CHAPTER 17

Digital Tools, Data Systems and AI in Food Security Policy

Syed Muhammad Subtain Abbas[1,*], Sharoon Aftab[1], Tayyab Ali[1], Mannan Aleem[2,3], Shoaib Sarwar[1], Yasir Abbas[1], Naeem Saddique[1] & Muhammad Imran Khan[1]

[1]Department of Irrigation and Drainage, Faculty of Agricultural Engineering and Technology, University of Agriculture Faisalabad, Pakistan

[2] Department of Structures and Environmental Engineering, Faculty of Agricultural Engineering and Technology, University of Agriculture, Faisalabad.

[3]Yantai Institute of Coastal Zone Research, Chinese Academy of Sciences, Yantai, China

***Corresponding authors' email:** subtainadeem48@gmail.com

Abstract

Digital technologies are rapidly reshaping the way food security is monitored, governed, and addressed across the world. This chapter examines the growing role of remote sensing, artificial intelligence (AI), big data analytics, and predictive modelling in strengthening food security policy and early warning systems. Drawing on recent scholarly literature, institutional reports, and comparative international experiences, it explores how digital tools enhance crop monitoring, climate risk assessment, supply chain management, and evidence-based policymaking. At the same time, the chapter highlights persistent challenges related to data governance, digital inequality, algorithmic transparency, data sovereignty, and the unequal distribution of technological capacity between the Global North and Global South. By integrating sociotechnical systems theory, digital sovereignty, and evidence-to-policy translation frameworks, the chapter argues that technology alone cannot solve food insecurity without strong institutions, inclusive governance, and equitable access to digital resources. It concludes by outlining policy direction that promotes responsible AI adoption, strengthened data governance, and international collaboration to build more resilient, transparent, and sustainable food systems.

https://doi.org/10.66529/book.9786277945039.2026.ch17
Received: 22-March 2026 Revised: 22-May 2026 Accepted: 28 June 2026

Keywords: Artificial Intelligence (AI); Food Security Policy; Remote Sensing; Big Data Analytics; Data Governance.

1. Introduction

Food security, encompasses its four pillars, availability, access, utilization and stability, is one of the inevitable and unresolved challenges confronting the international community in the present. Regardless of policy commitment, unprecedented technological advancement, sustained multilateral commitment, the world is still struggling to end hunger (SDG 2). Around 733M people faced hunger in 2023, one in eleven people globally and one in five people in Africa. It is estimated that approximately 582M people will be chronically undernourished by 2030 following the current trends (Unicef, 2024).

Integration of digital technologies (RS, AI and Big data) and food governance system have emerged as potential solutions to achieve food security. AI, remote sensing, machine learning and big data analytics have fundamentally transformed the capacity of governments international organizations and agricultural sector to monitor food production systems, soil health detection, disease control, forecast supply disruptions and enabled the researchers and policymakers to develop efficient policies. Building a more sustainable food system to reduce food insecurity and uncertainty in the global food markets require concurrent near-real-time and reliable crop information for decision making. It is within this imperative that remotely sensed satellite data of crops has become the primary method of deriving crop information at local regional and global levels, revealing spatial and temporal dimensions of crop growth status and production.(Wu *et al.*, 2023) .

Revolutionary potential of these technologies is substantial and well documented. Remote sensing and artificial intelligence when integrated with climate smart agriculture can improve agriculture resilience, production and sustainability, through AI's capacity for predictive analytics, crop modeling and precision agriculture alongside remote sensing in climate projections, land management and continuous surveillance (Mmbando, 2025)**.** FAO uses remote sensing data to monitor global production of food and climate impact on food systems quite often, tracking crop yields, drought conditions and soil moisture at a global scale. (Li *et al*., 2025)**.**

Vast amount of structured and unstructured data from diverse origins is generally referred to as big data. Availability of this big data allows researchers and policymakers to delve deeper resulting in improved decision-making (Marvin *et al*., 2017)**.** Big data analytics enhancing agricultural productivity by optimizing the resources, improving crop management, irrigation scheduling, fertilization and pest control using IoT integrated systems. Yet there is underutilization of this revolutionary technology due to certain limitations (Hussein *et al*., 2025)**.** Big data analytics enables early warning systems that allow anticipation of food crisis before acute circumstances. WFP's Vulnerability Analysis Mapping (VAM) unit uses earth observation data to monitor the impact of natural disasters, armed conflicts, extreme weather events and agricultural production while simultaneously monitoring global and regional production to predict the area of concern (Buczkowski, 2022).

