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Statio-Temporal Modeling and Deep pŷ Learning Based Forecasting O Food Insecurity In Africa

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Bahir Dar University
College of Science
Department of Statistics

**Spatio-Temporal Modeling and Deep
Learning–Based Forecasting of Severe Food
Insecurity in Africa**

By:
Mesfin Mulu Ayalew

July, 2026
Bahir Dar, Ethiopia

Bahir Dar University
College of Science
Department of Statistics

**Spatio-Temporal Modeling and Deep
Learning–Based Forecasting of Severe Food
Insecurity in Africa**

By:

Mesfin Mulu Ayalew

A Dissertation Submitted in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy in
Statistics

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July, 2026

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Declaration

This is to certify that the dissertation entitled "**Spatio-Temporal Modeling and Deep Learning–Based Forecasting of Severe Food Insecurity in Africa**", submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Statistics in the Department of Statistics, Bahir Dar University, is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been duly acknowledged.

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Scientific Research Contributions and Dissemination

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3. Conference and Seminar Paper Presentations

- **Seminar Presentation:** Bayesian Spatio-Temporal Analysis of the Dynamics and Determinants of Severe Food Insecurity Across Africa, 02/08/2018 E.C, Bahir Dar, Ethiopia.
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- **13th Annual Conference on Recent Trends in Scientific Research:** Exploring the spatial and spatiotemporal patterns of severe food insecurity across Africa (2015–2021), June 20–21, 2025, at Bahir Dar University, Bahir Dar, Ethiopia.
- **African Graduate Student Conference (AGSC):** Machine learning-based approaches to identify key drivers and predict severe food insecurity in Africa, May 12–13, 2025, at Bahir Dar University, Bahir Dar, Ethiopia.
- **International Applied Statistics (UYIK-2025):** Machine learning-based approaches to identify key drivers and predict severe food insecurity in Africa, May 14–16, 2025, Ankara, Turkey.
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Abstract

Food insecurity remains a major humanitarian and development challenge in African countries. Understanding its distribution, underlying determinants, and future trajectories is essential for strengthening early-warning systems and targeted interventions. Therefore, this study examined the spatio-temporal dynamics and determinants of severe food insecurity across 52 African countries during 2015–2021 and projected its future trajectories. The dataset was sourced and compiled from food and agricultural organization, world bank, malaria atlas project, and Ethiopian statistical service. Inference was carried out using integrated nested Laplace approximation algorithm with Gaussian Markov random fields. The analyses employed different methodological approaches including spatial and spatio-temporal clustering analytical tools, machine learning models, spatial models, spatio-temporal models, spatio-temporal varying coefficient model and deep learning architectures. Among the models considered in each methodological class, extreme gradient boost, geoadditive mixed model, spatio-temporal type I interaction model, and spatio-temporal graph convolutional network outperformed the other models within their respective classes. The results showed that malaria incidence ($\beta = 0.01$, $SD = 0.003$), climate change ($\beta = 0.65$, $SD = 0.31$), livestock production ($\beta = -0.05$, $SD = 0.02$), and investment inflow ($\beta = -0.03$, $SD = 0.01$) exhibited relatively consistent and statistically significant linear fixed effects across countries and over time at 95% credible intervals, whereas unemployment, greenhouse gas emissions, gross domestic product per capita, dietary energy supply, and dietary protein supply demonstrated statistically significant spatial and temporal heterogeneity in both the magnitude and, in some instances, the direction of their effects. The findings also showed that severe food insecurity was significantly spatially dependent ($\tau_\theta^2 = 2705.77$) and temporally correlated ($\tau_\alpha^2 = 10.75$) across the continent. In addition, the space-time interactions ($\tau_\delta^2 = 29,438.77$) contributed additional variability. The findings also revealed substantial and persistent disparities across African countries over time. Throughout the study period, South Sudan, Central Africa Republic, Republic of the Congo, Malawi, Guinea, Cameroon, and Somalia experienced higher severe food insecurity risks compared to other countries. The southern, eastern and central subregions exhibited strong spatial dependence in severe food insecurity. In addition, across much of the study period, Kenya, Ethiopia, Niger, and Burkina Faso frequently experienced unusual country-year-specific shocks in severe food insecurity crises compared to other countries. Data-driven forecasts further suggested that severe food insecurity is expected to intensify in Africa. In particular, severe deterioration was projected in South Sudan, the Central African Republic, the Republic of Congo, Malawi, Guinea, Somalia,

Ethiopia, Kenya, Democratic Republic of Congo, Angola, Namibia, Niger and Nigeria. These findings indicated the coexistence of cross-country shared structural influences and country-specific factors in shaping severe food insecurity across Africa. Policy-makers should prioritize targeted and context-specific interventions in high-risk areas, strengthen national multi-sectoral and regional coordination, and emphasize proactive and anticipatory strategies, including early warning systems, to support progress toward achieving sustainable development goal 2 (Zero Hunger) across Africa.

Keywords: Severe Food Insecurity; Spatio-Temporal Analysis; Forecasting; Hotspot Areas; R-INLA; XGBoost; ST-GCN; Africa.

List of Abbreviations and Acronyms

AIC	- Akaike Information Criterion
AFSEWS	- African Food Security Early Warning System
AfDB	- African Development Bank
ARC	- African Risk Capacity
ARNS	- African Regional Nutrition Strategy
BFE	- Backward Feature Elimination
BIC	- Bayesian Information Criterion
CAADP	- Comprehensive Africa Agriculture Dev't Program
CAR	- Conditional Autoregressive
CNN	- Convolutional Neural Network
ConvLSTM	- Convolutional Long Short-Term Memory
DAGG	- Data Adaptive Graph Generation
DIC	- Deviance Information Criterion
DL	- Deep Learning
EAC	- East African Community
ECOWAS	- Economic Community of West African States
ESS	- Ethiopian Statistical Service
FAO	- Food and Agriculture Organization
FEWS NET	- Famine Early Warning Systems Network
FIES	- Food Insecurity Experience Scale
FFS	- Forward Feature Selection
GAMM	- Generalized Additive Mixed Model
GDP	- Gross Domestic Product
GMRF	- Gaussian Markov Random Field
GNN	- Graph Neural Network
GRU	- Gated Recurrent Unit
ICAR	- Intrinsic Conditional Autoregressive Model
INLA	- Integrated Nested Laplace Approximation
LISA	- Local Indicators of Spatial Association
MAE	- Mean Absolute Error
MAPE	- Mean Absolute Percentage Error
MCMC	- Markov Chain Monte Carlo
MLP	- Multilayer Perceptron
MSE	- Mean Squared Error
NAPL	- Node Adaptive Parameter Learning

RFE - Recursive Feature Elimination

REML - Restricted Maximum Likelihood

RMSE - Root Mean Squared Error

SDG - Sustainable Development Goals

ST-GCN - Spatio-Temporal Graph Convolutional Network

STVC - Spatio-Temporal Varying Coefficient

WAIC - Widely Applicable Information Criterion

WB - World Bank

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Chapter 1

Introduction

1.1 Background of the Study

Food insecurity constitutes a major global humanitarian and development challenge, particularly in low- and middle-income countries. According to the 1996 World Food Summit, food (in)security is defined as a condition in which “ all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life ” ([FAO, 1996](#)). This definition is operationalized through four interrelated pillars: availability, access, utilization, and stability. These pillars reflect the multidimensional nature of food insecurity and provide a widely accepted conceptual framework for identifying policy-relevant drivers and pathways.

Within this conceptual framework, food insecurity is closely aligned with the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), and is strongly linked to SDG 1 (No Poverty), SDG 3 (Good Health and Well-being), and SDG 13 (Climate Action). Addressing food insecurity has therefore become a central priority in global and regional development and public health agendas. To achieve these goals, various international and regional initiatives have been implemented to strengthen agricultural development, enhance food supply chains, and improve resilience to climate and economic shocks. At the regional level, programs such as Comprehensive Africa Agriculture Development Program (CAADP), African Regional Nutrition Strategy (ARNS), and African Risk Capacity (ARC) support agricultural productivity, nutrition outcomes and risk management across the continent. In addition, regional economic communities have developed their own coordinated policy frameworks, such as Economic Community of West African States (ECOWAS), Southern African Development Community (SADC) and East African Community (EAC), which emphasize regional coordination in agricultural development, market integration and food security governance. Other continental initiatives such as African Development Bank (AfDB), Famine Early Warning Systems Network (FEWS NET), and African Food Security Early Warning System (AFSEWS) was established to monitor food insecurity risks and informing timely responses. Despite sustained global and regional efforts, achieving the targets of SDG 2 (Zero Hunger) remains a significant challenge across African countries ([FAO et al., 2021a](#)). This persistent gap highlights

the limited effectiveness of existing strategies in adequately addressing the underlying drivers of food insecurity across the continent.

Empirical evidence indicates that the burden of severe food insecurity has increased substantially over time. Recent estimates show a steady rise in severe food insecurity both globally and across the African continent. Since 2020, the risk of severe food insecurity has been begun rising largely due to the COVID-19 pandemic (FAO et al., 2021a). Globally, the annual estimates of severe food insecurity were 7.6% (2015), 9.3% (2019), 10.8% (2020), 11.7% (2021) and 11.3% (2022). Notably, this rising trend in Africa began in 2015 before the start of the global crisis with annual estimates of 17.2% (2015), 20.2% (2019), 22.4% (2020), 23.8% (2021) and 24.0% (2022) (FAO et al., 2023). These figures demonstrate that Africa bears a disproportionate share of the global food insecurity burden.

Substantial disparities were also observed across the subregions of Africa over time. In 2020, the prevalence of severe food insecurity was highest in the central region of the continent (37.8%), followed by Eastern Africa (28.7%), Western Africa (21.7%), Northern Africa (11.2%) and Southern Africa (11.0%), as reported by (FAO et al., 2023). A similar pattern persisted in 2022, with Central Africa again reporting the highest prevalence (39.1%), followed by Eastern Africa (27.7%) and Western Africa (22%), while Southern Africa (12.5%) and Northern Africa (12%) recorded comparatively lower rates. These figures indicates that severe food insecurity is neither spatially uniform nor temporally stable, but rather evolves dynamically across countries and over time. Such trends underscore the urgency of developing robust analytical frameworks capable of capturing both spatial and temporal variations in food insecurity dynamics.

The persistence and disparities of food insecurity dynamics are driven by a wide range of interrelated economic, social, political and environmental factors, including climate change (Campbell et al., 2016; Ali et al., 2022; Baptista et al., 2022; Osman, 2023), incidence of malaria (Debash et al., 2024; Gari et al., 2018; Lewnard et al., 2014; Madaki, 2017; Mezieobi et al., 2025; Oldenburg et al., 2018; Tusting et al., 2016), inflation (Bogmans et al., 2024; Nord et al., 2014; Olufemi-Phillips et al., 2024; FAO, IFAD, UNICEF, WFP, WHO, 2025), social and political instability and conflicts (Mushed et al., 2018; Shemyakina, 2022; Soffiantini, 2020), unemployment (Mekonnen and Amede, 2022; Etana and Tolossa, 2017; Huang et al., 2016; Milovanska-Farrington, 2023; Nord et al., 2014), greenhouse gas emissions (Eshete et al., 2020; Gobezie and Boka, 2023; Kaur, 2022; Mahdavian et al., 2025; Mulusew and Hong, 2024; Ntiamoah et al., 2023), caloric loss (Munesue et al., 2015; Sawaya, 2017), cereal import dependency (Bofa and Zewotir, 2024b), livestock production or ownership (Falvey, 2015; FAO et al., 2018; Molina-Flores et al., 2020; Nkomoki et al., 2019; Pica-Ciamarra et al., 2015; Wubetie et al., 2024a), investment inflow (Guyalo et al., 2022; Osinubi and Apanisile, 2021), GDP per capita (Awad, 2023; Świetlik, 2018), crop production (Wu-

betie et al., 2024a), dietary energy supply and protein supply (Bofa and Zewotir, 2024b; Coles et al., 2016), and electricity access (Candelise et al., 2021). These drivers rarely operate independently and; rather, they interact in complex and context-dependent ways that influence food security outcomes across countries and time periods.

Most of these existing empirical studies have examined the determinants of food insecurity using classical statistical models, spatial models, spatio-temporal models and, most recently, machine learning approaches. However, these analyses have been conducted predominantly at the household- or district-level across various countries. For instance, studies in Ethiopia (Wubetie et al., 2024a; Dessie et al., 2022), the Democratic Republic of Congo (Marivoet et al., 2019), South Africa (Tomita et al., 2020), and Kenya (Mathenge et al., 2023) as well as multi-country analyses within Sub-Saharan Africa (Gafa and Chachu, 2023; Sassi, 2015; Tchimeutcheu and Ngono, 2024), consistently demonstrated substantial spatial heterogeneity and clustering of food insecurity at the lower geographic units. Similarly, other studies report strong spatial clustering and uneven distribution of food insecurity across small-scale geographic units (Bartolucci and Farcomeni, 2022; Bitew, 2020; Guha and Chandra, 2021; Mathenge et al., 2023; Sassi and Trital, 2021; Tomita et al., 2020; Ukwajunor et al., 2023).

While these studies are valuable for identifying localized vulnerabilities and community-specific risk factors, their scope is inherently limited. In particular, analyses at small-scale geographic units often fail to capture broader national-level structural drivers that shape national food systems in which households and communities operate. They are also frequently constrained by data sparsity, small sample sizes, and limited external validity, leading to unstable estimates and reduced statistical power (Rao and Molina, 2015). As a result, findings derived from the local level analyses may have limited generalizability and policy relevance at national and international levels. Therefore, the existing literature provides an incomplete understanding of cross-country interdependencies and broader macro-level determinants influencing the dynamics of food insecurity at the national and regional levels, thereby underscoring the need for national-level investigations.

The absence of national-level evidence constrains the ability to generate comprehensive and policy-relevant insights into the evolution of food insecurity across countries and over time. Strategic decisions regarding the structural determinants of food insecurity are predominately formulated and implemented at the national level, making national-level analyses crucial for policy-making, resource allocation, cross-country comparisons, and SDG monitoring. A national-level perspective thus provides a complementary lens to subnational research by capturing population-wide exposures and structural vulnerabilities. It can address the broader policy-relevant questions regarding the influence of macroeconomic instability, trade dependency, political instability, and climate variability in shaping national food security outcomes.

Despite the availability of harmonized national-level FAO datasets across the African continent, comprehensive country level spatio-temporal analyses and modern data-driven predictive modeling approaches remain limited. The FAO provides country-level assessments of severe food insecurity across African countries over time, primarily using percentage estimates. While these estimates offer valuable insights into the magnitude and distribution of food insecurity, they do not provide information on statistical significance and lack sufficient spatial and temporal depth. As such, they tend to capture conditions at a specific point in time or locations without adequately reflecting the dynamics and interconnected nature food insecurity across space and time. These limits their usefulness for understanding underlying processes and for informing targeted, evidence-based policy interventions.

In response to these limitations, several studies have attempted to account for spatio-temporal dependence using spatial and spatio-temporal models with Markov Random Field Priors (MRFPs), particularly intrinsic Conditional Autoregressive (iCAR) priors ([Bofa and Zewotir, 2024b](#); [Mathenge et al., 2023](#); [Sassi, 2015](#)). While these approaches represent an important methodological advancement, they commonly rely on the assumption that the marginal effects of covariates on food insecurity are homogeneous in both magnitude and direction across space and time. Such an assumption of globally constant effects imposes spatial and temporal stationarity, which may mask important local variations or context-specific relationships, potentially leading to misleading inferences and limiting their relevance for policy design. These limitations are particularly consequential in the African context, where there exists pronounced spatio-temporal heterogeneity in economic, social, political, and environmental conditions. Such contextual differences influence food insecurity differently across countries and over time. Consequently, modeling approaches that assume homogeneous effects are unlikely to adequately capture these complex dynamics.

For example, livestock ownership can improve food security through income generation and dietary diversity but may increase vulnerability in arid and semi-arid regions because of climatic variability and resource scarcity ([Danso-Abbeam et al., 2024](#); [Nuvey et al., 2022](#)). Similarly, while agricultural crop production generally enhances food availability, its benefits may be constrained by weak governance, poor market conditions, and environmental degradation ([Kopittke et al., 2019](#)). Likewise, foreign direct investment can stimulate economic growth and employment but may also contribute to land-use change and the displacement of smallholder farmers, thereby increasing food insecurity in affected areas ([Guyalo et al., 2022](#)). These contrasting effects or apparent inconsistencies illustrates the complex and context-specific nature of food insecurity dynamics and may be attributable to spatial, institutional, and environmental heterogeneity.

Recognizing this heterogeneity, recent methodological developments have in-

roduced spatially varying coefficient models (Comber et al., 2024; Fotheringham et al., 2017), temporally varying coefficient models (Hauzenberger et al., 2023), and spatio-temporally varying coefficient models (Bakar et al., 2016; Cai et al., 2020; Comber et al., 2024; Lei et al., 2025; Murakami et al., 2025; Que et al., 2020; Song et al., 2020; Thorson et al., 2023; Wang et al., 2024). These models offer important methodological advantages than the classical spatio-temporal regression-based models by treating regression coefficients as spatial and/or temporal stochastic processes rather than fixed parameters, thereby capturing heterogeneity in covariate effects across space and time (Bakar et al., 2016; Cai et al., 2020; Comber et al., 2024; Lei et al., 2025; Murakami et al., 2025; Que et al., 2020; Song et al., 2020; Thorson et al., 2023; Wang et al., 2024). By doing so, they enable the identification and quantification of where and when specific covariates exert stronger or weaker associations with severe food insecurity and reduce bias that arising from ignoring underlying heterogeneity. Moreover, these modeling frameworks allow for the simultaneous estimation of global (stationarity) effects and the local-scale spatio-temporal (non-stationarity) effects in covariate–outcome relationships (Song et al., 2020), thereby offering a more nuanced and policy-relevant analytical framework.

Nevertheless, despite these advances, existing empirical applications remain limited. Some household level studies have acknowledged nonlinear and spatio-temporally varying covariates effects, yet they do not explicitly identify where and when such effects are relatively stronger or weaker (Dessie et al., 2022; Wubetie et al., 2024a). This gap underscores the need for comprehensive, country-level spatio-temporal modeling approaches that can both detect and interpret heterogeneity in covariate effects, thereby providing more actionable insights for addressing severe food insecurity across Africa.

Moreover, previous studies have typically examined the impacts of economic, social, political, and environmental drivers on food insecurity in isolation, without adequately accounting for their combined effects. This simplified approach may lead to oversimplified or misleading conclusions, reduce predictive accuracy, and result in biased or less effective policy recommendations. It also overlooks the possibility that determinants operate in a coupled manner, where effects are conditioned by spatial and temporal contexts. Consequently, the existing literature lacks a comprehensive analytical framework that simultaneously accounts for the combined and interacting effects of drivers, spatial and temporal dependencies, space-time interaction dependencies, confounding influences arising from space and time, and nonlinear and spatio-temporally varying effects of country-level determinants. This incomplete representation of food insecurity dynamics constrains the development of effective and context-specific policy interventions. In addition, failure to properly model spatio-temporal dependencies may result in biased parameter estimates, misleading inferences, and misidentification of key determinants, ultimately leading to inefficient resource allocation and undermining

progress toward achieving SDG 2 (Zero Hunger). This gap is particularly significant in the African context, where food insecurity is shaped by highly interdependent and context-specific processes operating across multiple scales.

Addressing these gaps is therefore essential for advancing empirical understanding by more accurately representing the complexity of food insecurity. It is also important for improving predictive performance through the capture of nonlinear effects, heterogeneous effects, and dependence structures that simpler models often omit. Furthermore, it strengthens the reliability and policy relevance of findings by providing more robust evidence on how multiple drivers jointly influence food insecurity outcomes across spatial and temporal contexts. Accordingly, the development of integrated modeling frameworks that explicitly accommodate these complexities is critical for generating robust, interpretable, and policy-relevant insights to support more effective interventions.

Beyond explanatory analysis, progress toward the interconnected United Nations SDGs requires not only effective interventions but also robust and forward-looking analytical tools capable of identifying emerging risks and anticipating future food insecurity conditions. Despite this need, existing forecasting studies have primarily relied on traditional statistical and machine learning approaches ([Alelign et al., 2021](#); [Christensen et al., 2021](#); [Dan et al., 2023](#); [Dharmawan et al., 2022](#); [Qasrawi et al., 2023](#); [Lentz et al., 2019](#); [Busker et al., 2024](#); [Westerveld et al., 2021](#); [Herteux et al., 2024](#); [Al-turif et al., 2025](#)). While these approaches have demonstrated utility in prediction tasks, they generally do not explicitly account for spatial spillover effects or complex temporal dependencies. As a result, their capacity to capture the interconnected and evolving nature of food insecurity across countries over time remains limited. Given that future food insecurity is influenced by underlying factors, historical conditions and conditions of neighboring countries through cross-border interactions and regional clustering ([Liu and Shen, 2025](#)), forecasting approaches that explicitly incorporate spatial and temporal dependencies are essential for strengthening early warning systems, improving resource allocation, and supporting proactive policy decisions rather than reactive responses ([Cressie and Wikle, 2011](#); [Herteux et al., 2024](#); [Tomes et al., 2025](#)). Furthermore, scenario-based projections can help policymakers anticipate future crises and evaluate alternative intervention strategies before implementation ([Funk et al., 2019](#); [Krishnamurthy and Choularton, 2020](#)).

Despite this need, there remains a notable gap in the application of advanced spatio-temporal deep learning models for forecasting severe food insecurity at the country level across Africa. Although recent deep learning models offer promising frameworks for jointly modeling spatial and temporal dependence structures, their application to food insecurity forecasting remain largely unexplored. This gap constrains the development of spatially explicit and forward-looking evidence required for monitoring

progress toward SDG2 and for informing regional policy planning. Accordingly, this study seeks to address these limitations by developing and applying advanced spatio-temporal forecasting frameworks that explicitly account for both spatial spillovers and temporal dynamics, thereby contributing to more accurate, policy-relevant, and scalable approaches to food insecurity prediction at the continental level.

To address the identified methodological and empirical gaps, this study integrates spatial and temporal dependence structures, space–time interactions, and non-linear and heterogeneous covariate effects within a unified analytical framework. In addition, the study explicitly accounts for spatial and temporal dependencies within advanced deep learning models to forecast the future trajectories of severe food insecurity. Therefore, the study aims to provide a robust and comprehensive assessment of the spatio-temporal dynamics, determinants, and future patterns of severe food insecurity across African countries using data from 2015–2021. These contributions are expected to strengthen early warning, planning, and monitoring systems; facilitate the identification of emerging high-risk hotspots; improve resource allocation; and support more targeted, proactive, and forward-looking policy interventions, thereby contributing to progress toward Sustainable Development Goal 2 (Zero Hunger).

1.2 Motivation

Severe food insecurity remains one of the most pressing public health and development challenges in Africa, affecting millions of people and threatening human well-being, economic development, and progress toward Sustainable Development Goal 2 (Zero Hunger). Understanding the spatial distribution, underlying drivers, and future trajectories of severe food insecurity is essential for designing effective policies, allocating resources, and strengthening early-warning systems.

The burden of severe food insecurity is not uniformly distributed across the continent but exhibits persistent geographical inequalities. Emerging evidence indicates that food insecurity exhibits spatial clustering and spatio-temporal dependence, implying that neighboring countries are often influenced by shared socioeconomic, environmental, and political conditions. These complex spatial dynamics indicate that conventional analytical approaches, which assume independence among observations, may not adequately capture the underlying processes driving food insecurity.

In addition, severe food insecurity is influenced by multiple interacting socioeconomic, environmental, and nutritional factors whose effects are often nonlinear and vary across space and time. Understanding these heterogeneous relationships is essential for identifying context-specific drivers and designing targeted policy interventions that reflect local conditions and evolving risks.

Furthermore, the increasing frequency of climate change, conflicts, economic

instability, and other external shocks has heightened the need for reliable forecasting and early warning systems. Accurate prediction of future severe food insecurity trajectories can support proactive decision-making, improve resource allocation, and enable timely interventions before food crises escalate. These challenges collectively motivate the development of advanced spatio-temporal statistical and deep learning approaches capable of capturing complex dependencies, heterogeneous relationships, and future food insecurity dynamics across Africa.

1.3 Statement of the Problem

Despite sustained global and regional efforts to combat food insecurity, severe food insecurity continues to affect many African countries and remains unevenly distributed across space and time. Existing studies have primarily focused on household- or subnational-level analyses or individual countries, providing limited evidence on cross-country spatial dependence, spatio-temporal variations in determinants, and future food insecurity trajectories. Consequently, the spatial dependence and temporal evolution of severe food insecurity across African countries remain insufficiently understood.

The continued persistence of severe food insecurity highlights important limitations in the current evidence base for informing effective interventions. In particular, inadequate understanding of how food insecurity evolves across space and time constrains the development of context-specific policies capable of addressing regional heterogeneity and changing risk patterns. As a result, existing interventions may not fully target the populations and locations at greatest risk.

A major methodological limitation in the literature lies in the inadequate representation of spatio-temporal dependence structures underlying severe food insecurity. In particular, many studies fail to simultaneously account for spatial dependence, temporal dynamics, and space–time interactions within a unified modeling framework. Consequently, conventional approaches may not fully capture the interconnected and evolving nature of food insecurity across countries and over time. These limitations may result in biased parameter estimates, misleading inferences, and inadequate identification of high-risk regions and vulnerable populations, thereby weakening the effectiveness of policy interventions and early warning systems.

Moreover, most previous studies have relied on conventional statistical models that assume linear and homogeneous relationships between determinants and food insecurity. Such approaches often fail to capture the complex nonlinear and heterogeneous influence of predictors on severe food insecurity. In practice, African countries exhibit substantial heterogeneity in socioeconomic, political, and environmental conditions. These contextual differences imply that the determinants of food insecurity

may operate differently across countries and periods. As a result, the context-specific drivers of food insecurity across different countries and over time remain inadequately characterized. This limitation may lead to misleading conclusions and reduce the policy relevance of empirical findings.

Another important gap is the limited application of advanced forecasting models that explicitly incorporate both spatial and temporal dependencies. Existing forecasting studies have primarily relied on traditional statistical methods and machine learning techniques (Alelign et al., 2021; Alturif et al., 2025; Busker et al., 2024; Christensen et al., 2021; Dan et al., 2023; Dharmawan et al., 2022; Herteux et al., 2024; Lentz et al., 2019; Qasrawi et al., 2023; Westerveld et al., 2021). While these approaches have demonstrated utility in prediction tasks, they generally do not fully exploit the interconnected dynamics and evolving nature of food insecurity across countries and over time. As a result, existing forecasting models provide limited support for identifying emerging hotspots and anticipating future food insecurity trajectories, thereby reducing their value for proactive planning, early warning systems, and efficient resource allocation.

To overcome these methodological and empirical gaps, the present study aims to provide a comprehensive assessment of the spatio-temporal dynamics, determinants and future trajectories of severe food insecurity Across African countries using temporal data from 2015-2021. Specifically, the study seeks to account for spatial and temporal dependencies, heterogeneous and nonlinear covariate effects, and evolving spatio-temporal interaction structures in food insecurity systems. The finding may support early warning systems, inform resource allocation, and facilitate more targeted and proactive interventions, thereby contributing to progress toward Sustainable Development Goal 2 (Zero Hunger).

1.4 Research Questions

The following research questions are formulated to provide a rigorous empirical basis for evaluating the stated objectives. They enable a systematic assessment of the drivers, spatio-temporal dependencies, and future trajectories of severe food insecurity across Africa.

1. Where is severe food insecurity most prevalent across Africa?
2. What factors are associated with severe food insecurity across Africa?
3. Is severe food insecurity spatially dependent?
4. Is severe food insecurity spatio-temporally dependent?
5. Do the effects of drivers vary across space and time?

6. How is severe food insecurity expected to evolve in the future?

1.5 Objectives of the Study

This section outlines the objectives of the study, which are formulated to guide the empirical investigation of the spatial and spatio-temporal dependencies of severe food insecurity and its associated determinants across Africa.

1.5.1 General Objective

- To examine the spatial and spatio-temporal clustering patterns, dependence structures, determinants and future trajectories of severe food insecurity across Africa.

1.5.2 Specific Objectives

1. To explore the spatial, temporal and spatio-temporal patterns of severe food insecurity in Africa.
2. To identify and rank the most influential country-level determinants of severe food insecurity using machine learning–based feature selection techniques.
3. To examine the determinants and spatial dependence of severe food insecurity across African countries.
4. To investigate the spatio-temporal dependence and determinant effects of severe food insecurity across countries over time.
5. To assess the spatio-temporally varying effects of key determinants on severe food insecurity across Africa.
6. To forecast severe food insecurity crises across the African countries using spatio-temporal deep learning–based predictive models.

1.6 Contribution of the Study

This study makes important methodological and empirical contributions to the literature on severe food insecurity in Africa. Methodologically, it advances existing analytical approaches by integrating spatio-temporally varying covariate effects, nonlinear relationships, confounding effects of spatial, temporal and their interaction components within the unified modeling frameworks. By explicitly modeling these complexities, this approach provides a more comprehensive representation of the spatial and temporal dynamics of severe food insecurity across African countries. It also enables the

identification of where and when severe food insecurity crises and determinant effects intensify or weaken. This improves the understanding of evolving vulnerabilities pattern and regional disparities.

Empirically, the study extends existing knowledge by providing comprehensive cross-country evidence on the spatial distribution, temporal evolution, determinants, and future trajectories of severe food insecurity in Africa. The finding demonstrates that the effects of key socioeconomic, political, environmental, and nutritional determinants are nonlinear and vary across space and time, challenging the conventional assumptions of linear and homogeneous relationships. In addition, the study identifies evolving hotspots of severe food insecurity and provides spatially informed forecasts of future risk, thereby contributing new evidence on the dynamic nature of food insecurity across the continent. Collectively, these contributions provide a more context-specific understanding of food insecurity systems and establish a robust foundation for future methodological and empirical research. The proposed framework is readily adaptable to finer spatial resolutions, alternative spatial dependence structures, and emerging learning architectures. This flexibility supports further methodological advances in spatio-temporal and predictive modeling while facilitating comparative research across different regions, sectors, and policy domains.

1.7 Significance of the Study

The significance of this study lies in its potential to enhance the understanding, monitoring, forecasting, and management of severe food insecurity in Africa. By generating comprehensive evidence on the spatial distribution, temporal evolution, determinants, and future trajectories of severe food insecurity, the study provides valuable information that can support evidence-based decision-making at local, national, and continental levels.

Severe food insecurity remains one of the major barriers to achieving sustainable development in Africa because of its adverse consequences for health, nutrition, education, economic productivity, social stability, and human well-being. The findings of this study provide evidence that can contribute to improving food security strategies aimed at reducing vulnerability, strengthening resilience, and enhancing the well-being of populations affected by food insecurity. By improving understanding of the geographic and temporal patterns of severe food insecurity, the study supports more effective responses to one of Africa's most persistent development challenges.

For policymakers and planners, the study provides evidence that can support the design of more targeted, context-specific, and evidence-based food security policies. The identification of countries experiencing persistent or emerging food insecurity enables governments and regional institutions to prioritize interventions according

to the severity and dynamics of local conditions. Such information can contribute to improving the efficiency, effectiveness, and equity of resource allocation, particularly in resource-constrained settings where intervention priorities must be carefully determined.

The study is also significant for humanitarian organizations, development partners, and disaster risk management agencies involved in food security monitoring and emergency response. The findings can strengthen early warning and anticipatory action systems by providing evidence that supports preparedness planning, timely intervention, and proactive management of emerging food insecurity crises. Improved anticipation of future food insecurity patterns may reduce response delays and enhance the effectiveness of humanitarian assistance.

From a planning and development perspective, the study provides information that can support the formulation of long-term strategies for building resilient food systems. Understanding how severe food insecurity evolves across countries and over time enables governments and regional organizations to develop coordinated responses that address both immediate food crises and the structural factors contributing to persistent vulnerability.

The study is further significant for researchers and the scientific community by providing comprehensive evidence on severe food insecurity across African countries. The findings offer a valuable reference for future studies seeking to investigate food insecurity and other complex spatially and temporally dynamic phenomena. They also provide an empirical basis for comparative studies, methodological extensions, and interdisciplinary research aimed at improving food security analysis and decision-making.

More broadly, the study contributes to regional and global efforts to achieve Sustainable Development Goal 2 (Zero Hunger) by providing evidence that supports more effective monitoring, planning, and policy implementation. The findings may also assist governments, regional organizations, and international development partners in strengthening collaboration, improving food security governance, and promoting sustainable and resilient food systems across Africa.

1.8 Scope and Limitations

This study covered the period from 2015-2021 and included 52 countries across the African continent. The unit of analysis was the country-level, using aggregated national-level data. Due to data availability constraints, household- or district-level observations were not included across the continent. Furthermore, certain potentially important contributors such as exchange rates, numbers of conflict-induced displaced persons, religious practices, and dietary or feeding cultures were not incorporated due to lack of data availability, although they could have significantly affected food insecurity.

1.9 Dissertation Structure and Analytical Roadmap

This dissertation was organized into ten chapters. Chapter one introduces the study by presenting the background, statement of the problem, objectives, significance, scope, and limitations. This chapter establishes the overall rationale, relevance, research gaps and analytical direction of the dissertation. Chapter two reviews the relevant theoretical and empirical literature related to the research topic. It identifies key research gaps that motivate the present study and develops the conceptual and analytical framework that guides the subsequent analysis. Chapter three describes the data, data sources, variables and their measurements used in the analysis. Chapter four presents exploratory data analysis, providing an initial characterization of patterns, trends, and distributions in severe food insecurity to address the first objective of the study. Chapter five discusses the identification and ranking of key predictors of severe food insecurity using machine learning approaches, thereby addressing the second objective. Chapter six focuses on the identification and quantification of the determinants of severe food insecurity while accounting for spatial dependence, and addresses the third objective. Chapter seven extends the analysis by incorporating both spatial and temporal dimensions of the outcome, thereby addressing the fourth objective. Chapter eight assesses the spatio-temporally varying effects of the predictors, thereby addressing the fifth objective. Chapter nine illustrates the forecasting of future trajectories of severe food insecurity and thereby addresses the sixth objective.

Chapter ten synthesizes and discusses the main empirical findings of the study in relation to existing literature and outlines the policy implications and potential limitations. It also provides a summary of conclusion of the study's key findings and presents recommendations, along with directions for future research.

A summary diagram illustrating the relationship between the research objectives, methodological framework, and the corresponding dissertation chapters is presented in Figure 1.1.

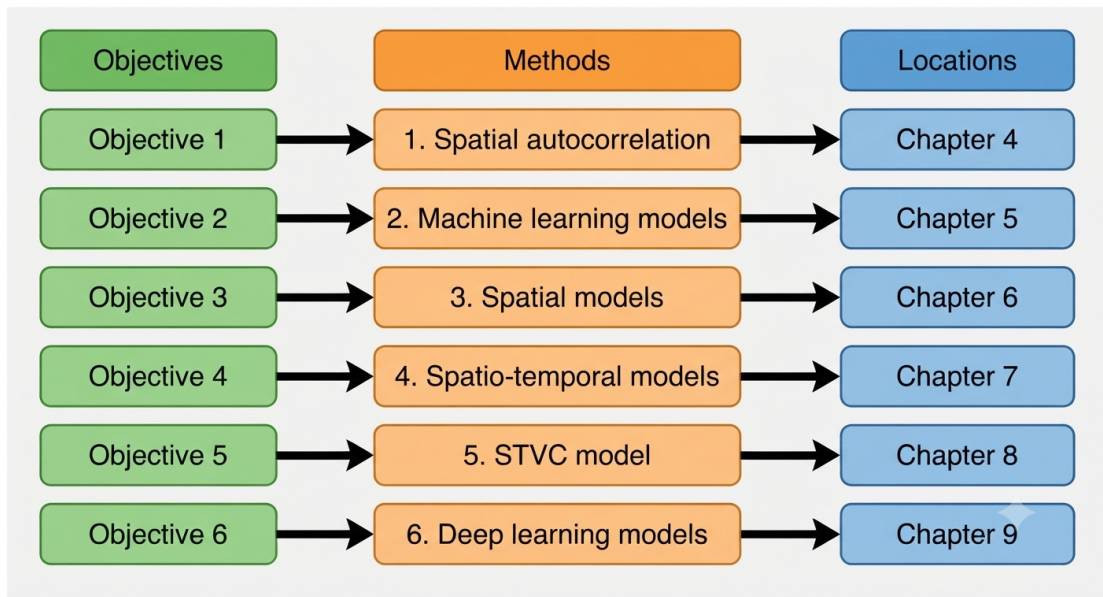


Figure 1.1: Analytical roadmaps

Chapter 2

Literature Review

2.1 Basic Concepts and Definitions of Food (In)security

This study adopts the FAO definition of food insecurity. According to the 1996 World Food Summit, food security is defined as a condition in which “ all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life ” (FAO, 1996). This definition is operationalized through four interrelated pillars of food security: availability, access, utilization, and stability. These pillars reflect the multidimensional nature of food insecurity and serve as a widely recognized conceptual framework in both empirical and policy-oriented food insecurity research, facilitating the identification of policy-relevant drivers and pathways.

Food availability, defined as the physical presence of sufficient food through production, imports, or aid, does not guarantee that all individuals can obtain it. Even when food is available, it may not be accessible physically, economically, or socially to everyone who needs it. Food availability operate on the demand side, while access to food operate on the supply side. Moreover, food that is available and accessible may still fail to provide the necessary nutrients to nourish the body to develop, grow, resist diseases, and meet ordinary physiological functioning, thereby compromising utilization. Food must be stable and reliably obtainable over time; even when it is abundant, accessible, and nutritious, it may not be acceptable culturally or sustainable ecologically in face of shocks or disruptions such as droughts, conflicts, pandemics, and macroeconomic crises, as well as the effectiveness of early warning and safety-net systems. All such instances constitute potential food insecurity.

2.2 Theoretical Frameworks

A clear understanding of the theory of food insecurity is an essential element to better understand food insecurity status and its determinants at the individual, households, national or global level. Different researchers have come out with a number of theories to explain food insecurity.

2.2.1 Food Availability Approach

This approach was rooted in two classical economic perspectives associated with [Smith \(2002\)](#) and [Malthus \(1809\)](#). From an Adam Smith's perspective, food availability was shaped primarily by markets functioning, specialization, and productivity growth. By contrast, Malthusian perspective emphasizes demographic pressure, arguing that population growth tends to outpace the growth of food production, implying that food insecurity and famine arise from natural constraints on agricultural production relative to demographic growth. These theories primary emphasizes food insecurity primarily as a problem of production capacity and population growth.

Building on these foundations, the food availability approach conceptualizes food insecurity as a shortfall in the adequacy of aggregate (per capita) food supply at the national or global level. Food insecurity is therefore understood to arise when total domestic food production and/or food imports are insufficient to meet the food requirements of the population. This indicates that the growth rate of food availability should not be lower than the growth rate of the population. Analytical and policy emphasis is consequently placed on increasing food production, improving storage and food stock management, stabilizing food supplies and expanding imports and food aid. In a closed economy, food availability depends mainly on food production and stocks, whereas in an open economy it also depends on food trading.

The framework further rests on the implicit assumption that increases in national food supply are transmitted to households through markets and distribution systems. The policy implications of this approach are twofold: On the "demand side", the policies emphasize the need to reduce the growth rate of population particularly through fertility rate. On the "supply side", the need to boost (per capita) food production through improved agricultural production. For such purposes, the foremost policy that is generally prescribed and implemented is to increase agricultural productivity. Until the early 1970s, this was the dominant reference approach for the international community, both at the political and the academic level.

2.2.2 Income-Based Approach

This approach shifts the analytical focus from aggregate food availability at the macro level to household and individual income at the micro level ([Griffin and Khan, 1977](#); [Haq, 1976](#); [Reutlinger, 1977](#); [Reutlinger and Selowsky, 1976](#)). Within this framework, food insecurity arises when an individual lacks sufficient income to purchase the amount of food required for survival, or a minimum standard of living, under prevailing conditions ([Sibrián et al., 2007](#)). Conceptually, food insecurity is implicitly treated as a sub-category of poverty, commonly referred to as "food poverty".

2.2.3 Basic Needs Approach

This framework conceptualizes food as one component of a broader set of minimum essential human requirements at the individuals or households' levels, alongside health care, shelter, education, safe water and sanitation. Consistent with the "food first" perspective in the development literature ([Maxwell, 1996](#)), it prioritizes the immediate satisfaction of food consumption needs over broader economic objectives. The basic needs approaches therefore concentrate mainly on the access dimension of food security and places particular emphasis on whether people actually consume sufficient food. By focusing on realized consumption and service access, the framework contributes to a shift in food security analysis from macro-level food supply and economic performance toward micro-level welfare outcomes. It emphasizes the direct provision of essential goods and services to poor and vulnerable groups and interprets food insecurity as a failure to meet minimum nutritional requirements necessary for physical functioning and social participation, regardless of aggregate economic growth. In this perspective, ensuring adequate caloric intake, together with access to basic education, health services, and safe water and sanitation, constitutes the core policy priority.

2.2.4 Entitlement Approach

This approach shifts the analytical focus from national food availability and the Malthusian view of famine and hunger ([Malthus, 1809](#)) toward people's effective access to food, as proposed in entitlement theory ([Sen, 1981](#)). In entitlement approach, food insecurity occurs when individuals or households lack the legally, economically or socially recognized means to obtain food through their personal endowments and exchange mechanisms, even when sufficient food is available in markets ([Sen, 1981](#)). Endowments refer to the resources that a person legally owns or can legitimately command, such as labor force, housing, livestock, land, financial assets and non-tangible resources such as social memberships ([Osmani, 1993](#)). Exchange mechanisms, in turn, represent the set of commodities bundles to which a person has access through own production, wage employment, trade, transfers and the prevailing of prices of food and non-food goods and services ([Sen, 1981](#)). Consequently, starvation and chronic hunger may result not only from a loss of endowments, but also from adverse shifts in exchange conditions. For example, a sharp fall in the price of a commodity produced by a household can substantially reduce the capacity to buy food, even if production levels and overall food availability remain unchanged.

From this perspective, famines and persistent food deprivation are therefore interpreted primarily as failures of access rather than failures of food supply. Adequate food availability at the national level is therefore regarded as a necessary, but not sufficient, condition for food security. The policy implications of the entitlement approach

therefore extend beyond food availability and emphasize on improving incomes and employment opportunities, strengthening market functioning, expanding social transfers and asset ownership, enhancing social protection systems and protecting legal and institutional access rights.

2.2.5 Sustainable Livelihoods Approach

This approach is an extension of the entitlement approach. This approach has been applied to a variety of development issues, including food security (Devereux et al., 2004; Hussein, 2002; Young et al., 2001). For instance, Devereux et al. (2004) argues that food insecurity and famine cannot be explained solely by entitlement failures, but must be understood within a broader political economy and vulnerability context. This framework conceptualizes food security as an outcome of people's ability to build and sustain livelihoods through access to multiple forms of capital: human, physical, financial, natural and social within a wider prevailing institutional and vulnerability conditions. Accordingly, food insecurity occurs when people lack assets and strong institutions to construct resilient and sustainable livelihood strategies under shocks and structural constraints. Hence, the sustainable livelihoods approach emphasizes access and stability. Stability is addressed through the concepts of risk, resilience, and vulnerability. The principal strengths of this framework over previous approaches are its explicit linkage of food security to long-term livelihood sustainability, rather than short-term consumption alone, and its emphasis on contextual factors (political, economic, physical, social, cultural, etc.), although this contextual focus is often confined to agricultural activities and rural settings.

2.2.6 A Human Development and Capability Approach

The entitlement approach is insufficient as a comprehensive framework for addressing hunger and therefore need to move beyond food entitlements towards nutritional capabilities. The entitlements are concerned with the command over commodities, and the capability approach emphasizes individuals' real opportunity to achieve adequate nutrition, health and well-being, and escape deprivations associated with hunger' (Drèze and Sen, 1990), i.e., the capability to be free from hunger. The approach goes beyond the "access" dimension of food security, which is the main concern of the basic needs, entitlement and sustainable livelihood approaches, and also includes the "utilization" dimension of food insecurity. This is one of the most important innovations of the capability approach to food security. Indeed, the relationship between food intake and nutritional achievement can vary greatly depending not only on features such as age, sex, pregnancy, metabolic rates, climatic conditions, and activities, but also access to complementary inputs' including health services, sanitation, and care (Drèze

and Sen, 1990). The capability approach is the most comprehensive in addressing the core dimensions of food security, explicitly integrating availability, access, and utilization. While it is conceptually consistent with the stability dimension, this aspect is less explicitly operationalized than in the sustainable livelihood framework. The capability approach to food security should also include the fourth dimension of food security, as defined at the 1996 World Food Summit, which is stability that is much more than just food price stability.

2.3 Global and Africa Food Insecurity Situations

Empirical evidence indicates that the burden of severe food insecurity has increased substantially over time. Recent estimates show a steady rise in severe food insecurity both globally and across the African continent. Since 2020, the risk of severe food insecurity has been begun rising largely due to the COVID-19 pandemic (FAO et al., 2021a). Globally, the annual estimates of severe food insecurity were 7.6% (2015), 9.3% (2019), 10.8% (2020), 11.7% (2021) and 11.3% (2022). Notably, this rising trend in Africa began in 2015 before the start of the global crisis with annual estimates of 17.2% (2015), 20.2% (2019), 22.4% (2020), 23.8% (2021) and 24.0% (2022) (FAO et al., 2023). These figures demonstrate that Africa bears a disproportionate share of the global food insecurity burden.

