Advanced Spatial Analytics for Policy Support

Use cases from One CGIAR

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Table of Contents

Table of Figures

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Section 1: Chun Song. Section 2: Chun Song, Athanasios Petsakos, Abhijeet Mishra. Section 3: Chris Mwungu, Gloria Mbabazi. Use case 1 Fertilizer response: Bisrat Gebrekidan, Jordan Chamberlin, Maxwell Mkondiwa. Use case 2 Spatial Production Allocation Model (SPAM): Shuang Zhou, Zhe Guo, Liangzhi You. Use case 3 Spatial mapping of crop vulnerability for targeting investment: Tim Thomas. Use case 4 Improving the Spatial Granularity in Impact Evaluation: Chris Mwungu, Felix Otieno, Agnes Wanjau, Anirudha Ghosh. Use case 5: Simulated Land Use/Land Cover change: Richard Robertson. Use case 6 Spatial Dimensions of Poverty and Agricultural Productivity: Valerian Pede, Bert Lenaerts. Use case 7 Spatial Downscaling future food demand for local food policy making: Chun Song, Francis Yego, Athanasios Petsakos, Elisabetta Gotor. Use case 8 PlaSA as a spatial online supporting tool for policy: Carlos Gonzalez. Use case 9 Spatial assessment of Landscape complexity: implications for agricultural policies: Nicola Cenacchi Nicola Cenacchi, Athanasios Petsakos, Richard Robertson, Chun Song, Abhijeet Mishra. Use case 10 Assessing potential impact of avian influenza on poultry in West Africa: Liangzhi You, Xinsheng Diao. Use case 11 Where to strength water governance for preventing future water conflicts? Chun Song, Athanasios Petsakos, Elisabetta Gotor.

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Abbreviations

AGLINK-COSIMO	Agricultural Linkage – Commodity Simulation Model
AI	Avian Influenza
AoW	Area of Work
CAP	Common Agricultural Policy
CAPRI	Common Agricultural Policy Regional Impact Model
CATE	Conditional Average Treatment Effects
CF	Causal Forests
CGIAR	Consultive Group on International Agricultural Research
CIMMYT	International Maize and Wheat Improvement Center
CLI	Canada Land Inventory
COVID-19	Coronavirus Disease 2019
DEM	Digital Elevation Model
DiD	Difference-in-Differences
DMU	Decision Making Unit
DnD	Differences-in-Discontinuities
DSSAT	Decision Support System for Agrotechnology Transfer
EO	Earth Observation
EOSDIS	Earth Observing System Data and Information System
EU	European Union
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
FLW	Food, Land and Water
FSSIM-Dev	Farming System Simulator for Developing Countries
GCM	General Circulation Models
GEOGLAM	Group on Earth Observations Global Agricultural Monitoring Initiative
GIS	Geographic Information System
GLOBIOM	Global Biosphere Management Model
HLPE	High Level Panel of Experts
IFM-CAP	Individual Farm Model for Common Agricultural Policy Analysis
IFPRI	International Food Policy Research Institute
IGSM	Integrated Global System Model
IIASA	International Institute for Applied Systems Analysis
IMPACT	International Model for Policy Analysis of Commodity Trade
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
IRIO	Interregional Input–Output Model
IRRI	International Rice Research Institute
ISDC	Independent Science for Development Council
ISFM	Integrated Soil Fertility Management
ITE	Individual Treatment Effect
LAC	Latin America and the Caribbean

LMIC	Low- and Middle-Income Country
LSMS-ISA	Living Standards Measurement Study – Integrated Surveys on Agriculture
MAGNET	Modular Applied General Equilibrium Tool
MAgPIE	Model of Agricultural Production and its Impact on the Environment
MapSPAM	Spatial Production Allocation Model
MENA	Middle East and North Africa
MIT	Massachusetts Institute of Technology
NASA	National Aeronautics and Space Administration
NCD	Non-Communicable Disease
NDVI	Normalized Difference Vegetation Index
NEG	New Economic Geography
OECD	Organization for Economic Cooperation and Development
PIK	Potsdam Institute for Climate Impact Research
PISA	Performance, Innovation and Strategic Analysis for Impact
PlaSA	Plataforma de Sistemas Alimentarios (Food Systems Platform)
RCMRD	Regional Centre for Mapping of Resources for Development
RCSSMRS	Regional Centre for Services in Surveying, Mapping and Remote Sensing
RCT	Randomized Control Trial
RD	Regression Discontinuity
SDiD	Spatial Difference-in-Differences
SDnD	Spatial Differences-in-Discontinuities
SMS	Short Message Service
SRD	Spatial Regression Discontinuity
SSU	Shamba Shape Up
WFP	World Food Programme
WPS	Working Paper Series
WUR	Wageningen University & Research
WWF	World Wildlife Fund

Executive Summary

The CGIAR Science Program on Policy Innovations (“Policy Program”) is committed to driving transformation across Food, Land, and Water (FLW) systems. Identifying viable policies and investment options through Foresight and Prioritization exercises (Area of Work 1) is key to reaching this goal. However, prioritizing interventions that are relevant to local needs and conditions, while addressing global drivers and megatrends that affect FLW systems across different scales remains a challenge.

This report seeks to address this challenge. It demonstrates how spatial analytics, a fast-evolving field that sits at the intersection of economics, public policy, geography, and data science, can provide actionable policy insights. It also aims to equip policymakers and partners with advanced and accessible spatial analytical tools to design and implement tailored policies, investments and programs.

The report starts by providing a unified framework that brings together diverse spatial analytics approaches to support policy. It reviews the evolution of spatial analytics, spanning geographic information systems (GIS), spatial economics, and economic models with spatially explicit inputs and outputs. It also introduces a taxonomy of building blocks to illustrate how different spatial tools and methods can address various policy questions.

This report draws on 11 use cases from across CGIAR centers in which spatial analytics have been applied to inform policies across Africa, Asia, and Latin America. It demonstrates how spatial analytics can identify priority intervention areas and appropriate actions at the local level while accounting for global drivers. Key challenges in scaling spatial analytics for policy application are also identified, including data gaps, methodological complexities, and computational constraints. The report concludes by outlining future directions to fully leverage spatial analytics for policy support.

This report aims to advance the integration of spatial analytics across disciplines and scales, enabling the translation of local spatial patterns into regional and global policy frameworks. The curated use cases show that spatial analytics is no longer a niche technical exercise, but an operational tool that facilitates FLW systems transformation towards desirable futures. By systematically linking spatial heterogeneity to multi-scale policy needs, spatial analytics can generate actionable and scalable insights for policy development and implementation.

1. Introduction

1.1 Background

CGIAR Science Program on Policy Innovations (*Policy Program*) focuses on the transformation of Food, Land, Water (FLW) Systems as a whole. To support this objective, Foresight and Prioritization (Area of Work 1) charts potential future development pathways and identifies cost-effective policy options to drive transformation in FLW systems to enhance nutrition, livelihoods, gender equity, social inclusion, climate resilience, and environmental sustainability.

However, identifying policy options and modelling the impacts of these policies are confounded by a great deal of heterogeneity and interactions among agents at local level: Farming activities occur across landscapes characterized by varying soil properties, microclimates, and water availability. Farmer's choice of varieties is affected by location-specific risks. Farmers' decisions on crop selection are influenced by neighboring farmers and local market demands. These phenomena lead to the question: How can policymakers incorporate local variations in determining where actions are (or will be) most needed, while still accounting for drivers at aggregate or even global scales?

Spatial analytics provides one way to answer this question.

As part of the broader suite of quantitative disciplines in the social sciences, spatial analytics stands at the crossroads of economics, geography, and data science. Since the 1960s, spatial analytics including GIS has been supporting policy formulation and delivery, in areas ranging from rural development to forest management. The integration of subnational level information into foresight modelling improves simulation of possible future, and the robustness of projected tradeoffs and synergies between alternative policy options at local geographical scales, while still accounting for the general impacts of mega drivers. Recently, advancements in causal inferences, machine learning, and big data from Earth Observation provide opportunities to model impact pathways at a granular scale.

Building on these advances, in the past decades, the global south countries have witnessed a significant increase in investments in spatial-related research and development in the FLW system (Oyewole, 2017). More operational information services have become available in Sub Sahara African countries (e.g., early warning systems for food security, pest and disease monitoring, climate information services). Spatial analytics have also been used to guide infrastructure investment in Indonesia ($267 million) (The World Bank, 2013), Haiti ($20 million) (The World Bank, 2024)) and Horn of Africa (Dappe & Lebrand, 2021).

Despite the increasing capabilities that spatial analytics offer for policy support, there remains no synthesis of how these analytical tools can be leveraged for policy purposes. What are the common building blocks and shared concepts for spatial analytics that bridge the disciplinary gap between economists, geographers, and policy experts? What are the examples of different use cases? This report aims to address those questions.

1.2 Scope and Objectives of this synthesis report

This synthesis report provides an overview of advanced spatial analytics for policy support in the global south, including recent use cases in One CGIAR. The objective is to synthesize the state-of-the-art spatial analytics for policy, identifying key building blocks, show recent applications in different use cases, discuss persistent challenges to incorporate more spatial granularity into foresight modelling, and suggest some future directions for researchers and stakeholders. This synthesis has two parts:

Part 1 provides a review of the evolution of spatial analytics in supporting policy. It reviews three strands over this evolution: GIS, spatial/regional economics, and economic models with spatial inputs. A taxonomy of the different building blocks and their properties are provided. It can be seen that spatial analytics can support the answer of two policy needs: first, contextualization of local situation for policy. Second, informing targeting and prioritization within a country. Each need can be met by different spatial analytics that allow policymakers to move beyond mapping. Figure 1 illustrates those options.

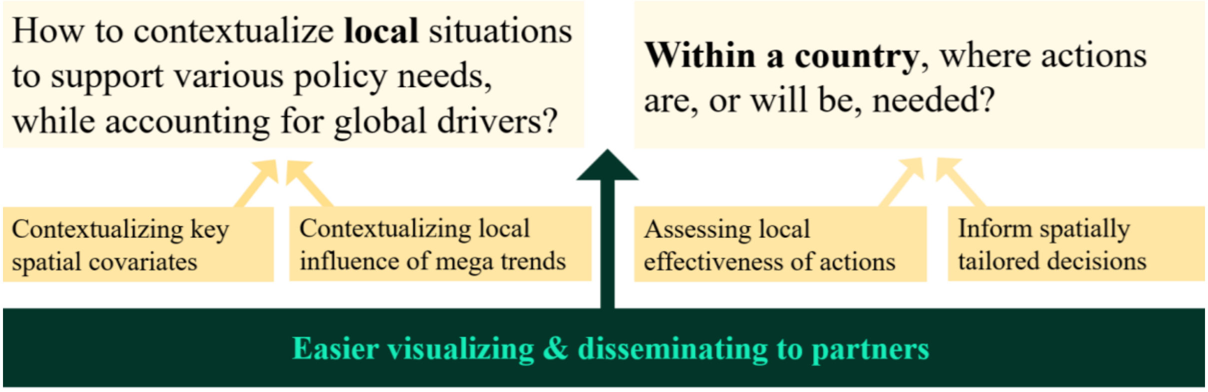

Figure 1: Different ways spatial analytics can support policy questions.

Part 2 showcases 11 use cases that apply spatial analytics for policy support at the global scale but focus on the global south, and different ways these cases contribute to foresight and prioritization. These use cases represent a set of CGIAR projects and innovative methodological approaches. These cases demonstrate how spatial analytics can be used in different ways for supporting policy and communicating with partners and citizens.

The way forward section summarizes key insights arising from this synthesis, and what are the contexts that spatial analytics can be relevant and appropriate for policy. We also reflect on the skill set, background, and experience that can make up a successful scientist's team that uses spatial analytics for supporting policy analysis. We comment on major challenges and ways forward in improving the spatial granularity in Foresight economic modeling.

Amid increasing demand for more granular evidence to support policy making, this report is also relevant for a broad audience of researchers and practitioners from a variety of policy backgrounds interested in learning about the potential to meet the growing demand for using spatial analytics for policy support. We close with a discussion of the need for a systematic change in policy analysis to fully leverage the potential of spatial analytics for improving the granularity of activities within One CGIAR.

2. Spatial analytics for policy support: history and building blocks

Credit: ©CIAT

2.1. Basic concepts and terminologies

We start by setting common ground for basic terminologies. In this synthesis, “spatial analytics” refers to the geo-referenced data and spatial models (including statistical and economic models) used to support various policy purposes, including integrating different spatial datasets into analytical frameworks that can capture local heterogeneity (e.g., differences in productivity, costs, or constraints across locations) and agents interactions (e.g., spillovers, diffusion of innovations, social learning). We use the term “policy” to refer broadly to government strategies and interventions designed to influence FLW systems towards desirable outcomes. We focus on policy needs that require quantitative evidence to inform different options, tradeoffs, and assess their impact. Combining these concepts, we define spatial analytics for policy support as the use of geo-referenced data and spatial tools (including statistical and economic frameworks) to provide quantitative evidence for policy design and evaluation. It integrates heterogeneous datasets (e.g., georeferenced household surveys, social-economic, biophysical and climatic data layers, and remote sensing including drone or satellite-based Earth Observation) into analyses that capture spatial interactions across Decision Making Units (DMU) (such as spillovers, diffusion, and agglomeration) and spatial heterogeneity (such as differences in productivity, costs, and constraints across /locations).

2.2 The evolution of spatial analytics for policy support

We introduce the evolution of spatial analytics for supporting policy, which started over three related strands that were initially developed as separate lines but recently became more integrated for policy purposes. Figure 2 shows the evolution of these strands.

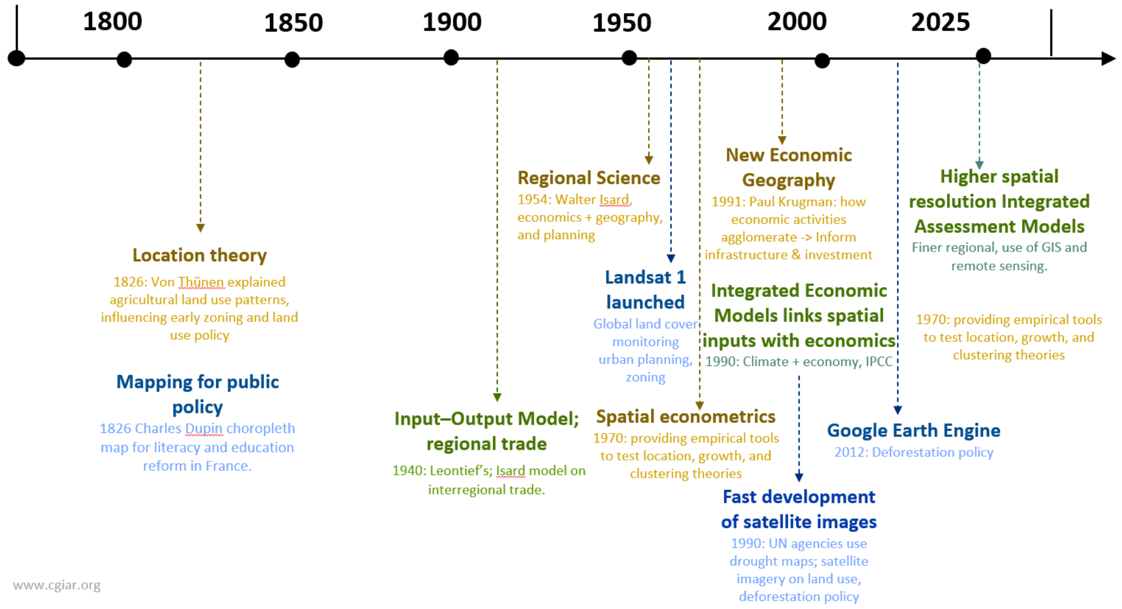

Figure 2: Evolution of spatial analytics for policy support (source: authors)

2.2.1 GIS for guiding public investment and service delivery.

In 1963, the world's first Geographic Information System (GIS) was developed in Canada by the Federal Department of Forestry and Rural Development. It was first used to store, analyze, and manipulate data collected for the Canada Land Inventory (CLI). The CLI was used by The Department to decide where to invest in rural development and how to allocate land for different purposes including infrastructure agriculture, forestry, recreation, or wildlife conservation (Maguire, 1991).

Later, GIS was increasingly used in supporting different public services delivery (Hannum et al., 2025). In the late 1960s to early 1970s, the Landsat program was started for environmental monitoring, resource management, and land policy making. Since then, Governments in the global north have been relying on Landsat imagery to track whether land-use practices align with policy goals or legal requirements.

For instance, in US, Landsat data has helped legislators and State and local officials to determine land use policy and by planners to project transportation demand, to identify areas where future development pressure will be greatest, in order to estimate future infrastructure requirements, and to develop more effective plans for regional development (Anderson, 1977). Brazilian government has been using Landsat data to monitor deforestation and design policies for reforestation (Shimabukuro et al., 2022). More recently, Sentinel imagery data supports the European Union’s Common Agricultural Policy (CAP) by verifying farmers’ land use declarations and corresponding subsidy eligibility (Terres et al., 1995).

In the Global south, the use of GIS for policy also started in a similar period. In 1975, the Regional Centre for Mapping of Resources for Development (RCMRD) was established in Nairobi, Kenya by Kenya, Uganda, Somalia, Tanzania, and Malawi and involved in developing spatial data infrastructure among its member states, including capacity building on natural resource mapping in Africa (Regional Centre for Mapping of Resources for Development (RCMRD), 2006).

In recent years, GIS has continued to offer policy support. More advanced GIS involves image classification using machine learning and platforms such as Google Earth Engine. Models like the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) can also be integrated with GIS to assess the impact of land management practices on soil-related ecosystem services. Researchers have also developed methods for mapping crop production. These products include Spatial Production Allocation Model (SPAM) for subnational crop distribution. Policymakers can use these insights to prioritize investments, target adaptation measures, and align agricultural policy with food security and sustainability goals.

2.2.2 Economic geography and spatial economics for regional development policy

The second strand of spatial analytics for policy begins early with location theory, which attempts to explain the geographical placement of economic activities (like firms, industries, or cities) and implications on economic outcomes. It began in 1826 when Von Thünen model (Walker, 2022) explained agricultural land use patterns based on distance to markets. The DMU in Von Thünen's model (1826) is profit-maximizing farmer. Landowners allocate crops across space by weighing market prices against transport costs and land rents. The model shows how rational decisions by individual producers, made under assumptions of an isolated market and uniform plain, yield the famous concentric rings of land use. Although stylized, this approach established the micro-foundations of land-use theory and continues to inform agricultural policy and land zoning analyses. Later, Alfred Weber (1909) extended the theory to industrial location (Fearon, 1909). The Von Tunen framework has been widely used to study early zoning and land use policy such as land sparing (Fontes & Palmer, 2018).

