefficients for lagged exogenous variables.
- ε_t is a $K \times 1$ vector of realized innovations at time t.

In this time-series model, ε_t should not be considered simply as regression residuals; rather, from a data-generating perspective, they represent the sequence of exogenous innovations that drive Y_t. These innovations reflect shocks or unexpected changes that cause fluctuations in the endogenous variables. Rather than viewing ε_t as random noise, it can be interpreted as representing the influences of unforeseen events–such as market disruptions, policy shifts, or environmental factors (e.g., unexpected weather conditions)−that are not accounted for by the lagged endogenous or observed exogenous variables. To better illustrate the model, we expand this matrix notation into a system of K equations, focusing only on the endogenous part:

$$\begin{aligned}
y_{1,t} &= c_1 + a_{11}y_{1,t-1} + a_{12}y_{2,t-1} + \cdots + a_{1K}y_{K,t-1} + \varepsilon_{1,t} \\
y_{2,t} &= c_2 + a_{21}y_{1,t-1} + a_{22}y_{2,t-1} + \cdots + a_{2K}y_{K,t-1} + \varepsilon_{2,t} \\
\vdots & \qquad\qquad\qquad \vdots \\
y_{K,t} &= c_K + a_{K1}y_{1,t-1} + a_{K2}y_{2,t-1} + \cdots + a_{KK}y_{K,t-1} + \varepsilon_{K,t}
\end{aligned} \tag{5}$$

Each variable $y_{i,t}$ depends not only on its own lagged value $y_{i,t-1}$ but also on the lagged values of all other variables $y_{j,t-1}$ for $j \neq i$. This structure enables the model to capture dynamic interactions among variables, where changes in one variable can indirectly influence others over time through feedback loops within the system. The VAR model serves as a tool to understand how shocks propagate throughout the system over time, allowing for an analysis of the complex interplay between climate variables, food prices, and wages, and their impact on food security. For example:

- A weather shock (entering through the residual ε_t) affecting agricultural wages ($y_{i,t}$) at time t can influence food prices ($y_{j,t+1}$) in the next period through supply and demand adjustments.

- This initial impact on food prices may further affect agricultural wages in subsequent periods ($t > 2$), creating a chain of indirect effects that impact food security.

Traditionally, the individual components in equation (5) are univariate. However, Andrée (2020) and Gheasi et al. (2023) demonstrate that this approach can be applied to spatial time series, where each variable $y_{1,t}, y_{2,t}, \dots, y_{K,t}$ is itself a vector time series consisting of subnational data that evolve over time. We generalize this idea further by noting that each equation is a generalized linear model (GLM) that can have different link functions. We thus consider a system of equations:

$$
\begin{aligned}
L^1(y_{1,t}) &= c_1 + a_{11}y_{1,t-1} + a_{12}y_{2,t-1} + \cdots + a_{1K}y_{K,t-1} + \beta_1 x + \varepsilon_{1,t} \\
L^2(y_{2,t}) &= c_2 + a_{21}y_{1,t-1} + a_{22}y_{2,t-1} + \cdots + a_{2K}y_{K,t-1} + \beta_2 x + \varepsilon_{2,t} \\
\vdots \qquad & \qquad\qquad\qquad\qquad \vdots \\
L^K(y_{K,t}) &= c_K + a_{K1}y_{1,t-1} + a_{K2}y_{2,t-1} + \cdots + a_{KK}y_{K,t-1} + \beta_K x + \varepsilon_{K,t}
\end{aligned}
\tag{6}
$$

where $L^1, L^2, \ldots, L^K$ are different link functions. To model the relationship between climatic shocks and food security, we employed a logistic link function. This leads to the well-known logit model, which is suitable when the dependent variable is binary. This has been effectively utilized in various food security-related studies, such as Ruel et al. (2010), Lobell and Burke (2010), and Smith and Haddad (2015). The general form of the regression equation for the logit model is:

$$
\text{logit}(P_t(Y=1)) = \ln\left(\frac{P_t(Y=1)}{1-P_t(Y=1)}\right) = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_n X_{nt}
\tag{7}
$$

where $P_t(Y=1)$ represents the probability of Y occurring at time t, and $X_{1t}, X_{2t}, \ldots, X_{nt}$ are the independent variables at time t. To model the relationship between climatic shocks and agricultural prices and wages, the link function is linear.

We focus on the direct and indirect relationships between climatic shocks and food security, where the indirect effects operate through agricultural prices and wages. Climatic shocks are treated as exogenous; they influence agricultural wages, prices, and food security, but the causality is unidirectional. Climatic phenomena such as droughts or floods are external factors not influenced by short-term dynamics within the agricultural economy or food security system. This ensures that climatic conditions drive changes in wages, prices, and food security without feedback affecting the shocks themselves. This allows us to focus on a system of three layered vector equations that summarize the joint process of climatic shocks, the agricultural economy, and food security outcomes:

$$
\begin{aligned}
X_t &= h(X_{t-1}, \varepsilon_t^X), \\
Y_t &= c^Y + A^Y Y_{t-1} + B^Y X_t + \varepsilon_t^Y, \\
F_t &= \text{logit}^{-1}(c^F + A^F Y_{t-1} + B^F X_t + \varepsilon_t^F),
\end{aligned}
\tag{8}
$$

where:

- X_t is an $M \times 1$ vector of observations of exogenous variables at time t, where M is the number of exogenous variables. These variables are generated by an unknown function h, which depends on past values of the exogenous variables and innovations ε_t^X.
- Y_t is a $K \times 1$ vector of observations of endogenous variables at time t, where K is the number of endogenous variables. The endogenous variables are generated by an autoregressive

process, with c^Y as a $K \times 1$ vector of constants, A^Y as a $K \times K$ matrix of autoregressive parameters, B^Y as a $K \times M$ matrix of coefficients for the exogenous variables, and ε_t^Y as a vector of innovations.

- F_t is a $D \times 1$ vector of observations of binary outcomes, generated by applying the inverse logit transformation to a linear combination of the lagged endogenous variables Y_{t-1}, the exogenous variables X_t, and innovations ε_t^F. Here, c^F is a $D \times 1$ vector of constants, A^F is a $D \times K$ matrix of coefficients for the lagged endogenous variables, and B^F is a $D \times M$ matrix of coefficients for the exogenous variables.

The regression system can be estimated equation by equation and interpreted as interconnected panel time-series models, but the parameters should always be considered within the context of a larger dynamic system. Climatic conditions X_t, driven by external influences ε_t^X, affect the endogenous variables Y_t (representing the agricultural economy) and reverberate through the system via autoregressive dynamics. Food security outcomes F_t are determined by both the lagged state of the agricultural economy and climatic shocks, meaning food security is impacted by both direct and indirect climatic effects. As a result, climatic shocks can have lingering impacts on food security outcomes over multiple periods, capturing complex real-world phenomena.

For example, consider a drought event (entering the system as a shock in ε_t^X). In the first period, the drought reduces crop yields (entering through X_t), leading to a decline in agricultural wages, represented by Y_t, due to decreased demand for labor. In the following period, this wage reduction lowers household purchasing power, diminishing food demand and affecting prices. Over time, this initial drought shock propagates through the economy, influencing wages and prices (represented by Y_{t+h} for $h > 1$), which can have long-term effects on food security outcomes.

Finding insignificant coefficients for climatic impacts in the food security outcome equations, while observing significant coefficients in the wage or price equations, does therefore not imply that food security is unaffected by climatic shocks. Rather, it suggests that these shocks indirectly affect food security through their impact on the agricultural economy. Similarly, variables not explicitly included in the food security outcome equation can still influence the system. For instance, ε_t^Y may capture the price impacts of conflict shocks, which can subsequently propagate through F_t.

4.2 Regression Specification

For the food security outcomes, we employed two logit specifications to capture different levels of food insecurity. The first specification uses a binary indicator as the dependent variable, set to 1 when the IPC phase is 2 or higher (food stress). The second specification denotes 1 when the IPC phase is 3 or higher (food crisis). For food prices and agricultural wages, the dependent variables are the percentage changes in local domestic food prices and local agricultural wages, respectively.

The primary independent variables are drought and flood anomalies derived from rainfall data and vegetation health, measured using NDVI anomalies. We also include a range of control variables such as fuel prices, global food prices, demographic factors, seasonal dummies, and time trends. Compared to the conceptual model, this expands X_t (climatic shocks) by introducing W_t (additional economic variables like exchange rates and global food prices that enter contemporaneously and with lags), Z_t (additional economic variables that enter with lags) and G_t (time-invariant controls), to allow for additional covariates to enter the model differently.

The final form of the regression system is:

$$
\begin{aligned}
\text{logit}(P_t^{\text{stress}}) &= c_0^{\text{stress}} + \sum_{k=1}^{2}\sum_{p=0}^{12} \alpha_k^{\text{stress}} \frac{\Delta Y_{k,t-p}}{\Delta Y_{k,t-p-1}} + \sum_{m=1}^{4}\sum_{p=0}^{12} \theta_p^{\text{stress}} X_{m,t-p} \\
&+ \sum_{m=5}^{6}\sum_{p=0}^{12} \beta_m^{\text{stress}} \frac{\Delta W_{m,t-p}}{\Delta W_{m,t-p-1}} + \sum_{m=7}^{7}\sum_{p=1}^{12} \beta_m^{\text{stress}} \frac{\Delta Z_{m,t-p}}{\Delta Z_{m,t-p-1}} + \sum_{m=8}^{15} \beta_m^{\text{stress}} \ln(G_{m,t}) + \varepsilon_t^{\text{stress}} \\
\text{logit}(P_t^{\text{crisis}}) &= c_0^{\text{crisis}} + \sum_{k=1}^{2}\sum_{p=0}^{12} \alpha_k^{\text{crisis}} \frac{\Delta Y_{k,t-p}}{\Delta Y_{k,t-p-1}} + \sum_{m=1}^{4}\sum_{p=0}^{12} \theta_p^{\text{crisis}} X_{m,t-p} \\
&+ \sum_{m=5}^{6}\sum_{p=0}^{12} \beta_m^{\text{crisis}} \frac{\Delta W_{m,t-p}}{\Delta W_{m,t-p-1}} + \sum_{m=7}^{7}\sum_{p=1}^{12} \beta_m^{\text{crisis}} \frac{\Delta Z_{m,t-p}}{\Delta Z_{m,t-p-1}} + \sum_{m=8}^{15} \beta_m^{\text{crisis}} \ln(G_{m,t}) + \varepsilon_t^{\text{crisis}} \\
\Delta Y_t^{\text{price}} &= c_0^{\text{price}} + \sum_{k=1}^{2}\sum_{p=0}^{12} \alpha_k^{\text{price}} \frac{\Delta Y_{k,t-p}}{\Delta Y_{k,t-p-1}} + \sum_{m=1}^{4}\sum_{p=0}^{12} \theta_p^{\text{price}} X_{m,t-p} \\
&+ \sum_{m=5}^{6}\sum_{p=0}^{12} \beta_m^{\text{price}} \frac{\Delta W_{m,t-p}}{\Delta W_{m,t-p-1}} + \sum_{m=7}^{7}\sum_{p=1}^{12} \beta_m^{\text{price}} \frac{\Delta Z_{m,t-p}}{\Delta Z_{m,t-p-1}} + \sum_{m=8}^{15} \beta_m^{\text{price}} \ln(G_{m,t}) + \varepsilon_t^{\text{price}} \\
\Delta Y_t^{\text{wage}} &= c_0^{\text{wage}} + \sum_{k=1}^{2}\sum_{p=0}^{12} \alpha_k^{\text{wage}} \frac{\Delta Y_{k,t-p}}{\Delta Y_{k,t-p-1}} + \sum_{m=1}^{4}\sum_{p=0}^{12} \theta_p^{\text{wage}} X_{m,t-p} \\
&+ \sum_{m=5}^{6}\sum_{p=0}^{12} \beta_m^{\text{wage}} \frac{\Delta W_{m,t-p}}{\Delta W_{m,t-p-1}} + \sum_{m=7}^{7}\sum_{p=1}^{12} \beta_m^{\text{wage}} \frac{\Delta Z_{m,t-p}}{\Delta Z_{m,t-p-1}} + \sum_{m=8}^{15} \beta_m^{\text{wage}} \ln(G_{m,t}) + \varepsilon_t^{\text{wage}}
\end{aligned}
\tag{9}
$$

Where:

- P_t^{stress} is the probability of IPC level 2 or greater (food stress), and P_t^{crisis} is the probability of IPC level 3 or greater (food crisis).
- $\Delta Y_{k,t-p}$ are agricultural prices and wages, where $\Delta Y_t^{\text{price}}$ is the percentage change in domestic food prices, and ΔY_t^{wage} is the percentage change in local agricultural wages.
- There are $M = 15$ exogenous variables. Note that m indexes over (X, W, Z, G) in the notation:
    - $X_{m,t-p}$ represents the four main independent variables ($m = 1, \dots, 4$): flood and drought anomalies, derived from rainfall and NDVI.
    - $\Delta W_{m,t-p}$ represents the percentage changes in exchange rates and global food prices ($m = 5,6$)
    - $\Delta Z_{m,t-p}$ represents the percentage changes in fuel prices ($m = 7$).
    - $G_{m,p}$ includes eight additional control variables ($m = 8, \dots, 15$): time trend, population density, terrain ruggedness, cropland shares, pastureland shares, and seasonal dummies for winter, summer, and spring.
- α_k captures the dependencies on the endogenous variables, which result in autoregressive dynamics in the agricultural price equations, and β_m captures the dependencies on the exogenous variables.
- ε_t represents the error term.

We incorporated up to 12 lag periods to capture the delayed effects of climate shocks, consistent with studies such as Tang et al. (2021) and Prather et al. (2023). Economic variables like agricultural wages, fuel prices, domestic food prices, exchange rates, and global food prices often respond to climatic shocks with time lags, as indicated by Schmidhuber and Tubiello (2007).

The system includes many parameters, and to assess the cumulative impact of various factors, we sum the coefficients across all lags. This approach provides insights into the combined influence of these factors over time. For the logit equations, we convert the parameter estimates into marginal effects to aid interpretation, calculated over the full-year effects. Robust standard errors are used for all parameters to address potential heteroscedasticity. Finally, the estimated parameters allow us to predict the probabilities of food stress and food crisis, generating averages for each administrative area. This enables mapping variations in food insecurity risks between 2009 and 2023.

5. Results

This section presents the results of the logit regressions estimating the impact of climatic and economic shocks on food security. The results are presented in stages. First, we examine the direct effects of climatic shocks, particularly rainfall and NDVI anomalies, on food stress and food crisis. Next, we evaluate the role of economic factors, such as changes in food prices and agricultural wages, in influencing food insecurity, with a focus on how these variables react to climatic shocks.

5.1 Logit Regression Estimates for Food Stress and Food Crisis Drivers

Table 2 reports the results of the logit regressions for two thresholds of food insecurity: IPC phase 2 or greater (food stress) and IPC phase 3 or greater (food crisis). The model includes climatic variables (rainfall and NDVI anomalies), economic factors (food prices, agricultural wages), and a set of control variables to capture structural determinants of food security. The model is estimated using monthly data with twelve lags. To summarize, the coefficients are combined to represent the cumulative impact over 12 months, with marginal effects indicating the corresponding change in probability.

Seasonal Effects

Before analyzing the impacts of the climatic variables, it is useful to first consider the average seasonal dynamics captured by the seasonal controls. In Afghanistan, floods most often occur during the spring, particularly from March to June, due to snowmelt from mountainous regions and seasonal rainfall. As temperatures rise, snow from higher altitudes melts, and combined with heavy rainfall, this leads to flooding, especially in river valleys and lower-lying areas. Floods can also occur during the summer, particularly during the monsoon season from July to September, though this impact is less widespread than in the spring.

Droughts in Afghanistan typically occur during the summer and autumn, especially from June to November, due to limited rainfall. Areas that rely on seasonal rain or snowmelt for water are particularly affected. The arid and semi-arid climate, combined with climate variability, makes the country highly susceptible to droughts. Droughts are often worsened by insufficient winter snowpack or reduced spring rains, leading to water shortages, reduced agricultural output, and declining groundwater levels.

Table 2: Logit Regression Estimates for Food Stress and Food Crisis

The table presents logistic regression estimates for food insecurity under IPC ≥ 2 (food stress) and IPC ≥ 3 (food crisis). The coefficients represent the cumulative impact over 12 months of a one-unit change in each predictor variable, with the marginal effects indicating the corresponding change in probability. Note that flood anomalies are negative values, and combined with a negative coefficient, they result in an increased probability proportional to the severity of the flood indicator. To simplify interpretation, the negative anomalies are entered into the model as absolute values, ensuring that positive coefficients indicate an increase in risk.

	IPC ≥ 2 (Food Stress)		IPC ≥ 3 (Food Crisis)	
	Coefficient	**Marginal Effect**	**Coefficient**	**Marginal Effect**
Flood anomalies	1.194*** (0.026)	0.234*** (0.005)	0.628*** (0.036)	0.059*** (0.003)
Drought anomalies	0.227*** (0.039)	0.045*** (0.008)	-0.100* (0.052)	-0.009* (0.005)
Positive NDVI anomalies	0.918*** (0.021)	0.180*** (0.004)	0.158*** (0.028)	0.015*** (0.003)
Negative NDVI anomalies	0.449*** (0.024)	0.088*** (0.005)	0.399*** (0.032)	0.037*** (0.003)
Food prices	-0.006*** (0.001)	-0.001*** (0.0002)	0.001 (0.002)	0.000 (0.0002)
Agricultural wages	-0.005*** (0.001)	-0.001*** (0.0002)	-0.037*** (0.002)	-0.003*** (0.0002)
Fuel prices	0.050*** (0.001)	0.010*** (0.0001)	0.028*** (0.001)	0.003*** (0.0001)
Global food prices	0.034*** (0.001)	0.007*** (0.0001)	-0.002*** (0.001)	-0.0002*** (0.0001)
Exchange rate	-0.029*** (0.001)	-0.006*** (0.0003)	0.024*** (0.002)	0.002*** (0.0002)
Log Cropland	-0.129*** (0.004)	-0.025*** (0.001)	-0.463*** (0.007)	-0.043*** (0.001)
Log Ruggedness Terrain	0.465*** (0.011)	0.091*** (0.002)	1.958*** (0.031)	0.183*** (0.002)
Log Population Density	0.258*** (0.006)	0.051*** (0.001)	0.799*** (0.014)	0.075*** (0.001)
Log Pastureland	-0.108*** (0.016)	-0.021*** (0.003)	0.707*** (0.047)	0.066*** (0.004)
Winter Dummy	0.114*** (0.018)	0.022*** (0.004)	0.372*** (0.027)	0.035*** (0.003)
Summer Dummy	-0.163*** (0.019)	-0.032*** (0.004)	-0.197*** (0.028)	-0.018*** (0.003)
Spring Dummy	0.500*** (0.019)	0.098*** (0.004)	0.916*** (0.026)	0.086*** (0.002)
Constant (Fall)	-12.190*** (0.224)		-48.956*** (0.778)	
N	112,711		112,711	
Pseudo R2	0.147		0.293	
Correctly predicted	69.14%		87.89%	

Note: *p < 0.1, **p < 0.05, ***p < 0.01

The seasonal dummies reveal important variations in food insecurity risks throughout the year. Food insecurity is highest during the winter and spring months, with food stress increasing by 2.2 percentage points in winter and 9.8 percentage points in spring. Similarly, food crisis risks rise by 3.5 percentage points in winter and 8.6 percentage points in spring. These seasonal effects likely reflect reduced agricultural activity in winter and the pre-harvest lean season in spring when food stocks are low. They also coincide with the flooding season, which is important for interpreting the marginal effects of flood anomalies. In contrast, summer is associated with a decrease in food insecurity, with food stress and food crisis risks falling by 3.2 and 1.8 percentage points, respectively, as harvests replenish food supplies. This seasonal baseline is important when analyzing the marginal effects of the drought variables.

Climatic Shocks: Flood and Drought Anomalies, NDVI Anomalies

The results underscore the impact of climatic shocks on food insecurity outcomes. Both rainfall anomalies, characterized by flood and drought events, and NDVI anomalies, reflecting vegetation health, emerge as key predictors of food stress and food crisis, with differing effects across the two levels of food insecurity.

