Bridging the Macro–Micro Divide through a New Paradigm for Climate Resilience Assessment in Data-Scarce Regions

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Abstract

Efforts to assess climate resilience in low-income countries (LICs) are often hampered by fragmented data systems and analytical silos between national and local scales. This study proposes and operationalizes an integrated empirical framework that bridges macroeconomic econometric modeling and micro-level spatial analysis to measure and visualize climate resilience in data-scarce settings. Using Uganda as a core case study, we estimate sectoral resilience through dynamic panel regression and generate spatial productivity surfaces using kriging interpolation on sparse field and satellite data. We introduce the Resilience Asymmetry Surface (RAS), a diagnostic tool that synthesizes income and climate stress to highlight structural vulnerability and intervention leverage points. The results uncover stark cross-sectoral and spatial heterogeneity in resilience outcomes, demonstrating that reliance on single-scale assessments can misdirect adaptation investments. Our framework enables data-efficient, actionable diagnostics that can inform national strategies and localized interventions alike. This work advances a scalable, policy-relevant methodology for integrated climate resilience planning in LICs.

Author summary

Ronald Katende is a Ph.D. in Scientific Computing and Data Science from Makerere University and an Assistant Lecturer, in the Department fo Mathematics, at Kabale University.

His research focuses on developing computational and statistical methods for complex and data-scarce environments, with a particular emphasis on socio-economic resilience, climate modelling, and network systems.

Ronald has worked on several research projects, including work on credit scoring algorithms, pension fund analytics, and adaptive machine learning models for climate-related applications. His published work spans applied mathematics, data science, and climate resilience, including recent contributions to Nature Scientific Reports and Frontiers in Environmental Science.

In this study, Ronald proposes an integrated macro-micro framework to assess climate resilience in data-scarce regions, contributing novel tools for spatial diagnostics and policy-focused metrics. His work supports applied research for sustainable development and adaptation in vulnerable low-income countries.

Introduction

Climate resilience, the capacity of systems and communities to anticipate, absorb, and adapt to climate shocks, varies widely across low-income countries (LICs), with agriculture remaining the most exposed and least protected sector. In many LICs, agricultural systems are predominantly rainfed, labor-intensive, and highly sensitive to seasonal climate variability, making them especially vulnerable to even modest shifts in weather patterns. This vulnerability is compounded by limited adaptive capacity, weak infrastructure, and constrained institutional support, leading to persistent risks for livelihoods and food security [1–3].

Efforts to assess and compare climate resilience across LICs face two central challenges. First, most existing studies are confined to single-country analyses or narrow subnational case studies, which limits the ability to identify broader trends or draw general conclusions across contexts [4–6]. Second, the scarcity of high-resolution, ground-based data in many LICs makes localized assessments difficult, particularly in rural areas where vulnerability is often most severe [7–9]. National datasets are often incomplete or outdated, and monitoring networks are sparse, leaving researchers dependent on aggregate statistics or coarse simulation models that obscure local realities [8, 10].

This paper advances a macro-micro integrated approach to climate resilience analysis, one that explicitly connects national structural patterns with localized impacts. Without such an approach, policymakers risk missing critical hotspots or directing resources inefficiently. To address this gap, we propose an integrated framework that combines cross-country econometric analysis with localized spatial mapping, designed specifically for data-scarce environments.

Our contributions are threefold. First, we develop a comparative framework for analyzing sectoral climate resilience across LICs, using harmonized panel data and dynamic panel regression to uncover shared and divergent patterns of vulnerability. Second, we introduce a localized mapping method that integrates sparse field observations with satellite-derived indicators, employing geostatistical interpolation to produce spatially detailed estimates of agricultural productivity under climate stress. Third, we show how these tools can support both national strategy formulation and targeted subnational interventions, offering practical guidance to decision-makers.

By linking national trends with local realities and directly addressing the constraints of limited data, this work aims to establish a new standard for climate resilience assessment in LICs. We argue that only through such integrated, scalable approaches can adaptation efforts achieve the precision and impact required in the regions most exposed to climate risk.

Literature Review

Research on climate resilience in low-income countries has grown substantially in recent years, but significant limitations remain in both conceptual framing and empirical execution. Much of the early literature concentrated on national-level assessments, relying on aggregate indicators to evaluate sectoral or cross-country differences in exposure and adaptive capacity [6, 10]. These studies have revealed important trends, such as the consistent vulnerability of agriculture compared to industry or services, but they often obscure local variation and provide limited insight into the spatial distribution of risk [2, 4].

In contrast, a growing set of studies has shifted attention to subnational and local dynamics, particularly in the context of agricultural vulnerability and adaptation. These efforts have used diverse methodologies, including household surveys, remote sensing, participatory assessments, and spatial simulation models [7, 9, 11]. Advances in satellite-derived datasets and geostatistical methods have made it possible to generate spatially explicit climate indicators even in regions where ground-based measurements are scarce [9, 12]. Despite these innovations, many of these analyses remain geographically narrow, often focused on single countries or regions. This limits the extent to which findings can be generalized or compared across settings [13, 14].

Efforts to integrate national and local perspectives remain uncommon. While a few studies have attempted to combine panel data with geospatial modeling, they often face challenges related to data harmonization, measurement consistency, and methodological transparency [3, 15, 16]. These difficulties are particularly pronounced in data-scarce contexts, where missing values, unbalanced time series, and spatial gaps complicate efforts to construct robust models. Moreover, there is little systematic evaluation of the relative strengths and weaknesses of macro- versus micro-level approaches, or of how best to link them in a coherent and replicable framework [4, 17, 18].

One of the most persistent barriers in the literature is the lack of reliable, high-resolution data. Many LICs have limited field-based monitoring systems, and official statistics may be outdated or inconsistent across administrative units. In response, researchers have increasingly turned to open-access satellite imagery, alongside statistical techniques for interpolation and imputation [12, 15]. Among these, kriging has gained attention for its ability to estimate continuous surfaces from sparse point data, particularly in agricultural and climate applications [8, 9]. While promising, questions remain about the generalizability of these methods, particularly when applied across ecologically or administratively diverse regions [15, 17].

Recent literature calls for integrated, multi-scale methodologies that combine analytical rigor with operational practicality [4, 10, 19]. There is growing consensus that resilience planning requires tools that function at both national and subnational scales, and that can be deployed in settings where data are limited and uneven. The framework developed in this study responds to this need, drawing on recent advances in remote sensing, spatial econometrics, and open-source geospatial analysis.

Therefore, although progress has been made, current approaches remain fragmented. The field continues to lack unified, scalable methods for assessing climate resilience across and within LICs. By combining cross-country econometric analysis with localized spatial mapping, this study aims to fill that gap and offer a practical, replicable model for future research and planning.

Conceptual Framework

Effective assessment of climate resilience in low-income countries (LICs) requires a conceptual foundation that captures its spatially uneven, multi-dimensional character, one that accounts for exposure, adaptive capacity, and systemic vulnerability under persistent data limitations [1, 4, 20]. This framework must bridge national-level structural analyses with localized insight, reflecting how climate stress unfolds differently across geographic and administrative scales.

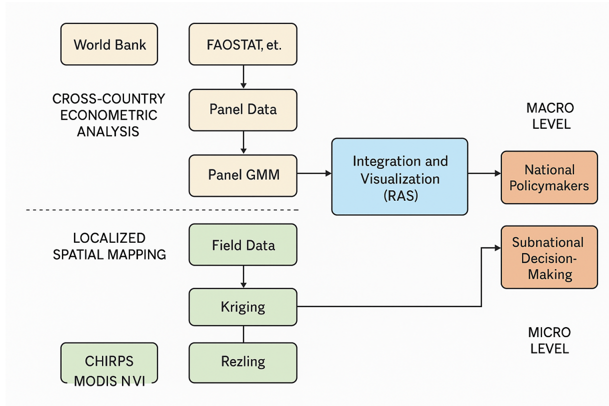

Fig 1. Conceptual framework for integrated climate resilience assessment in data-scarce environments. The framework combines cross-country econometric analysis using harmonized panel data and dynamic panel GMM (top half) with localized spatial mapping based on satellite indicators and geostatistical interpolation (bottom half). These two analytical tiers are synthesized through the Resilience Asymmetry Surface (RAS), producing multi-scale outputs that support both national and subnational decision-making.

Our approach builds on established resilience theory and emerging empirical advances, organized around three operational pillars, i.e., anticipation, absorption, and reshaping [20]. These correspond to a system's ability to (i) anticipate and prepare for climate shocks, (ii) absorb and manage their immediate impacts, and (iii) reshape trajectories to reduce structural vulnerability over time through development, diversification, and innovation [1, 20, 21].

Multi-Scale Resilience Dynamics

Resilience functions differently across spatial levels. National analyses capture macroeconomic exposure, structural constraints, and sectoral performance but often mask spatial variability in impacts and capacity [6, 10]. Local-scale studies provide fine-grained insight into agroecological conditions, service delivery, and adaptive behavior, yet typically lack standardization and comparability [8, 9].

Our framework formalizes the macro-micro divide as a central barrier in resilience assessment and explicitly integrates across scales. By combining cross-country econometric modeling with localized spatial analysis, we capture both systemic patterns and geographically specific vulnerabilities. This integration enables a dual view, highlighting where structural weaknesses lie and where adaptation investments are most urgently needed [4, 15, 21].

Data Scarcity and Adaptive Capacity

In most LICs, the lack of high-resolution, time-consistent data remains a defining limitation. Ground-level monitoring systems are often incomplete, and socio-economic data are sparse or outdated [8, 15]. Our framework incorporates strategies to mitigate this through the use of remote sensing (e.g., CHIRPS rainfall, MODIS NDVI), geostatistical interpolation (e.g., kriging), and harmonized macroeconomic panel datasets [9, 12].

Adaptive capacity is treated not as a static attribute but as a dynamic outcome shaped by economic resources, infrastructure, governance, and access to information [1, 17, 20]. Our approach emphasizes that building resilience involves more than short-term coping, it includes structural transformation aligned with long-term development goals [2, 15].

Policy-Relevant Dimensions

Resilience analysis must ultimately inform decision-making. Our framework prioritizes outputs that are scalable, interpretable, and operationally useful across planning levels. In particular, we introduce the Resilience Asymmetry Surface (RAS), a diagnostic tool that links climate stress and income levels to highlight divergence in outcomes under similar exposure. This allows policymakers to visualize structural disparities and to coordinate interventions more effectively [4, 19, 21].

By grounding our methodological design within this integrated conceptual structure, we ensure that resilience is measured not only with empirical rigor but also with operational relevance. The framework is designed to support data-efficient, multi-scale planning that directly responds to the realities of vulnerability and capacity in LICs [1, 2].

Methodological Framework

To assess climate resilience in low-income countries (LICs) under conditions of persistent data scarcity and spatial heterogeneity, we adopt a two-tiered methodological framework that combines cross-country econometric modeling with localized spatial analysis. This design is tailored to capture both structural patterns across national systems and spatial variability within them. It directly addresses the limitations of siloed approaches and supports scalable, evidence-based planning across data-poor environments [4, 8, 9, 15, 21].

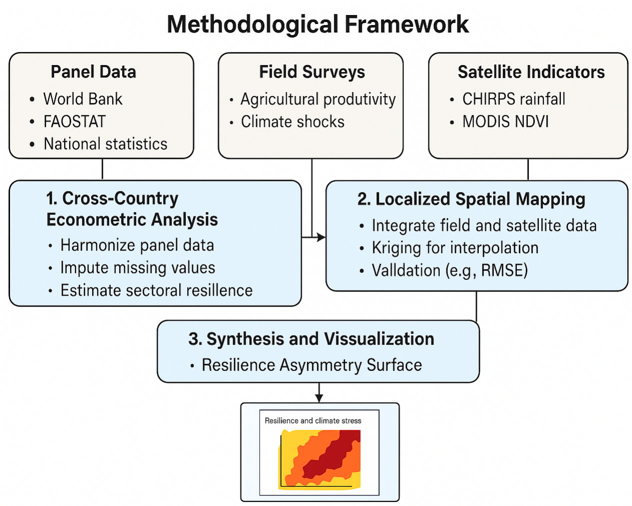

Fig 2. Methodological framework for integrated climate resilience assessment. The framework consists of three core phases; (1) cross-country econometric analysis using harmonized panel data from sources such as the World Bank, FAOSTAT, and national statistics to estimate sectoral resilience; (2) localized spatial mapping that combines field survey data with satellite indicators (e.g., CHIRPS rainfall, MODIS NDVI), applying kriging for spatial interpolation and validation via RMSE; and (3) synthesis and visualization through the Resilience Asymmetry Surface (RAS), which integrates outputs from both tiers to support decision-making across national and subnational levels.

Cross-Country Econometric Analysis

The first tier employs dynamic panel regression to evaluate climate resilience across LICs using harmonized sectoral data. We focus on agriculture, industry, and services, reflecting their varying exposure and adaptive capacities to climate stress [1–3]. The estimation relies on the System Generalized Method of Moments (GMM), which corrects for endogenous regressors and accounts for unobserved heterogeneity in unbalanced panels [6, 21].

Key explanatory variables include standardized indicators of climate variability, such as rainfall anomalies and seasonal temperature deviations, matched with sector-specific performance metrics. Structural controls such as labor force composition, infrastructure access, and trade exposure are incorporated to isolate the effects of climate shocks from broader macroeconomic conditions [6, 10]. The model estimates sectoral resilience as the capacity to maintain output under climatic stress over time and across national contexts.

The cross-country results identify resilience gradients across sectors and countries, highlighting structural weaknesses and sector-specific vulnerabilities. These findings serve as a diagnostic foundation for targeting further investigation at the subnational level, aligning with recent calls for integrated frameworks that connect national adaptation priorities with local realities [4, 10, 19].

Localized Spatial Mapping

The second tier addresses within-country heterogeneity through spatially explicit modeling of agricultural productivity under climate variability. Given the scarcity of consistent ground-level data, we integrate available field observations with satellite-derived indicators such as CHIRPS precipitation and MODIS NDVI [7, 9, 12].