Regardless of all these advancements, the use of data system and AI in food security policy is neither transparent nor equitable. Some key factors complicate the translation of technological potential into policy impact such as substantial governance, ethical and access-related challenges, and digital divide. A consistent digital divide means that the benefits of these technologies are concentrated in a disproportionate way across advanced nations, while food insecure population is still deprived of these resources. This digital divide is due to the unequal access to AI technology, shortage of field experts and qualified workers in AI development and administration, the potential benefits of AI can be limited by impediments to the effective and secure deployment of AI technologies. This requires the development of well-organized sophisticated policy framework to provide standards for governance of data privacy and the ethics of AI development. (Folorunso *et al*., 2024)**.**

The ethical and governance problems are multiplied as they are tied to issues of data sovereignty, transparency and accountability. The crop monitoring system has a lot of economic value in the marketplace when the public reports are issued but there is concern that crop monitoring systems will not release unfavorable reports from the sites, the algorithms and underlying data that produced these reports are most often not available for independent review. (Wu *et al*., 2023)**.** International policy frameworks have begun responding to the emerging challenges presented by agricultural AI applications like precision farming, crop monitoring/surveillance and climate resilient crops but there is still a considerable gap, such as inadequate technological infrastructure, limited data accessibility, skill deficit and persistent ethical concerns which together demand policy frameworks aimed at mitigating the risks while optimizing socio-economic and environmental interests (Omotayo *et al*., 2025)**.**

The current chapter has two related goals. The first goal is to provide a thorough analysis of how remote sensing, AI, big data, and predictive analytics are transforming food security monitoring, providing early warnings, and designing agricultural policies. The second goal is to analyze governance and ethical challenges to data access, digital inequality, algorithmic accountability, and data sovereignty, which affect the fair and effective use of these tools.

2. Literature Review

The convergence of data systems and artificial intelligence (AI) with food security policy has emerged as one of the most significant developments at the intersection of technological innovation and humanitarian governance. Over the past decade, scholarly interest in the application of remote sensing, big data analytics, machine learning, and predictive modelling has expanded rapidly, reflecting the growing recognition that

 | https://doi.org/10.66529/book.9786277945039.2026.ch17

digital technologies can reshape the way governments, international organizations, and agricultural institutions monitor and respond to food security challenges.

The literature reviewed in this chapter focuses primarily on studies published between 2015 and 2025 and examines five interrelated themes: remote sensing and crop monitoring; big data analytics and early warning systems; artificial intelligence and predictive modelling; digital technologies in developing-country contexts; and the governance, ethical, and data-access challenges associated with these innovations. For analytical clarity, the discussion is organized into two broad strands: first, the contribution of AI and big data to food security assessment and forecasting, and second, the role of remote sensing in supporting evidence-based food security policy.

Early research established the conceptual and analytical foundations for AI-driven food security assessment. Using Bayesian Network (BN) probabilistic reasoning with Global Food Security Index (GFSI) data, How *et al*. (2020) demonstrated that predictive simulations of critical food security scenarios could be generated without requiring advanced programming expertise, thereby providing policymakers with a practical decision-support tool. Building on this line of inquiry, Bostanci *et al*. (2025) introduced the Food Security Vulnerability Index (FSVI) for Africa, integrating Long Short-Term Memory (LSTM) networks, autoencoders, Random Forest (RF), XGBoost algorithms, and panel econometric techniques. Their findings showed that rising temperatures negatively affect maize production, while rainfall variability significantly influences wheat yields. These results informed multi-scenario analyses with direct implications for climate-smart agricultural policy across the Sahel, the Horn of Africa, and Southern Africa.

Although these studies illustrate the progression from relatively accessible probabilistic models to more sophisticated multimodal AI architectures, they converge on a common conclusion: technological capability alone is insufficient unless model outputs are effectively translated into institutional decision-making processes. The gap between AI innovation and practical policy implementation remains a persistent concern. A systematic review of 171 AI modelling studies by Sarku *et al*. (2023) identified three distinct patterns of stakeholder engagement: studies relying exclusively on biophysical data with no community involvement, those incorporating partial stakeholder consultation, and genuinely participatory and iterative approaches.

A particularly important observation from this review is that only a limited number of studies established complete feedback mechanisms with the communities they sought to serve. Furthermore, much of the existing research has been conducted by institutions in the Global North focusing on populations in the Global South, creating a structural imbalance that the authors characterize as a form of epistemic injustice. From an institutional perspective, Torero (2021) similarly argues that digital agricultural technologies are inherently skill-biased, productivity-biased, and voice-biased. According to the FAO perspective, the inclusive adoption of AI requires complementary investments in regulatory systems, human capital development, and accountable governance structures. Together, these studies underscore that AI is not a self-executing solution; rather, its effectiveness depends fundamentally on the institutional environments in which it is deployed.

The relationship between digital development and food security has also been examined from a macroeconomic perspective. Novak and Kobets (2023) analyzed 111 countries using self-organizing maps based on GFSI dimensions, the Global Connectivity Index, and added agricultural value. Their regression results indicated that each advancement along the digitalization continuum from “Absence” to “Starter,” and from “Starter” and “Adopter” to “Frontrunner” improved a country’s GFSI ranking by an average of 5.6 positions. At the same time, a one-percentage-point increase in agricultural value added as a share of GDP reduced digital connectivity by approximately half a position. Extending this discussion, Ahmad *et al*. (2024) synthesized evidence on AI applications in crop surveillance, disease detection, irrigation management, and supply-chain optimization. Their review identified inadequate infrastructure, financial constraints, limited data availability, and weak regulatory frameworks as the principal barriers to AI adoption in developing countries. Collectively, these findings reveal a persistent cycle in which economies with the greatest dependence on agriculture often face the highest levels of food insecurity while simultaneously possessing the least capacity to benefit from AI-enabled solutions, highlighting the need for targeted international policy support.