Building on location theory, regional science, which oriented toward the study of regions "from a multidisciplinary and spatial-analytical approach" (Kourtit et al., 2021), was formally founded by Walter Isard in 1954 (Boyce, 2004). Later, the Interregional input–output (IRIO) models capturing production and trade flows across multiple geographies, treating the sector within a region as DMU. Gravity models of interaction conceptualize the region as the decision-making entity, sending flows of people, goods, or capital to other regions in proportion to size and distance. In these frameworks, the region itself acts as the unit of analysis and decision.

In 1990s, New Economic Geography (NEG) (Krugman, 1998) introduced models of agglomeration and regional development (Krugman, 1991). Firms choose locations by balancing scale economies and transport costs, while workers and households decide where to live and work based on wages, amenities, and commuting costs (Fujita et al., 1999). By embedding these micro agents within general equilibrium frameworks, modern models restored individual decision-making to the forefront while capturing emergent spatial equilibrium. This approach provides a direct link between micro level behavior and macro level spatial patterns.

Urban economics emerged in the mid-20th century, focusing on the internal spatial organization of cities, and the purpose is to inform infrastructure, transport planning, housing policy, etc. Other early efforts to spatialize economics focused on understanding the distribution of economic activities across space (e.g., Maurel & Sédillot, 1999), particularly how factors such as natural resource endowments and local policies shape regional development.

With the growth of optimization and equilibrium economic models, spatial dimensions were gradually incorporated into forward looking modeling frameworks for land use, agricultural production, and policy evaluation. Since the 2000s, advances in Earth Observation (EO), spatial econometrics, and machine learning have transformed spatial analytics into a key tool for policy.

The strand of spatial econometrics emerged in the 1970s–1980s, when researchers recognized standard econometric models ignored spatial patterns in data. The formal foundations of spatial econometrics are usually attributed to Jean Paelinck, who first coined the term in the 1970s (Paelinck & Klaassen, 1979). His early work emphasized the need to adapt econometric techniques to account for spatial dependence and heterogeneity, later further developed by Luc Anselin. Spatial econometrics provides an empirically feasible way to estimate the strength of spatial heterogeneity and spatial dependence on economic and social outcomes.

2.2.3 Integrated Economic modelling with spatial explicit inputs

The term "economic model" encompasses a wide range of quantitative tools, we focus on models that satisfy the following criteria: (1) they are used for forward-looking analysis to support decision making in agriculture (ex-ante or foresight models); and (2) they can represent farmers' and/or consumers' decisions explicitly or implicitly, individually, for a representative sample, or on aggregate (economy-wide), allowing them to simulate the supply and/or demand of agricultural commodities at subnational to global levels. According to these criteria, we discuss the evolution of incorporation of spatial considerations in two types of economic models: farm/household optimization models, and large-scale economic equilibrium models.

The relevant literature and the capacity of these models to provide evidence-based support to policy makers has evolved significantly over the past few decades, driven by advances in computational capacity, data availability, and increasing policy demands for thematically and spatially nuanced insights. Spatially explicit policy analysis with these types of economic models aims to understand how (1) locally targeted policies or other interventions (e.g., investments and new technologies) could affect the agricultural economy and various elements of the food system at finer geographies or (2) how global/aggregate drivers affect each location differently in the agrifood system outcomes.

Spatial components start to enter broader economic models in the late 1990s. This is because a key limitation of the economic models covered in this report is that they are not spatially explicit by design (both the model inputs and outputs). For example, models such as Individual Farm Model for Common Agricultural Policy Analysis (IFM-CAP) and Farming System Simulator for Developing Countries (FSSIM-Dev) (developed and used by the European Commission), simulate production and consumption decisions at the farm/household level, assuming a profit or utility maximization decision criterion under policy and resource endowment constraints (Kremmydas et al., 2022; Louhichi et al., 2020). These models are built with individual or representative farm data and allow a bottom-up approach to the simulation of the agricultural sector. Farm/households are typically treated as independent Decision-Making Units, although there have been some recent attempts to simulate the interaction of DMUs in a non-spatially explicit fashion (Baldi et al., 2024).

Farm/household models can theoretically use spatially explicit inputs and generate spatial explicit outputs if the location of farms/households is known. However, such capacity remains unexplored for policy analysis purposes. One of the main reasons is that the use of datasets containing a sufficiently large number of farms and their geographical coordinates, like the Farm Accountancy Data Network (FADN) of the European Union (EU)[1] and the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA), is often subject to legal constraints for information protection and privacy reasons. Even though strategies for obfuscating farm household coordinates appear to have little impact on econometric estimates when such data is used for ex-post assessment purposes (Michler et al., 2022), we are not aware of any forward-looking studies using spatially explicit data for policy analysis with farm-level optimization models.

On the other hand, large-scale economic models such as Common Agricultural Policy Regional Impact Analysis (CAPRI of the European Commission), International Model for Policy Analysis of Commodity Trade (IMPACT from International Food Policy Research Institute, IFPRI), Modular Applied General Equilibrium Tool (MAGNET by Wageningen University & Research WUR), Model of Agricultural Production and its Impact on the Environment (MAgPIE from Potsdam Institute for Climate Impact Research, PIK), Global Biosphere Management Model (GLOBIOM from International Institute for Applied Systems Analysis, IIASA), and Agricultural Linkage (AGLINK from Organization for Economic Cooperation and Development; Food and Agriculture Organization, OECD-FAO) rely on aggregate/macro-level data for some of the model inputs that is often publicly available (e.g., FAOSTAT) and thus are not subject to similar data use constraints as their farm-level counterparts. Large-scale economic models operate at various levels of aggregation and are primarily concerned with commodity prices and market interactions. They are designed to capture the systemic interactions of interventions and global megatrends, such as population growth, climate change, and policy shifts, and their influence on food, land, and water systems. As such, their main objective is to simulate market behavior and macro-level outcomes, not to offer a spatially fine-grained outlook on micro-level production decisions.

In contrast to farm/household models, a DMU in large-scale economic equilibrium models is implicit[2] and typically concerns the lowest

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[1] https://agridata.ec.europa.eu/extensions/FarmEconomyFocus/FADNDatabase.html

[2] Equilibrium models focus on market closure and price formation and not on individual economic agents. As such, they do not explicitly consider a decision maker as do farm/household models. However, the main assumption behind the neoclassical concept of economic equilibrium is that it represents an aggregation of

spatial scale considered by the model during its solution. Thus, a DMU can be a world region, a country, and sometimes further disaggregated into agro-ecological zones or administrative districts within a country. When the spatial scale for this implicit DMU does not correspond to the scale on which prices are assumed to be formed, the aggregation of production and consumption outcomes across DMUs enables the model to ensure consistency in supply-demand balance and market clearing conditions. Some of the previously mentioned large scale models follow this approach of performing analyses at finer resolutions and aggregating outputs to the scale of market equilibrium.

For instance, MAgPIE[3] and CAPRI (Britz & Witzke, 2014) include modules that simulate land use decisions at a high spatial resolution (subnational) before feeding results into a broader market framework.[4] This hybrid approach allows for more spatially nuanced representation of economic decision-making at a subnational level yet remains very coarse in resolution.

DMUs are treated as largely spatially independent in the model structure. This means that large-scale economic models typically do not include endogenous spatial interaction, whereby, it is very plausible that changes in one DMU influence others through direct spatial processes.[5] Instead, DMU interactions in many economic models arise through market and international trade (though bilateral trade is often not modelled explicitly). For example, a productivity shock in one DMU may affect world prices and, through those prices, influence land use or production decisions elsewhere. This system-wide feedback is a core strength of economic equilibrium models but differs from the localized feedback mechanisms emphasized in other spatially explicit approaches.

The above discussion reveals that, although economic models are not inherently spatially explicit, they can broadly be considered as such, in the sense that their DMUs refer to a specific spatial scale. However, it is also clear that the term “spatially explicit” does not lend itself to the same interpretation as in other spatial quantitative modeling approaches such as spatial econometrics and agent-based modeling. The main reason is that the model solution depends more on the underlying assumptions and the overall economic logic in representing commodity markets and less on the spatial scale of the DMUs[6]. For farm/household models, spatial information is not even required as model input. Second, when DMUs are directly associated with specific spatial units (as in

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economic agents’ optimal consumption and production choices within the region or country of interest.

[3] https://www.pik-potsdam.de/en/institute/departments/activities/land-use-modelling/magpie

[4] The spatial scale in CAPRI is NUTS2 (Nomenclature of Territorial Units for Statistics 2), which is roughly equivalent to ADMIN1, in other words, the first administrative level within a country. The algorithm solves for every NUTS2 unit and simultaneously aggregates across NUTS2 to simulate the market equilibrium at national level.

[5] Such direct interactions may still exist in biophysical components of an economic model, like in the IMPACT water model.

[6] The spatial scale of the DMUs can, however seriously impact computation time and overall computational feasibility. We discuss this point in the next section.

large-scale equilibrium models), economic decision-making is represented at high levels of aggregation. On the contrary, traditional spatial analytic tools are usually applied at much finer spatial resolutions.

Finally, economic models often do not simulate the interaction between different spatial units (e.g., bilateral trade), which is typically the focus of traditional spatial analytic tools. The implication for all economic models mentioned previously is that spatial heterogeneity is captured only to the extent that it is assumed to be implicit in the constraint specifications at the DMU level. For instance, crop (or land) productivity, climate shocks, or technological adoption may vary across geographical scales, and these differences are reflected in model parameters or inputs. This point reflects a fundamental difference in modeling philosophies and objectives: economic models are not statistical constructs aiming to estimate empirical relationships among spatial units. Rather, they are optimization/market clearing frameworks that seek to represent decision-making under predefined constraints. These decisions may be made by producers and/or consumers and are modeled as either direct optimization of objective functions (e.g., cost minimization, utility maximization) or as part of an equilibrium condition where supply meets demand (implicit optimization).

2.3 Building blocks of spatial analytics for policy

There are several key building blocks of spatial analytics for policy. The choice of those building blocks depends on both computational and data availability and the specific needs of policymakers. Identifying the intersection of these factors ensures spatial analytics are feasible, relevant, and capable of delivering actionable, context-specific insights for effective policy decisions.

Spatial Data: there are several different spatial data types. Areal (Polygon) Data, for example administrative boundaries, villages, and districts. Point Data: discrete spatial events or features. Geostatistical Data are derived from samples across a continuous surface (e.g., precipitation, temperature).

Decision making unit (DMU): Decision-Making Unit means the level that economic decisions are made at. This may be the level of farm, a policy beneficiary, a community, an agro-ecological zone or administrative district within a country, or a world region.

Spatial unit: The spatial unit refers to the resolution at which data are collected or analyzed (e.g., point, village, district, region), while scope pertains to the geographical extent of analysis, ranging from communities to countries or even global systems. These choices are interdependent: high-resolution data (e.g., plot-level) may not be feasible or needed for global-scale studies due to data availability or processing constraints.

Raw spatial data at high resolution may be aggregated to lower resolution for different purposes (Todd & Dar, 1977) pointed out that in the early example of using Landsat for land use policy, many Federal and State agencies will only be concerned with coarse tabular aggregations of change data for entire urban regions. A large State agency, for example, may be interested in yearly indications of urban growth acreage as input to the formation of a statewide land use policy. Local agencies, however, may use maps and tabular data for more detailed analysis. Multicounty, county, or municipal maps of land-use and land-cover change might be prepared with tabular aggregations at smaller units, as input to planning models and decision making.

Spatial scope: refers to the spatial extent of which the analytics is applied to.

Interaction: Spatial interaction refers to how different spatial units or DMU influence one another in affecting the outcomes of policy interest. There are two types of spatial interactions. One happens at the same level, for example the interaction among decision makers in nearby locations, the movement of goods and labor across locations; the improved road infrastructure in one region may increase market access in neighboring areas; conflicts may spread out and influence more communities. Diffusion of innovations(Comin et al., 2012). One is through aggregate mechanisms. For example, through global trade and market, and the diffused influence of one's decision of using water or crop through water model (bilateral). Another example is social norms and aggregate behavior: These shape adoption of technology or health behavior across regions. Modelling the interaction of agents may not inform directly policy options but increase the accuracy of policy influence.

Neighbors: The concept of “neighbors” can be defined in several ways: Geographic neighbors that are based on contiguity (e.g., "rook" or "queen" adjacency on a map grid) or distance. Economic or social neighbor based on trade flows, shared infrastructure, or social networks. The neighbors can be endogenously formed or exogenously formed. Choosing an appropriate neighbor structure is key to capture the spatial relation of interest.

Spatial Patterns: Spatial analytics identifies patterns such as agglomeration, dispersion, equilibrium, or dispersion or disequilibrium. Patterns arise due to many reasons: behavioral diffusion: Local imitation or influence (e.g., farmers adopting nearby innovations). Attributional similarity: Shared characteristics due to common geography or socioeconomics. Understanding these patterns is essential for designing geographically targeted policies and evaluating their impact. Tools like Global and Local Moran's detect autocorrelation and help in identifying clusters or hotspots requiring policy attention.

3. How can spatial analytics support policy?

Credit: ©CIAT

We notice five major ways that spatial analytics has been used to support policy.

3.1.Contextualizing key spatial covariates for policy making

Spatial analytics provides a tool for contextualizing data points or a local policy challenge. For example, when deciding where to target a certain intervention, overlaying various spatial layers for the targeted region can give policy makers a context about what the surrounding look like, which households might be difficult to reach, and to what extent are the target areas representative of the entire country across diverse spatial contexts.

Some spatial layers such as population density and age-gender distribution from WorldPop can reveal communities with large young or elderly populations that might be disproportionately impacted by shocks related to nutrition and food security, thus informing where interventions or aid might be needed. Another example is land use policy aimed at improving soil health. Spatial analytics has played a fundamental role in supporting land use policy and soil management. They facilitate the creation of detailed soil maps, integrating data from soil surveys, laboratory analyses, sensor readings (e.g., for moisture, pH, organic matter, nutrients), and terrain models derived from Digital Elevation Models (DEMs). For example, GIS is used to assess and map soil degradation risks, such as erosion potential (often modeled using factors like slope, rainfall intensity, soil type, and land cover) and nutrient depletion or imbalances. This spatial understanding allows for the planning and implementation of targeted soil conservation measures (e.g., terracing, contour farming, cover cropping) and site-specific soil fertility management strategies, including integrated soil fertility management (ISFM) approaches.

3.2. Contextualizing local influence of mega trends

Food, Land, and Water (FLW) systems are at the intersection of the mega challenges, including climate change, population growth, poverty, food and nutrition insecurity, increasing inequality, political instability, and environmental degradation (ISDC, 2023). These mega-trends will have profound policy implications and address them through policy with the necessary evidence to inform decision making requires systems thinking and a strong, coordinated, and multidisciplinary response from CGIAR and its partners.

Spatial analytics plays a critical role in contextualizing the local influence of global megatrends by downscaling or disaggregating information traditionally modeled at large scales into finer spatial resolutions. Megatrends such as climate change, population growth, urbanization, and shifts in global economic structures are inherently aggregate and systemic, yet their manifestations and impacts vary significantly across local contexts. Spatial analytics such as SPAM (Spatial Production Allocation Model) (Use case 2 in this report), future land use change (Use case 5) and land complexity (Use case 9), and food demand at local level (Use case 7), provide more granular results given projections or results from national statistics or global model, provide examples of how to account for these interdependencies across scales, and enabling policy makers to identify hotspots that is anticipated to experience drastic changes such that current policy may not be adequate, or where vulnerability may appear. This helps assess the uneven impacts of megatrends, and tailor policy responses accordingly. Without such localized perspectives, global models risk obscuring the heterogeneity of impacts and leading to policies that are ineffective or inequitable at local level. In this sense, spatial analytics thus provides a bridge between mega trends and local heterogeneity.

3.3. Assessing (local) effectiveness of interventions

Spatial analytics has become an increasingly useful tool in impact evaluation and impact assessment, to evaluate the heterogeneous and autocorrelated causal impacts of an intervention across space. These applications emphasize that credible policy evaluation requires both recognizing localized variation and rigorously testing generalizability across diverse spatial contexts. We briefly review two strands of literature on this aspect: impact evaluation that incorporates spatial heterogeneity; and quasi-experimental design building on a spatial explicit setting.

First, spatial analytics has been increasingly used for understanding spatially differential treatment effects. This is critical because policy interventions often do not have uniform impacts across space. Geographic, socioeconomic, and institutional factors can shape how treatments work in different locations, leading to systematic heterogeneity in outcomes of policy interest. Recognizing and quantifying these spatial variations matters for policy, since it allows interventions to be tailored more precisely, resources to be allocated more efficiently, and unintended spillovers to be managed effectively. This strand of methods traditionally relies on regression that specifies the form of heterogeneity parametrically, but increasingly on machine learning and non-parametric methods. For example, Causal Forests (CFs) represent an advancement in estimating Individual Treatment Effects (ITEs). First introduced by Athey & Imbens (2016), this approach has then been improved by Athey et al (2019) and Chernozhukov et al. (2018).

In the past, CFs have mostly been applied to explore heterogeneity across demographic, socioeconomic, or behavioral factors. Recent work has started to use CFs in spatially explicit contexts. Kakimoto et al., (2022) applied CFs to estimate site-specific optimal nitrogen rates in precision agriculture, drawing on spatially detailed field trial data and accounting for spatially autocorrelated soil properties. Similarly, Credit & Lehnert (2024) showed that CFs can be adapted to include spatial lags of both dependent and independent variables, such as in a spatial Durbin specification, enabling the model to better capture spatial dependencies and spillover effects in treatment impacts.

However, spatial methods require high-resolution data, involve more complex model specifications, and may be sensitive to assumptions. Careful implementation and validation remain essential. In this report, use case 4 brings one recent example of how careful implementation is carried out in evaluating heterogeneous climate information services across space.

Second, spatial econometric extensions of causal inference methods, such as spatial difference-in-differences (SDiD), spatial regression discontinuity (SRD), and spatial differences-in-discontinuities (SDnD) adapt traditional identification strategies to account for spatial dependence and spillover effects. Luc Anselin and coauthors (Kolak & Anselin, 2020) reviewed how spatial econometric technics are applied in causal inference. This is important because in spatially explicit contexts, treatment effects may diffuse across geographic boundaries, and outcomes can be correlated due to spatial proximity. Compared to traditional settings, these spatial adaptations improve external validity in geographically structured interventions, but they also demand stronger modeling choices to disentangle direct, indirect, and heterogeneous effects. Thus, spatial causal methods enhance identification where geography itself shapes exposure and outcomes. In this report, use case 11 brings one recent application of this method to evaluate where climate risks might escalate water conflicts in Africa.