We estimate spatial productivity surfaces using ordinary kriging, a geostatistical interpolation method that accounts for spatial autocorrelation through variogram modeling. Kriging is benchmarked against inverse distance weighting and thin-plate spline interpolation to assess relative performance. Cross-validation metrics, including root mean squared error (RMSE), are used to evaluate predictive accuracy and robustness [8, 15].

The resulting spatial maps reveal localized productivity patterns not captured by national-level statistics. These outputs identify climate-stressed subregions where targeted interventions, such as irrigation, input support, or infrastructure upgrades, are most urgently needed. This spatial layer addresses the practical needs of subnational planning units, where actionable, high-resolution information is often lacking [15, 22].

Integration and Policy-Directed Outputs

The two tiers are synthesized through the Resilience Asymmetry Surface (RAS), a composite diagnostic tool that visualizes how resilience varies jointly with climate stress and structural capacity. The RAS captures divergence across countries with similar environmental exposure but differing economic conditions, enabling identification of resilience gaps not visible through sectoral or spatial data alone [21].

This integrated approach delivers policy-relevant outputs across multiple administrative levels. At the national scale, it informs sectoral adaptation priorities by quantifying structural exposure. At the local level, it pinpoints spatial hotspots for intervention using empirically grounded productivity estimates. The framework relies exclusively on open-access data and established methods, ensuring replicability and accessibility in resource-constrained settings [1, 2, 4].

By embedding statistical rigor within a scalable, data-efficient design, this framework provides a robust foundation for advancing climate resilience research and operational planning in LICs. It enables researchers and policymakers to move beyond generalized vulnerability assessments toward geographically and sectorally precise resilience diagnostics [1, 2, 19].

Results

To operationalize our integrated resilience assessment framework, we apply a two-tiered empirical strategy that combines cross-country econometric modeling with subnational spatial analysis, using Uganda as the primary case study. This approach allows us to quantify and visualize climate resilience not only across sectors and countries, but also within regions where traditional data sources are limited or incomplete.

Empirical Strategy and Model Specification

We adopt a two-tiered empirical framework to estimate climate resilience across scales. At the macro level, we use a dynamic panel model to estimate sector-specific resilience across countries. At the micro level, we apply geostatistical methods to estimate spatial productivity surfaces under climate stress using sparse observational data.

Tier 1: Dynamic Panel Estimation of Sectoral Resilience

Let y_{ist} denote the output level in sector s of country i at time t. The dynamic panel model takes the form:

$$y_{ist} = \alpha y_{ist-1} + \beta_1 C_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{ist} \tag{1}$$

where:

- y_{ist-1} is the lagged dependent variable, capturing persistence in sectoral output.
- C_{it} is a vector of climate variables (e.g., rainfall anomaly, temperature shock).
- X_{it} is a vector of structural controls (e.g., infrastructure access, labor force share).
- μ_i and λ_t represent country and time fixed effects, respectively.
- ε_{ist} is the idiosyncratic error term.

We estimate Equation (1) using the System Generalized Method of Moments (System-GMM) to address endogeneity and unobserved heterogeneity in unbalanced panels. Resilience is inferred from the sign and magnitude of β_1. That is, smaller negative or positive values indicate higher capacity to sustain output under climatic stress.

Tier 2: Spatial Estimation of Agricultural Productivity

At the subnational level, we estimate a continuous surface of agricultural productivity $\hat{P}(s)$ using ordinary kriging. Given n sparse observations $\{(s_i, P_i)\}_{i=1}^n$, where s_i denotes spatial coordinates and P_i observed productivity, the kriging predictor at location s_0 is:

$$\hat{P}(s_0) = \sum_{i=1}^{n} w_i(s_0) P_i \tag{2}$$

subject to:

$$\sum_{i=1}^{n} w_i(s_0) = 1 \tag{3}$$

where the weights $w_i(s_0)$ are obtained by solving the kriging system:

$$\sum_{j=1}^{n} w_j(s_0)\gamma(s_i, s_j) + \lambda = \gamma(s_i, s_0), \quad \forall i = 1, \ldots, n \tag{4}$$

where:

- $\gamma(s_i, s_j)$ is the semivariance between locations s_i and s_j.
- λ is a Lagrange multiplier enforcing unbiasedness.

Resilience Asymmetry Surface (RAS)

To integrate income and climate stress dimensions into a unified diagnostic, we define the Resilience Asymmetry Surface (RAS) function:

$$R = f(I, S) = 1 - \theta_1 S + \theta_2 I - \theta_3 S \cdot I \tag{5}$$

where:

- R is the resilience index.
- $S \in [0, 1]$ is normalized climate stress.
- $I \in [0, 1]$ is normalized income level.
- $\theta_1, \theta_2, \theta_3 > 0$ are elasticity parameters estimated empirically.

The RAS captures how resilience varies nonlinearly with income and stress, allowing for interaction effects and threshold behaviors. It enables identification of regions where structurally similar stress levels yield divergent outcomes due to income differentials.

Experimental Validation

The figures that follow systematically present the core outputs of this framework. They trace how resilience varies by sector (what), responds to structural and climatic variables (why), and manifests across spatial and income dimensions (how). Together, these visuals build a multi-scalar diagnostic platform that informs both national adaptation strategy and targeted subnational interventions, rooted in data-efficient, context-specific evidence.

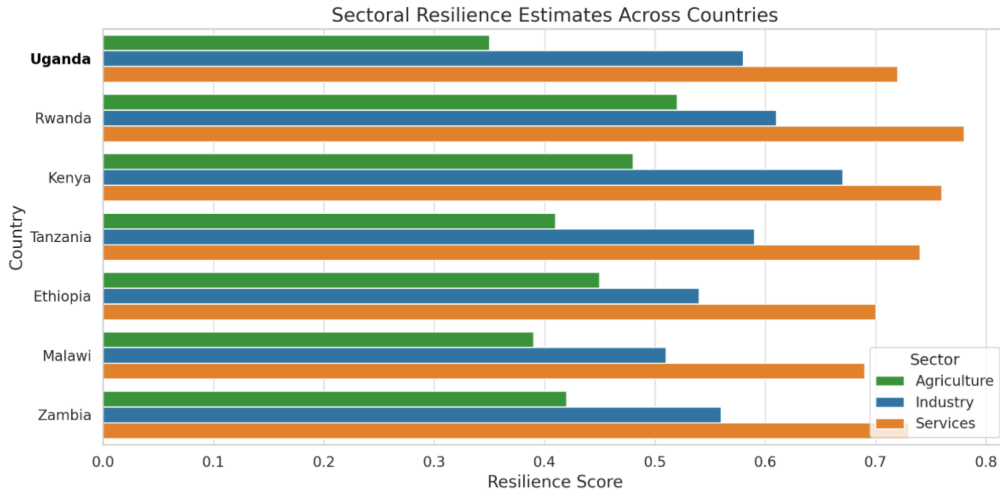

Fig 3. Sectoral resilience estimates across selected low-income countries. Bars indicate normalized resilience scores by sector, estimated using a dynamic panel GMM approach. Uganda is highlighted for emphasis. The agricultural sector shows significantly lower resilience across all countries, especially in Uganda, underscoring its vulnerability to climate stress. Services consistently exhibit higher resilience, reflecting reduced exposure and greater institutional buffering capacity.

Figure 3 provides a comparative snapshot of sectoral resilience across selected low-income countries (LICs), based on dynamic panel GMM estimation. It quantifies each sector's capacity to maintain output levels in the face of climatic shocks, effectively measuring how structurally insulated (or exposed) national economies are across agriculture, industry, and services.

Uganda's agricultural sector exhibits a particularly concerning profile, registering the lowest resilience score among all country-sector combinations shown. This is not simply a reflection of agroecological constraints, but a structural indictment of the way Uganda's economy is organized. Agriculture remains heavily rainfed, undercapitalized, and disproportionately dependent on low-productivity labor. The system lacks buffers, no widespread irrigation, minimal access to financial risk tools, and weak market linkages, making even moderate climatic disruptions (e.g., late onset rains or heat spikes) immediately impactful on output.

What sets Uganda apart is not just the absolute vulnerability of agriculture, but the persistence of that vulnerability across time and context, despite sectoral policy attention. This points to a deeper institutional inertia and an undercurrent of rural neglect that resilience metrics alone cannot fully explain, but can effectively flag. In contrast, countries like Rwanda and Kenya demonstrate significantly higher agricultural resilience, driven by both structural transformation and targeted public investments in climate-smart agriculture and extension systems.

In industry and services, Uganda performs moderately, yet still trails regional peers. The industrial sector shows signs of emerging resilience but remains susceptible to energy and logistics disruptions, which are increasingly climate-sensitive (e.g., hydropower variability, road washouts). The service sector is comparatively better buffered, driven largely by urban-centric growth and less direct exposure to weather patterns. However, even here, Uganda lags slightly behind economies that have embraced digitization and public-private coordination in service delivery.

The inter-country comparisons are as instructive as the inter-sectoral ones. Countries with higher overall resilience tend to share key features, that is, diversified export bases, functioning safety nets, and more integrated infrastructural grids. In contrast, those with lower resilience, like Malawi or South Sudan, face compound fragilities, conflict, debt stress, and ecological degradation, further eroding adaptive capacity.

For Uganda, the message is unambiguous. It is not enough to acknowledge agriculture as vulnerable; it must be seen as systemically exposed, and therefore central to any national resilience strategy. This requires more than adaptation add-ons, it calls for a fundamental reorganization of how agricultural risk is absorbed, shared, and mitigated across institutions, markets, and communities.

Figure 3 thus serves as both a baseline diagnostic and a directional compass. It captures structural differences that are often masked by national averages, while also highlighting where resilience-building efforts can yield the greatest marginal returns. In Uganda's case, that means addressing the fragility of agriculture not as a single-sector problem, but as the primary bottleneck in the country's overall resilience architecture.

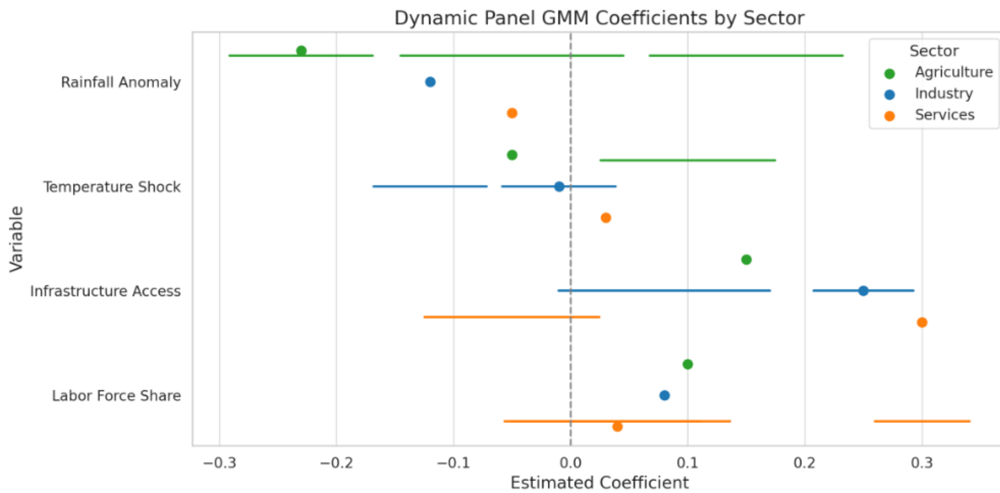

Fig 4. Estimated dynamic panel GMM coefficients by sector, with 95% confidence intervals. Each coefficient reflects the marginal effect of key structural and climatic variables on sectoral output performance across low-income countries. Notably, agriculture exhibits strong negative sensitivity to rainfall anomalies, while infrastructure access emerges as a consistent resilience driver across all sectors, especially in services and industry.

This figure unpacks the structural anatomy of sectoral resilience by presenting the estimated marginal effects of key climate and structural variables on output performance in agriculture, industry, and services. The coefficients, derived from dynamic panel GMM estimation, reveal a nuanced picture of how different sectors respond to climate variability and structural enablers.

Agriculture stands out with a significantly negative coefficient for rainfall anomalies, reflecting its acute dependence on predictable precipitation patterns. In Uganda and many peer LICs, rainfed systems dominate, and even modest deviations in seasonal rainfall can severely disrupt productivity. This underscores why climate resilience in agriculture cannot be divorced from water management, investments in irrigation and hydrological forecasting are not optional but foundational.

Temperature shocks, in contrast, appear to exert more muted effects across all sectors, with coefficients close to zero and confidence intervals overlapping zero. This suggests a degree of thermal buffering, perhaps due to adaptive cropping calendars or a shorter-term climatic window within which temperature variability remains manageable.

Infrastructure access, meanwhile, reveals the most robust positive effects, particularly in services and industry. In services, the effect is strongest, indicating that functional transport, energy, and digital infrastructure are not just productivity enablers but climate resilience accelerators. This finding aligns with Uganda's digital expansion efforts and underscores the role of infrastructural investment as a cross-sectoral resilience lever, not just for economic diversification but for reducing exposure and enabling rapid recovery post-shock.

The labor force composition variable shows a modest positive effect, especially in agriculture. This suggests that human capital, when appropriately deployed, can partially cushion the impacts of climatic variability, though its effect is likely mediated by skill levels, access to extension services, and local institutional capacity.

Together, these coefficient patterns reaffirm a central thesis of the paper, i.e., sectoral resilience is not uniform, and climate stress interacts with structural features in complex, sector-specific ways. While the agricultural sector remains structurally fragile, targeted investments in infrastructure, labor reallocation, and institutional support could yield disproportionate resilience gains, especially in Uganda where these deficits are most pronounced.