Alongside AI, remote sensing has become a cornerstone of contemporary food security monitoring by enabling researchers and policymakers to map and assess agricultural landscapes across extensive geographic areas. Shi *et al*. (2022) evaluated national food security trends in Egypt over multiple years and reported a gradual decline in food security conditions. The satellite imagery employed in the study achieved 82% crop identification accuracy, while yield estimates remained within 5% of FAO estimates. The study further observed that the excessive use of fertilizers and agrochemicals was contributing to land degradation and declining agricultural productivity, reinforcing the need for timely policy interventions.

The policy relevance of remote sensing is also evident in crop-specific monitoring applications. Shams Esfandabadi *et al*. (2022) employed Google Earth Engine (GEE) and MODIS datasets to analyze a decade of rice production data in northern Iran. Their results showed that a hybrid Vegetation Health Index (VHI) outperformed conventional standalone vegetation indices in predicting rice yields. By linking yield forecasting with broader issues of food security, supply-chain management, and index-based agricultural insurance, the study demonstrated the potential of remote sensing to support more informed and targeted policy decisions.

Despite these operational advances, the literature also highlights important technical limitations in remote sensing-based stress detection. A systematic review of 115 studies conducted by Wen *et al*. (2020) found that conventional vegetation indices exhibit inconsistent performance in characterizing crop responses to drought and salinity, with reported coefficients of determination ranging from $R^2 = 0.02$ to 0.80. This limitation is particularly significant given that drought and salinity are projected to affect approximately half of the world's cultivated land by 2050. The review further revealed substantial overlaps between the spectral signatures of drought and salinity stress, making simultaneous differentiation technically challenging. Although plant functional traits, particularly osmotic characteristics, demonstrated stronger and more consistent relationships with salinity stress, existing remote sensing systems are not yet capable of measuring these traits directly. To address these shortcomings, the authors recommend the integration of radiative transfer models and multi-sensor frameworks. Their analysis points to a notable disparity between the theoretical capabilities of remote sensing technologies and their reliable operational application in crop health monitoring.

Beyond technical constraints, one of the least explored areas in the existing scholarship concerns the governance gap between remote sensing capabilities and their incorporation into agricultural policy. Despite more than three decades of remote sensing research and the widespread expansion of Earth observation programs, only a limited number of operational information services have been established in Sub-Saharan Africa. Notable examples include the AGRHYMET early warning system and the FAO Desert Locust Information Service. According to Bégué *et al*. (2020), this gap cannot be explained solely by data availability. Instead, it reflects the absence of effective co-construction processes that bring together remote sensing scientists, operational service providers, and policy end-users. Consequently, the challenge is no longer simply generating data but creating institutional mechanisms capable of translating technological advances into meaningful, inclusive, and context-specific food security policies.

3. Policy framework

3.1. Conceptual and Theoretical Framework

The challenges identified in the preceding section require more than a single theoretical lens to analyze adequately. This section aims to show three inter-related frameworks that together guide the analysis: sociotechnical systems theory, which situates digital tools within broader social and institutional context; digital sovereignty and data governance theory, which foregrounds the political economy of food security data and evidence- based policy translation models, which help examine the conditions under which data derived knowledge achieves or fails to achieve the policy impact.

 | https://doi.org/10.66529/book.9786277945039.2026.ch17

3.2. Sociotechnical Systems Theory: Digital Tools as Social Artefacts

A foundational premise is that remote sensing satellites, machine learning models, and AI driven early warning systems are not neutral instruments they are socio-technical artefacts whose design and deployment shape what food insecurity is rendered visible, measurable and practical (MacKenzie & Wajcman, 1999; Smith, 1988). The concept of co-production developed within Science and Technology Studies, holds the way societies know and represent the world are inseparable from the way they govern it (Callon, 1999). Applied to food security this means that AI crop monitoring systems and big data platforms reconstitute what food security looks like determining which populations are legible, which pathways are foregrounded, and which policy responses are implied by the system's outputs (Araújo *et al*., 2023; D'Ignazio & Klein, 2020). Populations where data availability is a challenge are often the most chronically food insecure since they are underrepresented by AI-driven assessments precisely because they generate fewer of the digital signals these systems are designed to process (Sarku *et al*., 2023).

The multilevel perspective on sociotechnical transitions further shows the structural dynamics of digital tool adaption in food governance, distinguishing between the niche level where innovations such as machine learning crop models are piloted, the governance level where established institutional mandates and data standards prevail within organizations such as FAO and WFP, and ground level where political pressures including SDG framework and donor priorities shape the broader policy environment (Geels, 2020). The literature on the digital divide reveals that disparities persist not only in access and use of digital technologies but also in the ability of individuals and communities to derive benefits from them, with disadvantaged groups more likely to experience exclusion and limited outcomes from digital transformation (Lythreatis *et al*., 2022). Actor-Network Theory helps explain how algorithm-based systems can become central points in food governance that everyone must rely on. These systems gain authority over decisions, even though they are not always open to proper scrutiny. This is especially relevant to concerns that crop monitoring algorithms are often not accessible for independent review (Cresswell *et al*., 2010; Neisser, 2014).