3.4. Inform locally tailored actions and prioritization

Spatial analytics can help prioritize and find suitable sites for future intervention and how validated interventions can be scaled to broader locations and adapt to new contexts, scaling out small scale interventions addresses the challenge of external validity, ensuring results extend beyond single trial sites. This approach helps tailor programs to local conditions, uncover contextual factors that influence outcomes, and build political credibility by providing evidence from multiple regions rather than a single site. Ultimately, scaling out ensures that policy recommendations are robust, context-sensitive, and better suited for national or regional implementation.

For example, Randomized Controlled Trial (RCT) has been a “gold standard” tool to understand the causal impact of an intervention (Duflo et al., 2008) with high internal validity. Yet, if an RCT is to inform policy, it is critical to establish external validity (Rothwell, 2005) (Cartwright, 2010). This persistent gap risks producing results that, although internally sound, may have limited applicability in typical policy contexts (Peters et al. 2018, Banerjee et al., 2017). To this end, spatial analytics can examine the external validity of RCTs when participants are randomly assigned (Savoca et al., 2017). GIS method offers a visual, location-based assessment that only requires address data, making it particularly useful for community-based RCTs. Savoca et al. (2017) conclude that, while true representativeness can only be guaranteed through probabilistic sampling, combining graphical spatial analysis with simple statistical models provides a practical and more nuanced way to evaluate external validity beyond standard hypothesis-testing methods.

3.5. Easier visualizing & disseminating

Spatial analytics not only support identifying policy options or assessing heterogeneous impacts but also facilitates more effective visualization and dissemination of complex information to diverse stakeholders. Through maps and online mapping platforms, vast amounts of data can be communicated in a more clear, accessible, and transparent manner, and improving the decision-making process. Visualization tools allow policymakers, researchers, and practitioners to identify spatial patterns, overlaps, and disparities that are often less evident in textual or tabular data.

For example, FAO *Hand-in-Hand* [7]tool provides interactive maps for monitoring agricultural transformation. The Alliance of Bioversity and CIAT PLaSA platform supports evidence-based decisions for agrifood systems. Similarly, the World Food Programme (WFP) has developed visualization tools to assess food security and vulnerability; NASA's *Earth Observing System Data and Information System (EOSDIS)* for climate and environmental monitoring; and the Global Forest Watch platform by the World Resources Institute for real-time forest change analysis. While maps carry the advantage of condensing complex variables into intuitive visuals, they require cautious interpretation to avoid oversimplification or misrepresentation of underlying data.

In this report, use case 8 shows how an online platform can demonstrate a complex agrifood system to support policy making and engage various stakeholders in the food system.

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[7] www.fao.org/hand-in-hand/en/

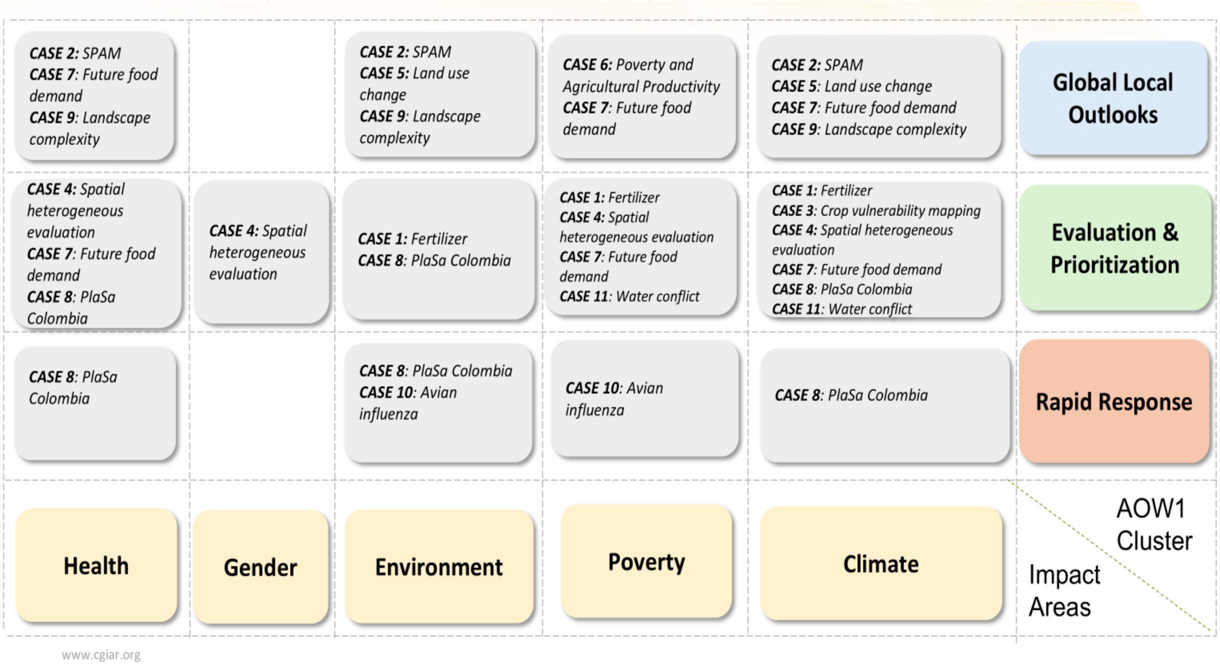
4. Use cases of applying spatial analytics for policy support

Credit: ©2016CIAT/NeilPalmer

In this section, we provide 11 use cases across CGIAR centers in Policy Innovation Program AoW1, to demonstrate different spatial analytics and policy relevance. Three criteria were considered when selecting those use cases. First, the use case must reflect either spatial heterogeneity or spatial interaction among agents, Second, the use case must have clear policy relevance of either global local outlook, prioritization, and rapid response. Finally, the use case must integrate both biophysical and social economic component in the case.

With those criteria, the selected use cases reflect a wide range of functions of how spatial analytics can contextualize spatial covariates, inform locally tailored action, or better visualization of complex FLW system information, in ex ante impact assessment, ex post impact evaluation, and foresight.

Figure 3 shows how this use case contributes to various impact areas and Policy Innovation Area of Work 1 efforts. These cases demonstrate how spatial analytics add value by capturing heterogeneity (e.g., localized productivity–poverty relationships, climate impacts on specific crops), enabling interaction analysis (e.g., between climate, policy, and biodiversity), and improving communication through compelling, multi-scale visualizations. These methods help policymakers design targeted, cost-effective interventions, enhance resilience, and respond rapidly to emerging crises—whether conserving habitats, optimizing food supply chains, mitigating water conflicts, or managing animal disease outbreaks.



CASE 2: *SPAM* ***CASE 7****: Future food demand* ***CASE 9****: Landscape complexity*		***CASE 2:*** *SPAM* ***CASE 5:*** *Land use change* ***CASE 9****: Landscape complexity*	***CASE 6:*** *Poverty and Agricultural Productivity* ***CASE 7****: Future food demand*	***CASE 2:*** *SPAM* ***CASE 5****: Land use change* ***CASE 7****: Future food demand* ***CASE 9****: Landscape complexity*	**Global Local Outlooks**
CASE 4: *Spatial heterogeneous evaluation* ***CASE 7****: Future food demand* ***CASE 8****: PlaSa Colombia*	***CASE 4:*** *Spatial heterogeneous evaluation*	***CASE 1:*** *Fertilizer* ***CASE 8****: PlaSa Colombia*	***CASE 1:*** *Fertilizer* ***CASE 4:*** *Spatial heterogeneous evaluation* ***CASE 7****: Future food demand* ***CASE 11****: Water conflict*	***CASE 1:*** *Fertilizer* ***CASE 3****: Crop vulnerability mapping* ***CASE 4:*** *Spatial heterogeneous evaluation* ***CASE 7****: Future food demand* ***CASE 8****: PlaSa Colombia* ***CASE 11****: Water conflict*	**Evaluation & Prioritization**
CASE 8*: PlaSa Colombia*		***CASE 8****: PlaSa Colombia* ***CASE 10****: Avian influenza*	***CASE 10****: Avian influenza*	***CASE 8****: PlaSa Colombia*	**Rapid Response**
Health	**Gender**	**Environment**	**Poverty**	**Climate**	AOW1 Cluster Impact Areas

Figure 3: Mapping each use case on impact areas and AOW1 cluster.

Use Case 1: Fertilizer Investment Risk Explorer (FIRE)


2016CIAT/GeorginaSmith

Meta Data for Use Case 1	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel: 5km * 5km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period [2000, 2005, 2010, 2017 (South of the Sahara), 2020] Both historic + future Future

By Bisrat Gebrekidan, Jordan Chamberlin, Maxwell Mkondiwa | CIMMYT

Introduction and policy relevance

Closing Africa's cereal yield gaps is a key factor in securing the region's future food supply, yet farm-level productivity in sub-Saharan Africa (SSA) remains well below the global average (van Ittersum et al., 2025). Poor soil fertility, characterized by acidity, depleted organic matter and unfavorable texture, is a persistent issue that limits the effectiveness of nutrient applications (Kihara et al., 2020; Sanchez, 2002; Vanlauwe et al., 2015). Rainfall variability further complicates matters: multi-decadal analyses reveal significant inter-annual fluctuations across SSA, and recent El Niño events have exacerbated production risks (Alahacoon et al., 2021; Hansen et al., 2019). Market conditions also play a critical role. Farmers often face high fertilizer costs, fragmented markets and volatile maize prices (Minot, 2014; Palmas & Chamberlin, 2020; Vorsah et al., 2025), all of which reduce incentives to adopt (Jayne & Rashid, 2013; Liverpool-Tasie, 2017; Oyinbo et al., 2022).

Policy efforts have largely relied on fertilizer subsidies to stimulate adoption (Jayne et al., 2018). While these programs have increased usage in some contexts, systematic reviews show mixed effects on yield and welfare, raising concerns about fiscal cost, targeting and displacement (Jayne et al., 2018; Mason & Smale, 2013). A central limitation of such programs is their neglect of spatial heterogeneity: profitability varies dramatically across locations, so national averages obscure where fertilizer is truly beneficial. While farmers in favorable zones may achieve high returns, those in marginal areas may incur losses, which discourages sustained adoption.

This use-case addresses these issues by developing a spatially explicit, risk-aware framework to estimate fertilizer profitability across SSA. By integrating soil, climate, and market data into a machine learning model, we generate pixel-level maps of yield response, returns, and profits. Crucially, we account for uncertainty through stochastic simulations of rainfall and maize price volatility, moving beyond point estimates to probabilistic assessments. The outputs not only highlight where fertilizer is profitable, but also where risks are high and where complementary investments are needed. This provides evidence for subsidies targeting resource allocation and farmer advisory services. While demonstrated here for maize, the framework is readily adaptable to other crops by substituting relevant yield, soil, and market data.

Method

We propose a spatially explicit modeling framework to estimate maize yield responses, returns, and profitability under fertilizer use across sub-Saharan Africa. The framework combines machine learning with harmonized biophysical, climatic, and market data to capture the diversity of production environments. Yield responses were estimated using a non-parametric modeling approach (random forest and causal Forest) capable of handling nonlinear relationships and interactions, with fertilizer application rates, soil characteristics, growing season total rainfall and variability, and market access included as key predictors. Profitability was assessed by comparing fertilized and unfertilized scenarios, translating yield differences into financial returns through spatially and temporally varying maize prices, and accounting for fertilizer costs derived from localized nitrogen price surfaces. To reflect the uncertainty farmers face, we designed a simulation procedure in which rainfall and market conditions were repeatedly sampled from historical distributions, producing multiple realizations of yield, returns, and profit outcomes. This allowed us to generate not only expected values but also measures of downside risk and the probability of achieving positive net returns.

Results and key maps

The framework generates spatially explicit estimates of fertilizer profitability and associated risks. It allows us to look beyond average responses and pinpoint patterns of opportunity and risk across different regions. The following maps illustrate continental-level patterns and highlight heterogeneity within countries.

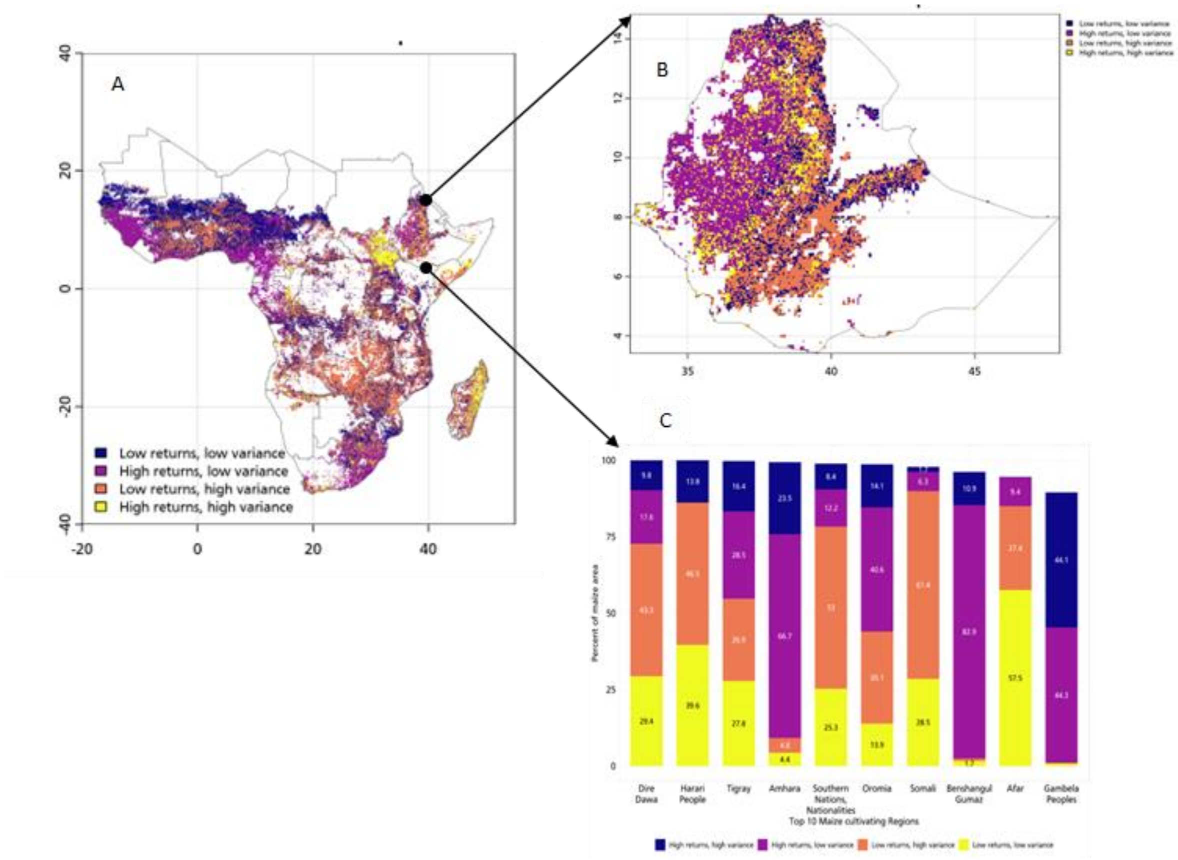


Figure 4: Spatial and regional patterns of fertilizer profitability and risk

Note: Panel A maps the model-predicted intervention areas across Sub-Saharan Africa, classifying each pixel into categories of expected returns and variability. Panel B zooms into Ethiopia to illustrate how the same framework can capture within-country heterogeneity. Panel C summarizes the model outputs at the administrative-region level, showing the share of maize area in each profitability–risk category for the top 10 producing regions. These show how modeling framework can be used not only to visualize local patterns but also to generate policy-relevant summaries that inform targeting of fertilizer subsidies, advisory services, and investment priorities.

Policy recommendations

The framework provides actionable insights for a wide range of stakeholders. For policymakers, it provides an evidence base to design fertilizer subsidy and extension programs that move beyond national averages. By identifying locations where fertilizer is profitable and where risks are high, governments can better target subsidies, avoid inefficient blanket recommendations, and prioritize complementary investments such as lime, credit schemes, or infrastructure in marginal areas. NGOs and development partners can utilize the outputs to strategically allocate resources, focusing interventions in areas with the highest potential for productivity, food security, and resilience gains. For private sector investors, including input suppliers and financial institutions, the results identify promising markets where demand is likely to be sustained and risks manageable, thereby supporting investment in supply chains, insurance products, and credit services. More so, this probabilistic framework can be embedded into existing decision-support tools, enriching them with risk-adjusted, spatially explicit layers offering localized, risk-adjusted guidance. This guidance can assist in mitigating financial losses and promoting greater confidence in the adoption of input.

Use case 2: Spatial Production Allocation Model (SPAM)

©2017CIAT/GeorginaSmith

Meta Data for Use Case 2	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel: 10km * 10km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period [2000, 2005, 2010, 2017 (South of the Sahara), 2020] Both historic + future Future

By Shuang Zhou, Zhe Guo, Liangzhi You | International Food Policy Research Institute (IFPRI)

Introduction and policy relevance

Feeding a growing global population while preserving forests, wetlands, and other natural ecosystems requires the development of more efficient and sustainable cropping systems (United Nations Department of Economic and Social Affairs, 2024). The expansion of farmland often comes at the expense of these critical ecosystems (Potapov et al., 2021), making it essential to improve agricultural productivity without further degrading natural resources. A crucial step in addressing this challenge is understanding the spatial distribution of crop types, their productivity, and the farming systems in which they are managed. This type of information allows policymakers, researchers, and development partners to better target interventions, enhance food security, and design effective climate adaptation strategies while conserving the ecosystem and biodiversity.

Global agricultural production data are typically reported at the national or subnational administrative level (such as states or regions). However, this level of statistical data fails to capture the diversity and spatial heterogeneity of agricultural production, lacking spatial explicitness. The Spatial Production Allocation Model (SPAM) uses an entropy-based approach (You & Wood, 2006) to downscale crop production data, generating global maps of agricultural area, yield, and production at a spatial resolution of 5 arc minutes (~9km at the equator), covering more than 40 crops and crop groups. The model offers valuable insights into where different crops are grown, how much they produce, and under what production conditions—forming a strong foundation for evidence-based agricultural planning and sustainable land management.

Method

The SPAM model disaggregates national and subnational crop production statistics to a fine spatial resolution by integrating a wide range of geospatial datasets, including satellite-based land cover, crop suitability, irrigation maps, population density, and market accessibility. This information is compiled and integrated to generate “prior” estimates of the spatial distribution of individual crops. Priors are then submitted to an optimization model that uses cross-entropy principles and area and production accounting constraints to simultaneously allocate crops into the individual “pixels” of a GIS database (You & Wood, 2006). The result for each pixel (notionally of any size, but typically from 1 to 100 square km) is the area and production of each crop produced, split by the shares grown under irrigated and rainfed conditions (each with distinct yield levels).