Flood anomalies, defined by excessive rainfall, have a significant positive effect on both food stress and food crisis risks. For food stress, the coefficient of 1.194 is significant at the 1% level, indicating that a one-unit increase in flood anomaly severity—a one-in-six-year flood event[1]—is associated with a 23.4 percentage point increase in the probability of food stress. Similarly, for food crisis, the coefficient of 0.628, also significant at the 1% level, implies a 5.9 percentage point increase in the probability of a food crisis. These findings are consistent with expectations, as severe flooding can damage crops, disrupt supply chains, and displace populations. When combined with the average spring increase in food stress (9.8%) and food crisis (8.6%), this translates to a 33.2 percentage point increase in food stress and a 14.5 percentage point increase in food crisis.

Drought anomalies, defined by rainfall shortfalls, present a nuanced picture. For food stress, the positive coefficient of 0.227 is significant at the 1% level, suggesting that worsening drought conditions correspond to a 4.5 percentage point increase in food stress risk, aligning with known adverse effects of drought on agriculture. For food crisis, however, the coefficient of -0.100, significant at the 10% level, indicates a slight reduction (0.9 percentage points) in the likelihood of a food crisis. This result may be due to market adjustments, aid interventions, or shifts in livelihood strategies that mitigate the immediate impacts of drought on severe food insecurity. An alternative explanation involves the joint effect of negative NDVI and rainfall anomalies, with the former reflecting poor vegetation health due to insufficient rainfall. The coefficient for negative NDVI anomalies is 0.399, significant at the 1% level, with a marginal effect of a 3.7 percentage point increase in food crisis probability. When a region experiences both a one-unit increase in drought severity and a similarly negative NDVI anomaly, the combined marginal effect on food crisis probability is a 2.8 percentage point increase (-0.9% from drought anomalies plus 3.7% from negative NDVI anomalies). Combining this figure with the typical post-harvest food security benefits captured by the summer dummy still results in a net 1% increase in food crisis risk.

Positive NDVI anomalies, indicating better-than-average vegetation health, have mixed effects on food insecurity. For food stress, the coefficient is 0.918, with a marginal effect of an 18 percentage point increase, significant at the 1% level. For food crisis, the coefficient is 0.158, with a marginal effect of a 1.5 percentage point increase, also significant at the 1% level. These results suggest that improved vegetation health is unexpectedly associated with increased food insecurity. A plausible explanation is that positive NDVI anomalies may result from previous excessive rainfall that has led to both flooding and subsequent lush vegetation. In this case, NDVI may indicate healthy natural vegetation while simultaneously capturing the destructive effects of floods on crops. High NDVI readings are also likely to coincide with spring and should be considered alongside the negative impacts of the lean season. In this light, the combined marginal effect on food stress probability is substantial at 41.4 percentage points (23.4% from flood anomalies plus 18% from positive NDVI anomalies). For food crisis, the total increase is 7.4 percentage points (5.9% from flood anomalies

[1] A one-unit increase in a z-score corresponds to an event becoming more extreme. To translate this into a "one-in-six-years" event, we consider that a z-score of 1 corresponds to an event that has a 15.87% probability of being more extreme (i.e., a 1 in 6.3 chance of occurring). This means such an event would be expected approximately once every six years.

plus 1.5% from positive NDVI anomalies). These figures increase to 51.2% and 16%, respectively, when considering the average lean season effect captured by the spring dummy.

Negative NDVI anomalies, reflecting below-average vegetation health, show the expected effect on food insecurity. For food stress, the coefficient is 0.449, with a marginal effect of an 8.8 percentage point increase, significant at the 1% level. For food crisis, the coefficient is 0.399, with a marginal effect of a 3.7 percentage point increase, also significant at the 1% level. These results indicate that poor vegetation health is indicative of poor agricultural yields. The effects are strong enough to offset the usual beneficial impact of summer. The joint effects of drought anomalies and negative NDVI anomalies further exacerbate food insecurity risks. For food stress, the combined marginal effect is a 13.3 percentage point increase (4.5% from drought anomalies plus 8.8% from negative NDVI anomalies). For food crisis, the net increase is 2.8 percentage points (-0.9% from drought anomalies plus 3.7% from negative NDVI anomalies). This highlights the significant rise in food insecurity risk associated with the simultaneous occurrence of drought and poor vegetation health.

These findings illustrate the complex interplay between different climatic shocks and their combined effects on food security. While individual climatic variables significantly affect food insecurity, their interactions can amplify these impacts, particularly when seasonality and joint occurrence are considered. The analysis underscores the economic importance of floods compared to droughts and highlights the need to consider multiple, interacting climatic factors in policy planning and interventions aimed at mitigating food insecurity risks.

Economic Factors: Food Prices and Agricultural Wages

The analysis highlights the complex influence of economic variables on food insecurity. Changes in food prices and agricultural wages play a key role in determining food security outcomes, though their effects are context-dependent.

The results for food prices, particularly for food stress, are somewhat counterintuitive. The coefficient of -0.006, with a marginal effect of -0.001, suggests that rising food prices reduce the likelihood of food stress by 0.1 percentage points for every 1% increase in food prices. This result, significant at the 1% level, likely reflects the dual nature of food prices in agricultural regions: while higher prices can limit access for net consumers, they may improve income and food security for producers benefiting from higher market prices. For food crisis, however, the marginal effects indicate no significant relationship, suggesting that other factors dominate in severe cases of food insecurity.

The impact of food prices becomes clearer when considered with other variables. For example, a 10% increase in food prices combined with a 10% rise in fuel prices results in a 9 percentage point increase in food stress probability. This suggests that while isolated food price increases may benefit producers and reduce food stress, broad-based inflation encompassing food, fuel, and other essentials exacerbates food insecurity. Alternatively, when a 10% increase in food prices coincides with global food price hikes, the net effect is a 6 percentage point increase in food stress probability (a 1% rise in global food prices results in a 0.7 percentage point increase in food stress probability). This highlights the importance of considering the source of inflation: global impacts on imported food prices versus isolated local price increases that benefit producers.

Further complexity arises when domestic inflation is unpacked further, considering climatic shocks as sources of inflation. For instance, when drought anomalies (+4.5%) and negative NDVI anomalies (+8.8%) are combined with a 10% rise in food prices (-1%), the net effect is a 13.2 percentage point increase in food stress.

Fuel prices alone show a consistent positive relationship with food insecurity risk. A 1% increase in fuel prices is associated with a 1 percentage point increase in food stress probability (coefficient of 0.050, marginal effect of 0.010) and a 0.3 percentage point increase in food crisis probability (coefficient of 0.028, marginal effect of 0.003), both significant at the 1% level. This reflects the role of fuel in food production and distribution, where higher costs raise transportation expenses and food prices, increasing the likelihood of food insecurity.

Agricultural wages also show a clear relationship with food security. Rising wages are linked to reductions in both food stress and food crisis risks. Specifically, a 10% increase in wages reduces food stress probability by 1 percentage point (coefficient of -0.005, marginal effect of -0.001) and food crisis probability by 3 percentage points (coefficient of -0.037, marginal effect of -0.003), both significant at the 1% level. This supports the view that higher wages improve purchasing power, enhancing access to food and reducing food insecurity. However, the effects of rising wages must be considered against inflationary pressures to assess real purchasing power changes. For example, a 10% increase in wages with a 10% increase in food and fuel prices results in an 8 percentage point increase in food stress risk (-1% from wages, +1% from food prices, +10% from fuel prices). For food crisis, a similar combination results in no net change (-3% from wages offset by +3% from fuel prices). This suggests that inflation, particularly rising fuel prices, erodes positive effects of wage growth on food security, making wage increases effective only when real wages rise.

The effects of exchange rate depreciation are mixed. A 1% depreciation reduces food stress probability by 0.6 percentage point (coefficient of -0.029, marginal effect of -0.006) but increases food crisis probability by 0.2 percentage point (coefficient of 0.024, marginal effect of 0.002), both significant at the 1% level. The reduction in food stress may reflect benefits to agricultural exporters, as a weaker currency boosts the competitiveness of locally produced food, acting as a stimulus. However, for severe food insecurity, the higher cost of imported goods—particularly food and fuel—due to depreciation increases food crisis likelihood. When exchange rate depreciation coincides with rising fuel and food prices, the effects on food insecurity are compounded. For example, a 10% depreciation combined with a 10% increase in fuel prices leads to a 3 percentage point increase in food stress risk (-6% from depreciation, +10% from fuel prices, -1% from food prices). For food crisis, the net effect is a 5 percentage point increase (+2% from depreciation, +3% from fuel prices).

Control Variables

The control variables, including cropland, pastureland, terrain ruggedness, and population density, significantly influence food security outcomes. Cropland has a protective effect, with a 10% increase reducing the probability of food stress by 2.5 percentage points and food crisis by 4.3 percentage points, highlighting the role of local agricultural production in bolstering food supply and reducing external dependence. In contrast, rugged terrain worsens food insecurity, increasing the likelihood of food stress by 9.1 percentage points and food crisis by 18.3 percentage points, likely due to challenges in agriculture, market access, and infrastructure development. Population density also correlates with increased food insecurity; a 10% rise in density leads to a 5.1 percentage point increase in food stress probability and a 7.5 percentage point increase in food crisis probability, indicating the resource competition and supply chain pressures faced by densely populated areas.

5.2 VAR Estimates for Climate Impact on Food Prices and Wages

Table 3 shows the VAR estimates assessing the impact of climatic shocks and economic variables on food prices and agricultural wages. The model includes climatic variables (rainfall and NDVI anomalies), economic factors (domestic and global food prices, fuel prices, exchange rates), and structural controls to capture regional characteristics. The coefficients are summarized to represent the cumulative impact over 12 months of a one-unit change in each predictor variable, indicating the corresponding percentage change in the month-over-month outcome variable. For easier interpretation, we annualize the inflation impacts.

Table 3: Vector Autoregression Estimates for Climate Impact on Food Prices and Wages

The table presents regression estimates for changes in food prices and wages. The coefficients represent the cumulative impact over 12 months of a one-unit change in each predictor variable, indicating the corresponding percentage change in the outcome variable. Note that flood anomalies are negative values, and when combined with a negative coefficient, they result in an increase in the outcome variable proportional to the severity of the flood indicator. To simplify interpretation, the negative anomalies are entered into the model as absolute values, ensuring that positive coefficients indicate an increase in the outcome variable.