3.3. Digital Sovereignty and Political Economy of Food Security Data

The concept of digital sovereignty which originate in debates over internet governance and national control over digital infrastructure address a concrete governance problem in food security, the agricultural, nutritional and climate data that underpin policy decisions are increasingly generated, processed and stored privately or foreign controlled systems whose governance arrangements largely escape the authority of the governments most dependent on their outputs (Clapp & Ruder, 2020). This comprises of three levels. At national level it concerns whether LMIC governments (Low- and Middle-income Countries) retain meaningful data generated within their territories or whether it migrates to foreign cloud platforms or donor managed systems (Dencik *et al*., 2019). At the institutional level, it involves the international bodies including IPC, FEWS NET, and GIEWS that set data standards and access protocols in global food information systems (Amar *et al*., 2026). At the knowledge level it raises the question of whose analytical models and assumptions are encoded into the AI systems that classify and communicate food insecurity to governments (D'Ignazio & Klein, 2020; Iazzolino & Stremlau, 2024)

3.4. Evidence to Policy Translation: From data to Decision

Even where digital tools produce robust, real-time evidence on food security, such evidence does not automatically translate into policy action. The evidence-to-policy translation literature (Cairney & Oliver, 2017; Nutley *et al*., 2007) provides theoretical tools to explain this persistent gap.

Multiple streams framework is particularly instructive about policy change such that policy change occurs not when evidence is most scientifically compelling, but when a problem stream (a politically recognized crisis), a policy stream (technically feasible solutions), and a politics stream (a government agenda) converge at a single point (Asante, 2023).

A critical extension of this framework concerns the digital mediation effect: the observation that algorithmic systems do not merely transmit evidence but actively construct its framing which determines which

 https://doi.org/10.66529/book.9786277945039.2026.ch17

indicators should have the priority, which populations are visible, and which policy responses are implied. Porter's (1995) idea of " trust in numbers" analysis shows that algorithmically generated outputs carry the appearance of scientific objectivity that can prevent questioning the assumptions behind the models or noticing populations missing due to data gaps (Levy, 2001). Similarly, the typology of research uses instrumental, conceptual and symbolic show that the influence of remote sensing or machine learning crop forecasts is rarely direct. Instead, these tools often shape what governments see as credible or urgent in food security discussions over time (Blewden *et al*., 2010).

3.5. Synthesis

The three frameworks outlined above are complementary to each other. Sociotechnical system theory reveals that digital tools are never institutionally neutral they come with embedded assumptions about what food insecurity is perceived and who is responsible for addressing it.

Digital sovereignty theory shows the political economy of food data, attending to structural asymmetries in who produces, controls and benefits from food security information. Evidence to policy translation models trace the politically mediated pathways through which digital insights can be made or fail to facilitate in meaningful idea in government decision making. Together, they provide integrated analytical architecture for examining the goals mentioned in the introduction: understanding the transformative capacity of digital tools for food security monitoring, analyzing the governance and ethical challenges surrounding data access and algorithmic accountability, and identifying the conditions under which equitable and effective data governance frameworks can be built.

4. Methodology

This section outlines the approach underpinning the analysis presented in this chapter. Given that the chapter addresses a multi-dimensional problem, the integration of digital tools, data systems and AI into food security policy is insufficient. Therefore, the methodology is structured around qualitative, drawing from literature review, secondary data analysis and comparative policy analysis. This approach is consistent with the established practice in policy research, where the complexity of governance questions requires connectivity across multiple data sources and analytical approaches.

4.1. Research Design

This chapter approaches a qualitative interpretive research design oriented towards understanding how, why and under what conditions digital technologies shape food security governance outcomes.

Rather than generating new primary data, it synthesizes and analyzes existing empirical evidence, policy documents, and institutional reports to develop theoretically grounded insights applicable across different national and institutional levels. The design focuses on three goals established in the introduction. The first goal is to analyze how remote sensing, AI, big data, and prediction analysis are transforming food security monitoring is addressed through a synthesis of peer reviewed empirical literature. The second goal is to examine governance and ethical challenges including data access, digital inequality, and algorithmic accountability draws on comparative analysis of institutional frameworks and policy documents from international organizations. The third goal is to develop an actionable framework and data governance food security policy that is addressed though case synthesis in context of governance models drawn from both high- and low-income countries. These three analytical moves correspond to a descriptive analytical normative progression common in policy oriented academic literature (Head, 2010).

4.2. Data Sources

The primary evidence base consists of peer reviewed journal articles and book chapters published predominantly between 2015 and 2025, reflecting the period of most intensive development and deployment of AI and remote sensing food security contexts.

The relevant literature was searched through Google Scholar, Scopus and Web of Science using search terms combining 'food security' with 'artificial intelligence', 'remote sensing', 'big data, 'machine learning', 'early

 https://doi.org/10.66529/book.9786277945039.2026.ch17

warning systems', 'data governance' and 'digital divide'. The literature review covers a range of country level crop mapping studies, systematic reviews of AI modelling approaches in food security and analyses remote sensing performance in crop health monitoring. Studies were selected based on methodological rigor, geographic and thematic relevance and recency, with preference given to studies which provided quantitative assessments of tool performance or governance outcomes.

