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Evaluating the spatial spillover effects of political stability and agricultural foreign direct investment on food security

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ABSTRACT

Despite significant economic progress, the lack of regular access to adequate and nutritious food remains one of the most pressing challenges in today's world, particularly in developing countries. This study investigates the spatial effect of political stability and agricultural foreign direct investment (FDI) on food security in 43 developing countries using the spatial Durbin model based on balanced panel data from 2005 to 2020. . Our findings indicate that agricultural FDI significantly enhanced food security within the host country and neighboring countries. Equally significant is the impact of political stability on food security locally and in nearby countries. Interestingly, the interaction between political stability and agricultural FDI is also positive and significantly affects food security in the given country and its adjacent countries. We advocate for policies that promote political stabilityand bolster FDI in agriculture, given their substantial contributions to improving food security at the regional level.

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Political stability; FDI in agriculture; food security; spatial Durbin Model

1. Introduction

Global economic activity, measured by Gross Domestic Product (GDP), rebounded significantly from a 4.3% contraction in 2020 to 4.7% growth in 2021, with developing countries (DCs) experiencing a vigorous recovery from a 2.5% decline to nearly 6% during the same period (United Nations, 2021). Despite the economic recovery, problems of food security persist.[1] According to the State of Food Security and Nutrition in the World report (FAO, IFAD, UNICEF, WFP WHO, 2022), the global number of undernourished individuals rose from 585 million (8% of the world population) in 2016 to 768 million (10%) in 2021, with the majority residing in DCs. This problem is not confined to individual countries, as factors affecting a country's food security can affect other countries' food security because of the growing interdependence of global economies (Abdullah Qingshi et al., 2021; Cai et al., 2020; Clapp, 2014; Tobler, 1970).

DCs' economic and social potential does not necessarily yield improved food security outcomes. It confronts a global economic context characterized by fluctuations in growth, trade, climate, and commodity prices Dethier and Effenberger (2012); Von Braun and Tadesse (2012). However, agricultural investment plays a crucial role in fostering agricultural growth and reducing poverty and undernourishment (FAO, IFAD, WFP, 2012; Reutlinger, 1986; World Bank, 2007). P. Liu (2014) summarizes the findings from FAO case studies on how foreign agricultural investment affects host communities and countries.[2] Hence, the recourse to foreign direct investments (FDI) can be an alternative for DCs (Reutlinger, 1986). FDI inflows to DCs have increased significantly, rising from 33.8% of global inflows in the early 2005s to 66% by 2020 (UNCTAD, 2021). This surge in FDI is crucial as it brings expertise, technology, and capital, which can enhance productivity and infrastructure. However, it is essential to recognize that developing nations are not monolithic in their economic structure. As such, the impact of increased FDI on economic outcomes

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[1]Food security is "a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2015).

[2]According to P. Liu (2014), agricultural investments have the potential to deliver a variety of developmental benefits, such as increased productivity and income. However, these advantages are not anticipated to materialize automatically. The case studies indicate that the drawbacks of large-scale land acquisitions – often driven by international commodity markets for soy, maize, and meat – may overweight the few benefits to the local community according to the local rights and the quality of governance in particular.

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varies regionally; Africa receives the smallest portion of FDI, while East and Southeast Asia attract the largest share among developing countries (UNCTAD, 2021), influencing their respective economic trajectories and development outcomes differently.

Based on the above stylized facts, a positive effect of FDI inflows on food security is anticipated. FDIs could play a positive role through their effect on agricultural productivity Hallam (2011); Santangelo (2018) (Slimane et al., 2016), and they can also be a source of economic development that improves access to food (Pingali, 2007). In fact, empirical research on the influence of FDI on food security dates back to the 1980s, with an emphasis on the distinction between dependency effects and modernization effects (Mihalache O'Keef & Li, 2011). Although FDI is generally expected to enhance food security through its role in agricultural productivity and economic growth, this relationship is contingent upon several factors, including governance quality (Dogan, 2022; P. Liu, 2014).

According to Tobler's (1970) first law of geography, the positive effects of FDI on the host country's food security can spill over into neighboring countries.[3] Specifically, FDI in the agriculture sector of host countries can improve food security in terms of food availability in both the host countries and their neighboring countries through increased regional trade (Bouzid & Toumi, 2020; Gunasekera et al., 2015). For example, a host country receiving agricultural FDI might adopt precision farming technologies like GPS-guided machinery, which enhance efficiency and crop yields (Gabel, 2024; Sharma & Shivandu, 2024). The productivity gain often leads to surplus food production (Cochrane, 1959), allowing host countries to export staples to neighboring nations. This increase in regional food supply enhances food availability and reduces food price volatility (Bouzid & Toumi, 2020; Cochrane, 1959; Gunasekera et al., 2015). Additionally, labor mobility is crucial. Workers trained in FDI-funded agricultural projects, such as operating precision farming equipment or managing high-yield crops, may seek or offer similar opportunities in adjacent countries for higher wages, leading to increased agricultural productivity (Antczak et al., 2018; Du et al., 2023).[4]

Political stability is one of the crucial factors that impact the investment decisions of multinational corporations (MNCs) (Howell, 2011).[5] It refers to the absence of sudden and unpredictable government changes, violence, riots, and conflicts under which business functions remain constant and reliable (Ake, 1975; Brewer, 1981; Kim, 2010; Root, 1972). MNCs seek political stability when investing in the host country because the level of political risk can influence the risk premium incorporated in any investment project (Kusek & Silva, 2018). Political stability by fostering effective governance might attract higher FDI and stabilize market conditions, reduce high food prices, and enhance food access for impoverished populations in both the host and neighboring countries (Abdullah Qingshi et al., 2021; Busse & Hefeker, 2007; Dogan, 2022). This can help to improve food security across borders and reduce the risk of supply chain disruptions. In summary, political stability can improve food security in the given politically stable country and its surrounding countries as well as create a favorable environment for FDI in agriculture, thereby enhancing agricultural production and contributing to food security in both the host country and its contiguous countries.

Considering the aforementioned discussion about the role of political stability and agriculture FDI in affecting regional food security, a number of key research questions arise. What is the spatial distribution of food security among developing countries? Does spatial dependence exist in the distribution of food security among these countries? Do alterations in political stability and FDI, as well as their interaction, have spatial spillover effects on food security?

Despite the growing body of literature examining the impact of FDI in agriculture on food security in developing countries, the interplay between political stability, agricultural FDI, and food security has not been extensively studied (Djokoto, 2012; Dogan, 2022; Gerlach & Liu, 2010; Hallam, 2011; Santangelo, 2018; Slimane et al., 2016; Wimberley, 1991; Yao et al., 2020). Specifically, existing studies often overlook the spatial dimensions of these relationships and fail to account for spatial dependencies and spillover effects that may

[3]Tobler's first law states that "everything is related to everything else, but near things are more related than distant things," highlighting the theory that geographic proximity enhances the intensity of interactions and spatial spillover effects.

[4]It is crucial to recognize that such spillovers can introduce challenges. Increased labor mobility, while beneficial for skills transfer, may lead to wage competition in neighboring countries, suppressing local wage growth and straining existing employment opportunities while also creating challenges for the home country in terms of labor shortages and potential skill gaps (Athukorala & Devadason, 2012; Dodini et al., 2023; Gadhok, 2016). In addition, the influx of lower-priced, high-yield crops from host countries can create stiff competition for the local agricultural sector (Khanal et al., 2024). Smaller farms in neighboring countries may struggle to keep pace, resulting in reduced profits, loss of market share, and even closures if they cannot quickly adapt to intensified competition (Btooz, 2024; Gadhok, 2016).

[5]Factors such as economic and political stability, exchange rate risks, infrastructure, labor costs, management skills, innovative product technologies, economies of scale, market structure and growth are important factors of FDI (Asiedu, 2002; Chakrabarti, 2001).

influence outcomes across different countries (Anselin & Bera, 1998; Elhorst, 2014b). Furthermore, there is inconsistency in how food security and political stability are measured, potentially affecting the generalizability of the findings (Abdullah Qingshi et al., 2021; Deaton & Lipka, 2015).

To address these research gaps, this study tests for spatial autocorrelation and identifies the presence of spatial dependence in food security outcomes. It explicitly investigates how factors contributing to a country's food security, such as political stability and agricultural FDI, affect the food security of the neighboring countries. Second, this study employs spatial panel data models to analyze how the interaction between political stability and FDI in agriculture affects food security across various DCs. By integrating spatial econometric techniques, our approach controls for spatial dependencies and identifies potential spillover effects, thereby providing a more nuanced understanding of how political stability and FDI interact to influence food security in different geographical contexts. Third, we use a combined indicator of food security to mitigate criticisms arising from disparate measurement approaches and to enhance comparability across different country categories. In addition, recognizing that political stability can be measured in multiple ways, we incorporate indicators from both the International Country Risk Guide (ICRG) and World Governance Indicators (WGI) to ensure the robustness and generalizability of our results. According to Slimane et al. (2016), FDI is more effectively utilized at the sectoral level rather than in the aggregate, which supports our focus on FDIs specific to the agricultural sector.

The following section provides a comprehensive review of the relevant literature. Section 3 describes the variables, data, and methods used for variable construction. Section 4 discusses spatial econometric methods. The findings are presented in Section 5 and subsequently discussed in Section 6. Finally, the paper concludes with key insights and implications in Section 7.

2. Literature review

The agricultural sector holds significant importance for DCs as it constitutes a crucial segment of their economy (FAO, 2009; Rajalahti, 2021). Investing in agricultural productivity is one of the best ways to avert long-term food crises. While many studies view agricultural investment as a potential solution to food insecurity by promoting the expansion of food production (Santangelo, 2018; Slimane et al., 2016; Wardhani & Haryanto, 2020), it is essential to analyze whether such increases in production directly lead to lower food prices and improved access to food for the poor. Despite the fact that global food production has more than doubled over recent decades, hunger persists, fueled by rising food prices and hidden challenges like political and economic instability (Subramaniam et al., 2023; Windfuhr, 2013). Further, FDI inflows in most DCs are predominantly allocated to sectors other than agriculture (P. Liu, 2014; Rakotoarisoa, 2011), which receives only a small fraction of the total investments (Gerlach & Liu, 2010).

However, the real-world implications of political stability in DCs could be complex since political stability is a dynamic and multifaceted construct driven by complex interactions between governance, corruption, internal and external pressure, accountability, and power structures (Howell, 2011). Many DCs with corruption or illegal lobbying practices can still attract foreign investments, though often at the expense of local populations and food security (Campos & Giovannoni, 2007; Guha et al., 2020). Therefore, establishing a conducive political environment is essential not only for attracting foreign investors but also for promoting regional collaboration and trade openness, which can foster market integration and potentially support a more stable food supply across the region (Abdullah Qingshi et al., 2021; Busse & Hefeker, 2007).

Our research is centered around the crossroads of three areas of academic literature. The nexus between FDI in agriculture and food security, the interaction effects of political stability and FDI on food security, and the nexus between political stability and food security. These studies are carried out with a spatial perspective and thereby examine the impetus behind the collaborative progress of food supply in DCs.