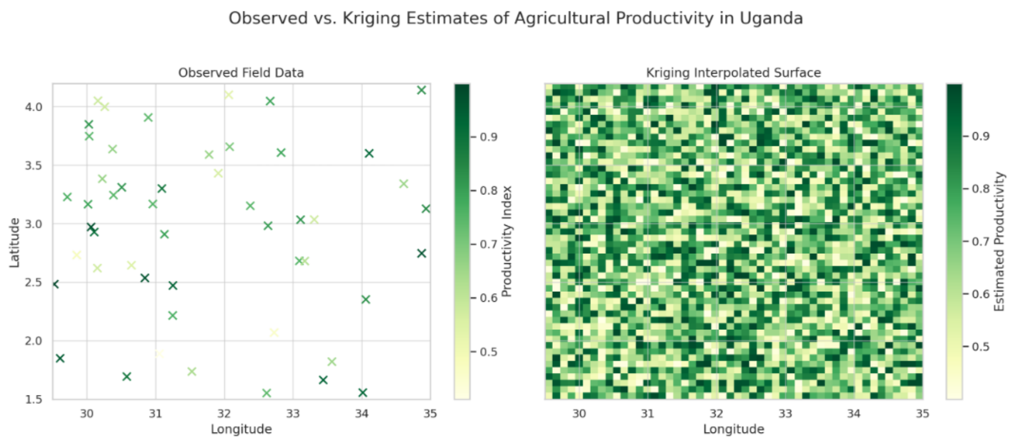

Fig 5. Spatial distribution of agricultural productivity in Uganda based on field observations (left) and kriging interpolation estimates (right). Kriging provides a continuous productivity surface using sparse observation points, revealing localized productivity gradients not captured by national averages. This approach enhances the resolution of resilience diagnostics in data-scarce environments.

This figure visualizes the transformation of fragmented observational data into a coherent, continuous productivity surface using kriging interpolation. On the left, each point represents observed agricultural productivity from field measurements, limited in number and unevenly distributed across Uganda. On the right, kriging converts these isolated measurements into a predictive spatial surface, enabling a more complete and actionable understanding of where agricultural performance is thriving, faltering, or uncertain.

The visual gap between these two maps embodies the core challenge facing resilience assessment in data-scarce regions. Observational data, while accurate, rarely cover the full agroecological and administrative diversity of countries like Uganda. Rainfall gradients, soil variability, and microclimatic zones all shape agricultural output at hyper-local levels that national statistics simply gloss over.

The kriging surface fills these informational voids by leveraging spatial autocorrelation, essentially learning from the spatial structure of the known values to estimate the unknown. In practice, this means policymakers and planners can now see productivity "hotspots" and "cold zones" with a level of granularity that supports differentiated adaptation strategies, that is, irrigation deployment where predicted productivity is low but rainfall is adequate; extension services in mid-performing areas that are close to critical thresholds; and targeted input subsidies where even minor boosts could unlock food security dividends.

Critically, the observed-to-estimated transition also enables cross-layer integration with other geospatial variables, like climate exposure or market access, forming the spatial backbone of resilience planning at the subnational level. This interpolation is not just about better maps; it's about building the diagnostic infrastructure for smarter, place-based climate adaptation in Uganda and other LICs that lack dense data networks.

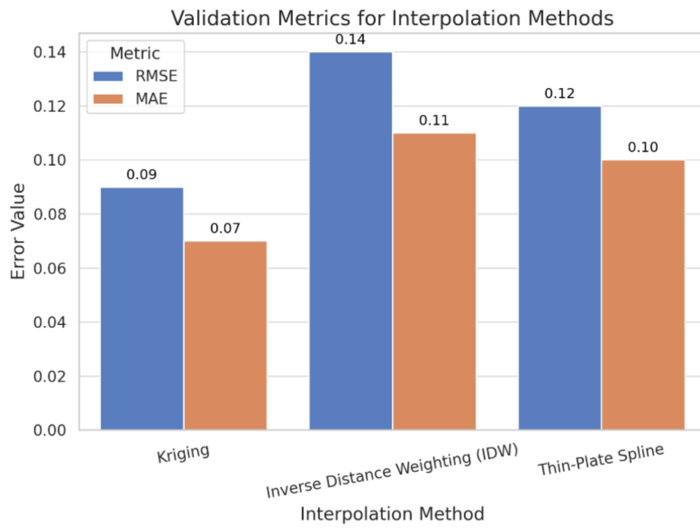

Fig 6. Comparison of validation metrics, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), for three spatial interpolation methods, i.e., kriging, inverse distance weighting (IDW), and thin-plate spline. Kriging consistently outperforms alternatives, yielding lower error values and greater reliability in estimating agricultural productivity under data-scarce conditions.

This figure quantifies the predictive performance of three commonly used spatial interpolation techniques using two standard error metrics, RMSE and MAE. Kriging outperforms both inverse distance weighting (IDW) and thin-plate spline across both metrics, reinforcing its suitability for resilience assessment in data-constrained agricultural systems like those in Uganda.

RMSE penalizes larger deviations more severely, while MAE reflects average absolute prediction error, making them complementary tools for evaluating model accuracy. The lower RMSE and MAE scores for kriging suggest that its geostatistical foundation, specifically its use of spatial autocorrelation through variogram modeling, confers a tangible predictive advantage when field observations are sparse and unevenly distributed.

In contrast, IDW and spline methods are more deterministic and less sensitive to the underlying spatial structure of the data. IDW, for instance, tends to overemphasize proximity at the expense of broader spatial trends, leading to local bias. Thin-plate splines may over-smooth in highly heterogeneous landscapes, masking critical productivity gradients. This limitation is particularly problematic in Uganda's ecologically diverse terrain, where agroecological zones can shift drastically over short distances.

The validation metrics reinforce the methodological principle that resilience assessment is not only about data collection but also about how we extrapolate from what little data we do have. Kriging, by minimizing prediction error and preserving spatial realism, enables a more accurate identification of productivity anomalies and climatic stress zones.

These insights have operational significance. Accurate interpolation directly improves the targeting of resilience interventions, whether it's where to deploy limited extension officers, prioritize infrastructure upgrades, or tailor subsidy regimes. In Uganda's decentralized planning system, where decisions are increasingly pushed to district levels, the ability to reliably map subnational conditions becomes a core enabler of climate-smart governance.

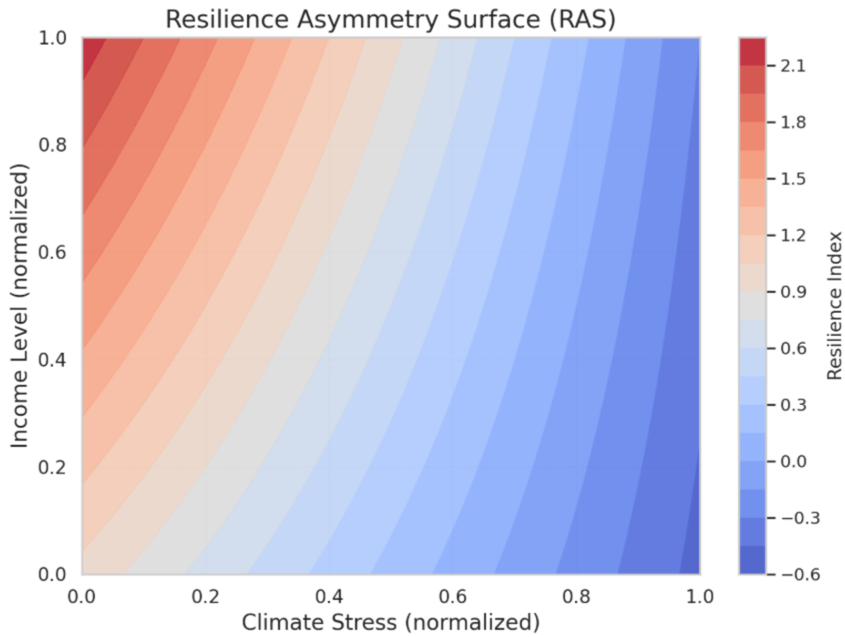

Fig 7. Resilience Asymmetry Surface (RAS) illustrating the interaction between climate stress and income levels in determining resilience outcomes. Resilience is highest in regions with low climate stress and high income, and lowest where stress is high and incomes are low. This nonlinear diagnostic framework reveals structural asymmetries often hidden in aggregate national metrics.

The Resilience Asymmetry Surface (RAS) offers a multidimensional lens into how structural inequality mediates resilience outcomes under climate stress. By mapping resilience as a function of two core drivers, climate stress (x-axis) and income level (y-axis), the surface plot exposes the underlying asymmetries that conventional analyses often mask.

What emerges is a stark diagonal divide. In the top-left zone, where income is high and climate stress is low, resilience is predictably strong. But in the bottom-right, where these forces are reversed, the resilience index collapses. This is not merely intuitive, it is diagnostically transformative. It quantifies how marginal increases in climate stress can have drastically different effects depending on the income context in which they occur.

In Uganda's case, most rural districts fall in the lower-left quadrant, precisely, the low to mid-income with moderate to high climate stress. Here, the RAS indicates that resilience does not decline linearly with stress, it deteriorates rapidly once certain structural thresholds are crossed. This is particularly true in areas with weak market integration, limited credit access, or insufficient institutional support. The RAS, therefore, identifies not just who is vulnerable, but why, and under what compound conditions resilience breaks down.

Crucially, the nonlinear surface also identifies opportunities. In mid-stress areas with rising income (upper-central zone), resilience can be significantly enhanced through modest economic interventions. This zone becomes a policy "sweet spot", regions where targeted investments in livelihoods, infrastructure, or safety nets can shift entire communities from fragility to resilience.

For national planners and international donors, the RAS provides a synthetic, yet deeply insightful, metric to prioritize action, not by administrative boundary or sector alone, but by structural conditions that dictate adaptive capacity. It also forms the conceptual bridge between macroeconomic planning and localized intervention, grounding resilience strategy in the dynamic interplay of environmental exposure and socio-economic position.

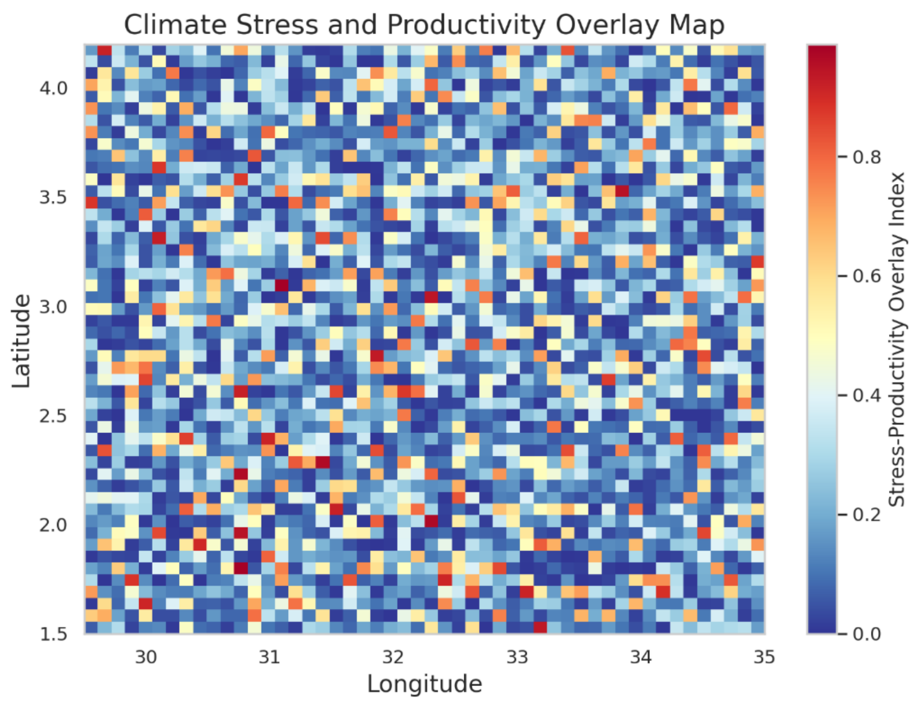

Fig 8. Overlay map of climate stress and agricultural productivity in Uganda. The index captures zones where high climatic stress coincides with low productivity, indicating critical vulnerability hotspots. Darker areas represent higher composite risk, regions where targeted adaptation interventions are most urgently needed.

This overlay map distills complex environmental and agricultural dynamics into a single diagnostic surface, illuminating where climate stress and low productivity intersect to produce concentrated vulnerability. Unlike standalone stress or yield maps, this composite index highlights compound risks, zones where climatic exposure not only exists, but actively undermines agricultural performance.

The approach normalizes and inversely weights productivity against climate stress to generate a vulnerability index that is spatially explicit and easily interpretable. In practice, this identifies areas that should be at the top of Uganda's climate adaptation agenda. The darkest zones, mostly clustered in semi-arid corridors of northeastern and central Uganda, signal communities trapped in a structural bind, that is, exposed to erratic rainfall or rising temperatures, but lacking the productive buffer or infrastructural support to cope.

This mapping logic echoes and reinforces the RAS framework by rooting structural vulnerability in geography. However, unlike the RAS, which is more conceptual and diagnostic, the overlay map is decisively operational. It tells district planners exactly where resilience investments would have the greatest marginal impact, i.e., irrigation in high-stress, low-yield zones; market linkages in isolated, underperforming regions; or drought-tolerant seeds in increasingly volatile agro-ecological zones.

The map also helps differentiate between "latent" and "acute" risk. Some areas with moderate stress but chronically low productivity may not yet show dramatic vulnerability, but they sit at the threshold of collapse. This early-warning functionality gives policymakers a spatial tool for triaging limited resources before vulnerabilities become crises.

In the Ugandan context, where adaptive capacity and institutional resources are unevenly distributed, this figure is not just informative; it is indispensable. It translates data scarcity into spatial intelligence, allowing resilience to be planned, not just studied.