Substantial disparities were also observed across the subregions of Africa over time. In 2020, the prevalence of severe food insecurity was highest in the central region of the continent (37.8%), followed by Eastern Africa (28.7%), Western Africa (21.7%), Northern Africa (11.2%) and Southern Africa (11.0%), as reported by (FAO et al., 2023). A similar pattern persisted in 2022, with Central Africa again reporting the highest prevalence (39.1%), followed by Eastern Africa (27.7%) and Western Africa (22%), while Southern Africa (12.5%) and Northern Africa (12%) recorded comparatively lower rates. These figures indicate that severe food insecurity is neither spatially uniform nor temporally stable, but rather evolves dynamically across countries and over time. Such trends underscore the urgency of developing robust analytical frameworks capable of capturing both spatial and temporal variations in food insecurity dynamics.

2.4 Empirical Literature Review

Numerous scholars have investigated the drivers of food insecurity across household, local, regional and global levels. Empirical evidence consistently indicated that food insecurity was influenced by an interrelated set of economic, social political and environmental related factors. Macroeconomic conditions such as GDP per capita (Awad, 2023; Świetlik, 2018), unemployment (Mekonnen and Amede, 2022; Etana and

Tolossa, 2017; Huang et al., 2016; Milovanska-Farrington, 2023; Nord et al., 2014), investment inflow (Guyalo et al., 2022; Osinubi and Apanisile, 2021), inflation (Bogmans et al., 2024; Nord et al., 2014; Olufemi-Phillips et al., 2024; FAO, IFAD, UNICEF, WFP, WHO, 2025), agricultural productivity such as livestock production or ownership (Falvey, 2015; FAO et al., 2018; Molina-Flores et al., 2020; Nkomoki et al., 2019; Pica-Ciamarra et al., 2015; Wubetie et al., 2024a), and crop production (Wubetie et al., 2024a), climate-related factor, including climate change (Campbell et al., 2016; Ali et al., 2022; Baptista et al., 2022; Osman, 2023) and greenhouse gas emissions (Eshete et al., 2020; Gobezie and Boka, 2023; Kaur, 2022; Mahdavian et al., 2025; Mulusew and Hong, 2024; Ntiamoah et al., 2023), social and political instability and conflicts (Murshed et al., 2018; Shemyakina, 2022; Soffiantini, 2020), market-related and food system characteristics such as cereal import dependency (Bofa and Zewotir, 2024b), caloric loss (Munesue et al., 2015; Sawaya, 2017), dietary energy supply and protein supply (Bofa and Zewotir, 2024b; Coles et al., 2016), electricity access (Candelise et al., 2021), and health-related factors particularly the incidence of malaria (Debash et al., 2024; Gari et al., 2018; Lewnard et al., 2014; Madaki, 2017; Mezieobi et al., 2025; Oldenburg et al., 2018; Tusting et al., 2016) are among the most important correlates of food insecurity outcomes.

Although there is broad consensus regarding these determinants, the literature differs considerably in its analytical scale and methodological design. Household- and district-level studies dominate the empirical literature, providing detailed insights into localized vulnerabilities, household coping strategies, and community-specific risk factors. These insights are also reported by Nicholson et al. (2021), who, through a literature review, highlight the predominance of micro-level analyses in the existing body of research. While these studies are valuable for identifying local drivers of food insecurity, their findings are often context-specific and therefore difficult to generalize to national or continental policy settings. Conversely, macro-level studies are better suited for identifying structural determinants that operate across countries and regions but frequently overlook within-country heterogeneity and localized dynamics.

Existing macro-level studies generally agree that economic development, agricultural productivity, infrastructure, and institutional quality are fundamental determinants of food security, although they differ in emphasis. Cross-country econometric analyses primarily highlight the importance of economic growth, food production, infrastructure, trade, and access to improved water sources in improving food security (Kaur and Kaur, 2015). In contrast, regional policy-oriented studies place greater emphasis on weak governance, inflation, climate change, rapid population growth, corruption, and inadequate investment in agricultural infrastructure as persistent barriers to food security in Sub-Saharan Africa (Wudil et al., 2022). Despite these differences, both approaches largely treat relationships as spatially homogeneous and static over time,

limiting their ability to explain why similar socioeconomic conditions produce different food insecurity outcomes across countries. Similar limitations were highlighted by [Cooper et al. \(2020\)](#), whose large-scale text mining analysis identified conflict, economic downturns, and climate change as dominant determinants of food insecurity but found that most existing studies considered spatial patterns while giving limited attention to their temporal evolution.

More recently, researchers have incorporated spatial and spatio-temporal dependence into food insecurity analyses. Across diverse geographical contexts and modeling frameworks, these studies consistently report significant spatial clustering and temporal persistence, demonstrating that food insecurity is neither randomly distributed nor independent across neighboring regions ([Marivoet et al., 2019](#); [Bofa and Zewotir, 2024b](#); [Tomita et al., 2020](#); [Mathenge et al., 2023](#); [Gafa and Chachu, 2023](#); [Mathenge et al., 2023](#); [Tchimeutcheu and Ngono, 2024](#); [Sassi, 2015](#)). Similarly, several studies have documented pronounced spatial clustering and heterogeneous geographic distributions of food insecurity at subnational levels using Bayesian hierarchical models, spatial regression models, and disease-mapping approaches ([Bartolucci and Farcomeni, 2022](#); [Bitew, 2020](#); [Guha and Chandra, 2021](#); [Mathenge et al., 2023](#); [Sassi and Trital, 2021](#); [Tomita et al., 2020](#); [Ukwajunor et al., 2023](#)). While these studies substantially improve upon conventional regression models by explicitly accounting for spatial dependence, most assume that regression coefficients remain constant across space and time. Such assumptions may obscure important local variations and nonlinear relationships, thereby limiting the ability of these models to identify context-specific drivers and support geographically targeted policy interventions.

The literature also reports inconsistent effects for several determinants, suggesting that their influence is inherently context dependent. For example, livestock ownership may enhance food security in many settings by supporting income generation and dietary diversity, yet it can also increase vulnerability in arid and semi-arid environments due to climatic variability, rangeland degradation and resource scarcity ([Danso-Abbeam et al., 2024](#); [Nuvey et al., 2022](#)). Similarly, agricultural crop production enhances food availability under stable institutional and market conditions but it may fail to ensure food security under weak market and governance mechanisms. Intensive crop production can also degrade soil fertility, reduce water availability, and disrupt ecosystem services, thereby undermining long-term food security ([Kopittke et al., 2019](#)). Likewise, although foreign direct investment is conventionally expected to reduce severe food insecurity by supporting economic growth, employment creation, and productivity gains, large scale investments in industries, commercial agriculture, or urban real estate can induce land use changes, displacement of smallholder farmers, and reduce availability of land for farming for the local people, thereby exacerbating severe food insecurity in affected areas ([Guyalo et al., 2022](#)). These contrasting effects

or apparent inconsistencies illustrates the complex and context-specific nature of food insecurity dynamics and may be attributable to spatial, institutional, and environmental heterogeneity.

These observations further suggest that food insecurity cannot be adequately understood as an isolated or static phenomenon. Emerging evidence indicates that future food insecurity trajectories depend not only on underlying socioeconomic and environmental drivers but also on historical conditions and the conditions of neighboring countries (Liu and Shen, 2025). Such interdependencies reflect the inherently spatio-temporal nature of food insecurity, whereby climatic shocks, conflicts, market disruptions, and policy interventions propagate across both space and time. Consequently, understanding the spatial distribution and temporal evolution of severe food insecurity is essential for strengthening early-warning systems, improving resource allocation, and supporting proactive policy responses (Cressie and Wikle, 2011; Herteux et al., 2024; Tomes et al., 2025). Furthermore, scenario-based forecasting approaches enable policy-makers to anticipate future crises and evaluate alternative intervention strategies before implementation (Funk et al., 2019; Krishnamurthy and Choularton, 2020).

A substantial body of literature has assessed the future trajectories of food insecurity crises using traditional statistical techniques and machine learning models (Alelign et al., 2021; Christensen et al., 2021; Dan et al., 2023; Dharmawan et al., 2022; Qasrawi et al., 2023; Lentz et al., 2019; Busker et al., 2024; Westerveld et al., 2021; Herteux et al., 2024; Alturif et al., 2025). While these approaches have demonstrated utility in prediction tasks, they generally do not explicitly account for spatial effects or complex temporal dependencies. As a result, their capacity to capture the interconnected and evolving nature of food insecurity across countries over time remains limited, particularly in the African context where cross-border influences, regional clustering, and dynamic temporal processes are empirical prominent.

The growing recognition of spatial dependence in complex systems has led to the development of Graph Convolutional Networks (GCNs), a class of deep learning models specifically designed to learn from graph-structured data (Kipf and Welling, 2017; Ghosh et al., 2020; Yan et al., 2018). Unlike conventional convolutional neural networks, which operate on regularly structured Euclidean grids, GCNs perform convolution directly on graphs, where nodes represent spatial entities and edges encode relationships such as geographical adjacency or functional connectivity. By aggregating information from neighboring nodes, GCNs effectively capture spatial dependence and higher-order neighborhood interactions while preserving the underlying graph topology. Consequently, GCNs have been successfully applied to a wide range of spatial prediction problems, including traffic forecasting, environmental monitoring, epidemiological modeling, and climate prediction, where spatial interactions play a fundamental role. However, conventional GCNs primarily model spatial relationships on static

graphs and do not explicitly account for temporal dynamics. Their predictive capability is therefore limited for phenomena characterized by both spatial dependence and temporal evolution, such as severe food insecurity.

Collectively, the existing literature demonstrates a clear methodological progression from conventional statistical regression models to spatial, spatio-temporal analyses, machine learning, and graph-based deep learning. Nevertheless, relatively few forecasting studies simultaneously accommodate nonlinear relationships, heterogeneous covariate effects, and dynamic spatio-temporal dependence within a unified modeling framework. These methodological limitations are particularly evident in food insecurity forecasting, where advances in predictive modeling have not been matched by equivalent progress in integrating spatial interactions and temporal dynamics. Addressing these limitations is essential for improving the accuracy, interpretability, and policy relevance of food insecurity forecasting across Africa.

To address this limitation, recent advances have integrated GCNs with temporal learning architectures, including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and temporal convolutional networks (TCNs), leading to the development of Spatio-Temporal Graph Convolutional Networks (ST-GCNs) (Kipf and Welling, 2017; Ghosh et al., 2020; Yan et al., 2018; Shi et al., 2015; Bai et al., 2020; Hammond et al., 2011; Defferrard et al., 2016; Xiao et al., 2025). These hybrid models jointly learn spatial interactions through graph convolutions and temporal dependencies through sequential modeling, enabling them to capture complex nonlinear spatio-temporal processes more effectively than models that consider either dimension separately. Such capabilities are particularly relevant for severe food insecurity, where neighboring countries often experience shared climatic shocks, conflict spillovers, trade disruptions, migration flows, and interconnected food systems that evolve over time.

A critical synthesis of the existing literature reveals several important limitations. First, many econometric and statistical studies impose linear covariate effects and homogeneous relationships across space and time, despite growing empirical evidence of nonlinear and context-dependent responses. Second, although Bayesian spatio-temporal models effectively represent structured and unstructured spatial effects, they are commonly applied using a relatively small set of covariates and may struggle to exploit the rapidly increasing volume of high-resolution environmental and socioeconomic data. Third, machine-learning approaches, while flexible, often neglect explicit spatio-temporal dependence and rarely integrate formal uncertainty quantification in a manner consistent with policy-oriented risk assessment.

These limitations indicate a clear gap in the literature. There remains insufficient integration of nonlinear and heterogeneous covariate effects with spatio-temporal dependence structures within unified and statistically principled spatio-temporal mod-

eling frameworks. Furthermore, the application of modern data-driven learning approaches for long-horizon forecasting of severe food insecurity under heterogeneous regional conditions remains limited.

The present study is positioned to address these gaps by explicitly incorporating spatial and spatio-temporal heterogeneity in the determinants of severe food insecurity, while also allowing for nonlinear relationships and high-dimensional predictors. By combining structured and unstructured spatial effects with temporally evolving components and flexible learning representations, the modeling framework is intended to provide both improved predictive performance and interpretable insights into the spatial distribution and temporal evolution of food insecurity across African countries.

2.5 Conceptual Framework

Food insecurity has been shaped by multiple and evolving determinants, as documented across diverse aspects of the literature. Based on a synthesis of existing review studies, this research categorized the determinants of severe food insecurity into seven broad groups: (i) economic and developmental factors; (ii) environmental and climatic factors; (iii) agricultural productivity levels; (iv) human capital and demographic pressures; (v) infrastructure and access-to-services constraints; (vi) food system vulnerabilities and instability; and (vii) political and health-related factors. This analytical framing emphasizes that national food insecurity cannot be examined in isolation, but must be understood within a broader and interconnected structural, environmental, and institutional contexts. The details of these factors were presented in the conceptual framework shown in Figure 2.1

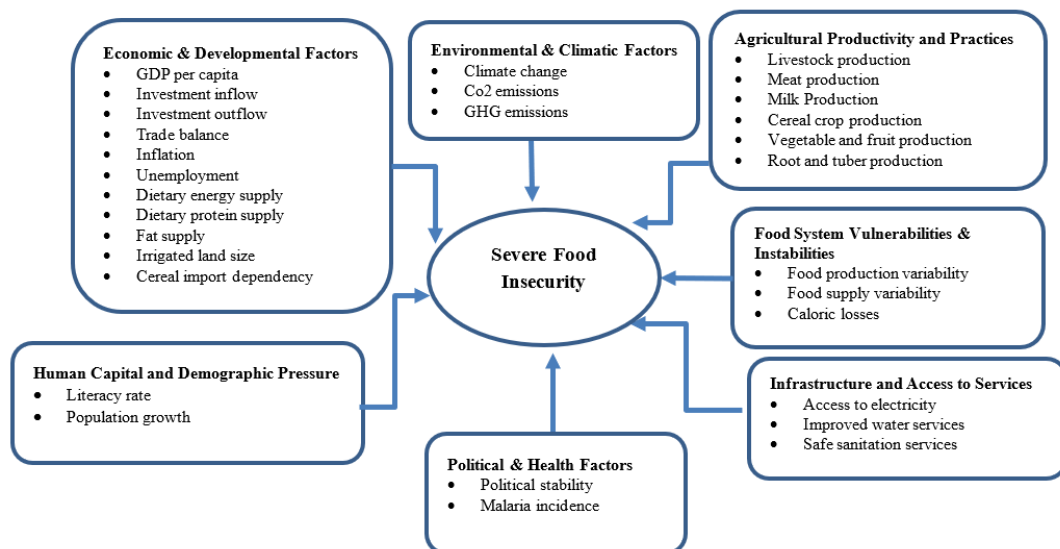


Figure 2.1: Conceptual framework

Chapter 3

Study Design, Data Sources, and Variables

3.1 Introduction

This chapter describes the study design, geographical settings, data sources, variables and their measurement, data quality and comparability across countries, data preprocessing and missing data handling procedures, and the software used in this study.

3.2 Study Design, Settings, and Populations

A retrospective study design was used to achieve the stated study objectives. The analysis was conducted at the country-level across Africa, covering the period from 2015-2021. However, Eritrea and Equatorial Guinea were excluded from the study due to data unavailability. The continent is bordered by the Red Sea (northeast), the Indian Ocean (southeast), the Atlantic Ocean (west), and the Mediterranean Sea (north). The continent is made up of 54 recognized countries, each with its own unique culture, history, and geography.

3.3 Data Sources, Variables, and Measurements

The data are publicly available online at <https://www.fao.org/faostat/en/#data>, <https://data.malariaatlas.org>, and <https://databank.worldbank.org/source/wdi-database-archives#>. Georeferenced point data were obtained from Google Maps, while polygon shapefiles representing the continent were sourced from the Ethiopian Statistical Service (ESS).

The target variable for this study was the prevalence of severe food insecurity at the country-level across Africa. Severe food insecurity refers to the condition in which a person has likely run out of food, experienced hunger and, at the most extreme, has gone for a day or longer without eating due to lack of money or other resources to obtain food (FAO et al., 2021a). It represents the most extreme level of difficulty in accessing adequate food. The prevalence is an estimate of the proportion of people in the population in a given country who live in households classified as severely food

insecure.

FAO measured food insecurity levels using Food Insecurity Experience Scale (FIES). FIES measures individuals' or households' direct experiences of constrained food access due to lack of enough money or other resources using eight standardized binary (yes/no) questions that capture food insecurity experiences over the course of the last 12 months. The questions ranges from mild concerns about the ability to obtain food to extreme situations such as going without eating for an entire day. The items are designed to represent increasing severity along a latent food insecurity continuum. The eight standard FIES questions are listed below.

1. Was there a time when you were worried about not having enough food?
2. Was there a time when you were unable to eat healthy and nutritious foods?
3. Was there a time when you ate only a few kinds of foods?
4. Was there a time when you had to skip meals?
5. Was there a time when you ate less than you thought you should?
6. Was there a time when you ran out of food?
7. Was there a time when you were hungry but did not eat?
8. Was there a time when you went without eating for a whole day?

Responses are analyzed using single-parameter logistic item response theory (IRT) measurement model (commonly known as the Rasch model), which is designed to estimates both the severity of each survey item and the food insecurity level of each respondent. It is used to model the relationship between an individual's underlying latent trait (e.g., food insecurity severity) and their probability of giving specific responses to survey items. This approach places individuals and survey items on a common latent severity continuum or scale (Nord, 2014). A global reference threshold is then used to classify severity levels, allowing meaningful comparisons across populations, countries, and time periods.

Let Y_{ij} denote the binary response (1= "yes", 0= "no") of individual or household i to item j . According to Nord (2014), the probability of responding "yes" to an item j depends on the respondent's severity level and the item's difficulty (severity). Mathematically, the probability that individual i affirms item j is given by:

$$\Pr(Y_{ij} = 1 \mid \theta_i, \beta_j) = \frac{\exp(\theta_i - \beta_j)}{1 + \exp(\theta_i - \beta_j)} \quad (3.1)$$

where: θ_i denotes the latent food insecurity severity (or ability) parameter for respondent i , representing their position on the underlying latent continuum of food

insecurity, and β_j denotes the severity (or difficulty) parameter for item j , representing the level of food insecurity required for a respondent to have a high probability of affirming that experience. Higher values of θ_i indicate more severe food insecurity, whereas the higher values of β_j indicate more severe (harder-to-endorse) items. The items describing mild conditions (e.g., worry about not having enough food) have lower β_j , whereas items describing more extreme conditions (e.g., going without eating for a whole day) have higher β_j values. Accordingly, individuals with higher θ_i are more likely to affirm severe food insecurity experiences (e.g., going a whole day without eating).

Classification of severe food insecurity is based on the estimated position of individuals' on the internationally calibrated FIES. Within this framework, the threshold for classifying an individual as severely food insecure is based on the estimated probability of experiencing the most severe FIES items, such as "being hungry but not eating" or "going without food for an entire day". Individuals whose latent severity scores exceed the globally calibrated cut-off threshold are classified as severely food insecure.

Covariates used in this study, listed in Table 3.1, were selected based on their theoretical relevance, empirical support in the previous studies and the availability of reliable and comparable cross-country data. To strengthen the theoretical foundation, this study adopted a food (in)security framework encompassing the four internationally recognized pillars of food security: availability, access, utilization, and stability. This framework conceptualizes severe food insecurity as a multifactorial outcome shaped by interconnected socioeconomic, environmental, agricultural, infrastructural, demographic, political, health and related factors, which collectively influence these pillars. For example, crop and livestock production, irrigation, GHG emissions, and climate variability primarily affect food availability. Economic indicators such as GDP per capita, inflation, unemployment, trade dependency, and investment inflow influence access to food. Health and social factors, including malaria incidence, sanitation, education, and access to clean water and electricity affect utilization, while political instability and conflicts affect stability by disrupting markets, livelihoods and food systems over time. Candidate predictors that lacked sufficient theoretical justification, exhibited substantial missing data, had limited temporal or spatial coverage, or were highly correlated with other variables were excluded to improve data quality, reduce redundancy, and enhance model stability and interpretability. This selection process ensured that the final set of predictors was both theoretically meaningful and statistically appropriate for robust spatio-temporal modeling and forecasting.

Table 3.1: Covariates and their descriptions

S. No	Main Categories	List of Covariates	Description of Covariates
1	Economic & Developmental Factors	GDP per capita	GDP per capita, PPP (constant 2017 USD)
		Investment inflow	Total FDI inflows (million USD)
		Trade balance	Value of FI in total merchandise export (%)
		Irrigation land size	Percentage of arable land equipped for irrigation (%)
		Inflation	Rate of increase in prices over a given period (%)
		Unemployment	Unemployment rate (%)
		Investment outflow	Total FDI outflows (million USD)
		Cereal import dependency	Cereal import dependency ratio (%)
		Dietary energy supply	Average dietary energy supply (kcal/cap/day)
		Dietary protein supply	Average protein supply (g/cap/day)
		Fat supply	Average fat supply (g/cap/day)
2	Environmental & Climate Factors	Climate change	Temperature change on land (°C)
		CO2 Emissions	Carbon (CO2) emissions (kilotons)
		GHG emissions	Greenhouse gas emissions (kilotons)
3	Political and Health Factors	Political stability	Political stability and absence of violence/terrorism (index)
		Malaria incidence	Rate of cases per thousand

Continued on next page

Table 3.1 – *Continued from previous page*

S. No	Main Covariate Categories	List of Covariates	Description of Covariates
4	Human Capital & Demographic Pressure	Literacy	Percentage of literate population aged 15+ (%)
		Population growth	Population growth rate (%)
5	Infrastructure & Access to Service	Electricity access	Percentage of population with access to electricity (%)
		Improved water services	Percentage using safely managed drinking water services (%)
		Safe sanitation services	Percentage using safely managed sanitation services (%)
6	Agricultural Productivity and Practices	Livestock production	Per capita livestock production indices
		Meat production	Per capita meat production indices
		Milk production	Per capita milk production indices
		Cereals crops production	Per capita cereal crop production indices
		Vegetables & Fruit production	Per capita vegetables & fruits production indices
		Roots & Tubers production	Per capita roots & tubers production indices
7	Food System Vulnerabilities & Instabilities	Food production variability	Per capita food production variability (cont. 2014-2016 thousand USD/capita)
		Food supply variability	Per capita food supply variability (kcal/cap/day)
		Caloric losses	Incidence of caloric losses at retail/distribution level (%)

Expand the discussion of data quality and comparability across countries.

3.4 Data Quality and Comparability across Countries

Given that the study integrated data from multiple international databases, data quality and cross-country comparability were carefully considered throughout the data compilation process. Only internationally recognized data sources that employ standardized definitions, harmonized data collection protocols, and rigorous quality assurance procedures were used to ensure consistency across countries and over time. Variables were aligned to a common annual temporal resolution and standardized country boundaries to facilitate comparable analyses. Country-specific national datasets were not used because differences in definitions, data collection methods, measurement practices and reporting standards and systems could reduce comparability across countries.

3.5 Data Preprocessing and Missing Data Handling

In this section, the dataset was systematically cleaned and preprocessed prior to conducting any statistical analyses. The preprocessing stage aimed to improve data quality, ensure consistency across variables and years, and minimize potential biases arising from incomplete observations and extreme values.

Initially, all variables were inspected for data-entry inconsistencies, duplicate observations, incorrect formatting, and outliers. Variable names were standardized to ensure compatibility across merged datasets and analytical procedures. Continuous variables were further examined using boxplots and distributional assessments to identify implausible values and extreme observations.

Special attention was given to the treatment of missing data because incomplete observations may substantially affect parameter estimation, prediction accuracy, and inferential validity. The study first investigated the underlying mechanisms of missingness to determine whether the missing values followed patterns of Missing Completely at Random (MCAR), Missing at Random (MAR), or Missing Not at Random (MNAR). Understanding the missing-data mechanism is essential because the validity of subsequent imputation procedures depends on these assumptions.

To assess whether the missing observations were MCAR, the study employed both Analysis of Variance (ANOVA) and Little's MCAR test based on the chi-square statistic. ANOVA was employed to examine whether the occurrence of missing observations was systematically associated with the observed variables in the dataset. For this purpose, a missingness indicator variable was created for each variable containing missing observations, where observations with missing values were coded as 1 and observed values were coded as 0. The dataset was subsequently divided into missing

and non-missing groups, and ANOVA was conducted to compare the mean values of the observed variables across these groups. The null hypothesis for ANOVA test is that H_0 : the means for the observed and missing categories are not statistically different. A non-significant result ($P > 0.05$) indicates that the missing observations do not systematically differ from the observed observations, thereby supporting the assumption of MCAR. This implying that the probability of missingness was unrelated to the observed data.

Little's MCAR test was further conducted to evaluate the missing-data mechanism within the longitudinal dataset. The test first identified distinct missing-data patterns across variables and grouped observations according to their missingness structure. For each missing-data pattern, the mean vector of the observed variables was estimated and compared with the overall mean vector of the complete dataset while accounting for the covariance structure among variables. The resulting test statistic follows a chi-square distribution and evaluates whether systematic differences exist between the observed and missing portions of the data. The null hypothesis of Little's MCAR test states that the missing data are MCAR, whereas the alternative hypothesis states that the missingness mechanism is not MCAR. Under the MCAR assumption, the probability of missingness is unrelated to either observed or unobserved data values. Therefore, the observed and missing portions of the dataset are expected to exhibit no systematic differences. A non-significant chi-square result ($P > 0.05$) indicates failure to reject the null hypothesis and suggests that the missingness mechanism is consistent with the MCAR assumption.

Since the results from both ANOVA and Little's MCAR test yielded non-significant p-values greater than 0.05, the study concluded that the missing observations occurred completely at random and were not systematically associated with either observed or unobserved variables. Consequently, the missing values were imputed using the mean of the nearest preceding and succeeding observations within each country-specific temporal sequence in order to preserve the longitudinal continuity and maintain the temporal structure of the dataset. The cleaned and preprocessed dataset was then subsequently used for exploratory analysis, spatio-temporal analysis, and forecasting of severe food insecurity trajectories across African countries.

3.6 Software

The study used R, Python and SaTScan software programs for data manipulation, statistical analysis, and visualization. In particular, R-INLA was used primarily for statistical modeling, including the specification and estimation of spatial and spatio-temporal hierarchical models. SaTScan was used to perform spatial and spatio-temporal cluster detection and hotspot analysis. Python was used for machine learning

and deep learning modeling, including variable reduction and forecasting tasks. Specifically, Pandas was employed for data cleaning and preprocessing, NumPy for efficient numerical and matrix computations, Matplotlib and Seaborn for data visualization, and SciPy and StatsModels for statistical tests and regression analyses.

Chapter 4

Exploratory Data Analysis

4.1 Introduction

This chapter presents the exploratory data analysis conducted to examine the distributional properties, underlying patterns, and relationships within the dataset. The analysis provides a preliminary understanding of the response variable and covariates, as well as their spatial and temporal characteristics. Through descriptive statistics, graphical techniques, and diagnostic tools, the chapter aims to identify trends, potential anomalies, and structural features of the data that inform subsequent modeling approaches. The insights obtained from this exploratory phase serve as a foundation for the specification and interpretation of the explanatory and predictive models employed in the study.

4.2 Models

It is vital to ascertain whether spatial dependencies (spatial autocorrelation) or temporal dependencies (autocorrelation over time) need to be taken into consideration in the modeling before using spatial and/or spatial-temporal models. Thus, this study employed Global and local Moran's I, Getis-Ord G_i^* and Kulldorff's space-time scan statistic to assess spatial clustering, detect high-risk (hotspot) areas and identify space-time clusters, respectively.

4.2.1 Moran's I Statistic

Global Moran's I statistic was utilized to assess the spatial autocorrelation, which measures the degree of similarity or dissimilarity of values between neighboring spatial units (Moran, 1950). Moran's I range from -1 to 1. A significant positive Moran's I indicates clustering of similar values (positive spatial autocorrelation), while a significant negative value suggests clustering of dissimilar values or spatial dispersion (negative spatial autocorrelation). Values near zero indicate a random spatial distribution, implying the absence of spatial autocorrelation. The measure I is calculated by comparing each observed area i to its neighboring areas using the weights, from the

proximity matrix for all $j = 1, \dots, K$. Moran's I is calculated as:

$$I = \frac{K}{\sum_{i \neq j} w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2} \quad (4.1)$$

where K is the total number of areas, w_{ij} is the spatial weight linking country i and j , Y_i and Y_j are the severe food insecurity values for country i and j , respectively, and $\bar{Y}$ is the mean of the severe food insecurity values.

4.2.2 Getis-Ord G_i^* Statistic

The Getis-Ord G_i^* statistic was used to identify the hotspot areas (cluster of high values) and coldspot areas (cluster of low values) of severe food insecurity. Even though a country has a high value, it might not be a statistically significant hotspot. A country with a high value of severe food insecurity is not necessarily a statistically significant hotspot unless it is surrounded by neighboring countries with similarly high values. Likewise, for a country to be classified as a coldspot, it must show low prevalence of severe food insecurity, along with neighboring countries sharing similarly low rates. A positive G_i^* value (positive Z score) indicates hotspots, while a negative G_i^* value (negative Z score) indicates coldspots (Getis and Ord, 1992). The G_i^* value near zero suggest no significant clustering. The G_i^* is computed as:

$$G_i^* = \frac{\sum_{j=1}^K w_{ij} y_j - \bar{Y} \sum_{j=1}^K w_{ij}}{S \sqrt{\frac{K \sum_{j=1}^K w_{ij}^2 - \left(\sum_{j=1}^K w_{ij} \right)^2}{K-1}}} \quad (4.2)$$

where:

$$\bar{Y} = \frac{\sum_{j=1}^K Y_j}{K}, \quad S = \sqrt{\frac{\sum_{j=1}^K Y_j^2}{K} - \bar{Y}^2}.$$

Here, w_{ij} denotes the spatial weight connecting country i and j , y_i and y_j represent the values of severe food insecurity for countries i and j , respectively, and K is the total number of countries considered in the study.

4.2.3 Kulldorff's Space-Time Scan Statistic

This statistical method was used to jointly detect areas of events and time periods with significantly higher incidence risks than expected. It compares the observed number of events in each cluster to the expected number under a uniform distribution. Clustering maps were generated using a scanning window to identify potential clusters and assess their statistical significance such as the likelihood ratio test, and associated P-value. The analysis was performed using SaTScan software designed by Kulldorff (1997). The hypothesis tested whether the relative risk inside the scanning window was

the same as outside, with $\mathbf{H}_0$ assuming equal risk and $\mathbf{H}_1$ suggesting a higher risk inside the window compared to outside. Under the assumption of the Poisson model, the likelihood function for a given window is proportional to:

$$\left(\frac{n}{E[n]}\right)^n \left(\frac{N-n}{N-E[n]}\right)^{N-n} I(\cdot) \quad (4.3)$$

Where N is the total number of severe food insecure people, n is the observed number of severe food insecure people inside the window, $E[n]$ is the expected number of severe food insecure people within the window under $\mathbf{H}_0$, $N-E[n]$ is the expected number of severe food insecure people outside the window and $I(\cdot)$ is an indicator function. When we scan only high-rate clusters, $I(\cdot) = 1$ if the window has more severely food-insecure people than expected under $\mathbf{H}_0$ and 0 otherwise. When we scan low-rate clusters, the situation is opposite. When we scan both high and low-rate clusters simultaneously, $I(\cdot) = 1$ for all windows.

4.3 Results

4.3.1 Descriptive Analysis

Table 4.1 summarizes the descriptive statistics for key socioeconomic, environmental, and agricultural factors associated with severe food insecurity across Africa. The results indicated notable patterns across the continent. For instance, the average household electricity access coverage in Africa was estimated at approximately 52.42% for the period 2015-2021, although this continental average mask significant disparities between urban and rural households. In addition to these infrastructural inequalities, the continent also experienced a considerable public health burden, with the average malaria incidence rate reaching 141 cases per 1,000 population at risk during the same period. The average cereal import dependency ratio in Africa was approximately 41%, indicating continued reliance on imported food products across many African countries. On the economic side, the average inflation and unemployment rates for Africa were approximately 10.36% and 12.07% respectively, although both indicators varied considerably across countries. Despite these socioeconomic and health-related challenges, the average dietary energy supply was estimated at 2441.66 kcal/capita/day.

In terms of variability, factors such as inflation (Std = 16.20, CV = 156.37), GHG emissions (Std = 149.85, CV = 119.35), investment inflow (Std = 27.89, CV = 145.41), GDP/ capita (Std = 1.91, CV = 102.31), and malaria incidence (Std = 129.22, CV = 91.92) exhibit high coefficient of variation among other factors, suggesting substantial disparities across countries. In contrast, factors such as caloric losses (Std = 0.83, CV = 37.05), livestock production (Std= 22.28, CV = 21.43), dietary energy sup-

ply (Std= 478.56, CV = 19.60), dietary protein supply (Std= 16.80, CV = 26.01), and political stability (Std = 1.01, CV = -219.57) show relatively lower variation, indicating greater consistency across countries. These results indicate that while some factors are consistent across countries, others vary widely, contributing to differences in severe food insecurity outcomes across countries.

Table 4.1: Summary of descriptive statistics for the study variables

S. No.	Features	Mean	Std	Q1	Q3	CV (%)
1	GDP_capita (in million \$)	7.79	7.97	1.91	12.30	102.31
2	Electricity_access (%)	52.42	27.65	31.08	71.57	52.75
3	Climate_change (°C)	1.10	0.70	0.54	1.53	63.64
4	Unemployment (%)	12.07	10.72	3.22	20.71	88.82
5	Political_stability (index)	-0.46	1.01	-1.28	0.32	-219.57
6	Inflation (%)	10.36	16.20	1.89	9.10	156.37
7	Malaria_Incidence (cases/1000)	140.58	129.22	15.05	261.05	91.92
8	GHG_Emissions (in million kilotons)	125.56	149.85	6.44	221.15	119.35
9	Caloric_losses (%)	2.24	0.83	1.53	3.09	37.05
10	Investment_inflow (in 100 million \$)	19.18	27.89	0.44	32.52	145.41
11	Cereal_import_dependency (%)	40.99	34.82	8.20	75.40	84.95
12	Livestock_production (indices)	103.97	22.28	89.86	121.19	21.43
13	Cereals_crops_production (indices)	126.38	79.96	74.01	200.10	63.27
14	Dietary_Energy_supply (kcal/cap/day)	2441.66	478.56	2154.76	2734.80	19.60
15	Dietary_Protein_supply (g/cap/day)	64.58	16.80	54.28	77.90	26.01

4.3.2 Correlation Analysis

The correlation heatmap in Figure 4.1 summarizes the correlations between severe food insecurity (Y) and the study features. The results indicate that many of the study features are significantly correlated with severe food insecurity. In Figure 4.1, red color denotes a positive correlation, green signifies a negative correlation and yellow color represents a weak or negligible correlation. For example, GHG emissions, unemployment, inflation, climate change, malaria incidence, caloric loss, and cereal import dependency are positively correlated with severe food insecurity. In contrast, livestock production, cereal crop production, investment inflow, dietary energy supply, dietary protein supply, electricity access, GDP per capita, and political stability are negatively correlated. The remaining features do not show a meaningful correlation with severe food insecurity, suggesting their limited predictive contribution within the model. These weakly correlated features may either be excluded from further analysis or require further investigation to better understand their role in the study.

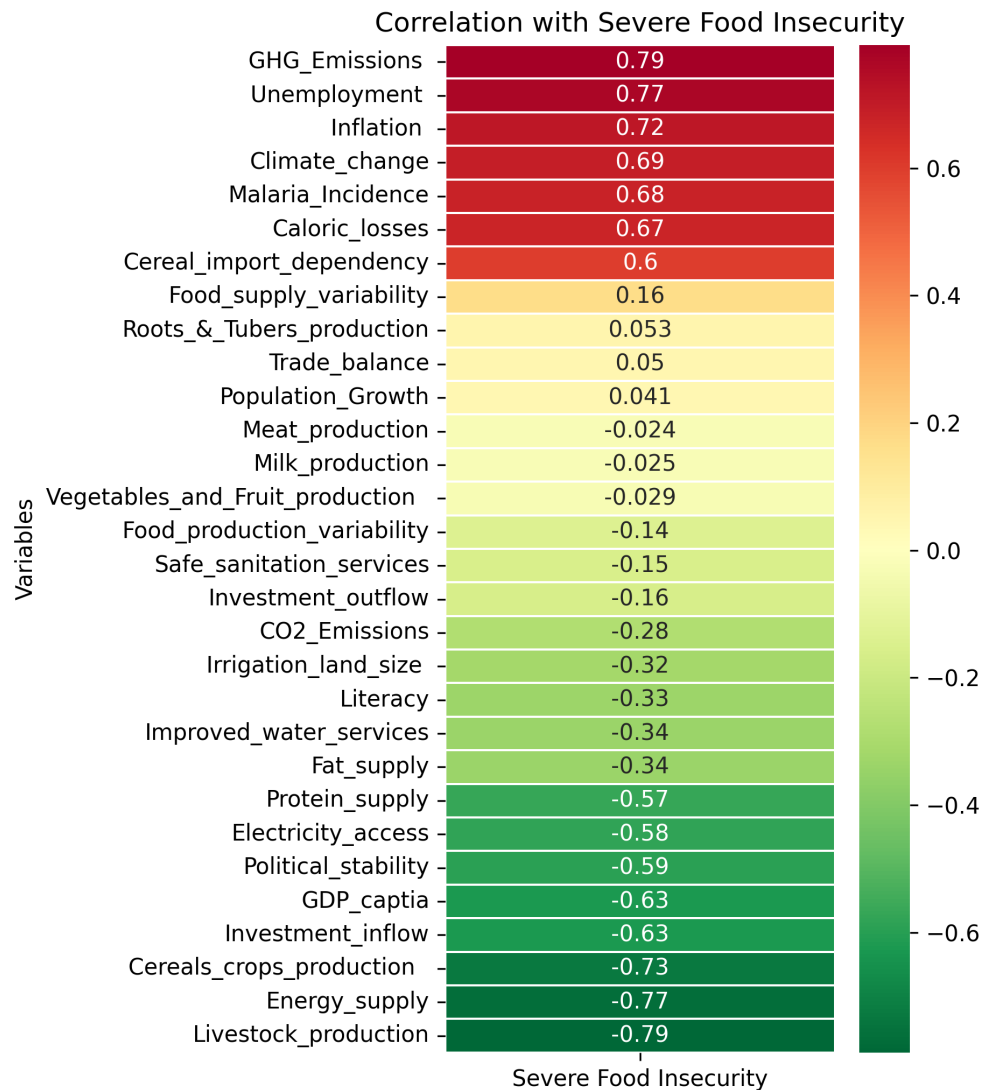


Figure 4.1: Correlation heatmap of predictors with severe food insecurity

4.3.3 Multicollinearity Assessment

Multicollinearity among the explanatory variables was assessed prior to model development to detect potential linear dependencies between covariates. High multicollinearity may inflate the variances of parameter estimates, reduce model stability, and adversely affect the interpretability and predictive performance of statistical models. In this study, the Variance Inflation Factor (VIF) was employed to evaluate the degree of multicollinearity among the predictor variables. The VIF quantifies the extent to which the variance of a regression coefficient is increased due to linear relationships with other explanatory variables. It assesses how well each predictor is explained by all other predictors combined, not just one.

The results indicated that VIF values for each predictors ranged from 1.3 to 4.89, suggesting low to moderate correlations among the predictors. These values fall within

the commonly accepted threshold, indicating that multicollinearity is not a serious concern in the dataset. Consequently, all predictor variables were retained for machine learning modeling, and the study identified the most influential predictors based on their importance scores. The selected predictors were then subsequently used in spatial, spatio-temporal, and deep learning modeling frameworks.

4.3.4 Linearity Assessment of the Outcome Variable

Before proceeding to model building and assessments, the study examined the distributional characteristics of severe food insecurity outcome. This examination facilitates the identification of whether or not strong skewness and extreme outliers exist in the outcome variable, which could influence the regression results and lead to non-normal residuals. If such conditions existed, a transformation or an alternative model might have been more appropriate. Graphical methods, including histogram and Q-Q plots, as well as formal statistical tests such as Shapiro–Wilk test and Anderson–Darling test were used for this purpose. Figure 4.2(A) and (B) illustrates the assessment of the normality of the response variable using histogram and Q-Q plots.

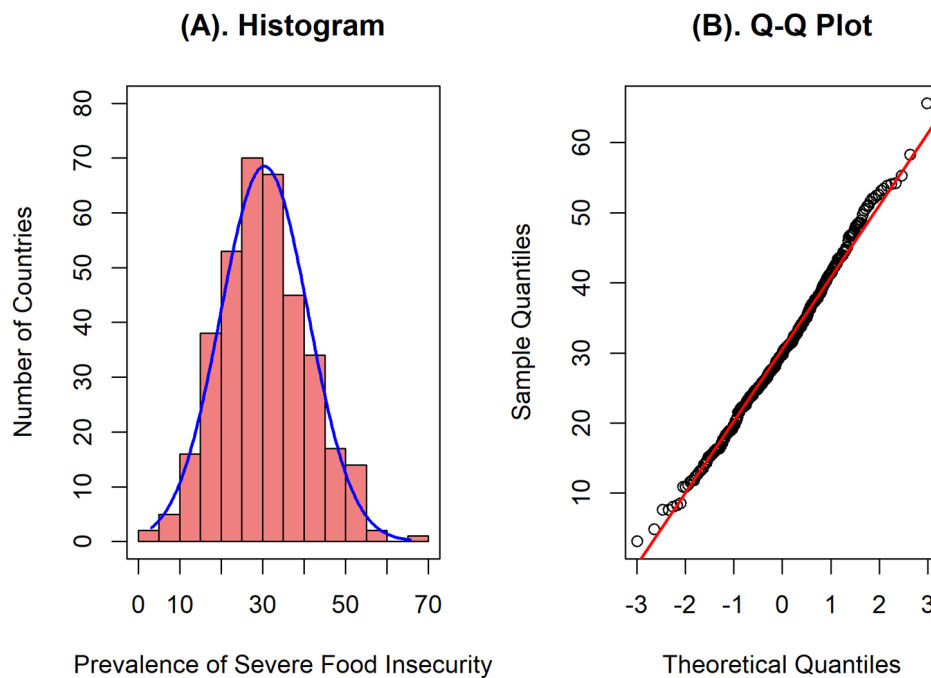


Figure 4.2: Distribution of severe food insecurity

In Figure 4.2 (A), the histogram indicate that the distribution is approximately symmetric. In Figure 4.2 (B), the points largely fall along the reference line. Both plots indicated that the data was approximately normal. Similarly, the formal statistical tests

such as Shapiro–Wilk Test and Anderson–Darling test were used to further assess the normality of the data. The hypotheses for these tests were H_0 : the data follow a normal distribution vs H_1 : the data do not follow a normal distribution. The results showed that the Shapiro–Wilk normality test provided $W = 0.99487$ and p-value = 0.268 and the Anderson–Darling normality test provided $A = 0.53528$ and p-value = 0.1696. The p-values for both tests were greater than 0.05, indicating that the data is considered approximately normal. Therefore, both graphical assessments and formal statistical tests indicated that the outcome variable was suitable for modeling using linear models in subsequent analyses.

4.3.5 Spatial Distribution of Severe Food Insecurity

Figure 4.3 illustrates a visual representation of the observed spatial distribution of the prevalence of severe food insecurity across the African continent from 2015 to 2021. The map suggests that the prevalence of severe food insecurity varied substantially across the countries within the continent. During the study periods, South Sudan, Somalia, the Central African Republic, the Democratic Republic of the Congo, Republic of the Congo, Malawi, Guinea, Mozambique, and Liberia notably experienced higher risk of severe food insecurity among African countries. In addition to these countries, Rwanda experienced a high prevalence of severe food insecurity, particularly between 2018 and 2021. Similarly, Zimbabwe exhibited a high prevalence from 2015 to 2017. The overall distribution suggests that while some regions faced persistent and chronic food insecurity, others experienced fluctuations in severity over time, underscoring the complexity and dynamic nature of the food security landscape across Africa during the study period.

Figure 4.3: Spatial pattern of severe food insecurity across Africa

4.3.6 Temporal Trends of Severe Food Insecurity

Figure 4.4 and Figure 4.5 illustrates the levels and temporal trends of severe food insecurity at the continent-wide and country-wise across Africa from 2015-2021, respectively. It was observed that continent-wide severe food insecurity consistently increased over the study period. At the country level, substantial variation was observed in prevalence across countries during the study period. Most countries experienced an upward trajectory from 2015 to 2021. These temporal patterns underscore the growing challenges faced by many countries in ensuring adequate food security for their populations.