2.1. FDI in agriculture and food security nexus

Research from the early 1980s began exploring the relationship between FDI inflows and food security, focusing on two contradictory theories: dependency theory and modernization theory. The post-World War II period saw significant FDI directed toward DCs, primarily in the extractive sector. Indeed, multinational corporations (MNCs) targeted these regions for their natural resources, low-cost labor, and profits. These corporations often penetrated into the most dynamic sectors of DCs, consequently steering the host nations toward unbalanced development (Amirahmadi & Wu, 1994). According to this theory, the effects of FDI can be destructive if MNCs manipulate goods prices to evade taxes, siphon profits back to their countries of origin, and affect local politics and economic conditions by controlling the means of production, in addition to unfavorable effects on income distribution and development (Adams, 2009; Dixon & Boswell, 1996; Heo & Hahm, 2007). In this context, dependence on foreign investment negatively influences DCs. Conversely, modernization theory proponents emphasize that internal and external forces lead to economic development. Internally, development stems from domestic investments, industrialization, education, and cultural modernization, ultimately providing social welfare (Jenkins & Scanlan, 2001). Externally, FDIs are viewed as a means of introducing advanced technology, organizational capabilities, management skills, and marketing expertise. FDI inflows promote easier access to international markets and encourage the spread of new skills and knowledge within the host economy (Kumar & Pradhan, 2002). The transfer of technology and expertise boosts productivity and improves resource allocation efficiency (Barua, 2013; Tambunan, 2005). However, the transfer of technology and expertise or know-how is not without its drawbacks; it can have negative repercussions, such as costly learning processes, disparities in managerial and technical capabilities, and uneven financial capacities among local firms for adopting advanced technologies (Z. Liu, 2008). Both theories are used to describe the effects of foreign investments on welfare.

Regarding the effects of agricultural FDI on food security, the literature review highlights that it can be positive or negative. According to Slimane et al. (2016), FDI in the agriculture sector specifically increases food security through improvements in agricultural production. Several case studies further exemplify this positive effect. For instance, investments by a transnational company significantly increased the total production of palm oil in Ghana, and investments from companies like Tilda (U) Ltd in Uganda nearly doubled rice production over the past decade after introducing the Nerica rice variety (Gerlach & Liu, 2010). When discussing positive spillovers, Poland appears as the most relevant example, as the horizontal and vertical FDI inflows have positively influenced the dairy sector (Dries & Swinnen, 2004). Spillovers with respect to the transfer of technology and know-how in Ghana have improved agricultural production (Djokoto, 2012). Moreover, spillover effects from services FDI and manufacturing FDI have a positive impact on agricultural productivity in Latin America, where FDI in agriculture also exerts a positive and significant effect (Tondl & Fornero, 2010). Thus, foreign direct investment contributes to food security by transferring technology, enhancing production, generating employment, increasing domestic productivity, and reducing prices, although it also brings positive and negative environmental impacts (Doytch & Uctum, 2016; Hallam, 2011). In this perspective, the Ugandan government has followed environmentally friendly production methods, such as investing in floriculture (Gerlach & Liu, 2010). Empirically, the pollution-haven theory can illustrate the possible adverse impact of FDI on environmental quality, public health, and agricultural production (Akabzaa & Darimani, 2001; Jorgenson, 2007). For instance, Jorgenson (2006) found that FDI in manufacturing has a positive effect on growth in organic water pollution intensity in less-developed countries. Similarly, Akabzaa and Darimani (2001) documented how FDI-driven mining activities in the Tarkwa region of Ghana have degraded and polluted the water table, resulting in negative health impacts on local households. Furthermore, FDI is often associated with land grabbing and significant ecological damage, compromising long-term food security by displacing small-scale farmers and damaging vital soil and water resources necessary for sustainable agriculture (Von Braun & Meinzen-Dick, 2009; White et al., 2012).

Moreover, multiple empirical studies have demonstrated that foreign direct investments from a source country not only influence the economic and developmental dynamics of the host country but also generate cross-border spillover effects in countries neighboring the host (Boly et al., 2020; Coughlin & Segev, 1999; Long et al., 2020; Mahmood, 2023). Despite these established spillovers, the spatial mechanisms of how FDI influences food security remain understudied, with no known study focusing specifically on agricultural FDI. In the context of agriculture, such spatial linkages may arise through open markets, cross-border integration of supply chains, labor mobility, and shared policy frameworks, all of which facilitate the transmission of both positive and negative spillover effects. For instance, increased agricultural FDI improves a host country's food security by transferring technology and boosting production capacity (Slimane et al., 2016). This, in turn, can influence nearby nations via trade flows, resource-sharing agreements, and policy spillovers (Abdullah Qingshi et al., 2021; Bouzid & Toumi, 2020; Gunasekera et al., 2015). Conversely, adverse shocks or inefficiencies in one country's food system can also affect adjacent areas. Specifically, the arrival of food from host countries increases competition for local agricultural sectors. This situation forces smaller farms in the adjoining areas to face reduced profits, a decline in market share, or even closure if they fail to adapt swiftly (Arita et al., 2014; Gadhok, 2016).

In summary, the theory is in favor of the nexus between foreign direct investment and food security, but according to the empirical analysis, there is a lack of evidence on how agricultural FDI directly affects food security, in particular at the regional level.

2.2. Political stability, FDI in agriculture, and food security nexus

The political economy theory emphasizes the importance of political stability in fostering an environment conducive to investment, economic growth, and development (De Schutter, 2017; Swinnen, 2010). Stable political systems create a more predictable environment for investors, enabling them to make long-term plans and investments (Busse & Hefeker, 2007). More particularly, political stability can affect the willingness of foreign investors to invest in the agricultural sector, impacting the flow of capital, technology, and knowledge transfer, which are all essential for improving agricultural productivity and food supply (Swinnen, 2010).

Political stability is an essential factor that can either facilitate or hinder the positive effects of agricultural FDI on food security. One of the key aspects of political stability is its impact on attracting and sustaining agricultural FDI. Mihalache O'Keef and Li (2011) revisit the debate between modernization and dependency theories regarding the effects of FDI on food security in less developed countries. They employ a large-N quantitative analysis using data from 1970 to 2005 and find that FDI generally improves food security by increasing agricultural production and food availability. However, they also highlight that the benefits of FDI on food security depend on the quality of governance, suggesting that better governance can enhance positive FDI effects. The authors argue that their findings support the modernization theory, as FDI can foster development and improve food security when combined with sound governance. In contrast, Haggblade et al. (2007) argued that political instability could lead to adverse effects on food security by hampering the flow of resources, obstructing infrastructure development, and creating uncertainty in the investment climate. Furthermore, political instability can result in a loss of confidence among investors, leading to reduced FDI inflows and diminished opportunities for economic growth in the agricultural sector.

Political stability also plays a role in the effectiveness of policy interventions aimed at promoting agricultural FDI and food security. In countries with strong institutions and sound macroeconomic policies, FDI can contribute to food security by increasing availability, accessibility, and stability (Arezki & Bruckner, 2011). However, in countries with weak institutions and high levels of corruption, FDI may not yield the desired outcomes and can even lead to negative consequences such as land grabbing and environmental degradation (Zoomers, 2010). In addition, political stability can influence the distribution of benefits derived from agricultural FDI. Cotula (2009) claimed that in stable political environments, FDI could contribute to inclusive growth by benefiting both smallholder farmers and commercial farming enterprises. In contrast, in politically unstable contexts, FDI may exacerbate income inequality by favoring large-scale commercial farming over smallholder farmers, potentially undermining food security for vulnerable populations. The governance of land and natural resources also affects the relationship between political stability, agricultural FDI, and food security. In countries with weak land governance systems and high levels of political instability, land grabbing and local communities' displacement may occur due to agricultural FDI (Cotula, 2009; Deininger & Byerlee, 2011). This can negatively affect food security, as local populations lose access to land and resources needed for their livelihoods.

As previously discussed, FDI in agriculture can improve the food security level of the host country by increasing production and in countries neighboring the host by trade openness. These positive effects in countries with political stability can be sustained and even amplified as stable conditions support long-term FDI inflows and strengthen cross-border collaboration (Dogan, 2022). Conversely, in countries with unstable political environments, the scenario often reverses. The absence of a reliable governance framework can lead to the withdrawal of investment and a reluctance to engage in long-term agricultural projects. Furthermore, political turmoil can disrupt regional collaboration and essential trade routes, critically affecting food supply chains (Jagtap et al., 2022). Thus, political stability is crucial in determining the impact of agricultural FDI on regional food security. Haggblade et al. (2007) emphasized the importance of accounting for regional differences in political stability when assessing the relationship between agricultural FDI and food security.

Besides, to control for the potential effects of political stability and agriculture FDI on food security, we incorporate five control variables that capture key mechanisms influencing food security outcomes (Wooldridge, 2010). First, GDP per capita serves as a proxy for economic development, which can affect food security by influencing income levels, government capacity, and the ability to invest in food systems (Fernandes & Samputra, 2022). Second, trade openness is included as it affects food availability and affordability through import and export policies, with open trade often improving access to food resources (Dithmer & Abdulai, 2017). Abdullah Qingshi et al. (2021) further support the inclusion of trade openness and GDP in spatial models, finding that they contribute to food security on a regional scale, with effects propagating from the local country to its neighboring countries. Third, unemployment is incorporated to account for the impact of labor market conditions on household income and food access, with higher unemployment often leading to reduced food security (Etana & Tolossa, 2017; Masron et al., 2020). The fourth control variable, domestic investment, is considered because investment in agriculture not only expands food production capacity, but also reduces smallholders' vulnerability to global market fluctuations and the risk of FDI withdrawal (Fan & Zhang, 2008; FAO, 2012). Moreover, domestic financing reflects a nation's commitment to agricultural resilience. It supports infrastructure (e.g., irrigation, cold chains) that is critical for buffering climate impacts and sustaining productivity amid political volatility – factors that FDI alone cannot address (FAO, 2012). Finally, the crop production index is used to account for agricultural productivity, directly linking the availability of food to food security levels (FAO, 2016). By controlling for these factors, the study aims to examine how political stability and FDI specifically impact food security, without the influence of other factors (Wooldridge, 2010).

2.3. Political stability and food security

The political economy of hunger theory, developed by Amartya Sen, provides a solid theoretical foundation for understanding the nexus between political stability and food security (Sen, 1981). The theory emphasizes the importance of political factors, including stability and good governance, in shaping food security outcomes by influencing entitlements, capabilities, and the overall enabling environment for food production and distribution.

Accordingly, a strand of past empirical studies is related to the relationship between political stability and food security (Q. Abdullah et al., 2020; Cai et al., 2020; Kousar et al., 2021; Masron et al., 2020; Ogunniyi et al., 2020; Smith & Haddad, 2015). All these authors agree that political stability plays a pivotal role in improving food security by creating a conducive environment for effective policy implementation, investments, and resource allocation. Governments can more effectively devise and implement policies in stable political environments to enhance agricultural productivity, develop infrastructure, and promote social safety nets for vulnerable groups. Furthermore, political stability can attract domestic and foreign agricultural investments, leading to increased productivity, job creation, and overall economic growth. By fostering good governance and ensuring the provision of basic rights and services, political stability contributes to a more efficient and equitable food production and distribution system. Ultimately, these factors work together to improve food availability, accessibility, and stability, thereby enhancing food security for the population. For instance, Masron et al. (2020) investigated the relationship between institutional quality and food security using panel data from 43 developing countries from 2002 to 2016. The study found that good governance and institutional quality play a critical role in improving food security outcomes. Specifically, the authors highlighted that factors such as the rule of law, control of corruption, government effectiveness, and political stability positively impact food security by creating an enabling environment for investments, policy implementation, and resource allocation. These findings suggest that strengthening institutional quality and governance is essential for addressing food security challenges in developing countries.