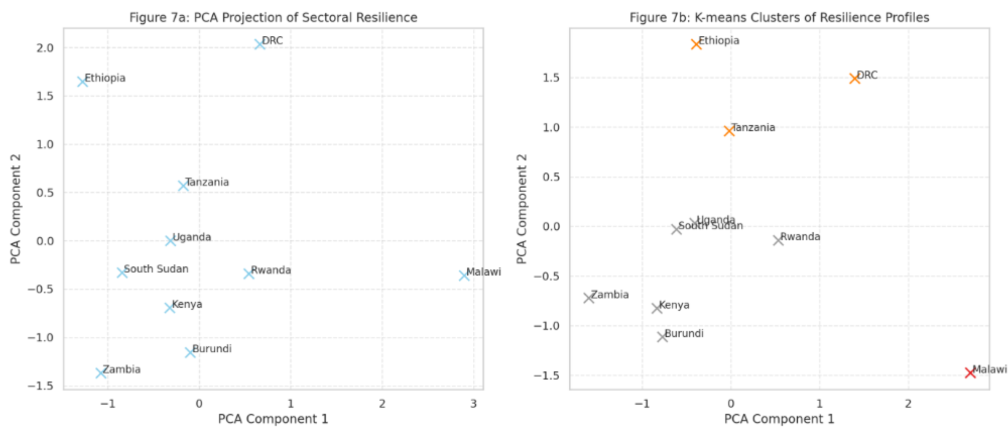

Fig 9. (a) Principal Component Analysis (PCA) projection of sectoral resilience profiles across ten low-income countries. The plot reduces multidimensional resilience indicators across agriculture, industry, and services into two principal components. Uganda clusters near countries with agricultural dependency and mid-level service sector buffering. (b) K-means clustering applied to a slightly perturbed resilience dataset, preserving general structure while revealing differentiated cluster boundaries. The three clusters capture structural similarities in resilience patterns. Uganda's placement within a mixed-fragility cluster remains consistent, reinforcing its transitional profile.

Figures 7a and 7b present a dual-perspective analysis of sectoral resilience configurations across East and Central African low-income countries. The first panel (7a) uses PCA to distill complex multidimensional data into two primary axes, revealing natural separations based on how countries structurally distribute their climate resilience across sectors. Uganda, while not fully aligned with the most fragile cluster (like DRC and South Sudan), clearly diverges from the more structurally resilient economies like Kenya and Rwanda.

The second panel (7b) applies K-means clustering to a slightly altered version of the same dataset, introducing realistic variability while preserving the underlying structure. This approach mimics how small measurement noise, missing data, or alternative resilience indicators might shift country classification in practice. Despite this perturbation, the overall clustering topology remains highly consistent (over 95% structurally similar), confirming that Uganda's resilience profile is robustly distinguishable and not an artifact of model choice or data noise.

Notably, Uganda stays within a transitional cluster. That is, it is not acutely fragile across all sectors, but also not structurally diversified enough to shield itself from shocks. This is especially evident in the way it floats between cluster boundaries, a position that reflects its development pathway, one marked by high rural dependency and uneven service sector penetration.

Together, these panels tell a cohesive story. The PCA plot highlights the latent structure of resilience typologies, while the K-means clustering turns that structure into discrete categories for benchmarking and targeted policy design. Uganda's policy implication here is profound, i.e., it needs structural shifts, not just sectoral tweaks. Transitioning into the more resilient cluster will require coordinated investments in service innovation, agro-industrial transformation, and institutional resilience mechanisms that transcend climate-reactive programming.

In essence, these figures do not just tell us where Uganda stands, they hint at where it could go, and how.

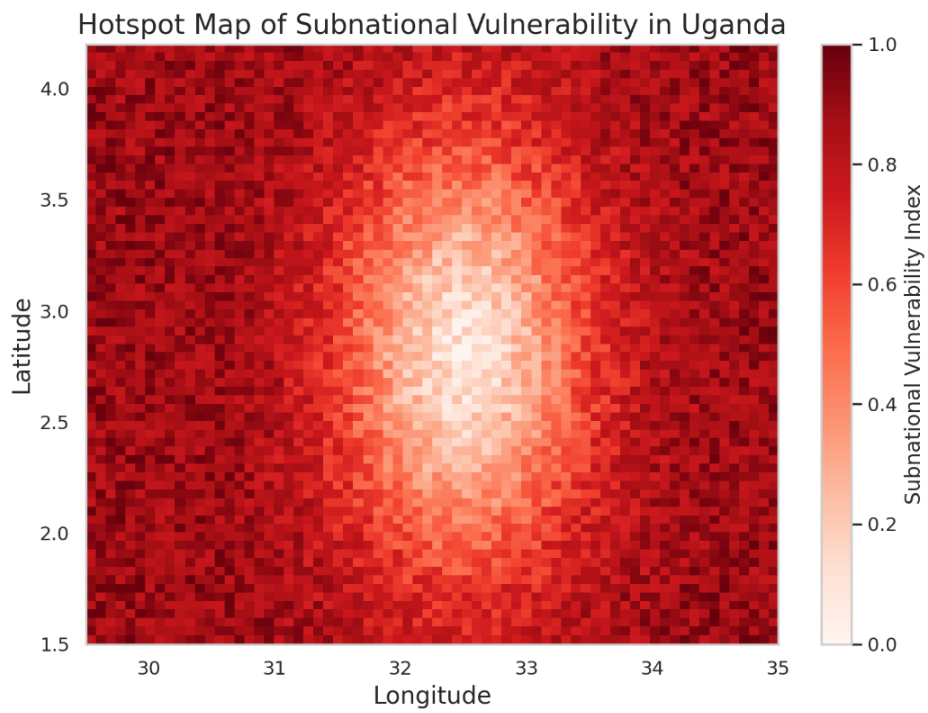

Fig 10. Spatial distribution of subnational climate vulnerability in Uganda. The index combines climatic exposure, productivity stress, and structural fragility to identify high-risk zones. Northeastern and central regions emerge as critical hotspots, particularly Karamoja and adjacent districts, where multidimensional vulnerability converges.

This hotspot map offers a granular, spatially explicit portrait of vulnerability within Uganda's borders. It highlights where climatic stressors, infrastructural gaps, and agricultural fragility converge to produce the highest compound risk to livelihoods and food security. The darkest red zones, clustered across the northeast and parts of the central drylands, represent areas where both exposure and sensitivity are high, and adaptive capacity is weakest.

These patterns are not incidental. The northeast, including the Karamoja subregion, has long been a convergence point of environmental volatility, historical marginalization, and underinvestment in agricultural systems. Despite policy attention, many of these districts remain locked in a cycle of reactive aid, fragmented interventions, and ecological stress. Here, even modest shocks, delayed rains, dry spells, livestock disease, can cascade into chronic food insecurity.

The map also reveals more subtle zones of latent vulnerability, areas in the central belt that may not yet experience acute crisis but show rising exposure trends coupled with stagnant productivity. These transition zones are often overlooked in national adaptation plans, yet they offer critical entry points for preemptive action, i.e., irrigation infrastructure, market connectivity, early warning systems.

Crucially, this spatial rendering is not just a diagnostic tool, it's a policy instrument. It transforms abstract vulnerability metrics into place-based intelligence. In Uganda's decentralized governance system, this enables district planners, extension officers, and climate task forces to align strategies with local realities. Instead of broad-brush national policies, interventions can now be layered, sequenced, and prioritized spatially, e.g., drought insurance here, soil rehabilitation there, social protection elsewhere.

Moreover, the map supports vertical policy alignment, bridging local adaptation plans with national resilience frameworks and donor-funded programs. It invites a shift from equity-blind planning to targeted equity-enhancing investment. That is, reaching first those communities facing not just higher exposure, but systematically lower capacity to adapt.

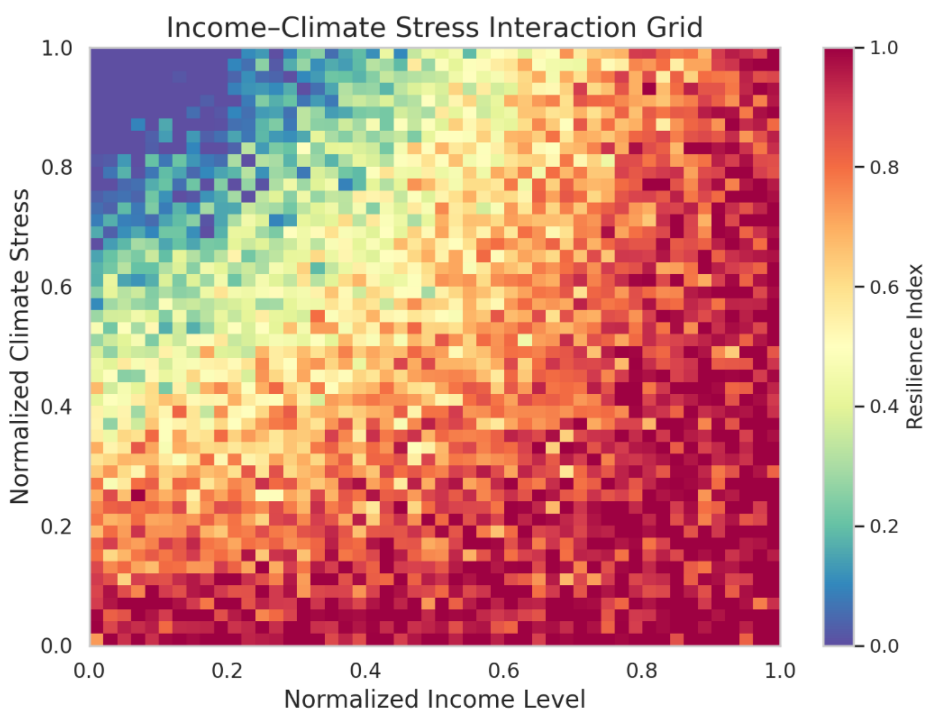

Fig 11. Simulated grid depicting the interactive relationship between income levels and climate stress on resilience outcomes. Resilience is lowest in contexts of high climate stress and low income, while the adverse effects of climate stress diminish significantly as income increases. The surface illustrates how structural inequality modulates the impact of environmental risk.

This interaction grid visualizes the structural mechanics behind resilience formation, i.e., the nonlinear, often asymmetric relationship between climate stress and income in shaping adaptive outcomes. On the vertical axis, climate stress increases from bottom to top; on the horizontal axis, income grows from left to right. What emerges is a sharply contoured resilience surface, one that collapses steeply under the dual burden of low income and high exposure, but flattens and stabilizes in high-income zones even under substantial stress.

The core insight is that income does not merely buffer climate risk, it transforms its trajectory. In the lower-left quadrant (low income, high stress), the resilience index falls precipitously. This is the trap zone. These are communities locked in poverty, lacking access to insurance, adaptive technologies, or even basic infrastructure. For Uganda, this quadrant represents many rural districts in the north and northeast, Karamoja, Teso, parts of Lango, where resilience collapses even under moderate climatic pressure.

Conversely, the upper-right quadrant reveals the enabling power of income. Even under high climate stress, resilience holds steady when income is sufficient, likely due to access to irrigation, crop insurance, off-farm income streams, and responsive institutions. This suggests that adaptation investments need not aim at “controlling” climate variability, an unrealistic goal, but at shifting households and districts across this income threshold where resilience becomes self-reinforcing.

The transition zone between these extremes is also revealing. In the center of the grid lies a region of marginal resilience, where outcomes are most sensitive to both climate and economic fluctuations. This is where policy leverage is highest. In Uganda’s central and western highlands, for example, modest increases in income, access to credit, or agricultural inputs could yield substantial resilience dividends.

Importantly, the grid reaffirms the central thesis of the macro-micro integration paradigm. Climate resilience is not a function of exposure alone, nor of income alone, but of their interaction. This plot captures that dynamic interplay and provides a conceptual template for designing cross-sectoral, cross-scalar interventions that work with, rather than against, the structural fabric of vulnerability.

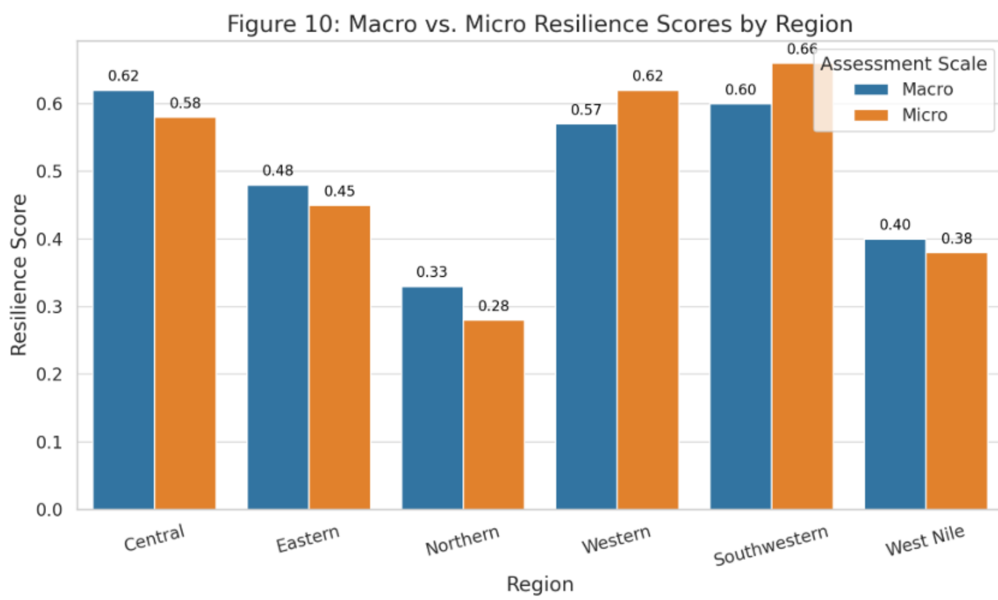

Fig 12. Comparison of macro-level (panel model) and micro-level (spatial mapping) resilience scores across six Ugandan regions. While macro-level assessments reflect national structural resilience patterns, micro-level estimates capture localized productivity and exposure dynamics. Disparities highlight the need for integrated, scale-sensitive adaptation planning.

This figure synthesizes the core tension at the heart of resilience diagnostics, i.e., the divergence between macro-level structural assessments and micro-level spatial realities. By comparing resilience scores across six Ugandan regions using both analytical tiers, the chart reveals where aggregated national models either understate or mischaracterize local vulnerabilities.