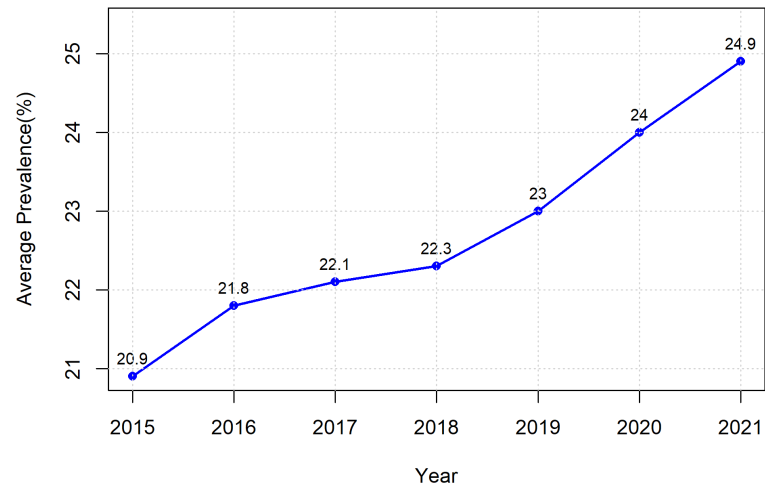


Figure 4.4: Continent-wide temporal trends of severe food insecurity

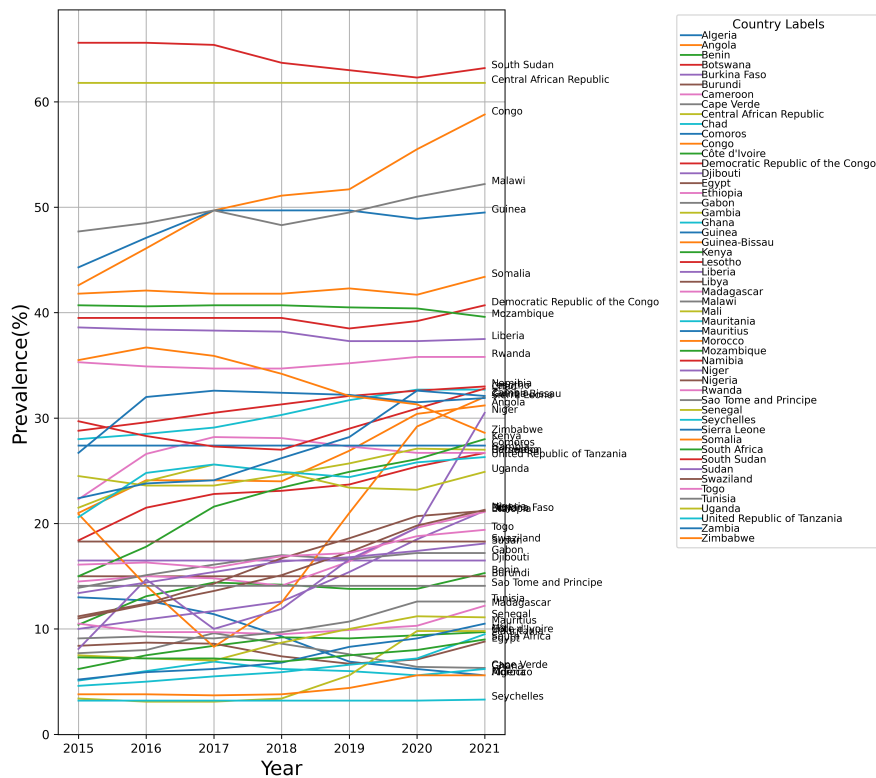


Figure 4.5: Country-specific temporal trends of severe food insecurity

4.3.7 Global Spatial Autocorrelation of Severe Food Insecurity

The degree of spatial clustering of the prevalence of severe food insecurity in Africa during the study period is displayed in Table 4.2. The analysis utilized the Global Moran's I statistic, which measures spatial autocorrelation. Across the study years, the Global Moran's I statistic remained positive (ranging from 0.22 to 0.285) and statistically significant ($P\text{-value} < 0.05$). This indicates the persistent spatial clustering of se-

vere food insecurity across Africa. The degree of clustering was higher in 2020 (Global Moran's $I = 0.2849$ and $P\text{-value} < 0.002$). These findings demonstrate that severe food insecurity is not randomly distributed across the continent but is concentrated in distinct geographic hotspots.

This spatial clustering suggests that severe food insecurity is driven by shared regional factors, including conflict, climate shocks, economic instability, and cross-border vulnerabilities. Consequently, interventions should prioritize identified hotspot regions, strengthen regional and cross-border collaboration, and strategically allocate resources beyond country-specific responses to effectively reduce severe food insecurity and enhance regional resilience.

Table 4.2: Summary of global Moran's I statistics results

Year	Moran's I Test Statistic	P-value	Remark
2015	0.2200	< 0.009	Clustered
2016	0.2258	< 0.009	Clustered
2017	0.2254	< 0.009	Clustered
2018	0.2459	< 0.005	Clustered
2019	0.2661	< 0.003	Clustered
2020	0.2849	< 0.002	Clustered
2021	0.2637	< 0.003	Clustered

4.3.8 LISA Cluster & Outlier Analysis of Severe Food Insecurity

The global Moran's I statistic provides a single summary measure of spatial autocorrelation. It indicates whether severe food insecurity is spatially clustered or spatially dispersed across countries. To obtain more detailed location-specific insights, this study also computed the local Moran's I statistic for each country. The local Moran's I statistic measures the similarity between an observation and the values observed in neighboring countries.

Figure 4.6 presents LISA thematic maps depicting the prevalence of severe food insecurity in each country relative to its neighboring across the continent. The map illustrates the five distinct types of spatial associations and outliers. The colors red (high-high) and green (low-low) regions represent the spatial clustering of the high (hotspot) and low (coldspot) prevalence rates, respectively. In these areas, countries are surrounded by neighboring countries with similar levels of severe food insecurity. This pattern indicates a statistically significant positive spatial autocorrelation. For instance, the Central African Republic (2015-2021), the Democratic Republic of the Congo (2015-2021), and Sierra Leon (2016-2021) experienced high rates of severe food insecurity and these countries were surrounded by neighboring countries with sim-

ilar high prevalence rates. Conversely, countries such as Madagascar (2015-2021) and Uganda (2020-2021) experienced low prevalence rates of severe food insecurity and were surrounded by neighboring nations with similarly low rates.

Countries colored orange (high-low) and yellow (low-high) represent spatial outliers characterized by significant negative spatial autocorrelation. These countries are surrounded by neighboring nations that exhibit dissimilar values. This means that while these outlier countries face either high or low rates of severe food insecurity, their immediate surroundings reflect the opposite trend. For instance, Zambia (2015-2021), Uganda (2015-2019) and Angola (2018-2021) experienced high prevalence of severe food insecurity despite being surrounded by countries with lower rates. On the other hand, Algeria (2015-2021) and Burkina Faso (2015-2021) illustrate low prevalence of severe food insecurity while neighboring countries experience higher levels. Furthermore, the gray regions in Figure 4.6 indicate countries where the prevalence of severe food insecurity doesn't show significant spatial autocorrelation. This suggests that the distribution of food insecurity in these areas is more random, without distinct clustering patterns, thereby requiring different analytical approaches for effective intervention and resource allocation.

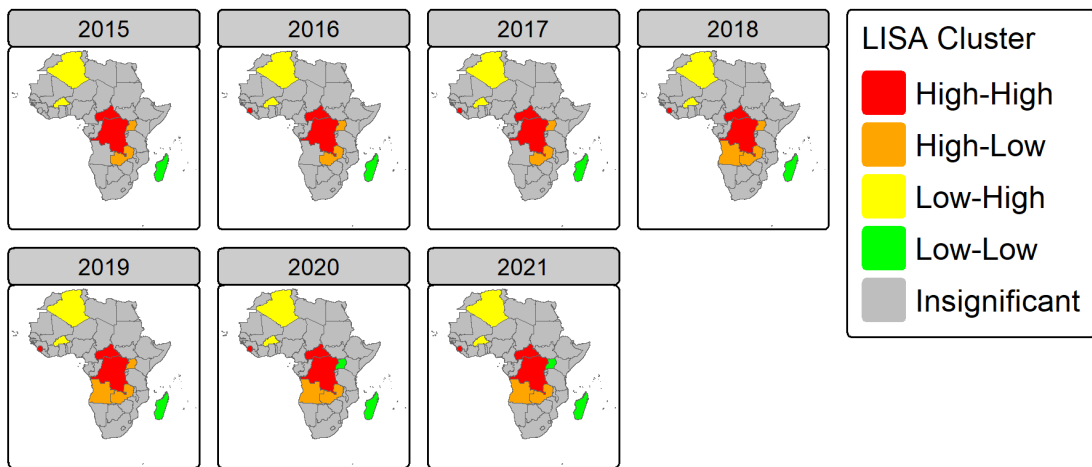


Figure 4.6: LISA cluster & outlier analysis of severe food insecurity

4.3.9 Hotspot Analysis of Severe Food Insecurity

The hotspot and coldspot areas are also identified in Figure 4.7 using the Getis-Ord G_i^* statistic. In the figure, areas marked in red color represent hotspots (high-risk areas), while blue areas indicate coldspots. The areas highlighted in gray reveal those countries where severe food insecurity doesn't show statistically significant spatial autocorrelation. Notably, the Democratic Republic of the Congo (2015-2021), the Central African Republic (2015-2021), Uganda (2015 and 2017-2020), Zambia (2019-2020), Angola (2019-2021), Cameroon (2021) and Sierra Leon (2017) were identified as high-

risky (hotspot) areas for severe food insecurity at 5% level of significance. The hotspot countries identified using local Moran's I and Getis-Ord G_i^* statistic underscore the urgent need for policymakers and development partners to prioritize resource allocations, design and implement location-specific interventions, strengthen social protection and early warning systems, and maintain sustained long-term support to reduce recurrent food insecurity and build resilience in these regions.

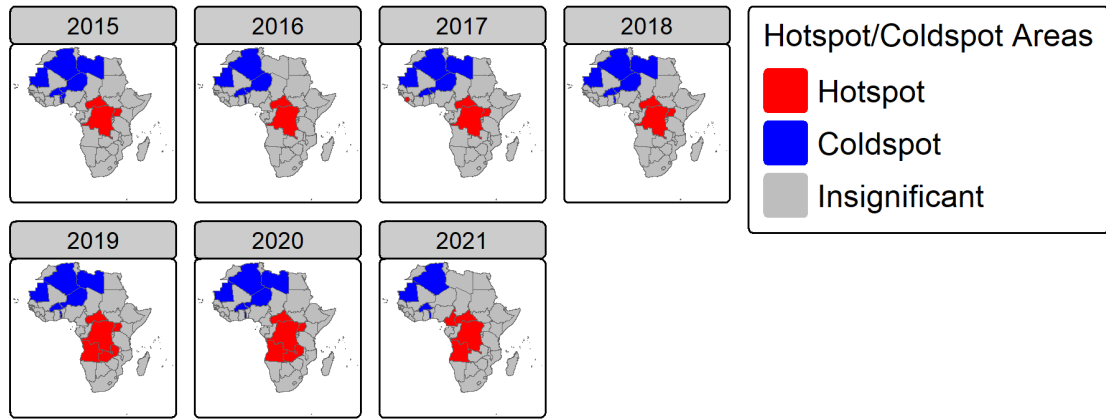


Figure 4.7: Hotspot and coldspot areas of severe food insecurity

4.3.10 Joint Spatio-Temporal Cluster Detection of Severe Food Insecurity

Table 4.3 and Figure 4.8 illustrate the results of Kulldorff's retrospective space-time scan statistic. A Poisson model was used for this purpose. This statistical approach helps pinpoint where and when the incidence of severe food insecurity was most concentrated across Africa at the country level from 2015 to 2021. Table 4.3 presents the statistical metrics for each detected cluster, including the relative risk (RR), log-likelihood ratio (LLR) and the corresponding time frames. Notably, the most likely significant spatio-temporal cluster was detected in Somalia, located in East Africa, (LLR = 6,081,314.44, RR = 2.41, $P < 0.0001$), which occurred between 2015 and 2017. The risk of severe food insecurity in Somalia was 2.41 times (RR = 2.41) higher than elsewhere.

Table 4.3: Spatio-temporal cluster analysis of severe food insecurity

S.No.	Clusters Detected	Time Frame	Observed/Expected	RR	LLR	P-value
1	Central African Republic, Cameroon, Congo, Chad, DRC, Gabon, South Sudan	2015–2017	2.13	2.26	44,393,763.97	< 0.0001
2	Mozambique, Malawi, Zimbabwe	2015–2017	2.12	2.17	17,583,608.32	< 0.0001
3	Somalia	2015–2017	2.39	2.41	6,081,314.44	< 0.0001
4	Sierra Leone, Guinea, Liberia	2015–2017	1.99	2.00	5,576,198.12	< 0.0001
5	All	2020–2021	1.09	1.13	2,968,266.73	< 0.0001
6	Libya	2020–2021	1.03	1.03	1,615.88	< 0.0001

Figure 4.8 depicts both the most likely and secondary statistically significant

spatio-temporal clusters of severe food insecurity rates in the study region. Circular windows indicate regions where severe food insecurity rates exceeded expected levels during specific periods. Six major secondary statistically significant clusters were identified across the continent. These clusters were predominantly located in the western, central, eastern and southeastern parts of the continent at different periods. The largest secondary cluster occurred in the central regions of the continent (LLR = 44,393,763, RR = 2.26, $P < 0.000$) (as indicated in Table 4.3 and Figure 4.8). Seven countries are clustered in this cluster, with a high-risk period from 2015 to 2017.

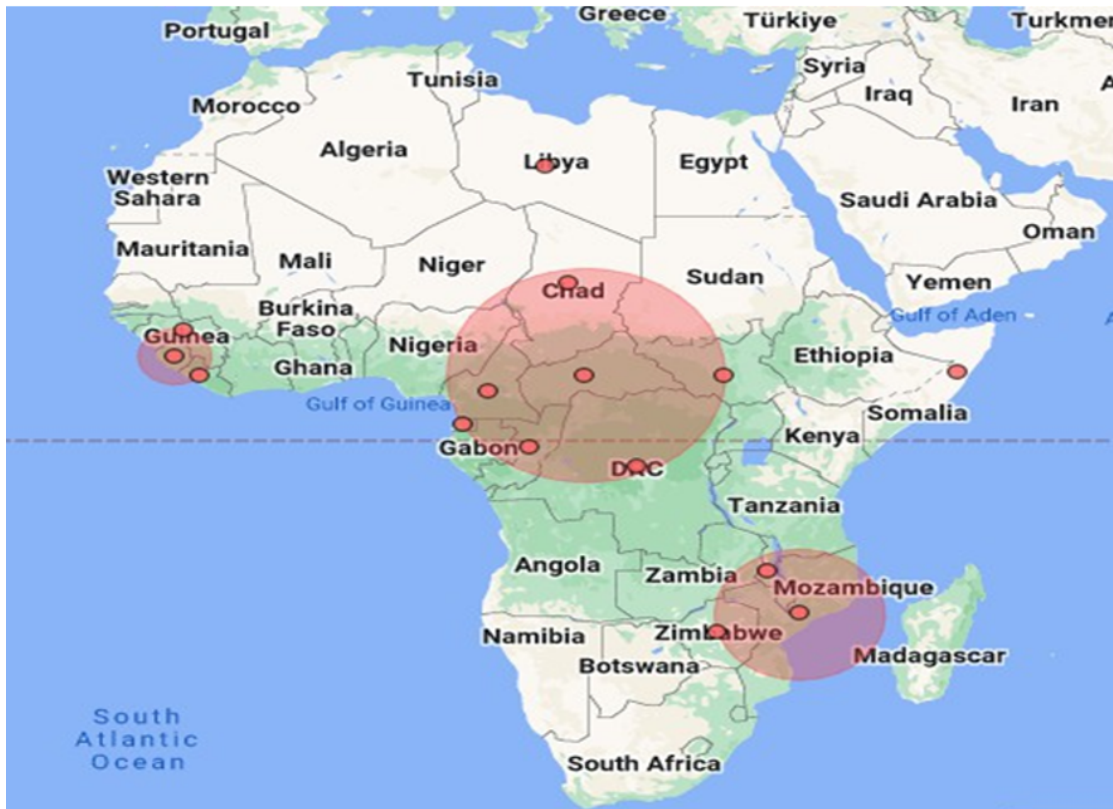


Figure 4.8: Space-time cluster detection of severe food insecurity

4.4 Summary

This chapter presents the exploratory data analysis to provide an initial characterization of patterns, trends, and distributions of severe food insecurity across Africa over the period 2015-2021. The analysis used Global and Local Moran's I statistic, Getis-Ord G_i^* statistic, and Kulldorff's space-time scan statistic to identify spatial clustering, hotspot patterns, and spatio-temporal variations in severe food insecurity outcome. The findings showed a consistent increase in severe food insecurity across Africa from 2015 to 2021, reflecting a growing humanitarian and development concern. The prevalence also varied across countries, with clear spatial clustering and temporal per-

sistence, suggesting that food insecurity was not randomly distributed. Distinct high- and low-risk areas are identified, with several Sub-Saharan African countries including Democratic Republic of the Congo (2015-2021), the Central African Republic (2015-2021), Sierra Leon (2016-2021), Zambia (2015-2021), Uganda (2015-2019), Angola (2018-2021), and Cameron (2021), persistently experiencing high risk.

Despite providing valuable insights into the distributional characteristics, spatial, temporal, and spatio-temporal patterns of severe food insecurity across Africa, the analyses presented in this chapter are primarily exploratory and descriptive in nature. The applied methods, including global and local spatial autocorrelation measures and space-time cluster detection techniques, identified geographic hotspot areas and clustering structures across African countries. While these exploratory analyses provided important insights into the patterns and clustering behavior of severe food insecurity, they did not quantify the relative importance of potential predictors or evaluate their joint effects within a unified framework. Moreover, these approaches are sensitive to the specification of the spatial weight matrix and are limited in their ability to address potential confounding factors and underlying causal mechanisms. As a result, while this chapter establishes important empirical regularities and justifies the presence of spatial and temporal dependence, it does not provide a comprehensive understanding of the key drivers of severe food insecurity. To address these limitations, the subsequent chapter employs machine learning-based approaches to identify and rank the most influential determinants. This approach enables a more robust multivariate analysis and provides a foundation for subsequent spatial and spatio-temporal modeling.

Chapter 5

Machine Learning-Based Feature Selection and Ranking

5.1 Introduction

This study initially considered a wide range of potential drivers of severe food insecurity. To improve model interpretability and reliability, the candidate variables were reduced to a parsimonious set of key predictors. In this context, machine learning approaches provide flexible and data-driven tools for uncovering complex patterns and evaluating the relative importance of predictors without imposing strict parametric assumptions. This chapter applied supervised machine learning methods to a set of country-level variables to select and rank predictors based on their predictive importance in explaining variations in severe food insecurity. A range of models was implemented, including regularized linear methods, tree-based models, instance-based models, and artificial neural networks. Feature importance was evaluated using embedded, wrapper, and model-agnostic approaches, and the results were used to derive a reduced set of key predictors for subsequent analysis.

5.2 Models

Food insecurity is a multidimensional phenomenon influenced by a wide set of interrelated factors, including economic volatility, agricultural productivity, climatic variability, demographic pressures, political instability and health-related determinants, which interact in dynamically and nonlinearly over time. Many of these determinants are interconnected. These characteristics, arising from spatial heterogeneity, temporal shocks, and cross-country dependencies inherent in the data, make the pattern of food insecurity dynamic and unpredictable. These limit the ability to represent the true complexity of the relationships among variables in classical statistical models.

Modern statistical approaches, including regularized regression models, address some of these challenges by reducing multicollinearity and controlling overfitting by coefficient shrinkage, but they remain constrained by linearity and normality assumptions. In contrast, machine learning methods provide substantially greater flexibility in modeling complex systems, as they can automatically capture nonlinear relationships, high-

dimensional and interdependent effects, high-order interactions, and context-specific patterns without requiring prespecified functional forms or strict distributional assumptions (Noorunnahar et al., 2023; Raschka and Mirjalili, 2019). Moreover, their use of regularization and cross-validation enhances predictive accuracy, making machine learning effective for identifying multifaceted drivers of severe food insecurity and supporting reliable policy forecasting and early warning systems.

Although machine learning models are often assumed to perform best with large datasets, data quantity alone does not guarantee more accurate models or deeper insights (Naser, 2026; Davenport, 2014; Naser, 2024). Large datasets may contain noisy or redundant observations and often require substantial computational resources for model development (Brownlee et al., 2021). In contrast, smaller datasets can reduce computational costs and training time while remaining effective when the data are of high quality, relevant, and representative of the problem under investigation (Menghani, 2023). Indeed, studies have shown that carefully curated small datasets can yield reliable and generalizable results, emphasizing that data quality can be more important than data volume (Faraway and Augustin, 2018; Kokol et al., 2022). Moreover, several machine learning methods, including penalized regression, tree-based algorithms, and nearest-neighbor approaches, are well-suited to small-data settings because they mitigate overfitting and efficiently exploit limited observations (Zhang et al., 2020; Malkov et al., 2014; Zhang et al., 2018). No universal cutoff exists for defining a small dataset; its classification depends on the application domain, data complexity, and observation-to-feature ratio. Consequently, datasets considered adequate today may be regarded as small in the future as model complexity and architectures continue to evolve.

Due to these theoretical and empirical advantages, the study employed diverse machine learning algorithms to identify the key drivers that contributed to severe food insecurity in countries across Africa. This variable selection process helped reduce dimensionality and improved model performance. The algorithms performed tasks by learning patterns in the data. In each learning process, the study estimated unknown dependencies from the available dataset and used these estimated dependencies for future prediction.

To do this, the dataset was split chronologically, with data from 2015–2019 (approximately 80%) used for training and data from 2020–2021 (approximately 20%) used for testing. This temporal split helps to prevent data leakage and ensures that the model predicts future observations based solely on past information. The study used the training datasets to build the prediction model or learner. Next, the study validated the model with the testing datasets.

To select the best predictive model, this study considered and compared four major classes of algorithms: linear models (linear, ridge, LASSO, and elastic net), tree-based models (decision tree, random forest, gradient boosting, and extreme gradient

boosting), instance-based models (k-nearest neighbors and support vector regression), and artificial neural networks. This approach enabled a systematic comparison of model complexity, interpretability, and capacity to learn nonlinear relationships. The final model was chosen based on predictive performance metrics.

5.2.1 Linear Regression

Given a vector of observed responses $\mathbf{y}$ and an input design matrix of covariates $\mathbf{X}^\top = (x_1, x_2, \dots, x_p)$, the model assumes a linear relationship between the predictors and a continuous response, expressed as:

$$y_i = x_i^\top \boldsymbol{\beta} + \varepsilon_i \quad (5.1)$$

The parameter estimates $\boldsymbol{\beta}$ are obtained by ordinary least squares (OLS):

$$\begin{aligned} \hat{\boldsymbol{\beta}}^{ols} &= \arg \min_{\boldsymbol{\beta}} \sum_{i=1}^n (y_i - \mathbf{x}_i^\top \boldsymbol{\beta})^2 \\ &= \arg \min_{\boldsymbol{\beta}} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \\ &= (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y} \end{aligned} \quad (5.2)$$

The fitted values are given by:

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}} \quad (5.3)$$

As in [Hastie et al. \(2010\)](#), the term $\hat{\beta}_0$ represents the intercept, also referred to as the bias in machine learning.

5.2.2 Ridge Regression

Ridge regression applies an ℓ_2 regularization or penalty to shrink the sum of squared regression coefficients ([Hastie et al., 2010](#)). The ridge coefficients minimize a penalized residual sum of squares:

$$\hat{\boldsymbol{\beta}}^{\text{ridge}} = \arg \min_{\boldsymbol{\beta}} \left[\sum_{i=1}^n (y_i - \mathbf{x}_i^\top \boldsymbol{\beta})^2 + \lambda \sum_{j=1}^p \beta_j^2 \right] = (\mathbf{X}^\top \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{y} \quad (5.4)$$

Here $\mathbf{I}$ is the $p \times p$ identity matrix, $\lambda \geq 0$ is a complexity parameter that controls the amount of shrinkage: the larger the value of λ , the greater the amount of shrinkage. The coefficients are shrunk toward zero.

5.2.3 LASSO Regression

Least Absolute Shrinkage and Selection Operator (LASSO) uses an ℓ_1 regularization to penalize the absolute values of coefficients (Hastie et al., 2010). The LASSO estimate is defined by:

$$\hat{\beta}^{\text{lasso}} = \arg \min_{\beta} \left[\sum_{i=1}^n (y_i - \mathbf{x}_i^\top \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \right]. \quad (5.5)$$

5.2.4 Elastic Net Regression

Elastic net combines ℓ_1 and ℓ_2 penalties (Zou and Hastie, 2005):

$$\hat{\beta}^{\text{en}} = \arg \min_{\beta} \left[\sum_{i=1}^n (y_i - \mathbf{x}_i^\top \beta)^2 + \lambda \left(\alpha \sum_{j=1}^p |\beta_j| + (1 - \alpha) \sum_{j=1}^p \beta_j^2 \right) \right]. \quad (5.6)$$

where $0 \leq \alpha \leq 1$.

5.2.5 Support Vector Regression (SVR)

SVR is an extension of the Support Vector Machine (SVM). It introduces a region called an “ ϵ – tube” around the function to be estimated. The objective is to identify the tube that best approximates a continuous-valued function while minimizing prediction error. The prediction error is defined as the difference between the predicted and the observed class label values.

SVR uses an ϵ -insensitive loss function, such as a linear or quadratic loss, which penalizes predictions that are farther than ϵ from the desired output. The value of ϵ determines the width of the tube. The functional form and estimation procedure of SVR are given as follows (see Drucker et al. (1996) and Vapnik (2013) for detailed derivations):

$$y_i = f(x; \alpha^*, \alpha) = \sum_{i=1}^N (\alpha_i^* - \alpha_i) \langle x, x_i \rangle + \beta_0. \quad (5.7)$$

Where, $\langle x, x_i \rangle$ is the inner product of two elements of Hilbert space.

To find the coefficients α_i^* and α_i , the study maximizes the following quadratic optimization problem:

$$\begin{aligned} f(\alpha^*, \alpha) = & -\epsilon \sum_{i=1}^N (\alpha_i^* + \alpha_i) + \sum_{i=1}^N y_i (\alpha_i^* - \alpha_i) \\ & - \frac{1}{2} \sum_{i,i'=1}^N (\alpha_i^* - \alpha_i) (\alpha_{i'}^* - \alpha_{i'}) \langle x_i, x_{i'} \rangle \end{aligned} \quad (5.8)$$

subject to the constraints:

$$\begin{aligned}
0 &\leq \alpha_i, \alpha_i^* \leq \frac{1}{\lambda}, \\
\sum_{i=1}^N (\alpha_i^* - \alpha_i) &= 0, \\
\alpha_i, \alpha_i^* &\geq 0, \quad \alpha_i \alpha_i^* = 0
\end{aligned} \tag{5.9}$$

leading to:

$$\begin{aligned}
\hat{\beta} &= \sum_{i=1}^N (\hat{\alpha}_i^* - \hat{\alpha}_i) x_i, \\
\hat{y}(x) &= \sum_{i=1}^N (\hat{\alpha}_i^* - \hat{\alpha}_i) \langle x, x_i \rangle + \beta_0.
\end{aligned} \tag{5.10}$$

Due to the nature of the constraints, typically only a subset of the solution values $(\hat{\alpha}_i^* - \hat{\alpha}_i)$ are nonzero, and the associated data values are called the support vectors.

5.2.6 k-Nearest Neighbors (KNN) Regression

Nearest-neighbor methods use observations closest to x in the input space to form $\hat{f}(x)$ (Hastie et al., 2010). Specifically, the KNN method predicts $\hat{f}(x)$ by averaging the outputs of the k nearest neighbors as follows:

$$\hat{f}(x) = \frac{1}{k} \sum_{x_i \in \mathcal{N}_k(x)} y_i \tag{5.11}$$

where $\mathcal{N}_k(x)$ denotes the neighborhood of x , defined by the k closest points x_i under a chosen distance metric (typically the Euclidean distance). More generally, a weighted form is often employed:

$$\hat{f}(x) = \sum_{x_i \in \mathcal{N}_k(x)} w_i(x) y_i \tag{5.12}$$

the weights $w_i(x)$ are non-negative, satisfy $\sum_{x_i \in \mathcal{N}_k(x)} w_i(x) = 1$, and typically decrease as the distance $\|x - x_i\|$ increases.

5.2.7 Decision Tree Regression

A single tree that splits data into branches based on feature values. A regression tree partitions the predictor space into M disjoint regions $\{R_m\}_{m=1}^M$. The resulting estimator, as specified in Breiman et al. (2017), can be written as:

$$\hat{f}(x) = \sum_{m=1}^M c_m \mathbb{I}(x \in R_m) \tag{5.13}$$

where $\mathbb{I}(\cdot)$ is the indicator function and c_m is the predicted value in region R_m .

Under the squared-error loss, the optimal prediction within each region is the sample mean of the responses belonging to that region:

$$c_m = \frac{1}{|R_m|} \sum_{x_i \in R_m} y_i \quad (5.14)$$

5.2.8 Random Forest Regression

Random Forest extends the decision tree approach by constructing M decision trees using different bootstrap samples of the data and random subsets of predictor variables. Each tree denoted by $\hat{f}^{(m)}(x)$ produces a prediction, and the final prediction for regression is obtained by averaging the predictions across all ensemble of bootstrap-grown trees (Breiman, 2001):

$$\hat{f}_{RF}(x) = \frac{1}{M} \sum_{m=1}^M \hat{f}^{(m)}(x) \quad (5.15)$$

Each individual tree $\hat{f}^{(m)}(\cdot)$ is fitted using a bootstrap sample drawn from the original dataset and is constructed via recursive binary splitting.

5.2.9 Gradient Boosting Regression

Gradient boosting regression constructs an ensemble of decision trees sequentially rather than independently. The first tree makes an initial prediction, and each subsequent tree is trained to correct the errors made by the previous trees, optimizing a loss function to achieve high accuracy (Friedman, 2001). The final prediction is obtained by combining the contributions of all trees as:

$$\hat{f}(x) = \sum_{m=1}^M f_m(x) \quad (5.16)$$

The model is obtained by minimizing the gradient of a loss function $L(y, f(x))$. At iteration m , the negative gradient of the loss function with respect to the current model is computed as:

$$r_{im} = - \left. \frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right|_{f=f_{m-1}} \quad (5.17)$$

A new base learner $h_m(x)$ is then fitted to $\{r_{im}\}$. The model is updated as:

$$\hat{f}_m(x) = f_{m-1}(x) + \nu h_m(x) \quad (5.18)$$

where $0 < \nu \leq 1$ is the learning rate controlling the contribution of each successive learner. After M iterations, the final predictor is given by:

$$\hat{f}(x) = f_M(x) \quad (5.19)$$

5.2.10 Extreme Gradient Boosting (XGBoost)

It is an optimized version of gradient boosting that effectively captures nonlinear feature interactions, complex relationships, and multicollinearity through regularization, shrinkage, tree pruning, recursive partitioning, and ensemble learning (Chen and Guestrin, 2016; Noorunnahar et al., 2023; Raschka and Mirjalili, 2019).

The objective function L for this model consists of a loss function $L(y_i, \hat{y}_i)$ and regularization terms $\Omega(f_m)$:

$$\begin{aligned} L &= \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{m=1}^M \Omega(f_m), \\ \Omega(f_m) &= \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2. \end{aligned} \quad (5.20)$$

where $L(y_i, \hat{y}_i)$ measures the discrepancy between the actual values (y_i) and corresponding predicted values ($\hat{y}_i$), while $\Omega(f_m)$ penalizes tree complexity. Here, T denotes the number of terminal nodes, w_j represents the leaf weights, γ a parameter that penalizes the number of leaves (controlling tree depth), and λ a parameter that penalizes the squared weights of leaf nodes, corresponding to an L_2 regularization term.

At iteration t , a new tree f_t is added to minimize the objective function using a second-order Taylor expansion based on the gradient g_i and Hessian h_i of the loss function. The gradient g_i represents the direction and magnitude of the steepest increase in the loss, indicating how much and in which direction the model's prediction needs to be adjusted. The Hessian h_i measures the curvature or rate of change of the gradient, allowing the model to take more informed, adaptive steps during optimization, resulting in faster, more stable convergence. Mathematically,

$$g_i = \frac{\partial L(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)}}, \quad h_i = \frac{\partial^2 L(y_i, \hat{y}_i^{(t-1)})}{\partial (\hat{y}_i^{(t-1)})^2} \quad (5.21)$$

Using these derivatives, the model constructs its predictions in an additive manner by combining multiple decision trees. Starting from an initial prediction $\hat{y}_i^{(0)}$, the model adds new trees $f_t(x_i)$ sequentially at each boosting round t to minimize residual errors from the previous iteration. The prediction at iteration t is given by:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (5.22)$$

This iterative process reduces residual errors over time, progressively refining predictions. The final prediction is obtained by summing the outputs of all K trees:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (5.23)$$

5.2.11 Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) learn hierarchical feature representations and capture complex nonlinear dependencies and higher-order interactions through multi-layer nonlinear activation functions. Perceptrons are the basic units of ANNs. According to [Goodfellow et al. \(2016\)](#), a feed-forward neural network with L hidden layers ($l = 1, \dots, L$) and a nonlinear activation function $\sigma(\cdot)$ is given as:

$$\begin{aligned} h^{(0)} &= x, \\ h^{(l)} &= \sigma(W^{(l)}h^{(l-1)} + b^{(l)}), \\ \hat{y} &= W^{(L+1)}h^{(L)} + b^{(L+1)} \end{aligned} \quad (5.24)$$

The parameters $\{W^{(l)}, b^{(l)}\}$ are estimated by minimizing:

$$\min_{\theta} \sum_{i=1}^n (y_i - \hat{y}(x_i))^2 \quad (5.25)$$

via backpropagation.

5.3 Feature Engineering and Hyperparameter Tuning

The data underwent preprocessing prior to building the ML models, including data cleaning, handling missing values, and feature scaling. Feature scaling ensures that all features contribute proportionally. It prevents any single feature from dominating the training process due to differences in scale. It also improves model convergence and predictive performance. Two feature scaling techniques, such as Min-Max scaling (normalization) and standardization (Z-score normalization) were applied and compared. Min-Max scaling transforms feature values to a fixed range, typically $[0, 1]$, by subtracting the minimum value of each feature and dividing by its range ([Raschka and Mirjalili, 2019](#)). Standardization (Z-score normalization) transforms features to have a mean of zero and variance one. This is accomplished by subtracting the mean and dividing by the standard deviation of each feature.

The results, presented in the Result section, indicated that Min–Max normalization achieved the best overall feature-scaling performance. The superiority and suitability of this scaling have also been demonstrated for gradient-based and distance-sensitive

algorithms (Raju et al., 2020), as well as for linear models applied to small datasets (Sujon et al., 2024).

To build a robust model, the study conducted hyperparameter optimization through systematic fine-tuning. Hyperparameter optimization, or parameter tuning, is the process of selecting the best hyperparameter settings before model training begins (Feurer and Hutter, 2019). The XGBoost algorithm uses different hyperparameter settings to control the construction and complexity of the decision trees, as well as the overall behavior of the model and the learning process. The setting includes number of boosting rounds or trees ($n_{estimators}$), maximum depth of each tree (max_depth), proportion of training instances used to build each tree (subsample), proportion of features randomly sampled for each tree ($colsample_bytree$), step size shrinkage used at each iteration to control the contribution of each tree (learning rate or eta), minimum loss reduction required to split a leaf node (gamma), ℓ_2 regularization term on weights required to penalize large coefficients (lambda), ℓ_1 regularization term on weights to encourage sparsity by driving some coefficients to zero (alpha). Choosing the right set of these hyperparameters improves model performance. The study used a grid search cross-validation method (GridSearchCV) with 5-fold cross-validation ($cv=5$), which involves specifying a set of hyperparameters and their possible values, and then exhaustively searching all possible combinations of those values (Yu and Zhu, 2020). The key is to perform hyperparameter tuning and model selection simultaneously by training a model for every hyperparameter combination. This makes it an efficient method for optimizing a model's hyperparameters. The best-performing set was selected, and the final model was used to predict new instances.

5.4 Feature Importance and Feature Selection

The study used permutation importance techniques to assess feature importance. This method involves randomly shuffling the values of a specific feature while keeping the values of other features constant (Kuhn and Johnson, 2019). Features that cause a significant decline in performance metrics are considered more important. In the context of linear models, features with larger absolute coefficient values after feature scaling, or larger standardized coefficients before feature scaling are regarded as more important.

The study examined multiple factors that could contribute to severe food insecurity. It implemented the selected optimal algorithm to identify the key features contributing to severe food insecurity. Although having more information can be beneficial, too much detail or feature duplication may increase the risk of overfitting and result in a poorly performing model (Zhang and Wen, 2019). This indicates that machine learning algorithms typically perform better when data dimensionality is reduced.

To identify the most relevant features and improve model performance, this study employed feature selection methods, including Forward Feature Selection (FFS), Backward Feature Elimination (BFE), and Recursive Feature Elimination (RFE) with cross-validation. Forward feature selection begins with an empty model and progressively adds features that improve the model's performance based on a chosen evaluation metric. In contrast, backward elimination starts with all features and iteratively removes the least significant ones. RFE recursively removes the least important features and builds the model iteratively until the desired number of features is reached (Kuhn and Johnson, 2019).

5.5 Model Validation and Performance Measures

All models were developed using the training dataset and assessed on previously unseen data. Testing the model on the same data used for training can lead to overfitting, as the model has already learned the existing patterns, which may not apply to new instances. Therefore, evaluating new data offers a more accurate measure of performance and efficiency. The study used several performance metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R^2 for the evaluation. The final model producing the lowest MSE, RMSE, MAE, and MAPE, and the highest R^2 was selected as the best-fitting model, indicating optimal accuracy and performance. The key features were then selected using this optimal model through feature selection techniques that provided lower performance error metrics and higher R^2 values.

5.6 Results

5.6.1 Performance Evaluation of ML Algorithms

The study applied various machine learning algorithms, including linear models, ensemble methods, instance-based methods and artificial neural networks (ANNs). At the first stage of the analysis, the aforementioned algorithms were spot-checked without undertaking extensive hyperparameter tuning. The dataset was split chronologically, with data from 2015–2019 (approximately 80%) used for training and data from 2020–2021 (approximately 20%) used for testing. Feature scaling and hyperparameter tuning were performed during model training. The resulting model was subsequently evaluated on unseen future observations. This approach ensured that information from future periods did not influence model development, thereby providing a more realistic assessment of the model's forecasting capability. Furthermore, model performance metrics were calculated for both the training and testing datasets. The results showed

comparable performance between the two datasets. This suggests that the model did not suffer from substantial overfitting or underfitting. Therefore, the consistency between training and testing performance further supports that information leakage was successfully avoided during the model development process.

To determine the most suitable feature-scaling method for the study datasets, Min–Max normalization and standardization were compared. For the optimal XGBoost model, results indicated that Min–Max normalization ($MSE = 5.94$, $R^2 = 0.97$) and standardization ($MSE = 6.5$, $R^2 = 0.95$) performed comparably, with Min–Max normalization providing the best overall feature-scaling performance. Consequently, Min–Max normalization was employed for feature scaling in this study. After scaling the features, the study evaluated and compared the performance of the candidate models using performance metrics.

Table 5.1 presents the performance metrics for each algorithm mentioned above. Among the candidate models, the Gradient Boost, XGBoost, and K-Nearest Neighbors algorithm achieved the lowest MSE, RMSE, MAE, and MAPE and the highest R^2 values, as illustrated in Table 5.1. This indicates that these three algorithms outperform the other candidate models in predicting severe food insecurity under spot-checking evaluation.

After conducting baseline models (spot-check algorithms), the study performed hyperparameter tuning to identify optimal settings for each candidate algorithm. This was achieved using GridSearchCV with 5-fold cross-validation ($cv = 5$) tailored to the specifications of each candidate model. During model development, performance metrics were calculated on the training data using cross-validation to guide hyperparameter selection and model tuning. The optimal hyperparameter settings were identified through exhaustive search of all possible combinations of hyperparameter values for each candidate model, thereby effectively enhancing their performance.

In this approach, the training dataset is partitioned into five equally sized folds, with the model trained on four folds and validated on the remaining fold. This process is repeated five times, with each fold serving once as the validation set, and the final performance is averaged across all folds. This technique provides reliable performance estimates, balances the bias–variance trade-off, and reduces overfitting during hyperparameter optimization, ensuring that the selected parameters generalize well to unseen data. The test dataset (unseen data), which was not used during training or hyperparameter tuning, was then used for final evaluation, providing an unbiased estimate of the model’s generalization performance.

Table 5.1: Comparison of ML algorithms under baseline and hyperparameter optimization

S. No.	ML Algorithms	Baseline Model					Hyperparameter Optimization				
		MSE	RMSE	MAE	MAPE	R^2	MSE	RMSE	MAE	MAPE	R^2
1	Linear Regression	20.22	4.50	3.59	30.05	0.91	20.22	4.50	3.59	30.05	0.91
2	Ridge Regression	20.08	4.48	3.56	29.73	0.91	19.57	4.42	3.50	28.43	0.91
3	LASSO Regression	19.91	4.46	3.55	28.98	0.91	19.90	4.46	3.59	28.36	0.91
4	Elastic Net Regression	19.91	4.46	3.55	28.98	0.91	19.82	4.45	3.58	28.17	0.91
5	Support Vector Regression	20.11	4.48	3.53	26.83	0.91	11.18	3.34	2.47	14.47	0.95
6	Decision Tree Regression	18.19	4.26	2.55	16.76	0.92	17.94	4.24	2.27	15.00	0.92
7	Random Forest Regression	11.44	3.38	2.64	18.41	0.95	8.86	2.98	1.79	12.16	0.96
8	Gradient Boosting Regression	7.06	2.66	1.73	12.00	0.97	5.76	2.40	1.65	10.77	0.97
9	XGBoost Regression	5.94	2.44	1.60	11.32	0.97	5.68	2.38	1.49	10.46	0.97
10	K-Nearest Neighbors	10.76	3.28	2.50	15.57	0.95	6.24	2.50	1.95	12.22	0.97
11	Artificial Neural Network	13.07	3.61	2.74	17.38	0.94	11.89	3.45	2.73	16.05	0.94

For each candidate model, the settings of the searching domain were determined through a combination of theoretical understanding of model behaviour, insights from preliminary experiments and empirical evidence from previous research (Bentéjac et al., 2021; Breiman et al., 2017; Chen and Guestrin, 2016; Elith et al., 2008; Moisen et al., 2006; Sun, 2020; Verma, 2024; Wang and Ni, 2019). This approach ensured model stability, reliable convergence, and robust predictive performance, while minimizing computational cost and the risks of overfitting or underfitting. For example, the following parameters were tuned for XGBoost in this study:

```

n_estimators : [50, 100, 150],
learning_rate : [0.01, 0.02, 0.1, 0.2],
max_depth : [3, 5, 7, 8],
subsample : [0.5, 0.6, 0.8, 1.0],
colsample_bytree : [0.6, 0.8, 1.0],
gamma : [0, 1, 2, 3, 4].

```

Learning rates between 0.01 and 0.2 were selected because smaller values (< 0.01) slowed convergence, while larger values (> 0.2) caused unstable updates and overfitting during preliminary tests. Similarly, a maximum tree depth below 3 leads to highly biased predictions that deviate from actual values, whereas depths exceeding 8 cause high-variance predictions on unseen data and increase computational cost. Limiting the maximum tree depth to 3-8 provided a balance between bias and variance, reducing the risk of both underfitting and overfitting. These empirically guided hyperparameter ranges ensure stable model performance, reduce the risks of overfitting and underfitting, and address convergence issues.

The results of optimal hyperparameter settings for each candidate model on the testing or unseen datasets are provided in Table 5.1. The results indicate that model performance improved following hyperparameter tuning relative to the baseline specifications. Similar to the baseline model results, Gradient Boosting, XGBoost, and K-

Nearest Neighbors algorithms provided lower MSE, RMSE, MAE, and MAPE values, along with higher R^2 values, indicating their superior predictive accuracy and performance compared to other candidate algorithms. Among these, the XGBoost algorithm was identified as the most efficient and served as the optimal final model for this study, achieving its best performance under the following hyperparameter settings:

```
n_estimators : [150],
learning_rate : [0.1],
max_depth : [7],
subsample : [0.8],
colsample_bytree : [0.8],
gamma : [1].
```

The XGBoost model was selected as the optimal algorithm based on both empirical performance and methodological suitability because it achieved the lowest prediction errors and the best overall predictive performance among the evaluated models. In addition to its superior predictive accuracy, XGBoost provides an effective balance between model flexibility, computational efficiency, and robustness, making it particularly well suited for modeling complex food insecurity data. Compared with linear regression and regularized regression, XGBoost can automatically capture complex nonlinear structural relationships and higher-order interactions among variables without requiring predefined functional forms and strong distributional assumptions. This is particularly important for severe food insecurity, where the effects of climatic, economic, social, and political factors are highly interconnected and vary across contexts. XGBoost is also robust to multicollinearity, heterogeneous data structures, and missing values, making it suitable for large-scale datasets. During model training, it sequentially constructs an ensemble of decision trees, where each new tree is fitted to minimize the residual errors of the previous iteration. To optimize the objective function, XGBoost exploits both first-order gradients and second-order Hessian information. The gradients determine the direction and magnitude of prediction updates, while the Hessian capture the curvature of the loss function, enabling more accurate parameter updates, faster convergence, and improved optimization stability.