At the core of SPAM is a cross-entropy optimization method, which is used to allocate crop area in a way that minimizes the divergence between prior estimates and the final allocation of area shares across grid cells, crop types, and production systems. The optimization process is subject to a range of constraints, such as land availability, irrigation area, and official crop statistics, ensuring that the results are both consistent with known data and yet spatially plausible (Yu et al., 2012).

Results and key maps

Figure 5 showcases some of the key results from SPAM2020, using maize as an illustrative example. Users can find more information for the SPAM model and the previous versions of SPAM datasets via the dedicated SPAM website (https://mapspam.info/)

Policy recommendations

The SPAM (Spatial Production Allocation Model) dataset series has evolved significantly since its first release in 2000, expanding from just over 20 crops to 46 in the latest SPAM2020 version. This detailed mapping of global agricultural production enables analysts and policymakers to design more targeted and effective agricultural and rural development strategies. By providing spatially disaggregated estimates of crop distribution by type and production system, SPAM supports policies that enhance food security, promote economic development, and reduce environmental impacts. For example, SPAM data can guide the allocation of input subsidies, irrigation investments, and infrastructure improvements to areas with high agricultural potential or vulnerability. It also helps identify regions suitable for adopting sustainable practices such as climate-smart agriculture or precision farming.

The SPAM model and its outputs have become a critical input to many studies, models and initiatives within and beyond the CGIAR. The critical role of SPAM, as spatial data input and baseline data, is to link economic models and biophysical models (e.g., crop growth model, water model), and explore the sub-national spatial heterogeneity within a country or region. Some researchers within Policy Science Program and Climate Action Science Program use SPAM almost weekly. SPAM data are frequently downloaded and widely used by researchers and analysts from international originations, academia, governments agencies all over the world. For example, African Growth and Development Policy (AGRODEP) Modeling Consortium features SPAM on its online library and uses SPAM data as inputs for its own modeling work (http://www.agrodep.org/fr/node/1794). The Group on Earth Observations Global Agricultural Monitoring Initiative which uses SPAM to monitor food security and potential crises(www.geoclam.org). The World Bank uses SPAM inputs for its study on Africa’s Infrastructure.

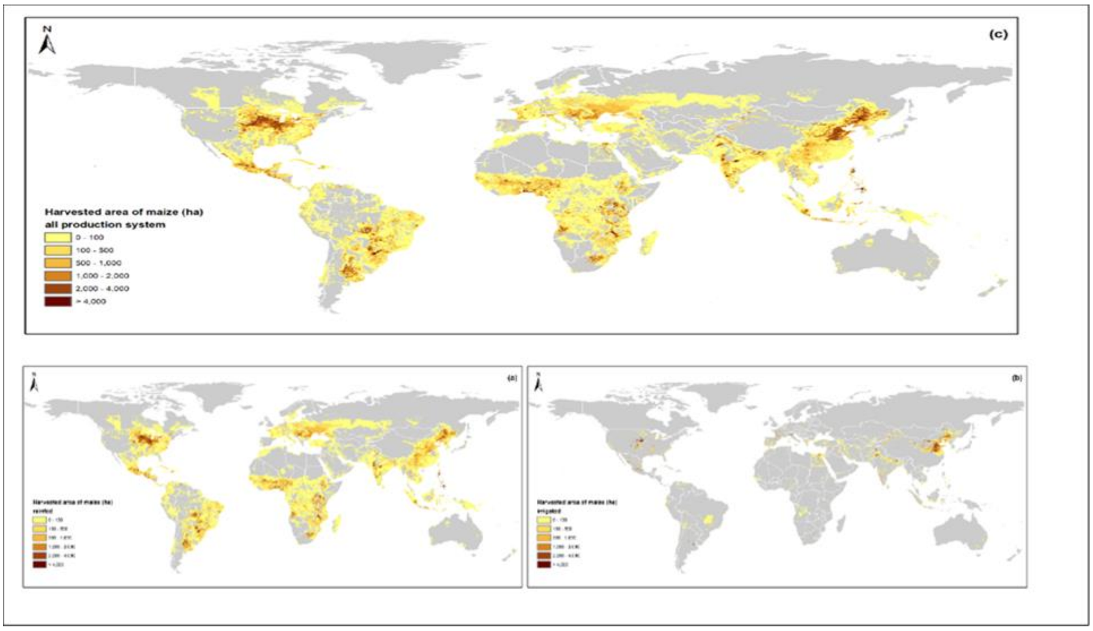


Figure 5: Harvested area maps for maize in rainfed (a), irrigated (b), and all (c) farming systems, SPAM 2020

Compare different global crop mapping products.

There are, broadly speaking, two groups of models to map cropping systems globally: one is statistical modelling which mainly relies on official statistics or survey data, the other is remote sensing-based modelling which relies on in-situ field data for both crop area and yield estimation. SPAM belongs to the first group. Others in this group include: (1) MIRCA2000: Provides monthly irrigated and rainfed crop areas around the year 2000(Siebert et al 2005). It's widely used for climate impact assessments and water use studies. (2) GAEZ (Global Agro-Ecological Zones): Developed by FAO and IIASA, GAEZ combines climate, soil, and terrain data to assess crop suitability and potential yields (Fischer et al., 2021). (3) M3 (Harvested Area and Yield for 175 Crops): A statistical model that harmonizes crop data from various sources to produce global maps of harvested area and yield around the year 2000(Monfreda et al., 2008). Lately, CROPGRIDS updated M3 product to the year of 2020 (Tang et al., 2024).

Remote sensing-based products include: (1) WorldCereal (ESA-funded. https://esa-worldcereal.org/en) – A dynamic, open-source system for seasonal crop and irrigation mapping at 10-meter resolution. It produces: Temporary crop extent maps, Seasonal maize and cereal maps, Irrigation maps, active cropland maps. WorldCereal allows users to upload their own field data to train localized crop classification models, enhancing accuracy for specific regions. (2) Crop Monitor (GEOGLAM. https://www.cropmonitor.org/) – Provides real-time monitoring of crop conditions globally using satellite data and expert assessments. It supports early warning systems for food security. While this approach is new with great promises, its application on a global scale is still quite limited. The availability of ground training and validation data is a major constraint.

Use case 3: Spatial mapping of crop vulnerability for targeting investment.


Credit: ©2016CIAT/NeilPalmer

Meta Data for Use Case 3	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel: 50 km * 50 km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future: 2050

By Tim Thomas | IFPRI

Introduction and policy relevance

Crop modelling has been used for around 2 decades in the CGIAR to understand the impact of climate change on crop yields (Rosegrant et al., 2025). The work has traditionally focused on changes in average yields over time at each pixel -- typically a half-degree (roughly 54 km) square. However, while the results are often mapped only for areas where the crop is grown, the focus has not been on whether the crop is of high importance to that specific location. If it is of high importance to farmers in that location, projected losses from climate change can impact on the food security and economic well-being of households which depend on local agricultural production.

We also know that farmers and policy makers care more about what will happen in "worst cases" (if the most adverse climate turns out to be the actual future climate) and in "extreme events" (in years in which climate is particularly adverse toward producing the crop – see (Murgatroyd et al., 2025; Thomas, Robertson, et al., 2022; Thomas, Schlosser, et al., 2022). In both, the well-being of households' dependent on agriculture will be critically affected by climate in that particular year.

If vulnerable areas can be identified in advance, spatially targeted policies and investments to reduce risk or adapt to climate change can be developed. Such knowledge allows them to be implemented at a lower cost than a national or global intervention. Furthermore, anticipating the problem can allow sufficient time to develop and implement solutions.

Method and results

The methodology involves a multi-step process to identify agricultural "hotspots" vulnerable to climate change. First, we use the most recent version of SPAM to identify the major crop(s) in each location of the world. Figure 6 shows the SPAM data for rainfed maize in Sub-Saharan Africa. To ensure that a crop is truly "major", we identify locations for which the crop has at least 25% of the cropland area in the grid square and that cropland represents at least 5% of the total land there.

Second, we use IFPRI's DSSAT model results for the world that feed into IMPACT (half-degree pixel or 54 kilometers at the equator) to determine the median impact of climate change across 5 climate models given an emissions scenario (Thomas, 2024; Thomas & Robertson, 2024) and identify locations that are above a specific threshold (e.g., 20%) for median losses from climate change. The median climate model results are shown in Figure 2 for rainfed maize. We note significant yield losses in West Africa, but some yield increases in the highlands of Ethiopia, Kenya, and a few other locations.

Third, we interact the identified key crop locations with locations that have significant reductions in yield to create maps of "hotspots" for median climate losses across 5 climate models available for the world. The example for rainfed maize in Sub-Saharan African is shown in Figure 8. The reader can examine Figure 9 to see that Figure 8 was created using the rules just described.

Fourth, it is possible that the worst-case climate model at each location will be like the actual climate the location experiences in the future. To account for this type of possibility, we interact the identified key crop locations with the worst case-scenario yield change to find "hotspots" for the maximum climate losses across 5 climate models in which the losses are projected to be greater than 20%. See Figure 9 for the example of rainfed maize in SSA, noting the increase in the number of hotspots compared to Figure 8 which was based only on the median yield results from the 5 climate models.

There is another way to think about hotspots, and that is by considering that climate change may alter the frequency of extreme events. Using a large ensemble of climate models, Thomas et al. (2022a, 2022b) explores the change in frequency of low-rainfall events and low-yield events under climate change. Figure 10 shows the change in frequency of 1-in-20 low-yield events for rainfed maize. In the map, a value of 20 indicates that it is a 1-in-20-year event in the 2060s based on the 1-in-20-year yield measure of a low-medium emissions scenario in the 2020s. What we see is that under the lowest emissions scenario, there is little change in the frequency of low-yield events in the 2060s. However, as the level of emissions rises, we see an increase in frequency of low-yield events, with most locations having those events every 8 years or less under the highest emissions scenario.

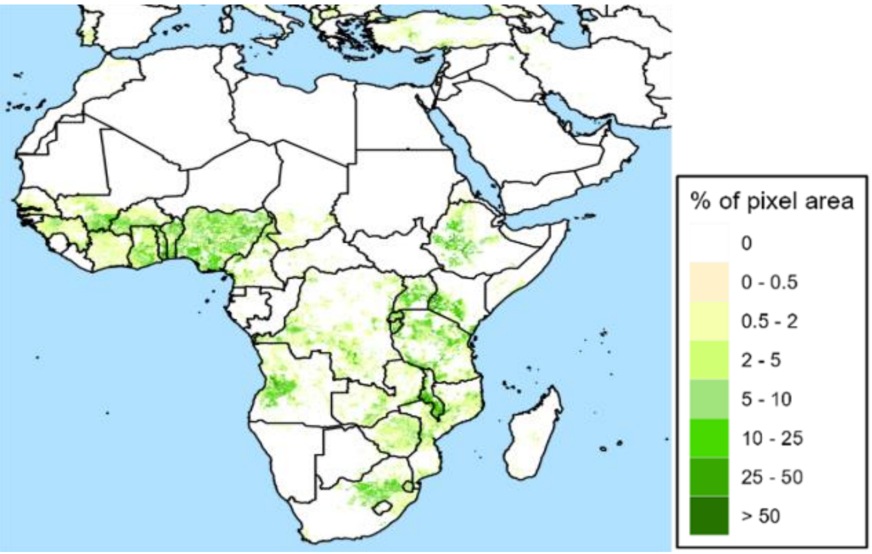


Figure 6: Map showing the percentage of each pixel that is rainfed maize in 2020 (Source: SPAM2020v2r0.)

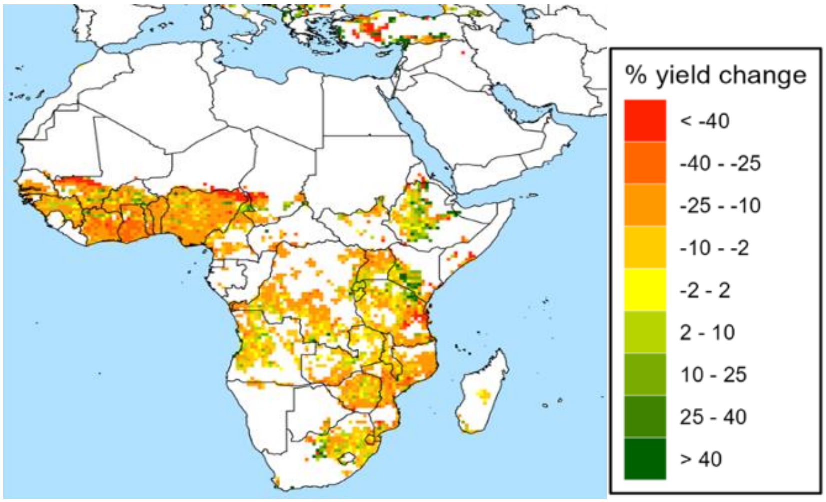


Figure 7: Projected yield change for rainfed maize for median climate model, RCP 7.0 (medium-high emissions scenario, 2005-2050) Source: Authors using DSSAT. Notes: At least 5% cropland in pixel. Maize represents at least 25% of cropland.

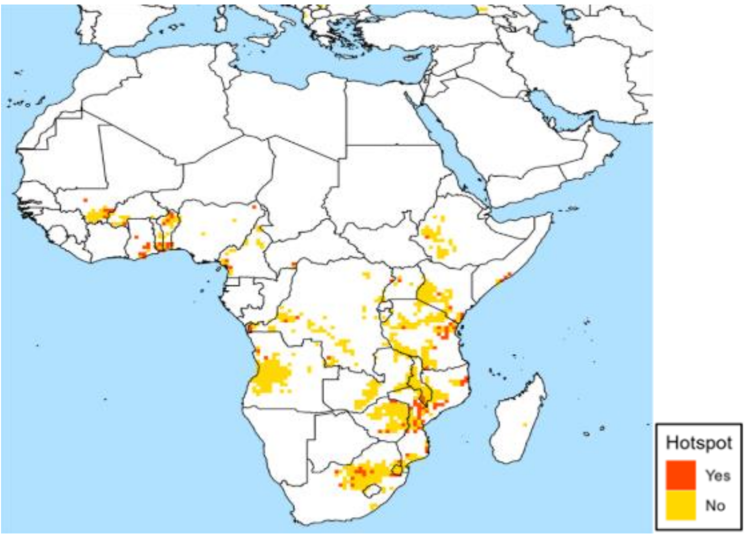


Figure 8: Hotspots for rainfed maize in Africa for median climate model, RCP 7.0 (medium-high emissions scenario). Source: Authors using DSSAT. Notes: At least 5% cropland in pixel. Maize represents at least 25% of cropland.

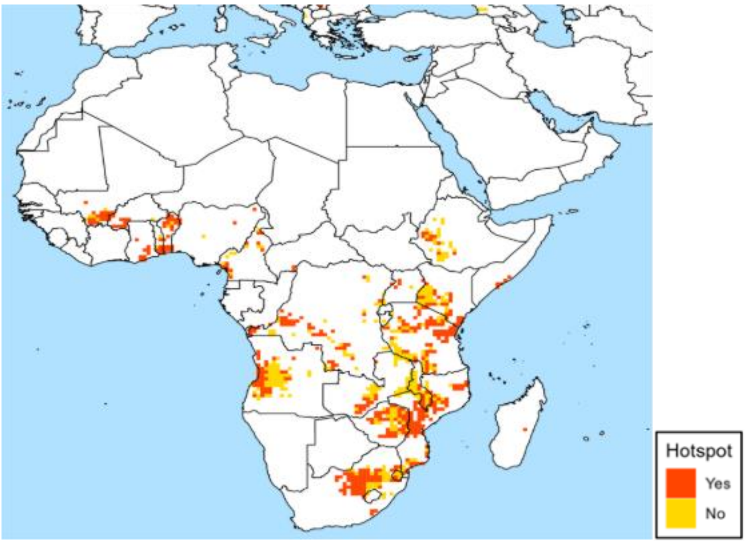


Figure 9: Hotspots for rainfed maize in Africa for worst-case climate model, RCP 7.0 (medium-high emissions scenario) Source: Authors using DSSAT. Notes: At least 5% cropland in pixel. Maize represents at least 25% of cropland.

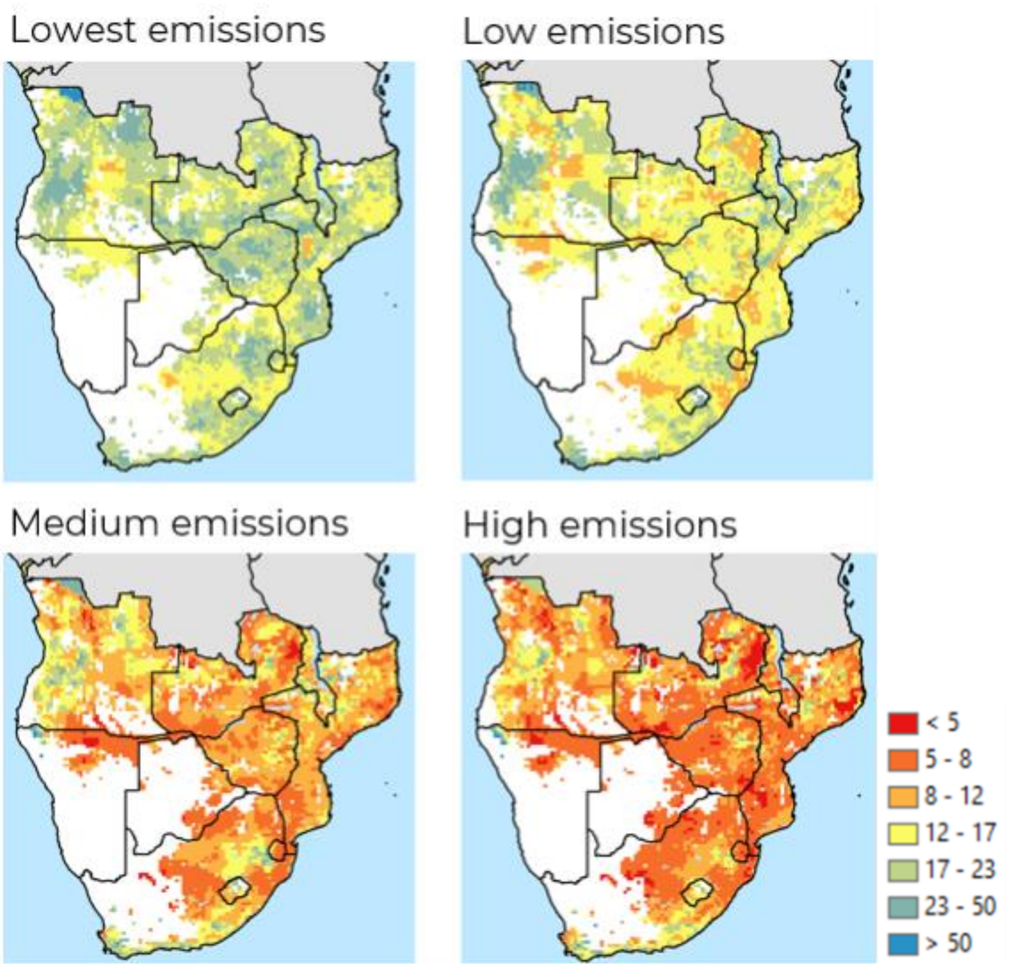


Figure 10: Frequency of 1-in-20-year low maize yield events in Southern Africa: comparing frequency in the 2020s to the 2060s under various emissions scenarios. Source: Thomas, TS, Robertson RD, Strzepek K, and Arndt C. (2022) Extreme Events and Production Shocks for Key Crops in Southern Africa Under Climate Change. Front. Clim. 4

Policy recommendations

The hotspot methodology could be useful to policy makers, development specialists, extensions workers, and donors in identifying locations which may require special focus to help farmers in those locations to adapt to climate change. The hotspots suggest a number of possible interventions, which may include developing new cultivars resistant to or tolerant of the kind of climate shocks expected; having extension workers train farmers in growing alternative crops more suited to the future climate or in moisture-preserving or water harvesting techniques, if the climate shock is related to inadequate water; helping farmers relocate to a more hospitable climate for growing the crop that they prefer; adding irrigation, if that would reduce risk of yield shocks; developing social protection plans to assist families adversely affected by climate change and extreme events; and, if appropriate, hasten the transition of some households from agriculture to the non-agricultural sector.