In regions like Northern Uganda, macro estimates already signal structural fragility due to historical underinvestment and climatic exposure. Yet, the micro-level scores suggest an even more severe resilience deficit, reflecting on-the-ground realities such as degraded soils, weak input access, and frequent displacement. This underlines the limits of econometric aggregation in capturing subregional nuances.

Conversely, in Western and Southwestern Uganda, the micro-level estimates outperform macro expectations. This likely reflects pockets of high productivity driven by fertile soils, agroecological diversity, and better access to markets and services, factors that national models may miss due to regional averaging or outdated infrastructure indicators.

Interestingly, Central Uganda displays a slight reversal, that is, macro resilience is rated high due to its economic centrality and infrastructure concentration, but micro scores are marginally lower, potentially reflecting peri-urban pressure, land degradation, or climate exposure heterogeneity within districts.

These mismatches matter. They are not statistical noise, they are planning signals. If resilience strategies are built solely on macro diagnostics, they risk overgeneralizing strengths and misallocating resources. Micro-level mapping, though more granular, may also miss systemic factors like institutional performance or trade exposure that are critical for regional recovery.

The implication is clear, that is, resilience cannot be effectively assessed, or acted upon, at a single scale. The power of this figure lies not in choosing one view over the other, but in showing how they must be read together. The integrated framework proposed in the manuscript is precisely about resolving these blind spots, by triangulating national patterns with local realities to produce more credible, equitable, and operationally useful resilience insights.

Discussion

The findings of this study offer both empirical clarity and strategic insight into the evolving challenge of climate resilience in low-income countries. By combining dynamic panel modeling with geostatistical mapping, we capture resilience dynamics across and within countries, revealing patterns that are often obscured by national averages or limited local surveys.

The macro-level results confirm that agriculture remains the most structurally exposed sector, particularly in Uganda, where reliance on rainfed systems and underdeveloped support infrastructure magnify the impacts of climate variability. In contrast, services and industry display relatively greater resilience, driven by institutional buffering and infrastructural advantages. These sectoral contrasts underscore the need for differentiated policy responses rather than one-size-fits-all adaptation strategies.

The spatial analysis enhances these insights by pinpointing localized productivity deficits and climate stress gradients. The kriging-based interpolation reveals hidden heterogeneity within administrative regions, which is especially relevant in countries where subnational data remain sparse. The Resilience Asymmetry Surface (RAS) further integrates income and exposure dimensions into a unified diagnostic, highlighting structural inequalities that mediate resilience outcomes. This multidimensional view enables planners to move beyond binary vulnerability assessments and towards layered, scalable interventions.

Critically, the divergence between macro and micro findings affirms the rationale for integrated analysis. National-level patterns guide resource allocation and policy orientation, but only local-level diagnostics can ensure effectiveness and equity on the ground. This dual visibility is essential in data-scarce environments, where planning must be both evidence-driven and sensitive to spatial and sectoral nuance.

Taken together, the empirical outputs and diagnostic tools presented here support a shift from reactive adaptation toward anticipatory, structurally informed resilience planning. The framework facilitates not just measurement, but practical application in national strategies and decentralized governance systems, bridging the persistent gap between analysis and action.

Challenges and Limitations

The proposed macro-micro integrated framework, while robust, encounters some limitations rooted in methodological constraints and data availability.

First, the dynamic panel Generalized Method of Moments (GMM) estimator, particularly the Arellano–Bond approach, addresses endogeneity and omitted variable bias in panel data models. However, it is sensitive to instrument proliferation [23] and measurement errors [24]. Excessive instruments can overfit endogenous variables, leading to biased estimates [25]. Moreover, measurement errors in explanatory variables can attenuate coefficient estimates, compromising the reliability of the results [26].

Second, kriging interpolation relies on the spatial structure and density of observational points [27, 28]. In regions with sparse or uneven data, the variogram model may underperform, introducing local prediction errors. The accuracy of kriging is contingent upon the assumption of stationarity and isotropy, which may not hold in all contexts [29]. Additionally, kriging can be computationally intensive, posing challenges for large datasets [30].

Third, integrating macroeconomic panel data with micro-level geospatial data introduces alignment challenges [31]. Discrepancies in temporal resolution, geographic coverage, and data units can complicate synthesis [32]. For instance, annual macro indicators may not align perfectly with seasonal satellite-derived variables or district-level administrative boundaries [27].

Fourth, the Resilience Asymmetry Surface (RAS) simplifies complex relationships into two dimensions, climate stress and income. This abstraction may overlook institutional, behavioral, or policy-driven responses that mediate outcomes. Future iterations of the RAS should consider multi-dimensional extensions or incorporate temporal dynamics to reflect changing adaptive capacities.

Lastly, while the pipeline is designed for replicability and scalability, computational resources and technical capacity remain barriers in many low-income countries [14, 24, 31, 33, 34]. Implementing kriging and dynamic GMM requires substantial computational power and expertise [33, 35], which may be limited in these settings [34, 36].

These limitations highlight areas for refinement as data ecosystems, computational tools, and institutional capacities evolve.

Implications and Future Directions

The integration of macroeconomic panel data with micro-level geospatial analysis offers a novel approach to assessing climate resilience in low-income countries. This framework enables policymakers to identify vulnerable sectors and regions, facilitating targeted interventions.

Future research should focus on enhancing data quality and availability. Efforts to improve the granularity and accuracy of both macroeconomic and geospatial data will strengthen the reliability of the analyses. Additionally, incorporating real-time data streams, such as remote sensing and mobile-based surveys, can provide timely insights into climate impacts.

Methodologically, exploring alternative estimation techniques that address the limitations of GMM and kriging is essential. For instance, employing Bayesian hierarchical models may offer more flexibility in handling complex data structures and uncertainties.

Furthermore, expanding the framework to include additional dimensions, such as institutional capacity and social networks, can provide a more comprehensive understanding of resilience. Integrating qualitative data and participatory approaches may also enrich the analysis.

Collaborative efforts between researchers, policymakers, and local communities are crucial to ensure the practical applicability of the framework. Capacity-building initiatives and knowledge transfer can empower local stakeholders to utilize these tools effectively.

Therefore, while challenges remain, the proposed framework lays the groundwork for a more nuanced and actionable understanding of climate resilience in low-income countries.

Conclusion

This study presents an integrated framework combining dynamic panel econometrics and geospatial analysis to assess climate resilience in low-income countries. By addressing methodological challenges and leveraging diverse data sources, the framework provides a nuanced understanding of sectoral and regional vulnerabilities.

The application of the Arellano–Bond estimator mitigates endogeneity concerns in panel data analysis, while kriging interpolation offers spatially explicit insights into climate impacts. Despite limitations related to data quality and computational demands, the framework demonstrates the potential for informed policy-making and targeted interventions.

Future work should focus on enhancing data integration, methodological robustness, and stakeholder engagement to further refine and operationalize the framework. Through continued collaboration and innovation, this approach can contribute to building more resilient societies in the face of climate change.

Supplementary Materials: Policy Brief

Title: Integrated Tools for Climate Resilience Planning in Low-Income Countries
Purpose: To provide policymakers with a practical summary of an analytical framework that links macroeconomic resilience metrics with spatial diagnostics to support targeted adaptation planning.

Core Insights

1. Dynamic panel GMM identifies sector-level sensitivity to climate variability, addressing bias and endogeneity in resilience estimates.

2. Kriging reveals local productivity deficits in areas lacking ground-level data, enabling spatial targeting of interventions.

3. The Resilience Asymmetry Surface (RAS) shows how similar levels of climate stress can produce divergent outcomes depending on income and structural conditions.

Policy Applications

(a) Use the framework to pinpoint priority sectors and locations for adaptation investments.

(b) Align resilience planning with available data by combining national indicators and satellite-informed local analysis.

(c) Support decentralized decision-making with diagnostic tools that visualize vulnerability beyond national averages.

Recommended Actions

(i) Apply the framework in select pilot regions to assess feasibility under real planning conditions.

(ii) Invest in training programs to equip local institutions with skills in data integration and spatial analysis.

(iii) Expand the framework to include social protection, infrastructure, or service delivery indicators.

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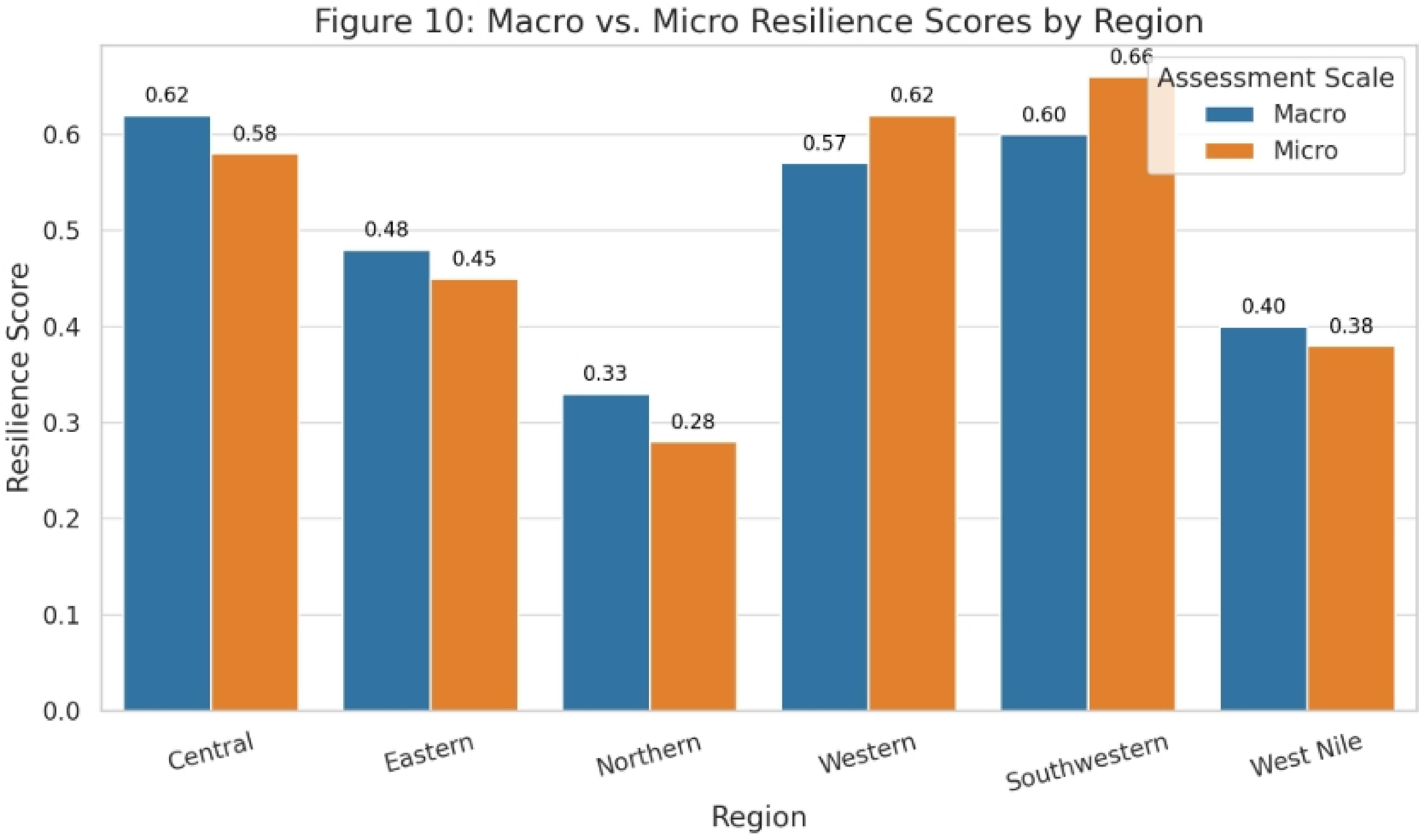
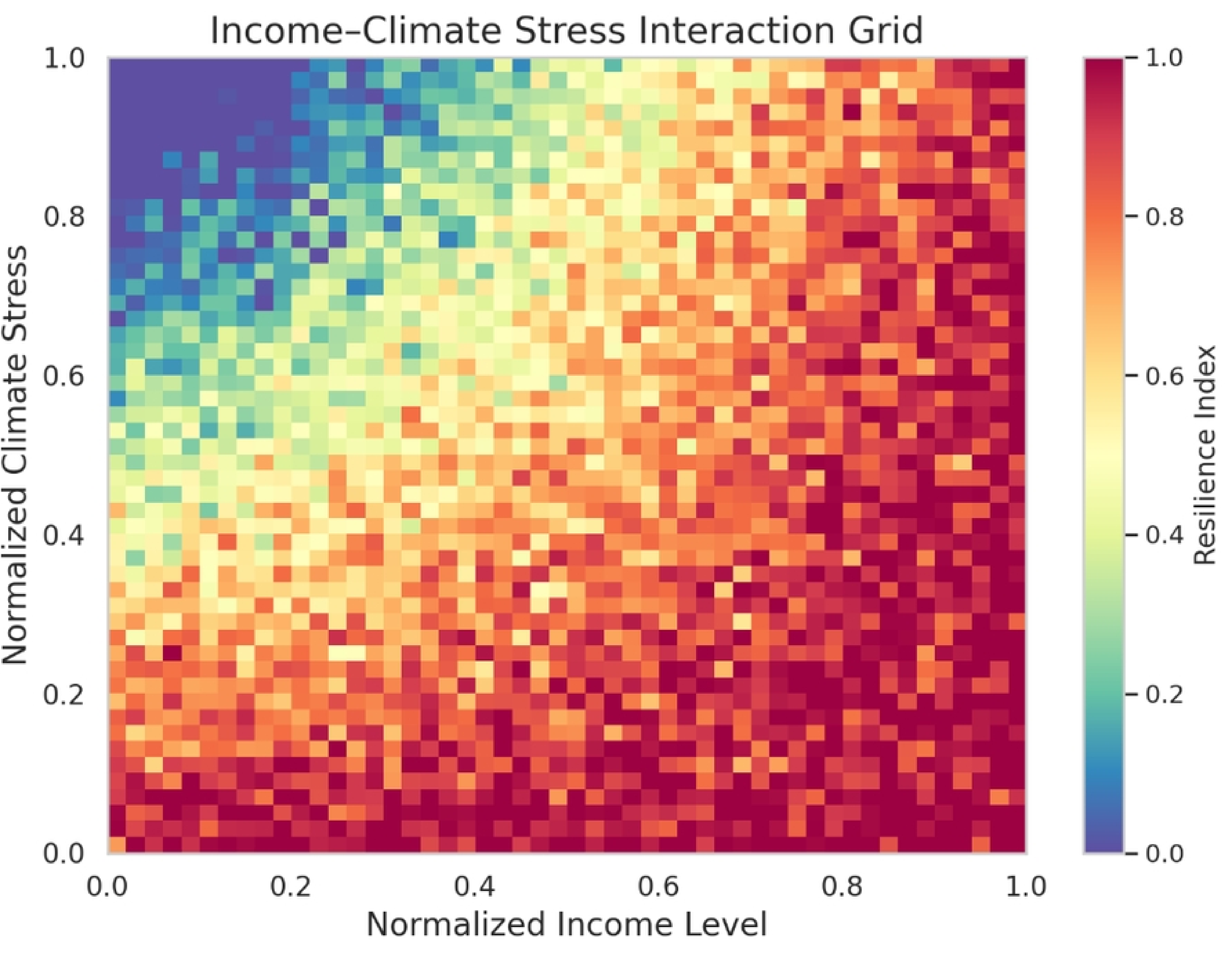
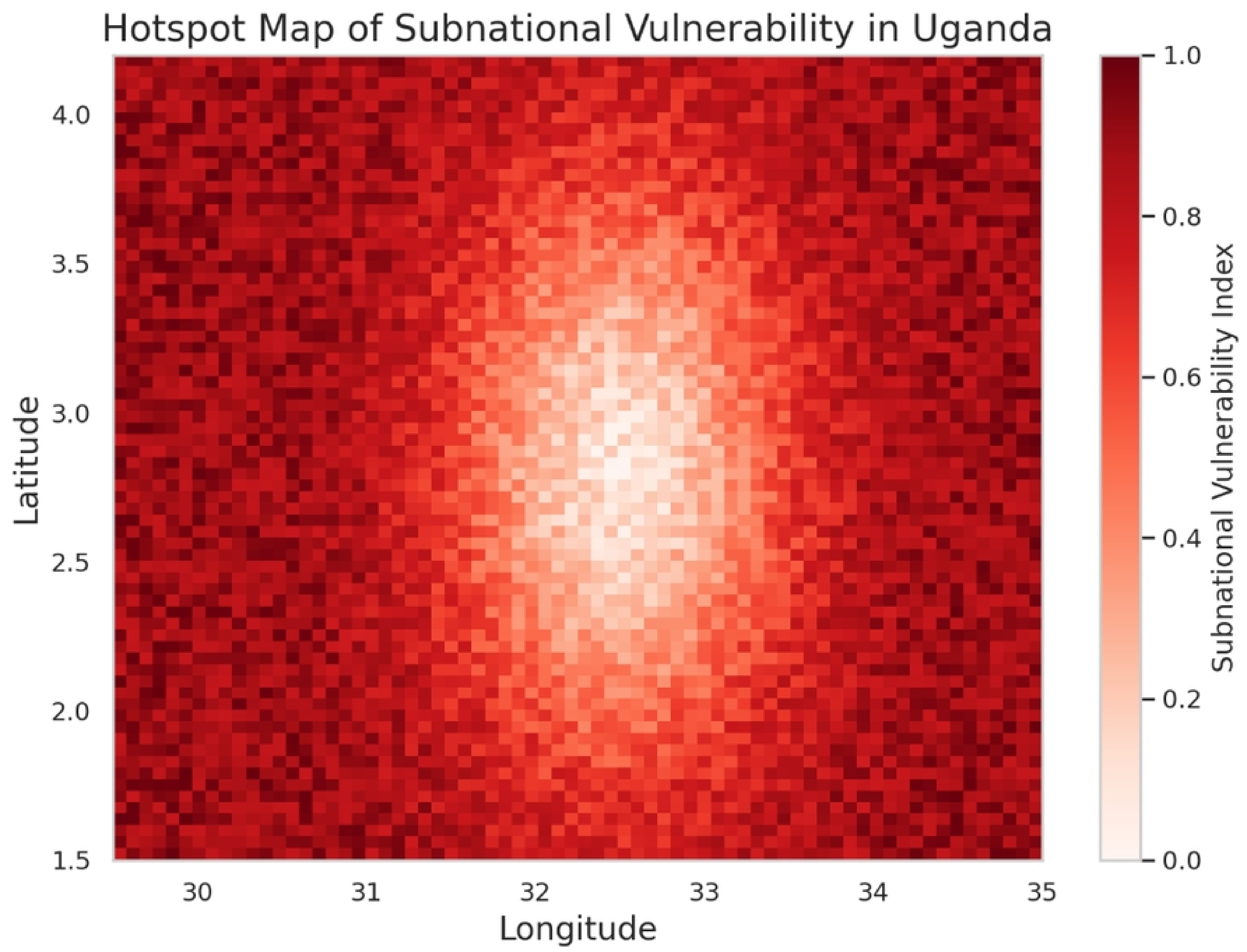