Furthermore, XGBoost incorporates several mechanisms to enhance predictive performance and generalization, including its built-in regularization mechanisms, shrinkage, column subsampling, and cross-validation. These techniques effectively control model complexity, reduce the risk of overfitting, and achieve an appropriate balance between bias and variance. In addition, XGBoost provides feature importance measures that facilitate the identification of the most influential predictors, thereby enhancing model interpretability and supporting subsequent analyses using SHAP values and

permutation importance. Consequently, XGBoost provides not only superior predictive accuracy but also robust and reliable predictions for unseen data. Therefore, its superior predictive accuracy, ability to model complex nonlinear relationships, and robustness to diverse data characteristics, and interpretability justified its selection as the final predictive model for this study. These insights are essential for developing evidence-based and context-specific policy interventions.

5.6.2 Model Diagnostics

The XGBoost models' performance was further evaluated using three key plots: a prediction error plot, a learning curve, and a validation curve, each offering unique insights into how well the models perform.

The prediction error plot in Figure 5.1 is a scatter plot that illustrates the closeness of actual values (x-axis) to predicted values (y-axis). Most points are concentrated on the diagonal line. The tight clustering of points around the diagonal line indicates accurate predictions. Points above the line represent overestimation (high variance), while points below the line indicate underestimation (high bias). This deviation from the diagonal line reflects a prediction error.

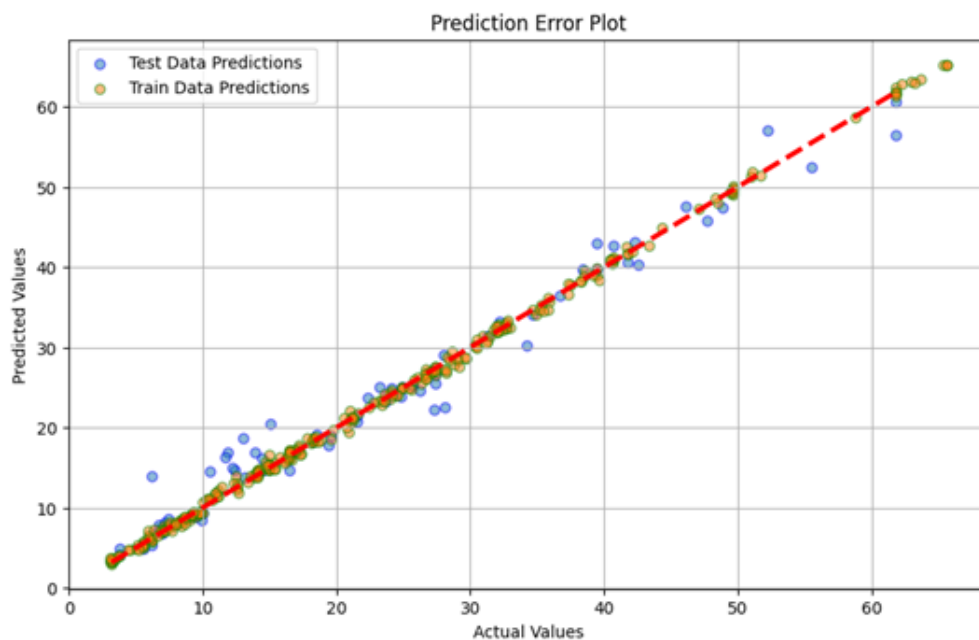


Figure 5.1: Prediction error plot

Figure 5.2 illustrates the learning curve of the XGBoost algorithm. The curve showed how performance metrics changed as more data was used for training. These curves helped to identify whether the model benefits from more data. It was useful diagnostic tool for assessing whether model suffered from underfitting (where both training

and validation scores were low and close together) or overfitting (where the training score was high but validation score was lower). The curves in Figure 5.2 showed that both the training and validation scores consistently improved as more training samples were added, suggesting that the model continued to benefit from additional data and became more stable as the size of the training set grew. This pattern indicated that the model had effectively learned the underlying high-dimensional and nonlinear relationships and had reached its optimal level of generalizability.

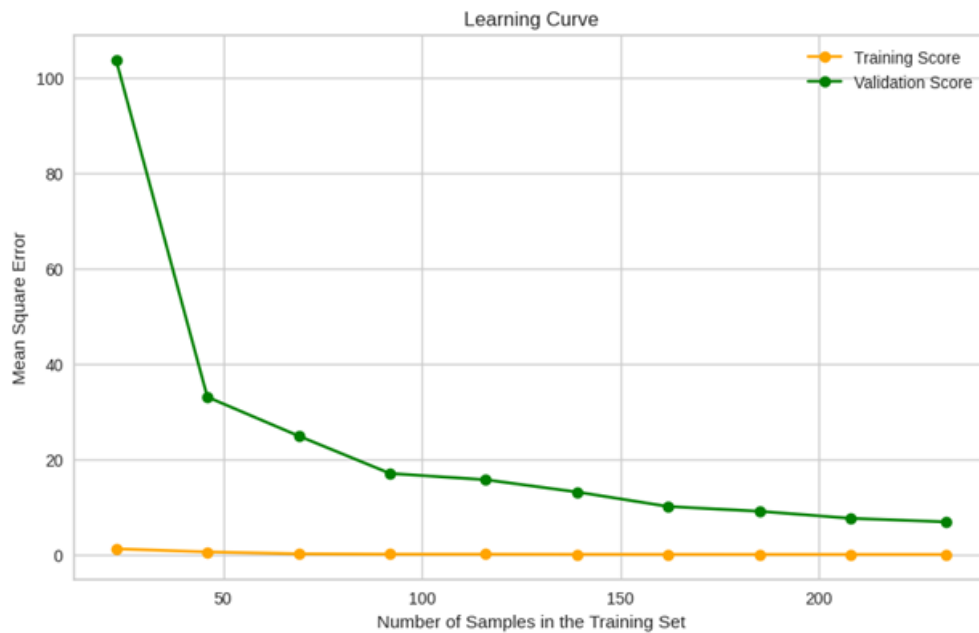


Figure 5.2: Learning curve

The validation curve in Figure 5.3 offered valuable insights into the behavior of the XGBoost algorithm under varying hyperparameter settings. The curve showed that both score lines continued to decrease up to a maximum depth of 7. Beyond this point, both scores became stable. This pattern suggested overfitting at higher maximum depth values and underfitting at lower depth values. The optimal hyperparameter setting was achieved when the testing score was highest and closest to the training score. Hence, a maximum depth of 7 was identified as the optimal value for maximizing the model's performance on unseen data.

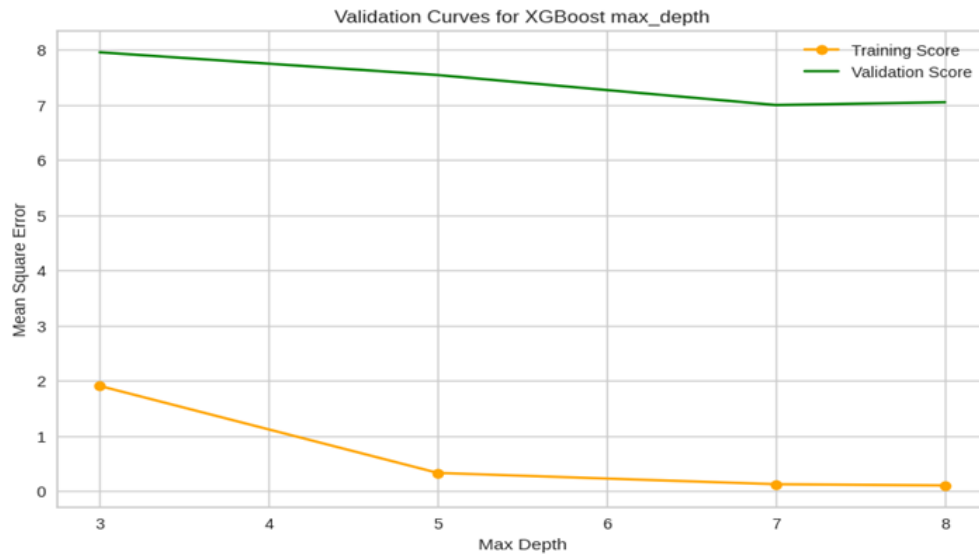


Figure 5.3: Validation curve

5.6.3 Feature Importance Analysis

The permutation importance technique was used to rank features by assessing the change in model's predictive performance when a values of each feature were randomly permuted. The importance score measures predictive importance rather than evidence of causal relationships. A significant decline in predictive performance after a feature was randomly permuted indicates that the feature plays an important role in the model's predictions. The resulting importance scores reflect predictive importance that quantifies the contribution of each predictor to improving forecasting accuracy by reducing prediction error rather than evidence of causal relationships. In contrast, causal interpretation requires establishing that changes in a predictor directly influence severe food insecurity while accounting for confounding factors, reverse causality, and other sources of bias. Such conclusions typically require causal inference frameworks. Therefore, the identified features in this section interpreted as influential predictors for forecasting rather than definitive causal determinants.

Permutation importance method was applied to the XGBoost algorithm, which was identified as the best-performing model due to its lowest performance error matrices and highest R^2 values compared to other candidate models. The ranked feature importance is visually presented in Figure 5.4. The graph showed that the impact of each feature on model performance varied significantly when its values were randomly shuffled. The top-ranked feature played the most crucial role in the model's predictive power, while the influence of each subsequent predictor decreased as the rank lowered. These indicated that lower-ranked predictors contributed less to the overall prediction of severe food insecurity.

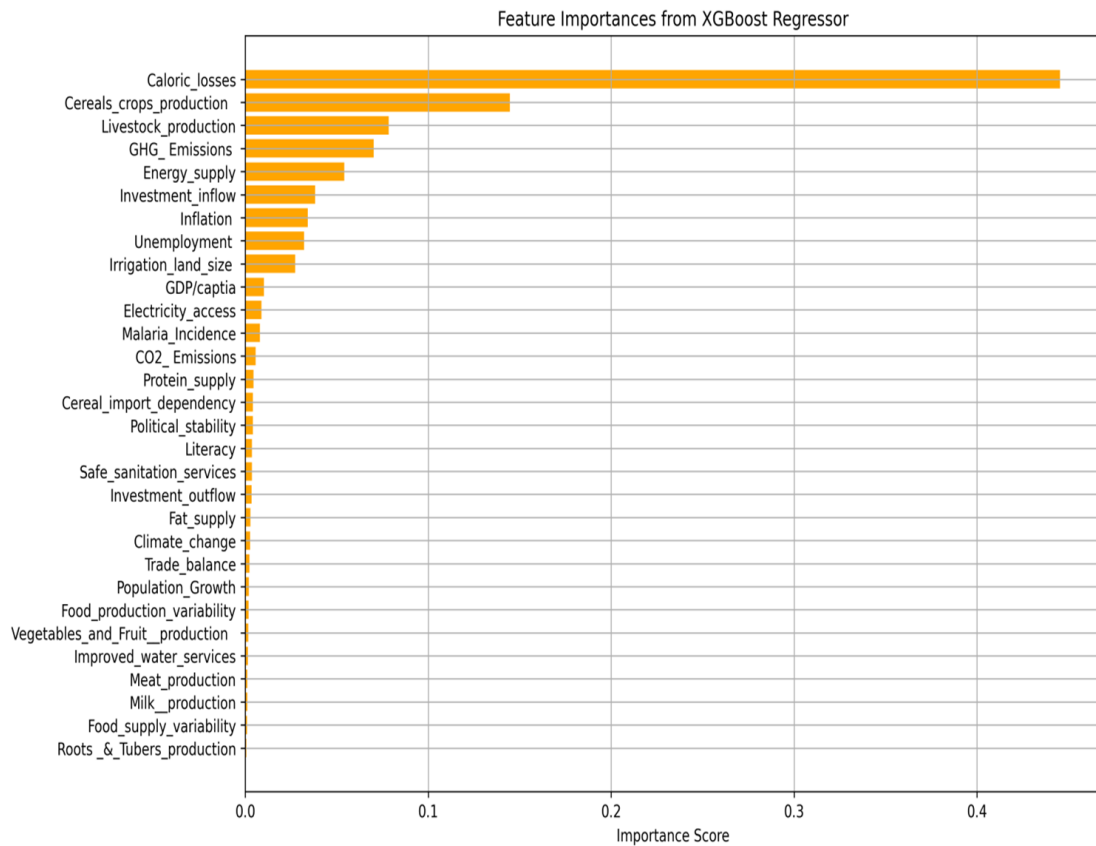


Figure 5.4: Feature importance score

Therefore, the selected features should be interpreted as key predictors associated with severe food insecurity rather than definitive causal determinants. Nevertheless, the identified predictors provide valuable insights into the factors most strongly associated with severe food insecurity and can help prioritize variables for monitoring, forecasting, and further investigation using appropriate causal inference methods.

5.6.4 Feature Selection and Ranking

Using the selected optimal XGBoost model, the study applied three feature selection techniques, including forward feature selection (FFS), backward feature elimination (BFE) and recursive feature elimination (RFE) with cross-validation to select the optimal number of features automatically. These methods iteratively or recursively add or remove features based on their contributions to model performance until no further improvements in predictive accuracy are observed (Raschka and Mirjalili, 2019; Kuhn and Johnson, 2019). The results were: FFS (MSE=7.50, $R^2=0.97$), BFE (MSE = 7.33, $R^2 = 0.97$), and RFE (MSE = 6.18, $R^2 = 0.97$), with RFE with CV demonstrating the best overall performance. Among the thirty candidate features, RFE with cross-validation selected fifteen features (50%) that maximized predictive performance.

Figure 5.5 illustrates the key features selected through RFE in XGBoost model,

which are identified as important predictors of severe food insecurity. These features are also selected by ridge regression; however, their relative importance ranking differs slightly between the two methods. Accordingly, the subsequent analysis was based on these selected features.

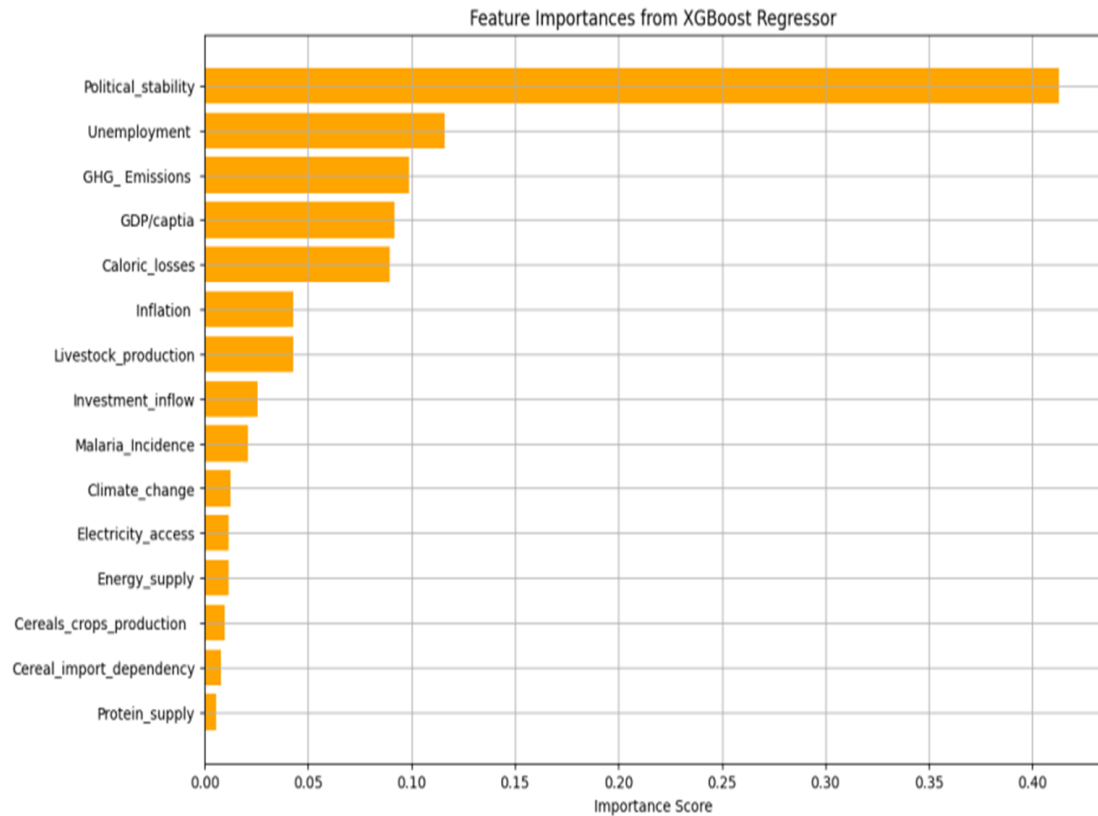


Figure 5.5: Selected features using RFE

Permutation importance does not offer direct insights into the direction of the relationships (positive or negative) between features and the target variable. Instead, it quantifies the overall contribution of each feature on the model's performance. To determine the direction of these relationships, the study employed the SHAP method. A SHAP is a powerful framework used to explain the magnitude and direction of the contribution of each feature to individual model predictions.

The SHAP summary plot in Figure 5.6 highlighted the relative importance of features in predicting severe food insecurity. Positive SHAP values indicate that, conditional on other features in the model, a feature is associated with an increase in the predicted values of severe food insecurity, whereas negative values indicate an association with a decrease in the predicted levels ([Aas et al., 2021](#); [Slack et al., 2020](#)).

The analysis revealed that higher national-level inflation, climate change, unemployment, malaria incidence, GHG emissions, caloric loss, and cereal import dependency were associated with higher predicted values of severe food insecurity. This

implied that, conditional on the factors included in the model, each driver contributed to escalating the risk of severe food insecurity in a given country. In contrast, greater livestock and cereal crop production, investment inflows, dietary energy and protein supply, electricity access, GDP per capita, and political stability contributed to reducing the risk of severe food insecurity. Specifically, high unemployment, conditional on other features, was associated with an increased predicted risk of severe food insecurity, while high livestock production, conditional on other features, was associated with a decreased predicted risk.

In addition to the direction of influence, the SHAP results in Figure 5.6 illustrate the relative weight of each driver. Features at the top of the plot, including unemployment, livestock production, GHG emissions, and caloric losses, are the most important key drivers influencing predictions of severe food insecurity. In contrast, features at the bottom, including political stability, cereal import dependency, and climate change, have a comparatively less impact on the prediction. These findings provide valuable evidence on the drivers of severe food insecurity, supporting the design of targeted interventions to mitigate its impact across Africa.

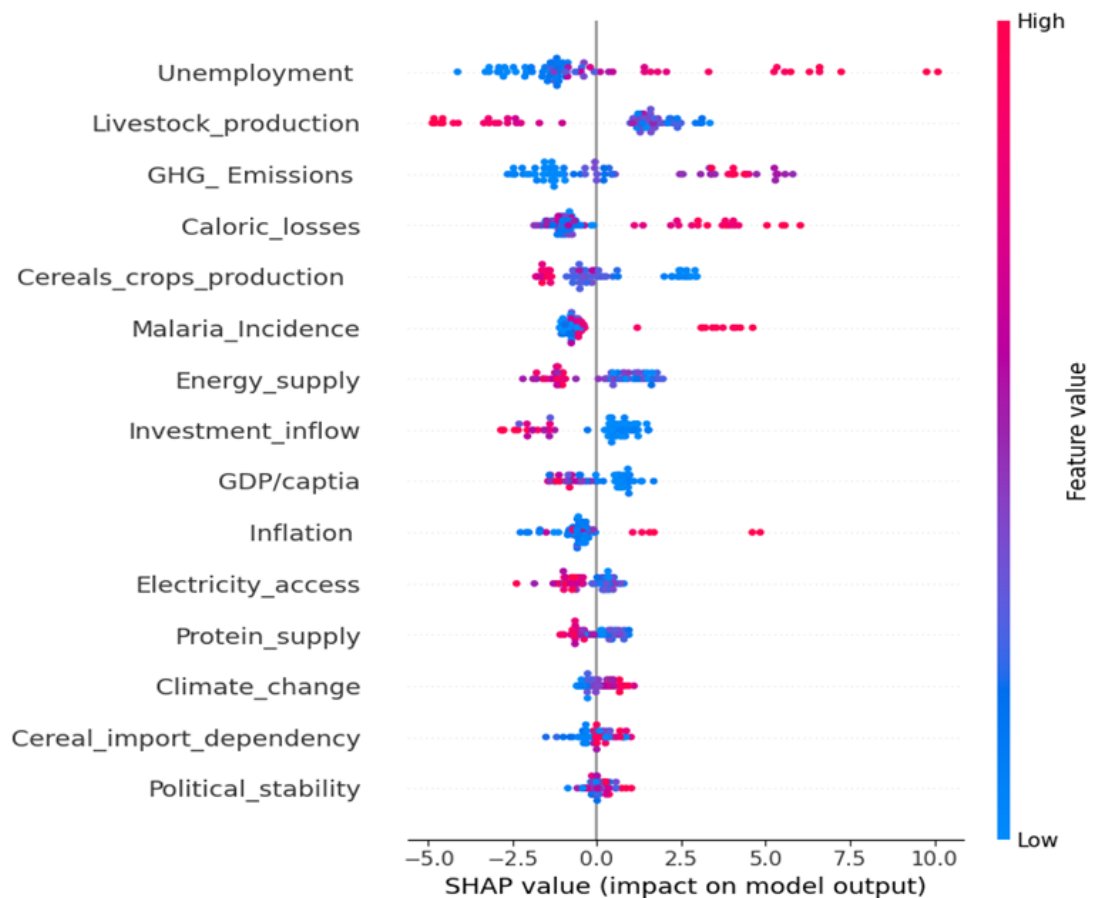


Figure 5.6: SHAP value for each feature

5.7 Summary

In this chapter, the study evaluates and compares various machine learning approaches to identify and rank the key predictors of severe food insecurity across Africa over the period 2015-2021. The findings indicate that hyperparameter tuning substantially improves predictive accuracy, underscoring the importance of model optimization. Among the evaluated models, XGBoost demonstrates the highest predictive performance, effectively capturing the complex, nonlinear relationships in severe food insecurity data. Among the thirty drivers considered, fifteen were selected using the RFE with CV technique. The analysis showed that higher national levels of inflation, climate change, unemployment, malaria incidence, GHG emissions, caloric loss, and cereal import dependency contributed to higher predicted rates of severe food insecurity. Conversely, a higher livestock production, cereal crop production, investment inflows, dietary energy supply, dietary protein supply, electricity access, GDP per capita, and political stability were contributed to reducing the risk of predicted rates. Among the variables examined, unemployment, livestock production, GHG emissions, and caloric losses identified as the most influential drivers in predicting severe food insecurity, listed here in priority order.

Despite the strong predictive performance and flexibility of the machine learning approaches employed in this chapter, several limitations should be acknowledged. First, the models do not explicitly account for spatial dependence across countries, potentially overlooking important geographic autocorrelation and spillover effects that characterize severe food insecurity. Second, feature importance measures derived from machine learning algorithms reflect predictive relevance rather than causal relationships for inference, and may vary across model specifications. Third, the analysis treats observations as independent, ignoring the structured spatial relationships inherent in the data. Consequently, while this chapter provides a robust selection and ranking of key predictors, it does not capture the spatial processes underlying their effects. To address these limitations, the next chapter extends the analysis by examining the effects of key determinants on severe food insecurity while explicitly accounting for spatial dependence across countries using spatial models.

Chapter 6

Spatial Dependence and Determinants of Severe Food Insecurity

6.1 Introduction

Severe food insecurity in a given country is determined not only by its domestic environmental, economic, and geopolitical conditions but also by conditions in neighboring countries through shared factors. Ignoring such spatial dependence may lead to biased parameter estimates, inefficient inference, and misinterpretation of the relationships between predictors and the response variable. Furthermore, the effects of key determinants may not be strictly linear, and their relationships with severe food insecurity may vary in magnitude across different levels of the covariates. Additive and geospatial mixed modeling frameworks provide such flexibility by modeling linear covariate effects, nonlinear covariate effects, and spatial random effects within a unified structure.

Accordingly, this chapter applied additive and geospatial mixed models to the set of predictors identified in Chapter 5 while incorporating spatial effects. The objective was to examine the effects of these determinants while accounting for spatial dependence and potential nonlinear relationships. This approach provides a more comprehensive and statistically rigorous understanding of the factors driving severe food insecurity across the continent.

6.2 Models

Let y be the prevalence of severe food insecurity, taking observed values y_i (for $i=1,2,\dots,364$) and belonging to the exponential distribution family. Let $\mathbf{X}$ = (electricity access, political stability, malaria incidence, climate change, livestock production, cereals crop production, investment inflow) denote the linear covariates and $\mathbf{Z}$ = (GHG emissions, GDP per capita, unemployment, inflation, cereal import dependency, caloric losses, dietary energy supply, and dietary protein supply) represent the nonlinear covariates related to severe food insecurity. This classification of functional forms was identified based on the examination of partial effect plots obtained from cubic spline estimates, which indicated whether the underlying relationships could be adequately approximated as linear or exhibited significant nonlinearity.

Subsequently, the nonlinear relationships modeled via cubic splines were represented as linear combinations of basis functions. The degree of smoothness or ‘wiggliness’ of the fit was determined by the $f_j(\cdot)$ function. Effectively, what the smooth does is to split the data into segments and fit piecewise relationships, rather than fitting a single straight line as in a standard linear regression. To examine the determinants and spatial dependence of severe food insecurity, four distinct spatial models were employed.

6.2.1 Additive Model (AM)

The additive model (AM) assumes that, conditional on covariates $\mathbf{X}$ and $\mathbf{Z}$, the response variable y_i follows a distribution from the exponential family and is related to its mean $\mu_i = E(y_i \mid x_i, z_i)$ and a random error term ϵ_i . Mathematically, this can be expressed as:

$$y_i = \mu_i + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2), \quad i = 1, 2, \dots, 364 \quad (6.1)$$

where $y_i \sim \mathcal{N}(\mu_i, \nu^2)$, and the variance parameter is assigned a weakly informative inverse-gamma prior: $\nu^2 \sim \text{IG}(1, 0.001)$.

The mean is typically linked to an additive semiparametric linear predictor η_i through an identity link function $g(\cdot)$, such that $g(\mu_i) = \eta_i$ (Hastie and Tibshirani, 1987). The linear predictor is linearly related to both fixed effects and unknown smooth functions of the nonlinear covariates. Mathematically,

$$\begin{aligned} \eta_i = & \beta_0 + \beta_1 \text{Electricity_access}_i + \beta_2 \text{Political_stability}_i + \beta_3 \text{Malaria_incidence}_i + \beta_4 \text{Climate_change}_i \\ & + \beta_5 \text{Livestock_production}_i + \beta_6 \text{Cereal_crop_production}_i + \beta_7 \text{Investment_inflow}_i \\ & + f_1(\text{GDP_per_capita}_i) + f_2(\text{Unemployment}_i) + f_3(\text{Inflation}_i) + f_4(\text{GHG_emissions}_i) \\ & + f_5(\text{Caloric_losses}_i) + f_6(\text{Dietary_energy_supply}_i) + f_7(\text{Dietary_protein_supply}_i) \\ & + f_8(\text{Cereal_import_dependency}_i) \end{aligned} \quad (6.2)$$

Where the parameters β_k ($k = 1, \dots, 7$) represent linear regression coefficients capturing fixed effects, while $f_j(\cdot)$ ($j = 1, \dots, 8$) denote smooth functions of the nonlinear covariates. The functions $f_j(\cdot)$ are modeled using second-order random walk (RW2) priors.

6.2.2 Additive Mixed Model (AMM)

The model in Equation 6.2 doesn’t consider the heterogeneity between units that are not observed by covariates and smooth functions of the covariates. Hence, the study incorporates the additive random effect in the linear predictor to account for the unobserved heterogeneity or correlation. This model is called the Additive Mixed

Model (AMM) or a semiparametric mixed model (Fahrmeir and Kneib, 2011; Lin and Zhang, 1999). Mathematically, an additive predictor has the form:

$$\begin{aligned}\eta_i = & \beta_0 + \beta_1 \text{Electricity_access}_i + \beta_2 \text{Political_stability}_i + \beta_3 \text{Malaria_incidence}_i + \beta_4 \text{Climate_change}_i \\ & + \beta_5 \text{Livestock_production}_i + \beta_6 \text{Cereal_crop_production}_i + \beta_7 \text{Investment_inflow}_i \\ & + f_1(\text{GDP_per_capita}_i) + f_2(\text{Unemployment}_i) + f_3(\text{Inflation}_i) + f_4(\text{GHG_emissions}_i) \\ & + f_5(\text{Caloric_losses}_i) + f_6(\text{Dietary_energy_supply}_i) + f_7(\text{Dietary_protein_supply}_i) \\ & + f_8(\text{Cereal_import_dependency}_i) + \mu_{s(i)}\end{aligned}\tag{6.3}$$

where $\mu_{s(i)}$ denotes an unstructured unit- or group-specific random effect capturing unobserved heterogeneity and within-group correlation. Specifically, $\mu_{s(i)} = \mu_s$ if observation i belongs to group s , where $s = 1, \dots, S = 52$.

6.2.3 GeoAdditive Model (GAM)

Equation 6.3 did not include the spatial effect, the spatial location where they were observed, in the model. To account for spatial heterogeneity, a spatial effect f_{spat} is incorporated into the additive predictor, resulting in a model known as the GeoAdditive Model (GAM), as proposed by Kammann and Wand (2003). Mathematically,

$$\begin{aligned}\eta_i = & \beta_0 + \beta_1 \text{Electricity_access}_i + \beta_2 \text{Political_stability}_i + \beta_3 \text{Malaria_incidence}_i + \beta_4 \text{Climate_change}_i \\ & + \beta_5 \text{Livestock_production}_i + \beta_6 \text{Cereal_crop_production}_i + \beta_7 \text{Investment_inflow}_i \\ & + f_1(\text{GDP_per_capita}_i) + f_2(\text{Unemployment}_i) + f_3(\text{Inflation}_i) + f_4(\text{GHG_emissions}_i) \\ & + f_5(\text{Caloric_losses}_i) + f_6(\text{Dietary_energy_supply}_i) + f_7(\text{Dietary_protein_supply}_i) \\ & + f_8(\text{Cereal_import_dependency}_i) + f_{\text{spat}}(s_i)\end{aligned}\tag{6.4}$$

where $s = 1, 2, \dots, 52$ denotes the spatial regions defined over a geographical map, and s_i indicates the region to which observation i belongs.

6.2.4 GeoAdditive Mixed Model (GAMM)

The spatial effect, $f_{\text{spat}}(s_i)$, in Equation 6.4 is further decomposed into two components: spatially correlated (structured) and spatially uncorrelated (unstructured) effects. This decomposition reflects the fact that spatial variation in the outcome is typically driven by a combination of unobserved or latent processes, some exhibiting clear spatial dependence while others are more random and localized in nature. The structured spatial effect captures spatial dependence between neighboring areas and is modeled using an intrinsic Conditional Autoregressive (ICAR) prior, which smooths estimates by borrowing strength across adjacent areas. In contrast, the unstructured

spatial effect captures independent, area-specific random variation that is not explained by spatial adjacency and is typically modeled using an independent and identically distributed (iid) Gaussian prior. This decomposition allows the model to distinguish between spatially correlated variation and random noise at the area level. This leads to the GeoAdditive Mixed Model (GAMM), whose additive predictor is rewritten as:

$$\begin{aligned} \eta_i = & \beta_0 + \beta_1 \text{Electricity_access}_i + \beta_2 \text{Political_stability}_i + \beta_3 \text{Malaria_incidence}_i + \beta_4 \text{Climate_change}_i \\ & + \beta_5 \text{Livestock_production}_i + \beta_6 \text{Cereal_crop_production}_i + \beta_7 \text{Investment_inflow}_i \\ & + f_1(\text{GDP_per_capita}_i) + f_2(\text{Unemployment}_i) + f_3(\text{Inflation}_i) + f_4(\text{GHG_emissions}_i) \\ & + f_5(\text{Caloric_losses}_i) + f_6(\text{Dietary_energy_supply}_i) + f_7(\text{Dietary_protein_supply}_i) \\ & + f_8(\text{Cereal_import_dependency}_i) + \phi_i + \theta_i \end{aligned} \quad (6.5)$$

where θ_i and ϕ_i denotes the structured and unstructured spatial effects, respectively.

The following goodness-of-fit statistics were obtained for the models specified above: linear regression model (DIC = 2135.66, WAIC = 2135.48), AM (DIC = 1776.01, WAIC = 1778.59), AMM (DIC = 1561.33, WAIC = 1571.22), GAM (DIC = 1560.99, WAIC = 1571.17), and GAMM (DIC = 1556.91, WAIC = 1568.30). Among these models, the GAMM had the lowest DIC and WAIC values. Therefore, the GAMM was employed to examine the determinants of severe food insecurity while accounting for spatial dependence across Africa.

To ensure progressively improved representation of the underlying data structure, the study adopts a sequential modeling strategy moving from the Additive Model (AM) to the Additive Mixed Model (AMM), then to the GeoAdditive Model (GAM), and finally to the GeoAdditive Mixed Model (GAMM). The Additive Model (AM) provides a flexible baseline for capturing nonlinear covariate effects but does not account for unobserved heterogeneity across units or spatial dependence. This limitation is partially addressed by the Additive Mixed Model (AMM), which introduces random effects to capture unobserved unit-level heterogeneity. The GeoAdditive Model (GAM) further extends this framework by incorporating spatial effects into the additive structure; however, it does not explicitly distinguish between structured and unstructured spatial dependence. The GeoAdditive Mixed Model (GAMM) overcomes this limitation by jointly modeling nonlinear covariate effects, spatially structured dependence, and unstructured random variation, thereby providing a more comprehensive and flexible framework for capturing the complex spatial structure of severe food insecurity.

6.3 Prior Assumptions and Inferences

In a full Bayesian framework, the vector of fixed-effect parameters β_k ($k = 1, \dots, 7$), the smooth functions $f_j(\cdot)$ ($j = 1, \dots, 8$), and the spatial effects θ_i and ϕ_i are treated as random variables and therefore require prior assumptions. In the absence of strong prior information, diffuse priors of the form $P(\beta) \propto \text{const}$ are assigned to the fixed effect parameters (Brezger et al., 2005; Fahrmeir and Kneib, 2011).

A spline function was employed to model the nonlinear effect of the covariates on severe food insecurity by including smooth terms in the linear predictor, ensuring a smooth relationship. However, inappropriate selection of the number and position of knots may cause overfitting, thereby requiring constraints on the spline coefficients (Hastie et al., 2010; James et al., 2013; Ruppert et al., 2003). In a Bayesian framework, including the penalty term is equivalent to setting a prior on the covariate coefficients (Fahrmeir and Kneib, 2011).

Accordingly, the smooth functions $f_j(\cdot)$, representing nonlinear effects of covariates such as GDP per capita, unemployment, caloric losses, dietary energy supply, dietary protein supply, GHG emissions, cereal import dependency, and inflation, are modeled using second-order random walk (RW2) priors with k knots and precision parameters τ_j^2 . For example, the RW2 prior for the nonlinear effect of inflation is defined as follows. Consider equally spaced observations $\text{inflation}_i, i = 1, \dots, m, m \leq N = 364$. Suppose that $\text{inflation}_{(1)} < \dots < \text{inflation}_{(t)} < \dots < \text{inflation}_{(m)}$ is an ordered sequence of distinct values for inflation. Define $f(t) := f(\text{inflation}_{(t)})$, and let $\mathbf{f} = (f(1), \dots, f(t), \dots, f(m))^\top$ denote the vector of function evaluations. Then, the RW2 prior for inflation is given by:

$$f(t) = 2f(t-1) - f(t-2) + u(t) \quad (6.6)$$

with Gaussian errors $u(t) \sim \mathcal{N}(0, \tau^2)$ and diffuse priors $f(1) \propto \text{const}$ and $f(2) \propto \text{const}$ for initial values. .

This RW2 specification penalizes deviations from linear trends of the form $f(t) = 2f(t-1) - f(t-2)$ (Brezger et al., 2005; Fahrmeir and Lang, 2001). The same RW2 structure is applied to the remaining nonlinear covariates.

The combined spatial effects was modeled using the Besag–York–Mollié (BYM) convolution prior (Besag et al., 1991). Specifically, for the unstructured (uncorrelated) spatial effect, an exchangeable Gaussian i.i.d prior was assumed: $\phi_i \sim \mathcal{N}(0, \tau_\phi^2)$ where τ_ϕ^2 controls the variability of the unstructured heterogeneity. For the structured (correlated) spatial components, a Gaussian Markov Random Field (GMRF) prior was employed, following an intrinsic conditional autoregressive (iCAR) specification of the

form:

$$\theta_i \mid \theta_{j \neq i} \sim \mathcal{N} \left(\frac{\sum_{j \in N(i)} \theta_j}{N(i)}, \frac{\tau_\theta^2}{N(i)} \right) \quad (6.7)$$

where $N(i)$ denotes the number of neighboring areas sharing a boundary with area i , and τ_θ^2 controls the variability of the structured spatial effect.

Equivalently, the structured spatial random effects can be expressed in matrix form as: $\theta_i \sim \mathcal{N}(\mathbf{0}, \tau_\theta^2 \mathbf{Q}^-)$, where $\mathbf{Q}$ is a $N \times N$ precision matrix that captures the spatial neighborhood structure and $\mathbf{Q}^-$ represents a generalized inverse due to the intrinsic nature of the model. Following the iCAR specification introduced by [Besag et al. \(1991\)](#), the precision matrix $\mathbf{Q}$ is defined as:

$$Q_{ij} = \begin{cases} N(i), & \text{if } i = j, \\ -1, & \text{if } i \sim j \text{ (area } i \text{ and } j \text{ are neighbors)}, \\ 0, & \text{otherwise,} \end{cases} \quad (6.8)$$

Where $N(i)$ is the number of countries that are geographically contiguous to country i .

6.4 Sensitivity Analysis for Hyperpriors

The choice of hyperpriors influences estimation results and should be inspected before use. In this study, highly dispersed (weakly or minimally informative) inverse gamma hyperpriors, $\tau^2 \sim IG(\alpha, \beta)$ were used for the precision of structured and unstructured spatial effects. Researchers have utilized various hyperprior settings. For instance, [Fahrmeir and Lang \(2001\)](#) used $\alpha = \beta = 0.0001$, [Klein et al. \(2014\)](#) proposed $\alpha = \beta = 0.001$, [Besag et al. \(1991\)](#) set $\alpha = 1$, $\beta = 0.0005$, [Brezger and Lang \(2006\)](#) used $\alpha = 1$, $\beta = 0.005$, [Blangiardo et al. \(2013\)](#) and [Khana et al. \(2018\)](#) adopted $\alpha = 1$, $\beta = 0.001$, [Kazembe and Kandala \(2015\)](#) employed $\alpha = 0.5$, $\beta = 0.0005$.

To investigate the impact of these different hyperprior settings on the estimation results, including model performance and parameter estimates, a sensitivity analysis was conducted using varying shape (α) and scale (β) parameter values mentioned above. Among the tested prior configurations, the lowest DIC (1556.91) and WAIC (1568.30) occurred at $\alpha = 1$, $\beta = 0.001$. Other settings showed minor variations, with DIC ranging from 1557.00 to 1559.47 and WAIC from 1572.81 to 1574.95. Therefore, $\alpha = 1$ and $\beta = 0.001$ were selected as the final hyperprior setting for this study.

Furthermore, the posterior estimates of the fixed effects, variance components, and overall model performance remained largely consistent across the different prior specifications. This indicates that the main findings were not unduly influenced by the choice of priors. Therefore, the results are considered robust and primarily driven by the observed data rather than being sensitive to prior assumptions, thereby increasing

confidence in the reliability of the model estimates.

6.5 Selection of Basis Dimensions

The GAMM was tested with different basis dimensions ($k = 15, 20, 25, 30$) on the nonlinear covariates to assess their impact on model performance. The results showed no significant improvement in goodness of fit or overall model performance. The lowest DIC (1557.00) and WAIC (1570.62) occurred at $k = 20$. For other knot values ($k = 15, 25, 30$), the DIC ranged from 1560.08 to 1560.59, and the WAIC ranged from 1570.77 to 1571.44. Based on these results, a basis dimension of 20 was considered for this study. Therefore, this study employed the GAMM with 20 knots for the nonlinear covariates and inverse gamma hyperprior settings ($\alpha = 1, \beta = 0.001$) for the precision of structured and unstructured spatial effects to assess the environmental, socioeconomic and spatial influences on severe food insecurity across Africa.

6.6 Parameter Estimation

In this study, the Integrated Nested Laplace Approximation (INLA), implemented in *R* statistical software, was used for parameter estimation due to its time efficiency and accuracy compared with Markov Chain Monte Carlo (MCMC) methods (Blangiardo et al., 2013; Martins et al., 2013; Rue et al., 2009). INLA utilizes a series of Laplace approximations to the posterior marginal of Bayesian model parameters in which the latent effects are a GMRF, while parameter estimation is performed using numerical integration techniques. In the INLA estimation processes, the study estimates the parameter vector $\theta = \{\beta, \mathbf{f}\}$ and the vector of hyperparameters $\pi = \{\tau_\phi^2, \tau_\theta^2\}$.

First, we compute the marginal distribution of each element in the hyperparameter vector as:

$$p(\pi_k | \mathbf{y}) = \int p(\pi | \mathbf{y}) d\pi_{-k} \quad (6.9)$$

Under conditional independence assumptions as stated in Blangiardo and Cameletti (2015), INLA uses Laplace Gaussian approximation to numerically estimate the joint posterior marginal distribution of the hyperparameters as:

$$p(\pi | \mathbf{y}) = \frac{p(\theta, \pi | \mathbf{y})}{p(\theta | \pi, \mathbf{y})} \propto \frac{p(\pi) p(\theta | \pi) p(\mathbf{y} | \theta)}{p(\theta | \pi, \mathbf{y})} \quad (6.10)$$

Replacing the denominator with a Laplace Gaussian approximation yield:

$$\tilde{p}(\pi | \mathbf{y}) \propto \frac{p(\pi) p(\theta | \pi) p(\mathbf{y} | \theta)}{\tilde{p}(\theta | \pi, \mathbf{y})} \Bigg|_{\theta = \theta^*(\pi)} \quad (6.11)$$

where $\tilde{p}(\boldsymbol{\theta} \mid \boldsymbol{\pi}, \mathbf{y})$ denotes the Laplace Gaussian approximation to $p(\boldsymbol{\theta} \mid \boldsymbol{\pi}, \mathbf{y})$, and $\boldsymbol{\theta}^*(\boldsymbol{\pi})$ is the mode for a given $\boldsymbol{\pi}$.

Next, we compute the marginal posterior distributions of each element of the latent parameter vector θ_i as is:

$$p(\theta_i \mid \mathbf{y}) = \int p(\boldsymbol{\pi} \mid \mathbf{y}) p(\theta_i \mid \boldsymbol{\pi}, \mathbf{y}) d\boldsymbol{\pi} \quad (6.12)$$

For $\boldsymbol{\theta} = (\theta_i, \boldsymbol{\theta}_{-i})$, the joint posterior distribution of the parameters is estimated again by Laplace approximation as:

$$\tilde{p}(\theta_i \mid \boldsymbol{\pi}, \mathbf{y}) = \frac{p(\theta_i, \boldsymbol{\theta}_{-i} \mid \boldsymbol{\pi}, \mathbf{y})}{p(\boldsymbol{\theta}_{-i} \mid \theta_i, \boldsymbol{\pi}, \mathbf{y})} \propto \frac{p(\boldsymbol{\theta}, \boldsymbol{\pi} \mid \mathbf{y})}{\tilde{p}(\boldsymbol{\theta}_{-i} \mid \theta_i, \boldsymbol{\pi}, \mathbf{y})} \Big|_{\boldsymbol{\theta}_{-i} = \boldsymbol{\theta}_{-i}^*(\theta_i, \boldsymbol{\pi})} \quad (6.13)$$

where $\tilde{p}(\theta_i \mid \boldsymbol{\pi}, \mathbf{y})$ is the Laplace approximation and $\boldsymbol{\theta}_{-i}^*(\theta_i, \boldsymbol{\pi})$ denotes the mode.

Then, the marginal posterior distributions as in Equation 6.12 can be approximated as:

$$\tilde{p}(\theta_i \mid \mathbf{y}) = \int \tilde{p}(\boldsymbol{\pi} \mid \mathbf{y}) \tilde{p}(\theta_i \mid \boldsymbol{\pi}, \mathbf{y}) d\boldsymbol{\pi} \quad (6.14)$$

and numerically Equation 6.14 can be solved through the following equation

$$\tilde{p}(\theta_i \mid \mathbf{y}) \approx \sum_l \tilde{p}(\boldsymbol{\pi}^{(l)} \mid \mathbf{y}) \tilde{p}(\theta_i \mid \boldsymbol{\pi}^{(l)}, \mathbf{y}) \Delta_l \quad (6.15)$$

with $\{\Delta_l\}$ a set of weights from some integration points $\{\boldsymbol{\pi}^{(l)}\}$.

6.7 Results

6.7.1 Introduction

This study examined the economic, social, political and environmental determinants of severe food insecurity and quantified the extent of spatial dependence across African countries. To achieve this objective, a range of statistical models was employed, including Linear Regression Model (LRM), Additive Model (AM), Additive Mixed Model (AMM), Geo-Additive Model (GAM), and Geo-Additive Mixed Model (GAMM). To support model selection and ensure the reliability of parameter estimates, multicollinearity was assessed within the reduced set of predictors. In the previous stage, thirty predictor variables were considered, and variance inflation factors (VIFs) were computed by regressing each predictor on all remaining predictors. In this section, the same procedure is applied to the selected set of predictor variables (fifteen out of thirty), where each predictor is regressed on the remaining predictors. The resulting VIF values range from 1.2 to 4.6, indicating that there is no serious evidence of

multicollinearity among the selected predictors.