Use case 4: Improving the Spatial Granularity in Impact Evaluation

Credit: ©2016CIAT/GeorginaSmith

Meta Data for Use Case 4	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country: Kenya Within country
Spatial unit of the OUPTUT of the use case	Subnational Pixel: 8km by 8km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period: 2021 - 2023 Both historic + future Future

By Chris Mwungu, Felix Otieno, Agnes Wanjau, Anirudha Ghosh | Alliance of Bioversity & CIAT

Introduction and policy relevance

Shamba Shape Up (SSU) is a makeover-style reality show that aims to meet smallholder farmers' information needs by combining entertainment with agricultural and climate advisories, helping them to improve their livelihoods in the face of climate change (CGIAR Research Program on Climate Change, 2015). This study examined spatially heterogeneous impacts of the SSU weather and farming news on smallholder farmers in Kenya on crop productivity, income, and food security.

The study's research question was to examine whether households that watched the weather and farming news segment on SSU had better outcomes in terms of crop productivity, crop income, and household food security. This aligns with the broader CGIAR goals of evaluating the role of climate information services in supporting local adaptation strategies. This study responded to a demand from Media (producers of SSU) to understand how spatial targeting of advisories can improve reach and effectiveness.

By applying Causal Forests (CFs), a machine learning method for estimating heterogeneous treatment effects, the study captures not only household-level variation but also spatial patterns across counties, to inform better-targeted climate advisories for the future for Kenyan extension services, digital broadcasters like Media, NGOs, or county-level government planners. Compared to aggregate or non-spatial analyses, this approach revealed localized variation in uptake and impact, which is essential for designing tailored advisory services.

Method

The study used CFs together with georeferenced household data to estimate the Individual Treatment Effects (ITEs) of watching SSU weather and farming news on agricultural outputs and household welfare. A cross-sectional household survey conducted in 2023 (Kiprop et al., 2024) was used to estimate the ITEs. CFs are a machine learning method that estimates heterogeneous treatment effects by leveraging variation in observed characteristics and treatment exposure across households. This method relies on causal inference using observed data, which is different from foresight analysis that explores multiple plausible futures to help prepare for uncertainty. The spatial dimension of the method is important for answering the research question, as it helps to identify where the intervention has the greatest uptake and impact. This enables more targeted and effective decision-making to enhance the delivery of climate advisory services.

Results and key maps

Significant spatial heterogeneity was observed in the impact of the SSU weather and farming news on household agricultural income. Figure 11 presents results from the CF analysis, showing the spatial variation in maximum, median, and minimum ITEs in agricultural income across counties in Kenya. In addition, raw ITE estimates for individual households are included to provide a more detailed view without aggregation.

The map of median ITEs reveals both positive and negative treatment effects, highlighting the location-specific influence of SSU. For example, negative median effects were observed in Nyandarua and Machakos, while counties such as Migori, West Pokot, and Makueni showed clearly positive median effects. These differences may be driven by county-level variations in agroecological conditions, access to complementary extension services, and baseline exposure to agricultural advisories.

The map of maximum ITEs further demonstrates the heterogeneity of impacts. Although nearly all counties showed some positive maximum effects, the size of these effects varied widely. Counties in central Kenya, such as Nyandarua, Nyeri, and Murang’a, had lower maximum ITEs, whereas Kilifi, Kwale, Migori, West Pokot, Makueni, and Isiolo had much higher values, suggesting a stronger influence of SSU on agricultural income in these counties.

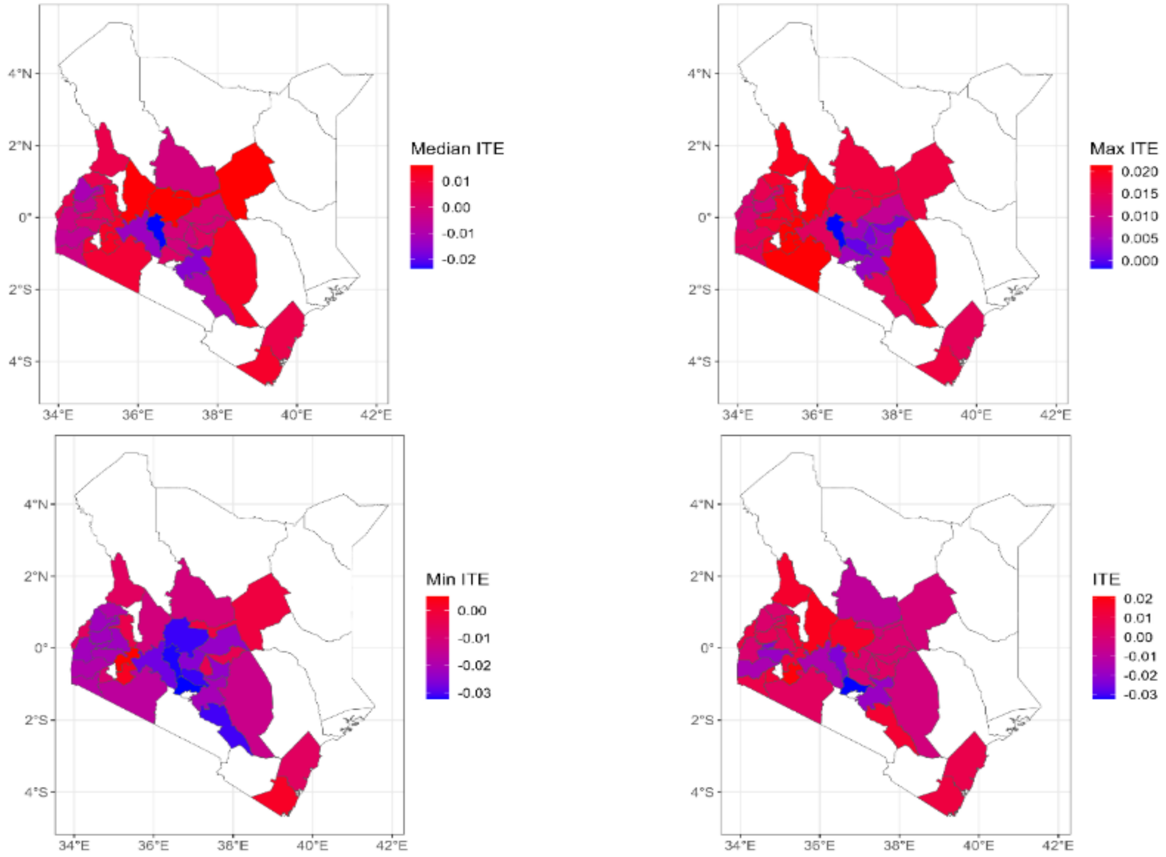


Figure 11: Spatial variation in impacts of watching SSU weather and farming news

It is important to note that exposure to SSU may be endogenous. To address potential bias, the coefficient of variation in temperature and rainfall over the past five years was used as an instrumental variable. This approach assumes that farmers experiencing greater climate variability are more likely to engage with weather-related advisory services. To get feedback on this study, study results were shared with SSU producers, who confirmed the value of county-level disaggregation for targeting advisory content. As part of advancing this work, the strength of the instrument requires further validation in follow-up studies.

Policy recommendations

This analysis reveals that the impact of SSU on agricultural income varies significantly across regions, with counties like Migori, Kilifi, and West Pokot showing stronger positive outcomes, while others such as Nyandarua display lower impacts. These findings highlight the importance of spatial targeting over uniform scaling. Policymakers such as Kenya's Ministry of Agriculture and Livestock Development, county-level agricultural departments, Media, and development partners should prioritize expanding similar programs in more areas while investing in tailored outreach strategies for marginalized and underserved areas with limited observed benefits. Integrating spatial analytics into decision-making processes can enhance targeting efficiency, optimize resource allocation, and strengthen monitoring and evaluation systems. The method is most applicable in contexts where high-quality, georeferenced household-level data are available, and where treatment exposure is clearly defined. However, its reliability decreases in areas with limited data or where relevant confounding variables are unobserved. The next steps include applying this method to other advisory platforms, such as iShamba SMS services, integrating spatial ITE maps with cost-effectiveness analysis, and co-developing region-specific media strategies. Future research should also explore the use of panel data and/or randomized controlled trials (RCTs) to strengthen causal inference of advisory services. These next steps will require collaboration with various extension partners such digital advisory producers, county extension services, and development partners to co-develop region-specific scaling strategies.

Use case 5: Simulated Land Use/Land Cover Change


Credit: ©2009CIAT/NeilPalmer

Meta Data for Use Case 5	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel: ½ degree (56km north to south) Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future (2005 and 2050) Future

By Richard Robertson | International Food Policy Research Institute (IFPRI)

Introduction and policy relevance

How will land use change in the future? Which kinds of ecosystems will be most disrupted by cropland expansion? These are the kinds of questions that can be addressed by this collection of spatially explicit land use simulations.

The term "land use" has at least three different meanings or uses, itself. One sense is concerned with crop allocation within a single farm. Another (often non-agricultural) idea is more about externally imposed regulation like "zoning" between plots which either designate or observe categories like natural, industrial, agricultural, residential, or commercial. A more expansive version of this looks beyond human managed land to consider different kinds of natural land such as deserts versus forest. Analyzing these different versions of "land use" usually views them as resulting from different drivers such as the hyper-local scale coming from profit maximization within a single farm/firm; the regional zoning type flowing from the legal, business, political, and economic environment; and the broad global natural ecology kind of land use because of climate and geology.

The datasets reported here bring parts of these different scales together into a single framework. It starts with the IMPACT model of global agriculture (Robinson, et al., 2004). IMPACT operates at roughly national levels for demand markets and some smaller regions for the production side. The supply part assumes the existence of cropland areas and their corresponding yields, both of which evolve through time subject to the forces of demographic and economic changes as well as the shocks to productivity expected as the climate changes. By taking these market-level simulations and developing internally consistent, fine grained spatial representations of the outputs, we can gain some insight at the different levels of land use thought: likely crop mixes (across broad categories) within pixels like the hyper-local, interplay between expansion/contraction of cropland and remaining natural areas like the regional and shifts within the natural land mixes driven by climate conditions. The resulting maps and various aggregations based on them can be used by modelers to assess whether their models are behaving as a changing world.

Method

Global maps are created showing the number of hectares of each land category that are simulated to be present in each half-degree pixel. Maps are developed for a historical case of 2005 and several future cases based on GCM simulated climates for 2050. This is done in three steps.

First, a statistical model based on historical data is developed to quantify the association between the temperature and rainfall of a location and the mixture of natural land types found there. The model is then used to simulate the likely amounts of natural land to be expected for each location on the map under the various climate situations of interest.

Second, the regional amounts of cropland areas for several major crops along with “all others” are extracted from IMPACT simulations for the time periods and climate situations of interest. Within each region, those areas (adjusted for multicopying) are allocated, bit by bit, to individual pixels so that the pixels within the region add up to the right amount of rainfed maize area, irrigated rice area, and so on. The allocation heuristic tries to balance spreading the areas out and allowing overlapping areas against concentrating particular crops in the most favorable locations. This is guided by attractiveness indices for each crop based on simulated potential yields, distance to population centers, how flat or uneven the elevation is within the pixel, and how similar the climate is to climates historically supportive of agriculture.

Finally, the natural areas in each pixel are scaled back to create space for the allocated cropland.

Results and key map

Pulling together the economic model (reflecting the interaction of demand and supply) along with the empirical model of natural land types (reflecting the influence of climate) allows us to extract several insights for the timeframe investigated (2005 to 2050).

First, climate change is likely to, overall, make cropland less productive and hence more croplands will be needed in the future than otherwise would have been. However, the increase due to climate change is fairly small compared to the overall increase in cropland need due to basic economic and demographic factors.

Second, the changes in the amounts of cropland needed for particular crops coupled with the pattern of which locations are better and worse for producing those crops do not result in major rearrangements of production regions.

Third, the natural land types exhibit much greater sensitivity to climate change. Tropical forests are typically of interest. In South America, the climate will shrink the area hospitable to forests much more than cropland expands. The other tropical forests face more balanced threats from both mechanisms. Overall, climate change seems to represent a larger danger to forests than cropland expansion.

The map below shows the spatial distribution of pixels exhibiting gains or losses of evergreen broadleaf forest (mainly tropical forests) with cropland changes over top. The changes in forest are broader than and more-or-less independent of cropland expansion. (Robertson et al., 2023a); Figure 12)

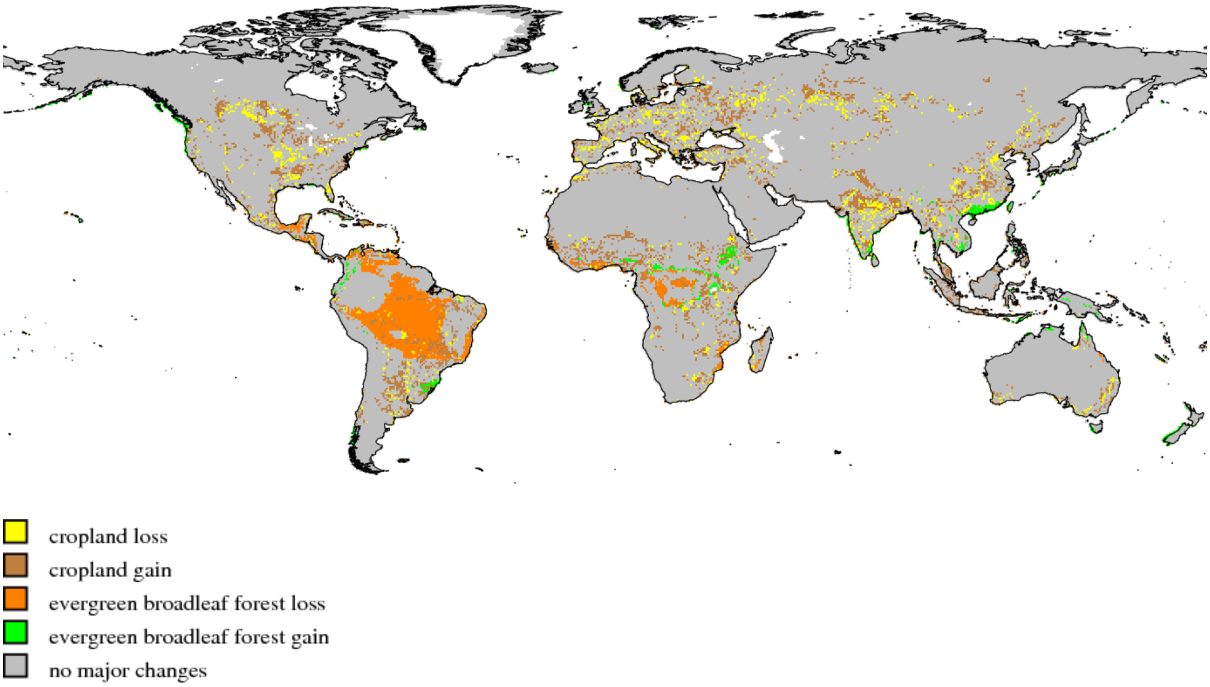


Figure 12: Land use changes

Policy recommendations

Forest protection will require more than fences and guards since the climate conditions conducive to forests will be found in progressively fewer places.

While the broad patterns of where cropland is located may change slowly, there will still be a significant portion that experiences upheaval where the mix of crops is likely to lose a major crop or gain a new one. Producers in those cases may need to learn to grow a different set of plants as well as deal with new marketing channels.

The model has a fundamental limitation in that it is a comparative static model that does not say how the world transitions between the various situations, but only what those situations are likely to look like. It also only looks at a few of the largest crops on their own; future work will expand consideration to more individual crops and reduce the size of “all others”.

Use Case 6: Spatial Dimensions of Poverty and Agricultural Productivity: A Spatial Econometric Analysis


Credit: ©2014CIAT/GianBetancourt

Meta Data for Use Case 6	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future (2005 and 2050) Future

By Valerien Pede & Bert Lenaerts | International Rice Research Institute (IRRI)

Introduction and policy relevance

The relationship between agricultural productivity and poverty has long been central to development discourse. Numerous studies have demonstrated that increases in crop yields contribute to poverty reduction, particularly in agrarian economies where agriculture remains a primary source of livelihoods. Numerous studies have examined the link been productivity and poverty reduction, and the evidence of a positive correlation is well established. Evidence that higher agricultural productivity can enhance household incomes, reduce food prices, and generate broader economic growth has been established at sub-national, regional, and global levels.

Despite this well-established link, the spatial dimensions of this relationship remain relatively underexplored. Poverty and crop yield outcomes are not evenly distributed across space. They often exhibit clear geographic patterns, driven by differences in agroecological conditions, market access, infrastructure, institutional capacity, and socio-economic factors.

While the existing literature provides valuable insights, there are still significant knowledge gaps. Most studies focus on static relationships, leaving questions about the direction of causality and temporal dynamics underexplored. Furthermore, many studies rely on coarse spatial data, which may not capture intra-regional variation in poverty or yield outcomes. Advances in spatial data collection, remote sensing, and machine learning are beginning to offer more granular insights. You et al. (2021) note that integrating spatial econometrics with high-resolution satellite data and socio-economic surveys could enhance the understanding of yield-poverty dynamics and improve the targeting of development interventions.