Besides, several research studies have identified the spatial cluster of food security, i.e., a country's contributing factors to food security may affect the food security of its contiguous countries, and vice versa (Abdullah Qingshi et al., 2021; Cai et al., 2020; Leonard et al., 2018). For example, Abdullah Qingshi et al.

(2021) conducted a spatial panel analysis to investigate the relationship between food security and political risk in 31 Asian countries from 2000 to 2019, using spatial panel data models to account for spatial dependence among the countries. The authors found a negative relationship between political risk and food security, indicating that higher levels of political risk are associated with lower food security outcomes in the region. Moreover, the study revealed significant spatial spillover effects, suggesting that political risk in one country can influence food security in neighboring countries. This highlights the importance of considering spatial dimensions and regional cooperation when addressing food security challenges in Asia. The findings of the study emphasize the need for stable political environments and effective governance to improve food security outcomes in the region, as well as the importance of considering spatial dependencies in policymaking. Similarly, George and Adelaja (2022) analyzed the impacts of the influx of Internally Displaced People (IDPs) via Armed conflicts on the food security of host communities in Nigeria using the instrumental variable technique. They measured food security by food consumption score and armed conflicts by IDPs during armed conflicts. However, they discovered that the influx of IDPs due to conflicts has a detrimental effect on the food security situations of the communities that are hosting them. They claimed that the spatial spillover of the IDPs by conflicts could adversely affect the food security of the hosting areas. In addition, Conflicts damage agricultural sectors through dislocations, insecurity, disease, and the loss of experienced farmers, affecting not only the country in conflict but also its neighbors (Lukongo & Rezek, 2018). Therefore, political stability enhances food security within a country and its neighbors by fostering effective policy implementation, investment, cross-border trade, and regional cooperation. This leads to increased agricultural productivity, improved infrastructure, and better food availability, benefiting both the stable country and the surrounding countries.

3. Variable Description, data, and methods

3.1. Variable Description and data

This study utilizes balanced panel data for 43 DCs spanning the period from 2005 to 2020. The selection of these DCs relied on data availability and insights drawn from prior research. The detailed list of the included DCs is reported in (Table 3. Spatial distribution of developing countries' food security in LISA map quadrants), where countries are categorized into distinct degrees of spatial clustering regarding food security. This means that a country's contributing factors to food security can influence the food security of neighboring countries. However, the data for both the regressand and regressor variables in this study are primarily sourced from the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT), the ICRG provided by the Political Risk Services (PRS) Group, and the WGI and World Development Indicators (WDI).

3.1.1. Regressand variable: food security index (FSI)

Food security is measured in this research by constructing a composite index using the principal component analysis technique (Carletto et al., 2013; Slimane et al., 2016). Appendix A displays indicators to measure the food security index. It features four key indicators sourced from FAOSTAT. Individually, the four food security indicators offer fragmented and occasionally conflicting perspectives, providing limited insight into the overall progress toward the overarching goal of food security (Masron et al., 2020). In contrast, a composite index consolidates this information into a more coherent and comprehensive measure (Slimane et al., 2016). Specifically, the first two indicators, the average value of food production and the average dietary energy supply adequacy, represent the food availability dimension of food security (Abdullah Qingshi et al., 2021; FAO, 2015). This dimension relates to the presence of sufficient quantities of food of appropriate quality for all people at all times, supplied through domestic production, stockpiling, or imports. The third and fourth indicators, access to water services and access to sanitation services, indicate the food utilization dimension, which concerns the effective use of food through a proper diet, clean water, sanitation, and healthcare to reach a state of nutritional well-being where all physiological needs are met (FAO, 2015). This highlights the importance of non-food inputs in achieving food security.

Although the composite index captures key aspects of food security through these four indicators, it does not directly incorporate critical dimensions such as food stability and affordability, both of which are essential for a complete understanding of food security. Stability ensures consistent food availability during crises and disruptions. Without this, the index might misrepresent security in regions prone to shocks. Similarly, affordability addresses the economic capacity of individuals to access nutritious foods. Even when food is physically available, it is not genuinely secure if its cost makes it inaccessible to a significant portion of the population. Omitting these dimensions limits the FSI's ability to fully capture the comprehensive reality of food insecurity in various contexts and accurately assess long-term food security trends.

3.1.2. Regressor 1: FDI in agriculture (FDI_{AGR})

Foreign Direct Investment (FDI) is defined as an investment that aims to acquire lasting management influence (i.e., 10 percent or more of voting power) in an enterprise operating in a foreign economy (FAO, 2023). In the context of the agricultural sector, this encompasses investments made by individuals, firms, or institutions from one country into enterprises engaged in crop production, forestry, fishing, livestock farming, aquaculture, agro-processing, and other agribusiness ventures in another country (FAO, 2022). Such investments often involve the transfer of capital, technology, managerial expertise, and best practices to the host country's agricultural sector. However, agriculture FDI can be measured using various indicators and data sources, often focusing on inflows to subsectors such as agriculture, hunting, forestry, and fishing. Many empirical studies have utilized sectoral-level FDI data instead of aggregated data in large samples and measured agricultural FDI by considering FDI inflows directed toward these subsectors (Dogan, 2022; Mihalache O'Keef & Li, 2011; Slimane et al., 2016; Yao et al., 2020).

Data on FDI_{AGR} has been acquired, with values measured in millions of US dollars, from the FAO's investment database, which covers agriculture, forestry, and fishing sectors. These data are used to analyze the spatial effects of FDI on food security in 43 DCs from 2005 to 2020. Several empirical studies have utilized the average FDI to account for missing observations (Busse & Hefeker, 2007; Slimane et al., 2016; Subramaniam et al., 2023). In our study, we employed the interpolation method to address missing observations, as we identified 34 (or 5%) missing data points out of the 688 total observations. Besides, as with most empirical research studies on FDI flows, logarithmic values are employed for investment flows and predictor variables. However, to maintain the negative sign of FDI observations that can be lost after applying the standard logarithmic transformation, a specific transformation procedure is employed for these variables (Busse & Hefeker, 2007), which is explained in Equation (1).

$$Y = \ln\left(x + \sqrt{(x^2} + 1\right)) \tag{1}$$

3.1.3. Regressor 2: political stability (PST)

Political stability refers to the absence of abrupt and unforeseen shifts in government, as well as the absence of violence, unrest, and disputes (Ake, 1975). Our study initially utilizes balanced panel data of political stability as a regressor variable. Its data is sourced from two well-regarded international organizations, ICRG and WGI, to guarantee the reliability of our results. The political stability data, sourced from ICRG, are utilized in an indexed form calculated from 12 political risk factors. Appendix B presents the factors to construct the political stability index and provides the construction details. While most factors – such as corruption, law and order, internal and external conflicts – directly influence both FDI and food availability and accessibility, other factors have only an indirect influence, potentially weakening the overall impact of the political stability index on food security outcomes through its role in FDI (Busse & Hefeker, 2007; Smith & Haddad, 2015). Additionally, due to the proprietary nature of the dataset – whose complete methodology and underlying raw data are often not publicly available – fewer studies have established the relationship between ICRG factors and food security (Q. Abdullah et al., 2020; Smith & Haddad, 2015).

When gathering data from WGI, political stability and non-violence are two interrelated dimensions that assess the likelihood of political unrest and the prevalence of peaceful conditions within a country (Kaufmann et al., 2010). These dimensions are integrated into a composite indicator through an unobserved components statistical model. The resulting index is scaled from −2.5 to 2.5, with higher scores representing greater stability and peace, while lower scores indicate instability and heightened violence. While WGI data are freely accessible and widely utilized, their reliance on perception-based evaluations from diverse sources introduces subjectivity, which can affect temporal consistency and comparability across countries.

Nevertheless, their significant effects on food security are widely acknowledged in empirical literature (Cai et al., 2020; Kousar et al., 2021; Masron et al., 2020; Ogunniyi et al., 2020).

3.1.4. Regressor 3: interaction term (PST * FDI_{AGR})

As per Brambor et al. (2006), when examining an interactive model, it is essential to concentrate on the interaction term, such as the interplay between political stability (PST) and foreign direct investment (FDI) in the agriculture sector (PST * FDI_{AGR}), instead of focusing on individual terms like PST or FDI_{AGR}. This is because the estimated coefficients of PST and FDI_{AGR} only capture the effect of political stability (or agriculture FDI) on food security when political stability (or agriculture FDI) is absent. Conversely, as illustrated in Equation (2), political stability serves as a mediator and is anticipated to buffer the impact of FDI in the agriculture sector on food security. As a result, β3 is anticipated to be marginally positive or negative, depending on the political stability conditions. Brambor et al. (2006) propose that at the margin, the net influence of decreasing or increasing food security due to foreign investment in the agriculture sector can be assessed by investigating the partial derivative of food supply, as demonstrated in Equation (2):

$$FSI_i = \beta_o + \beta_1 FDI_{AGR_{1,i}} + \beta_2 PST_{2,i} + \beta_3 \left(FDI_{AGR1,i} PST_{2,i}\right) + \epsilon_{i,t}, \frac{\partial FSI_i}{\partial FDI_{AGR1,i}} = \beta_1 + \beta_3 PST_{2,i}, \tag{2}$$

3.1.5. Regressor 4 to 8: control variables (CV)

According to the references (Abdullah Qingshi et al., 2021; Abdullah & Wang, 2024; Dogan, 2022; Godfray et al., 2010; Kalkuhl et al., 2016; Masron et al., 2020; Slimane et al., 2016; Subramaniam et al., 2019; Yao et al., 2020), we employ the given five variables as control variables to control for the potential effect of other factors on food security: crop production index (CRP), GDP per capita, unemployment (UNE), domestic investment (DOI), and trade openness (TRO). The crop production index shows yearly agricultural production relative to the base period 2014–2016. GDP per capita in constant 2015 US dollars. Unemployment is taken as a percentage of the total labor force. Domestic investment is measured by gross fixed capital formation as a percentage of GDP. Trade is the sum of exports and imports of goods and services measured as a share of gross domestic product. The data for all these variables are obtained from WDI.

4. Methods

4.1. Spatial autocorrelation test

This study aims to examine the spatial effects of political stability and agricultural FDI on food security in DCs. As stated by Goodchild et al. (1992), spatial autocorrelation is present in nearly all data sets. This autocorrelation indicates the level of association between a country's attribute value and the identical attribute value in its neighboring countries, which can be evaluated using global and local spatial autocorrelation tests before employing spatial econometric models (Anselin, 1988). In the context of a global spatial autocorrelation analysis, the global Moran's I index is employed to evaluate the overall spatial autocorrelation within a dataset, reflecting the degree of similarity or clustering between countries based on a specific attribute. It helps to understand the general spatial pattern across countries. For calculating the global Moran's I, Equation (3) provides the formula.

$$Global\ Moran's I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(Z_i - \bar{Z})(Z_j - \bar{Z})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{3}$$

Where $\bar{Z} = \frac{1}{n}\sum_{i=1}^{n} Z_i$ and $S^2 = \frac{1}{n}\sum_{i=1}^{n} (Z_i - \bar{Z})^2$, n denotes the total number of spatial units, Z_i and Z_j are the attribute values for spatial unit i and spatial unit j, and w_{ij} represents the entry in the spatial weight matrix W located at row i and column j. The appropriate method to establish the W matrix is K-nearest neighbor (K-nn) when the spatial units being analyzed are irregularly spaced or when there is no natural adjacency-based structure

(Anselin, 2005).[6] This method calculates spatial weights based on the distance between observations, considering a fixed number of nearest neighbors (k) for each spatial unit. Meanwhile, global Moran's I values span from −1, indicating negative spatial autocorrelation, to + 1, signifying positive spatial autocorrelation. A Moran's index value of −1 or + 1 represents perfect dispersion or perfect correlation, respectively, while a zero value corresponds to a random spatial distribution. Regarding the local spatial autocorrelation test, Local Indicators of Spatial Association (LISA) statistics can be used, which can be visualized using a LISA cluster map. Typically, this map comprises four categories of observations. The HH category represents areas with high values surrounded by other high-value areas, while the LL category consists of regions with low values neighbored by other low-value regions. Analogous principles apply to the HL and LH categories.