6.7.2 Identification of Linear and Nonlinear Covariate Effects

To ensure appropriate model specification, this study further systematically identified covariates exhibiting either linear or nonlinear effects using partial effect plots from the classical additive model and scatter plots of each covariate against the outcome variable. This process used flexible smoothing techniques, including P-splines, cubic splines, and thin-plate splines, which allow for a flexible representation of nonlinear relationships in the data. At this stage, since the INLA function in R doesn't support P-splines, cubic splines, or thin-plate splines, the study used the Restricted Maximum Likelihood (REML) method to identify the relationship between covariates and severe food insecurity. Among the tested spline basis functions, cubic splines provided the lowest AIC (1772.29) and BIC (2127.87), followed by thin-plate spline (AIC: 1786.78, BIC: 2154.54) and P-spline (AIC: 1809.11, BIC: 2133.96). These results suggest that the cubic splines were the best smoothing function for modeling nonlinear covariates in severe food insecurity.

Figure 6.1 shows the effect plots of covariate relationships with severe food insecurity using cubic splines. The results indicated that the effect estimates for climate change, livestock production, crop production, political stability, malaria incidence, investment inflow, and electric access were not significantly different from zero and/or were close to linear. This indicated that these covariates exhibited linear effects on severe food insecurity. Conversely, the effect estimates for the GDP, unemployment, inflation, GHG emissions, caloric loss, dietary energy supply, dietary protein supply and cereal import dependency significantly deviated from zero and/or were nonlinear. This indicated that these covariates exhibited nonlinear effects on severe food insecurity, requiring smoothing functions to capture their relationships with severe food insecurity. As a result, this study modeled linear covariate effects parametrically and nonlinear effects nonparametrically.

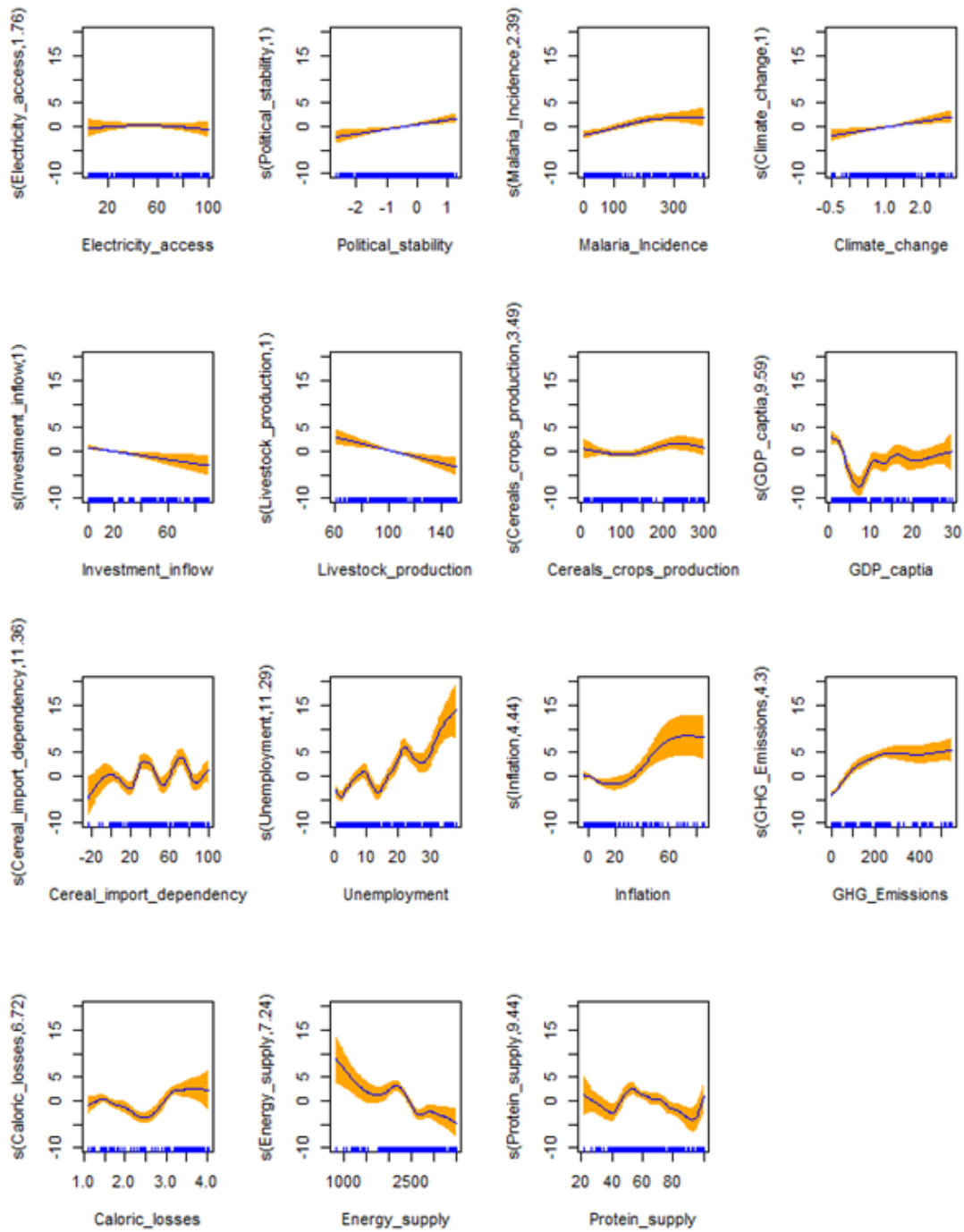


Figure 6.1: Cubic spline-based estimates of covariate effects

6.7.3 Estimates of Fixed Covariate Effects

The linear fixed effects of the GAMM estimated by INLA were presented in Table 6.1. The results showed that the 95% credible interval for electricity access, malaria incidence, climate change and livestock production didn't include zero, suggesting that their effects on severe food insecurity across African countries were sta-

tistically significant. Among the significant predictors, malaria incidence and climate change contributed to increasing the risk of severe food insecurity, while electricity access and livestock production significantly reduced the risk. A one-unit increase in malaria incidence and climate change is expected to increase the prevalence of severe food insecurity by 0.0099 and 0.7976, respectively. In contrast, a one-unit increase in electricity access and livestock production is expected to reduce the prevalence by 0.0260 and 0.0670, respectively. These effects are assumed to be constant across the observed range of covariate values among countries.

Table 6.1: Estimates of linear fixed covariate effects in the GAMM

Linear Covariates	Estimate	SD	95% CIs	
			Lower	Upper
Intercept	33.2607	2.6400	28.0798	38.4340*
Electricity access	-0.0260	0.0119	-0.0493	-0.0027*
Political stability	0.4792	0.2878	-0.0851	1.0439
Malaria Incidence	0.0099	0.0033	0.0034	0.0163*
Climate change	0.7976	0.3319	0.1467	1.4485*
Livestock production	-0.0670	0.0169	-0.1002	-0.0339*
Cereals crops production	-0.0016	0.0036	-0.0087	0.0056
Investment inflow	-0.0236	0.0124	-0.0479	0.0008

*Significant at 5%

6.7.4 Estimates of Nonlinear Covariate Effects

In addition to the fixed covariate effects, the model incorporated nonlinear covariate effects which were handled nonparametrically. The estimated variability parameters associated with cereal import dependence, dietary energy supply, GHG emissions, GDP, unemployment, inflation, caloric loss, and dietary protein supply were statistically significant at the 95% credible interval. This finding provide evidence that the relationship between these covariates and severe food insecurity are not adequately characterized by simple linear functions. This implies that the magnitude of their effects may vary across the range of observed values. Consequently, small changes in a covariate may have strong effects in certain regions of its distribution while exerting weaker or negligible effects in others. Therefore, a one-unit increase in a nonlinear covariate does not necessarily correspond to a constant change in severe food insecurity.

Figure 6.2 presents the estimated nonlinear effects of these covariates on severe food insecurity. The graph showed that the 95% CIs for the estimated effects of GHG emissions, energy supply, GDP per capita, protein supply, unemployment, and inflation exclude zero over some portions or all of their observed ranges. This provides evidence that these covariates exert statistically significant nonlinear effects on severe food in-

security. The estimated smoothed effects of GDP per capita, dietary protein supply, unemployment, and inflation exhibited approximately linear patterns across their observed ranges, whereas the smoothed effects of dietary energy supply and GHG emissions exhibited a significant nonlinear functional form. In contrast, the 95% CI for the estimated effects of cereal import dependency and caloric loss includes zero throughout their observed ranges. This indicates that these covariates do not exert statistically significant nonlinear effects on severe food insecurity.

The estimated smoothed effects of GDP per capita, dietary protein supply, unemployment, and inflation exhibited approximately linear patterns across their observed ranges, whereas dietary energy supply and GHG emissions showed more pronounced nonlinear patterns. The prevalence of severe food insecurity was higher at lower values of dietary energy supply and decreased as energy supply increased. This suggests that improved energy availability is associated with a reduced risk of severe food insecurity. With respect to GHG emissions, severe food insecurity decreased at lower emission levels and increased at higher levels across the observed range. The estimated smooth functions for unemployment and inflation showed positive associations with severe food insecurity. This indicates that higher unemployment and inflation rates contributed to in aggravating the risk of severe food insecurity. In contrast, GDP per capita and dietary protein supply were negatively associated with severe food insecurity. The estimated risk was higher at lower levels of GDP and dietary protein supply and declined as these covariates increased. This suggests that improvements in economic conditions and dietary protein supply contribute to reducing severe food insecurity. The 95% credible intervals for caloric loss were wide, particularly at the lower and upper ends of the covariate range, likely due to a small number of observations in these cases.

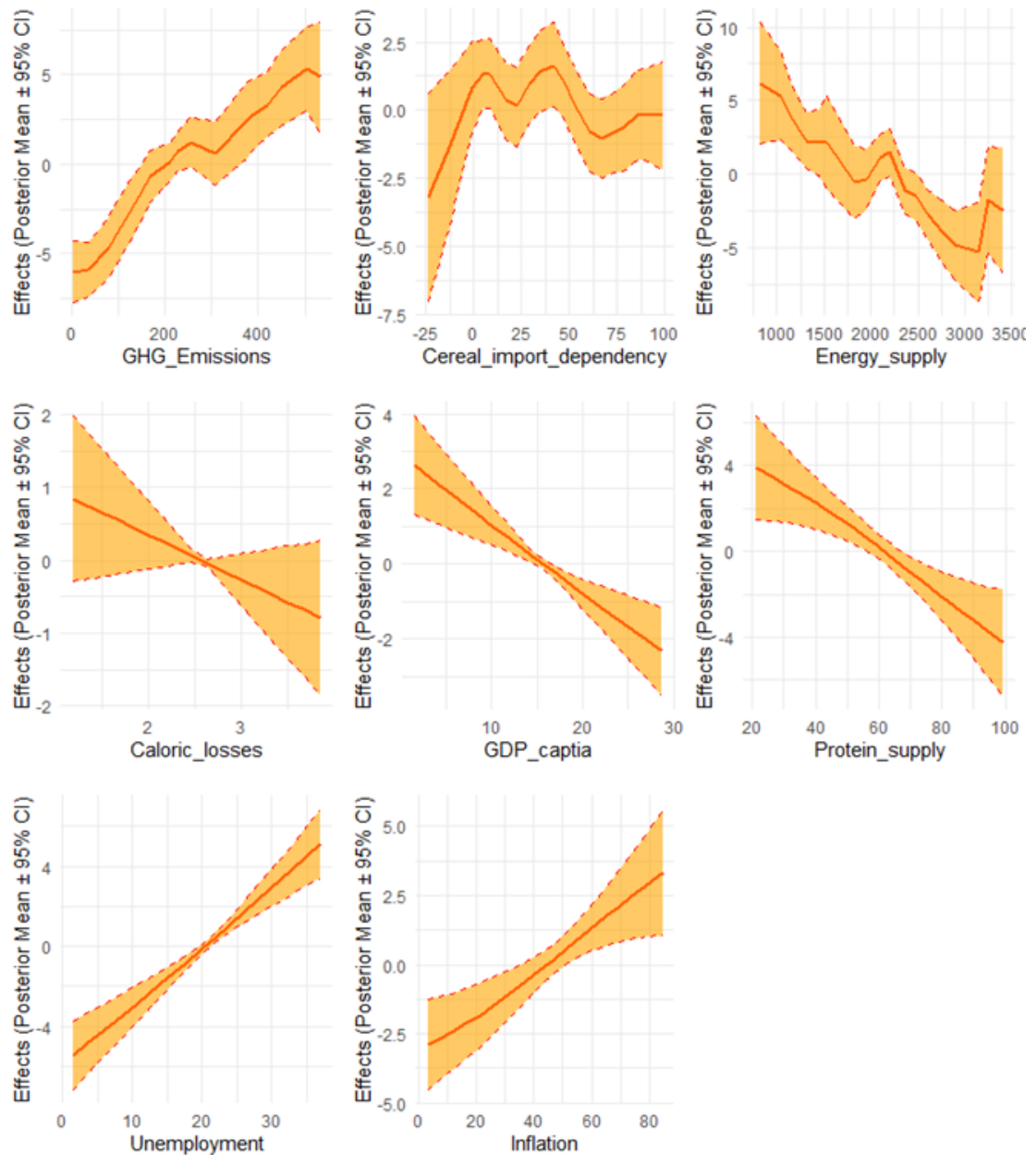


Figure 6.2: Smoothed estimates of nonlinear covariate effects (with 95% CI)

6.7.5 Estimates of Spatial Effects

The variance estimates of the structured and unstructured spatial random effects for severe food insecurity are presented in Table 6.2. The model estimated 52 spatial effects for each of the structured and unstructured components, corresponding to the 52 spatial units (countries) included in the analysis. Both the structured and unstructured spatial effects showed positive and negative posterior estimates. Positive posterior estimates indicate a higher spatial random-effect contribution to the prevalence of severe food insecurity in a given country, whereas negative estimates indicate a lower contribution, relative to the overall model level.

In Table 6.2, the variance estimates for the structured ($\tau_{\theta}^2 = 1238.18$) and unstructured ($\tau_{\phi}^2 = 0.04$) spatial effects, which capture spatial autocorrelation, were both positive and their 95% credible intervals did not include zero. These results indicate the existence of spatial heterogeneity in severe food insecurity, suggesting that geographic location plays a role in its distribution even after accounting for the observed covariates. These spatial random effects represent the influence of unobserved or unmeasured location-specific and cross-country shared factors that were not explicitly included in the model. These latent influences may reflect regional similarities in governance, conflict dynamics, economic conditions, infrastructure, environmental conditions, policy implementation, or other contextual characteristics that exhibit spatial dependence. Consequently, neighboring countries may experience similar levels of severe food insecurity due to shared geographic, socioeconomic, or political conditions beyond those captured by the measured predictors. This finding highlights the importance of incorporating spatial dependence into the modeling framework and suggests that regional coordination and cross-border interventions may be necessary to effectively address severe food insecurity.

Table 6.2: Estimates of spatial random effects

Spatial Effects	Estimate	SD	95% CIs	
			Lower	Upper
τ_{θ}^2	1238.18	1393.31	95.40	4921.57
τ_{ϕ}^2	0.04	0.01	0.02	0.06
σ^2	0.30	0.03	0.24	0.35

The variability of structured and unstructured random components are not directly comparable in terms of their intrinsic variance specifications (Besag et al., 1991). Because the structured component is defined through an iCAR model, whereas the unstructured component follows an i.i.d. Gaussian specification. Nevertheless, an estimate of the posterior marginal variance of the structured effect is obtained empirically from the posterior marginal distributions of the latent effects using the standard variance formula. Based on these posterior summaries, the findings revealed that the structured component exhibited greater variability than the unstructured component. This suggests that a larger proportion of the latent variation in severe food insecurity is captured by spatially structured dependence compared to unstructured or uncorrelated heterogeneity.

Figure 6.3(A) & (B) depicted the risk maps of severe food insecurity across Africa for the unstructured and structured spatial effects of the model, respectively. The maps showed geographic patterns of severe food insecurity and displayed countries with varying levels of risk. The observed distinct spatial patterns suggested that severe food

insecurity was not uniformly distributed across the continent.

In Figure 6.3(A), the different colors represented the varying levels of severe food insecurity in unstructured spatial effects. The light red color indicated countries with lower rates of severe food insecurity, while the dark red color denoted countries with higher prevalence. As depicted in Figure 6.3(A), countries labeled in dark red color, Central African Republic, South Sudan, Malawi, Cameroon, Rwanda, Somalia, the Republic of the Congo, Chad, Guinea, Lesotho, and Namibia exhibited a higher risk of severe food insecurity due to unstructured spatial influences. In these countries, such effects arose from unpredictable, localized shocks, short-term events, or country-specific policies that operated independently of broader regional trends. The effects on these countries can be changed rapidly in response to interventions or temporary shocks.

On the other hand, Figure 6.3(B) illustrated the structured spatial effects and reveals distinct geographical patterns. Many countries in the Southern, Eastern, and Central African subregions exhibited strong spatial dependence. These patterns indicate that severe food insecurity in these regions is driven not only by temporary shocks but also by persistent structural constraints and unobserved spatially correlated factors. To address these deeply rooted problems, long-term regionally coordinated strategies are needed to achieve sustainable improvements in food security.

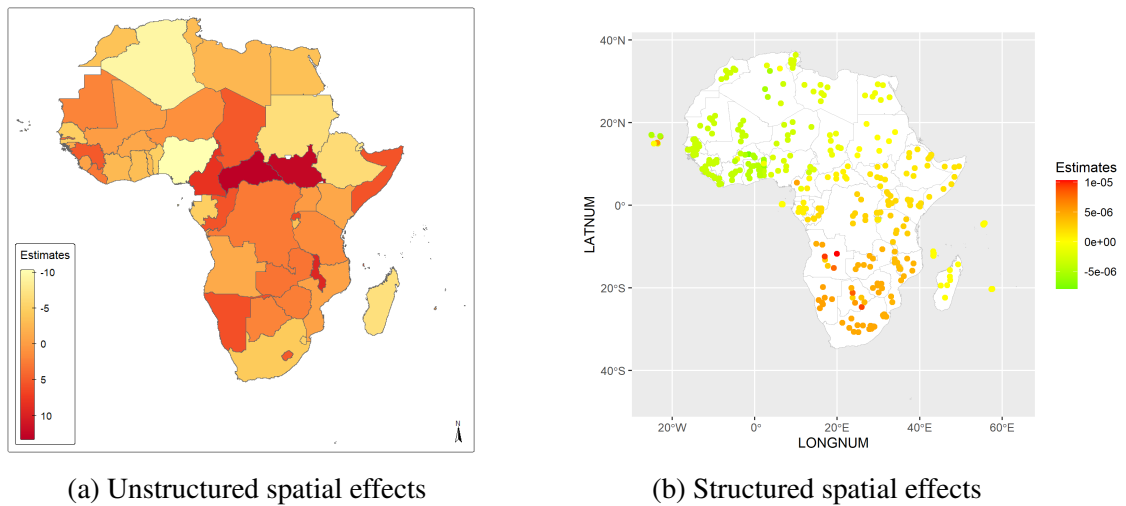


Figure 6.3: Posterior mean estimates of spatial effects

6.7.6 Model Diagnostics

This analysis confirmed stable parameter estimates, improved goodness-of-fit and adequate variance capture (no excessive peaks or dispersion). Model assumptions were assessed through residual analysis and posterior predictive checking. The plots in Figure 6.4(A-D) showed that the model satisfied the normality assumption

(Figure 6.4(A)) and the homoscedasticity assumption Figure 6.4(B)), with residuals approximately following a normal distribution and exhibiting consistent variance, respectively. Furthermore, the distributions of observed and posterior predictive values (Figure 6.4(C-D)) were strongly overlapped, indicating the model effectively captured the data structure. Based on these evaluations, the GAMM provided a good fit to the data.

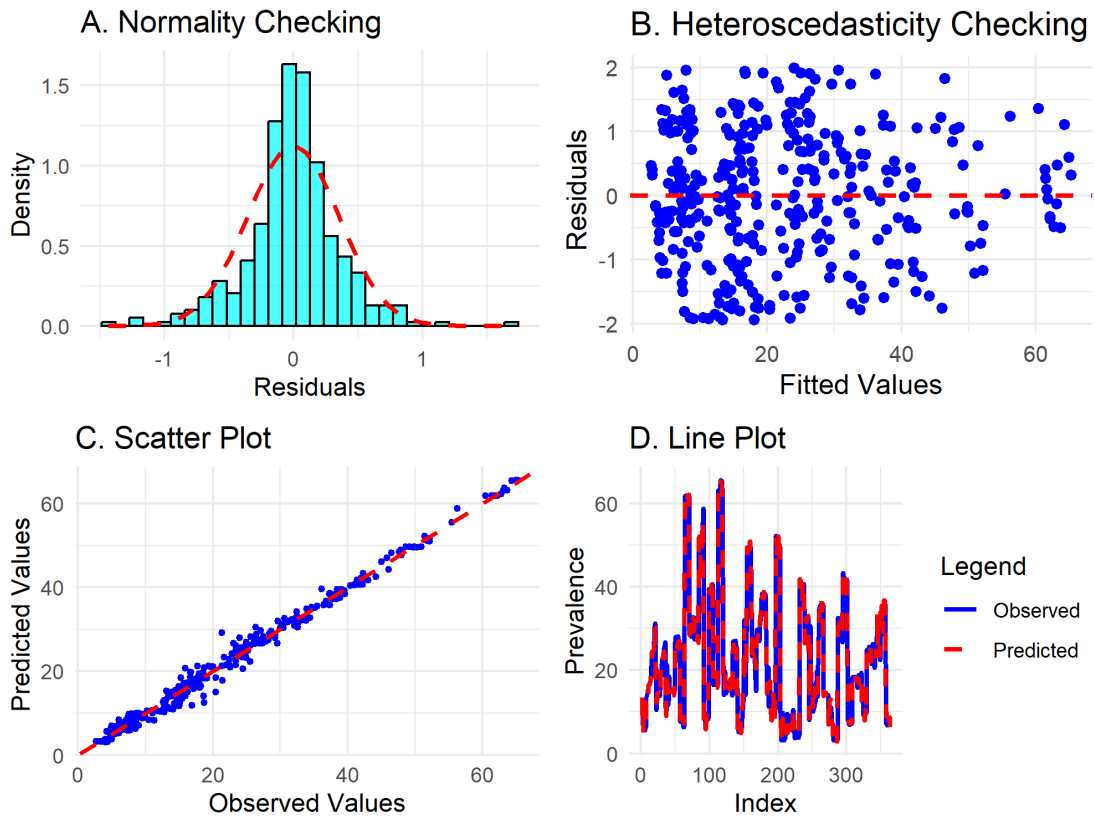


Figure 6.4: Normality (A), heteroscedasticity (B), and posterior predictive checking (C-D).

6.8 Summary

This chapter employed different spatial models, including additive model, additive mixed model, geospatial model and geospatial mixed model, to examine the determinants and spatial dependence of severe food insecurity across Africa. The results indicated that electricity access, malaria incidence, climate change, and livestock production had significant linear effects on severe food insecurity at the 95% CIs. In contrast, greenhouse gas (GHG) emissions, gross domestic product (GDP), unemployment, inflation, dietary energy supply, and dietary protein supply exhibited statistically significant nonlinear effects. In addition, severe food insecurity exhibited pronounced spatial dependence, with substantial disparities across countries. The results revealed that countries such as the Central African Republic, South Sudan, Malawi, Cameroon,

Rwanda, Somalia, the Republic of the Congo, Chad, Guinea, Lesotho, and Namibia experienced elevated levels of severe food insecurity due to localized shocks. In contrast, many countries in the Southern, Eastern, and Central African subregions exhibited strong spatial dependencies in severe food insecurity. These dependencies were driven by persistent structural constraints and unobserved spatially correlated factors.

Despite the flexibility and strong inferential capacity of the geoadditive mixed model employed in this chapter, several limitations should be acknowledged. First, the analysis focuses primarily on spatial dependence and does not explicitly incorporate temporal dynamics, potentially overlooking important time-related trends and persistence in severe food insecurity. Second, the models assume that covariate effects are constant over time, which may mask temporal variations in the relationships between predictors and the response variable. Third, although spatial heterogeneity and nonlinear effects are captured, the absence of space–time interaction terms limit the ability to fully characterize the joint evolution of severe food insecurity across both space and time. Consequently, while this chapter provided a rigorous assessment of spatial dependence and determinants, it did not capture the dynamic spatio-temporal processes underlying food insecurity. Purely spatial models that assume time-invariant relationships may fail to capture these dynamic process and the complex interaction between space and time. Ignoring spatio-temporal dependencies can lead to an incomplete understanding of the underlying mechanisms, biased parameter estimates, and less effective policy recommendations. To address these limitations, Chapter 7 extended the analysis by employing spatio-temporal models that explicitly incorporated temporal dependence and space–time interactions. This approach enabled a more comprehensive understanding of the evolving dynamics of severe food insecurity across Africa.

Chapter 7

Spatio-Temporal Dependence and Determinants of Severe Food Insecurity

7.1 Introduction

The exploratory analysis presented in Chapter 4 revealed that severe food insecurity was not uniformly distributed across countries or over time; rather, it exhibited pronounced spatio-temporal dynamics. The level of severe food insecurity in a given country was influenced by country-specific environmental, economic, and geopolitical factors, conditions in neighboring countries, and its own historical levels of food insecurity. These findings highlight the need to account for both spatial and temporal dependencies when modeling severe food insecurity.

Accordingly, this chapter extended the spatial modeling framework developed in Chapter 6 into a spatio-temporal modeling framework. By jointly incorporating covariate effects, spatial dependence, temporal dynamics, and space–time interaction effects within a unified framework, it addressed the limitations identified in Chapter 6. A series of spatio-temporal models were implemented to examine the dynamic behavior of severe food insecurity, quantify the effects of key predictors, and assess the contributions of spatial effects, temporal effects, and their interactions. This approach provides a more comprehensive and policy-relevant understanding of the evolving dynamics of severe food insecurity across African countries over time.

7.2 Models

The study region comprises a set of $i = 1, \dots, K = 52$ non-overlapping areal units $S = \{S_1, \dots, S_{52}\}$, and data are recorded for each unit for $t = 1, \dots, T = 7$ consecutive time periods. By sharing information across neighboring locations and time periods, spatio-temporal models capture spatial and temporal dependencies, as well as space-time interaction effects.

Let y_{it} denote the prevalence of severe food insecurity for country i ($i = 1, \dots, 52$) during year t ($t = 1, \dots, 7$). This structure forms a rectangular array or matrix for the

response data $\mathbf{Y} \in \mathbb{R}^{52 \times 7}$ with $\mathbf{y}_t \in \mathbb{R}^{52 \times 1} \forall t$. In this form, rows represent countries and columns represent years. Furthermore, let x_{it} = (electricity access, political stability, malaria incidence, climate change, livestock production, cereals crop production, investment inflow) denote the linear covariates and z_{it} = (GHG emissions, GDP per capita, unemployment, inflation, cereal import dependency, caloric losses, dietary energy supply, and dietary protein supply) represent the nonlinear covariates related to severe food insecurity for country k and time-period t . The linear and nonlinear effects of covariates on severe food insecurity were identified using cubic spline analysis.

In the first stage of the modeling hierarchy, a general spatio-temporal model can be expressed as:

$$y_{it} = \mu_{it} + \epsilon_{it}, \quad i = 1, \dots, 52, \quad t = 1, \dots, 7. \quad (7.1)$$

where $y_{it} \sim \mathcal{N}(\mu_{it}, \nu^2)$, $\nu^2 \sim \text{IG}(1, 0.001)$, and $\mu_{it} = E(y_{it} \mid x_{it}, z_{it})$ denotes the spatio-temporal mean process of y_{it} which is typically linked to the linear predictor η_{it} through an identity link function $g(\cdot)$, where $g(\mu_{it}) = \eta_{it}$. The error term $\epsilon_{it} \sim GP(\mathbf{0}, \Sigma_\epsilon)$ represents a zero-mean Gaussian white noise process and variance-covariance matrix Σ_ϵ . It involves the $KT \times KT$ covariance structure of the error vector $\epsilon \in \mathbb{R}^{KT \times 1}$, where $\epsilon = \{\epsilon_{it}\}$ for $i = 1, \dots, K$ and $t = 1, \dots, T$ (Gneiting, 2002). The diagonal elements of Σ_ϵ are given by the constant variance σ_e^2 , commonly referred to as the nugget effect, which captures microscale variability and measurement error.

The linear predictor η_{it} of the data can be specified as follows:

$$\begin{aligned} \eta_{it} = & \beta_0 + \beta_1 \text{Electricity_access}_{it} + \beta_2 \text{Political_stability}_{it} + \beta_3 \text{Malaria_incidence}_{it} \\ & + \beta_4 \text{Climate_change}_{it} + \beta_5 \text{Livestock_production}_{it} + \beta_6 \text{Cereal_crop_production}_{it} \\ & + \beta_7 \text{Investment_inflow}_{it} + f_1(\text{GDP_per_capita}_{it}) + f_2(\text{Unemployment}_{it}) \\ & + f_3(\text{Caloric_losses}_{it}) + f_4(\text{Dietary_energy_supply}_{it}) + f_5(\text{Dietary_protein_supply}_{it}) \\ & + f_6(\text{GHG_emissions}_{it}) + f_7(\text{Cereal_import_dependency}_{it}) + f_8(\text{Inflation}_{it}) + \psi_{it} \end{aligned} \quad (7.2)$$

where $\beta \sim \mathcal{N}(\mu_\beta, \Sigma_\beta)$ is the vector of fixed-effect coefficients, the functions $f_j(\cdot)$ represent smooth functions of the nonlinear covariate effects, and ψ_{it} denotes latent spatio-temporal autocorrelated random effects for the country i at time t , with $\psi \in \mathbb{R}^{K \times T}$ and $\psi_t \in \mathbb{R}^{K \times 1}$.

This study considered different structures or assumptions for modeling spatio-temporally autocorrelated random effects, ψ_{it} . These include: classical parametric trend model, spatio-temporal ANOVA model, dynamic nonparametric trend model, and spatio-temporal interaction model.

7.2.1 Classical Parametric Trend Model

This model estimates area-specific temporal trends in the random effects ψ_{it} . The model assumes linear temporal trends and assigns a distinct linear slope (δ_i) to each area (Bernardinelli et al., 1995). This approach facilitates the detection of countries showing linear upward or downward trajectories in the outcome over time. Mathematically,

$$\psi_{it} = \beta_0 + \phi_i + (\alpha + \delta_i) \frac{(t - \bar{t})}{T}, \quad i = 1, \dots, 52, \quad t = 1, \dots, 7 \quad (7.3)$$

Where,

$$\begin{aligned} \phi_i \mid \phi_{-i}, \mathbf{W} &\sim N \left(\frac{\rho_{\text{int}} \sum_{j=1}^K w_{ij} \phi_j}{\rho_{\text{int}} \sum_{j=1}^K w_{ij} + 1 - \rho_{\text{int}}}, \frac{\tau_{\text{int}}^2}{\rho_{\text{int}} \sum_{j=1}^K w_{ij} + 1 - \rho_{\text{int}}} \right) \\ \delta_i \mid \delta_{-i}, \mathbf{W} &\sim N \left(\frac{\rho_{\text{slo}} \sum_{j=1}^K w_{ij} \delta_j}{\rho_{\text{slo}} \sum_{j=1}^K w_{ij} + 1 - \rho_{\text{slo}}}, \frac{\tau_{\text{slo}}^2}{\rho_{\text{slo}} \sum_{j=1}^K w_{ij} + 1 - \rho_{\text{slo}}} \right) \\ \tau_{\text{int}}^2, \tau_{\text{slo}}^2 &\sim \text{Conjugate IG}(a, b) \\ \rho_{\text{int}}, \rho_{\text{slo}} &\sim \text{Uniform}(0, 1) \\ \alpha &\sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2) \end{aligned}$$

Here, β_0 denotes the overall intercept and α denotes the overall (global) temporal slope parameter. The terms ϕ_i and δ_i denote the area-specific deviations from the global intercept and slope, respectively, for the i^{th} country where $i = 1, \dots, 52$. Thus, the linear temporal trend for each country is characterized by a country-specific intercept $\beta_0 + \phi_i$ and slope $\alpha + \delta_i$. The terms ϕ_i and δ_i are modeled using CAR prior specifications as defined by Leroux et al. (2000) and are mean-centered (i.e., $\sum_{k=1}^{52} \phi_k = \sum_{k=1}^{52} \delta_k = 0$). $\phi_{-i} = (\phi_1, \dots, \phi_{i-1}, \phi_{i+1}, \dots, \phi_{52})$ & $\delta_{-i} = (\delta_1, \dots, \delta_{i-1}, \delta_{i+1}, \dots, \delta_{52})$ denote the vectors excluding the i^{th} element. The linear temporal trend is standardized as $t^* = (t - \bar{t})/T$, where $\bar{t} = (\sum_{t=1}^T t)/T$ is the average time, ρ_{int} and ρ_{slo} are spatial dependence parameters. The spatial autocorrelation is controlled by a symmetric non-negative adjacency matrix $\mathbf{W} = (w_{ij})$, where $w_{ij} = 1$ if areal units (S_i, S_j) share a common border and zero otherwise. Under this binary specification, ψ_{it} and ψ_{jt} are spatially autocorrelated for neighboring units and conditionally independent for non-neighboring units.

7.2.2 Spatio-Temporal ANOVA Model

This model, adopted from Knorr-Held (2000), decomposes the spatio-temporal variation into three components: a common set of spatial effects (ϕ_i) $\forall t$, temporal effects (δ_t) $\forall i$, and independent space-time interactions (γ_{it}) $\forall i, t$. It is suited for estimat-

ing overall spatial patterns and time trends. The specification is provided below.

$$\psi_{it} = \phi_i + \delta_t + \gamma_{it}, \quad i = 1, \dots, 52, \quad t = 1, \dots, 7 \quad (7.4)$$

Where,

$$\begin{aligned} \phi_i \mid \phi_{(-i)}, \mathbf{W} &\sim \mathcal{N} \left(\frac{\rho_S \sum_{j=1}^K w_{ij} \phi_j}{\rho_S \sum_{j=1}^K w_{ij} + 1 - \rho_S}, \frac{\tau_S^2}{\rho_S \sum_{j=1}^K w_{ij} + 1 - \rho_S} \right) \\ \delta_t \mid \delta_{(-t)}, \mathbf{D} &\sim \mathcal{N} \left(\frac{\rho_T \sum_{j=1}^K d_{tj} \delta_j}{\rho_T \sum_{j=1}^K d_{tj} + 1 - \rho_T}, \frac{\tau_T^2}{\rho_T \sum_{j=1}^K d_{tj} + 1 - \rho_T} \right) \\ \gamma_{it} &\sim \mathcal{N}(0, \tau_I^2) \\ \tau_S^2, \tau_T^2, \tau_I^2 &\sim \text{IG}(1, 0.001) \\ \rho_S, \rho_T &\sim \text{Uniform}(0, 1) \end{aligned}$$

Here, the terms ϕ_i and δ_t are captured using mean-centered CAR priors, as formulated by [Leroux et al. \(2000\)](#). Where $\mathbf{D} = (d_{ij})$ is a binary $T \times T$ temporal neighborhood matrix, $d_{ij} = 1$ if $|i - j| = 1$ and 0 otherwise. Similarly, $\mathbf{W} = (w_{ij})$ is the spatial adjacency matrix where $w_{ij} = 1$ if areal units (S_i, S_j) share a common border and 0 otherwise.

7.2.3 Dynamic Nonparametric Trend Model

Equation 7.3 assumes a linearity in the temporal trends whereas the dynamic nonparametric trend model in Equation 7.5 removes this assumption by modeling the temporal trend nonparametrically. Specifically, it replaces the global temporal effect (α) and area-specific deviation from the global slope (δ_i) with the correlated temporal component (α_t) and uncorrelated temporal component (γ_t) ([Knorr-Held, 2000](#)). Mathematically,

$$\psi_{it} = \theta_i + \phi_i + \alpha_t + \gamma_t \quad (7.5)$$

The unstructured spatial effect ϕ_i was modeled using a Gaussian exchangeable prior $\phi_i \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \tau_\phi^2)$ whereas the structured spatial effect θ_i was captured using an intrinsic CAR prior ([Besag et al., 1991](#)), which is given as:

$$\theta_i \mid \theta_{j \neq i} \sim \mathcal{N} \left(\frac{\sum_{j \neq i} w_{ij} \theta_j}{\sum_{j \neq i} w_{ij}}, \frac{\tau_\theta^2}{\sum_{j \neq i} w_{ij}} \right) \quad (7.6)$$

Where: w_{ij} is the suitable adjacency weights for the areas.

The uncorrelated temporal effect γ_t was modeled via a Gaussian exchangeable prior $\gamma_t \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \tau_\gamma^2)$, whereas the correlated temporal effect α_t was captured dynamically using the first-order random walk: $\alpha_t - \alpha_{t-1} \sim \mathcal{N}(0, \tau_\alpha^2)$ or a second-order random walk: $\alpha_t - 2\alpha_{t-1} + \alpha_{t-2} \sim \mathcal{N}(0, \tau_\alpha^2)$ through a temporal neighboring structure ([Rue](#)

and Held, 2005). The first-order random walk can be represented in its GMRF form as:

$$\alpha_t \mid \alpha_{(-t)} \sim \begin{cases} \mathcal{N}(\alpha_{t+1}, \tau_\alpha), & t = 1, \\ \mathcal{N}\left(\frac{\alpha_{t-1} + \alpha_{t+1}}{2}, \tau_\alpha/2\right), & t = 2, \dots, T-1, \\ \mathcal{N}(\alpha_{t-1}, \tau_\alpha), & t = T \end{cases} \quad (7.7)$$

Equivalently, each of the four main effects can be expressed in matrix form as: $\psi = (\theta, \phi, \alpha, \gamma) \sim \mathcal{N}(\mathbf{0}, \tau_\psi^2 \mathbf{Q}^-)$ where $\mathbf{Q}$ is a known precision matrix, $\mathbf{Q}^-$ is the generalized inverse of $\mathbf{Q}$, and τ_ψ^2 is the precision parameter (an unknown scalar to be estimated from the data) governing the spatial and temporal effects (Clayton, 1996; Rue and Held, 2005). The unstructured spatial and uncorrelated temporal effects were modeled using identity precision matrices, $\mathbf{Q}_\phi = I_{52 \times 52}$ and $\mathbf{Q}_\gamma = I_{7 \times 7}$, respectively, implying independence across countries and time points. The correlated temporal effect was captured using a 7×7 structure precision matrix ($\mathbf{Q}_\alpha$) derived from first- or second-order random walk (RW1/RW2) formulations (see the details in Rue and Held (2005)). For the structured spatial effect, a 52×52 spatial neighborhood structure precision matrix ($\mathbf{Q}_\theta$) was employed, following the iCAR specification introduced by Besag et al. (1991):

$$Q_{ij} = \begin{cases} N(i), & \text{if } i = j, \\ -1, & \text{if } i \sim j \text{ (areas } i \text{ and } j \text{ are neighbors)}, \\ 0, & \text{otherwise.} \end{cases} \quad (7.8)$$

Where $N(i)$ is the number of countries that are geographically contiguous to country i .

7.2.4 Spatio-Temporal Interaction Nonparametric Trend Model

This model extends Equation 7.5 by including a spatio-temporal interaction parameter (δ_{it}) in the linear predictor, capturing residual spatiotemporal variation unexplained by the spatial and temporal random effects. Mathematically,

$$\psi_{it} = \theta_i + \phi_i + \alpha_t + \gamma_t + \delta_{it} \quad (7.9)$$

Here, $\theta_i, \phi_i, \alpha_t$ & γ_t were modeled according to the respective prior specifications detailed in Equations (7.5)–(7.8), respectively. The spatio-temporal interaction effect $\delta_{it} = (\delta_{11}, \dots, \delta_{KT})' \sim \mathcal{N}(\mathbf{0}, \tau_\delta^2 \mathbf{Q}_\delta^-)$, where τ_δ^2 is the precision parameters, $\mathbf{Q}_\delta$ is the precision matrix and $\mathbf{Q}_\delta^-$ is the general inverse matrix for the precision matrix. Following Clayton (1996) approach, the interaction precision matrix ($\mathbf{Q}_\delta$) was constructed as the Kronecker product of the main effects' structure precision matrices involved in

the interaction. This approach is analogous to tensor product interactions in spline regression (Stone et al., 1997). Accordingly, this study considered four (2×2) types of spatio-temporal interaction, as defined by Knorr-Held (2000). These interactions arise as the product of one of the two spatial effects and one of the two temporal main effects, as presented in Table 7.1.

Table 7.1: Types of spatio-temporal interaction effects

Type	Interacting Effects	Precision Matrix (Q_δ)	Assumption / Interpretation
I	Uncorrelated temporal (γ) $\times$ Unstructured spatial (ϕ)	$Q_\delta = Q_\gamma \otimes Q_\phi = I \otimes I = I$	Random noise (no space-time structure), $\delta_{it} \sim \mathcal{N}(0, \tau_\delta^2)$
II	Correlated temporal (α) $\times$ Unstructured spatial (ϕ)	$Q_\delta = Q_\alpha \otimes Q_\phi = Q_\alpha \otimes I$	Linear temporal dependence to each specific area; varies by area without any spatial structure; this is the non-parametric analogue of the Bernardinelli et al. (1995) formulation.
III	Uncorrelated temporal (γ) $\times$ Structured spatial (θ)	$Q_\delta = Q_\gamma \otimes Q_\theta = I \otimes Q_\theta$	Spatial dependence (CAR) at each time point; spatial pattern varies over time without temporal dependence.
IV	Correlated temporal (α) $\times$ Structured spatial (θ)	$Q_\delta = Q_\alpha \otimes Q_\theta$	Both temporal and spatial dependence are present.

Potential confounding in this study was addressed through both covariates and random effects. Observed confounders were incorporated into the model via both linear fixed effects and nonlinear smooth terms, while unobserved spatial, temporal, and spatio-temporal confounders were partially accounted for by the spatial effects, temporal effects, and space–time interaction effects, respectively.

Temporal autocorrelation arises from repeated observations of the same populations over time. Spatial autocorrelation may result from neighborhood effects, grouping (clustering) effects, or unmeasured confounders (spatially patterned risk factors) omitted from the model. Confounding can also occur when the effects of space, time, or their interaction are not clearly separable from one another or from the model’s overall intercept (for instance, the overall intercept may be absorbed by θ_i , α_t ; θ_i and δ_{it} may be confounded if both capture spatial structure; α_t and δ_{it} may confound if both capture temporal trends) (Goicoa et al., 2018). This can lead to identifiability problems, where the model cannot uniquely determine which component is responsible for observed variation (Knorr-Held, 2000). To ensure model identifiability, sum-to-zero constraints were imposed on θ_i , α_t and δ_{it} , as proposed by Goicoa et al. (2018). Specifically, the constraints are: $\sum_{i=1}^K \theta_i = 0$ (spatial effects), $\sum_{t=1}^T \alpha_t = 0$ (temporal effects), $\sum_{i=1}^K \sum_{t=1}^T \delta_{it} = 0$ (Type I interaction), $\sum_{t=1}^T \delta_{it} = 0 \quad \forall i$ (Type II interaction) $\sum_{i=1}^K \delta_{it} = 0 \quad \forall t$ (Type III interaction) and both Type II and III constraints applied for Type IV interaction.

7.3 Parameter Estimation

For parameter estimation in spatio-temporal models, the study adopted the same inferential framework as that used for purely spatial models. In particular, model parameters and hyperparameters are estimated using the INLA approach, in which the latent field is assumed to follow a GMRF. INLA provides accurate approximations to posterior marginal distributions and offers faster computation and resolves convergence issues commonly found in MCMC methods (Rue et al., 2009; Martins et al., 2013).

In the spatio-temporal setting, the parameter vector of interest is defined as $\theta = \{\beta, \mathbf{f}\}$, where $\beta = (\beta_0, \beta_1, \dots, \beta_p)$ denotes the vector of fixed-effect regression coefficients and $\mathbf{f}$ represents the latent spatio-temporal random effects. The corresponding vector of hyperparameters is given by $\pi = \{\tau_\theta^2, \tau_\phi^2, \tau_\alpha^2, \tau_\gamma^2, \tau_\delta^2, \sigma^2\}$ and they controls the variability of the structured and unstructured spatial, temporal, and spatio-temporal interaction components, as well as the observation-level error term.

7.4 Results

7.4.1 Model Comparison

The DIC and WAIC values of the classical parametric trend model, spatio-temporal ANOVA model, dynamic nonparametric trend model, and spatio-temporal interaction nonparametric trend model are summarized in Table 7.2. Among the fitted models, the spatio-temporal interaction model incorporating Type II and Type IV interactions had the lowest WAIC and DIC values. However, these interaction models rendered all covariate effects statistically insignificant, indicating that almost all variation was attributed to spatial, temporal, and interaction components. This dominance suggested over-parameterization and instability in the estimated model parameters, thereby reducing the reliable of covariate-specific inference.