There is growing recognition that poverty and agricultural productivity are spatially interlinked phenomena that must be studied in conjunction. Spatial econometric methods are uniquely suited to uncover these complex relationships, offering both diagnostic insights and practical implications for policy. As governments and development agencies seek to make agriculture more inclusive and equitable, understanding where and how yield improvements can most effectively reduce poverty remains a critical research and policy frontier. Given that poverty is often spatially clustered (Curtis et al., 2012, 2019), this study leverages recent spatially explicit cereals yield data to quantify the poverty-agricultural growth effect more accurately.

Method

For our estimation, we consider a panel data regression model and apply spatial econometric techniques. We begin with a simple Productivity–Poverty model, controlling for several covariates as well as time and location fixed effects.

The non-spatial version of the model is presented in Equation (1):

$$Poverty_{ct} = \alpha + \beta \cdot AgProductivity_{ct} + \gamma Z_{ct} + \mu_c + \lambda_t + \epsilon_{ct} \qquad (1)$$

where *Poverty* represents the poverty headcount, *AgProductivity* denotes agricultural yield (growth), and *Z* includes control variables such as per capita GDP, education, infrastructure, macroeconomic policies, and population growth.

The spatial panel version of Equation (1) incorporates spatial dependency, heterogeneity, and spatial effects in both productivity and poverty, as well as in the control variables.

To increase robustness and improve modelling capacity, we consider three types of spatial models: (1) the Spatial Auto-Regressive (SAR) model (Anselin, 1988), (2) the Geographically Weighted Regression (GWR) [Brunsdon et al. 1996; Fotheringham et al. 2002] model, and (3) the Spatial Temporal Auto-Regressive (STAR) model (Pede et al., 2014).

Results and key maps

As the study is still ongoing, the final results are not yet available. However, preliminary descriptive analyses have been conducted to provide an initial overview and visualization of the key variables that will form the basis of the econometric model estimations. These exploratory insights not only help in understanding the underlying patterns and relationships in the data but also guide the refinement of the modelling approach and the specification of the econometric framework. Figure 13 shows the GDP per capita PPP (2021); Figure 14 shows the Poverty headcount ratio at $2.15, 2021; Figure 15 shows the Population density (people per sq. km), 2021; and Figure 16 shows the Rice production (SPAM), 2020.

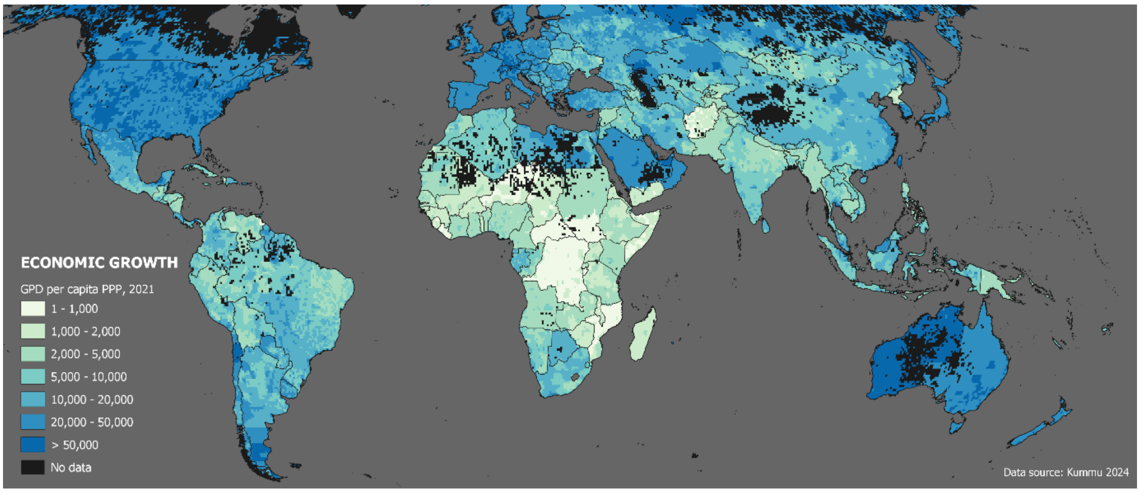


Figure 13: GDP per capita, PPP (2021)

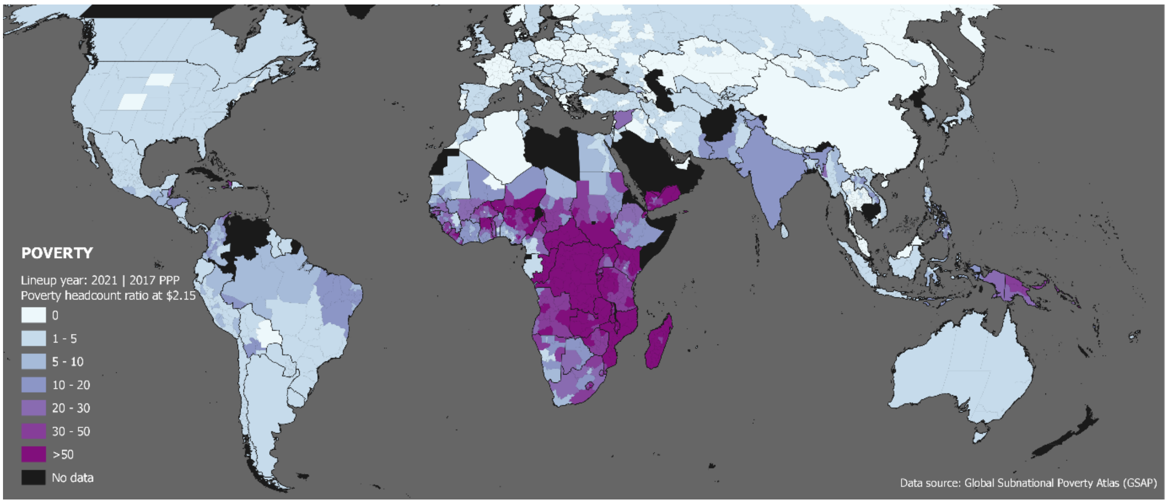


Figure 14: Poverty headcount ratio at $2.15, 2021

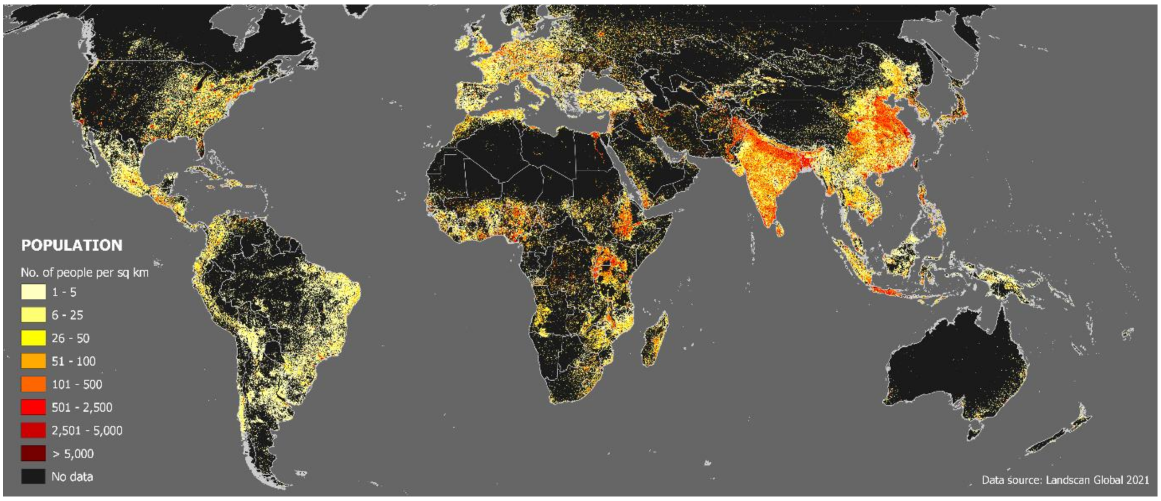


Figure 15: Population density (people per sq. km), 2021

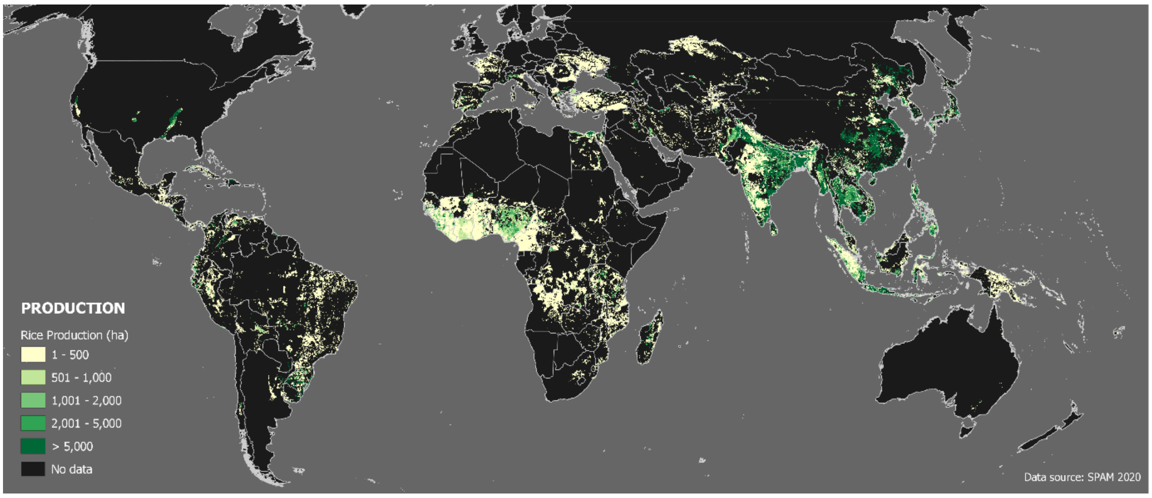


Figure 16: Rice production (spam, 2020)

Policy recommendations

The study's recommendations will provide policymakers with more precise evidence on the link between cereal yield improvements and poverty reduction, using spatially explicit data that capture local variations in productivity and welfare. By identifying where yield growth has the strongest poverty-reducing effects, the study can guide more targeted investments in agricultural research, infrastructure, and extension services. This evidence-based prioritization will help ensure that limited resources are directed to regions and farming systems where interventions are most likely to maximize both agricultural growth and poverty alleviation, ultimately supporting more inclusive and effective rural development strategies.

Use case 7: Spatial Downscaling Future Food Demand for Informing Local Food Policy Making.

Credit: ©2016CIAT/GeorginaSmith

Meta Data for Use Case 7	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country Within country
Spatial unit of the OUPTUT of the use case	Pixel Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future

By Chun Song, Francis Yego, Athanasios Petsakos, Elisabetta Gotor | Alliance of Bioversity & CIAT

Introduction and policy relevance

Understanding the subnational dynamics of food demand, while accounting for the evolution of the agrifood system at the global level, remains a challenge for designing food policy to ensure food security. There has been increasing demand for spatial explicit results for various analysis among policy makers and organizations that influence policy. For food policy, as an example, shifts in food preferences and changes in the quantity of food demanded can bring both opportunities and challenges for designing food policy that aims to ensure food security (Gandhi & Zhou, 2014). Understanding where food will be demanded in the future is thus critical for identifying those dynamics. Many studies have projected future food demand on a global scale at aggregated level (i.e., national, for example, (Tilman et al., 2011; van Dijk et al., 2021). However, what is happening at the aggregate level does not give the picture within-country level (Kearney, 2010) or design locally tailored economic interventions to ensure food security. Policy makers and international agencies have highlighted the need for more spatially disaggregated food demand projections. For instance, the India National Food Security Mission (NFSM) (Government of India, 2018) recognizes "…the changing trend in demand for different food across regions.". In 2024, under the theme 'Good food for all, for today and tomorrow,' the World Food Forum emphasizes that "we must innovate and adapt our actions to diverse local contexts… by science-backed evidence" (FAO, 2024).

This case presents an effort to downscale future food demand results from national to subnational level to support food security policy making at local level. In both cases, the results are based on International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT v3.0) (Robinson et al., 2015), which is the most frequently used agricultural multimarket model for global food demand projections (van Dijk et al., 2021). We choose IMPACT as a showcase because of its capacity to reflect the interaction of global drivers across scales, the focus on agricultural sector, and the rich set of food commodities represented in the model.

Method

There are two downscaling methods that generate subnational food demand estimates: one is through a data driven approach based on statistical models and validated with household survey data. The other relies on household survey data for selected crops.

The first method uses high resolution spatial inputs, a machine learning model and a matching estimator to downscale food demand from national to subnational level, given the national level demand projections from IMPACT. In this approach, the observed relationships between demand and social-demographic-spatial features provide a means of downscaling future food demand. Each subnational unit is seen as a "counterfactual" combination of countries in terms of historic trajectory of food demand. The approach downscales food demand projections for 62 food commodities from 159 countries to 3,064 subnational units (province or state equivalent, henceforth admin 1 units).

Results and key maps

With the first methods, as an example, in Kenya, while at the national level per capita maize demand is expected to decrease in the future, downscaled results suggest that per capita maize demand may grow in specific counties. Focusing on national level trends can thus give decision makers a misleading impression that maize demands in all counties are declining.

Figure 17 presents the spatial distribution of the dietary diversity between 2005 and 2030 in Kenya. The top figures are original country level results. The bottom figures are downscaled results. Sub-nationally, the increase in dietary diversity in 2030 is mostly driven by dietary changes in those areas that already exhibit medium-high dietary diversity in 2005. Counties with higher income levels are expected to have higher dietary diversity. Counties that are likely to have the highest dietary diversity often have access to a wide range of foods, including imported goods and a diversity of locally grown produce from across Kenya.

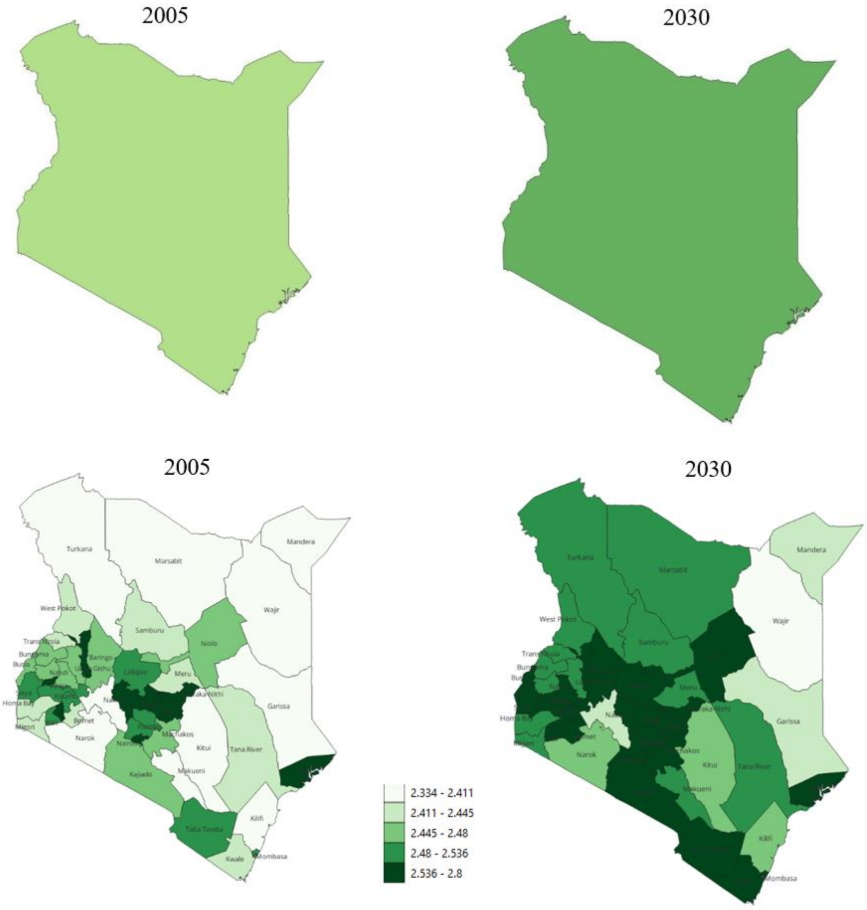


Figure 17: Dietary diversity index 2005-2030 in Kenya (SSP2, RCP 4.5)

Policy recommendations

The spatial downscaling results can help pinpoint areas where major changes in food demand are expected, where ensuring food security for the local population will be one of the most important policy challenges for the foreseeable future. The result in Kenya suggests that this challenge may not be addressed solely by traditional supply-side interventions that increase food availability. It may require the transformation of the food retail sector and the vertical integration of the food supply chain to facilitate physical and economic access to food, and to better link the consumers' plate to the farmers' plow (Pingali, 2007). Second, our framework can facilitate the mapping out of market gaps and opportunities for local producers to better link with local consumers and markets, and direct policy makers where small producers might need increasing enabling services to grasp those market opportunities.

Use case 8: PLaSA as a spatial online supporting tool for policy

Credit: ©2021 CIAT/Juan Pablo Marin García

Meta Data for Use Case 8	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country: Colombia Within country
Spatial unit of the OUPTUT of the use case	Subnational: 1100 political administrative divisions in Colombia Pixel: 8km by 8km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future

By Carlos Gonzales, the Alliance of Bioversity and CIAT

Introduction and policy relevance

Agrifood systems contain broad factors and stakeholders across locations. How to depict a country's agrifood system to the public and decision makers? Colombian Food Systems Platform(www.plasacolombia.com), or PlaSA Colombia (Alliance Bioversity International - CIAT, 2025d) offers one solution to this questions.

This platform collects, organize, and visualize a range of spatial data of Colombia's agrifood system and present them to the public. The statistics report that there are more than 9,000 users. The topics with the highest interest from policy makers are a) food supply and kilometers of food travel (12%), b) municipal comparisons, supply (9%), c) food mobilization: routes and trips by type of vehicle (8%) and d) PlaSA CoP-community of practice food systems allies (8%).

The most active users include organizations and research centers (WWF, PROESA, etc.), public and private universities (National University of Colombia, ICESI, Javeriana, Universidad de los Andes), organizations and local governments (Corpovalle, Cali Mayor's Office, Bolivar Governor's Office, etc.). PlaSA displays spatial data (departments, municipalities, pixels, vectors, and so on) that captures different dimensions of the agrifood system: goods volumes, distances to market, rates and percentages (emissions by food mobilization, contribution to food supply, etc.). The data covers various spatial scales, ranging from departmental, municipal, and grid level. The data are then translated into visualizations and messages to policy maker/producer/consumers.

The platform also establishes Community of Practice in Food Systems with universities, Colombian government agencies, international entities, foundations, which use, feed, and research on topics related to the data and themes of the tool (Figure 18).

Los sistemas alimentarios en Colombia

¿Qué son? ¿Cómo funcionan? ¿Cuál es su importancia?

Explora nuestra guía interactiva.