A second category of sources comprises reports, frameworks and technical manuals and strategic documents produced by the key international organizations operating at the intersection of digital technology and food security. These include the Food and Agriculture Organization of the United Nations (FAO), the world Food Program (WFP), the Integrated food security phase classification (IPC), the Famine Early Warning Systems Network (FEWS NET), the Global Information and Early Warning System on Food and Agriculture (GIEWS), and the United Nations Conference on Trade Development (UNCTAD). These documents are treated not only as sources but as data, showing normative assumptions, institutional priorities and power relations embedded in international food data governance (Prior, 2003).

To avoid abstraction, the analysis is grounded in case evidence drawn from specific country and regional settings referenced in the literature. These include Sub-Saharan Africa, Iran (Rice yield monitoring using GEE and MODIS), India and China (Irrigated Agriculture Reporting). These cases are not treated as representative samples but as illustrations that reveal broader structural patterns in the relationship between digital tool capability and food policy governance (Flyvbjerg, 2006).

4.3. Limitations

Several limitations of the methodological approach should be acknowledged, as they impact the chapter's findings. A secondary synthesis relying on published literature and organization documents are bound by existing evidence base, which may reflect structural biases in academic knowledge production. As shown in literature review, the majority of AI and remote sensing research in food security is conducted by Global North institutions about Global South populations having limited co-construction involving local researchers, communities, or policymakers. The analysis is therefore subject to the same biases it aims to critique.

The chapter's temporal scope primarily 2015 to 2025 captures a period of rapid technological change in which capabilities, development contexts, and governance of AI and remote sensing have evolved considerably. Some findings from earlier literature are necessary to build basis of analysis as well as context however, they may not accurately reflect the current state of tools or institutional frameworks, particularly given the pace of development in large language models, satellite imagery and international governance negotiations. Comparative analysis is necessarily selective. A comprehensive review of national level food data governance frameworks across all UN member states is beyond the scope of a single chapter.

The country and institutional cases selected are intended to be illustrative of broader patterns, and readers should show caution in generalizing from specific regional or national governance models without additional empirical grounding. Lastly, the chapter does not engage in primary research such that no original surveys, interviews, field observations or remote sensing analysis are conducted. This limits the capacity to make claims about the ground situation experiences of food insecure populations or on the ground implementations of digital tools,

5. Results and Discussions

The literature review resulted in three major converging streams of evidence regarding the role of digital tools, data systems and artificial intelligence (AI) in food security policy. Empirical findings from the studies focusing on these themes are given below in tables. (1) Remote sensing in precision agriculture, crop monitoring and decision making at multiple scales, (2) AI and big data analysis improving the accuracy and timeliness of food insecurity measurement and early warning, (3) Role of digital platforms and data governance frameworks in shaping food systems, their management and governance.

 | https://doi.org/10.66529/book.9786277945039.2026.ch17

Besides the benefits of these technological advancements there exists a considerable disproportion in distribution and digital divide, Global South remains underrepresented both in terms of research and technology deployment. The following subsections present synthesized empirical findings from the reviewed literature, organized thematically and supported by summary tables.

Table 17.1 Key Studies on Remote Sensing Applications in Food Security and Agricultural Policy

Title	Journal	Key Findings	Reference
Applying Tipping Point Theory to Remote Sensing Science to Improve Drought Monitoring and Food Security Early Warning	Earth's Future	Remote sensing allows policymakers to design crisis response policies by enhancing early warning for food security, disease detection in vegetation and marking the critical points.	(Krishnamurthy R *et al*., 2020)
A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses	Journal of Hydrology	Remote sensing allows yield estimation and irrigated area mapping which supports policymakers to develop tailored and efficient policies and resource allocation to enhance global food availability	(Karthikeyan *et al*., 2020)
A Review of Remote Sensing Challenges for Food Security with Respect to Salinity and Drought Threats	Remote Sensing	This study identified the limitation of remote sensing detecting stressed crops urging policy investment in spectral indices for food security in stress prone areas	(Wen *et al*., 2020)
Estimating yields of household fields in rural subsistence farming systems to study food security in Burkina Faso	Remote Sensing	Remote sensing has the ability to predict the yield before harvest, which can help policymakers to identify the climate affected, small landholders to get benefits from government's policies.	(Karst *et al*., 2020)
Probabilistic forecasting of remotely sensed cropland vegetation health and its relevance for food security	Science of The Total Environment	Satellite imagery integrated probabilistic VHI forecasts aid early warning systems for sound interventions during vegetation stress	(Hammad & Falchetta, 2022)
Satellite forecasting of crop harvest can trigger a cross-hemispheric production response	Communications Earth & Environment	Yield forecasting at appropriate time can reduce fluctuation in price in importing countries, enhances trade policies and securing food availability	(Tanaka *et al*., 2023)

Table 17.2: Selected Studies on AI, Big Data, and Digital Technologies for Food Security Policy