This behavior may be attributed to the high structural complexity of the spatio-temporal Type II and Type IV interaction models, which can lead to identifiability challenges during estimation, as these specifications combine multiple structured latent components representing spatial, temporal, and their interaction effects. The inclusion of highly flexible interaction terms substantially increased the dimensionality of the latent field. It may induce strong dependence and confounding between the main spatial and temporal effects with the interaction component. Consequently, the effects of the observed covariates became weakly identifiable, leading to inflated posterior uncertainty and an apparent loss of statistical significance. In addition, the increased complexity of the latent structure gave rise to numerical and convergence difficulties during model estimation, further destabilizing parameter estimates and compromising

the reliability of inference on covariate effects.

Therefore, the study selected the Type I interaction model, which yielded the lowest DIC and WAIC values among the remaining candidate models. The Type I interaction assumes independent (unstructured) deviations for each country–year combination, thereby capturing localized random shocks that cannot be explained by the main spatial or temporal effects. Unlike the more complex Type II and Type IV interaction specifications, the Type I interaction model maintained the explanatory power of the covariates while providing a better balance between model fit, complexity and interpretability. Accordingly, all subsequent analyses in this study were based on the spatio-temporal additive model with a Type I interaction.

Table 7.2: Spatio-temporal models fit comparison

S.No	Model	DIC	WAIC
1	Classical Parametric Trend Model	1737.06	1739.67
2	Spatiotemporal ANOVA Model	1736.86	1739.46
3	Dynamic Nonparametric Trend Model	1514.69	1521.03
4	Space–Time Interaction Nonparametric Trend Models		
	Type I Interaction	1443.94	1446.76
	Type II Interaction	−2213.83	−2325.52 (RW1)
		1290.20	1363.62 (RW2)
	Type III Interaction	1493.33	1478.60
	Type IV Interaction	1601.16	1598.82 (RW1)
		1351.66	1394.30 (RW2)

7.4.2 Estimates of Fixed Covariate Effects

The estimation results for the spatio-temporal type I interaction model with fixed-effect parameters are presented in Table 7.3. The results showed that malaria incidence, climate change, livestock production and investment inflow significantly contributed to the risk of severe food insecurity. Higher malaria incidence and greater climate change intensity contributed to escalating the risk of severe food insecurity, whereas higher levels of livestock production and investment inflow contributed to reducing the risk. Specifically, a one-unit increase in livestock production is expected to reduce the prevalence of severe food insecurity by 0.0449 units, while a one-unit increase in investment inflows is expected to reduce it by 0.0315 units. In contrast, a one-unit increase in malaria incidence is expected to increase the prevalence of severe food insecurity by 0.0076 units. Similarly, a one-unit increase in the climate change index expected to increase the prevalence by 0.6476 units. These covariate effects are assumed to be constant across their observed value ranges.

Table 7.3: Posterior mean estimates for fixed-effect covariates

Fixed-Effect Covariates	Estimate	SD	95% Credible Interval	
			Lower	Upper
Intercept	31.4676	2.5248	26.5192	36.4160
Electricity_access	-0.0091	0.0233	-0.0548	0.0365
Political_stability	0.3823	0.2753	-0.1573	0.9219
Malaria_incidence	0.0076	0.0031	0.0015	0.0137*
Climate_change	0.6476	0.3132	0.0337	1.2615*
Livestock_production	-0.0449	0.0158	-0.0758	-0.0140*
Cereals_crops_production	-0.0010	0.0034	-0.0076	0.0056
Investment_inflow	-0.0315	0.0115	-0.0541	-0.0090*

7.4.3 Estimates of Nonlinear Covariate Effects

In addition to examining the effects of linear fixed-effect covariates, the spatio-temporal model investigated the dynamic and nonlinear relationships between selected covariates and outcome non-parametrically. Similar to the spatial model results, the estimated variability parameters associated with cereal import dependence, dietary energy supply, GHG emissions, GDP, unemployment, inflation, caloric loss, and dietary protein supply in the spatio-temporal model were also statistically significant at the 95% credible interval. This finding provides evidence that the relationships between these covariates and severe food insecurity are not adequately captured by simple linear functions. This implies that the magnitude of their effects may vary across the range of observed values.

Figure 7.1 displayed the estimated posterior means and 95% CIs for the nonlinear effects of the selected covariates. The graph showed that the 95% CIs for the smoothed estimates of GHG emissions, unemployment, GDP per capita, dietary energy supply, and protein supply don't include zero over some portions or across their observed ranges. This indicates that these covariates have statistically significant nonlinear effects on severe food insecurity. The magnitude and direction of these effects varied across their ranges of observed values. Consequently, small changes in a predictor may have strong effects in certain regions of its distribution and weak or negligible effects in others. In other words, a one-unit change in a nonlinear covariate does not produce a constant change in severe food insecurity. This emphasize the importance of accounting for complex relationships between predictors and severe food insecurity.

The graph further showed that the estimated smooth functions for GHG emissions and unemployment increased within their observed ranges, whereas those for GDP per capita, dietary energy and protein supply declined within their observed ranges. These results indicated that GHG emissions and unemployment contributed to intensifying the risk of severe food insecurity, while GDP per capita, dietary energy and protein

supply contributed to reducing the risk.

In contrast, the 95% CIs for cereal import dependency, caloric loss, and inflation includes zero across their ranges. This suggest that these nonlinear covariates do no have statistically significant effects on severe food insecurity. The 95% CIs for caloric loss and inflation are relatively wide, particularly at the lower and upper ends of their ranges. These likely reflecting a limited number of observations in these cases.

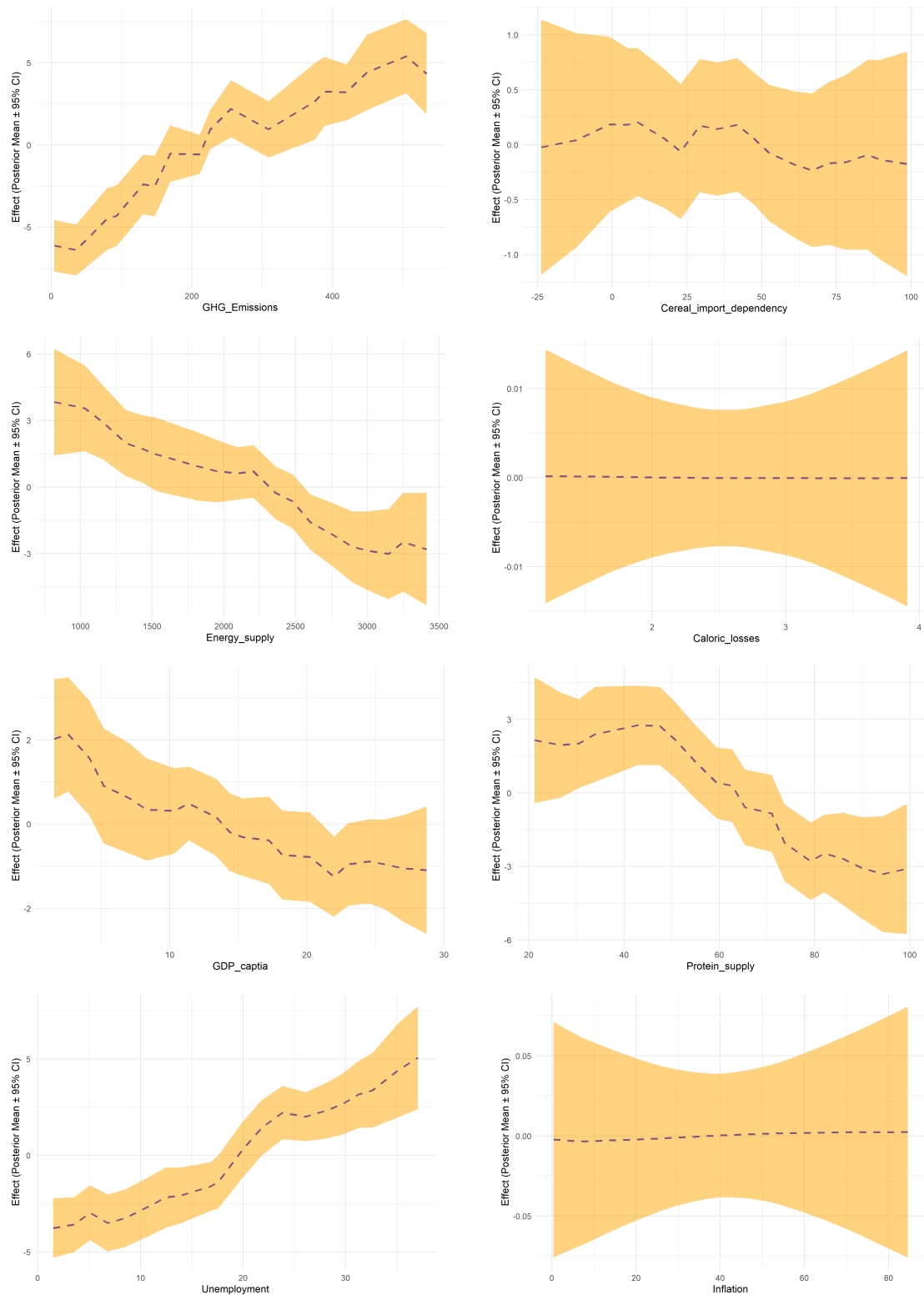


Figure 7.1: Smoothed estimates of nonlinear covariate effects

7.4.4 Estimates of Spatio-Temporal Effects

The estimates of the spatial, temporal, and interaction components are presented in Table 7.4. The results revealed that these random components were statistically sig-

nificant at the 95% credible intervals. This finding indicated the existence of strong spatial and temporal dependencies in the patterns of severe food insecurity. These estimates provided insights into the relative contributions of structured, unstructured, and spatio-temporal interaction sources of variability to severe food insecurity across Africa during the 2015-2021 period.

The significance of structured spatial effect ($\tau_\theta^2 = 2705.77$) suggested a geographic correlation, indicating that neighboring countries tend to exhibit similar patterns of severe food insecurity. In contrast, the unstructured spatial effect ($\tau_\phi^2 = 0.03$) reflected substantial country-specific variability that was not explained by spatial proximity. Temporally, the structured effect ($\tau_\alpha^2 = 10.75$) captured systematic changes over time, whereas the unstructured temporal component ($\tau_\gamma^2 = 28318.18$) showed irregular, year-to-year random fluctuations rather than systematic temporal trends.

The inclusion of spatio-temporal interaction effects provides important insights into how severe food insecurity evolves differently across countries and over time. The significant spatio-temporal interaction term ($\tau_\delta^2 = 29438.77$) also exhibited additional variability beyond the separate spatial and temporal effects. This suggests that temporal changes are not uniform across locations and that countries experience distinct trajectories influenced by their unique socioeconomic, environmental, and political contexts.

In practical terms, the interaction effects capture country-specific deviations from the overall temporal trend, reflecting the influence of localized shocks and circumstances that cannot be explained solely by spatial patterns or common time trends. These effects highlight that countries may respond differently to similar external pressures due to variations in resilience, institutional capacity, resource availability, and local conditions. Consequently, countries with similar geographic characteristics or socioeconomic conditions may still experience different food insecurity trajectories because their exposure and responses to shocks vary.

For example, a drought, conflict escalation, or economic instability may lead to a rapid increase in severe food insecurity in one country while having a relatively limited effects in another due to differences in resilience, infrastructure, governance capacity, or adaptive mechanisms. Therefore, understanding country-specific temporal shocks is essential for designing timely and targeted interventions, as countries may require different response strategies depending on their unique risk trajectories and contextual vulnerabilities.

Table 7.4: Posterior estimates for the random components

Random Components	Estimate	SD	95% CIs	
			Lower	Upper
τ_{θ}^2	2705.77	2983.89	255.04	10561.98
τ_{ϕ}^2	0.03	0.01	0.02	0.05
τ_{α}^2	10.75	8.06	2.27	32.00
τ_{γ}^2	28318.18	31831.42	2810.63	111780.89
τ_{δ}^2	29438.77	34970.93	2769.75	120403.54
σ^2	0.37	0.04	0.30	0.44

Figure 7.2 depicts the unstructured spatial effect, which represents residual spatial variation not explained by neighborhood correlation. This component captures country-specific influences that operate independently of spatial dependence. In this map, darker red shades indicate positive unstructured effects, suggesting that a country experienced relatively higher levels of severe food insecurity due to factors not shared with neighboring countries. Countries like South Sudan, the Central Republic of Africa, Malawi, Guinea, Republic of Congo, Cameroon, and Somalia showed large positive unstructured effects. Conversely, lighter shades indicate negative unstructured effects, reflecting relatively lower levels of severe food insecurity attributable to country-specific conditions. Countries exhibiting negative unstructured effects may be characterized by stronger governance structures or more effective food security programs.

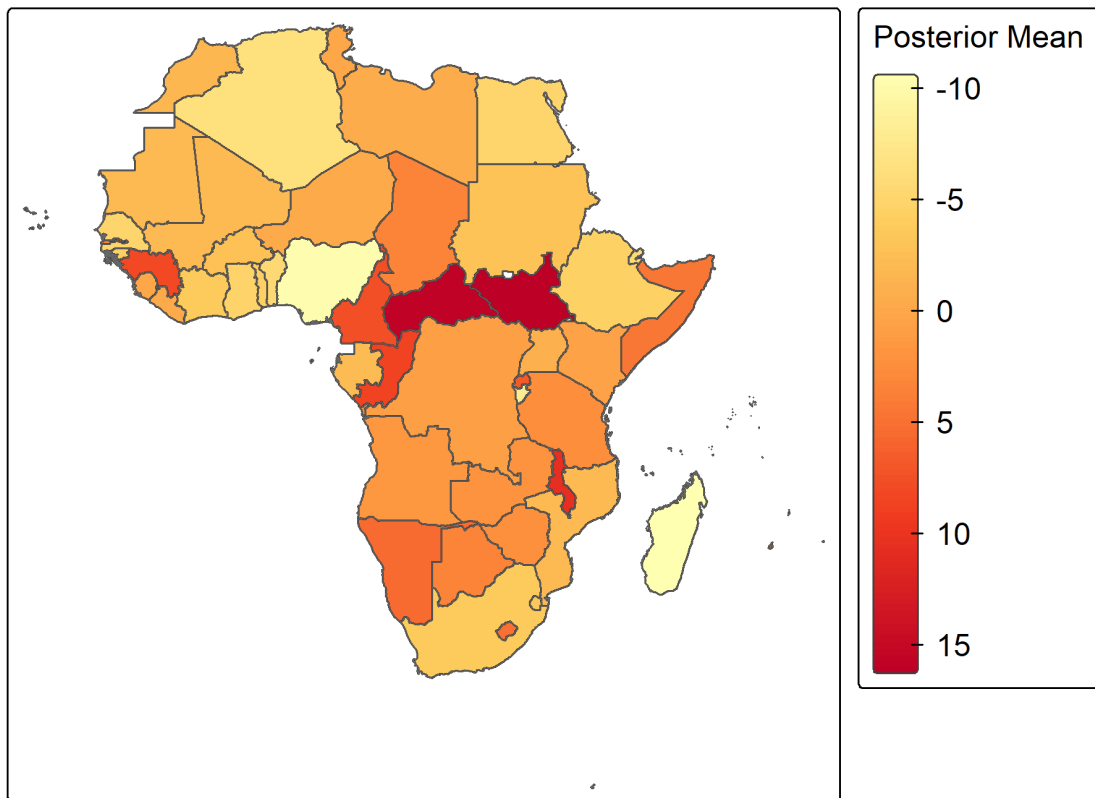


Figure 7.2: Posterior mean estimates of unstructured spatial effects

Figure 7.3 illustrates the structured spatial effect of severe food insecurity. This effect captured the spatial correlation among neighboring countries. Dark red shades on the map represent countries with positive structured spatial effects. This indicates that the risk of severe food insecurity in these countries was higher than the overall mean and that neighboring countries also experienced relatively high levels. Many countries in the Southern, Eastern and Central African subregions exhibited strong spatial dependence in severe food insecurity due to persistent structural constraints and unobserved spatially correlated factors. In contrast lighter red shades represent negative structured spatial effects. This indicates that both the country and its neighboring countries exhibited levels of severe food insecurity below the overall average. The northern part of the continent exhibited comparatively lower risks of severe food insecurity. This pattern reflected weaker spatial dependencies in that region. The findings also indicated that severe food insecurity did not exhibit improvement over time.

Figure 7.3: Posterior mean estimates of structured spatial effects

Figure 7.4 shows the estimated spatio-temporal interaction effects of severe food insecurity across African countries from 2015-2021. The interaction maps identify the countries that experienced unusual deviations in a particular year, representing distinct country-year-specific variations in severe food insecurity that are not explained by the main spatial or the common temporal component of the model. A negative interaction effect (shaded in light red color) indicates that a country experienced lower-than-expected levels of severe food insecurity, whereas positive interaction effect (shaded in dark red color) indicates that a country experienced higher-than-expected levels of severe food insecurity for a given year relative to the country's spatial contexts and the overall continental temporal trend. Across much of the study period, Kenya, Ethiopia, Niger, and Burkina Faso frequently experienced unusual deviations in a given year. During the initial periods (2015–2017), the interaction effect was relatively low in most regions of the continent. Between 2018 and 2021, the patterns shifted, and many countries experienced an escalation in severity, moving into higher levels of severe food insecurity.

Specifically, Kenya, Ethiopia, Niger, and Burkina Faso experienced these deviations in the later years of the study period. These frequently exhibited positive interaction effects during the study period reflect the presence of country-specific shocks or circumstances that were not shared with neighboring countries or captured in the

overall temporal trend. In contrast, the negative deviations may reflect country-specific improvements or effective policy interventions that mitigate food insecurity despite unfavorable regional conditions.

Figure 7.4: Posterior mean estimates of interaction effects

Figure 7.5 presents the posterior mean and 95% CIs for the correlated temporal effect (RW1) on severe food insecurity over the study period. This component captured the common temporal trends shared across all countries, representing the continent-wide evolution of severe food insecurity rather than country-specific temporal patterns. This reflects changes in severe food insecurity driven by continental- or global-level influences, including fluctuations in global food prices, climate events, or widespread socioeconomic disruptions. The results showed a clear and steady upward temporal trend continent-wide over the study period. In the early years (2015–2017), the estimated temporal effect remained negative, indicating that the continent-wide level of severe food insecurity during these specific years was below the overall long-term mean.

Around 2018, the temporal effect crossed the zero line and subsequently exerted an increasingly positive influence on severe food insecurity. These positive estimated temporal effect values in a year indicate that, on average, the continent-wide risk of severe food insecurity was higher than the long-term mean for that year. The 95% credible intervals in both early and later years exclude zero, confirming that the observed

increase in severe food insecurity was statistically significant and persistent throughout the period. This escalation likely reflects the cumulative impact of temporal drivers, such as prolonged conflict, macroeconomic instability, climate change, and other external shocks, on the trajectory of severe food insecurity across Africa.

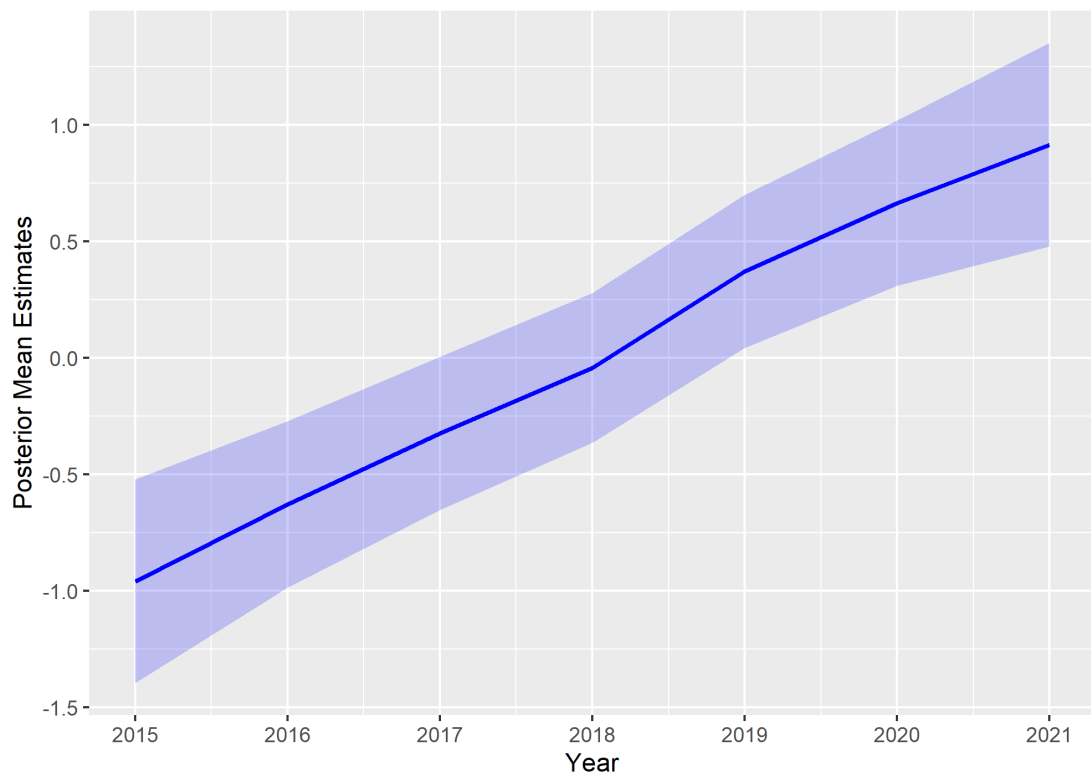


Figure 7.5: Posterior mean estimates of continental-level correlated temporal effects

Figure 7.6 illustrates the temporal trends in the fitted values of severe food insecurity across all countries in the continent, incorporating all model components, including covariate, spatial, temporal, and interaction effects. The results showed that all these model components collectively contributed to an escalation in the risk of severe food insecurity across many countries over time, a pattern consistent with broader continent-wide temporal trends.

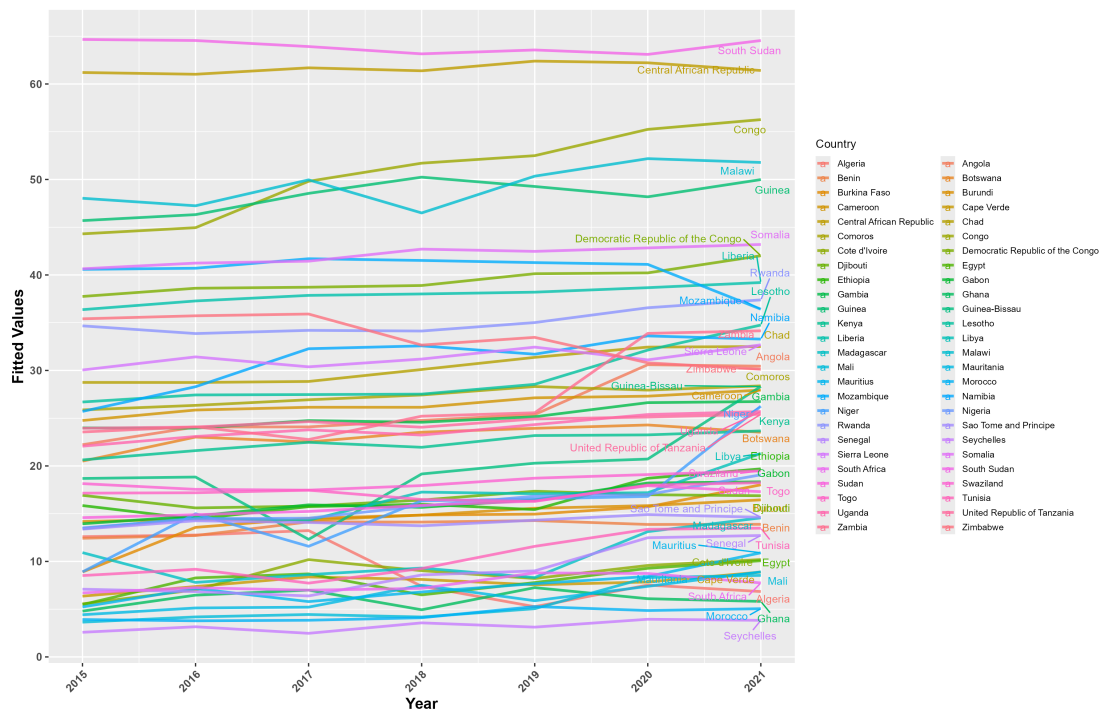


Figure 7.6: Posterior mean estimates of country-level temporal effects

Figure 7.7 illustrates the spatial distribution of the posterior mean of fitted values of severe food insecurity in Africa over 2015-2021, incorporating all model components including covariate effects, spatial effects, temporal effects, and any interaction terms. On the map, dark red shades represent countries with a higher risk of severe food insecurity, whereas light shades represent countries with a lower risk relative to other regions. Throughout the study period, South Sudan, Central Africa Republic, Republic of the Congo, Malawi, Guinea and Somalia exhibited the highest risk of severe food insecurity. In contrast, countries in the northern part of the continent consistently experienced a lower risk of severe food insecurity than those in other parts of the region.

Figure 7.7: Geographic distribution of posterior mean estimates of the fitted values

7.4.5 Model Diagnostics

Figure 7.8 compares the observed and estimated values of severe food insecurity across the study period. Most data points are closely aligned with the straight lines for each year, indicating strong agreement between the model's predictions and the observed values. This suggested that the model accurately captured the patterns and magnitudes of severe food insecurity. Each year, represented by distinct colors, followed a similar linear trend, suggesting that the model's predictive performance remained consistent across different temporal contexts. Importantly, no significant systematic bias was observed in any specific year, further reinforcing the robustness of the model in estimating the risk of severe food insecurity throughout the study period.

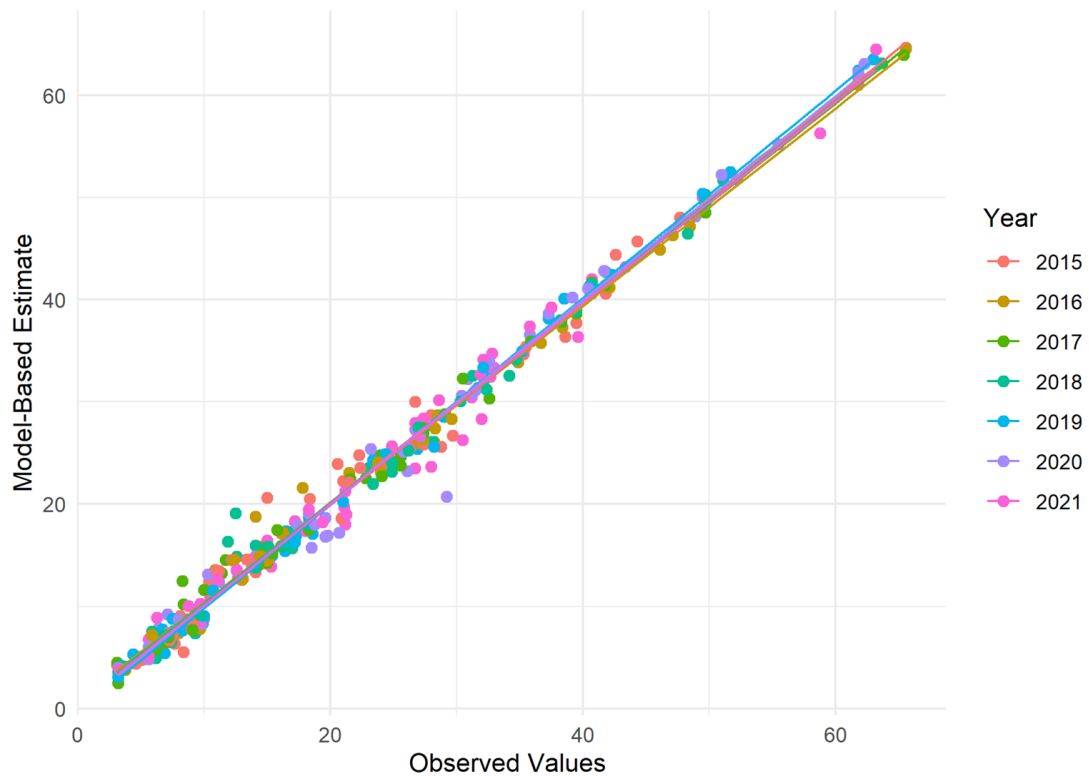


Figure 7.8: Comparisons of observed and model-based estimates across year

Figure 7.9 illustrated the autocorrelation function (ACF) and partial autocorrelation (PACF) plots used to assess temporal dependence in the model residuals. The ACF showed a gradual decay with significant positive autocorrelations at lag 1 and lag 2, followed by significant negative correlations up to lag 6. The PACF plot, on the other hand, showed a significant spike at lag 1, with subsequent lags falling within the confidence bounds. This pattern indicated the presence of short-term temporal dependence in residuals, which was largely captured by a first-order autoregressive (AR (1)) process.

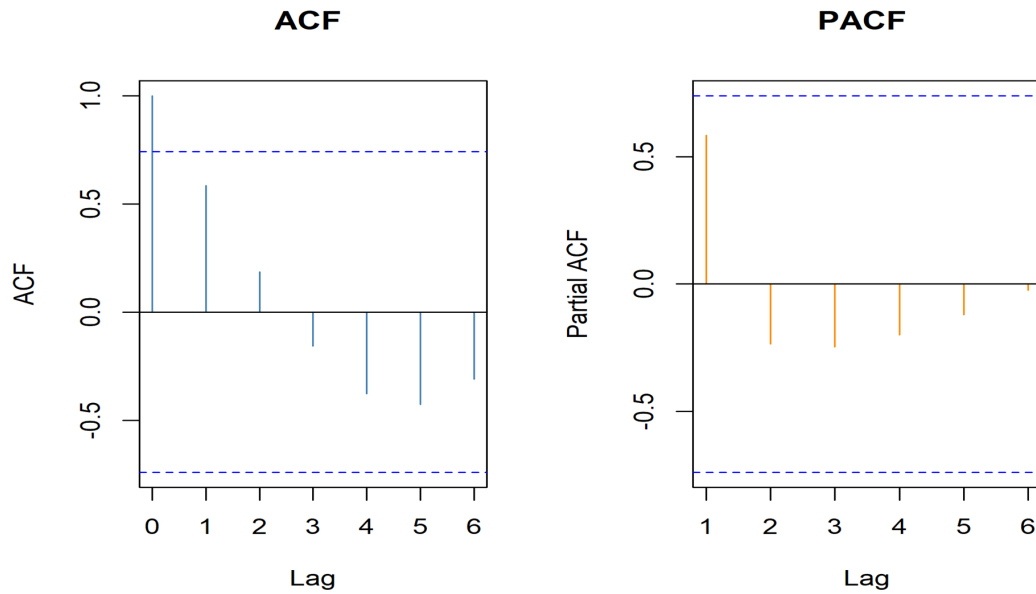


Figure 7.9: ACF and PACF plots of the temporal component (RW1)

Figure 7.10 showed diagnostic checks assessing normality and homoscedasticity. The residuals appeared approximately normally distributed and they exhibited constant variance across fitted values, indicating that the assumption of homoscedasticity was satisfied. Moreover, the observed and predicted values are closely aligned, confirming that the model meets key assumptions and fits the data well.

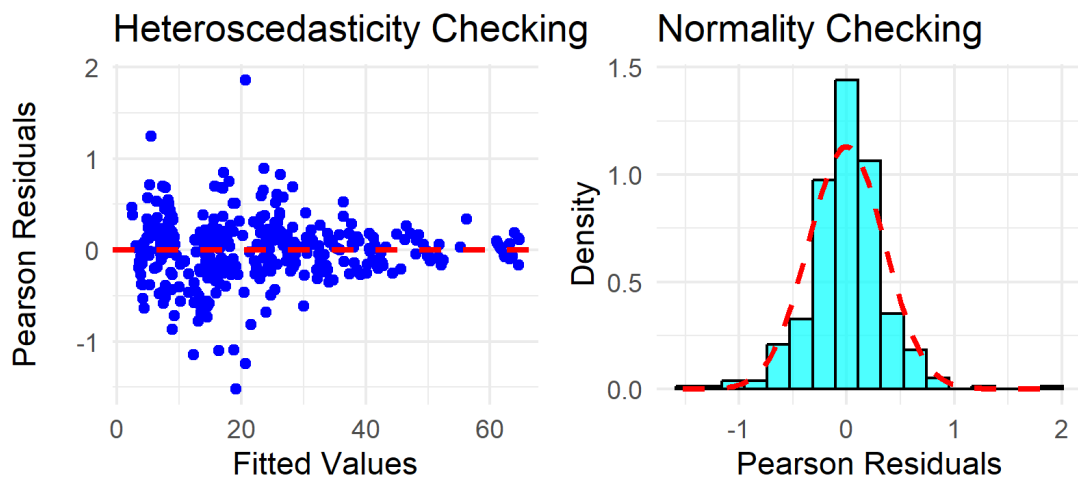


Figure 7.10: Assessment of normality and heteroscedasticity assumptions

7.5 Summary

This chapter used spatio-temporal models, including the classical parametric trend model, the dynamic nonparametric trend model, the spatio-temporal interaction

nonparametric model, and the spatio-temporal ANOVA model, to assess the determinants and spatio-temporal dependence of severe food insecurity. The findings showed that severe food insecurity was significantly spatially dependent, temporally correlated, and influenced by their interactions. In addition, the risk exhibited an increasing trend, with substantial disparities observed across African countries over time.

Throughout the study period, South Sudan, Central African Republic, Republic of the Congo, Malawi, Guinea, Cameroon, and Somalia experienced higher risk than other countries due to country-specific factors, whereas the southern, eastern, and central subregions exhibited strong spatial dependencies in severe food insecurity due to persistent structural constraints and unobserved spatially correlated factors. In addition, across much of the study period, Kenya, Ethiopia, Niger, and Burkina Faso frequently experienced unusual country-year-specific deviations compared to other countries. Furthermore, the study identified that malaria incidence, climate change, livestock production, and investment inflow had statistically significant linear fixed effects on the risk of severe food insecurity. In contrast, GHG emissions, GDP per capita, unemployment, dietary energy and protein supply exhibited statistically significant, complex and non-linear influences on severe food insecurity.

Despite the comprehensive understanding and modeling of spatio-temporal dependence, interaction effects and determinate effects in this chapter, several limitations should be acknowledged. First, the models assume that the marginal effects of covariates are globally constant over space and time. This may mask important local variations and context-specific relationships in the determinants of severe food insecurity. Second, although nonlinear effects and spatio-temporal structures are incorporated, the framework does not explicitly allow regression coefficients to vary simultaneously across both space and time. To address these limitations, Chapter 8 extended the analysis by employing spatio-temporally varying coefficient models. This approach enabled the effects of key predictors to vary flexibly across both space and time for a more nuanced and policy-relevant interpretation.

Chapter 8

Spatio-Temporally Varying Effects of Predictors on Severe Food Insecurity

8.1 Introduction

The influence of economic, environmental, and institutional factors on severe food insecurity is unlikely to be uniform across countries or stable over time. Instead, these effects may vary in both magnitude and direction depending on local conditions and temporal contexts. Ignoring such spatio-temporal heterogeneity may obscure important local insights and limit the policy relevance of the findings.

To address the limitations identified in Chapter 7, more flexible modeling approaches are required that allow covariate effects to vary across both space and time. Accordingly, this chapter extended the classical spatio-temporal modeling framework to a spatio-temporally varying coefficient (STVC) model. The STVC model enables the estimation of dynamic, location-specific relationships between predictors and severe food insecurity. It also facilitates the identification of where and when covariate effects exert stronger or weaker influences on severe food insecurity outcomes. Consequently, this approach provides a more nuanced, context-specific, and policy-relevant understanding of the determinants of severe food insecurity across Africa.

8.2 Model Specification

Traditional or global regression assumes that the model's parameters are constant across space and time. This assumption is relaxed in STVC models by allowing the parameters to vary spatially and temporally. The STVC model also allows the co-existence of both global and local relationships ([Song et al., 2020](#)).

Let y_{it} represent the annual prevalence of severe food insecurity for country $i = 1, \dots, 52$ during year $t = 1, \dots, 7$, forming $\mathbf{Y} \in \mathbb{R}^{52 \times 7}$ with $\mathbf{y}_t \in \mathbb{R}^{52 \times 1}, \forall t$. The mean process $\mu_{it} = E(y_{it} \mid x_{it}, z_{it})$ is linked to the linear predictor η_{it} through identity link function, such that $g(\mu_{it}) = \eta_{it}$. The x_{it} = (electricity access, political stability, malaria incidence, climate change, livestock production, cereals crop production, investment inflow) represents the linear covariates and z_{it} = (GHG emissions, GDP per capita, unemployment, inflation, cereal import dependency, caloric losses, dietary

energy supply, and dietary protein supply) represents the nonlinear covariates related to severe food insecurity for country k and over time-period t . This classification of covariates is addressed in the preceding chapters. To account for both global and local spatio-temporal covariate effects, the STVC model was used and mathematically represented as follows:

$$y_{it} = \mu_{it} + \epsilon_{it}, \quad i = 1, \dots, 52, \quad t = 1, \dots, 7 \quad (8.1)$$

$$\eta_{it} = \mathbf{X}_{it}\boldsymbol{\alpha} + f(\mathbf{Z}_{j,it}) + \theta_i + \phi_i + \alpha_t + \gamma_t + \delta_{it} \quad (8.2)$$

$$f(\mathbf{Z}_{j,it}) = \sum_{j=1}^q \beta_j(s, t) \mathbf{Z}_{(j,it)} \quad (8.3)$$

Where $y_{it} \sim N(\mu_{it}, \nu^2)$, $\nu^2 \sim IG(1, 0.001)$, $\mathbf{X}_{it} \in \mathbb{R}^{K \times p}$ denotes the design matrix for the fixed effect covariates at country i and time t , $\boldsymbol{\alpha} \sim N(\boldsymbol{\mu}_\alpha, \boldsymbol{\Sigma}_\alpha)$ is the $p \times 1$ vector of global fixed-effect coefficients that are assumed to be constant across space and time corresponding to x_{it} , f_j represents smooth functions of the nonlinear covariates, $\mathbf{Z}_{it} \in \mathbb{R}^{K \times q}$, with $KT \times 1$ spatio-temporally varying coefficients or local predictors $\beta_j(s, t) \sim GP(\mathbf{0}, \boldsymbol{\Sigma}_\beta)$. The diagonal elements of $\boldsymbol{\Sigma}_\beta$ are equal to σ_β^2 , which serves as a hyperparameter controlling the variability of $\beta_j(s)$ for $j = 1, \dots, q$.

The error term $\epsilon_{it} \sim GP(\mathbf{0}, \boldsymbol{\Sigma}_\epsilon)$ represents a zero-mean Gaussian white noise process with variance–covariance matrix $\boldsymbol{\Sigma}_\epsilon$. It is defined over the $KT \times KT$ covariance structure of the error vector $\boldsymbol{\epsilon} \in \mathbb{R}^{KT \times 1}$, where $\boldsymbol{\epsilon} = \{\epsilon_{it}\}$ for $i = 1, \dots, K$ and $t = 1, \dots, T$ (Gneiting, 2002). The diagonal elements of $\boldsymbol{\Sigma}_\epsilon$ are given by the constant variance σ_ϵ^2 .

The parameters $\theta_i, \phi_i, \alpha_t, \gamma_t$ and δ_{it} denote the random components of the model, where the first two represents spatial effects, the next two captures temporal effects and the last represent the spatio-temporal interaction effect across locations and time, respectively. These random components were modeled according to the priors defined in Equations (7.5)–(7.9).

8.3 Results

8.3.1 Global Effects of Covariates

Table 8.1 reported the global-effect estimates from the best-performing spatio-temporal Type I interaction model. The findings indicated that malaria incidence, climate change, livestock production, and investment inflow were statistically significant determinants of severe food insecurity, with their marginal effects remaining consistent across countries and over time. A one-unit increase in livestock production and investment inflow reduced severe food insecurity by 0.0449 and 0.0315 units, respectively.

In contrast, a one-unit increase in malaria incidence and climate change increased it by 0.0076 and 0.6476 units respectively.

Table 8.1: Estimates of global covariate effects on severe food insecurity

Global Effect Covariates	Estimate	SD	95% CIs	
			Lower	Upper
Intercept	31.4676	2.5248	26.5192	36.4160
Electricity_access	-0.0091	0.0233	-0.0548	0.0365
Political_stability	0.3823	0.2753	-0.1573	0.9219
Malaria_incidence	0.0076	0.0031	0.0015	0.0137*
Climate_change	0.6476	0.3132	0.0337	1.2615*
Livestock_production	-0.0449	0.0158	-0.0758	-0.0140*
Cereals_crops_production	-0.0010	0.0034	-0.0076	0.0056
Investment_inflow	-0.0315	0.0115	-0.0541	-0.0090*

8.3.2 Spatio-Temporally Varying Covariate Effects

This study further investigated the spatio-temporally varying relationships between selected covariates and severe food insecurity across African nations to account for potential heterogeneity in the effects of covariates across geographic locations and over time. Unlike standard regression models that assume a constant covariate effect throughout the study area and period, this approach allows the effect of a covariate to vary spatially and temporally.

The detailed estimates of the results of the random components related to spatial, temporal and interaction components are summarized in Table 8.2. The significance of random component estimates indicated that both neighboring countries and past incidence influenced a country's severe food insecurity crises. Specifically, the estimates of structured spatial effect ($(\tau_{\theta}^2 = 2705.77)$) suggested that neighboring countries tended to exhibit similar levels of severe food insecurity, while the unstructured spatial effect ($(\tau_{\phi}^2 = 0.03)$) reflected the country-specific variability beyond spatial proximity. Temporally, the structured effect ($(\tau_{\alpha}^2 = 10.75)$) reflected temporal autocorrelation, suggesting that current prevalence were partly influenced by past trends, while the unstructured effect ($(\tau_{\gamma}^2 = 28,318.18)$) represented that year-to-year variation arising from unpredictable random fluctuations. The space-time interaction ($(\tau_{\delta}^2 = 29,438.77)$) component further contributed to additional variability in severe food insecurity dynamics across Africa over time.

Table 8.2: Posterior estimates of the spatial, temporal, and spatio-temporal interaction random effects.

Random Components	Estimates	SD	95% CIs	
			Lower	Upper
τ_{θ}^2	2705.77	2983.89	255.04	10561.98
τ_{ϕ}^2	0.03	0.01	0.02	0.05
τ_{α}^2	10.75	8.06	2.27	32.00
τ_{γ}^2	28318.18	31831.42	2810.63	111780.89
τ_{δ}^2	29438.77	34970.93	2769.75	120403.54
σ^2	0.37	0.04	0.30	0.44

Similar to the findings of the spatial and spatio-temporal model presented in the preceding chapter, the 95% credible intervals associated with the variability parameters of the spline (smooth) terms for GDP per capita, unemployment, caloric losses, dietary energy supply, dietary protein supply, GHG emissions, cereal import dependency, and inflation indicate significant variability in their smooth effects. These results provide evidence that the relationships between these covariates and severe food insecurity are not adequately described by simple linear functions and contain nonlinear components that should be retained in the model.

The significance of spatio-temporally variability parameters associated with the smoothed covariates further indicates that their effects vary locally across space and time (i.e., spatio-temporally), whereas insignificant variability parameter suggest that the corresponding effects don't exhibit substantial local variations across space and over time (Comber et al., 2024). However, significant variability in a smooth term does not necessarily imply that the covariate exerts a statistically significant effect across its observed range.

The estimated smooth functions of the nonlinear covariates are presented in Figure 8.1. The figure showed that the 95% credible intervals for GHG emissions, unemployment, GDP per capita, dietary energy supply, and dietary protein supply exclude zero over some portions or across their observed ranges. This indicates that these covariates exhibited statistically significant nonlinear associations with severe food insecurity. Furthermore, these results suggest that the effects of these covariates on severe food insecurity vary across locations and over time.