4.2. Spatial regression model specification

In instances where different degrees of spatial correlation exist, utilizing appropriate spatial panel data models is more advantageous than using conventional models (Abdullah Qingshi et al., 2021; Elhorst, 2014b). This is due to the fact that spatial dependence can result in dependent error terms and skewed estimation outcomes, contravening the assumptions of independence and identical distribution present in traditional models. Consequently, it is advisable to select spatial regression models for analysis. Frequently employed spatial models encompass the spatial lag model or spatial autoregressive model (SLM or SAR), spatial error model (SEM), and spatial Durbin model (SDM). The spatial autoregressive model (SAR) takes into account the spatial spillover effect of the regressand variable. Thus, in accordance with our study, Equation (4) presents the SAR model that includes a spatial lag term for the regressand variable food security.

$$lnFSI_{\mathrm{i,t}} = \rho \sum_{j=1}^{N} W_{i,j} lnFSI_{i,t} + \beta_1 lnFDI_{AGR_{i,t}} + \beta_2 lnPST_{i,t} + \beta_3 \left(lnPST_{i,t} * lnFDI_{AGRi,t} \right) + lnCV_{i,t} + \mu_i + \nu_t + \epsilon_{i,t} \tag{4}$$

$lnFSI_{i,t}$ represents the logarithmic form of the regressand variable, the food security index, where "i" refers to spatial units (1 to N) in the cross-sectional dimension, and "t" denotes time periods (1 to T) in the time dimension. $\rho \sum_{j=1}^{N} W_{ij} FSI_{it}$ is regarded as the spatial lag term for the regressand variable, with ρ recognized as the spatial autocorrelation coefficient. $lnFDI_{AGR_{i,t}} and lnPST_{i,t}$ denotes the core regressor variables, which correspond to the logarithmic form of foreign direct investment in the agriculture sector and political stability, respectively. $lnPST_{i,t} * lnFDI_{AGRi,t}$ indicates the interactive term of political stability and agriculture FDI. $lnCV_{i,t}$ signifies control variables, encompassing crop production index (CRP), gross domestic product (GDP) per capita, unemployment (UNE), domestic investment (DOI), and trade openness (TRO). β s implies estimating parameters for these regressor variables, respectively. Where W is a square matrix of size N by N that characterizes the correlation or association among the spatial units, $\mu_i and \nu_t$ represents the cross-sectional and time-specific effects, and ε_{it} is the error term.

The spatial error model (SEM) described in Equation (5) is appropriate for analyzing situations where spatial heterogeneity and dependence need to be considered, especially when the correlation of target variables is affected by a random error term. The autoregressive factor φ indicates the presence of spatial autocorrelation with omitted regressor variables when φ is statistically significant. A significant value of φ implies a noticeable spatial dependency in the residual outcomes. The term ε_{it} represents the random error term commonly assumed to be identically and independently distributed (i.i.d.).

$$lnFSI_{\mathrm{i,t}} = \beta_1 lnFDI_{AGR_{i,t}} + \beta_2 lnPST_{i,t} + \beta_3 \left(lnPST_{i,t} * lnFDI_{AGRi,t} \right) + \beta lnCV_{i,t} + \mu_i + \nu_t + \zeta_{i,t}, \tag{5}$$

[6]We selected spatial units according to data availability, which results in varying distances between countries. Therefore, we employ the k-nn method to construct the spatial weight matrix W.

$$where\zeta_{i,t} = \varphi \sum_{j=1}^{N} W_{i,j}\zeta_{i,t} + \epsilon_{i,t}$$

The Spatial Durbin Model (SDM), represented by Equation (7), is a general form of the spatial measurement model that can be determined into the spatial autoregressive or error models, depending on specific conditions (LeSage & Pace, 2009). SDM can be considered a spatial autoregressive model when $\Psi = 0$, and it can be degraded into a spatial error model when $\Psi + \rho\beta = 0$. However, SDM includes both the spatial lag term of the regressand variable and the spatial term of the regressor variable. The SDM theory reveals that the observed values of regressand variables are influenced by regressand variables in neighboring regions as well as by regressor variables in surrounding areas. This approach allows for a more comprehensive assessment of the key factors impacting the regressand variables from both endogenous and exogenous perspectives. However, in this study, SDM is described in Equation (6):

$$\begin{aligned} lnFSI_{\mathrm{i,t}} &= \rho \sum_{j=1}^{N} W_{i,j} lnFSI_{i,t} + \beta_1 lnFDI_{AGR_{i,t}} + \Psi_1 \sum_{j=1}^{N} W_{i,j} lnFDI_{AGR_{i,t}} + \beta_2 lnPST_{i,t} + \Psi_2 \sum_{j=1}^{N} W_{i,j} lnPST_{i,t} \\ &+ \beta_3 \left(lnPST_{i,t} * lnFDI_{AGRi,t}\right) + \Psi_3 \sum_{j=1}^{N} W_{i,j}\left(lnPST_{i,t} * lnFDI_{AGRi,t}\right) + \beta CV_{i,t} + \Psi \sum_{j=1}^{N} W_{i,j} CV_{i,t} \\ &+ \mu_i + \nu_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

Conveniently, we may write Equation (7) more generally as it appears in Equation (7):

$$lnFSI_{\mathrm{i,t}} = \rho \sum_{j=1}^{N} W_{i,j} lnFSI_{\mathrm{i,t}} + X_{i,t}\beta + \Psi \sum_{j=1}^{N} W_{i,j} X_{i,t} + \mu_i + \nu_t + \epsilon_{i,t} \tag{7}$$

In the spatial Durbin model, the primary influence of regressor variables on the regressand variable within a specific area takes into account the feedback effect that arises after considering the spatial spillover effects of regressor variables on the variables in neighboring areas. Therefore, the coefficients in the SDM do not signify the marginal impact of a change in regressor variables on the regressand variable; it is advisable to employ the estimates of direct and indirect effects for a more accurate representation (LeSage & Pace, 2009). Hence, Equation (8) depicts the restructured version of the spatial Durbin model, which is used to estimate direct and indirect effects.

$$lnFSI_{\mathrm{i,t}} = (1 - \rho W_{i,j})^{-1}\left(X_{i,t}\beta + W_{i,j}\right)X_{i,t}\Psi + (1 - \rho W_{i,j})^{-1}\partial_i + (1 - \rho W_{i,j})^{-1}\varphi_i + (1 - \rho W_{i,j})^{-1}\mu_i \tag{8}$$

The partial derivative of the regressand variable *lnFSI* with respect to the regressor variable X_k, considering the relationship from spatial unit i to spatial unit N, is:

$$\begin{aligned} \left[\frac{\partial lnFSI}{\partial X_{ik}} \cdots\cdots \frac{\partial lnFSI}{\partial X_{nk}}\right] &= \begin{bmatrix} \frac{\partial YlnFSI_1}{\partial_{1k}} & \cdots & \frac{\partial YlnFSI_1}{\partial_{nk}} \\ \vdots & \cdots_c & \vdots \\ \frac{\partial YlnFSI_n}{\partial YlnFSI_{1k}} & \cdots & \frac{\partial lnFSI_n}{\partial lnFSI_{nk}} \end{bmatrix} \\ &= (1 - \rho W_{ij})^{-1} \begin{bmatrix} \beta_k & w_{12}\Psi_k & \cdots & w_{1j}\Psi_k \\ w_{21}\Psi_k & \beta_k & & w_{2j}\Psi_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1}\Psi_k & w_{i2}\Psi_k & \cdots & \beta_k \end{bmatrix} \end{aligned} \tag{9}$$

In this context, W_{ij} represents the spatial weight matrix based on geographical distance, with i and j referring to distinct spatial units. The direct effect corresponds to the average of the diagonal elements' sum in the rightmost matrix, while the indirect effect is equivalent to the average of the off-diagonal elements' sum.

However, the quasi-maximum likelihood method is employed to estimate all the spatial models developed by Lee and Yu (2010). To choose an appropriate model, the literature recommends various statistical tests (Abdullah & Wang, 2024; Akbar et al., 2021; Li & Xiong, 2019). The Hausman test is employed as a first step in model selection to determine whether to use fixed effects or random effects (Hausman, 1978). Second, the Lagrange Multiplier (LM) test is employed to determine the presence or absence of spatial lag and spatial error terms, as well as to diagnose spatial dependence in the context of these models (Anselin et al., 1996). Third, the Wald and Likelihood ratio (LR) tests are performed to assess whether the spatial Durbin model should be specified as a spatial lag or error model (Elhorst, 2014a). Once the best-fitting spatial models have been identified, the Akaike Information Criterion/Bayesian Information Criterion (AIC/BIC) determines whether the model should include spatial, time, or two-factor fixed effects (Akaike, 1974; Burnham, 1998). All the diagnostic tests and analyses are independently conducted using SATA 17. Furthermore, the standard linear panel data regression model is used without any spatial effects as a baseline to show the nexus between political stability, FDI in agriculture, and food security and verify the robustness of the findings (Guliyev, 2020; Yang et al., 2017).

5. Results

5.1. Exploratory analysis of food security's spatial dependence

Before delving into the spatial autocorrelation test results, we offered an overview of the variables. Table 1 displays the descriptive statistics. The Food Security Index (FSI) has a mean of 125.527 with a standard deviation of 41.347, indicating moderate variability. This means that while the data points are spread around the mean, the spread is not excessive. In other words, the values are neither tightly clustered nor overly dispersed across the range. Given this moderate variability, there is a possibility that similar values of food security are geographically clustered across developing countries (Cai et al., 2020).

Table 2 presents the global Moran's I statistics of the food security index from 2005 to 2020, which strongly suggest the existence of spatial dependence in the distribution pattern of food security in developing countries (Cai et al., 2020). Moran's I values have also shown an upward trend in recent years.

In addition, Figure 1 provides the LISA map of developing countries' food security, which indicates that 32 developing countries exhibit significant spatial clustering with four distinct degrees (HH, LL, LH, HL).

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
FSI	688	125.527	41.347	45.667	280.407
FDI_{AGR}	688	121.871	409.58	−273.647	4932.21
PST_{ICRG}	688	62.716	7.105	41.542	81.75
PST_{ICRG}*FDI_{AGR}	688	7627.228	24174.35	−15866.48	274354.2
PST_{WGI}	688	7.582849	1.03031	5	10
PST_{WGI}* FDI_{AGR}	688	1037.675	3646.23	−2462.823	44389.89
CRP	688	93.747	15.036	35.91	144.82
GDP	688	5298.044	3978.976	389.08	16192.16
UNE	688	6.823	4.079	.25	24
DOI	688	24.009	6.778	10.523	48.412
TRO	688	70.461	29.802	16.352	166.698

Table 2. Global Moran's I of the food security index from 2005 to 2020.