Title	Journal	Key Findings	Reference
IoT, big data and artificial intelligence in agriculture and food industry	IEEE Internet of Things	AI, IoT and social media have capacity to turn the work of weeks into minutes and seconds, detection and surveillance through sensors is improving yield and supply chain in agri food systems. Social media is also playing a pivotal role in connecting masses, turning the policy into more efficient and robust policy.	(Misra *et al*., 2020)
Predictive Insights for Improving the Resilience of Global Food Security Using Artificial Intelligence	Sustainability	AI modeling with big data allows users to make worst case scenarios as future projections that direct policymakers to make policies to mitigate these worst-case scenarios and secure the resources.	(How *et al*., 2020)
Artificial intelligence, big data, and blockchain in food safety	IJFE	These technologies are improving farm level operations, processing and trade related operations making policies robust and efficient	(Zhou *et al*., 2022)
Making food systems more resilient to food safety risks	Comprehensive Reviews in Food Science and Food Safety	Climate change is one of the biggest drivers of food security risks, AI and big data analytics can accurately detects the disease posing threat to food security	(Mu *et al*., 2024)
Transforming Agrifood Supply Chains with Digital Technologies	Operations Research Forum	Industry 4.0 technologies can revolutionize the agriculture food system and supply chain, by detecting microbial level contaminations, food frauds, and chemical traceability, helping decision makers to take sound measures and targeted policy interventions.	(Plakantara & Karakitsiou, 2025)

6. Conclusion

This chapter presents a holistic approach to understanding food security policy with the lens of artificial intelligence, digital tools and big data analysis. Food security has multi-dimensions, it cannot be attained by traditional methods, but it can be addressed by integrating primary and secondary data, technological fusion with ground data and future projections to make the food security policy efficient and robust, besides these advancements some concerns are very critical and posing limitations towards achieving food security.

Most of the research is done by the global north nations on the global south nations without local feedback incorporated in it which makes them far away from real-world scenarios. To avoid this one suggestion may help, global north nations can help global south nations by supporting them technically and financially and allowing them to use their resources for their own, to do research and draw results by incorporating the local stakeholders and their feedback. As they are the inhabitants and are directly influenced by the climatic and political conditions of these regions.

To mitigate hunger, it is crucial to end this digital divide and make an honest and equal proportion of benefits of AI and other technologies as most of their benefits are centered in urban and developed nations. There are less opportunities both in terms of institutions and infrastructure and in policies. There is a need to uplift the local scholars, to train them and make them work for their local community, which may contribute to the big picture of food security.

Food security also possesses a political and geopolitical background; to uplift the developing nations of global south it is crucial to keep the national interest at first place no matter which party is ruling a certain

 https://doi.org/10.66529/book.9786277945039.2026.ch17

country, regardless of their inclination towards certain projects, food security should be considered as the most important project, technical and institutional investments and collaboration with developed countries in AI, big data and digital tools for monitoring and surveillance is of great importance.

Food security policy is dynamic, there is a need for experts in policymaking sectors in collaboration with researchers, scientists and politicians and analysts that consider local and geo-politics and take the local community onboard while decision making. This way a particular developing country may have robust policy for food security and can mitigate hunger while eliminating the digital divide, securing its data sovereignty and making it accessible to most of its population.

References

Ahmad, A., Liew, A. X., Venturini, F., Kalogeras, A., Candiani, A., Di Benedetto, G., Ajibola, S., Cartujo, P., Romero, P., & Lykoudi, A. (2024). AI can empower agriculture for global food security: challenges and prospects in developing nations. *Frontiers in artificial intelligence*, *7*, 1328530. https://doi.org/10.3389/frai.2024.1328530

Amar, S., Bori, N., & Cörvers, R. (2026). From collection to control: Data governance, digital technologies, and the politics of inclusion in the digitalisation of smallholder agriculture. *Outlook on Agriculture*, *55*(1), 19-27. https://doi.org/10.1177/00307270251410944

Araújo, S. O., Peres, R. S., Ramalho, J. C., Lidon, F., & Barata, J. (2023). Machine Learning Applications in Agriculture: Current Trends, Challenges, and Future Perspectives. *Agronomy*, *13*(12), 2976. https://www.mdpi.com/2073-4395/13/12/2976

Asante, W. (2023). The multiple streams framework and forest policy change process in Ghana. *Cogent Social Sciences*, *9*(1), 2228062. https://doi.org/10.1080/23311886.2023.2228062

Bégué, A., Leroux, L., Soumaré, M., Faure, J.-F., Diouf, A. A., Augusseau, X., Touré, L., & Tonneau, J.-P. (2020). Remote sensing products and services in support of agricultural public policies in Africa: Overview and challenges. *Frontiers in Sustainable Food Systems*, *4*, 58. https://doi.org/10.3389/fsufs.2020.00058

Blewden, M., Carroll, P., & Witten, K. (2010). The use of social science research to inform policy development: case studies from recent immigration policy. *Kōtuitui: New Zealand Journal of Social Sciences Online*, *5*(1), 13-25. https://doi.org/10.1080/1175083X.2010.498087

Bostanci, S. H., Kantar, G., & Yildirim, S. (2025). AI-Based Assessment of Food Security and Climate Change: Multi-Scenario Analysis for Africa. *IEEE Access*, *13*, 205991-206005. https://doi.org/10.1109/ACCESS.2025.3639349

Buczkowski, A. (2022). *How satellite data is contributing to global food security*. https://geoawesome.com/eo-hub/how-satellite-data-is-contributing-to-global-food-security/

Cairney, P., & Oliver, K. (2017). Evidence-based policymaking is not like evidence-based medicine, so how far should you go to bridge the divide between evidence and policy? *Health Research Policy and Systems*, *15*(1), 35. https://doi.org/10.1186/s12961-017-0192-x