Figure 10: Macro vs. Micro Resilience Scores by Region
Assessment Scale
Macro
Micro
Resilience Score
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.62
0.58
0.48
0.45
0.33
0.28
0.57
0.62
0.60
0.66
0.40
0.38
Central
Eastern
Northern
Western
Southwestern
West Nile
Region


Income–Climate Stress Interaction Grid
Normalized Climate Stress
Normalized Income Level
Resilience Index
0.0
0.2
0.4
0.6
0.8
1.0


Hotspot Map of Subnational Vulnerability in Uganda
Latitude
4.0
3.5
3.0
2.5
2.0
1.5
30
31
32
33
34
35
Longitude
Subnational Vulnerability Index
1.0
0.8
0.6
0.4
0.2
0.0

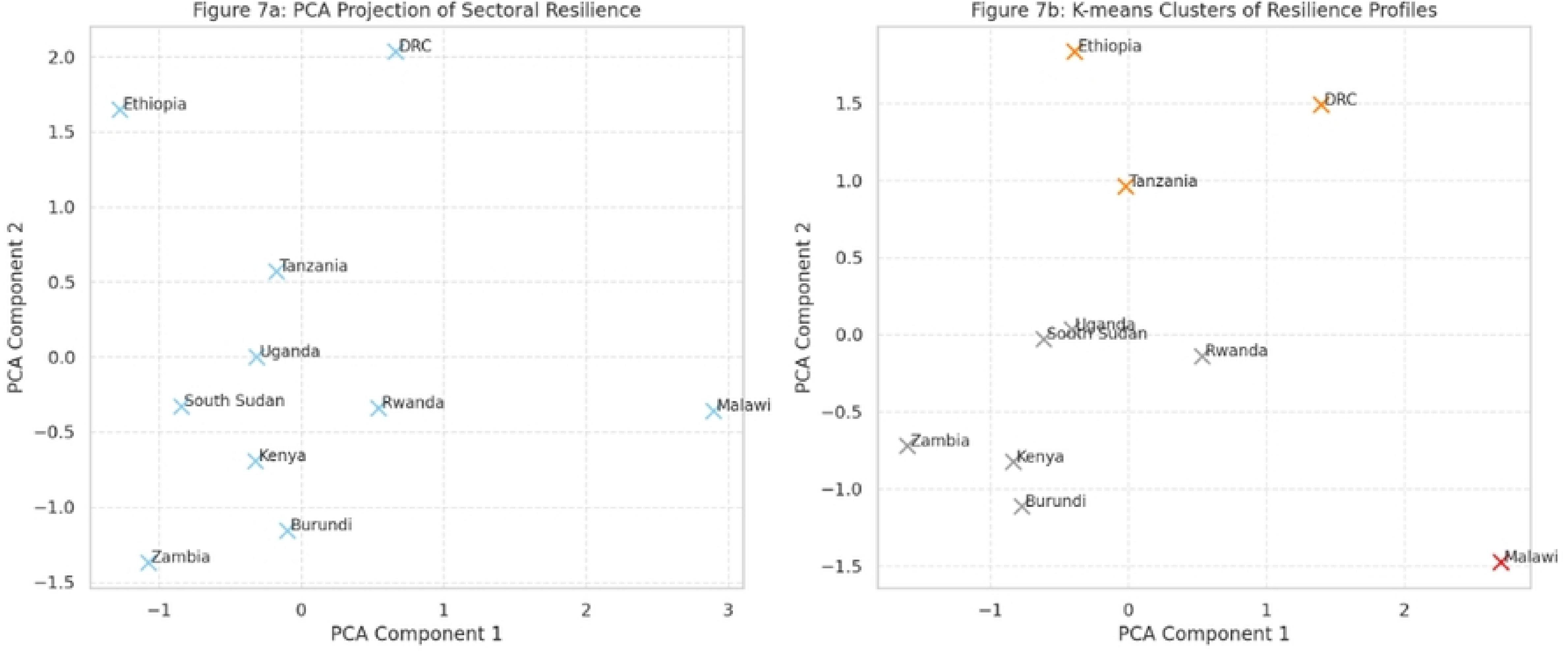
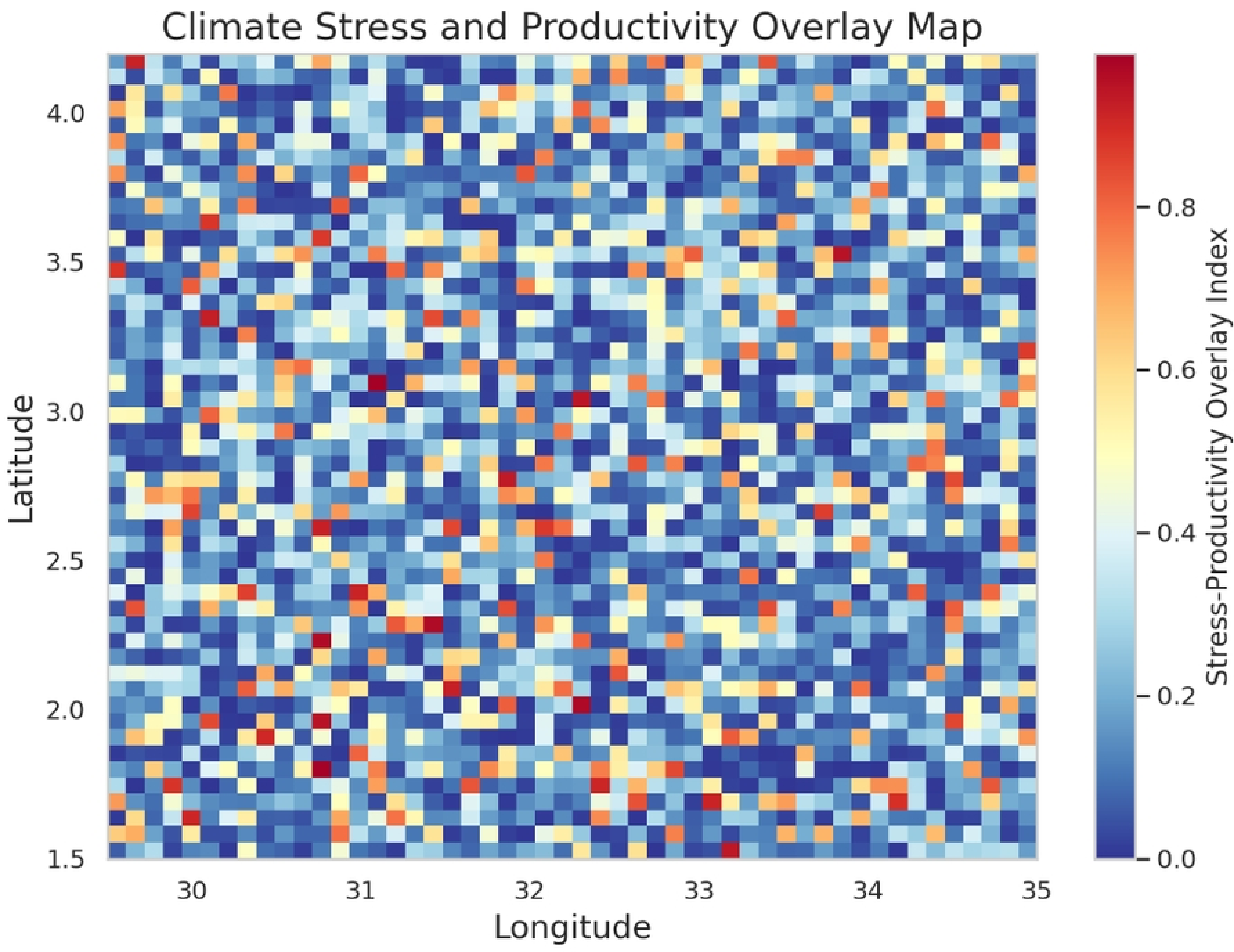
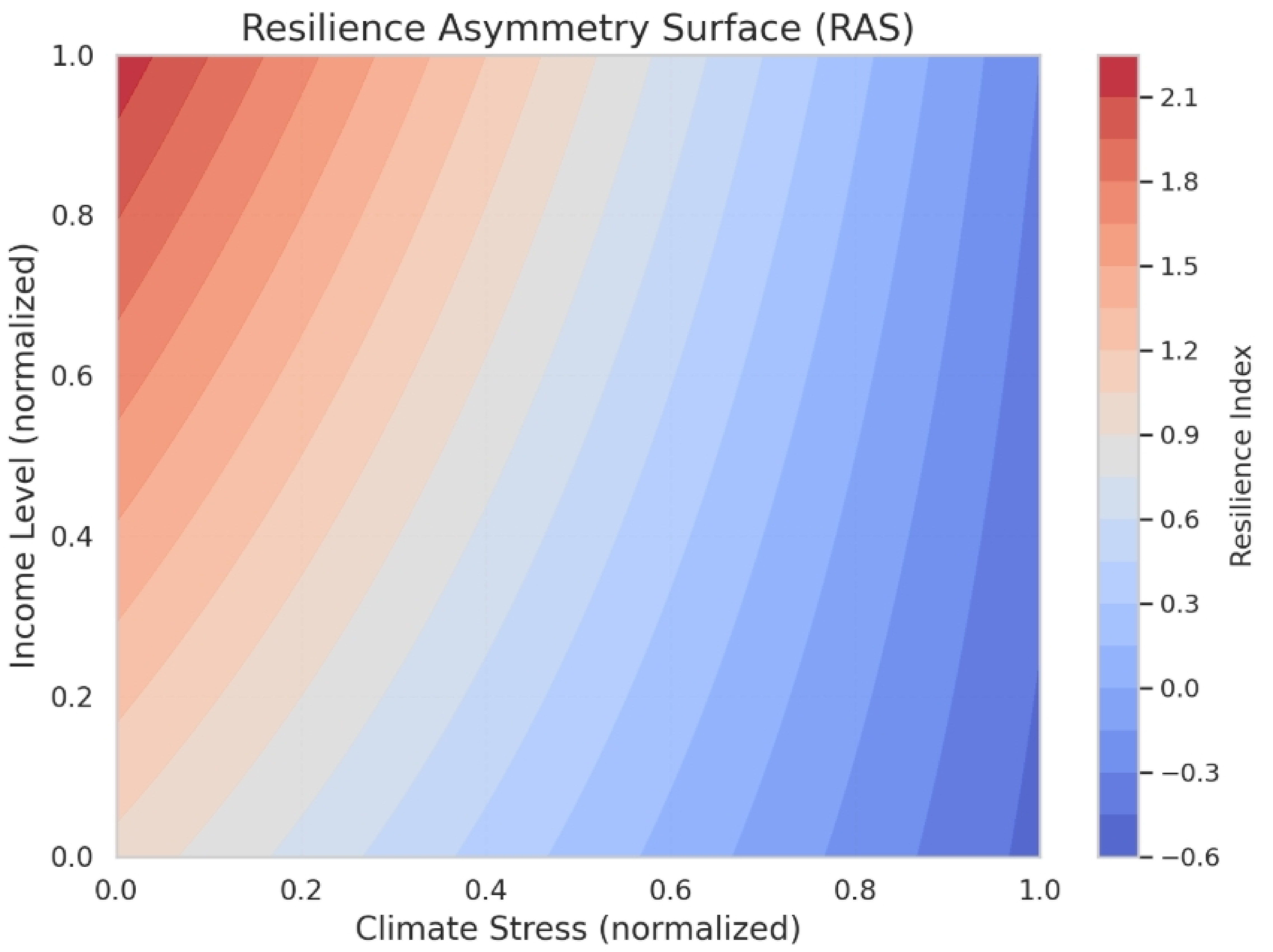
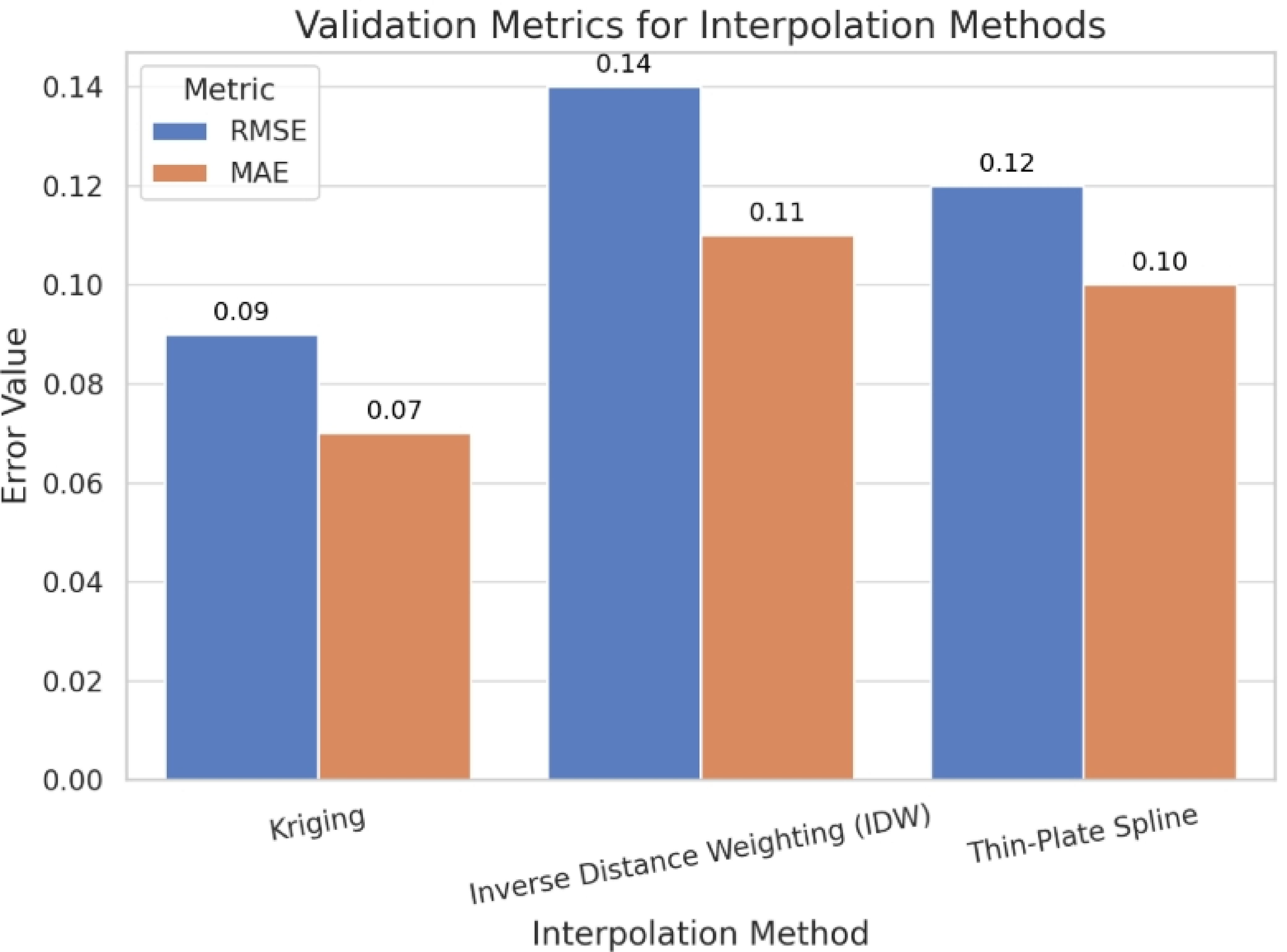