Year	Moran's I	Year	Moran's I	Year	Moran's I	Year	Moran's I
2005	0.6118*** (5.5772)	2009	0.6273*** (6.1964)	2013	0.6458*** (6.3819)	2017	0.6468*** (6.3353)
2006	0.7295*** (7.2420)	2010	0.6359*** (6.1154)	2014	0.6367*** (6.1454)	2018	0.6540*** (6.6476)
2007	0.6092*** (5.7727)	2011	0.6481*** (6.1104)	2015	0.6399*** (6.0491)	2019	0.6846*** (6.5142)
2008	0.6191*** (6.0872)	2012	0.6513*** (6.3500)	2016	0.6416*** (6.4516)	2020	0.7452*** (7.1164)
Average (2005–2020)	0.6536*** (6.2216)						

Notes: The values enclosed within parentheses are for "z". P-values, which were calculated using 999 permutations, are all less than 0.01.

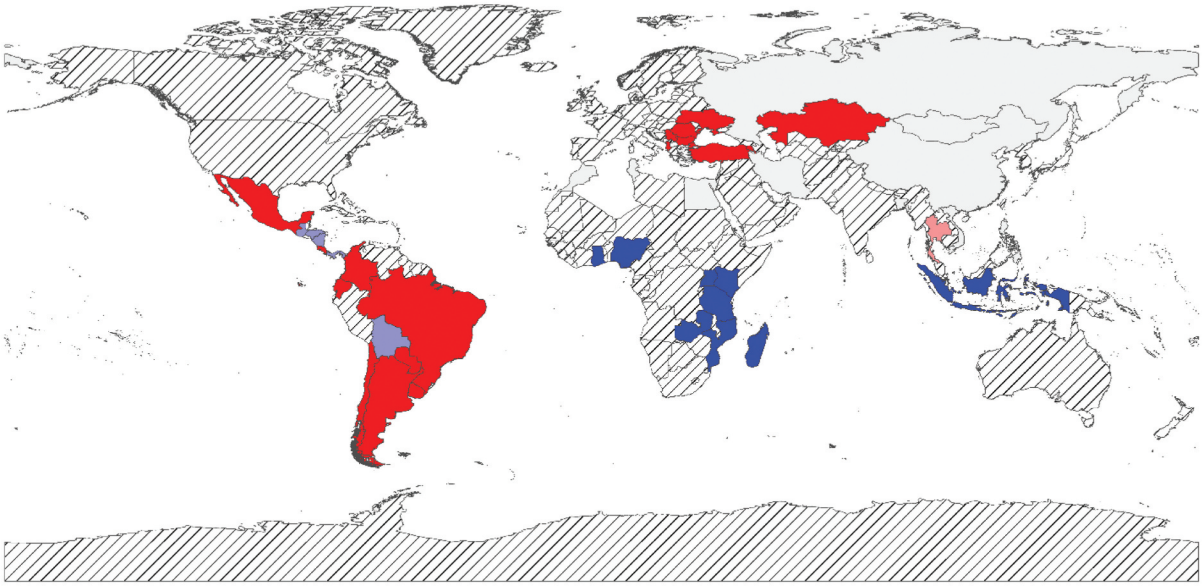

Figure 1. LISA map of developing countries' food security.

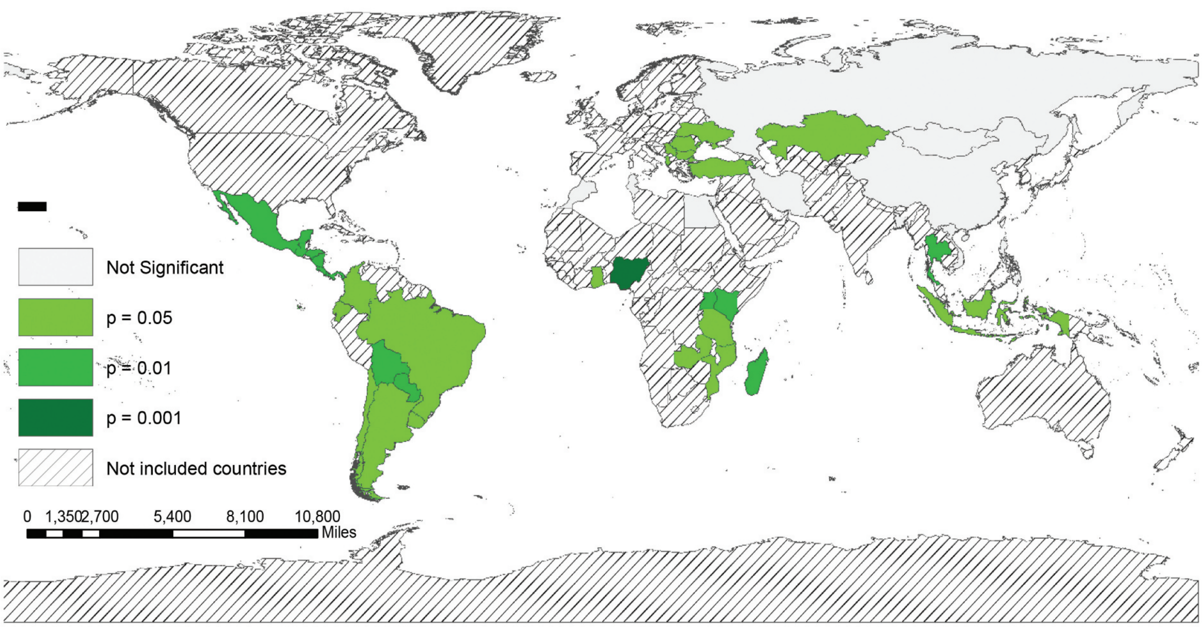

Figure 2. LISA significance map.

Table 3. Spatial distribution of developing countries' food security in LISA map quadrants.

Year	HH-Quadrant	LL-Quadrant	LH-Quadrant	HL-Quadrant	Insignificant
Average (2005–2020)	Albania, Argentina, Armenia, Brazil, Bulgaria, Chile, Colombia, Ecuador, Kazakhstan, Romania, Serbia, Turkey, Ukraine, Uruguay, Costa Rica, Mexico, Paraguay	Ghana, Indonesia, Mozambique, Tanzania, Zambia, Kenya, Madagascar, Uganda, Nigeria	Bolivia, Guatemala, Honduras, Nicaragua, Panama	Thailand	Bangladesh, China, Croatia, Egypt, Iran, Mongolia, Morocco, Philippines, Russia, Tunisia, Vietnam

Notes: Countries in all these categories also represent a sample of developing nations in our study.

Conversely, 11 countries do not display significant clustering. Specifically, the LISA classification identified 17 developing countries as HH type, 9 as LL type, 5 as LH type, and 1 as HL type, all exhibiting significant spatial clustering, as shown in (Figure 2. LISA significance map). Table 3 provides the spatial distribution of developing countries' food security in LISA map quadrants. Hence, the LISA map strongly suggests significant positive spatial dependence in food security among developing countries, accounting for approximately 74% (or 32 out of 43) of the total sample. Most developing countries, categorized as HH, LL, and LH, are located in South America, Sub-Saharan Africa, and North America, respectively. However, the regional clustering of food security types in the LISA map proposes that a variety of interconnected factors, including geography, climate, political stability, investment, infrastructure, and access to technology, play a significant role in shaping food security outcomes in developing countries (Barrett, 2010). For instance, one potential explanation for the South American HH-type countries could be their abundant natural resources, political stability, agricultural potential, and favorable climate conditions (FAO, 2017). These factors enable higher food production and availability, contributing to better food security outcomes.

5.2. Non-spatial model results and statistical test analysis

Table 4 presents the estimation results for non-spatial panel data models, along with the associated statistical test results for optimal model selection. We first chose to employ fixed effects models based on the Hausman test results, which reject the random effects hypothesis at a 1% significance level. We separately estimate spatial, time, and two-way fixed effects, with their respective results displayed in columns (2 to 5), (6 to 9), and (10 to 13). The spatial-fixed effects model (columns 2–5) is preferred, as indicated by AIC/BIC and R-square values. In columns 2 and 3, the estimated coefficients of foreign direct investment in agriculture (FDI_{AGR}) demonstrate a positive and significant relationship with food security (FSI) in developing countries (Slimane et al., 2016). However, the political stability variable (PST_{ICRG}) obtained from the International Country Risk Guide data shows an insignificant effect, while the political stability (PST_{WGI}) derived from the World Governance Indicators is significant (Masron et al., 2020).

In columns 4 and 5, the interaction between PST_{ICRG} (or PST_{WGI}) and FDI_{AGR}reveals a significant positive influence on food security in both instances, respectively. Additionally, all control variables exhibit the anticipated signs and are statistically significant, except for domestic investment (DOI), which appears to be insignificant. Nevertheless, domestic investment still significantly affects food security, as demonstrated in column 2 with PST_{WGI}.

However, both classical and robust-LM test results reject the null hypothesis at a 1% significance level, regardless of whether time and/or two-way fixed effects are included, indicating that both spatial error and spatial lag effects should be taken into account (Elhorst, 2010). Hence, the spatial panel model may outperform the conventional panel data model that does not account for spatial effects.

5.3. Results of spatial model evaluations and tests

Table 5 presents the estimation results of spatial panel data models, accompanied by relevant statistical test results to identify the most appropriate spatial model. The outcomes from Wald and likelihood ratio (LR) tests decisively reject the hypothesis that the Spatial Durbin Model (SDM) – regardless of the specific fixed effects under consideration – can be simplified into Spatial Autoregressive (SAR) or Spatial Error Model (SEM) at a 1% significance level. This indicates that the SDM employed in this study is a more suitable and justifiable model for the analysis. Meanwhile, the Hausman test results in the spatial model context were consistent with those from the non-spatial panel data models, consistently rejecting the null hypothesis of random effects. Once more, we separately calculate spatial, temporal, and bidirectional-fixed effects for the spatial Durbin model. The corresponding outcomes of these estimations are systematically detailed in Table 5, where columns (2 to 5) illustrate the spatial-fixed effects, columns (6 to 9) denote the time-fixed effects, and columns (10 to 13) encapsulate the bidirectional or two-way fixed effects.

In a comprehensive evaluation of model fit, both the AIC and BIC advocate for the adoption of spatial-fixed effects within the framework of the spatial Durbin model, thereby attesting to their significant relevance in this study's context. The statistical robustness of the spatial-fixed effects in the SDM is further

Table 4. Estimation results of non-spatial panel data models.