Platform for monitoring, information and analysis of the food system

Colombia's food system in a click

Figure 18: Front page, modules, and an example of PlaSA

The tool is co-developed with multiple stakeholders who participated in various ways by providing data, analysis, use, and dissemination. As a result, a community of practice of food systems (Alliance of Bioversity International and CIAT, 2023) was consolidated with 15 partners from different regions of the country. The scope and incidence of the data are valuable if they represent and adjust to geographic spaces where local (municipal) and departmental policy interventions are operational and functional.

Method

PlaSA combines data from three sources: i) statistics from authorities and government agencies; ii) data collected from the community of practice, such as per diem costs and emissions; and iii) calculations by the research team, using Foresight analysis integrating climate and agricultural inputs. The underlying codes and data are hosted on servers; the data analysis tools used were Tableau and Power BI to visualize the data (14 dashboards). The data and visualization follow the Food System framework suggested by the High-Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security(Serra-Majem, 2017) See supplementary material A.

Results

The Platform gets recognition as one of the innovations with the greatest contribution and mobilization of stakeholders in the Alliance about food system transformations(Alliance Bioversity International - CIAT, 2025g) Colombian universities incorporate PlaSA Colombia as a pedagogical tool to promote food system education among young people (Rankin et al., 2025), ORCID category. This platform has contributed to developing proposals and projects associated with deforestation and food security (Alliance Bioversity International - CIAT, 2025f), hidden hinger in Amazon regions, Cost of diets by 13 cities in Colombia (PUJ Cali, 2025).

Policy recommendations

The initial audience is civil society, including students, housewives, entrepreneurs and voters in general. They demand a better understanding of how food systems work, and they want scientific data to inform their policy advocacy work during electoral processes and political debates.

Regional and local technicians, as well as policy developers, also benefit from the tool by accessing quality data that can guide their local interventions. Often, these professionals lack the capacity to obtain this information, which makes the service open and generous.

Academics, educators, students, and research centers are stimulating alternative areas of knowledge beyond traditional study options. For example, studying the importance of food and the systems surrounding it has gained interest due to global phenomena such as pandemics and social events like mobilizations, protests, and blockades. This sector should promote research and topics that integrate spatial data and food systems, generating new technologies, tools, and alternative methods to monitor critical issues such as nutrition, food availability, and accessibility, among others.

Use case 9: Spatial assessment of Landscape complexity: implications for agricultural policies.


Credit: ©2015CIAT/GeorginaSmith

Meta Data for Use Case 9	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country: Kenya Within country
Spatial unit of the OUPTUT of the use case	Pixel (50 by 60 km at the Equator) Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future: changes between 2005 and 2050

By Nicola Cenacchi Athanasios Petsakos, Richard D. Robertson, Chun Song, Abhijeet Mishra

Introduction and policy relevance

Landscape complexity is a key feature of resilient landscapes. It is associated with greater biodiversity richness, and with the delivery of a wider range of ecosystem services (ES) valuable to human wellbeing, including some that have a direct or indirect effect on agricultural production (Dainese et al., 2019; Estrada-Carmona et al., 2022a; Martin et al., 2019).

Landscape complexity is inherently a spatial concept because it rests on the variety and extent of different land covers, as well as on their relative position in the territory. In this study we use a system of models and the Shannon Diversity Index to spatially estimate how the complexity of agricultural landscapes may change in the future due to socioeconomic trends and climate pressures. We explore global and regional changes, as well as in Kenya, selected as a country test-case. At these different scales we also perform additional analysis to test how broad stylized policies affecting agricultural land use planning may interact with global and regional climate and socioeconomic trends to further influence landscape complexity outcomes.

The main audience of this study is decision-makers and land use planners who have a vested interest in understanding how the complexity of agricultural landscapes might evolve in the future. The global food system and its global market dynamics, along with demographic and climatic trends may affect the complexity of agricultural landscapes in ways that should be factored in when planning for biodiversity conservation, climate change adaptation and mitigation, resources management and sustainable land use, and other goals. Our audience, the institutions involved in planning decisions and in the management and development of land, vary depending on a country's administrative structure, which can range from local to regional, state, or federal level. These institutions must recognize the factors that influence land use and incorporate them into their decision-making processes. Key actors typically include local and state planning commissions, zoning boards, regional or state planning and environmental agencies, as well as ministries of transportation and infrastructure, agriculture, lands, public works, housing, and urban development, among others.

This case highlights the value of combining spatially explicit results with Foresight scenarios to understand how global forces could reshape territories in conjunction with land management policies.

Method

This study estimates future changes in landscape compositional complexity. Compositional complexity is determined by the number of different land cover types and their area extent, including natural habitats and crops grown (K. S. Nelson & Burchfield, 2021; von Jeetze et al., 2023).

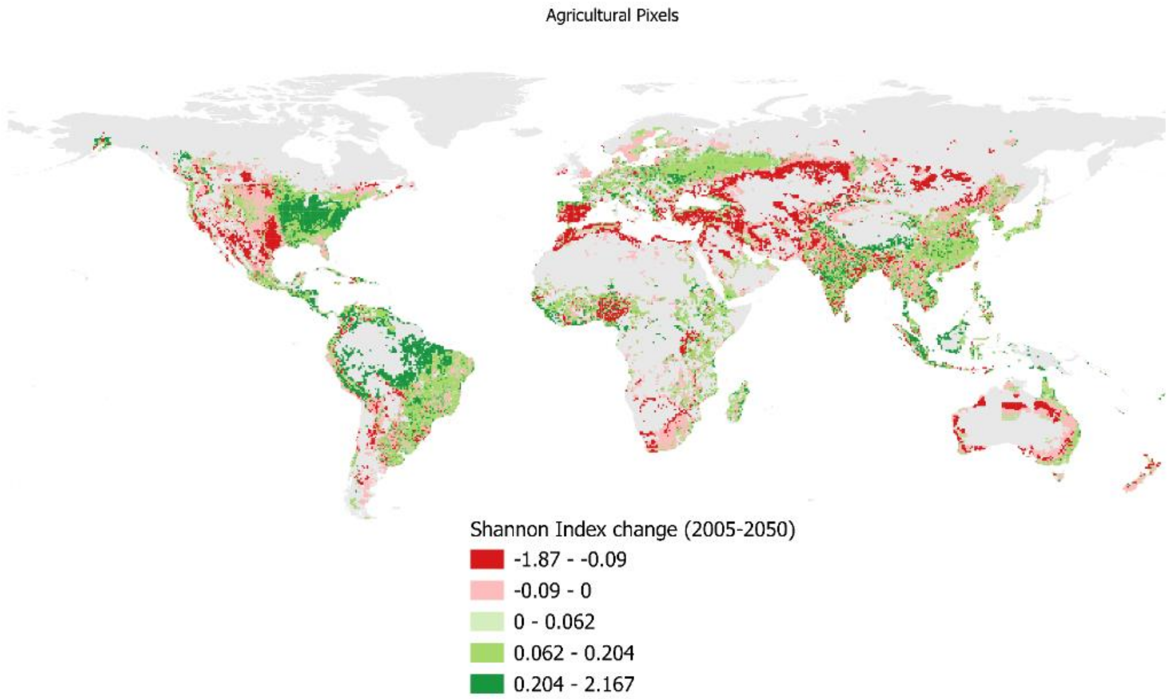


Figure 19: Changes in complexity of agricultural landscapes between 2005 and 2050 under the Mid scenario

The foresight analysis relies on the link between the IMPACT partial equilibrium economic model (Robinson et al., 2024a) and an IFPRI global land use model that works at the pixels level (pixels of about 50kmx50km at the equator) (Robertson et al., 2023b). Based on area outputs from IMPACT, and climate shocks, the land use model projects how socioeconomic and climate pressures may affect the spatial distribution of both cropland and natural habitats, globally, and under three different scenarios of potential future agricultural development. These agricultural scenarios represent a range of landscape management practices guided by policy choices, within which varying levels of active adaptation take place.

Scenario analysis and models have been widely used as decision support tools to explore and design interventions to manage agricultural landscapes (Heidenreich et al., 2024). However, existing modeling work has been so far lacking in appropriately considering the effects that driving factors (e.g., abiotic, biotic, and management factors), as well as linkages to the food system (including the global food system) may have on agricultural landscapes (Heidenreich et al., 2024). Our study helps fill this gap.

Results and key map(s)

Across agricultural development scenario, between 50 to 60% of agricultural landscapes globally (pixels in Figure 19 below) are projected to experience an increase in complexity, between 2005 and 2050. Under the agricultural concentration scenario, the increase in landscape complexity across most regions is associated with a net decrease in cropland and an increase in natural habitats. However, under scenarios that maintain or enhance the current dispersal of agricultural land the effect is reversed.

In most regions, agricultural landscapes that show an increase in complexity experience a net increase in cropland and a net decrease in natural land. The exceptions are Europe, and South Asia, where the agricultural pixels that grow more diverse show a net decrease in cropland and a net increase in natural habitats. The MENA region diverges from these general trends because most agricultural landscapes decline in complexity while cropland increases at the cost of natural land cover. Africa south of the Sahara is projected to see the largest net changes both for cropland and natural land, with a net increase of almost 55 million ha of cropland, and a corresponding loss of the same amount of natural land. Kenya was used as a country test case. Cropland expansion takes place at the expense of several natural habitats, but especially shrubland, mixed forest and savanna.

Policy recommendations

This study aims to contribute to existing research by simulating how the future complexity of agricultural landscapes may be shaped by the combined effects of global food market dynamics, climate change, and different scenarios of agricultural development.

In at least two scenarios of agricultural development the migration of cropland into some areas, and corresponding decrease in theextent of natural habitats, causes landscape complexity to increase. In other words, the increase in complexity across agricultural landscapes is associated with the expansion of cropland. Diversifying cropland composition and spatial arrangement across a landscape may compensate for some losses in natural habitats (Tscharntke et al., 2021), but there is a growing understanding that focusing only on farm diversity is inadequate to build truly complex landscapes (Estrada-Carmona et al., 2022b)). Therefore, the loss of natural cover over a large share of agricultural landscapes shown in our results raises questions about the multifunctionality of such landscapes. Climate change is the main driver of retreat of some key natural habitats. In absence of strong mitigation actions, specific interventions in support of conservation targets may be necessary to preserve natural habitats and their critical contribution to landscape complexity.

The design and inclusion of more comprehensive scenarios representing conservation policies would enrich the current analysis and allow to explore potential synergies and trade-offs between agricultural development and environmental protection objectives. From a planning perspective, this type of spatially explicit analysis not only reveals where socioeconomic pressures or climate change are shifting crops and habitats, but may also highlights trade-offs across sectors, and pinpoints geographic ‘hotspots’ for targeted action. By enabling scenario testing and prioritization of resources, it becomes a powerful tool to support more sustainable land-use planning.

Use case 10: Assessing potential impact of avian influenza on poultry in West Africa


Credit: ©2012CIAT/NeilPalmer

Meta Data for Use Case 10

AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional: West Africa Country: Nigeria Within country: Kogi, Kwara, Ondi, Abuja, Katsina
Spatial unit of the OUPTUT of the use case	Subnational Pixel: 1km * 1km Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future: scenario analysis of next few weeks/months of bird flu

By Liangzhi You and Xinshen Diao, International Food Policy Research Institute

Introduction and policy relevance

Before COVID-19 pandemic, there was avian influenza in the mid-2000s. The potential for the avian H5N1 virus to cause a deadly global human pandemic has convinced the international community to mobilize resources to implement prevention and eradication measures in the poultry population. While highly pathogenic avian influenza (HPAI) had been successfully checked in Western Europe and much of Southeast Asia, apart from Indonesia, it is still spreading in Africa and will remain a threat in the future. Since February 2006, HPAI outbreaks had been reported in Burkina Faso, Cameroon, Ghana, Niger, and Nigeria. The spread of HPAI poses a challenge to the poultry industry in West Africa. Once domestic birds are infected, AI outbreaks can become difficult to control, causing major economic damage to poultry farmers in affected countries. While attention has focused on preventing the spread of the disease, little has been conducted on the impact of these preventive measures on the poultry industry and livelihoods of smallholder farmers at country and regional levels in West Africa. Decision-makers need the tools and analyses to respond rapidly to crises like this while improving their capacity to design policies that enhance social inclusion and social safety nets to protect vulnerable populations.

Method

The spread of avian influenza (AI) and the risk of exposure is spatial, depending on the distance from AI transmission routes and contact with infected flocks. Thus, analyzing the impact of AI requires a methodology that captures the spatial pattern. We combine several spatially explicit data sets and develop a spatial equilibrium model to assess the likely impact of HPAI on poultry production and price and on the income of farmers in West Africa. The spatial data sets include information on the distribution of poultry and humans, the location of recent HPAI outbreaks, and the flyways of migratory birds. The model is employed to analyze the potential economic impacts of avian influenza (AI) in Nigeria.

Results and key map

Depending on the size of the affected areas, the direct impact of the spread of AI along the two major migratory bird flyways would be the loss of about 4 percent of national chicken production. The indirect effect—consumers' reluctance to consume poultry if AI is detected, causing a decline in chicken prices—is generally larger than the direct effect. The study estimates that Nigerian chicken production would fall by 21 percent and chicken farmers would lose US$250 million of revenue if the worst-case scenario occurred. The negative impact of AI would be unevenly distributed in the country, and some states and districts would be seriously hurt. This study is based on a spatial equilibrium model that makes use of the most recent spatial distribution data sets for poultry and human populations in West Africa.

Policy recommendations

Evaluating the potential impact of avian influenza is challenging because knowledge about the virus (and the methodology for analyzing it) is limited. Based on what is known about the spread and transmission of the disease, the spatial equilibrium model used recent spatial data on the distribution of both chicken and human populations, to analyze the potential economic impact of AI in West Africa.

The study shows that, while most of the attention has focused on preventing global influenza pandemic, preventive measures are also needed at the national, subnational, and local levels, because avian influenza could potentially have a huge negative impact on the poultry industry and the livelihood of smallholder farmers in many regions in West Africa. It also shows the critical value of spatial analytics and foresight tools in rapid response decision making during the AI epidemic.

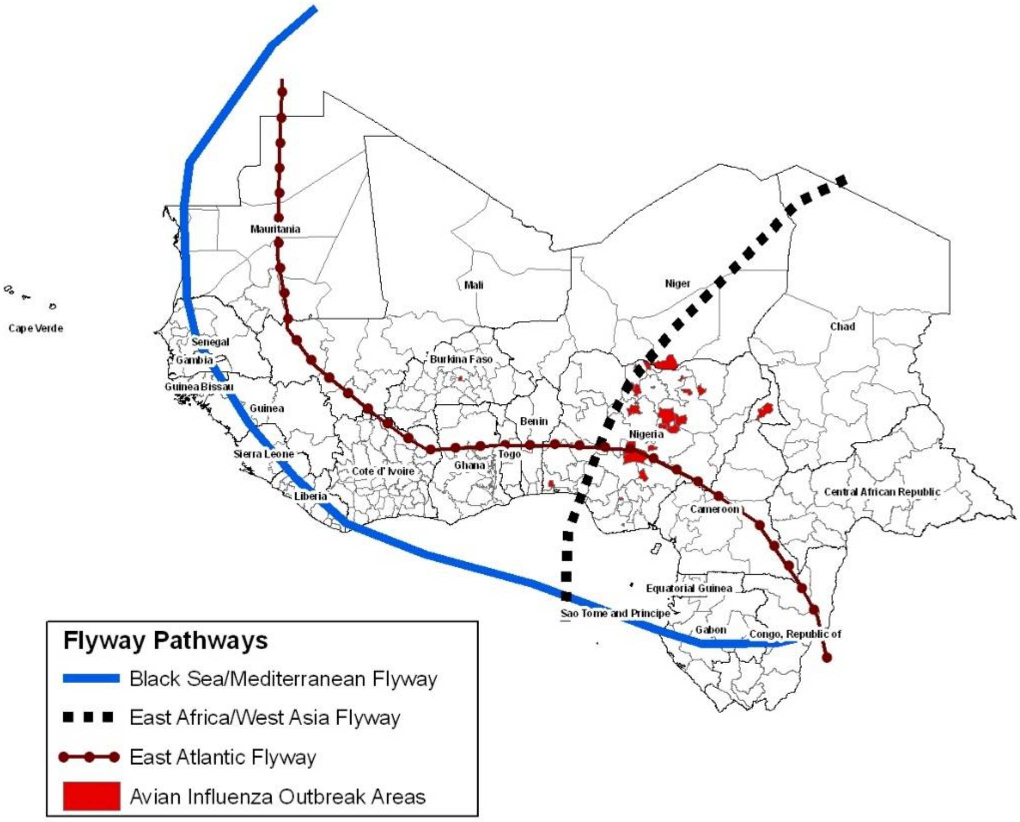


Figure 20: Flyways and outbreak areas in West Africa

Use case 11: Where to strength water governance for preventing future water conflicts?

Credit: ©2014CIAT/ManonKoningstein

Meta Data for Use Case 11	
AOW1 Areas	Global local outlook Prioritization and Evaluation Rapid response
Impact Areas	Climate adaptation & mitigation Environmental health & biodiversity Gender equality, youth & social inclusion Nutrition, health & food security Poverty reduction, livelihood and jobs
Spatial Scope	Global Regional Country: 21 SSA countries Within country
Spatial unit of the OUPTUT of the use case	Pixel Community Households Other
Time scope of the OUPTUT of use case analytics	Historic period Both historic + future Future

By Chun Song, Athanasios Petsakos, Elisabetta Gotor | The Alliance of Bioversity and CIAT

Introduction and policy relevance

Over the past 20 years, water conflicts in SSA have increased in their spatial coverage, fatalities, frequency, and in the share relative to the total number of conflicts reported in the region. Identifying regions most susceptible to intrastate water conflicts can help prioritize policy and interventions in the most vulnerable areas, ensuring water security and peace—especially in resource-constrained settings. Answering this question thus requires spatial analytics to offer a way to answer this need.

We apply a multi-scale spatial approach to analyze past and present data on intrastate water conflicts and droughts, to examine if the influence of drought on intrastate water conflicts in African differs across locations within a country, and if so, how does it shape future water conflict patterns and the implications for water policy formulation that aims at preventing and deescalate those risks.

Method

We integrate data and results across multiple spatial levels. We first estimate interactions between drought, border distance and water conflict (2010–2024), then extend findings to 2030–2040. In the second step, we incorporate country-level water governance and household-level perceived governance strength. We find that drought increases water conflict intensity (represented herein as the number of fatalities). The level of intensity increases proportionally as drought occurs nearer to the country border, after controlling for possible confounding factors. Future drought may alter the locations of water conflicts. We further present findings in support of the postulate that there is an empirical linkage between within-country location and (perceived) governance strength. At the country level, stronger water governance may offset (partially) the influence of physical water scarcity on water conflicts.