	Percentage change in food prices	**Percentage change in agricultural wages**
Flood anomalies	0.279*** (0.072)	0.149** (0.075)
Drought anomalies	-0.093 (0.107)	0.418*** (0.111)
Positive NDVI anomalies	0.593*** (0.057)	0.085 (0.059)
Negative NDVI anomalies	0.515*** (0.063)	0.018 (0.065)
Food prices	0.737*** (0.003)	-0.039*** (0.004)
Agricultural wages	0.017*** (0.004)	0.628*** (0.004)
Fuel prices	0.061*** (0.002)	0.010*** (0.002)
Global food prices	0.045*** (0.002)	-0.028*** (0.002)
Exchange rate	0.195*** (0.004)	-0.091*** (0.004)
Log Cropland	-0.010 (0.012)	-0.034*** (0.012)
Log Ruggedness Terrain	0.039 (0.030)	0.064** (0.031)
Log Population Density	-0.042** (0.018)	-0.018 (0.019)
Log Pastureland	0.030 (0.044)	-0.219*** (0.046)
Winter Dummy	0.100* (0.052)	0.119** (0.054)
Summer Dummy	-0.182*** (0.054)	-0.056 (0.056)
Spring Dummy	-0.017 (0.052)	-0.016 (0.054)
Constant (Fall)	-0.204 (0.599)	0.826 (0.620)
N	112,711	112,711
R^2	0.813	0.527

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

Seasonal Effects

Seasonal dynamics play a key role in Afghanistan's agricultural production and labor demand. Winter months typically see reduced agricultural activity due to cold temperatures and snow cover, leading to lower labor demand and potentially higher food prices due to limited supply. Spring marks the start of the planting season, while summer and fall are associated with increased agricultural output and labor demand, potentially resulting in lower food prices and higher wages.

The regression results confirm the variations in food prices and agricultural wages across the year, captured by the seasonal dummy variables. During winter, food prices increase at an annualized rate of 1.27% (coefficient of 0.100, significant at the 10% level), while agricultural wages rise by 1.50% (coefficient of 0.119, significant at the 5% level). This suggests that despite reduced agricultural activity, there may be higher labor demand for non-agricultural activities or preparation for planting.

In contrast, summer is associated with a decrease in food prices, with an annualized effect of -2.13% (coefficient of -0.182, significant at the 1% level), likely reflecting increased food supply due to harvests. However, the impact on agricultural wages during summer is not statistically significant, indicating that labor demand may not change significantly during this season. These seasonal effects provide important baselines for interpreting the effects of climatic and economic variables on food prices and wages throughout the year.

Climatic Shocks: Flood and Drought Anomalies, NDVI Anomalies

The regression results confirm flood, drought, and NDVI anomalies as key predictors of food prices and wages.

Flood anomalies have a positive effect on both. For food prices, the coefficient of 0.279 is significant at the 1% level, indicating that a one-unit increase in flood anomaly severity over 12 months leads to a 0.279 percentage point increase in monthly food price inflation, translating to an annualized increase of about 3.40%. This aligns with expectations, as floods damage crops and disrupt supply chains, reducing supply and driving up prices. For wages, the coefficient of 0.149 is significant at the 5% level, corresponding to an annualized increase of about 1.80%. This suggests floods may boost labor demand for recovery efforts, raising wages. Floods often coincide with positive NDVI anomalies due to excess rainfall resulting in lush vegetation despite crop damage. Combining the annualized effects of flood anomalies (3.40%) and positive NDVI anomalies (7.36%) results in an approximate 10.76% increase in food prices. The impact on wages is driven by flood anomalies, as positive NDVI anomalies do not have a significant effect on wages. The estimated impact on prices (10.76%) exceeds that on wages (1.80%), creating a net negative purchasing power effect (-8.96%). The compound effect of floods during spring further exacerbates these impacts, as floods during planting season disrupt agricultural activities, delay planting, and reduce yields. This amplifies inflationary pressure on food prices, and modest wage increases do not offset the higher food costs, increasing food insecurity.

Drought anomalies present a different picture. For food prices, the coefficient of -0.093 is not statistically significant. For wages, the coefficient of 0.418 is significant at the 1% level, corresponding to an annualized increase of 5.17%. This suggests drought conditions increase labor demand for mitigation efforts, raising wages. Droughts often coincide with negative NDVI anomalies, reflecting poor vegetation health due to insufficient rainfall. The coefficient for negative NDVI anomalies on food prices is 0.515, significant at the 1% level, indicating a one-unit increase leads to an annualized 6.36% increase in food prices. Combined, drought anomalies (no significant effect on prices) and negative NDVI anomalies (6.36% increase) suggest that negative NDVI anomalies primarily drive price increases during droughts. For wages, the combined effect of drought and negative NDVI anomalies results in a 5.17% annualized increase, driven by drought anomalies, as negative NDVI anomalies do not significantly affect wages. This simultaneous increase in food prices and wages suggests that while workers earn more for mitigation efforts during droughts, higher food prices offset these gains, resulting in a net negative purchasing power effect (-1.19%). Droughts during summer can intensify these impacts. Summer usually sees increased output and lower prices after harvest, but droughts can reduce yields, causing price increases that exceed the typical seasonal decrease. This disrupts the benefits of summer harvests, worsening food insecurity as wage increases fail to compensate for higher prices.

Positive NDVI anomalies, indicating better vegetation health, unexpectedly increase food prices. The coefficient of 0.593 is significant at the 1% level, corresponding to an annualized increase of about 7.36%. This suggests positive NDVI anomalies may be linked to factors like excessive rainfall causing floods, which damage crops despite lush vegetation. The lack of a significant effect on wages (coefficient of 0.085, not significant) indicates positive NDVI anomalies do not impact labor demand or wages. Combined with flood anomalies, the cumulative annualized increase in food prices reaches about 10.76% (7.36% from positive NDVI anomalies and 3.40% from flood anomalies).

Negative NDVI anomalies have a significant effect on food prices, shown by a coefficient of 0.515, significant at the 1% level, corresponding to an annualized increase of about 6.36%. This aligns with expectations, as poor vegetation reduces yields, leading to higher prices. The effect on wages is not significant, suggesting negative NDVI anomalies alone do not influence wages. However, combined with drought anomalies (which significantly increase wages), the overall impact includes a 6.36% increase in prices and a 5.17% increase in wages. Similar to the drought scenario, purchasing power may erode due to the larger increase in prices compared to wages.

Economic Factors: Food Prices, Agricultural Wages, Fuel Prices, Global Food Prices, Exchange Rates

The estimates highlight the influence of economic variables on food prices and agricultural wages and show how their interplay shapes food security dynamics in Afghanistan.

The coefficients for the percentage change in food prices and agricultural wages on their own lagged values are significant at the 1% level, indicating strong persistence. For food prices, the coefficient of 0.737 suggests that past increases lead to sustained future increases, with a decay rate of 16 months for an impact to dissipate by 99%. For agricultural wages, the coefficient of 0.628 corresponds to a 10-month decay rate at the same threshold. This persistence compounds the effects of climatic shocks on prices and wages.

Agricultural wages have a small but significant positive effect on food prices, with a coefficient of 0.017 (significant at the 1% level), corresponding to an annualized effect of about 0.20%. This suggests that wage increases can raise production costs, which are passed on to consumers as higher food prices, consistent with a wage-inflation spiral. However, the effect remains relatively weak. The percentage change in food prices has a significant negative effect on agricultural wages, with a coefficient of -0.039 (significant at the 1% level), corresponding to an annualized effect of about -0.47%. This indicates that rising food prices adversely impact wages, implying that nominal wages do not keep up with inflation, leading to a decline in purchasing power.

Fuel prices have a significant positive relationship with both food prices and wages. A 1% increase in fuel prices is associated with an annualized increase of about 0.74% in food prices (coefficient of 0.061, significant at the 1% level) and 0.12% in wages (coefficient of 0.010, significant at the 1% level). Higher fuel costs increase transportation and production expenses, contributing to higher food prices. The modest wage increase may reflect higher labor demand in sectors affected by fuel costs, though the impact on wages is smaller than on prices, potentially reducing purchasing power.

Global food price increases have a significant positive effect on domestic food prices, with a coefficient of 0.045 (significant at the 1% level), corresponding to an annualized increase of about 0.55% per 1% increase in global prices. This confirms a pass-through effect from global to domestic markets. For agricultural wages, the coefficient is -0.028 (significant at the 1% level), corresponding to an annualized decrease of about -0.33% per 1% increase in global food prices. This wage suppression may result from higher input costs, reducing employer profitability.

Exchange rate depreciation significantly affects both food prices and wages. A 1% depreciation leads to an annualized increase of about 2.39% in food prices (coefficient of 0.195, significant at the 1% level) and an annualized decrease of about -1.08% in wages (coefficient of -0.091, significant at the 1% level). Currency depreciation raises the cost of imported goods, including food and agricultural inputs, driving up food prices. At the same time, increased costs can reduce employer profitability, lowering nominal wages for agricultural workers. Exchange rate depreciation typically leads to inflationary effects on food prices and general price levels. If combined with a similar rise in fuel prices, the impact on food prices compounds. A 1% increase in both exchange rate depreciation and fuel prices results in an annualized increase of about 3.13% in food prices (2.39% from exchange rate and 0.74% from fuel prices). For wages, the combined annualized effect is about -0.96% (-1.08% from exchange rate and 0.12% from fuel prices). This illustrates how currency devaluation raises prices but not wages, eroding purchasing power and worsening food insecurity.

Control Variables

The control variables highlight key determinants of food price and wage inflation, indicating regional convergence and divergence dynamics.

Cropland shows a negative relationship with wage growth, where a 10% increase in cropland area links to an annualized wage decrease of about -0.40% (coefficient of -0.034, significant at the 1% level), possibly due to labor oversupply or productivity improvements reducing labor demand. It could also signal a labor shift to other sectors as agricultural efficiency rises.

Terrain ruggedness is associated with higher wage growth, with a coefficient of 0.064 (significant at the 5% level), indicating an annualized wage increase of about 0.79%. This suggests that accessibility challenges in rugged areas require higher wages to attract labor, with difficult conditions and higher living costs contributing to this effect.