	Fixed effects model											
Dep. FSI	Spatial fixed-effects model				Time fixed-effects model				Two-ways fixed-effects model			
FDI_{AGR}	0.0053***	0.0048***			0.0028	0.0036			0.0006	0.0006		
	(3.35)	(2.97)			(0.66)	(0.93)			(0.86)	(0.76)		
PST_{ICRG}	0.0001				−0.0018				0.0029**			
	(0.09)				(−0.56)				(2.14)			
PST_{WGI}		0.0795***				−0.0213				0.0063		
		(10.86)				(−0.57)				(0.54)		
$PST_{ICRG} \times FDI_{AGR}$			0.0013***				0.0005				0.0007***	
			(3.51)				(1.27)				(3.14)	
$PST_{WGI} \times FDI_{AGR}$				0.0038***				0.0030				0.0012***
				(2.97)				(1.15)				(2.98)
CRP	0.0638*	0.0732**	0.0624*	0.0625*	−0.1852**	−0.1745*	−0.1854*	−0.1861*	0.0871**	0.0893**	0.0893**	0.0873**
	(1.85)	(2.33)	(1.78)	(1.78)	(−2.04)	(−1.71)	(−1.99)	(−1.99)	(2.43)	(2.42)	(2.41)	(2.25)
GDP	0.1484***	0.1688***	0.1448***	0.1423***	0.3065***	0.3045***	0.2974***	0.2978***	0.1508***	0.1550***	0.1529***	0.1541***
	(3.34)	(4.39)	(3.40)	(3.36)	(7.77)	(9.92)	(9.13)	(9.15)	(3.99)	(4.19)	(4.00)	(4.15)
UNE	−0.0614**	−0.0285*	−0.0414**	−0.0413**	0.0345	0.0257	0.0327	0.0325	−0.0143	−0.0131	−0.0124	−0.0126
	(−2.61)	(−1.85)	(−2.49)	(−2.49)	(1.00)	(0.66)	(0.92)	(0.92)	(−1.21)	(−1.05)	(−1.02)	(−1.03)
DOI	0.0152	0.0679**	0.0143	0.0143	−0.1429**	−0.1365*	−0.1473**	−0.1458**	−0.0018	0.0053	0.0014	0.0015
	(0.53)	(2.54)	(0.51)	(0.51)	(−2.11)	(−2.01)	(−2.06)	(−2.05)	(−0.07)	(0.23)	(0.06)	(0.06)
TRO	0.0954***	0.0488*	0.0817***	0.0856***	0.0363	0.0531	0.0459	0.0450	0.0520*	0.0530*	0.0528*	0.0523*
	(3.37)	(1.69)	(3.52)	(3.55)	(0.66)	(0.93)	(0.86)	(0.84)	(1.71)	(1.81)	(1.75)	(1.75)
Hausman	138.64***	141.589***	128.6372***	120.13***	37.72***	91.89***	31.996***	32.43***	21.8816**	68.303***	25.6326**	26.4832**
R^2	0.1751	0.2992	0.1823	0.1841	0.0459	0.1252	0.0453	0.0429	0.1321	0.1538	0.1349	0.1349
AIC/BIC	−2237.768/ −2201.498	−2223.084/ −2186.813	−2223.959/ −2187.688	−2223.964/ −2187.694	−562.916/ −526.646	−564.896/-528.625	−562.751/ −526.480	−562.036/ −525.766	−1435.260/ −1398.990	−1778.743/ −1742.473	−1441.265/ −1404.995	−1442.820/ −1406.550
Groups/panel length	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16
Number of obs	688	688	688	688	688	688	688	688	688	688	688	688
LM_Spatial lag	877.65***	438.42***	874.87***	872.15***	109.99***	107.11***	110.05***	110.3***	84.384***	84.425***	86.722***	86.952***
LM_Spatial error	737.09***	196.08***	718.9***	713.06***	107.49***	105.83***	107.39***	107.48***	98.345***	97.62***	103***	103.44***
Robust LM_Spatial lag	164.02***	253.20***	197.78***	201.96***	2.7886*	2.0159	2.9198*	3.0544*	19.956***	19.23***	27.237***	27.838***
Robust LM_Spatial error	23.46***	10.86***	41.808***	42.879***	0.29703	0.72807	0.26544	0.23006	33.917***	32.425***	43.517***	44.323***

Notes: "t" values enclosed within parentheses. *$p \le 0.1$, **$p \le 0.05$, ***$p \le 0.01$. All variables, both regressand and regressor, are employed in their natural logarithmic form in the analysis.

Table 5. Estimation results of spatial panel data models.

	Spatial Durbin Model with fixed effects											
Dep. FSI	Spatial fixed-effects model				Time fixed-effects model				Two-ways fixed-effects model			
FDI_{AGR}	0.0026***	0.0021**			0.0027	0.0039**			0.0007	0.0006		
	(3.12)	(2.30)			(1.45)	(2.07)			(0.94)	(0.75)		
PST_{ICRG}	0.0052***				0.0010				0.0035***			
	(3.91)				(1.04)				(4.67)			
PST_{WGI}		0.0406***				0.0426***				0.0164*		
		(6.13)				(3.00)				(1.71)		
$PST_{ICRG} \times FDI_{AGR}$			0.0004**				0.0003				0.0002***	
			(2.11)				(1.06)				(3.40)	
$PST_{WGI} \times FDI_{AGR}$				0.0020**				0.0010				0.0017**
				(2.28)				(0.56)				(2.23)
CRP	0.0841***	0.0659***	0.0887***	0.0886***	−0.0914**	−0.0777*	−0.1031***	−0.1010**	0.0877***	0.0888***	0.0904***	0.0907***
	(4.54)	(3.64)	(4.73)	(4.72)	(−2.24)	(−1.91)	(−2.59)	(−2.51)	(5.27)	(5.24)	(5.37)	(5.38)
GDP	0.1524***	0.1406***	0.1717***	0.1706***	0.2046***	0.2216***	0.2057***	0.2064***	0.1523***	0.1627***	0.1643***	0.1639***
	(5.46)	(5.21)	(6.13)	(6.08)	(22.94)	(25.46)	(25.68)	(25.81)	(6.02)	(6.38)	(6.46)	(6.44)
UNE	−0.0206**	−0.0172*	−0.0195*	−0.0195*	−0.0252**	−0.0307***	−0.0265**	−0.0259**	−0.0140	−0.0137	−0.0128	−0.0127
	(−2.04)	(−1.75)	(−1.91)	(−1.92)	(−2.31)	(−2.84)	(−2.49)	(−2.43)	(−1.58)	(−1.52)	(−1.42)	(−1.41)
DOI	0.0245*	0.0292**	0.0180	0.0175	−0.0759***	−0.0813***	−0.0808***	−0.0775***	0.0142	0.0176	0.0139	0.0138
	(1.81)	(2.20)	(1.33)	(1.29)	(−3.70)	(−3.97)	(−3.92)	(−3.76)	(1.17)	(1.41)	(1.15)	(1.13)
TRO	0.0266*	0.0244*	0.0338**	0.0342**	−0.0026	−0.0065	0.0085	0.0077	0.0349***	0.0374***	0.0397***	0.0399***
	(1.77)	(1.66)	(2.22)	(2.25)	(−0.18)	(−0.49)	(0.65)	(0.59)	(2.59)	(2.73)	(2.91)	(2.92)
W^*FDI_{AGR}	0.0029**	0.0053***			−0.0031	−0.0051			0.0016	0.0016		
	(2.09)	(2.98)			(−0.88)	(−1.46)			(1.12)	(1.10)		
W^*PST_{ICRG}	0.0027***				−0.0046**				0.0018**			
	(3.29)				(−2.25)				(2.27)			
W^*PST_{WGI}		0.0181***				−0.0211**				0.0084		
		(3.48)				(−2.49)				(1.54)		
$W^*(PST_{ICRG} \times FDI_{AGR})$			4.49e-05				−2.50e-06***				6.03e-05*	
			(1.51)				(−3.93)				(1.98)	
$W^*(PST_{WGI} \times FDI_{AGR})$				0.0006**				−0.0002***				0.0010*
				(2.13)				(−3.95)				(1.77)
W*CRP	0.0646***	0.0136**	0.0776***	0.0773***	−0.0251	−0.0490	−0.0565	−0.0508	0.0226***	0.0195***	0.0336***	0.0275***
	(3.36)	(2.32)	(2.84)	(2.83)	(−0.36)	(−0.70)	(−0.81)	(−0.73)	(3.07)	(2.68)	(3.97)	(3.21)
W*GDP	0.1370***	0.1006***	0.1331***	0.1327***	0.1039***	0.0752***	0.1046***	0.1026***	0.0406***	0.0431***	0.0529***	0.0445***
	(3.78)	(3.00)	(3.71)	(3.70)	(5.04)	(3.89)	(5.34)	(5.25)	(2.98)	(3.01)	(3.96)	(3.23)
W*UNE	−0.0005	−0.0039	−0.0008	−0.0002	−0.0053	−0.0047	−0.0146	−0.0155	−0.0071	−0.0100	−0.0102	−0.0097
	(−0.03)	(−1.63)	(−0.05)	(−0.01)	(−0.39)	(−0.35)	(−1.01)	(−1.07)	(−0.52)	(−0.72)	(−0.73)	(−0.70)
W*DOI	0.0004	0.0085	0.0030	0.0020	−0.1140***	−0.1294***	−0.0908***	−0.0913***	−0.0236	−0.0046	−0.0147	−0.0148
	(0.02)	(0.43)	(0.15)	(0.10)	(−3.36)	(−3.78)	(−2.66)	(−2.67)	(−1.22)	(−0.24)	(−0.78)	(−0.78)
W*TRO	0.0366*	0.0040	0.0124	0.0128	0.0983***	0.0876***	0.0694***	0.0732***	0.0671***	0.0477*	0.0415*	0.0407*
	(1.99)	(0.17)	(0.51)	(0.52)	(4.31)	(3.84)	(3.12)	(3.29)	(2.83)	(1.99)	(1.75)	(1.71)
Spatial rho	0.6574***	0.4038***	0.6584***	0.6565***	0.1932***	0.1946***	0.2042***	0.2049***	0.0812*	0.0667	0.0792*	0.0783*
	(30.29)	(11.67)	(30.15)	(29.89)	(4.30)	(4.37)	(4.60)	(4.62)	(1.78)	(1.44)	(1.72)	(1.70)

(Continued)

Table 5. (Continued).

	Spatial Durbin Model with fixed effects											
Dep. FSI	Spatial fixed-effects model				Time fixed-effects model				Two-ways fixed-effects model			
R^2_within	0.2390	0.3244	0.2017	0.2109	0.0632	0.1687	0.0666	0.0616	0.1476	0.1743	0.1420	0.1405
Groups/ panel length	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16	43/16
Number of obs	688	688	688	688	688	688	688	688	688	688	688	688
Wald_spatial lag	932.97***	271.65***	850.02***	846.94***	257.09***	258.54***	260.72***	260.18***	5.02**	3.58*	3.34*	3.30*
LR_spatial lag	52.38***	106.78***	51.26***	50.10***	53.48***	58.88***	63.16***	62.73***	15.94**	12.30*	12.74*	12.04*
Wald_spatial error	1111.14***	384.48***	1008.69***	1004.58***	98.55***	105.13***	100.95***	101.72***	5.43**	3.99**	4.30**	4.25**
LR_spatial error	28.67***	135.37***	25.54***	25.05***	197.02***	199.14***	208.81***	207.62***	15.48**	11.89*	11.80*	11.11
AIC/BIC	−2242.544/ −2170.004	−2223.969/ −2151.428	−2222.884/- 2150.343	−2223.236/ −2150.695	−809.7787/- 737.2381	−818.1858/- 745.6452	−821.7447/ −749.204	−820.4367/ −747.8961	−1960.739/- 1888.199	−2071.029/- 1998.488	−1942.271/ −1869.73	−1941.661/ −1869.12

Notes: All the regressand and regressor variables in this analysis have been utilized in their natural logarithmic form. "z" values enclosed within parentheses. *$p \le 0.1$, **$p \le 0.05$, ***$p \le 0.01$.

substantiated by substantial R-squared values, elevated and statistically significant spatial rho values, and a considerable number of significant variables.