Results and key map

We find robust evidence of the impact of drought on water conflicts. Between 2010 and 2024, drought is associated with an increase in water conflict fatalities, which is consistent with previous literature (Ide et al., 2021).

The impact of drought on conflicts depends highly on where the drought occurs. During both mild and severe droughts, there is an increase in water conflict fatalities for every kilometer closer to the country border. Remote areas on average appear to experience more water conflicts. This may stem from geographical isolation and logistical challenges that hinder the central government from maintaining a strong presence, and/or limit the governance capacity of local authorities.

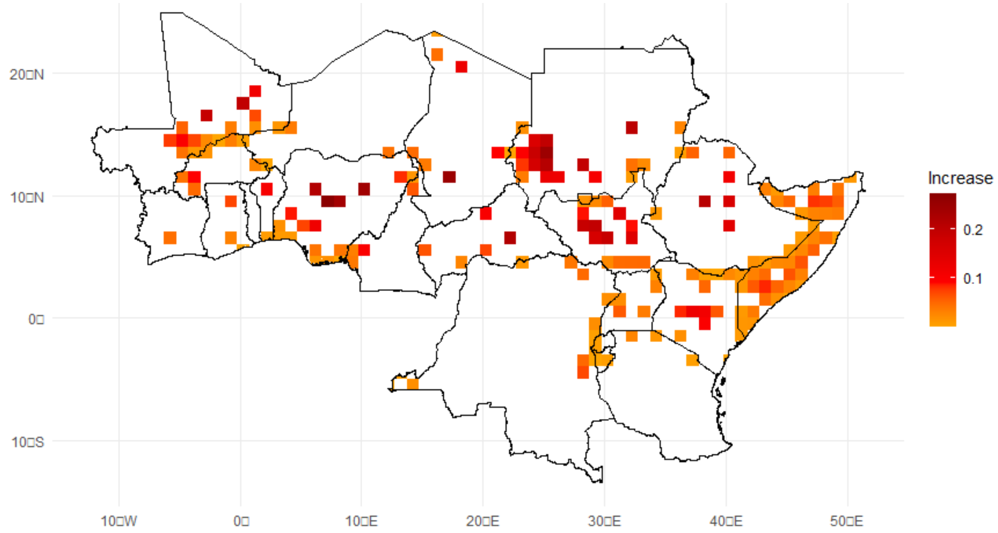


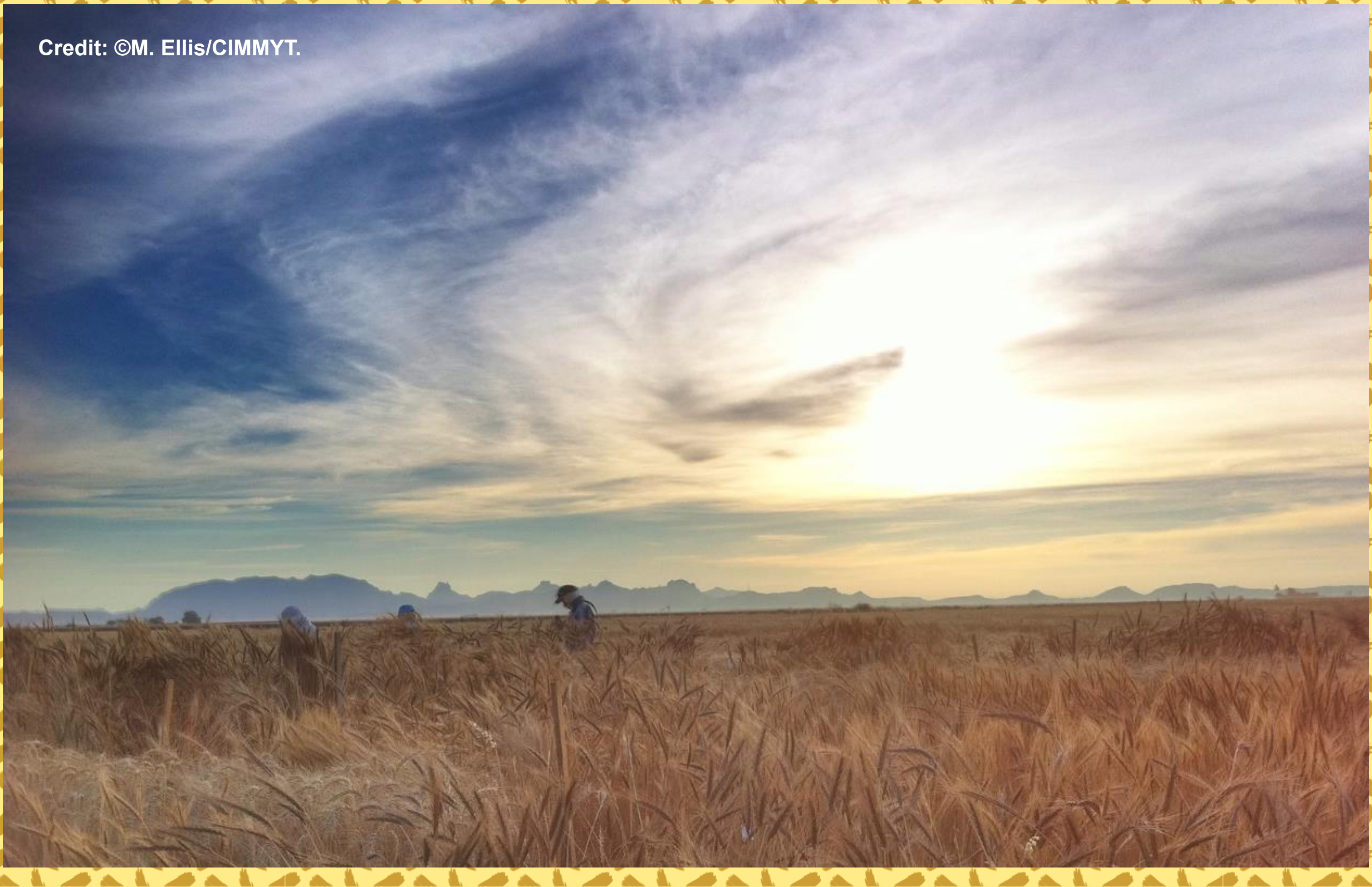
Figure 21: Estimated increase in water conflict fatality (monthly average): 2030-2040

Second, at the country level, our results support the above postulate that there is significant interplay between drought and water governance (proxied by distance to borders) in affecting water conflicts. A third key finding is that in the future we anticipate an increase in water conflict fatalities in most pixels. However, some pixels that are currently peaceful may experience a substantial increase in water conflicts, suggesting that future drought may exacerbate water conflict risks in vulnerable, drought-prone regions that are currently not the hotspots of water conflicts. Since climate change is expected to alter the spatial distribution of drought, it is important to identify areas that are currently water secure but may face water scarcity in the future and design interventions that can either prevent water-related conflicts or mitigate their impact on local communities., for example, enhancing water storage and safeguarding critical water facilities from being damaged during conflicts.

Policy recommendations

Our study highlights the importance of identifying areas that face a dual risk from drought and inadequate governance to inform decision-making that strengthens water governance and de-escalates water conflicts. Our analysis shows that areas close to a country’s borders tend to face more fatal water conflicts after drought. This effect cannot be explained by differences in overall conflicts, irrigation, population, and underground water storage, which we explicitly controlled for in the model. Our postulation is that this may be partially due to overall weaker policy enforcement and management. Water policies should be tailored to different regions, considering the local governance capacity, vulnerability to drought and conflicts, and the prevalent type of water conflicts. Our study provides a starting point for a discussion on how to address these, largely methodological, issues. Therefore, we believe that it can motivate further policy research on unravelling the complex spatial relationship between conflicts, droughts and governance at the local level.

5. Way forward



Credit: ©M. Ellis/CIMMYT.

This synthesis provides an overview of what spatial analytics can do in supporting policy need in the global south. It reviews the evolution, most recent development and applications of various spatial analytics in One CGIAR. The use cases show that spatial analytics can substantially strengthen policy analysis by revealing how spatial analytics can bridge global analysis with local heterogeneity, and inform the effectiveness of interventions across heterogeneous geographies, now and in the future.

In contrast, spatially aggregated approaches often overlook within-country disparities, masking how drivers such as climate shocks, technology adoption, or resource constraints vary across locations. By incorporating spatial detail, policy analysis can identify localized vulnerabilities, hotspots of opportunity, and areas of potential spillover. These insights help policymakers design more targeted, efficient, and equitable interventions. They also support foresight analysis, allowing decision-makers to anticipate how policies interact at the local level with biophysical conditions, infrastructure, and markets in specific places. Recent advances in Earth Observation, georeferenced survey data, and high-resolution climate projections have greatly expanded the empirical foundation for spatial analytics to support policy work. At the same time, open-source tools in Python, R, and cloud platforms like Google Earth Engine make spatial analytics technically accessible to a broader range of researchers and institutions.

However, challenges remain. Subnational economic and farm-level data are often constrained by privacy restrictions or missing altogether, limiting the precision of spatialized economic models. Computational intensity also grows with finer resolution and the need to simulate interactions across multiple decision-making units. Thus, the value of adding spatial detail must be weighed against costs and policy needs. In practice, the most feasible applications are those where local heterogeneity is highly consequential for policy outcomes, and where spatial analytics demonstrably add value to resource allocation, targeting, or scaling strategies.

5.1 Future integration of spatial analytics into economic models for policy support

Moving forward, we identify two approaches through which spatial analytics can be further incorporated more into economic models in supporting policy questions: (1) spatially endogenize the model solution, for instance, by increasing the spatial scale of the DMU; or (2) post-solution modules to report results at higher resolutions without changing the spatial scale of the DMUs. Hereafter we will refer to the two modeling approaches as “structural spatialization” and “output spatialization” respectively. Structural spatialization involves substantial changes to a model’s code to accommodate data at finer resolutions, as well as additional modeling assumptions to consistently represent economic decision-making across scales.

5.1.1 Equilibrium models

In general, the capacity of economic equilibrium models to operate at a given spatial resolution for spatially explicit policy analysis is constrained by data availability and computational complexity. Specifically, the need for computational power and infrastructure scales rapidly with the increase in spatial scales at which models are prescribed and solved. Detailed spatial modeling, especially when it involves thousands or even millions of grid cells (e.g., individual farms/households, farm types, or administrative regions), as well as interaction between DMUs (e.g., trade), significantly increases the dimensionality of the model and the computational burden.

Although most models do rely on spatially explicit data, such as biophysical data, land cover maps, crop yields, or climate projections as inputs, they manage the above computational constraint by aggregating this information to the level of the DMU during the data preparation stage, prior to solving. This aggregation of input data is very common in large-scale economic models that are linked with crop simulation models to simulate the impact of climate on crop yields (G. C. Nelson et al., 2014).

In contrast to biophysical data, the availability of economic data is another critical constraint to structural spatialization of large-scale economic models; particularly for many low- and middle-income countries, reliable subnational economic data simply does not exist. Attempting to impose spatial granularity where this granularity is not supported by data availability risks undermining the credibility of a model and its results. Even if such data existed, many of the current global agricultural sector models are not equipped to endogenously represent spatial interactions at fine resolutions. For example, the behavioral and market parameters that govern IMPACT (Robinson et al., 2024b), such as supply functions, income and price elasticities, and demand systems, are not easily or reliably calibrated at subnational levels, especially on a global scale.

Given the above difficulties, a key question about the structural spatialization of large-scale economic models is cost-effectiveness. Although not having a sub-national or spatially explicit representation of system drivers and their interactions limits a model’s ability to analyze highly localized outcomes, the difficulties involved in introducing spatial detail at high resolution far outweigh any analytical value added. In a sense, requiring large-scale economic equilibrium models to be spatially explicit – at lower scales than their implicit DMUs – appears conceptually and technically misaligned given their scientific scope. For example, IMPACT was developed to simulate global market-clearing conditions for agricultural commodities, with a focus on international trade, supply-demand balance, and policy shocks. In other words, the kinds of questions that models like IMPACT are designed to address, such as how global food systems respond to investments in agriculture, climate shocks, or dietary shifts, are most effectively analyzed at macro-regional or national scales.

Ultimately, the appropriate spatial scale for an economic model's DMU is shaped by computational feasibility, data availability and policy or research relevance. The most relevant use-case for a spatially explicit large-scale economic model is the analysis of how different system drivers can jointly affect land-use (LU) change globally. Decisions on optimal distribution of land require the representation of each LU type and of the biophysical and market constraints associated with them. Yet not all economic models can represent the various LU categories with the same level of detail. For instance, forestland, pasture, and cropland may be aggregated or simplified differently depending on the model's purpose and structure. For the cropland LU category, in particular, the representation of crop activities among different economic models varies substantially.

Because of the difficulties in the structural spatialization of large-scale economic models, most models do not endogenously simulate LU change at resolutions lower than their DMUs. Instead, they follow an output spatialization approach whereby they downscale their aggregate land use results using external LU models. For example, the AIM/CGE model relies on a global land-use allocation model that provides downscaled results for six land use categories, which are further subdivided into 12 crop categories (including irrigated and rainfed variants, and energy crops) and three vegetation categories including forest, pasture, and other natural vegetation (Hasegawa et al., 2017). Similarly, IMPACT relies on a post-solution land use model which consists of a natural vegetation component that simulates LU change across nine vegetation categories, and a cropland component with an allocation algorithm that distributes six crop categories (maize, rice, wheat, sorghum, soybeans, and other crops) across pixels at 0.5-degree resolution (Robertson et al., 2023c).

5.1.2 Farm/household models

In contrast to large-scale equilibrium models, spatially endogenizing farm/household models could be simply interpreted as introducing the geographical coordinates of the individual farms/households as input data. This data would allow linking each farm/household to their locally specific physical conditions (soil, climate) in which their agricultural activities take place. Given that the core strength of farm/household models is their ability to simulate micro-level economic decision making, the value added for using such georeferenced information is a more detailed representation of agronomic practices at farm or field level, and of their potential yield and environmental outcomes when these outcomes are simulated with crop models.

Enhancing the agronomic aspects of farm/household models for policy analysis is a contemporary research issue that has led to the development of various approaches for circumventing the legal constraints related to the use of georeferenced data. An example is the Agricultural Regionalized Optimization Model with Joint production (AROPAj) of the French National Agricultural Research Institute (Jayet et al., 2023), which uses FADN data and is coupled with the crop model STICS. Because of the FADN data use constraints, AROPAj maximizes an objective function for independent farm types rather than individual farms. To estimate input-yield response functions and related emissions per crop and farm type, STICS first generates many such functions (30-2400), followed by a calibration algorithm that selects the most appropriate function based on a set of economic criteria and agronomic assumptions (Godard et al., 2008; Humblot et al., 2017). It is obvious that modeling individual farms, whose geographical location was available, would allow for a direct linkage between the two models without the need for external calibration algorithms to align the non-spatial concept of a farm type with the spatially explicit biophysical inputs and outputs in STICS.

Because of the restrictions in the use of spatially explicit farm information, some farm/household models have followed output spatialization approaches for visualizing the results that generate. Such downscaling approaches are comparable to those previously described for large-scale equilibrium models as they are also based on post-solution models, and they are similarly concerned primarily with LU decisions. However, a difference exists in that the focus is on crop allocation across space since the simulation of changes for non-agricultural LU categories is beyond the scope of farm/household models used for policy analysis. An example is the approach developed by Chakir (2009) and implemented in AROPAj. It involves a three-step procedure that utilizes information from the CORINE Land Cover (CLC)[8] and the Land Use/Cover Area frame Statistical Survey (LUCAS)[9] databases to estimate the probability that a specific FADN farm group in AROPAj can be found in a given spatial unit (pixel).

Overall while economic models for agricultural policy analysis are not inherently spatially explicit by design, they possess varying degrees of spatial representation that fundamentally differ from traditional spatial modeling approaches. Both farm/household optimization models and large-scale economic equilibrium models face distinct but interconnected challenges in achieving true spatial explicitness. For farm/household models, legal constraints surrounding georeferenced data limit their potential for structural spatialization, despite their natural capacity for micro-level spatial analysis. Large-scale equilibrium models, conversely, are constrained by computational complexity, data availability, and the fundamental mismatch between their macro-economic objectives and the fine spatial resolutions demanded for localized policy analysis. The emergence of output spatialization approaches represents a pragmatic compromise, allowing models to maintain their core economic logic while providing spatially disaggregated results through post-solution downscaling algorithms. However, this review suggests that the pursuit of spatial explicitness in economic models should be guided by cost-effectiveness

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[8] http://www.eea.europa.eu/publications/COR0-landcover.

[9] http://eusoils.jrc.ec. europa.eu/projects/LUCAS/

considerations and alignment with model objectives rather than spatial detail for its own sake. Ultimately, the appropriate spatial scale for economic models must balance computational feasibility, data availability, and policy relevance, recognizing that different modeling approaches serve distinct analytical purposes within the broader ecosystem of agricultural policy analysis tools.

5.2 Improving capacity to harness the potential of spatial analytics for policy support.

To fully harness the value of spatial analytics for policy analysis, interdisciplinary scientists' teams with diverse and complementary skill sets are essential. We recommend that effective teams must integrate expertise across spatial data science, economics, agronomy, geography, statistics, and computer science. Spatial modelers and GIS specialists are needed to handle geospatial data processing, Earth Observation analysis, and land use modeling. Economists bring knowledge of causal inference, system approach for policy modeling (including economy wide models), and welfare analysis, Agronomists and environmental scientists ensure contextual relevance by interpreting local bio-physical realities such as climate variability or soil constraints.

There are also some challenges in fully leveraging spatial analytics for policy. First, even when spatial data exists, it may be held by different agencies, stored in incompatible formats, or subject to restrictive sharing policies, and this can hinder the integrated analysis required for evidence-based decision-making. Furthermore, the technical capacity to utilize spatial analytics effectively within policy institutions may be limited. Finally, it remains a challenge to build a team with diverse skill sets, backgrounds, and experiences that form an effective scientific team for applying spatial analytics to policy analysis.

We also envision that through more dissemination and participatory event, more stakeholders be involved in spatial analytics to provide more real-world institutional and political contexts and translate complex spatial outputs into actionable insights for decision-makers and generating policy-relevant evidence that reflects local diversity, enhances targeting precision, and supports adaptive, inclusive, and impact-driven policy development.

In conclusion, spatial analytics is emerging as a cornerstone for evidence-based policy design and implementation across Food, Land, and Water systems. To fully realize its potential, continued investment is needed in data infrastructure, methodological innovation, and capacity building within One CGIAR and partner institutions. Embedding spatial thinking into policy processes will enable more adaptive, inclusive, and sustainable pathways toward resilient FLW systems in the global south.

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