Callon, M. (1999). The Role of Lay People in the Production and Dissemination of Scientific Knowledge. *Science, Technology and Society*, *4*(1), 81-94. https://doi.org/10.1177/097172189900400106

Clapp, J., & Ruder, S.-L. (2020). Precision Technologies for Agriculture: Digital Farming, Gene-Edited Crops, and the Politics of Sustainability. *Global Environmental Politics*, *20*(3), 49-69. https://doi.org/10.1162/glep_a_00566

Cresswell, K. M., Worth, A., & Sheikh, A. (2010). Actor-Network Theory and its role in understanding the implementation of information technology developments in healthcare. *BMC Medical Informatics and Decision Making*, *10*(1), 67. https://doi.org/10.1186/1472-6947-10-67

D'Ignazio, C., & Klein, L. F. (2020). *Data feminism*. MIT Press. https://doi.org/10.7551/mitpress/11805.001.0001

Dencik, L., Hintz, A., Redden, J., & Treré, E. (2019). Exploring Data Justice: Conceptions, Applications and Directions. *Information, Communication & Society*, *22*, 873-881. https://doi.org/10.1080/1369118X.2019.1606268

Flyvbjerg, B. (2006). Five misunderstandings about case-study research [Article]. *Qualitative Inquiry*, *12*(2), 370-387. https://www.scopus.com/pages/publications/33645708913

Folorunso, A., Olanipekun, K., Adewumi, T., & Samuel, B. (2024). A policy framework on AI usage in developing countries and its impact. *Global Journal of Engineering and Technology Advances*, *21*(01), 154-166.https://doi.org/10.30574/gjeta.2024.21.1.0192

Geels, F. W. (2020). Micro-foundations of the multi-level perspective on socio-technical transitions: Developing a multi-dimensional model of agency through crossovers between social constructivism, evolutionary economics and neo-institutional theory. *Technological Forecasting and Social Change*, *152*, 119894. https://doi.org/10.1016/j.techfore.2019.119894

Hammad, A. T., & Falchetta, G. (2022). Probabilistic forecasting of remotely sensed cropland vegetation health and its relevance for food security. *Science of the Total Environment*, *838*, 156157. https://doi.org/10.1016/j.scitotenv.2022.156157

Head, B. W. (2010). Reconsidering evidence-based policy: Key issues and challenges. *Policy and Society*, *29*(2), 77-94. https://doi.org/10.1016/j.polsoc.2010.03.001

How, M.-L., Chan, Y. J., & Cheah, S.-M. (2020). Predictive Insights for Improving the Resilience of Global Food Security Using Artificial Intelligence. *Sustainability*, *12*(15), 6272. https://www.mdpi.com/2071-1050/12/15/6272

Hussein, J. B., Workneh, T. S., Kassim, A., Ntsowe, K., Melesse, S. F., & El-Mesery, H. S. (2025). A review on the impact of big data analytics in transforming agricultural practices, food processing, and preservation strategies. *Applied Food Research*, *5*(2), 101234. https://doi.org/10.1016/j.afres.2025.101234

Iazzolino, G., & Stremlau, N. (2024). AI for social good and the corporate capture of global development. *Information Technology for Development*, *30*, 1-18. https://doi.org/10.1080/02681102.2023.2299351

Karst, I. G., Mank, I., Traoré, I., Sorgho, R., Stückemann, K.-J., Simboro, S., Sié, A., Franke, J., & Sauerborn, R. (2020). Estimating yields of household fields in rural subsistence farming systems to study food security in Burkina Faso. *Remote Sensing*, *12*(11), 1717. https://doi.org/10.3390/rs12111717

Karthikeyan, L., Chawla, I., & Mishra, A. K. (2020). A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. *Journal of hydrology*, *586*, 124905. https://doi.org/10.1016/j.jhydrol.2020.124905

Krishnamurthy R, P. K., Fisher, J. B., Schimel, D. S., & Kareiva, P. M. (2020). Applying tipping point theory to remote sensing science to improve early warning drought signals for food security. *Earth's future*, *8*(3), e2019EF001456. https://doi.org/10.1029/2019EF001456

Levy, E. (2001). Quantification, Mandated Science and Judgment. *Studies in History and Philosophy of Science Part A*, *32*(4), 723-737. https://doi.org/10.1016/S0039-3681(01)00019-X

Li, L., Wang, J., Wang, X., Peng, P., Shen, J., Zhu, H., & Zhang, Z. (2025). Big data and data science in global governance: anticipating future needs and applications in the UN and beyond [Review]. *Frontiers in Political Science*, *Volume 7 - 2025*. https://doi.org/10.3389/fpos.2025.1583772

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, *175*, 121359. https://doi.org/10.1016/j.techfore.2021.121359

MacKenzie, D., & Wajcman, J. (1999). *The Social Shaping of Technology*. Open University. https://researchonline.lse.ac.uk/id/eprint/28638/

Marvin, H. J., Janssen, E. M., Bouzembrak, Y., Hendriksen, P. J., & Staats, M. (2017). Big data in food safety: An overview. *Critical reviews in food science and nutrition*, *57*(11), 2286-2295. https://doi.org/10.1080/10408398.2016.1257481