Population density correlates with lower food price inflation; a 10% increase results in an annualized price decrease of about -0.50% (coefficient of -0.042, significant at the 5% level). Higher density may enhance market efficiency and reduce transaction costs due to better infrastructure, competitive markets, and efficient supply chains.

Pastureland has a significant negative impact on wages, with a 10% increase linked to an annualized wage decrease of about 2.57% (coefficient of -0.219, significant at the 1% level). This may stem from the lower labor intensity of livestock farming compared to crop farming and the seasonal nature of pastoral activities, often reliant on family labor.

5.3 Estimates for Food Stress and Food Crisis Risks

The logit models show strong predictive performance, correctly classifying 69.14% of food stress cases and 87.89% of food crisis cases. These results highlight the importance of climatic and economic variables in shaping food security and demonstrate the models' ability to capture complex dynamics. The predictive power also points to their potential use in targeting and monitoring efforts.

To estimate the population at risk, we multiplied the population of each period by its predicted probability of food stress and food crisis. These estimates were rescaled by fitting a linear regression model, using the share of the population exceeding IPC levels 2 and 3 as the dependent variable and the population-weighted probabilities as the predictor. The rescaled values were then used to estimate the population at risk over time.

Geographical Variation in Modeled Risks

Tables 4 and 5 provide a detailed breakdown of the probability of food stress and food crisis across Afghan provinces, along with provincial demographic data (NSIA, 2021) to capture population exposure to these risks. Overall, while food stress is widespread, food crisis risk is more concentrated but significant in certain areas.

Table 4 shows the probability of food stress, indicating moderate levels of food insecurity. Most provinces fall into higher risk categories, with 28 of 34 provinces showing an average probability of food stress above 50%, representing over 28 million people (89% of the country's population). Notably, 12 provinces have probabilities between 61%-70%, and two provinces exceed 71%, exposing large populations to chronic food stress. The distribution highlights widespread vulnerability, particularly in provinces with larger populations facing high food stress likelihood.

Table 4: Probability of Food Stress across Provinces in Afghanistan

Table 4 shows the average probability of food stress over the full study period across Afghan provinces, broken down into ranges of 0.1. The columns provide a demographic breakdown of the provincial statistics to understand overall population exposure to relative risks. The majority of administrative areas are in the higher risk ranges, with probabilities over 50%.

Probability of food stress	Number of Province	Female Population	Male Population	Total Population
0.31-0.4	1	302,409	311,072	613,481
0.41-0.5	5	1,442,998	1,490,696	2,933,694
0.51-0.6	14	5,583,803	5,799,679	11,383,482
0.61-0.7	12	7,506,594	7,781,242	15,287,836
0.71 and above	2	906,737	943,930	1,850,667

Table 5 focuses on the probability of food crisis, a more severe form of food insecurity. Unlike the food stress estimates, most provinces (22 out of 34) show a relatively low average probability of food crisis, with rates below 10%, covering over 21 million people. However, four provinces stand out with crisis probabilities over 30%, affecting a combined population of over 2.5 million. This points to concentrated areas of acute food insecurity where immediate interventions may be needed to build resilience and prevent further deterioration.

Table 5: Probability of Food Crisis across Provinces in Afghanistan

Table 5 shows the average probability of food crisis over the full study period across Afghan provinces, broken down into ranges of 0.1. The columns provide a demographic breakdown of the provincial statistics to understand overall population exposure to relative risks. The majority of administrative areas are in the lower risk ranges of under 10%, but there are four hotspots with a combined population of 2.5 million where crisis risks have averaged over 30%.

Probability of food crisis	Number of Province	Female Population	Male Population	Total Population
0-0.1	22	10,677,500	11,070,559	21,748,059
0.11-0.2	6	3,243,391	3,358,709	6,602,100
0.21-0.3	2	577,507	598,622	1,176,129
0.31 and above	4	1,244,143	1,298,729	2,542,872

The maps in Figures 4 and 5 visually represent the spatial variation in food stress and crisis probabilities across Afghan provinces.

The first map shows the probability of food stress, measured on a scale from 0.364 to 0.743. Darker shades indicate higher probabilities of food stress. The provinces with the highest risk of food stress are concentrated in the central and northern regions, with provinces like Ghor and Badakhshan showing probabilities above 70%. This highlights a significant regional disparity in food stress risks, where some areas consistently face moderate food insecurity. The western provinces such as Nimroz and Hilmand, in contrast, show lower probabilities of food stress, which may reflect differences in agricultural productivity and access to markets, as captured by our models.

The second map focuses on the probability of food crisis, with probabilities ranging from 0 to 0.547. Similar to food stress, darker shades indicate higher risks of food crisis. The provinces most at risk are Ghor and Badakhshan, where the probability of a food crisis is notably elevated, reaching around 55%. These provinces appear to be food insecurity hotspots, where chronic vulnerability may be exacerbated by climatic shocks or economic disruptions due to conflict. The majority of other provinces show relatively low probabilities of food crisis, under 20%, but the existence of a few high-risk provinces raises concerns about concentrated humanitarian needs.

The maps reveal an important contrast between food stress and food crisis. While food stress risks are widespread, affecting many provinces at high levels, food crisis risks are more localized, with only a few provinces showing significant probabilities. This spatial clustering suggests that while many regions experience moderate food insecurity, a smaller subset of provinces faces acute crises, requiring targeted interventions. Provinces like Ghor and Badakhshan stand out in both maps, indicating persistent and severe food security challenges that may require longer-term strategies to address structural vulnerabilities.

Figure 4: Probability of Food Stress Across Provinces in Afghanistan

This map illustrates the probability of food stress across Afghan provinces, with darker shades representing higher probabilities. Provinces like Ghor and Badakhshan exhibit the highest probabilities, exceeding 70%, indicating widespread moderate food insecurity. The western provinces, such as Nimroz and Hilmand, show lower food stress probabilities.

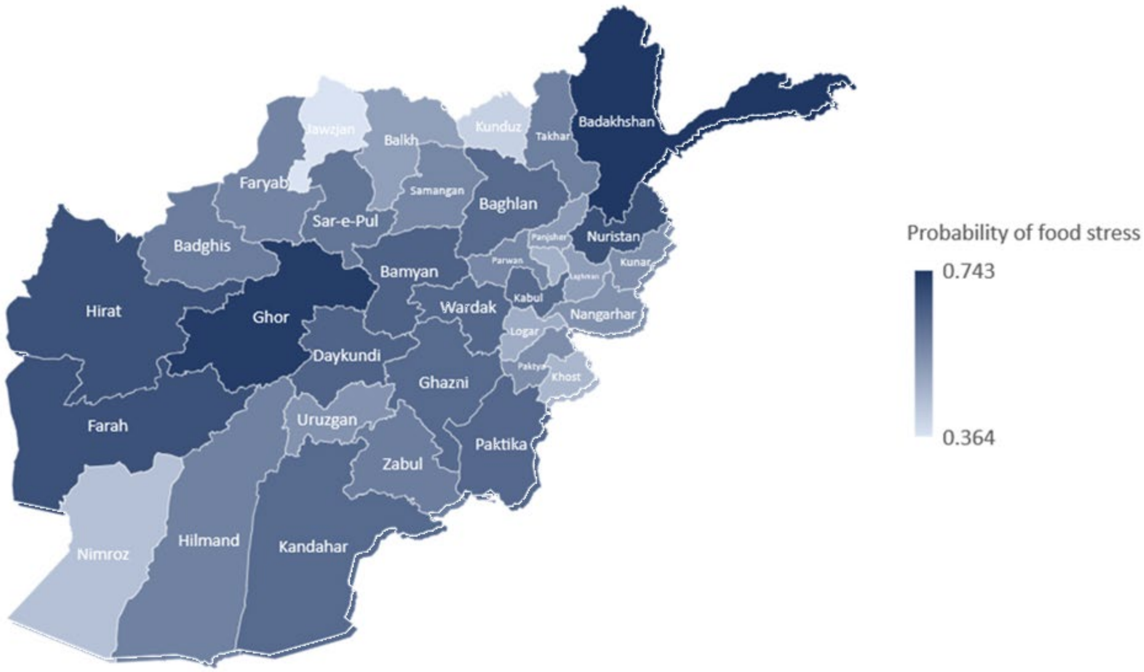
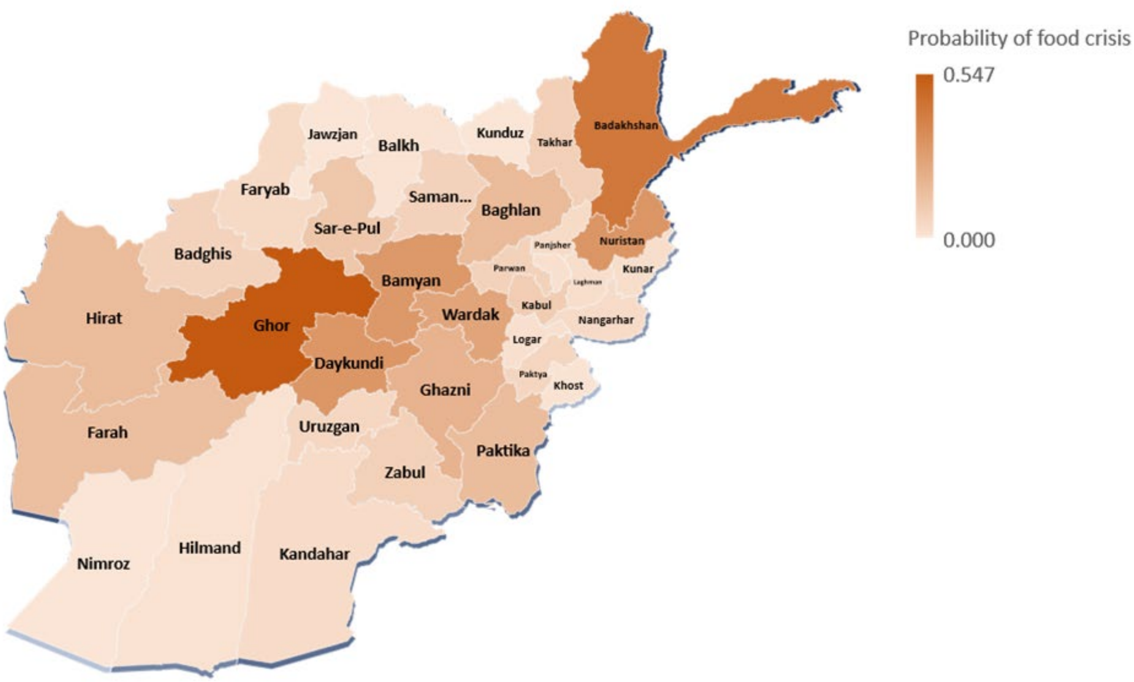


Figure 5: Probability of Food Crisis Across Provinces in Afghanistan

This map shows the probability of food crisis across Afghan provinces. Darker shades represent higher probabilities, with provinces like Ghor and Badakhshan showing crisis probabilities of over 50%. In contrast, most other provinces have relatively low crisis probabilities, below 10%.