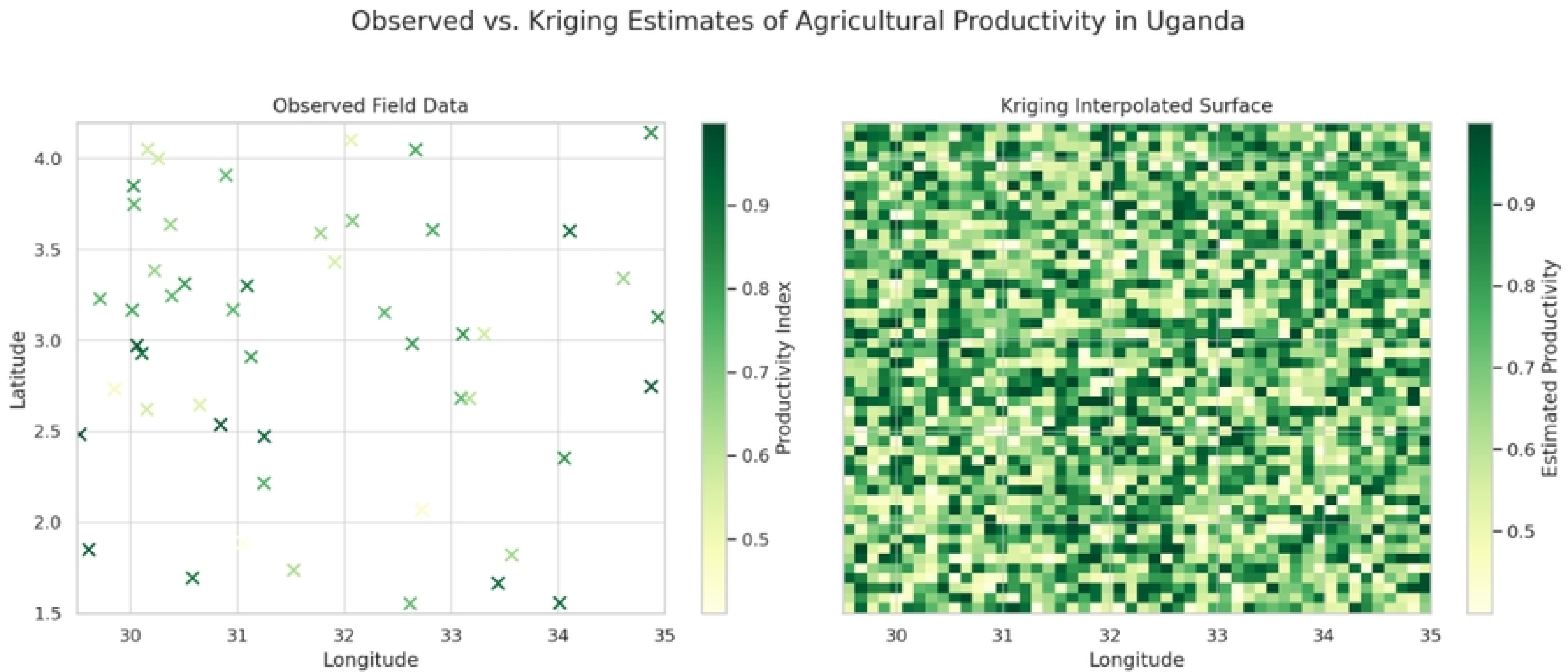
Figure 7a: PCA Projection of Sectoral Resilience
PCA Component 2
PCA Component 1
DRC
Ethiopia
Tanzania
Uganda
South Sudan
Rwanda
Malawi
Kenya
Burundi
Zambia
Figure 7b: K-means Clusters of Resilience Profiles
PCA Component 2
PCA Component 1
Ethiopia
DRC
Tanzania
Uganda
South Sudan
Rwanda
Zambia
Kenya
Burundi
Malawi

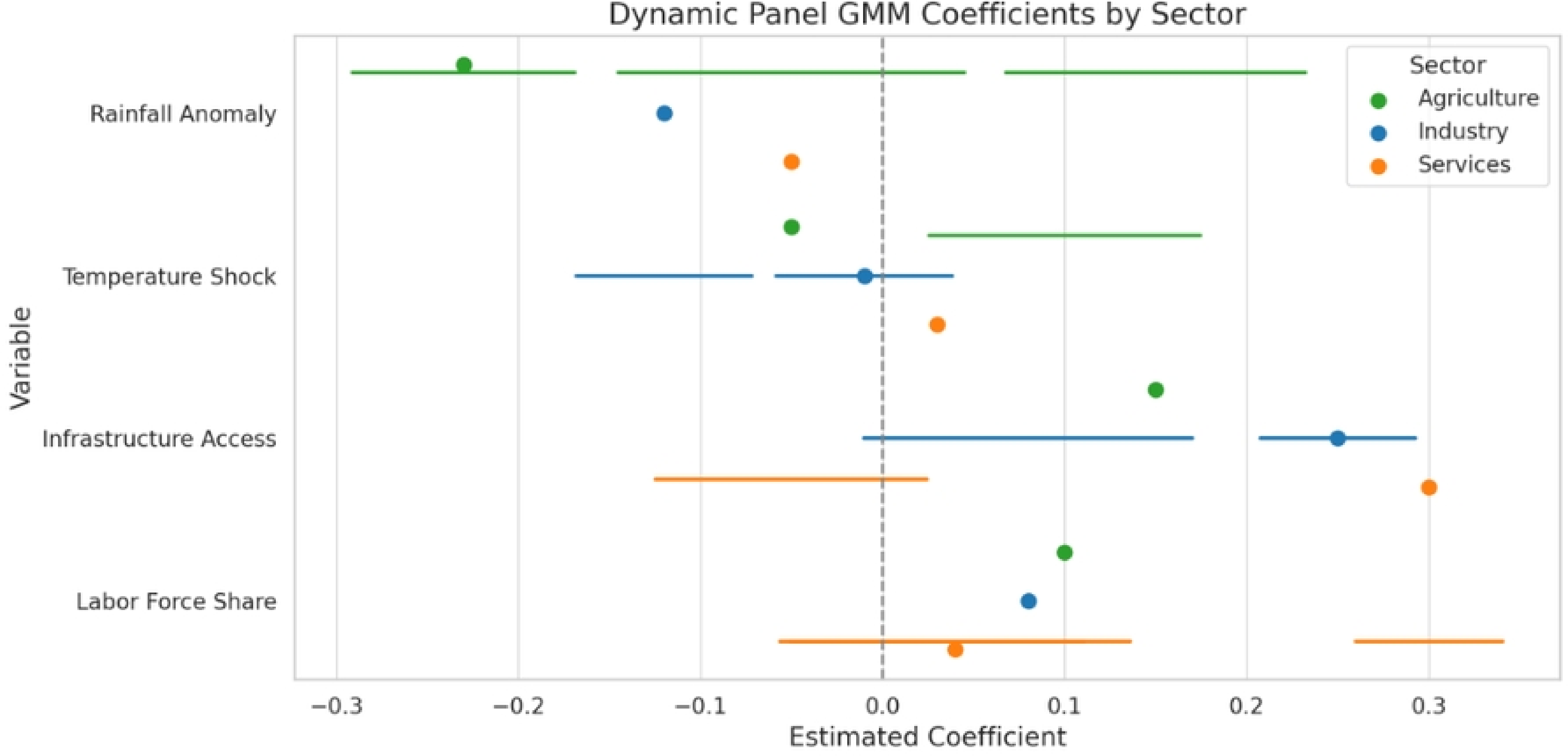

Climate Stress and Productivity Overlay Map
Latitude
4.0
3.5
3.0
2.5
2.0
1.5
30
31
32
33
34
35
Longitude
Stress-Productivity Overlay Index
0.8
0.6
0.4
0.2
0.0