Thus, our empirical analysis provides significant insights into the interplay between political stability (sourced from either the International Country Risk Guide data ($\mathrm{PST_{ICRG}}$) or the World Governance Indicators ($\mathrm{PST_{WGI}}$), agricultural foreign direct investment ($\mathrm{FDI_{AGR}}$), and food security (FSI) within the context of developing nations. Our study discovered that $\mathrm{PST_{ICRG}}$(or $\mathrm{PST_{WGI}}$), $\mathrm{FDI_{AGR}}$, and their interactions $\mathrm{PST_{ICRG}} \times \mathrm{FDI_{AGR}}(or \mathrm{PST_{WGI}} \times \mathrm{FDI_{AGR}})$ all exert positive primary effects on food security. In addition to these primary effects, our results also indicate that there are significant spatial spillover effects from $\mathrm{PST_{ICRG}}$(or $\mathrm{PST_{WGI}}$), $\mathrm{FDI_{AGR}}$ on food security. Moreover, only the interaction of $\mathrm{PST_{WGI}} \times \mathrm{FDI_{AGR}}$ displayed significant positive spatial spillover effects. However, the substantial coefficients associated with $W * \mathrm{PST_{ICRG}}, \mathrm{W} * \mathrm{FDI_{AGR}}, and W * (\mathrm{PST_{WGI}} \times \mathrm{FDI_{AGR}})$ demonstrates notable spatial dependence.

5.4. Effect decomposition of the refined spatial Durbin Model

As previously noted, the regression coefficients of the SDM model may not directly and accurately depict the actual marginal effects of the regressor variables on the regressand variable (LeSage & Pace, 2009). In response to this point, we have decomposed the direct and indirect effects of each regressor based on the coefficient estimates derived from the spatial fixed effect SDM. Table 6 provides the estimates of direct, indirect, and total effects of spatial fixed-effect SDM.

The direct effects of nearly all regressor variables are significantly positive. Compared with these direct effects, the estimated coefficients of GDP, CRP, DOI, and $\mathrm{PST_{ICRG}}$ in the non-spatial spatial-fixed model are underestimated by between 11.8 percent to 98.9 percent, whereas the coefficient estimates of other variables are overestimated by between 5.9 percent and 93.7 percent. Appendix C shows the comparative analysis of direct effects and non-spatial spatial-fixed effect model. Nevertheless, these observed direct effects deviate slightly from their coefficient estimates due to the presence of feedback effects, which occur as impacts pass through neighboring countries and return to the countries themselves. The point to be noted is that the effects of the feedback are relatively small. On the other hand, the indirect effects in the non-spatial model are set to zero by construction, whereas the indirect effect of a change in the regressor variables in the SDM appears. For example, the indirect effect of $\mathrm{PST_{ICRG}}$ (0.0021) accounts for 31.6 percent of its direct effect (0.0091), suggesting that a particular country's political stability could significantly influence its neighboring countries' food security.

5.5. Robustness evaluation

To assess the robustness of our findings, we employed three approaches. First, we transitioned from non-spatial to refined spatial regression models by using an alternative proxy for political stability. In the initial analysis, political stability was measured using the 12 factors from the ICRG. In contrast, for the robustness check, we incorporated the political stability and absence of violence/terrorism indicator from the World Bank's WGI. To facilitate a thorough comparison, the results derived from non-spatial and spatial regression models using the WGI and ICRG political stability measures are presented in a side-by-side format. The decomposition estimates from the refined spatial fixed-effect SDM showed consistent results, especially for key variables such as political stability, agricultural FDI, and their interaction term, which confirms the reliability of our findings. The decomposition outcomes presented in Table 6 (Estimates of direct, indirect, and total effects of spatial fixed-effect SDM) are our main findings.

Second, we replaced the K-nearest neighbors (K-nn) method with the inverse distance method to construct the spatial weight matrix, ensuring better capture of spatial dependencies. This ensures a more robust model and better captures spatial dependencies across all observations, regardless of a fixed neighborhood size. The inverse distance method calculates weights based on the inverse of the distance between units, with closer units receiving higher weights (Anselin, 1988; StataCorp, 2017). The outcomes using the inverse distance method, reported in (Appendix D. Estimates of direct, indirect, and total effects of spatial fixed-effect SDM), are similar to our main findings. Although there are minor variations in the significance levels, they are negligible and do not compromise the overall comparability with this study's finalized decomposed results of the spatial Durbin model.

Table 6. Estimates of direct, indirect, and total effects of spatial fixed-effect SDM.

Dep. FSI	Direct				Indirect				Total			
FDI_{AGR}	0.0040***	0.0031**			0.0120***	0.0231***			0.0160***	0.0262***		
	(3.73)	(2.23)			(3.21)	(3.05)			(3.53)	(3.45)		
PST_{ICRG}	0.0091***				0.0021***				0.0112***			
	(3.46)				(3.21)				(3.70)			
PST_{WGI}		0.0749***				0.0237***				0.0986***		
		(11.55)				(5.03)				(17.48)		
$PST_{ICRG} \times FDI_{AGR}$			0.0007*				6.11e-5				0.0008	
			(1.89)				(0.67)				(1.37)	
$PST_{WGI} \times FDI_{AGR}$				0.0027**				0.0003*				0.0030**
				(2.34)				(2.01)				(2.23)
CRP	0.0836***	0.0586***	0.0853***	0.0851***	0.0209**	0.0185***	0.0466***	0.0462***	0.1045***	0.0771**	0.1319***	0.1313***
	(4.12)	(3.35)	(4.15)	(4.15)	(2.30)	(2.95)	(3.67)	(3.66)	(4.77)	(2.11)	(4.47)	(4.48)
GDP	0.1401***	0.2426***	0.1642***	0.1630***	0.1003***	0.1209***	0.1184***	0.1110***	0.2404***	0.3635**	0.2826***	0.2740***
	(5.08)	(5.13)	(6.00)	(5.96)	(4.26)	(4.83)	(3.76)	(4.78)	(5.44)	(2.48)	(4.23)	(6.20)
UNE	−0.0347**	−0.0207**	−0.0231*	−0.0228*	−0.0319	−0.0469**	−0.0331	−0.0303	−0.0666	−0.0676**	−0.0562	−0.0531
	(−2.06)	(−2.11)	(−1.94)	(−1.92)	(−0.79)	(−2.08)	(−0.80)	(−0.74)	(−1.17)	(−2.54)	(−1.15)	(−1.09)
DOI	0.0299*	0.0382**	0.0214	0.0211	0.0401	0.0309	0.0228	0.0245	0.0700	0.0691*	0.0442	0.0456
	(1.77)	(2.37)	(1.30)	(1.28)	(0.69)	(1.01)	(0.41)	(0.44)	(0.99)	(1.71)	(0.66)	(0.68)
TRO	0.0529**	0.0252*	0.0443**	0.0449**	0.1442**	0.0107	0.0143	0.0156	0.1971**	0.0359	0.0586*	0.0605*
	(2.39)	(1.76)	(2.43)	(2.46)	(2.30)	(0.30)	(1.52)	(1.54)	(2.55)	(0.87)	(1.89)	(1.92)

Notes: "z" values are enclosed within parentheses. $^{*}p \le 0.1$, $^{**}p \le 0.05$, $^{***}p \le 0.01$.

Third, we conducted sequential control variable inclusion tests to assess the robustness of the SDM's decomposed effect estimates. We first estimated a baseline model with only the dependent variable (FSI) and the key regressor (FDI_{AGR}andPST_{WGI}), and their interaction ($PST_{WGI} \times FDI_{AGR}$). Subsequently, we introduced each control variable (CRP, GDP, UNE, DOI, TRO) incrementally and finally estimated a full specification with all controls. Throughout this process, the coefficients for the key regressor and control variables remained stable in magnitude, statistical significance, and expected signs across all model iterations, with only minor and statistically insignificant variations observed. The results of this robustness test, reported in (Appendix E. Estimates of direct, indirect, and total effects of spatial fixed-effect SDM), confirm that our main findings are robust against potential omitted variable bias.

6. Discussions

In the spatial Durbin model and similar spatial econometric models, decomposing regressor variables into direct and indirect effects is essential, as the regression coefficients may not perfectly reflect the actual marginal impacts of these variables on the regressand variable (Elhorst, 2014a; LeSage & Pace, 2009), an approach we have utilized.

Table 6 presents the estimates of direct, indirect, and total effects of spatial fixed-effect SDM. The direct effect of FDI in agriculture (FDI_{AGR}) on food security is positive and significant at a significance level of 1% when considering the political stability variable (PST_{ICRG}) from ICRG and 5% when considering the political stability (PST_{WGI}) from WGI, demonstrating the robustness of the findings. These results indicate that foreign investments in the agricultural sector can markedly enhance the availability, accessibility, and consistency of food supplies in the local country. This result aligns with the findings of Slimane et al. (2016), who, employing a simultaneous equation model, identified the positive and statistically significant impacts of FDI in the agricultural sector on food security in developing nations. However, the indirect effects of agriculture FDI on food security, including either PST_{ICRG} or PST_{WGI} in the model, have a significantly positive impact at a 1% level, with the indirect effects exerting a stronger influence on food security than the direct effects.[7] This means that an escalation in FDI in a country's agricultural sector significantly improves food security not only within the recipient country but also within neighboring nations (Mercer-Blackman et al., 2021; World Bank, 2016). Thus, one of our research inquiries has established that changes in FDI in the agriculture sector can generate spatial spillover effects on food security. Remarkably, it appears that the indirect benefits of agricultural FDI, which might include technological spillovers, capacity building, and regional economic growth, carry more weight in bolstering food security than the direct effects of the investment itself. While direct agricultural investments play an important role, it is these indirect ripple effects that seem to hold more potential in terms of enhancing food security. Hence, this underscores the need for policies that not only foster direct investment in agriculture but also cultivate an environment that maximizes the broader, indirect benefits of such investments, ultimately contributing to a robust food security framework in the context of FDI.