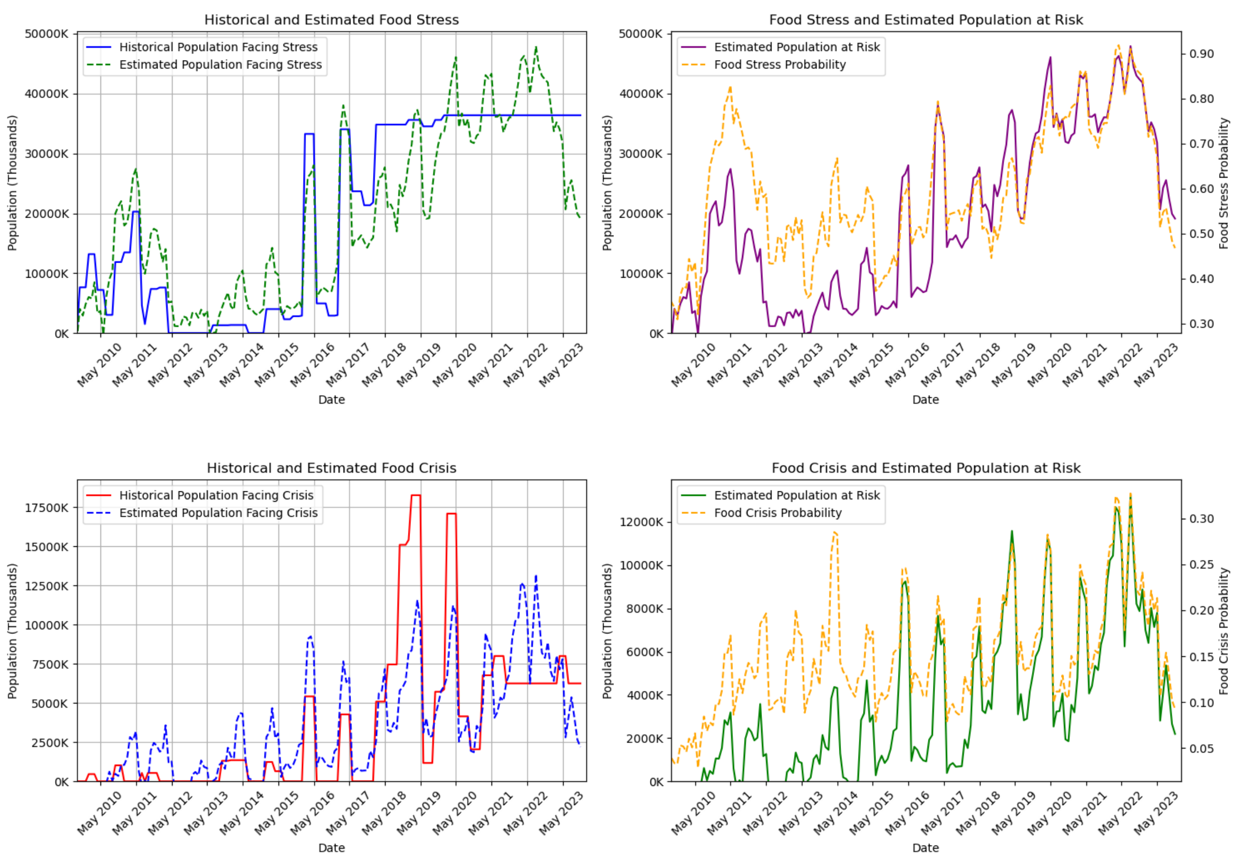
Temporal Variation in Modeled Risks

The logit models extend previous methodologies for tracking IPC exposure at the national level. Andrée et al. (2020) showed how models can predict food crises using climatic and economic data, while Penson et al. (2024) developed Yemen's Joint Monitoring Report, which integrates indicator thresholds to assess IPC risks in a logit framework. Similarly, the current models offer a scalable tool for monitoring food insecurity in Afghanistan, providing timely information to guide humanitarian responses and resource allocation.

Figure 6 visualizes the model's ability to track food security trends over time. Following Andrée et al. (2020) and Penson et al. (2024), probabilities were converted to percentages using a linear regression and overlaid with administrative populations. By tracking historical and estimated populations at risk of food stress and crisis, the model reveals temporal fluctuations in food insecurity. Comparisons of historical data with estimated probabilities show the model's predictive alignment with real-world events, making it a valuable monitoring tool.

Figure 6: Population at Risk of Experiencing Deterioration in Food Security

Figure 6 illustrates historical and estimated food stress in Afghanistan. The left plot compares the actual historical population facing food stress (blue line) with the estimated population (green dashed line). The right plot shows the estimated population at risk (purple line) alongside the food stress probability (orange dashed line). The upper panel presents results for food stress, while the bottom panel tracks crisis risks. These visualizations demonstrate how modeled populations are derived from probability outputs and how estimates align with historical data, revealing temporal trends and fluctuations that categorical historical data may obscure.



From 2010 to 2011, food stress probability and the affected population rose sharply, peaking during the global food price crisis. After stabilizing in mid-2011, food stress declined from 2012 to 2014, reaching a low in 2013, reflecting economic stabilization and better climatic conditions. Starting in 2015, the model estimates show a sharp rise, with peaks in 2016 and 2017 that align with FEWS NET trends, climatic shocks, and political instability.

From 2018 onward, the model indicates worsening food insecurity, with consistently high food stress from 2019 to 2022. These levels highlight Afghanistan's ongoing challenges, driven by conflict, economic disruptions, and adverse climatic events. After 2022, a slight improvement in food stress aligns with a stabilizing exchange rate and lower food and fuel prices. FEWS NET data during this period are interpolated due to the absence of assessments between June 2021 and February 2023.

The bottom panel of Figure 6 shows sharper fluctuations in food crisis risks compared to food stress. The model reveals significant volatility from 2016 to 2020, coinciding with droughts, conflict, and economic shocks. The left panel shows that food crisis estimates are more variable than food stress estimates, indicating that severe food security shocks are typically shorter. Estimated values spiked during the 2010-2011 global food price crisis, while historical values remained low, possibly due to under-reporting or the model's sensitivity to early warning signs.

Peaks in estimated values during the crises of 2016, 2017, and 2018 demonstrate the model's ability to detect early warnings of risk escalation. From 2019 onward, historical and estimated trends converge, though the model shows higher peaks, capturing extreme events not fully reported. Note that no assessments were caried out between June 2021 and February 2023 and the FEWS NET data is held constant over the period. This suggests the model's utility as a versatile tool for identifying potential crisis escalation before periodic assessment data reflect it.

6. Discussion

6.1 Joint Effects of Climatic Shocks and Economic Variables

This study analyzed the impact of climatic and economic shocks on food security in Afghanistan. The findings highlight that the impacts of climatic shocks, economic factors, and structural constraints on food insecurity must often be interpreted together, emphasizing the need to monitor interconnected indicators. For instance, monitoring drought risks alone is insufficient for early warning applications or policy interventions and must be combined with additional indicators for context. In our model, droughts measured by rainfall and negative NDVI anomalies show higher food insecurity risks when occurring together. Drought alone increases food stress by 4.5 percentage points (1 z-score deviation), while its joint occurrence with negative NDVI anomalies results in a 13.3 percentage point increase, illustrating compounded effects. Seasonal factors further heighten these risks, especially during the pre-harvest lean season.

Economic variables add complexity. In our model, rising food prices reduce food stress by 1 percentage point for every 10%, reflecting mixed impacts for producers and consumers. However, food prices often rise concurrently with fuel prices and exchange rates, collectively worsening food insecurity conditions. A 10% increase in both food and fuel prices leads to a 9 percentage point increase in food stress probability. We also found that global food price hikes amplify food insecurity, making domestic inflation resulting from global pass-through net negative for food security. Finally, price impacts must be interpreted alongside nominal wage effects and vice versa. For instance, floods raise food prices by about 3.4% annually and agricultural wages by 1.8%, but the greater rise in food prices erodes purchasing power, making food less accessible—an effect not fully captured by wage data alone.

6.2 Food Security Monitoring

The interplay between environmental shocks and economic factors can create complex, counterintuitive outcomes—for example, rising food prices may slightly reduce food stress in agricultural regions due to increased income for producers, but when combined with inflationary pressures, they exacerbate overall food insecurity. Effective early warning systems must therefore target both direct and market-mediated food insecurity drivers.

Despite these complexities, the risks are well captured within a highly interpretable modeling framework. Our final estimates demonstrate that significant spatial and temporal variations in food insecurity can be tracked using readily observable data, making the model practical for real-time monitoring and early intervention. For example, the model captures widespread food stress across Afghanistan, with 28 out of 34 provinces exhibiting average probabilities of over 50% of being classified as IPC phase 2 or higher. In contrast, food crisis risks are more localized, with provinces like Ghor and Badakhshan showing probabilities exceeding 50%. These areas are likely more vulnerable due to structural factors such as geographical isolation, limited infrastructure, and greater exposure to climatic shocks.

The model's ability to reflect historical trends in food insecurity, such as through the global food price crisis of 2010–2011 and periods of increased conflict and climatic shocks, reinforces its practical proposition. Its capacity to detect early warning signals of escalating risks highlights the utility of this approach for continuous monitoring. By leveraging such models, policy makers and humanitarian organizations can anticipate food security crises, allocate resources efficiently, and implement timely interventions that address the compounded risks of climatic and economic factors. This ongoing monitoring is essential for managing the dynamic nature of food insecurity and improving resilience in vulnerable regions.