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of things Journal*, *9*(9), 6305-6324.https://doi.org/10.1109/JIOT.2020.2998584

Mmbando, G. S. (2025). Harnessing artificial intelligence and remote sensing in climate-smart agriculture: the current strategies needed for enhancing global food security. *Cogent Food & Agriculture*, *11*(1), 2454354. https://doi.org/10.1080/23311932.2025.2454354

Mu, W., Kleter, G. A., Bouzembrak, Y., Dupouy, E., Frewer, L. J., Radwan Al Natour, F. N., & Marvin, H. (2024). Making food systems more resilient to food safety risks by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools. *Comprehensive Reviews in Food Science and Food Safety*, *23*(1), e13296. https://doi.org/10.1111/1541-4337.13296

Neisser, F. M. (2014). 'Riskscapes' and risk management – Review and synthesis of an actor-network theory approach. *Risk Management*, *16*(2), 88-120. https://doi.org/10.1057/rm.2014.5

Novak, O., & Kobets, V. (2023). Artificial intelligence impact on food security of states in the world. International Conference on Information and Communication Technologies in Education, Research, and Industrial Applications.https://icteri.org/icteri-2023/proceedings/preview/01000237.pdf

Nutley, S. M., Walter, I., & Davies, H. T. O. (2007). Index. In *Using evidence: How research can inform public services* (pp. 0). Policy Press.

Omotayo, A. O., Adediran, S. A., Omotoso, A. B., Olagunju, K. O., & Omotayo, O. P. (2025). Artificial intelligence in agriculture: ethics, impact possibilities, and pathways for policy. *Computers and Electronics in Agriculture*, *239*, 110927. https://doi.org/10.1016/j.compag.2025.110927

Plakantara, S. P., & Karakitsiou, A. (2025). Transforming Agrifood Supply Chains with Digital Technologies: a Systematic Review of Safety and Quality Risk Management. Operations Research Forum.https://doi.org/10.1007/s43069-025-00511-3

Prior, L. (2003). *Using Documents in Social Research* [Book]. Sage Publications Ltd.https://www.torrossa.com/en/resources/an/4913877

Sarku, R., Clemen, U. A., & Clemen, T. (2023). The Application of Artificial Intelligence Models for Food Security: A Review. *Agriculture*, *13*(10), 2037. https://www.mdpi.com/2077-0472/13/10/2037

Shams Esfandabadi, H., Ghamary Asl, M., Shams Esfandabadi, Z., Gautam, S., & Ranjbari, M. (2022). Drought assessment in paddy rice fields using remote sensing technology towards achieving food security and SDG2. *British Food Journal*, *124*(12), 4219-4233. https://doi.org/10.1108/BFJ-08-2021-0872

Shi, S., Ye, Y., & Xiao, R. (2022). Evaluation of Food Security Based on Remote Sensing Data Taking Egypt as an Example. *Remote Sensing*, *14*(12), 2876. https://www.mdpi.com/2072-4292/14/12/2876

Smith, J. K. (1988). The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology. Edited by Wiebe E. Bijker, Thomas P. Hughes, and Trevor Pinch. Cambridge, Mass.: MIT Press, 1987. 405 pp. Illustrations, charts, notes, bibliography, and index. $35.00. *Business History Review*, *62*(2), 341-342. https://doi.org/10.2307/3116018

Tanaka, T., Sun, L., Becker-Reshef, I., Song, X.-P., & Puricelli, E. (2023). Satellite forecasting of crop harvest can trigger a cross-hemispheric production response and improve global food security. *Communications Earth & Environment*, *4*(1), 334. https://doi.org/10.1038/s43247-023-00992-2

Torero, M. (2021). Robotics and AI in food security and innovation: why they matter and how to harness their power. In *Robotics, AI, and humanity: Science, ethics, and policy* (pp. 99-107). Springer. https://doi.org/10.1007/978-3-030-54173-6_8

Unicef. (2024). The state of food security and nutrition in the world 2024. https://openknowledge.fao.org/handle/20.500.14283/cd1254en

Wen, W., Timmermans, J., Chen, Q., & van Bodegom, P. M. (2020). A review of remote sensing challenges for food security with respect to salinity and drought threats. *Remote Sensing*, *13*(1), 6. https://doi.org/10.3390/rs13010006

Wu, B., Zhang, M., Zeng, H., Tian, F., Potgieter, A. B., Qin, X., Yan, N., Chang, S., Zhao, Y., Dong, Q., Boken, V., Plotnikov, D., Guo, H., Wu, F., Zhao, H., Deronde, B., Tits, L., & Loupian, E. (2023). Challenges and opportunities in remote sensing-based crop monitoring: a review. *Natl Sci Rev*, *10*(4), nwac290. https://doi.org/10.1093/nsr/nwac290

Zhou, Q., Zhang, H., & Wang, S. (2022). Artificial intelligence, big data, and blockchain in food safety. *International journal of food engineering*, *18*(1), 1-14. https://doi.org/10.1515/ijfe-2021-0299

Declaration: AI-assisted tools (LLMs) were used to improve the language and grammar of this chapter. The authors reviewed and approved all content and assume full responsibility for its accuracy.