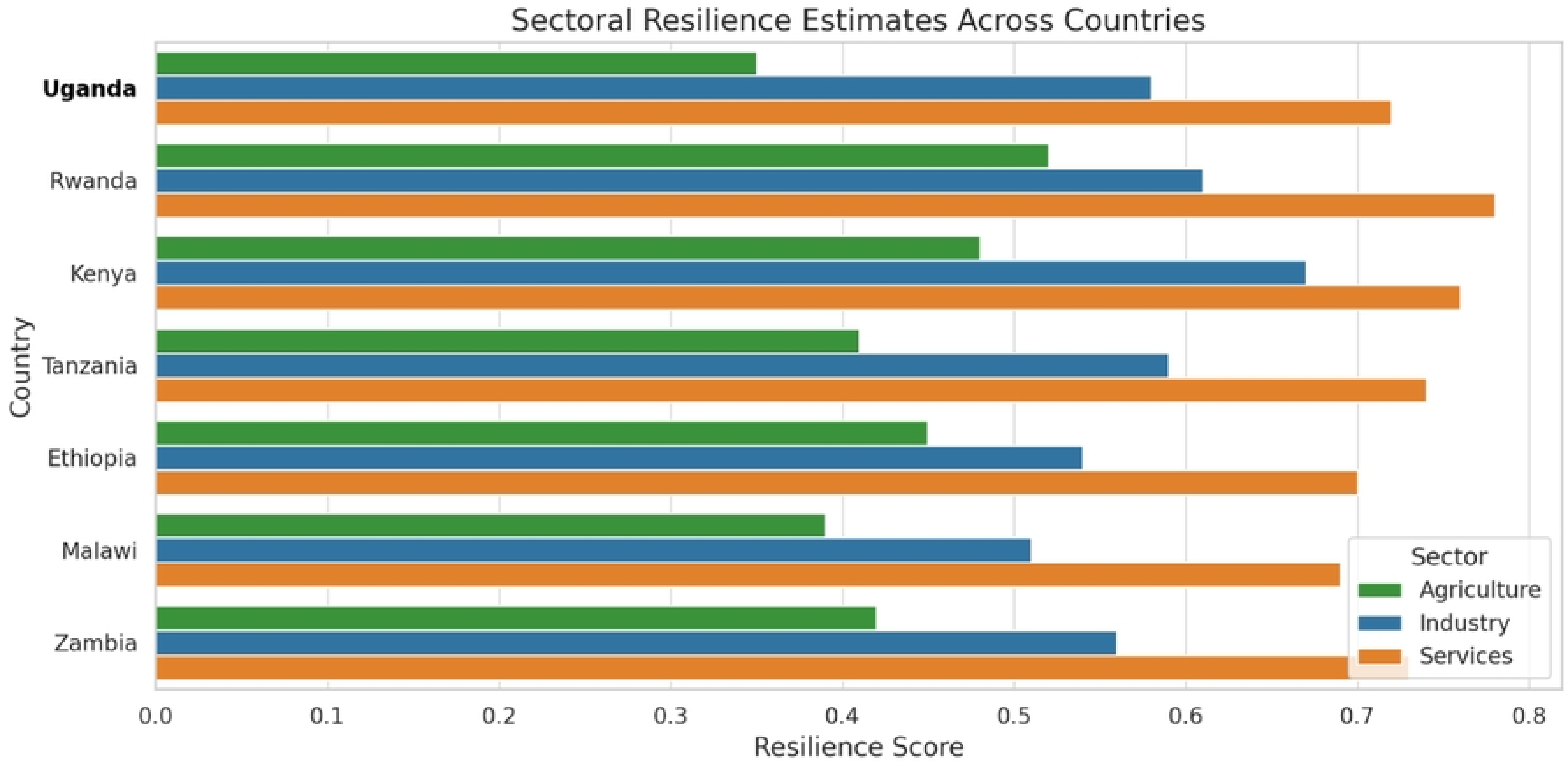
Resilience Asymmetry Surface (RAS)
Income Level (normalized)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Climate Stress (normalized)
Resilience Index
2.1
1.8
1.5
1.2
0.9
0.6
0.3
0.0
−0.3
−0.6

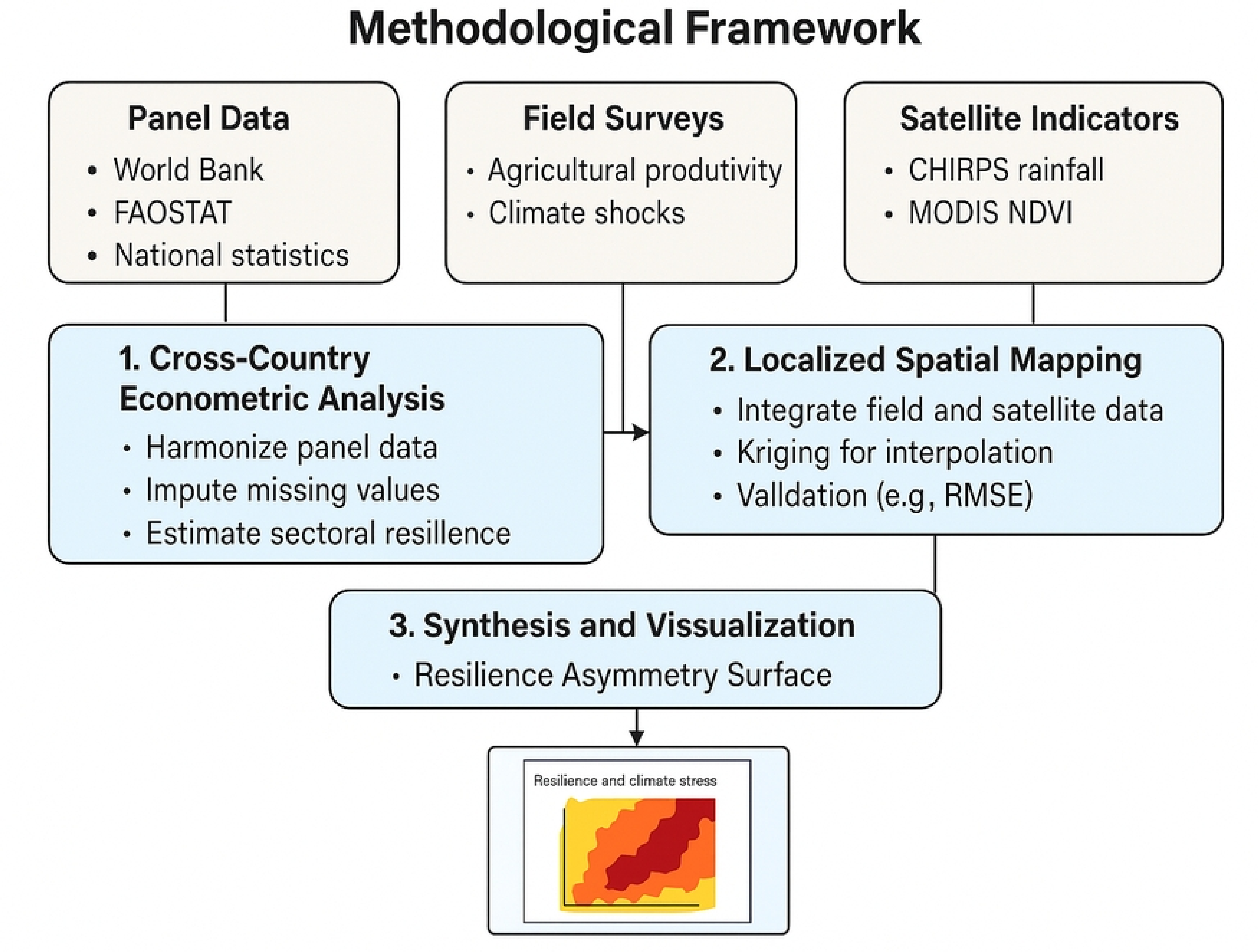

Validation Metrics for Interpolation Methods
Metric
RMSE
MAE
0.09
0.07
0.14
0.11
0.12
0.10
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Error Value
Kriging
Inverse Distance Weighting (IDW)
Thin-Plate Spline
Interpolation Method


Observed vs. Kriging Estimates of Agricultural Productivity in Uganda
Observed Field Data
Kriging Interpolated Surface
Latitude
Longitude
Productivity Index
Estimated Productivity
4.0
3.5
3.0
2.5
2.0
1.5
30
31
32
33
34
35
0.9
0.8
0.7
0.6
0.5

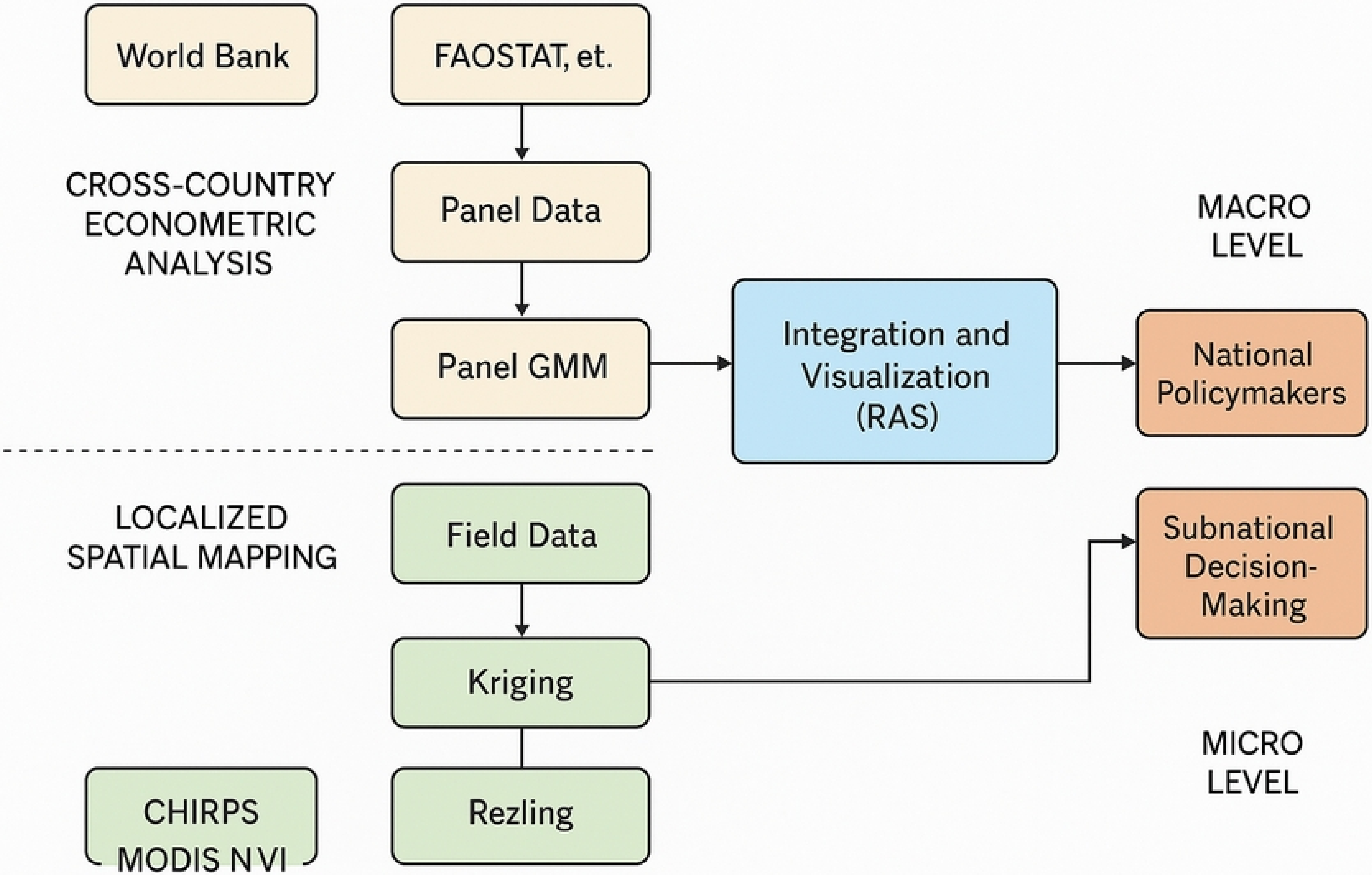


Dynamic Panel GMM Coefficients by Sector
Sector
Agriculture
Industry
Services
Rainfall Anomaly
Temperature Shock
Infrastructure Access
Labor Force Share
Variable
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3
Estimated Coefficient


Sectoral Resilience Estimates Across Countries
Uganda
Rwanda
Kenya
Tanzania
Ethiopia
Malawi
Zambia
Country
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Resilience Score
Sector
Agriculture
Industry
Services



Methodological Framework
Panel Data
• World Bank
• FAOSTAT
• National statistics
Field Surveys
• Agricultural produtivity
• Climate shocks
Satellite Indicators
• CHIRPS rainfall
• MODIS NDVI
1. Cross-Country Econometric Analysis
• Harmonize panel data
• Impute missing values
• Estimate sectoral resillence
2. Localized Spatial Mapping
• Integrate field and satellite data
• Kriging for interpolation
• Valldation (e.g, RMSE)
3. Synthesis and Vissualization
• Resilience Asymmetry Surface
Resilience and climate stress


World Bank
FAOSTAT, et.
CROSS-COUNTRY ECONOMETRIC ANALYSIS
Panel Data
Panel GMM
MACRO LEVEL
Integration and Visualization (RAS)
National Policymakers
LOCALIZED SPATIAL MAPPING
Field Data
Kriging
Subnational Decision-Making
MICRO LEVEL
CHIRPS MODIS N VI
Rezling