Upon further examination, a notable finding is that both the direct and indirect effects of the political stability variables ($PST_{ICRG}$and PST_{WGI}) significantly and positively influence food security at the 1% level. This robust finding underscores that political stability not only enhances food security within the given country but also contributes positively to the food security of neighboring nations. This outcome aligns with Abdullah Qingshi et al. (2021) and Food Security Information Network (2020), who confirmed that political risk poses a significant threat to food security both locally and in surrounding nations, arguing that such risk exacerbates food security issues on a regional level. Our findings complement Abdullah Qingshi et al. (2021)'s work by revealing the other side of the coin: while political risk can undermine food security, political stability can promote it, even beyond national borders. However, while our findings affirm the potential for positive spatial spillover effects – commonly through mechanisms such as stable governance

[7]In the case of domestic investment (DOI), the direct effect is positive and significant, whereas the indirect effect – although positive – does not attain conventional significance under either PST_ICRG or PST_WGI. Substantively, DOI appears to strengthen food security primarily within countries with limited measurable cross-border spillovers (Abdi et al., 2024). This localization of impact can be attributed to the inherent nature of the DOI, which is typically more focused on national economic development priorities. Importantly, our measurement of DOI as gross fixed capital formation (a broad economy-wide percentage of GDP) rather than specifically agricultural investment may also weaken its clear link to agricultural spillover mechanisms. In short, while DOI remains crucial for national food security strategies, its inherently more localized focus does not generate the same level of measurable regional spillovers as FDI.

that supports coordinated regional policies and strengthens cross-border trade and regional market integration – they must be understood in light of the varying levels of political stability, as outlined in (Appendix B. Factors to construct the political stability index), which affect the effectiveness of these mechanisms. The categorization in this table underscores the multidimensional factors and variability of political stability, ranging from very high risk/low stability to very low risk/high stability, which suggests that the positive effects we observed are not uniformly applicable and are contingent on the quality and depth of stability (Q. Abdullah et al., 2020). For example, countries with lower scores on the political stability index may not enjoy the same local or regional advantages as those with higher scores (Abdullah Qingshi et al., 2021; Guha et al., 2020). Moreover, the persistent food insecurity in developing nations, despite seemingly stable political conditions, suggests that several factors, such as corruption and poor institutional quality, can inhibit the translation of political stability into food security gains (Q. Abdullah et al., 2020; Masron et al., 2020). Therefore, our study contributes to the discourse by emphasizing that while political stability can extend its benefits across borders, the actual impact is conditional upon the stability related to multifaceted factors within each country (Howell, 2011). This necessitates a more nuanced understanding of how political stability – or its absence – shapes food security outcomes. Our results prompt further exploration into how political stability can be strategically managed to bolster food security, especially in regions where it is most needed. This exploration is crucial for formulating policies that recognize and address the disparities in political conditions across different regions, ensuring that everyone's needs are considered.

Regarding the interaction between political stability and foreign direct investment in the agricultural sector, our findings demonstrate that both interactive terms, $PST_{ICRG} \times FDI_{AGR}$ and $PST_{WGI} \times FDI_{AGR}$, exert a positive and statistically significant direct effect at the 10% and 5% significance levels, respectively. This suggests that during the period from 2005 to 2020, the interaction between political stability and FDI in agriculture within the local country of developing countries has a statistically significant positive impact on the food security index. Nonetheless, it's important to note that the direct impact of these interactive terms, $PST_{ICRG} \times FDI_{AGR}(0.0007)$ and $PST_{WGI} \times FDI_{AGR}(0.0027)$, is found to be less pronounced compared to the coefficients of their individual components $PST_{ICRG}(0.009), FDI_{AGR}(0.0040), PST_{WGI}(0.0749)$, and $FDI_{AGR}(0.0031)$. These findings, while complex, serve as a gateway to a deeper understanding of the intertwined relationship between political stability, FDI in agriculture, and food security – a relationship that holds substantial implications for developing nations. Underlining the significance of these findings in the sense that the political stability of a country can influence many aspects of the economy, including agriculture and food policies (Swinnen, 2010). When political conditions are stable, it tends to foster an environment conducive to growth, as it reduces uncertainties and risks that could deter potential investors (Busse & Hefeker, 2007, Nazeer & Masih, 2017). In such a stable setting, domestic and foreign investors alike are more likely to commit their capital to agricultural projects (Santangelo, 2018). This investment can lead to improved agricultural productivity and innovation, improving food security. For instance, according to the World Bank's WGI, Rwanda's political stability score improved from −1.58 in 2005 to −0.14 in 2019, marking a significant enhancement in political stability (World Bank, 2021). During the same period, FDI inflows into the agricultural sector increased from $67 million in 2005 to $409 million in 2019, as reported by the Rwanda Development Board (RDB).[8] With improved political stability and increased agricultural FDI, Rwanda made impressive strides in food security. The Global Hunger Index (GHI), which can be used as a proxy for the food security index, indicates that Rwanda's score improved from 40.9 (extremely alarming) in 2005 to 27.1 (serious) in 2020.[9] However, similar outcomes can vary in other developing nations. Many countries continue to attract foreign investments despite corruption and illicit lobbying, often at the expense of local populations and food security (Campos & Giovannoni, 2007; Guha et al., 2020). In these cases, high corruption levels and strong agricultural lobbying can divert public investments away from rural development, ultimately undermining efforts to improve food security (López, 2005). Rwanda's success highlights that the progress was not merely a function of political stability but of targeted improvements in specific governance dimensions that deterred the misallocation of resources and attracted FDI. Therefore, for policymakers, our findings imply that broad appeals for political stability must be grounded

[8]https://rdb.rw/
[9]https://www.globalhungerindex.org/ranking.html

in institutional reforms targeting the factors of our stability index. Crucially, our operationalization of political stability encompasses multidimensional factors, including government stability, corruption levels, law and order, regulatory quality, and government effectiveness. These factors directly shape the channels through which stability influences food security outcomes (Masron et al., 2020).[10] For instance, the combination of low corruption and effective control over it ensures that the public investments in agriculture are not diverted or remain protected, while the robust rule of law and regulatory quality help minimize risks for foreign investors (Busse & Hefeker, 2007, Nazeer & Masih, 2017). Thus, political stability amplifies the positive impact of FDI on food security by addressing systemic risks embedded in institutional frameworks.

In addition, the indirect (or spatial spillover) effect of the interaction between political stability and FDI in agriculture is significantly positive when the political stability variable is sourced from WGI and is insignificant when political stability is obtained from ICRG. This positive spillover effect of the combination of political stability from WGI and agricultural FDI (denoted as $PST_{WGI} \times FDI_{AGR}$) on the Food Security Index (FSI) is significant, albeit at a modest 10% level, with a coefficient of 0.0003. This value is lower than the individual coefficients of PST_{WGI} (0.0237) and FDI_{AGR} (0.0231). This outcome implies a crucial dynamic that transpired between 2005 and 2020. The synergy of political stability, as per WGI, and agricultural FDI within individual countries seemed to have triggered a significant and beneficial ripple effect on the state of food security in their surrounding nations. One practical example can be drawn from the relationship between India and its surrounding nations within South Asia. India, being the largest economy in this region, has seen significant improvements in political stability along with a rise in FDI in agriculture during the 2005–2020 period. India's political stability improved significantly over this period. The WGI political stability and absence of violence/terrorism index improved from −0.883 in 2005 to −0.440 in 2019. Correspondingly, agricultural FDI inflows into India surged over the same period. According to the Department for Promotion of Industry and Internal Trade (DPIIT), India's agricultural sector attracted FDI worth $4.8 billion between April 2000 and March 2020 (DPIIT, 2020). In terms of the spillover effect on neighboring countries, it is plausible that the combination of improved political stability and increased agricultural FDI in India indirectly benefited food security in these countries. For instance, there's evidence that India's agro-industry exports to countries like Bangladesh, Nepal, and Sri Lanka increased during this period (World Bank, 2020). This could have enhanced food security in these countries by ensuring a steady supply of agricultural goods, increasing food availability, lowering food prices, and improving accessibility. While these exports probably improved short-term food security in recipient nations by stabilizing prices and availability, the spillover effects depend on the context. In countries with weak governance or underdeveloped agricultural sectors, such export surges can disrupt local systems. For instance, smaller farms in importing countries may face reduced profits, loss of market share, or even closures if they are unable to adapt quickly to the increased competition from cheaper and high-yield crop imports, undermining long-term agricultural resilience(Btooz 2024; Gadhok 2016; Khanal et al., 2024) Moreover, while our findings emphasize efficiency gains from positive spillovers in stable political conditions, they also implicitly indicate inefficiencies in systems where governance gaps or structural vulnerabilities exacerbate negative spillovers. This duality underscores the need to qualify the type of exports (e.g., high-volume staples vs. diversified value-added products) and the institutional capacity of recipient regions when evaluating transnational food security impacts.

7. Conclusion

Food security has taken more attention from policy analysts, policymakers, and researchers in the developing world over recent decades, with political stability and agricultural FDI emerging as key catalysts for development and growth in these countries. While the existing literature frequently underscores a direct association between agricultural FDI and food security in DCs, significant gaps persist concerning the spatial moderating effects of political stability on this relationship. To address this gap, we initially explore the macroeconomic dimension of food security along with political stability from both the ICRG and WGI perspectives using

[10]More specifically, government effectiveness ensures the credibility of the government's commitment to implemented policies, while regulatory quality strengthens the ability to formulate and enforce regulations (Masron et al., 2020). Robust rule of law and control of corruption promote accountability and efficient policy execution, and government stability fosters a secure environment for sustainable development.

a balanced panel dataset of 43 DCs for the period 2005–2020. Specifically, this study empirically examines the moderating role of political stability in shaping the relationship between agricultural FDI and food security, emphasizing spatial interdependencies through the application of the spatial Durbin model.

Our analysis yielded several key findings. First, both global and local spatial autocorrelation tests confirmed the presence of significant spatial dependence in the distribution pattern of food security in DCs, underscoring the necessity of incorporating spatial econometric approaches into food security analyses. Second, agricultural FDI in a host country significantly enhances food security both locally and in surrounding countries. Third, political stability, whether assessed via ICRG or WGI indicators, substantially contributes to improving food security locally and regionally. Fourth, and importantly, our results indicate that the interaction between political stability (WGI) and agricultural FDI positively impacts food security both domestically and in neighboring countries. However, when using ICRG indicators, the positive effects of the interaction term on food security are limited to the host country, with no significant regional impact.

Based on these findings, a cohesive strategy for enhancing food security in DCs can be proposed. Primarily, governments should actively foster agricultural FDI by creating an investor-friendly environment, instituting favorable policies, and reducing barriers for foreign investors, leveraging their dual-level (local/regional) benefits. Concurrently, efforts to strengthen political stability through improved governance, enhanced transparency, robust institutions, and effective mitigation of social unrest are critical. Enhanced political stability not only attracts agricultural investments but also independently boosts food security domestically and regionally. Moreover, the evident spatial dependence in food security underscores the need to incorporate spatial considerations into food security policy planning. This suggests that region-specific strategies that consider the interconnectedness among neighboring nations may prove more effective. Additionally, our findings underline the significance of cross-border cooperation in promoting food security and advocate regional collaborations, such as shared best practices, coordinated policy frameworks, and joint agricultural initiatives. Given the varying impacts observed with different political stability data sources, this suggests the need for a balanced approach to policy formulation that ensures increased agricultural FDI without compromising political stability.

Despite making a significant contribution to understanding the determinants of regional food security, this study acknowledges certain limitations that present avenues for future studies. Primarily due to data limitations, the study includes only 43 developing countries, although similar issues may exist in other nations. Future research could expand the geographic scope globally or focus on detailed country-specific analyses. Additionally, our analysis primarily adopts a generalized perspective at the regional level, yet there might be regional variations regarding the issues at hand. For instance, our study discovered various clusters of HH, LL, and LH located, respectively, in South America, Sub-Saharan Africa, and North America, as evidenced by our LISA findings. Therefore, future research should evaluate regional heterogeneity using regional division data or through comparative regional analysis. Methodologically, to enhance the depth of the current study and its practical relevance, future studies might incorporate threshold effect models to account for nonlinear relationships and apply difference-in-differences (DID) models to comprehensively assess policy effectiveness. Finally, extending the analysis using dynamic spatial panel data models could better capture the temporal dimensions and further elucidate the complex interplay between political stability, agricultural FDI, and food security outcomes.

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Data availability statement

The data and STATA statistical scripts used in this study are publicly available in the Figshare repository: https://doi.org/10.6084/m9.figshare.29877977

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