6.3 Limitations and Future Research

While this study provides insights into the impacts of climatic and economic shocks on food security, several limitations exist related to data availability, model specifications, and variable interactions.

The analysis relies on available datasets, limiting the granularity of certain indicators. Gaps in data, such as from FEWS NET, highlight the need for higher-frequency monitoring and underscore challenges in model validation when target data are missing. This introduces potential uncertainties about precision during critical periods and may bias training. For example, data gaps during conflicts or restricted access to regions may lead to underrepresentation of actual food insecurity, resulting in lower risk estimates.

Although the models capture joint effects of climatic and economic shocks, disentangling causal pathways remains challenging. The interactions between environmental conditions, market dynamics, and food security are complex, even with linear models. Lagged effects in climatic and economic variables may obscure short-term interactions or create feedback loops not fully accounted for in this framework. Further refinement is needed to capture these dynamics more effectively.

The models show strong predictive power in tracking spatial and temporal variations in food insecurity but are limited by their focus on specific climatic and economic variables. Excluding factors such as conflict intensity, political instability, or migration may result in unobserved risks affecting model assessments. Including these variables in future models could enhance comprehensiveness and predictive suitability. This study provides a data-driven foundation for future research to build upon.

6.4 Policy Implications

The results highlight the interconnected nature of food security risks. Climatic shocks, economic variables, and structural factors all contribute to food insecurity, often in ways not apparent when considered separately. Examining their joint effects provides a more complete understanding of the drivers of food insecurity. Despite the complexity of food insecurity in Afghanistan, clear areas of interest for policy makers emerge from the results:

1. Climatic Shocks: The combined impact of drought and negative NDVI anomalies significantly amplifies food insecurity risks, even when the effect of drought alone is muted. This underscores the need for integrated policies addressing both water scarcity and vegetation health, such as investments in drought-resistant crops, improved irrigation, and vegetation monitoring.

2. Economic Variables: Rising food prices, fuel prices, and exchange rate depreciation collectively exacerbate food insecurity, especially when inflation affects essential goods. Measures like currency stabilization, and income support for vulnerable households are critical for mitigating these risks.

3. Seasonal Interventions: The seasonal variation in food insecurity points to the need for targeted support during winter and spring when food stocks are low and agricultural activity is limited. Expanding food assistance programs during these periods can help alleviate temporary spikes in food insecurity. The seasonal fluctuations also suggest that goods of global markets do not flow freely into the country, so trade policies can be enacted to counter offset seasonal shortages.

6.5 Clarification on Cumulative Effects

We focused on cumulative effects over a 12-month period, interpreted as the impact over a full year following a one-unit deviation in the first month, or equivalently, as the impact at month thirteen after a one-unit deviation spread over the preceding 12 months. These interpretations simplify the assessment of economic significance, though real-world dynamics are unlikely to mirror such exact scenarios. Our data indicate that rainfall shocks are often short-lived and more intense, while NDVI shocks are more persistent, extending over several months. This contrasts with the stronger marginal effects seen for rainfall z-scores at the 12-month cumulative level. If NDVI shocks last two to three times longer than rainfall shocks, an NDVI marginal effect half or one-third the size of a rainfall z-score change would be economically comparable.

Cumulative effects may also understate short-term risks. The impact of a one-unit increase in rainfall anomaly over a single month depends on the specific lag coefficient, with contributions varying—

some amplifying, others offsetting the total effect. Short-term impacts within three months post-shock may exceed those observed over 12 months.

When assessing the impact of the preceding 12 months on month 13 outcomes, our inflation models indicated significant persistence extending from month 14 onward, influencing annualized rates in subsequent months. Long-duration shocks can extend their effects over multiple periods, making the logit model's probabilistic nature crucial for interpretation. For instance, if the probability of food stress increases by 25 percentage points over four consecutive months, at least one month is likely to reach IPC phase 2 or higher, even if none individually surpasses a 50% threshold. During such periods, community adaptation or aid may prevent escalation to severe food crises. Ngcamu and Chari (2020) highlight that while droughts often increase food insecurity by reducing agricultural output and affecting rural livelihoods, the shift from moderate to severe insecurity depends on drought length, severity, and coping strategies.

Over longer horizons, the dynamic relationships confirmed by our model should be considered in predictions. Although impulse response methods help trace shock propagation, they do not account for community adaptation, complicating long-term impact assessments. This study focused on the VAR's directional parameters to reveal underlying dynamics in the data.

7. Conclusion

This study analyzed the impact of climate and economic shocks on food security in Afghanistan. Using logit and vector autoregression models, we captured how climatic anomalies, economic variables, and structural factors collectively influence food stress (IPC phase 2 or greater) and food crisis (IPC phase 3 or greater) outcomes.

The findings show that floods and droughts significantly impact food insecurity with effects varying by impacts on vegetation health. Economic factors like food prices, agricultural wages, fuel costs, and exchange rates further shape these effects, often in complex ways. Joint climatic and economic shocks can erode purchasing power, limiting food access and raising food insecurity risks. Spatial and temporal analyses highlight the uneven distribution of food stress and localized severe food crises.

The models' predictive strength demonstrated its potential for ongoing monitoring and early warning, supporting timely policy responses. By updating these models with new data, policy makers and humanitarian organizations can track food insecurity risks in near real-time and understand regional vulnerability dynamics.

Addressing food insecurity in Afghanistan requires a comprehensive approach that considers the interplay of climatic shocks, economic factors, and structural constraints. Effective strategies should include targeted interventions, infrastructure development, market stabilization, and robust monitoring systems.

The study's findings underscore key areas where further research is needed to enhance food security policies in Afghanistan. Given that food prices, agricultural wages, and food security at stress and crisis levels are significantly influenced by local supply disruptions and seasonality, research should focus on:

1. Climate-Resilient Agricultural Practices: Investigate adaptation measures such as conservation agriculture, agroforestry, integrated soil fertility management, crop diversification, and water management for local effectiveness and prevention strategies.

2. Market Integration and Infrastructure: Study ways to enhance trade, reduce post-harvest losses, and improve market access to stabilize food supply and prices.

3. Shock-Responsive Safety Nets: Assess the effectiveness of pre-allocated, community-based support programs that activate during crises, focusing on scalability, cost-effectiveness, timeliness, and integration into existing social protection systems.

4. Data Monitoring, Early Warning Systems, and International Cooperation: Address data gaps, enhance data collection, monitor key risk indicators, and foster regional partnerships. This would support faster decision-making when observed indicators exceed preset action thresholds, bolstering resilience through shared best practices.

By understanding these dynamics, policy makers can anticipate challenges and implement solutions that safeguard vulnerable populations. The study shows that model-based approaches can enhance agricultural resilience and food security, setting the stage for future research to include additional controls, such as conflict intensity and unemployment, and conduct long-term analyses for greater insight into trends and structural changes. This would refine models and broaden their application, contributing to better early warning systems and policy interventions.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics, 65*, 103207. https://doi.org/10.1016/j.jmacro.2020.103207

Ahmed, M. R. (2024). Climate shocks' impact on agricultural income and household food security in Bangladesh: An implication of the Food Insecurity Experience Scale. *Heliyon, 10*(4), e25687.

Almouctar, M. A. S., Wu, Y., Zhao, F., & Qin, C. (2024). Drought analysis using normalized difference vegetation index and land surface temperature over Niamey region, the southwestern of Niger between 2013 and 2019. *Journal of Hydrology: Regional Studies, 52*, 101689.

Adewopo, J., Andrée, B. P. J., Peter, H., Solano-Hermosilla, G., & Micale, F. (2024). Comparative analysis of AI-predicted and crowdsourced food prices in an economically volatile region. *Policy Research Working Paper,* 10758. Washington, DC: World Bank Group. http://hdl.handle.net/10986/41467

Andrée, B. P. J. (2020). *Theory and application of spatial time series models*. Rosenberg Publishers and Tinbergen Institute. https://hdl.handle.net/1871.1/2a3dfd7e-310b-4309-b9da-c2ff4bcd30f7

Andrée, B. P. J. (2021a). Estimating food price inflation from partial surveys. *Policy Research Working Paper,* 9886. Washington, D.C.: World Bank Group. https://doi.org/10.1596/1813-9450-9886

Andrée, B. P. J. (2021b). Monthly food price estimates by product and market. *World Bank Microdata Library*. https://doi.org/10.48529/2ZH0-JF55

Andrée, B. P. J. (2022). Machine learning guided outlook of global food insecurity consistent with macroeconomic forecasts. *Policy Research Working Paper,* 10202. Washington, D.C.: World Bank Group. http://hdl.handle.net/10986/38139

Andrée, B. P. J. (2023a). Monthly energy price estimates by country. *World Bank Microdata Library*. https://microdata.worldbank.org/index.php/catalog/study/WLD_2023_RTEP_v01_M

Andrée, B. P. J. (2023b). Monthly exchange rate estimates by country. *World Bank Microdata Library*. https://microdata.worldbank.org/index.php/catalog/study/WLD_2023_RTFX_v01_M

Andrée, B. P. J. (2023c). World food security outlook. *World Bank Microdata Library*. https://microdata.worldbank.org/index.php/catalog/6103

Andrée, B. P. J., & Pape, U. J. (2023). Machine learning imputation of high frequency price surveys in Papua New Guinea. *Policy Research Working Paper,* 10559. Washington, DC: World Bank Group. https://doi.org/10.1596/1813-9450-10559

Andrée, B. P. J., Chamorro, A., Kraay, A., Wang, D., & Spencer, P. (2020). Predicting food crises. *Policy Research Working Paper,* 9412. Washington, DC: World Bank Group. http://hdl.handle.net/10986/34510

Andrée, B. P. J., Chamorro, A., Spencer, P., Koomen, E., & Dogo, H. (2019). Revisiting the relation between economic growth and the environment: A global assessment of deforestation, pollution, and carbon emission. *Renewable and Sustainable Energy Reviews, 114*, 109221.

Arreyndip, N. A. (2021). Identifying agricultural disaster risk zones for future climate actions. *PLoS One, 16*(12), e0260430.