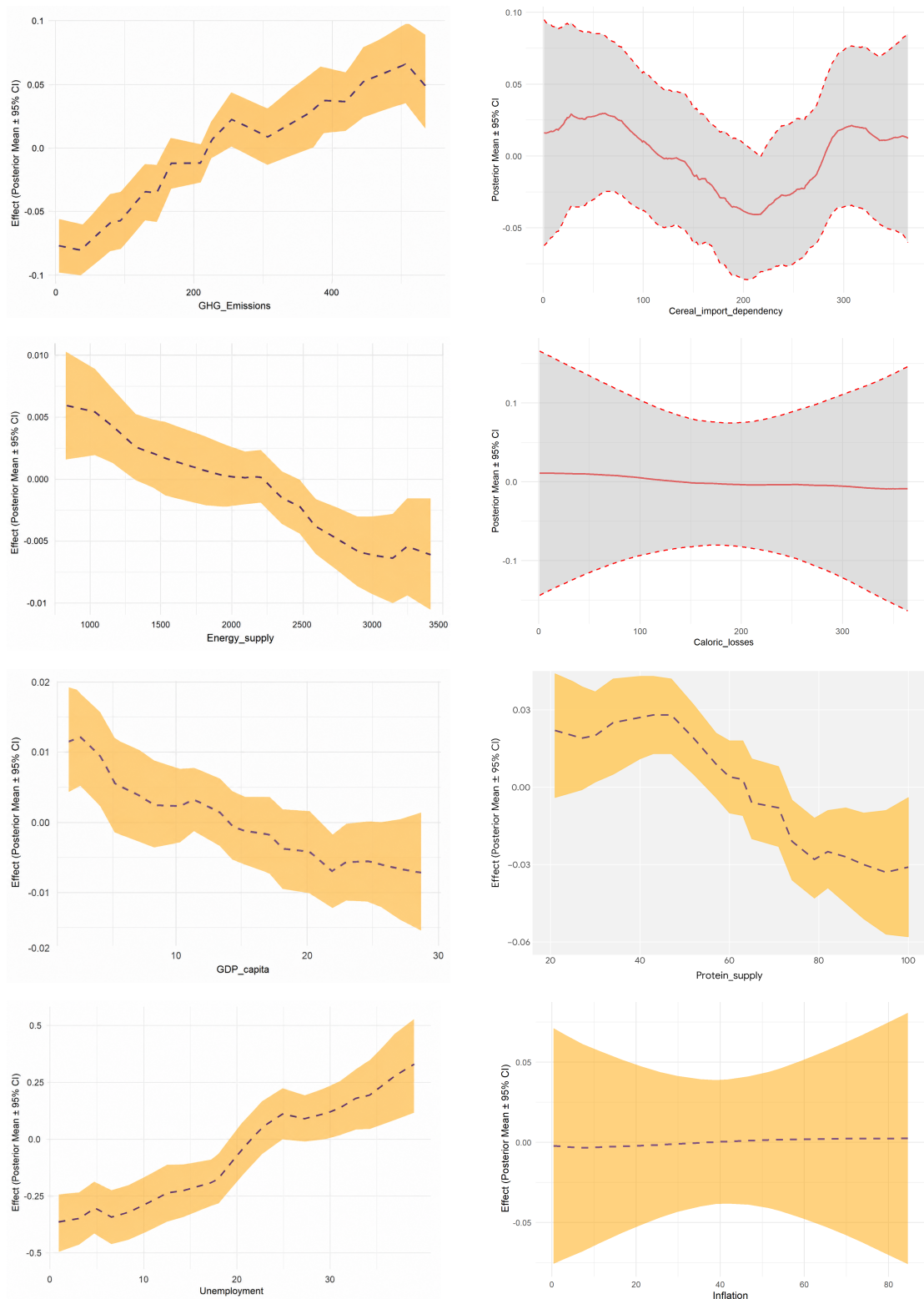


Figure 8.1: Smoothed estimates of nonlinear covariate effects

In contrast, although cereal import dependency, caloric losses, and inflation exhibited variability in their smooth effects, their 95% credible intervals include zero across the observed ranges. This suggests that these covariates do not have statistically significant effects on severe food insecurity. This further confirmed that their effects

did not exhibit substantial variation across space and time.

The estimated regression coefficients of the statistically significant nonlinear covariates associated with severe food insecurity were further examined to assess the presence of spatial and temporal variation. This analysis was conducted by first extracting the coefficient estimates and subsequently modeling them using a linear specification over space and time. The results indicate that the random components associated with both the spatial and temporal terms of the coefficients are statistically significant. This finding provides evidence of spatial and temporal heterogeneity in the estimated effects of GHG emissions, unemployment, GDP per capita, dietary energy supply, and dietary protein supply with magnitude and in some cases, the direction of the effects varying across locations and over time. These results reinforce the earlier findings from the nonlinear smooth term analysis, demonstrating that the relationships between the key covariates and severe food insecurity are not spatio-temporally constant. These suggest that a single global effect was insufficient to fully capture the complexity of these relationships.

Although accounting for joint spatial and temporal dimensions resulted in a better-performing model, this does not imply the absence of distinct spatial or temporal effects (Comber et al., 2024). Rather, it suggests that covariate effects that do not vary significantly across space and time may still exert a global influence. These results emphasize the importance of capturing the complex spatio-temporal heterogeneity in the relationships between covariates and severe food insecurity.

The results of spatio-temporally heterogeneity of the estimated covariate effects on severe food insecurity across Africa are visually presented in Figure 8.2. In the figures, darker red shades indicated a higher contribution of a predictor to severe food insecurity, whereas the lighter color shades represented a lower contribution. The observed heterogeneity in the estimated coefficients suggested the presence of localized and time-varying relationships between country-level determinants and severe food insecurity. This enabled the identification of countries and periods where specific covariates exerted comparatively stronger or weaker influences on severe food insecurity outcomes. Such variation likely reflected differences in national economic structures, agricultural systems, climatic conditions, and policy environments, which may differentially shaped food access, availability, and stability.

For instance, unemployment emerged as a widespread positive contributor in escalating severe food insecurity across most African countries, with stronger effects in Ethiopia, Libya, Niger, Malawi, Namibia, Liberia, Somalia, and Madagascar, where labor market constraints may more strongly exacerbated food access challenges. Similarly, the contribution of GDP to severe food insecurity was relatively pronounced in Algeria, Libya, Angola, Botswana, Malawi, Lesotho, Liberia, Benin, Kenya and Madagascar over the study period, suggesting that macroeconomic conditions may played a

particularly influential role in these contexts.

Beyond these macroeconomic drivers, environmental and structural factors also showed substantial spatial heterogeneity in their contributions to the escalation of severe food insecurity. GHG emissions contributed in intensifying severe food insecurity in nearly all African countries, with particularly strong contributions observed in the Democratic Republic of the Congo, Republic of Congo and Côte d'Ivoire. Dietary energy supply also demonstrated marked spatial variation in its relation with severe food insecurity, with relatively high contributions observed in Zimbabwe, Zambia, Tanzania, Kenya and Lesotho, reflecting persistent challenges in meeting minimum energy requirements. In parallel, dietary protein supply contributed to severe food insecurity across much of the continent; however, its effect was comparatively stronger in Sudan, South Sudan, Tunisia, Somalia, Uganda, Tanzania, Zambia, Zimbabwe, South Africa, Senegal, Sierra Leone, and Togo.

(A) GHG emissions

(B) Unemployment

(C) GDP

(D) Energy supply

(E) Protein supply

Figure 8.2: Estimates of spatio-temporally varying covariate effects

8.3.3 Model Diagnostics

Figure 8.3 compares observed and estimated severe food insecurity over time. The close alignment between points and fitted lines indicates strong predictive accuracy with no evidence of systematic bias, suggesting that the model reliably captures temporal patterns. Figure 8.4 presents ACF and PACF plots of residuals. The results indicate short-term dependence with a dominant lag-1 effect, suggesting that most temporal autocorrelation is captured by a first-order autoregressive structure. Figure 8.5 shows diagnostic checks for normality and homoscedasticity. The residuals are approximately normal with constant variance, indicating that key model assumptions are satisfied and that the model fits the data well.

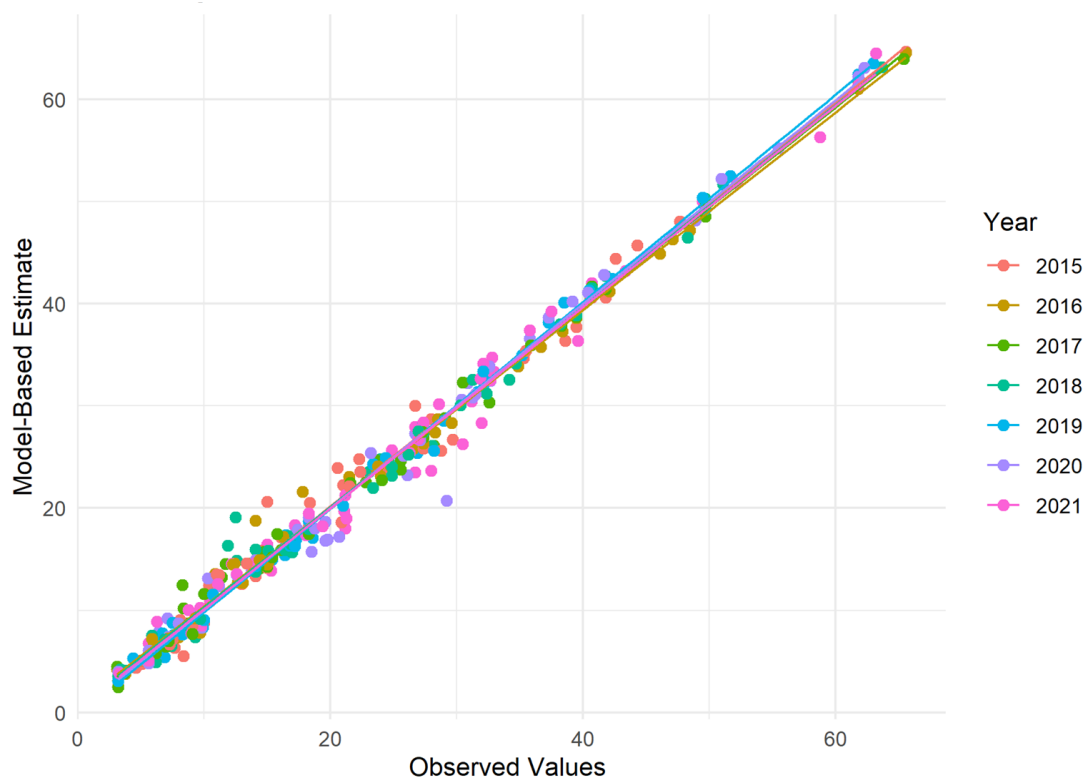


Figure 8.3: Comparisons of observed and model-based estimates across year

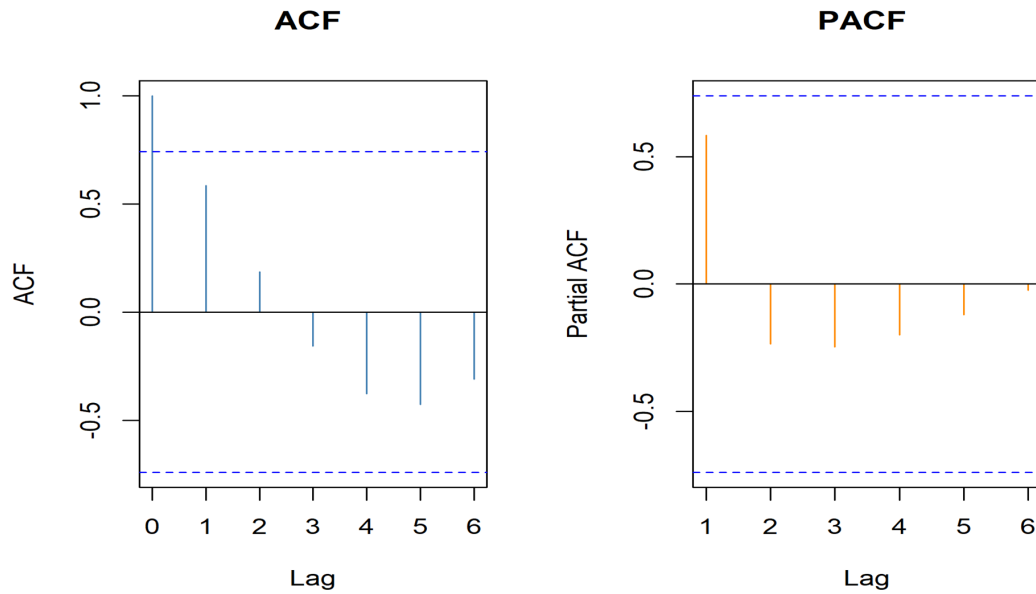


Figure 8.4: ACF and PACF plots of the temporal component (RW1)

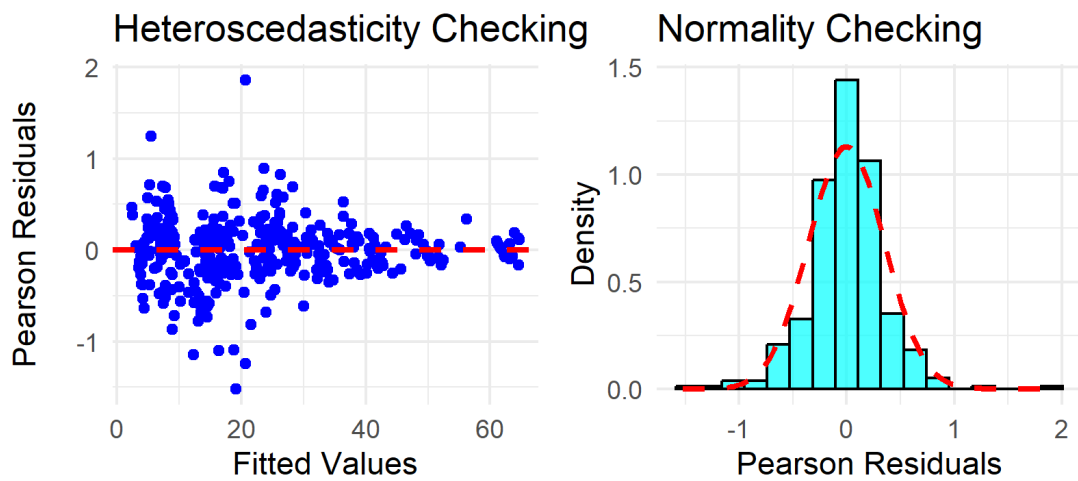


Figure 8.5: Assessment of normality and heteroscedasticity assumptions

8.4 Summary

This chapter employs a spatio-temporally varying coefficient (STVC) model to examine the heterogeneous effects of covariates on severe food insecurity across African countries over the period 2015–2021. The results showed that malaria incidence, climate change, livestock production, and investment inflow exhibited relatively significant uniform effects across countries and over time at the 95% CI, whereas unemployment, GDP per capita, GHG emissions, dietary energy supply, and dietary protein

supply demonstrated substantial spatial and temporal heterogeneity in both the magnitude and, in some instances, the direction of their effects. The findings also showed that severe food insecurity was significantly spatially dependent and temporally correlated, with substantial disparities observed across African countries over time. Throughout the study period, South Sudan, Central African Republic, Republic of the Congo, Malawi, Guinea, Cameroon, and Somalia experienced higher risk than other countries due to country-specific factors, whereas the southern, eastern, and central subregions exhibited strong spatial dependencies in severe food insecurity.

Despite the flexibility of the spatio-temporally varying coefficient framework employed in this chapter, the analysis is primarily retrospective and explanatory, focusing on understanding historical patterns and heterogeneous relationships rather than predicting future levels of severe food insecurity. As such, it does not provide a forecasting framework capable of capturing complex nonlinear temporal dynamics and future trajectories of severe food insecurity for forward-looking decision-making. To address this limitation, Chapter 9 extended the analysis by employing deep learning–based forecasting approaches. This approach enabled more accurate prediction of future food insecurity trends across African countries. The forecasts were intended to support proactive and data-driven policy interventions for future high risk areas.

Chapter 9

Deep Learning–Based Forecasting of Severe Food Insecurity

9.1 Introduction

The preceding chapters do not examine the feature trajectories of severe food insecurity. Their policy recommendations primary focused on reactive and retrospective policy responses. This limits their capacity to provided early warning of future crises. Accordingly, this chapter projects future crises and identified potential hotspots in the coming decays using deep learning models. This facilitates proactive policy responses based on anticipation, forecasting, or early warning systems aimed at preventing or mitigating future risks before a shock occurs.

To forecast severe food insecurity crises, the study implemented and compared the optimal regression-based models selected in the previous chapters, including XGBoost, GAMM, and Type I spatio-temporal interaction model, alongside advanced spatio-temporal deep learning (DL) architectures such as Convolutional Long Short-Term Memory (ConvLSTM), Spatio-Temporal Graph Convolutional Network (ST-GCN), and Adaptive Graph Convolutional Recurrent Network (AGCRN). These DL models were selected because of their ability to jointly capture temporal dependencies and spatial interactions among interconnected geographic units. The best-performing model was then used to forecast future scenarios to support crisis preparedness.

Despite sharing this common objective, the DL models differ primarily in how spatial and temporal dependencies are represented and learned. ST-GCN integrates graph-based spatial learning with temporal convolution to model how food insecurity evolves over time while propagating information across neighboring countries using a predefined adjacency matrix. ConvLSTM, by contrast, captures spatio-temporal patterns by replacing fully connected operations in standard LSTM with convolutional layers within recurrent neural network frameworks. AGCRN further extends graph-based spatio-temporal modeling by adaptively learning spatial relationships among countries through data-driven mechanisms, such as learnable node embedding matrix, rather than relying on a fixed adjacency matrix. All models were implemented using the TensorFlow framework and trained under comparable experimental conditions to ensure fair evaluation.

9.2 Graph Representation and Problem Formulation

Let the graph be denoted as $G \triangleq [E, V, A]$, where the vertex $V = \{v_1, \dots, v_N\}$ represents the nodes (countries), E denotes the set of edges encoding spatial connectivity between node _{i} and node _{j} , allowing the model to capture how each country's severe food insecurity rate is influenced by its neighbors and $\mathbf{A} \in \mathbb{R}^{N \times N}$ is the adjacency matrix derived from inter-node relationships. The adjacency entry A_{ij} takes the value 1 if node _{i} and node _{j} are connected (share a border), and 0 otherwise. At each time step t , a node v_i generates severe food insecurity data $x_i^t = \{x_1^t, x_2^t, \dots, x_N^t\}$. The node feature (input data) matrix for all time steps is represented as $\mathbf{X} = \{X^{(t-T+1)}, X^{(t-T+2)}, \dots, X^{(t)}\} \in \mathbb{R}^{T \times N \times F}$, where N , T , and F denote the numbers of nodes, time steps, and features per node in the input layer, respectively. That is, row i of $\mathbf{X}$ stores the features of node i , with $\mathbf{X}^t \in \mathbb{R}^{N \times F}$. Given the observed historical prevalence of severe food insecurity (x), the objective is to forecast the future severe food insecurity prevalence for all countries at time t , $\hat{\mathbf{y}}^t = [\hat{x}_1^{(t+1)}, \hat{x}_2^{(t+2)}, \dots, \hat{x}_N^{(t+k)}]$ over the prediction horizon k .

9.3 Models

9.3.1 Spatio-Temporal Graph Convolutional Network (ST-GCN)

In this architecture, spatial and temporal convolutional layers are integrated into a unified block to capture both spatial and temporal dependencies by applying graph convolution to each time slice (Ghosh et al., 2020; Yan et al., 2018). Before we dive into the full-fledged ST-GCN model, we first look at the GCN model applied to a single frame. The study adopt a similar implementation of graph convolution as in Kipf and Welling (2017).

Let $f(\mathbf{X}, \mathbf{A})$ be a function defined on a graph G that takes the node feature matrix ($\mathbf{X}$) and the adjacency matrix ($\mathbf{A}$) as input. The graph operation at the l^{th} layer is computed as a 1^{st} order approximation of localized spectral filters on graphs and is implemented through the following layer-wise propagation rule (Defferrard et al., 2016; Hammond et al., 2011; Kipf and Welling, 2017):

$$\begin{aligned} \mathbf{H}^{(l+1)} &:= g(\mathbf{H}^{(l)}, \mathbf{A}) = \sigma(\tilde{\mathbf{D}}^{-1/2} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-1/2} \mathbf{H}^{(l)} \mathbf{W}^{(l)}) \\ &= \sigma(\tilde{\mathbf{P}} \mathbf{H}^{(l)} \mathbf{W}^{(l)}) \end{aligned} \quad (9.1)$$

Here, $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}_N \in \mathbb{R}^{N \times N}$ is the adjacency matrix with added self-loops, $\mathbf{I}_N \in \mathbb{R}^{N \times N}$ is the identity matrix and $\tilde{\mathbf{D}} \in \mathbb{R}^{N \times N}$ is a diagonal degree matrix of $\tilde{\mathbf{A}}$ with $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$. $\mathbf{H}^{(l)} \in \mathbb{R}^{N \times F}$ ($\mathbf{H}^{(0)} = \mathbf{X}$) is the node feature matrix at the l^{th} layer, $\mathbf{W}^{(l)} \in \mathbb{R}^{F \times F_{l+1}}$ is the weight matrix for spatial convolutions, $\tilde{\mathbf{P}} = \tilde{\mathbf{D}}^{-1/2} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-1/2} \in$

$\mathbb{R}^{N \times N}$ is the normalized adjacency matrix (normalized propagation), $\sigma(\cdot)$ denotes an activation function that injects non-linearity into the model, such as $\text{ReLU}(\cdot)$, N is the number of nodes, F and F_{l+1} are feature dimensions in the l^{th} and $(l+1)^{\text{th}}$ layers, respectively. Given a specific node, the graph convolution operation $\tilde{\mathbf{P}}\mathbf{H}^{(l)}$ performs the aggregation of features or message passing step between the current node and its neighboring nodes, then embeds the aggregated features in another latent space. The new features become that node's features. Due to matrix multiplication, $(\tilde{\mathbf{P}}\mathbf{H}^{(l)})\mathbf{W}^{(l)}$, all the aggregated nodes' feature vectors get updated at once. This is the way convolution is carried out in a graph.

This GCN-based model produces an output feature matrix $\mathbf{Z} \in \mathbb{R}^{N \times F}$, where F denotes the number of output features per node, and each row corresponds to the updated feature vector of a node. Kipf and Welling (2017) derives the output feature matrix $\mathbf{Z}$, also referred to as a convolved matrix, from an input $\mathbf{X} \in \mathbb{R}^{N \times C}$, with C input channels (i.e., a C -dimensional feature vector per node) and F filters or feature maps as follows:

$$\mathbf{Z} = \tilde{\mathbf{D}}^{-1/2} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-1/2} \mathbf{X} \Theta \quad (9.2)$$

where $\Theta \in \mathbb{R}^{C \times F}$ is now a matrix of filter parameters and $\mathbf{Z} \in \mathbb{R}^{N \times F}$ is the convolved signal matrix.

Consequently, the forward propagation of a two-layer GCN model is expressed as:

$$\mathbf{Z} = f(\mathbf{X}, \mathbf{A}) = \text{softmax}\left(\tilde{\mathbf{P}} \text{ReLU}\left(\tilde{\mathbf{P}}\mathbf{X}\mathbf{W}^{(0)}\right) \mathbf{W}^{(1)}\right) \quad (9.3)$$

Here, $\mathbf{W}^{(0)} \in \mathbb{R}^{C \times H}$ is an input-to-hidden weight matrix with C feature maps in the input layer and H feature maps in the hidden layer, $\mathbf{W}^{(1)} \in \mathbb{R}^{H \times F}$ is a hidden-to-output weight matrix with F feature maps in the output layer.

Stacking multiple spatial and temporal convolutional layers in one block, the full ST-GCN operation, as derived by Ghosh et al. (2020), is mathematically represented as follows:

$$\mathbf{H}^{(l+1)} = g_t(\mathbf{H}_s^{(l)}, \mathbf{A}_t) = \sigma\left(\tilde{\mathbf{D}}_t^{-1/2} \tilde{\mathbf{A}}_t \tilde{\mathbf{D}}_t^{-1/2} \mathbf{H}_s^{(l)} \mathbf{W}_t^l\right) \quad (9.4)$$

where

$$\mathbf{H}_s^{(l)} = g_s(\mathbf{H}^{(l)}, \mathbf{A}_s) = \tilde{\mathbf{D}}_s^{-1/2} \tilde{\mathbf{A}}_s \tilde{\mathbf{D}}_s^{-1/2} \mathbf{H}^{(l)} \mathbf{W}_s^l. \quad (9.5)$$

Due to the fixed grid-like temporal connections, Ghosh et al. (2020) reduces Equation 9.4 into:

$$\mathbf{H}^{(l+1)} = g(\mathbf{H}^{(l)}, \mathbf{A}_s) = \sigma\left(\tilde{\mathbf{D}}_s^{-1/2} \tilde{\mathbf{A}}_s \tilde{\mathbf{D}}_s^{-1/2} \mathbf{H}^{(l)} \mathbf{W}_s^l \mathbf{W}_t^l\right) \quad (9.6)$$

where $\mathbf{A}_s, \mathbf{A}_t, \mathbf{W}_s^l$ and $\mathbf{W}_t^l$ represent the spatial and temporal adjacency and weight matrices of the l^{th} convolution layer, respectively.

9.3.2 Convolutional Long Short-Term Memory (ConvLSTM)

This hybrid architecture replaces fully connected (dense) transformations in classical LSTM gates with convolutional operations in both input-to-state and state-to-state transitions, thereby jointly capturing spatial and temporal dependencies using convolutional neural networks (CNNs) and LSTM networks, respectively (Shi et al., 2015). The network regulates information flow through memory cell state (C_t), forget gate (f_t), input gate (i_t), and output gate (o_t) (Gers et al., 2000; Hochreiter and Schmidhuber, 1997), which control what information (X_t) is retained, updated, and propagated at each time step.

The new memory cell state ($\tilde{C}_t$) encodes information from the current input (X_t) and the previous hidden state (H_{t-1}) and stores it in the cell state. The forget gate (f_t) regulates information retained or removed from the previous cell state (C_{t-1}). The input gate (i_t) controls new information entering the current cell state (C_t). Using these gates, the final memory cell state is updated by retaining information from C_{t-1} (via f_t) and adding new information (via i_t and $\tilde{C}_t$). Next, the output gate (o_t) decides what parts of useful information from the updated current cell state will be outputted as hidden state (output). This sequence of operations enables the ConvLSTM cell to control what information is remembered, updated, and output at each time step, thus capturing long-term spatio-temporal dependencies. Due to the function of these gates, LSTM networks have better convergence performance and outperform ‘standard’ RNNs in learning long- and short-term dependencies (vanishing gradient) (Goodfellow et al., 2016; Hochreiter and Schmidhuber, 1997; Pascanu et al., 2013).

To mathematically represent the flow of information, let the inputs be $X_1, \dots, X_t$, cell outputs $C_1, \dots, C_t$, hidden states $H_1, \dots, H_t$, and gates i_t, f_t, o_t . ConvLSTM forecasts the future state of each cell in a spatial grid based on inputs and past states of its local neighbors using convolution operator in the input-to-state and state-to-state transitions (Shi et al., 2015). The ConvLSTM model, as defined in Shi et al. (2015), is given by:

$$\begin{aligned}
 f_t &= \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \odot C_{t-1} + b_f) \\
 i_t &= \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \odot C_{t-1} + b_i) \\
 C_t &= f_t \odot C_{t-1} + i_t \odot \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \\
 o_t &= \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \odot C_t + b_o) \\
 H_t &= o_t \odot \tanh(C_t)
 \end{aligned} \tag{9.7}$$

Where ‘*’ denotes the convolution operator and ‘ $\odot$ ’ denotes the Hadamard product, $\mathbf{W} = \{W_{.f}, W_{.i}, W_{.o}\}$ and $\mathbf{b} = \{b_f, b_i, b_o\}$ represents the learnable weights and bias parameters for the forget, input, and output gates, respectively.

By stacking multiple ConvLSTM layers, an encoder-decoder forecasting network was constructed. The encoder network compresses a sequence of T historical severe food insecurity crises, $\mathbf{X} = (\hat{X}_{t-T+1}, \hat{X}_{t-T+2}, \dots, \hat{X}_t)$, into a latent hidden state tensor, while the decoder reconstructs and concatenates the outputs, which are passed through a 1×1 convolutional layer or an end-to-end trainable network to generate k -step forecasts across African countries. The mathematical formulation of the information flow, as detailed in [Shi et al. \(2015\)](#), is given below.

$$\begin{aligned} \tilde{X}_{t+1}, \dots, \tilde{X}_{t+K} &= \arg \max_{(X_{t+1}, \dots, X_{t+K})} p(X_{t+1}, \dots, X_{t+K} \mid \hat{X}_{t-T+1}, \dots, \hat{X}_t) \\ &\approx \arg \max_{(X_{t+1}, \dots, X_{t+K})} p(X_{t+1}, \dots, X_{t+K} \mid f_{\text{encoding}}(\hat{X}_{t-T+1}, \dots, \hat{X}_t)) \quad (9.8) \\ &\approx g_{\text{forecasting}}(f_{\text{encoding}}(\hat{X}_{t-T+1}, \dots, \hat{X}_t)) \end{aligned}$$

9.3.3 Adaptive Graph Convolutional Recurrent Network (AGCRN)

In graph convolutional networks (GCN), spatial features are typically extracted using a fixed adjacency matrix $\mathbf{W}$ based on distance or similarity measures ([Bai et al., 2020](#); [Defferrard et al., 2016](#); [Kipf and Welling, 2017](#); [Xiao et al., 2025](#)). Such static structures may inadequately capture heterogenous and time-varying spatial dependencies. For instance, adjacent neighboring countries may exhibit dissimilar food insecurity patterns at certain times due to country-specific factors, while geographically disjoint countries may exhibit similar trends. As a result, relying solely on shared patterns across all countries is insufficient for accurately forecasting severe food insecurity crises across space and time ([Bai et al., 2020](#); [Xiao et al., 2025](#)). This emphasizes the need of country-specific parameterisation to adequately capture localized patterns.

To overcome these limitations, the Node Adaptive Parameter Learning (NAPL) and Data Adaptive Graph Generation (DAGG) framework replaces the fixed adjacency matrix with a learnable node embedding matrix $\mathbf{E} \in \mathbb{R}^{N \times d}$ where each row represents a node embedding and d represents the node embedding dimension ([Bai et al., 2020](#)). The NAPL module learns node-specific parameters adapted to local characteristics, while the DAGG module dynamically infers interdependencies among nodes and constructs the graph structure during training.

In the NAPL module, a node-embedding matrix $\mathbf{E}_G \in \mathbb{R}^{N \times d}$ and a weight pool $\mathbf{W}_G \in \mathbb{R}^{d \times C \times F}$ are learned to generate the weight parameter as $\Theta = \mathbf{E}_G \cdot \mathbf{W}_G$ and bias term $\mathbf{b} = \mathbf{E}_G \cdot \mathbf{b}_G$. For each node i , NAPL extracts node-specific parameters Θ^i and bias term b^i from the shared weight pools $\mathbf{W}_G$ and bias pool $\mathbf{b}_G$ based on the node embedding $\mathbf{E}_G^i$. Then, according to [Bai et al. \(2020\)](#), the node-adaptive graph

convolution is then formulated as:

$$\mathbf{Z} = (\mathbf{I}_N + \mathbf{D}^{-1/2} \mathbf{A} \mathbf{D}^{-1/2}) \mathbf{X} \mathbf{E}_G \mathbf{W}_G + \mathbf{E}_G \mathbf{b}_G \quad (9.9)$$

The DAGG module, on the other hand, adaptively learns spatial dependencies among nodes instead of relying on a fixed adjacency matrix. It infers spatial relationships from the product $\mathbf{E}_A \cdot \mathbf{E}_A^T$, where $\mathbf{E}_A \in \mathbb{R}^{N \times d}$ is a learnable node embedding matrix (Bai et al., 2020). These inferred relationships are then used to compute the adaptive adjacency matrix for graph convolutions as:

$$\mathbf{A}_{adp} = \text{softmax}(\text{ReLU}(\mathbf{E}_A \cdot \mathbf{E}_A^T)) \quad (9.10)$$

where $\text{Softmax}(\cdot)$ normalizes the learned relationships across nodes, and the Rectified Linear Unit, $\text{ReLU}(\cdot)$, is an activation function that enhances the model's nonlinearity.

During training, $\mathbf{E}_A$ is updated automatically, allowing the model to learn hidden spatial dependencies among food insecurity series. Based on $\mathbf{A}_{adp}$, the data-adaptive graph convolution is then formulated as:

$$\mathbf{Z} = (\mathbf{I}_N + \mathbf{A}_{adp}) \mathbf{X} \mathbf{\Theta} \quad (9.11)$$

where $\mathbf{X} \in \mathbb{R}^{T \times N \times C}$ is the input feature matrix and $\mathbf{\Theta}$ is the learnable weight parameters.

Finally, the NAPL and DAGG modules are then fed into a GRU-like recurrent unit to simultaneously capture country-specific spatial and temporal dependencies in severe food insecurity data. This unified model, called the Adaptive Graph Convolutional Recurrent Network (AGCRN), replaces the GRU's multilayer perceptron (MLP) with NAPL-enhanced graph convolution, enabling more effective learning of country-specific patterns. In this model, All node embedding from each NAPL-GCN layer and the DAGG module are learned jointly within a unified embedding matrix ($\mathbf{E}$) rather than being learned separately (Bai et al., 2020). The mathematical formulation that regulates the flow of information in AGCRN, as presented in Bai et al. (2020), is given as follows:

$$\begin{aligned} \tilde{\mathbf{A}} &= \text{softmax}(\text{ReLU}(\mathbf{E} \mathbf{E}^T)) \\ z_t &= \sigma(\tilde{\mathbf{A}}[X_t, h_{t-1}] \mathbf{E} \mathbf{W}_z + \mathbf{E} \mathbf{b}_z) \\ r_t &= \sigma(\tilde{\mathbf{A}}[X_t, h_{t-1}] \mathbf{E} \mathbf{W}_r + \mathbf{E} \mathbf{b}_r) \\ \hat{h}_t &= \tanh(\tilde{\mathbf{A}}[X_t, r \odot h_{t-1}] \mathbf{E} \mathbf{W}_{\hat{h}} + \mathbf{E} \mathbf{b}_{\hat{h}}) \\ h_t &= z \odot h_{t-1} + (1 - z) \odot \hat{h}_t \end{aligned} \quad (9.12)$$

Where X_t , z_t , r_t , and h_t are the input, update gate, reset gate, and output at time

t , respectively, and $[\cdot]$ denotes the concatenation operation. The parameters $E, W_z, W_r, W_{\hat{h}}, b_z, b_r$, and $b_{\hat{h}}$ are learnable parameters that are trained in an end-to-end manner with backpropagation through time.

9.4 Results

9.4.1 Hyperparameter Tuning and Model Evaluation

To evaluate predictive performance and prevent information leakage, the dataset was split chronologically into training and testing subsets. The first 80% of the temporal observations (2015–2019) were used for model training, while the remaining 20% (2020–2021) were reserved for out-of-sample testing. This temporal split reflects realistic forecasting conditions in which future values are predicted using past information.

To enable a fair comparison among candidate models, hyperparameters were first optimized for each architecture using grid search. The tuned hyperparameter included the network depth defined as the number of LSTM/GRU/GCN hidden, stacked, or embedding layers (1, 2, 3), hidden layer dimensions (16, 32, 64), learning rates (1e-3, 5e-4, 1e-4), dropouts (0.1, 0.2, 0.3), weight decays (1e-4, 5e-4, 5e-5), batch sizes (8, 16, 32), kernel sizes (3, 5), and the number of training epochs (30, 50), depending on the network architecture. These settings were informed by prior studies in the literature (Bai et al., 2020; Ghosh et al., 2020; Shi et al., 2015; Yan et al., 2018). The Adam optimizer, as proposed by Kingma and Ba (2014), was employed for all models to ensure consistent and stable training. Grid search was conducted exclusively on the training set, and the optimal hyperparameter combination for each model was selected based on cross-validation performance. The test set was then used for out-of-sample evaluation to assess generalization and to detect potential overfitting.

Accordingly, ConvLSTM performed best with one hidden layer of size 64 LSTM unit, learning rate 0.0005, dropout 0.1, weight decay 0.0001, 50 epochs, and a batch size 32. ST-GCN achieved the best performance using two stacked layers with 64 GCN hidden units, a temporal hidden dimension of 64, a learning rate of 1e-3, dropout of 0.1, weight decay of 5e-5, batch size of 8, kernel size of 5, and 50 training epochs. AGCRN performed best with GRU hidden dimensions of 64, channel embedding dimensions of 32, a learning rate of 0.0005, a weight decay of 0.0005, and 50 training epochs. Using these optimized configurations, each model was evaluated on the training and testing sets to assess model fit, generalizability, and the risk of overfittings or underfittings. Performance was comparable across all three candidate models. However, the ST-GCN achieved the lowest MSE, RMSE, MAE, and MAPE and was therefore identified as the best-performing model, as shown in Table 9.1. These results suggested that the ST-GCN model was well-suited for forecasting future severe food insecurity.

Table 9.1: Performance metrics of candidate models for training and testing datasets

Model	Training Dataset				Testing Dataset			
	MSE	RMSE	MAE	MAPE	MSE	RMSE	MAE	MAPE
ST-GCN	2.0508	1.4321	0.9185	5.0559	1.9670	1.4025	0.9118	5.0368
ConvLSTM	3.8557	1.9636	1.3003	7.9088	3.8622	1.9652	1.2959	7.8846
AGCRN	6.7083	2.5900	1.5092	12.3460	3.8526	1.9628	1.2569	6.7668

9.4.2 Forecast Evaluation Across Prediction Horizons

A recursive multi-step forecasting strategy was then employed for each models across different forecasting horizons (years ahead), as depicted in Figure 9.1. This recursive forecasting strategy allows the study to capture long-term trends. The predictions for each year were iteratively used as inputs to generate forecasts for subsequent years. This approach enabled long-term projections of severe food insecurity prevalence up to 2050, while leveraging the model's demonstrated strength in short-horizon prediction.

The results indicated that the one-year-ahead forecasting horizon consistently yielded the lowest prediction errors compared to longer horizons (two years and beyond) for all candidate models. This finding indicated that prediction accuracy declined as the forecast horizon increased. This decline may reflect the accumulation of uncertainty over time, arising from unobserved shocks, policy changes, and evolving socioeconomic and environmental conditions. Moreover, the findings revealed that the ST-GCN consistently outperformed the other models across all forecasting horizons, achieving the lowest MSE, RMSE, MAE, and MAPE. This demonstrates its superior predictive performance in forecasting future severe food insecurity scenarios, as shown in Figure 9.1. Based on this evidence, the ST-GCN model was employed using one-year-ahead recursive forecasting strategy. The model provided reliable and accurate projections of severe food insecurity. These projections improved understanding of its future trajectory and supported evidence-based planning and interventions.

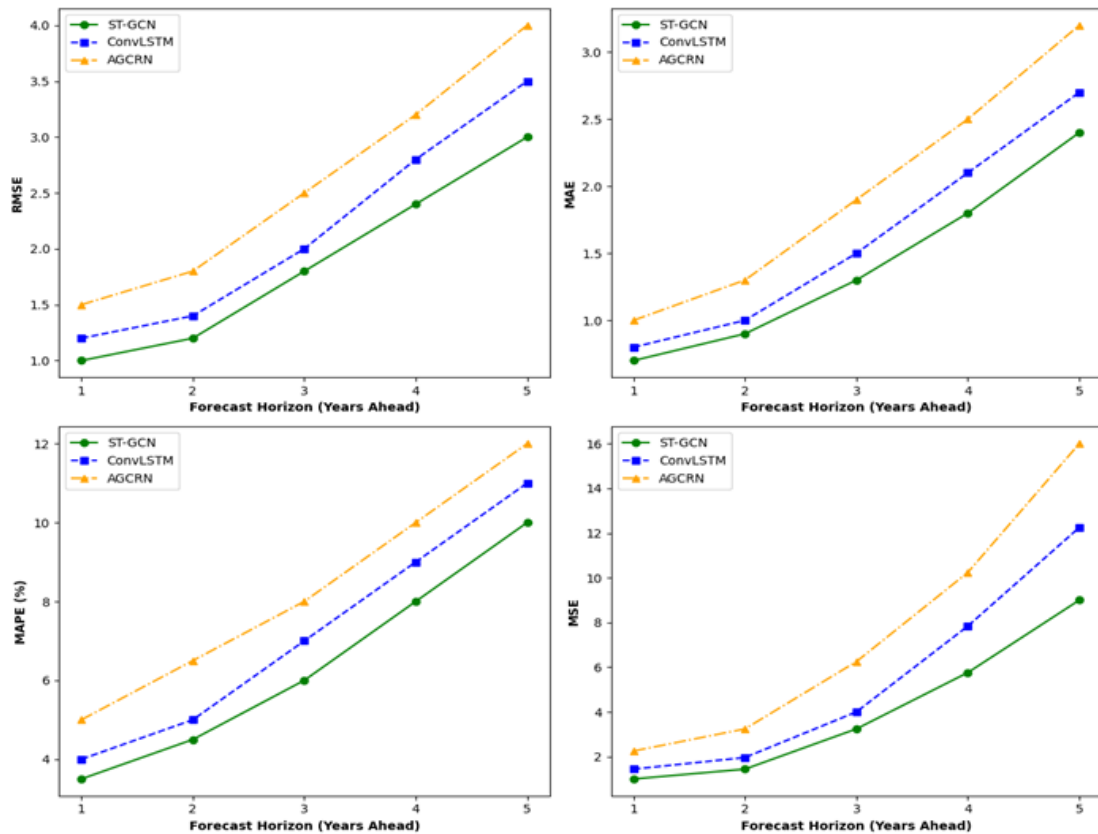


Figure 9.1: Performance metrics of the models across multiple forecasting horizons

9.4.3 Regression-Based vs. Deep Learning Forecasting

This study employed several modeling approaches to achieve the stated objectives. Within each modeling category, the best-performing model was identified based on information criteria and/or predictive performance metrics. Specifically, XGBoost was chosen among machine learning models, GAMM among spatial models, a Type I spatio-temporal interaction model among spatio-temporal models, and ST-GCN among deep learning models. These selected models were then systematically compared using performance metrics to determine the most suitable predictive framework for forecasting severe food insecurity across African countries. The results of this comparison are summarized in Table 9.2. Based on the evaluation, ST-GCN demonstrated superior predictive accuracy and was subsequently adopted as the primary model for forecasting future scenarios of severe food insecurity across the continent.

Table 9.2: Comparison of predictive models for food insecurity forecasting

S.No.	Model	MSE	RMSE	MAE	MAPE
1	GAMM	522.41	22.86	17.09	112.23
2	XGBoost Regression	5.68	2.38	1.49	10.46
3	ST-Type I Interaction	2.12	1.46	1.04	6.96
4	ST-GCN	1.97	1.40	0.92	5.04

9.4.4 Spatial Distribution of Forecasted Severe Food Insecurity

Figure 9.2 shows the geographic distribution of ST-GCN forecast values of severe food insecurity across African countries upto 2050. These forecast values were generated using a one-year forecast horizon recursive forecasting strategy, in which the forecast values from the current year served as inputs for forecasting subsequent years. The ST-GCN framework captured not only the temporal dynamics of food insecurity but also the underlying spatial variations in prediction results among neighboring countries, which were essential for understanding regional patterns and interconnected vulnerabilities.

The color scales in the maps in Figure 9.2 represent the magnitude of forecast values of severe food insecurity over time, with deeper shades correspond to countries with higher projected prevalence. The findings indicated that future severe food insecurity crises were expected to intensify and vary considerably across geographic locations. In particular, severe deterioration was anticipated in South Sudan, the Central African Republic, the Republic of Congo, Malawi, Guinea, Somalia, Ethiopia, Kenya, Democratic Republic of Congo, Angola, Namibia, Niger and Nigeria. These countries consistently remained persistent hotspots of vulnerability over the coming decades. The visualization thus highlighted the uneven spatial distribution of future food insecurity across Africa, emphasizing areas where the humanitarian burden was projected to remain highest. These insights were crucial for enhancing early warning systems, informing targeted policy interventions, and supporting evidence-based resource allocation to mitigate food insecurity challenges in the most affected regions.

Figure 9.2: Projected trajectories of severe food insecurity across African countries

The forecasting models developed in this study provide valuable insights into future severe food insecurity trajectories; however, predictions are inherently associated with uncertainty due to the complex and dynamic nature of food insecurity processes. Forecast uncertainty may arise from several sources, including uncertainty in historical observations, future changes in socioeconomic and environmental conditions, and the inability of any model to fully capture unexpected shocks such as conflicts, climate extremes, economic crises, or policy changes. The forecasted values were not interpreted as fixed outcomes but rather as probabilistic estimates that represent the most likely future trajectories under existing patterns and assumptions.

9.4.5 Projected Temporal Progression of Severe Food Insecurity

Figure 9.3 depicts the projected temporal progression of severe food insecurity among the most affected African countries from 2022 to 2050. The results showed a persistently worsening trajectory across all selected countries, with no clear evidence of improvement throughout the forecasting horizon. These forward-looking predictions were crucial for enhancing preparedness, strengthening early warning systems, and guiding governments and international partners in evidence-based policy responses to mitigate future food insecurity. Without such targeted and sustained interventions,

populations in these countries were likely to face escalating risks of hunger, malnutrition, and related socioeconomic consequences.

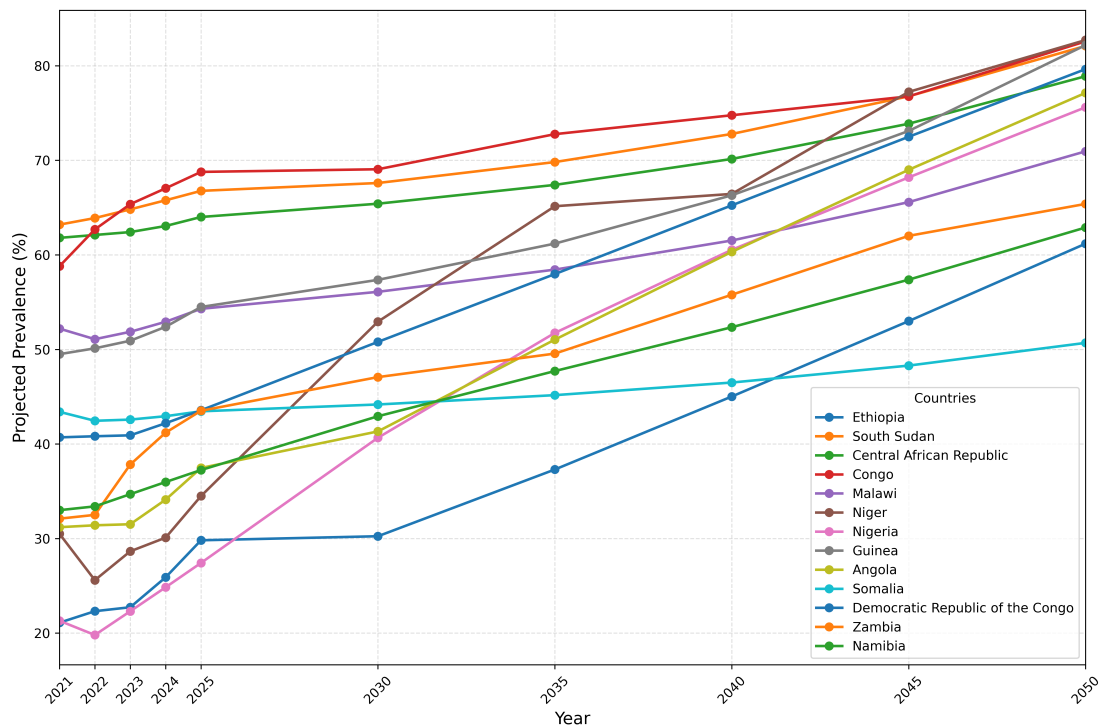


Figure 9.3: Projected severe food insecurity in selected African countries

9.4.6 Observed vs. Predicted Values of Severe Food Insecurity

Figure 9.4 depicted the actual versus predicted values on the test set to demonstrate out-of-sample predictive accuracy and to assess how well the model generalized to unseen data. The figure showed that the actual and predicted values were very closely aligned along the perfect fit line. This close alignment indicated that the model effectively captured the underlying patterns in the data and generalized well to unseen observations. These results provided visual evidence of the model's reliable predictive capability for future severe food insecurity rates.