Aweke, C., Sassi, M., Lahiff, E., & Wordofa, M. (2022). Seasonality and food security among smallholder rural households in eastern Ethiopia: Evidence from panel data analysis. *Cogent Economics and Finance, 10*(1). https://doi.org/10.1080/23322039.2022.2035492

Baptista, D., Spray, J. A., & Unsal, F. D. (2023). Coping with climate shocks: Food security in a spatial framework. *IMF Working Papers*, 2023/166. International Monetary Fund, Washington, DC.

Blekking, J., Giroux, S., Waldman, K., Battersby, J., Tuholske, C., Robeson, S. M., & Siame, G. (2022). The impacts of climate change and urbanization on food retailers in urban sub-Saharan Africa. *Current Opinion in Environmental Sustainability, 55*, 101169.

Cartuyvels, R., Fierens, T., Coppieters, E., Moens, M.-F., & Sileo, D. (2023). Spatiotemporal self-supervised pre-training on satellite imagery improves food insecurity prediction. *Environmental Data Science, 2*, e48. https://doi.org/10.1017/eds.2023.42

Cevik, S., & Jalles, J. T. (2023). *Eye of the storm: The impact of climate shocks on inflation and growth*. International Monetary Fund, Washington, DC.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change, 4*(4), 287–291.

Coumou, D., & Robinson, A. (2013). Historic and future increase in the global land area affected by monthly heat extremes. *Environmental Research Letters, 8*(3), 034018.

Coumou, D., & Rahmstorf, S. (2012). A decade of weather extremes. *Nature Climate Change, 2*(7), 491–496.

Diogo, V., Reidsma, P., Schaap, B., Andrée, B. P. J., & Koomen, E. (2017). Assessing local and regional economic impacts of climatic extremes and feasibility of adaptation measures in Dutch arable farming systems. *Agricultural Systems, 157*, 216–229.

Erdoğan, S., Kartal, M. T., & Pata, U. K. (2024). Does climate change cause an upsurge in food prices? *Foods, 13*(1), 154.

Feng, L., Li, Z., & Zhao, Z. (2021). Extreme climate shocks and green agricultural development: Evidence from the 2008 snow disaster in China. *International Journal of Environmental Research and Public Health, 18*(22), 12055.

Gatti, R., Lederman, D., Islam, A. M., Bennett, F. R., Andrée, B. P. J., Assem, H., Lotfi, R., & Mousa, M. E. (2023). Altered destinies: The long-term effects of rising prices and food insecurity in the Middle East and North Africa. *MENA Economic Update; April 2023*. Washington, DC: World Bank. http://hdl.handle.net/10986/39559

Gbadegesin, T. K. (2020). A Review on Impact of Changing Climate on Sustainable Food Consumption. *Global Food Politics and Approaches to Sustainable Consumption: Emerging Research and Opportunities*, 54-76.

Gheasi, M., Andrée, B. P. J., Nijkamp, P., & Roth, D. (2023). Internal migration dynamics of native and foreign workers: An impulse–response analysis of perturbation and resilience by means of a spatial vector autoregressive model. *Regional Studies, 57*(12), 2473–2490.

Hou, Q., Ji, Z., Yang, H., & Yu, X. (2022). Impacts of climate change and human activities on different degraded grassland based on NDVI. *Scientific Reports, 12*(1), 15918.

Jawid, A., & Khadjavi, M. (2019). Adaptation to climate change in Afghanistan: Evidence on the impact of external interventions. *Economic Analysis and Policy, 64*, 64–82.

Kabundi, A., Mlachila, M., & Yao, J. (2022). How persistent are climate-related price shocks? Implications for monetary policy. *IMF Working Papers*, 2022/207. International Monetary Fund, Washington, DC.

Khalily, R. (2022). Evaluation of climate change on agricultural production in Afghanistan. *Eurasian Journal of Agricultural Research, 6*(2), 91–100.

Khurshid, N., Fiaz, A., Khurshid, J., & Ali, K. (2022). Impact of climate change shocks on economic growth: A new insight from non-linear analysis. *Frontiers in Environmental Science, 10*.

Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., & Naylor, R. L. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science, 319*(5863), 607–610.

Lobell, D. B., & Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and Forest Meteorology, 150*(11), 1443–1452.

Mehmood, K., Anees, S. A., Rehman, A., Tariq, A., Zubair, M., Liu, Q., Rabbi, F., Khan, K. A., & Luo, M. (2024). Exploring spatiotemporal dynamics of NDVI and climate-driven responses in ecosystems: Insights for sustainable management and climate resilience. *Ecological Informatics*, 102532.

Mirzabaev, A., Bezner Kerr, R., Hasegawa, T., Pradhan, P., Wreford, A., Tirado von der Pahlen, M. C., & Gurney-Smith, H. (2023). Severe climate change risks to food security and nutrition. *Climate Risk Management, 39*, 100473.

Moore, F. C., Baldos, U., Hertel, T., & Diaz, D. (2017). New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications, 8*(1), 1607.

Mukherjee, K., & Ouattara, B. (2021). Climate and monetary policy: Do temperature shocks lead to inflationary pressures? *Climatic Change, 167*(3–4), 32.

Müller, B., Hoffmann, F., Heckelei, T., Müller, C., Hertel, T. W., Polhill, J. G., Van Wijk, M., Achterbosch, T., Alexander, P., Brown, C., Kreuer, D., Ewert, F., Ge, J., Millington, J. D. A., Seppelt, R., Verburg, P. H., & Webber, H. (2020). Modelling food security: Bridging the gap between the micro and the macro scale. *Global Environmental Change, 63*, 102085.

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications, 14*(1), 6103.

Ngoma, H., Finn, A., & Kabisa, M. (2024). Climate shocks, vulnerability, resilience, and livelihoods in rural Zambia. *Climate and Development, 16*(6), 490–501.

National Statistics and Information Authority. (2021). *Estimated population of Afghanistan 2021-22*. Kabul, Afghanistan: NSIA. https://nsia.gov.af/

Omerkhil, N., Chand, T., Valente, D., Alatalo, J. M., & Pandey, R. (2020). Climate change vulnerability and adaptation strategies for smallholder farmers in Yangi Qala District, Takhar, Afghanistan. *Ecological Indicators, 110*, 105863. https://doi.org/10.1016/j.ecolind.2019.105863

Oskorouchi, H. R., & Sousa-Poza, A. (2021). Floods, food security, and coping strategies: Evidence from Afghanistan. *Agricultural Economics, 52*, 123–140. https://doi.org/10.1111/agec.12610

Pei, F., Zhou, Y., & Xia, Y. (2021). Application of normalized difference vegetation index (NDVI) for the detection of extreme precipitation change. *Forests, 12*(5), 594.

Penson, S., Lomme, M., Carmichael, Z. A., Manni, A., Shrestha, S., & Andrée, B. P. J. (2024). A data-driven approach for early detection of food insecurity in Yemen's humanitarian crisis. *Policy Research Working Paper*, 10768. World Bank Group. https://doi.org/10.1596/1813-9450-10768

Prather, R., Dalton, R., Barr, B., Blumstein, D., Boggs, C., Brody, A., Inouye, D. W., & Underwood, N. (2023). Current and lagged climate affects phenology across diverse taxonomic groups. *Proceedings of the Royal Society B, 290*(1990), 20222181.

Přívara, A., & Přívarová, M. (2019). Nexus between climate change, displacement, and conflict: Afghanistan case. *Sustainability, 11*(20), 5586.

Qutbudin, I., Shiru, M. S., Sharafati, A., Ahmed, K., Al-Ansari, N., Yaseen, Z. M., Shahid, S., & Wang, X. (2019). Seasonal drought pattern changes due to climate variability: Case study in Afghanistan. *Water, 11*(5), 1096.

Ruel, M. T., Alderman, H., & the Maternal and Child Nutrition Study Group. (2013). Nutrition-sensitive interventions and programs: How can they help to accelerate progress in improving maternal and child nutrition? *The Lancet, 382*(9891), 536–551.

Schmidhuber, J., & Tubiello, F. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences, 104*(50), 19703–19708.

Semakula, H. M., Liang, S., McKune, S. L., Mukwaya, P. I., Mugagga, F., Nseka, D., Wasswa, H., Kayima, P., Achuu, S. P., Mwendwa, P., & Nakato, J. (2024). Integrated modeling of the determinants of household food insecurity during the 2020–2021 COVID-19 lockdown in Uganda. *Agriculture and Food Security, 13*(1), 1–19.

Smith, L., & Haddad, L. (2015). Reducing child undernutrition: Past drivers and priorities for the post-MDG era. *World Development, 68*, 180–204.

Tang, W., Liu, S., Kang, P., Peng, X., Li, Y., Guo, R., Jia, J., Liu, M., & Zhu, L. (2021). Quantifying the lagged effects of climate factors on vegetation growth in 32 major cities of China. *Ecological Indicators, 132*, 108290.

Tay, J. E. F., Tung, S. E. H., Kaur, S., Gan, W. Y., Che'Ya, N. N., & Tan, C. H. (2023). Seasonality, food security, diet quality, and nutritional status in urban poor adolescents in Malaysia. *Scientific Reports, 13*(1), 15067.

Vermeulen, S., Campbell, B., & Ingram, J. S. I. (2012). Climate change and food systems. *Annual Review of Environment and Resources, 37*, 195–222.

Wang, D., Andrée, B. P. J., Chamorro, A. F., & Spencer, P. G., (2020). Stochastic modeling of food insecurity. *Policy Research Working Paper*, 9413. World Bank. http://hdl.handle.net/10986/34511

Wang, D., Andrée, B. P. J., Chamorro, A. F., & Spencer, P. G. (2022). Transitions into and out of food insecurity: A probabilistic approach with panel data evidence from 15 countries. *World Development, 159*, 106035.

Wheeler, T., & Von Braun, J. (2013). Climate change impacts on global food security. *Science, 341*(6145), 508–513.

Yolchi, J., Wang, H., & Pede, V. (2024). Impact of floods on food security in rural Afghanistan. *International Journal of Disaster Risk Reduction, 112*, 104746. https://doi.org/10.1016/j.ijdrr.2024.104746

Zhou, Z., Yu, Z., & Gao, S. (2022). Climate shocks and farmers' agricultural productive investment: Resisting risk or escaping production? *Frontiers in Ecology and Evolution, 10*, 895265.