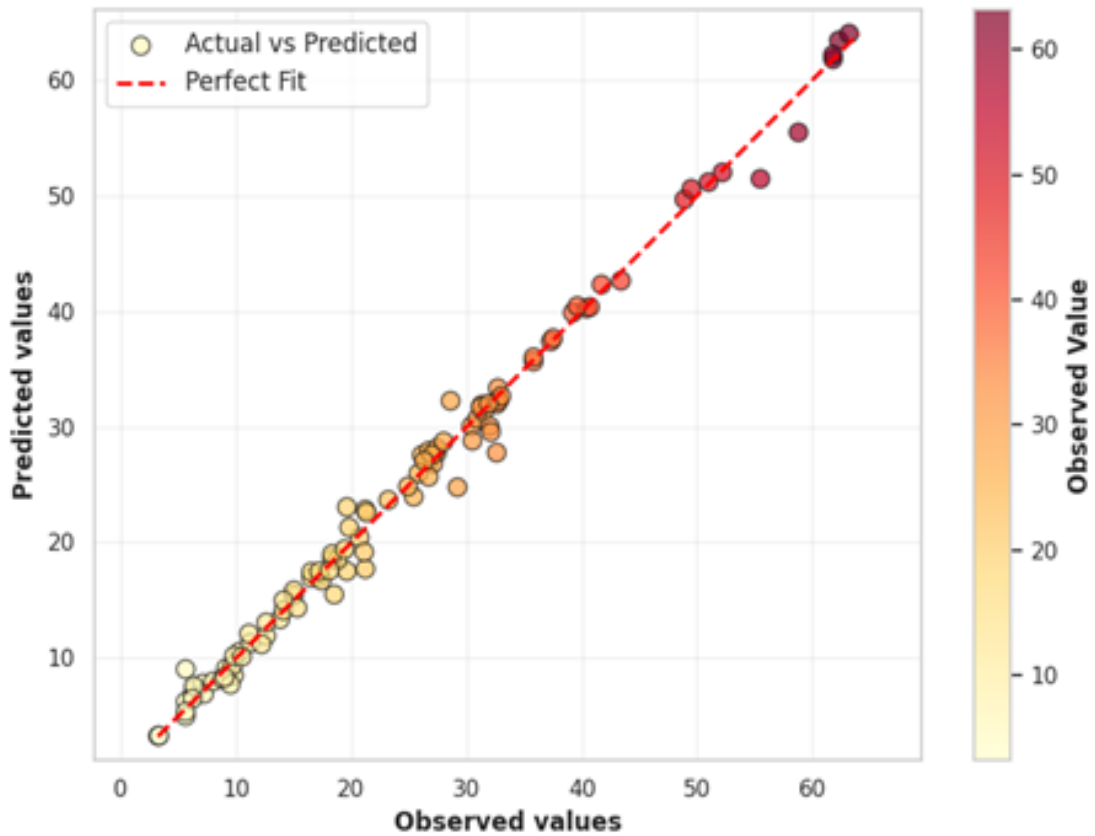


Figure 9.4: Actual vs. predicted values of the test sets

9.5 Summary

This chapter uses deep learning models, including ST-GCN, ConvLSTM, and AGCRN, to predict the future trajectories of severe food insecurity across African countries up to 2050 using temporal data from 2015-2021. The framework jointly models temporal dynamics and spatial interconnections between neighboring countries. Models that explicitly incorporated both spatial and temporal dependencies consistently outperformed alternative approaches. The study compares forecasts across different forecasting horizons up to 2050. The results revealed that one-year-ahead recursive forecasts provides the best predictive performance. Forecasts further indicate that severe food insecurity is likely to intensify across much of African countries in the coming decades. Persistent and worsening hotspots are identified in South Sudan, the Central African Republic, the Republic of Congo, Malawi, Guinea, Somalia, Ethiopia, Kenya, Democratic Republic of Congo, Angola, Namibia, Niger and Nigeria, with projected levels remaining substantially higher than the continental average throughout the forecast period. These indicate that, without sustained and targeted interventions, existing inequalities in food insecurity across countries are likely to widen.

Chapter 10

Discussion, Conclusions and Recommendations

10.1 Introduction

This chapter synthesized and discussed the main empirical findings of the study within the context of existing literature on severe food insecurity. It revisited the study's core objectives and linked them to the results from the descriptive, spatial, and econometric analyses presented in earlier chapters, providing a clear interpretation of key patterns, trends, and relationships across countries and over time. The chapter also examined how the findings compared with previous studies and highlighted important insights into the structural and spatial drivers of food insecurity in Africa. Furthermore, it outlined the policy relevance of the results by translating the evidence into practical implications for governments and policymakers, particularly in designing targeted and effective interventions to address high-risk areas and enhance resilience to shocks. The chapter acknowledged key limitations of the study, including data and methodological constraints, and concluded by summarizing the main findings, offering policy recommendations, and suggesting directions for future research.

10.2 Discussion

10.2.1 Introduction

This study provided a comprehensive analysis of spatial and spatio-temporal patterns of severe food insecurity by explicitly incorporating spatial and temporal effects, space–time interactions, and spatio-temporally varying nonlinear covariate effects across African countries from 2015 to 2021. In doing so, it identified key country-level determinants, characterized spatial, temporal, and interaction dependence structures, evaluated heterogeneity in covariate effects across space and time, and assessed future trajectories to inform forward-looking risk assessment. To achieve this, the study employed a range of machine learning, spatial, spatio-temporal, and deep learning models.

The descriptive analysis showed that continent-wide prevalence was 20.9%, 21.8%, 22.1%, 22.3%, 23.0%, 24.0%, and 24.9% over the period 2015–2021, respec-

tively, indicating an increase from 20.9% in 2015 to 24.9% in 2021. Similarly, at the country level, most African countries exhibited rising levels over the study period. These temporal trends indicated that the continent did not experience any improvement in severe food insecurity during this period. These findings are consistent with previous studies (FAO et al., 2021a; Wudil et al., 2022), which reported similar trends across the continent.

10.2.2 Clustering Patterns of Severe Food Insecurity

Clustering pattern analysis revealed that severe food insecurity exhibited significant geographic clustering rather than a random distribution over time. This indicated that neighboring countries exhibited similar levels of severe food insecurity. High-risk countries were typically surrounded by similarly high-risk neighbors, whereas low-risk countries tended to be bordered by low-prevalence areas. These patterns may have been driven by neighboring countries sharing similar economic, social, political, and environmental challenges. Specifically, several Sub-Saharan African countries, including the Democratic Republic of the Congo (2015-2021), the Central African Republic (2015-2021), Sierra Leon (2016-2021), Zambia (2015-2021), Uganda (2015-2019), Angola (2018-2021), and Cameroon (2021), were identified as high-risk areas of severe food insecurity at the 5% significance level. In contrast, countries such as Madagascar (2015-2021), Uganda (2020-2021), Algeria (2015-2021), and Burkina Faso (2015-2021) were identified as low-risk areas. These increasing temporal trends and the spatial concentration of high-risk areas underscored a growing humanitarian and development challenge. This highlighted the urgent need for geographically targeted, sustained, and coordinated cross-border policy interventions to address the underlying drivers of food insecurity and prevent further deterioration in population well-being.

These results aligned with previous studies (Bofa and Zewotir, 2024a; Cai et al., 2020; FAO et al., 2021a; Sassi, 2015; Wiesmann, 2007), which similarly identified these regions as facing significant food security challenges. For instance, study by Cai et al. (2020) reported that Western Europe, North America, Oceania and parts of East Asia are among the most food-secure regions, whereas Sub-Saharan Africa, South Asia, West Asia and parts of Southeast Asia face the greatest challenges in food security. The analysis revealed that Europe was the most food-secure while Sub-Saharan Africa represents the least food-secure region. Similarly, studies by Akombi et al. (2017) and Okunlola and Kassouri (2023) indicated that Eastern Africa exhibits a higher prevalence of severe malnutrition than other regions.

10.2.3 Feature Selection and Ranking

The observed persistent spatio-temporal disparities and clustering of severe food insecurity were linked to multiple interacting drivers identified in previous studies. In this context, the relative contributions of a range of potential predictors were assessed using machine learning models, with and without hyperparameter tuning, to better understand the factors behind these patterns. The results indicated that hyperparameter tuning substantially improved predictive accuracy, consistent with previous studies (Chen and Guestrin, 2016; Noorunnahar et al., 2023; Raschka and Mirjalili, 2019; Tadege et al., 2024). This highlights the importance of model optimization in enhancing the reliability of forecasts used in policy and decision-making. Among the algorithms evaluated, the XGBoost demonstrated the highest predictive performance, in line with earlier findings (Chen and Guestrin, 2016; Noorunnahar et al., 2023). The superior performance of XGBoost suggests that advanced machine learning approaches provide robust tools for modeling the complex, nonlinear relationships inherent in food insecurity data.

The findings of the XGBoost model indicated that several national-level factors were strongly associated with severe food insecurity, with the relative contributions of individual predictors varying across covariates. The results showed that, conditional on other features, higher levels of inflation, climate change, unemployment, malaria incidence, GHG emissions, caloric loss, and cereal import dependency contributed to increased predicted rates of severe food insecurity. In contrast, a higher livestock production, cereal crop production, investment inflows, dietary energy supply, dietary protein supply, electricity access, GDP per capita, and political stability contributed to reducing the predicted risk. The relevance of most of these drivers was further supported by statistical inference from the spatial and spatio-temporal models. These results emphasize the multidimensional nature of severe food insecurity, with the predictors collectively encompass economic, social, political and environmental elements. Among the examined variables, unemployment, livestock production, GHG emissions, and caloric losses identified as the most influential drivers, listed here in priority order. This suggests that prioritizing policy interventions targeting these top-ranked factors may yield substantially reductions in severe food insecurity and strengthen resilience across African countries.

10.2.4 Spatio-Temporal Dependence Structures of Severe Food Insecurity

The dynamics of severe food insecurity were assessed using spatial and spatio-temporal models. The findings revealed that models accounting for spatial, temporal,

and interaction random components performed better than purely spatial or purely temporal models. This finding is consistent with previous studies ([Bofa and Zewotir, 2024b](#); [Wubetie et al., 2024b](#)) that have reported the superiority of spatiotemporal models over purely spatial or purely temporal models. The improved performance may suggest that the inclusion of space–time interaction components and space–time varying nonlinear covariates enables the model to capture additional variability that is not adequately explained by the main spatial and temporal components alone.

This interpretation aligned with the methodological arguments advanced by [Knorr-Held \(2000\)](#) and [Leroux et al. \(2000\)](#), which emphasize the critical role of interaction structures in accounting for complex dependence patterns. These findings suggest that severe food insecurity is governed by inherently complex and interdependent processes that evolve across both space and time. Within this modeling framework, the integration of linear covariate effects, nonlinear covariate effects represented through cubic spline functions, spatial dependence captured via intrinsic Conditional Autoregressive (iCAR) specifications ([Knorr-Held, 2000](#)), and temporal dependence modeled through random walk structures ([Rue and Held, 2005](#)) provides a flexible and robust representation of these dynamics.

The statistical significance of the spatial, temporal, and interaction components suggests that the dynamics of severe food insecurity are influenced by geographic and temporal processes, together with their interdependent process. In particular, the severity of food insecurity in a given country appears to be influenced by conditions in neighboring countries as well as by its own historical experiences, indicating the presence of spatial and temporal dependence. Similar patterns have been reported in previous studies ([Bofa and Zewotir, 2024b](#); [Cai et al., 2020](#); [Dessie et al., 2022](#); [Wubetie et al., 2024b](#)), indicating that food insecurity evolves as an interdependent process rather than independently across space or time. These results further imply that interventions and policy measures should account for spatial, temporal and interaction dependencies, as ignoring them may lead to underestimating risks or misallocating resources.

Furthermore, the significant spatio-temporal random effects indicate that additional spatially and temporally structured factors influencing severe food insecurity remain unaccounted for in the current model. This highlights the need for future research to incorporate additional covariates, such as governance, conflict, market accessibility, environmental conditions, and policy-related factors, to better explain the remaining spatio-temporal variation. Such improvements would enhance model performance and support the development of more targeted, context-specific, and coordinated policy interventions.

The estimated spatial effects indicated significant geographic variation in severe food insecurity across the continent, consistent with the findings of previous studies ([Ayalew et al., 2024](#); [Bofa and Zewotir, 2024b](#); [FAO et al., 2023, 2021a](#)). The risk didn't

also show any improvement over time. The decomposition of spatial effects into structured and unstructured components demonstrated that both random country-specific heterogeneity and systematic spatial dependence contributed to the observed geographic disparities, providing insight into both localized and broader regional drivers of severe food insecurity. For example, the analysis revealed countries such as South Sudan, Central Republic of Africa, Malawi, Guinea, Republic of Congo, Cameroon, and Somalia experienced high prevalence of severe food insecurity primarily due to country-specific factors. These effects may fluctuate over time in response to interventions or temporary shocks.

In contrast, many countries in the Southern, Eastern, and Central African subregions exhibited strong spatial dependence in severe food insecurity. This indicated that in these regions, high prevalence is not merely the consequence of transitory shocks but associated with persistent structural constraints and unobserved spatially correlated factors. The pronounced spatial heterogeneity observed over time underscores the complex interplay between localized factors and broader regional processes, highlighting that severe food insecurity is shaped by both country-specific dynamics and persistent structural spatial patterns across the continent. These patterns underscore the need for interventions tailored to the local context while also underscoring the importance of coordinated efforts at regional and international levels.

These high-risk areas have also been identified by previous studies (Bofa and Zewotir, 2024b; Cai et al., 2020; FAO et al., 2021a). For instance, a global spatio-temporal analysis done by Cai et al. (2020) reported that Europe represent the most food-secure region while Sub-Saharan Africa remains the least food-secure. In addition, Nigeria, the Democratic Republic of the Congo, Zambia, Uganda, and Ethiopia have been identified as among the most vulnerable countries in terms of food security (Bofa and Zewotir, 2024b). Furthermore, FAO et al. (2021a) reported that the central and eastern regions of the African continent exhibit the highest prevalence of food insecurity compared with other subregions.

The estimated temporal effects showed a consistent and notable upward trend in severe food insecurity over the study period. This indicated a worsening situation across the continent. Similarly, the majority of countries experienced rising trends of severe food insecurity. This indicated that countries with high prevalence in a given year were more likely to continue experiencing high prevalence in subsequent years. This finding aligned with previous research that documented rising levels of severe food insecurity across Africa (Bofa and Zewotir, 2024b; FAO et al., 2023). This persistence trend signals the urgent need for sustained monitoring, scalable interventions, and proactive policy measures to address the structural drivers of severe food insecurity before conditions worsen and mitigate long-term vulnerability and disparities.

The interaction between space and time also introduced additional variability

in severe food insecurity across the continent. These effects captured country-year-specific deviations that were not explained by the main spatial or temporal components of the model. The interaction effects also facilitated the identification of countries experiencing a typical fluctuations in particular years. This reflected distinct deviations from expected patterns based on their spatial context and the broader continental trend. Across much of the study period, the results showed that Kenya, Ethiopia, Niger, and Burkina Faso frequently experienced higher-than-expected levels of severe food insecurity in specific years. These countries have also been reported as high-risk countries in previous studies ([Bofa and Zewotir, 2024b](#); [Cai et al., 2020](#); [FAO et al., 2021a](#)). Such deviation showed the influence of country-specific shocks or circumstances that were not shared by neighboring countries or reflected in the temporal trajectory. These implied that national severe food insecurity dynamics are shaped not only by persistent spatial and temporal processes but also by country-specific disruptions over time. Consequently, the results highlight the importance of accounting for such sudden deviations from expected trends to avoid delayed responses to rapidly evolving food insecurity crises.

The persistence of these high-risk areas was attributed to a combination of structural socioeconomic vulnerabilities and environmental stressors during the study periods. These conditions contributed to food scarcity and limited access to essential resources, thereby reinforcing persistent inequalities in food security across regions. For instance, South Sudan and the Central African Republic have experienced prolonged armed conflicts and full-scale civil war during the study period which have displaced millions of people, destroyed livelihoods, disrupted agricultural production, hindered market access, and limited humanitarian interventions, thereby contributing to chronic food deficits ([African Union, 2015](#); [Gerenge, 2015](#)). In South Sudan, the civil conflict was beginning in 2013 between the elite struggle for power between President Salva Kiir and former Vice President Riek Machar, representing the Dinka and Nuer ethnic groups, respectively. This conflict undermines food systems throughout much of the study period by perpetuating insecurity and limiting post-conflict recovery efforts.

In Somalia, recurrent droughts, ongoing armed conflict with militant groups such as al-Shabab, weak institutional capacity, and economic impacts of COVID-19 pandemic are causing rising of food scarcity and malnutrition ([FEWS NET and FSNAU, 2022](#)). These factors have jointly reduced agricultural productivity, disrupted trade and humanitarian assistance, and increased vulnerability to malnutrition, particularly among pastoral and agro-pastoral communities. Similarly, Republic of Congo has persistently experienced severe food insecurity due to heavy dependence on oil revenues and the collapse in global oil prices beginning in 2014–2015, reliance on food imports, recurrent droughts and floods, and localized conflict, particularly in the "Pool region" between 2016 and 2018 ([IMF, 2021](#)). In addition, Malawi and Guinea have been particularly

affected by economic shocks and climate-related extremes, including recurrent droughts and flooding events, which have reduced crop yields and constrained food availability (FAO et al., 2021a,b).

10.2.5 Spatio-Temporally Varying Effects of Predictors

Previous studies have often conceptualized the effects of drivers of food insecurity as consistent across space and time, while allowing variations primarily across range of covariate values (Bofa and Zewotir, 2024b; Mathenge et al., 2023; Sassi and Trital, 2021). For instance, studies focusing cereal import dependency by (Bofa and Zewotir, 2024b), GHG emissions by (Bofa and Zewotir, 2024b; Eshete et al., 2020; Gobezie and Boka, 2023; Kaur, 2022; Mahdavian et al., 2025; Mulusew and Hong, 2024; Ntiamoah et al., 2023), GDP per capita by (Bofa and Zewotir, 2024b; Coles et al., 2016; Verpoorten et al., 2013), unemployment by (Mekonnen and Amede, 2022; Etana and Tolossa, 2017; Huang et al., 2016; Milovanska-Farrington, 2023; Nord et al., 2014), caloric loss by (Munesue et al., 2015; Sawaya, 2017), inflation by (Bogmans et al., 2024; Jacobs, 2010; Nord et al., 2014; Olufemi-Phillips et al., 2024; Verpoorten et al., 2013), livestock production (Falvey, 2015; Wubetie et al., 2024b), dietary energy supply and dietary protein supply by (Bofa and Zewotir, 2024b; Coles et al., 2016) have largely relied on this assumption. These studies have potentially overlooked important spatial and temporal variations in covariate effects.

In contrast, the present study found evidence that the effects of determinants of severe food insecurity varied across both space and time. This difference may partly be attributed to the broader geographic scope of the present study, which examined continental-scale patterns across Africa, whereas many previous studies focused on smaller geographic areas. The result showed that GHG emissions, unemployment, GDP, dietary energy supply, and dietary protein supply exhibited significant spatial and temporal heterogeneity in shaping severe food insecurity over the 2015–2021 period. This indicates that the magnitude and direction of their effects varied across countries and over time. In fact, this study also found that some factors, including climate change, investment flows, malaria incidence, and livestock production, exhibited relatively consistent and statistically significant effects across African countries over time. These findings suggest that uniform policy interventions may not be equally effective across all settings. Instead, mitigation strategies should be tailored to country-specific socio-economic, environmental, and institutional conditions to more effectively address severe food insecurity.

Building on this contrast, the present analysis further identified specific countries and periods in which individual determinants exert relatively stronger or weaker effects. For instance, GDP showed a relatively stronger protective effect against severe

food insecurity in Algeria, Libya, Angola, Botswana, Malawi, Lesotho, Liberia, Benin, and Madagascar, suggesting that sustained economic growth and macroeconomic stability in these countries are likely to yield greater reduction in severe food insecurity in these countries than elsewhere. In contrast, countries where the GDP effect was weaker may require complementary interventions beyond economic growth alone, such as strengthening social protection systems and improving food access. Unemployment contributed positively to severe food insecurity across most countries, with particularly strong effects observed in Ethiopia, Libya, Niger, Namibia, Liberia, Somalia, and Madagascar. These findings indicate that labor market conditions play a more prominent role in shaping severe food insecurity outcomes in these countries. These findings underscore the importance of employment creation, income-generating opportunities and targeted social safety-net programs.

Similarly, Greenhouse gas (GHG) emissions exhibited strong effects in the Democratic Republic of the Congo and Côte d'Ivoire, suggesting that environmental degradation and climate-related pressures contribute more substantially to severe food insecurity in these settings. This finding highlights the importance of integrating climate adaptation, sustainable land management, and environmental conservation into national food security strategies. Likewise, dietary energy supply showed stronger protective effects in Zimbabwe, Zambia, and Lesotho, while the effect of dietary protein supply was comparatively stronger in Sudan, South Sudan, Tunisia, Somalia, Uganda, Tanzania, Zambia, Zimbabwe, South Africa, Senegal, Sierra Leone, and Togo. This suggests that improving food availability, access, diet quality, and nutritional diversity could yield particularly large benefits in these countries.

These country-specific differences in covariate effects demonstrate that the determinants of severe food insecurity are not spatially uniform across Africa. Consequently, uniform policy interventions are unlikely to be equally effective in achieving comparable food security outcomes across different settings. Instead, policy responses should be tailored to the dominant drivers of food insecurity within each country.

10.2.6 Consistency of Identified Determinants with Previous Evidence

This study identified climate change as a significant determinant that contributed to the escalation of severe food insecurity risk. This result was consistent with existing empirical evidence emphasizing the adverse implications of climate variability for food security. For instance, the World Bank reports that climate change and extreme weather events pose severe threats to farmers in Eastern and Southern Africa, jeopardizing food security and economic stability in the region ([Tumushabe, 2017](#)). Similarly, the International Monetary Fund (IMF) notes that climate change intensifies food

insecurity in Sub-Saharan Africa, with lasting adverse effects on economic growth and poverty levels (Baptista et al., 2022). Furthermore, research findings from studies Ali et al. (2022); Baptista et al. (2022); Campbell et al. (2016); Osman (2023) indicate that climate change such as rising temperatures, changing precipitation, and unpredictable weather patterns disrupt agricultural productivity, leading to lower crop yields and reduced food supply stability. The consistent patterns observed in these studies underscore the urgent need for comprehensive strategies to mitigate climate change impacts and enhance regional food security resilience. The findings of the present study indicated that higher levels of climate change contributed to the escalation of severe food insecurity trajectories. However, this driver was ranked among the least important features in the SHAP analysis of the predictive model, yet stronger effects in the spatio-temporal regression models, indicating a lower predictive influence than suggested by previous literature. This may be due to the relatively short study period (2015-2021) and the use of temperature change as a proxy for climate impacts, which may not adequately capture climate variability and extreme events.

In contrast, this study found that an increase in livestock production significantly contributed to reductions in the severity of food insecurity. This suggests that greater livestock availability enhances nutritional intake, income stability, and overall food system resilience. Empirical studies by Falvey (2015), FAO et al. (2018), Molina-Flores et al. (2020), Nkomoki et al. (2019), Pica-Ciamarra et al. (2015), and Wubetie et al. (2024a) have similarly shown that higher livestock production and ownership significantly reduce the risk of household food insecurity. In many African contexts, livestock serves as a source of income, nutrition, and savings. Households can maintain food access during economic or climatic shocks by selling livestock or their products. Despite these general patterns, the literature has also indicated that higher dependence on livestock production or its availability can increase vulnerability. For instance, in arid and semi-arid regions, studies reported that heavy reliance on livestock may increase vulnerability during climate shocks such as droughts, disease outbreaks, and pasture degradation (Danso-Abbeam et al., 2024; Nuvey et al., 2022). Recurrent droughts, land degradation, and overgrazing diminish pasture resources. In such contexts, livestock losses may occur, exacerbating food insecurity rather than mitigating it, indicating that the protective effect of livestock depends on ecological conditions and context. These dynamics underscore the need for climate-sensitive and context-dependent strategies to strengthen the productivity and sustainability of livestock systems across Africa.

Environmental pressures related to GHG emissions further represented a significant threat to the sustainability of food systems, a finding consistent with previous studies (Bofa and Zewotir, 2024b; Eshete et al., 2020; Gobeze and Boka, 2023; Kaur, 2022; Mahdavian et al., 2025; Mulusew and Hong, 2024; Ntiamoah et al., 2023). GHG emissions intensify climate variabilities, including droughts, floods and broader environ-

mental degradation. These, in turn, reduce the nutritional quality and quantity of agricultural products, including crops, livestock, and fisheries. These climate-induced disruptions ultimately aggravate food insecurity among vulnerable populations. National GHG emissions also reflect patterns of economic development, energy use patterns and industrial structure, making a country's own emissions less likely to generate immediate local climate effects. Instead, they contribute to global climate change, whose impacts are distributed across regions rather than confined within national boundaries. This underscores the need to strengthen climate adaptation policies to address the cross-border and long-term effects of GHG emissions on the sustainability of food systems.

This study also found evidence that malaria incidence played a critical role in exacerbating severe food insecurity. This is consistent with previous studies indicating that higher malaria incidence intensifies food insecurity, undernutrition, and poverty (Debash et al., 2024; Gari et al., 2018; Girardin et al., 2004; Lewnard et al., 2014; Madaki, 2017; Mezieobi et al., 2025; Oldenburg et al., 2018; Oluwatayo, 2014; Tusting et al., 2016; Uwimana et al., 2025). This effect likely occurs through reduced labor availability, diminished agricultural productivity, lower household and national incomes, and increased healthcare burdens. In agrarian economies, malaria-related morbidity constrains farm labor supply during critical agricultural production periods, thereby limiting food production and income generation. In addition, household spending on malaria prevention (bed nets, insecticides) and treatment (medications, hospital visits) may divert scarce household resources from food consumption, further intensifying food insecurity. Moreover, malaria interacts bidirectionally with food insecurity and undernutrition. For example, a study by Oldenburg et al. (2018) reported that nutritional status did not significantly influence malaria incidence (Cox regression), whereas malaria infection significantly worsened nutritional status (linear regression), a finding further confirmed by logistic regression analyses (Debash et al., 2024; Uwimana et al., 2025). Since undernutrition is a recognized indicator of food insecurity by FAO, these findings suggest that the causes of undernutrition largely mirror the causes of food insecurity. In this study, malaria incidence is treated as a causes of severe food insecurity; therefore, the estimated relationship may partially capture reverse causation or feedback effects inherent in the bidirectional relationship, rather than strictly unidirectional causal relationship. These results emphasize the complex interdependence between malaria and food insecurity, highlighting the need for caution in interpreting the observed associations.

Furthermore, this study found evidence that macroeconomic conditions, including GDP per capita, unemployment, and investment inflow, exerted a substantial influence on severe food insecurity outcomes in African countries. Higher GDP per capita significantly contributed to the reduction of severe food insecurity risks, consistent with the previous studies (Awad, 2023; Świetlik, 2018; Verpoorten et al., 2013). This likely

reflects greater national wealth and economic strength to support employment, household income, access to nutritious food, public services, infrastructure, and social safety nets. In contrast, higher national unemployment contributed to the aggravation of severe food insecurity, in line with earlier evidence (Mekonnen and Amede, 2022; Etana and Tolossa, 2017; Huang et al., 2016; Milovanska-Farrington, 2023; Nord et al., 2014). This relationship may reflect economic stress, weakened labor markets, and reduced household income and purchasing power, thereby limiting access to sufficient and nutritious food. For instance, a study by Nord et al. (2014) reported that a 1%-point increase in the unemployment rate was linked with a 0.5%-point rise in food insecurity, while Huang et al. (2016) found a similar effect during the 2007–2009 economic recession. These findings suggest that macroeconomic stability, including robust economic growth and low unemployment, is critical for reducing food insecurity and strengthening resilience against economic shocks in African countries.

Investment inflow was significantly contributed to a reduction in severe food insecurity. It may reflect, in part, a country's economic growth and political stability, thereby facilitating improved resource allocation for food systems and infrastructure development. However, the effect of FDI was context-dependent. While investment in agriculture, infrastructure, and manufacturing can enhance food security by boosting productivity and employment (Samdrup et al., 2023), land-intensive or extractive investments may displace smallholder farmers, reduce access to productive land, and undermine local food availability (Guyalo et al., 2022). These adverse effects indicated that the impact of investment inflows on severe food insecurity was contingent upon the nature of investments, their sectoral allocation, and the quality of land governance. This emphasizes the importance of complementary policies that ensure investments are inclusive and aligned with local food security objectives.

Beyond macroeconomic conditions, the findings of the present study further indicated that Africa continues to face challenges in ensuring adequate energy and protein food supply to meet the nutritional needs, consistent with previous studies (Bofa and Zewotir, 2024b; Coles et al., 2016; Deaton and Deaton, 2020; Grote et al., 2021). In particular, a studies by Bofa and Zewotir (2024a) and Coles et al. (2016) showed that dietary protein supply reduces food insecurity by improving both quantity and quality of food access and affordability. These patterns emphasize the need to strengthen agricultural productivity, food distribution or supply systems, and nutritional policy frameworks across the continent.

10.2.7 Future Trajectories of Severe Food Insecurity

Furthermore, this study forecasts future trajectories of severe food insecurity across African countries using advanced deep learning models that explicitly account

for covariate effects, temporal dependence, and spatial interdependencies among neighboring countries. The finding revealed that ST-GCN demonstrated superior predictive performance compared with other candidate models. The strength of prediction performance for ST-GCN has also been described in previous studies ([Ghosh et al., 2020](#); [Yan et al., 2018](#)). The model effectively captured hidden spatio-temporal structures within the data by integrating graph convolutional layers ([Kipf and Welling, 2017](#)) and temporal convolutional layers ([Hochreiter and Schmidhuber, 1997](#)). As a result, it generated more reliable and robust forecasts for medium- and long-term projections. This leverages ST-GCN model over traditional statistical and machine learning models used in previous studies.

While ST-GCN provided superior predictive performance, the results of the present study showed that forecast accuracy declined as the prediction horizon increased, a pattern consistent with previous spatio-temporal forecasting studies ([Bai et al., 2020](#); [Jiao et al., 2025](#); [Lucas et al., 2023](#)). This decline may reflect the accumulation of uncertainty over time, arising from unobserved shocks, policy changes, and evolving socioeconomic and environmental conditions. While short-term forecast was therefore more reliable for operational decision-making, longer-term projections remained valuable as scenario-based risk signals that inform strategic planning and preparedness rather than precise point predictions.

The projections further indicated that severe food insecurity was likely to intensify across African countries, with pronounced regional variability. In particular, pronounced deterioration was projected in South Sudan, the Central African Republic, the Republic of Congo, Malawi, Guinea, Somalia, Ethiopia, Kenya, Democratic Republic of Congo, Angola, Namibia, Niger and Nigeria, consistently indicating persistent hotspots of vulnerability over the coming decades. These countries have also been identified as hotspots in previous studies ([Alinovi et al., 2007](#); [Bofa and Zewotir, 2024a](#); [Cai et al., 2020](#); [FAO et al., 2021a](#); [Marivoet et al., 2019](#); [Sassi, 2015](#); [Wiesmann, 2007](#)). This underscores the need for prioritizing targeted, country-specific interventions and resource allocation to address long-term severe food insecurity and strengthen resilience in the most vulnerable areas. This forward-looking evidence provided additional insights to support risk assessment, early-warning, and strategic planning systems aligned with the SDGs at the continental scale. It enables the timely anticipation of emerging crises. It also facilitates cost-effective responses and strengthens the operational capacity for preventive actions and evidence-based interventions across the continent.

10.2.8 Strength and Limitation of the Study

The study has its own strengths and limitations. This study has its own strengths that enhance its scientific contribution and policy relevance. First, its broad geographic

coverage across African countries and over seven-year periods. This broad coverage provides a comprehensive and representative assessment of severe food insecurity dynamics at the continental level. This extensive spatial and temporal coverage enhances the generalizability of findings and supports their applicability for regional and national policy formulation.

Second, the analysis focused on country-level factors that affect entire national populations, rather than individual-level characteristics, thereby providing evidence that was directly aligned with macro-level policy and planning needs. In addition, the study explicitly modeled the spatio-temporally heterogeneity in covariate effects and incorporated spatio-temporal interaction effects, which remain insufficiently addressed in much of the existing literature. This framework identified both shared and location-specific factors of severe food insecurity, thereby offering a more nuanced basis for geographically targeted interventions.

Third, this study generated forward-looking evidence to support risk assessment, early warning systems, and strategic policy planning aligned with SDG at the continental scale. Such projections may assist governments and development partners in strengthening preparedness and anticipatory actions before severe food insecurity crises occur.

Despite its strengths, this study has also important limitations that should be considered in the future research. First, this study used country-level as geographic unit of analysis because as comparable data for lower administrative levels were not consistently available across African countries. The use of countries as spatial units of analysis and aggregated national-level data may obscure subnational heterogeneity in both severe food insecurity and its associated drivers and may mask local patterns essential for designing context-specific interventions. As a result, the observed estimated associations and relative importance of identified drivers represent average national-level relationships and may over- or under-estimate effects. This may not accurately reflect conditions at specific community levels. Localized hotspots and context-specific mechanisms that are critical for operational planning and targeted interventions may therefore remain undetected. Consequently, policy recommendations based solely on national-level findings may be less targeted or effective for specific communities and may limit the generalizability of the findings to finer spatial scales. Nevertheless, the study provides valuable evidence for understanding continental and national patterns of severe food insecurity and for informing macro-level policy decisions. Future research should seek and explore disaggregated sub-national data at smaller geographic units, where available, throughout the continent in order to capture within-country variation and improve the relevance of findings for local policy and program design.

Second, the analysis did not include some important variables that may substantially influence severe food insecurity due to a lack of accessible data across countries

and years. For instance, large-scale climate phenomena (e.g., El Nino and La Nina events) and the number of displaced people due to political instability or conflict, which can have significant implications for severe food insecurity, are not accounted for. The omission of such variables may lead to residual confounding and may partly explain unexplained spatial or temporal variation in the outcome. Future research should incorporate climate anomaly indicators, displacement and migration statistics, etc. to improve model completeness and to better understand the complex dynamics influencing severe food insecurity.

Third, although several covariates were included, the study does not explicitly account for heterogeneity in severe food insecurity across population subgroups and geographic characteristics, such as gender, age groups or structural country attributes (e.g., landlocked status vs access to seaports). Consequently, the reported relationships reflect population-averaged effects and may conceal important distributional differences in vulnerability. Future work should therefore adopt subgroup-specific and stratified comparative analytical strategies to identify heterogeneous patterns of severe food insecurity across population groups and geographic contexts, thereby providing evidence to support more equitable and targeted policy responses.

Fourth, the spatial dependence structure was specified using a contiguity based neighborhood matrix. Due to convergence difficulties, alternative distance-based specifications were not explored in the present analysis. This modeling choice may affect the estimated magnitude and structure of spatial effects and, consequently, the identification of spatial clustering and spillover patterns. Future research should systematically compare contiguity-based and distance-based spatial structures, and assess their implications for inference and forecasting performance using robust model comparison and sensitivity analyses.

Fifth, this study is adopted relatively for short temporal dimension of the annual dataset. Although the machine learning and deep learning models demonstrated strong predictive performance, the limited number of time points may constrain its ability to learn complex long-term temporal dependencies and increase sensitivity to short-term fluctuations. Nevertheless, the use of temporal validation, regularization, and recursive one-year-ahead forecasting helped mitigate overfitting and information leakage. Future studies using higher-frequency or longer time-series data could further improve the robustness and generalizability of the forecasting model.

Sixth, the proposed deep learning models were designed for prediction and association analysis rather than causal inference. Although the deep learning models employed in this study demonstrated strong predictive capability, they provide limited interpretability regarding the contribution of individual features to the resulting forecasts. This may constrain the transparent communication of model outputs to policymakers, who often require explainable evidence to support resource allocation and intervention

design. Future research should develop and evaluate hybrid modeling frameworks that integrate deep learning architectures with interpretable statistical or causal inference approaches. Such models could preserve high predictive performance while improving model transparency, identifying the causal mechanisms linking socioeconomic, environmental, and nutritional factors to severe food insecurity, and enhancing their value for evidence-based policy making.

10.3 Conclusion

This study investigated the spatial and spatio-temporal clustering patterns, dependence structures, heterogeneous effects of key determinants and future trajectories of severe food insecurity across Africa. The findings revealed that severe food insecurity exhibited significant spatial dependence and temporal persistence, leading to geographically clustered and sustained patterns over time. Furthermore, Moreover, substantial spatial and temporal heterogeneity was observed, indicating considerable variation in the magnitude of severe food insecurity across countries and years.

The analysis further showed that spatial (neighborhood) effects were stronger than temporal effects, highlighting the dominant influence of geographic proximity on severe food insecurity. In addition, the space–time interaction effects also introduced additional localized variability in severe food insecurity across the continent. This suggests that vulnerability patterns are jointly shaped by interconnected spatial and temporal processes rather than by purely spatial or purely temporal processes alone. Therefore, incorporating integrated spatio-temporal dependence and interaction structures is essential for accurately characterizing the distribution and evolution of severe food insecurity and for informing more targeted interventions across Africa.

This study also concludes that severe food insecurity in Africa is jointly driven by cross-country shared factors and evolving country-specific environmental pressures, socioeconomic dynamics, and agricultural conditions. This revealed that the determinants of severe food insecurity exhibited both globally consistent and locally varying effects across the period 2015–2021. Some factors exerted relatively stable influence across countries over time, whereas others exhibited significant spatial and temporal heterogeneity, with magnitude and, in some cases, the direction of effects differing across locations and the period 2015–2021. Specifically, malaria incidence, climate change, livestock production, and investment inflows exhibited statistically significant globally consistent effects across countries over time. In contrast, GHG emissions, unemployment, GDP per capita, dietary energy supply, dietary protein supply, exhibited statistically significant spatio-temporally varying effects. Moreover, the effects of these covariates were not only heterogeneous across countries and over time but also varied across their ranges of observed values. This indicates that the determinants of severe

food insecurity exhibit complex nonlinear and context-dependent relationships. This coexistence of stable and varying effects underscores the need for policy responses that integrate continent-level structural interventions with context-specific and geographically targeted strategies.

During the study period, countries such as South Sudan, the Central African Republic, the Republic of the Congo, Malawi, Guinea, and Somalia consistently experienced the highest levels of vulnerability. This was largely driven by localized shocks, country-specific policy environments, and context-specific disturbances. These factors operated independently of broader regional dynamics. In contrast, many countries in the Southern, Eastern, and Central African subregions exhibited strong spatial dependence in severe food insecurity. This may be associated with persistent structural constraints and unobserved spatially correlated factors. Furthermore, across much of the study period, Kenya, Ethiopia, Niger, and Burkina Faso frequently exhibited pronounced year-specific shocks. These shocks reflect localized, time-specific disturbances that are not captured by purely spatial or temporal structures. They may be associated with conflict escalation, drought events, and policy disruptions.

Looking forward, data-driven predictive models that account for spatial and temporal dependence achieved higher predictive accuracy than purely spatial and spatio-temporal statistical models. The deep learning-based forecasting results indicated that severe food insecurity is expected to intensify over time across African countries. The projected trajectories also exhibited marked spatial heterogeneity. Particularly severe deterioration is anticipated in South Sudan, the Central African Republic, the Republic of the Congo, Malawi, Guinea, Somalia, Ethiopia, Kenya, the Democratic Republic of the Congo, Angola, Namibia, Niger, and Nigeria. These countries emerged as long-term vulnerability hotspots in the coming decades. Urgent and sustained interventions are likely to be most critical to prevent further deterioration. The findings provide an empirical basis for strengthening anticipatory risk assessment and prioritizing geographically targeted interventions. They may also contribute to efforts to advancing progress towards SDG2 (Zero Hunger) through earlier and more precise identification of populations at greatest risk.

10.4 Recommendations

Based on the empirical findings and methodological contribution of this study, the following recommendations are proposed.

1. Geographically and context-targeted operational interventions

- **Prioritize high-risk areas:** National and regional disaster risk management institutions and development partners should prioritize geographically tar-

geted interventions in persistent and emerging hotspots, particularly South Sudan, Central Africa Republic, Republic of the Congo, Malawi, Guinea and Somalia in order to improve the efficiency of resource allocation and support anticipatory action.

- **Adopt context-specific policy responses:** The significant spatial and temporal heterogeneity in covariate effects indicates that uniform policy designs may be ineffective. Governments should design and implement policy responses tailored to the nature of vulnerability, whether driven by long-standing structural conditions or by country- or context-specific socioeconomic, environmental, and institutional conditions. This approach ensures that interventions address both continent-wide constraints and country-specific risks in a targeted and evidence-based manner. Policymakers are therefore encouraged to adopt context-dependent strategies. For instance, strengthening livestock production may enhance food availability, income stability, and dietary diversity in many settings; however, in arid and semi-arid regions, greater reliance on livestock can increase vulnerability to climate-related shocks.
- **Adopt long-term and sustained interventions:** The observed temporal persistence of severe food insecurity suggests that short-term responses are insufficient. Policymakers should focus on long-term strategies on structural transformation of food systems to achieve sustained improvements.

2. Integrated and adaptive policy frameworks

- **Strengthen national multi-sectoral coordination:** National planning commissions should strengthen coordination with national disaster risk management institutions, food security and nutrition agencies, ministry of agriculture, ministry of health and development partners to establish integrated and adaptive policy frameworks capable of responding to changing economic conditions, environmental vulnerabilities, climate shocks, agricultural productivity constraints and health-related risks. These frameworks support sustainable food security improvements in line with SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-Being), SDG 8 (Decent Work and Economic Growth), SDG 13 (Climate Action) and SDG 17 (Partnerships for the Goals). Such systems will support the timely identification of emerging risks and enable rapid, evidence-based adjustment of policy and operational responses to protect vulnerable populations.
- **Strengthening regional and cross-country partnerships:** Given the presence of strong spatial dependence, national planning commissions should

build collaboration with regional institutions and neighboring countries to address cross-boundary drivers of severe food insecurity that cannot be effectively addressed by individual countries acting alone. Such collaboration will enhance regional preparedness, institutional cooperation, knowledge exchange, and support SDG 17 (Partnerships for the Goals). This would help manage spillover effects and shared vulnerabilities among neighboring countries.

3. Measurement, data, and monitoring systems

- **Embedding advanced data-driven analytical models into early-warning systems:** Regional and national food security monitoring agencies should integrate spatio-temporal deep learning models within national and regional early-warning and monitoring platforms. Such integration aims to improve the early detection of high-risk areas and periods, thereby strengthening anticipatory action, preparedness planning, and evidence-based decision-making.
- **Prioritize proactive and anticipatory action:** Regional and national planning commissions, disaster risk management institutions and food security monitoring agencies should place greater emphasis on proactive and anticipatory action, rather than predominantly reactive responses to realized crises. Early identification of emerging risks should be embedded as a core operational objective of national early-warning systems.
- **Context-specific measurement of food insecurity:** FAO and national planning authorities should adapt the measurement of severe food insecurity for each country by developing context-sensitive indicators that accurately reflect local living conditions, consumption patterns and livelihood strategies.
- **Establish subnational data repositories:** FAO and Africa union commission (AUC) should establish and maintain data repositories at lower administrative levels rather than solely at the national level throughout African countries. This approach is intended to capture and address the subnational heterogeneity in food insecurity risks and determinants, thereby supporting more precise monitoring, early warning and targeted policy interventions.

4. Macro-level interventions

- **Addressing macro-level and systemic drivers of food insecurity:** Policy responses should prioritize macro-level interventions that address structural and systemic drivers of severe food insecurity, rather than relying primarily

on fragmented micro-level actions. Such approaches may include strengthening regional food systems, enhancing macroeconomic stability, improving cross-country coordination, and investing in large-scale climate adaptation and agricultural resilience strategies. This broader policy orientation is more consistent with the observed spatial dependence and cross-country shared determinants of food insecurity.

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