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From complementarities to constraints: stratified adoption pathways and equity in Kenyan smallholder systems – A Bayesian-Ising diagnostic

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ABSTRACT

Climate-smart agriculture (CSA) is promoted as a key strategy for enhancing food security and resilience in Kenya, yet adoption remains uneven across gender and agroecological strata. Conventional adoption studies struggle to diagnose the root causes of these disparities. We introduce a Bayesian-Ising framework that unifies the analysis of simultaneous practice interactions and sequential adoption pathways under an intersectional lens, using survey data from 569 smallholders in Western Kenya. Three key findings emerge. First, complementarities are stratified, not universal. The pooled Ising network shows negative interactions between soil management (CSA1) and resilient crops (CSA3: $\hat{J} = -0.385$, 95% CI −0.577 to −0.199) and between CSA1 and agroforestry (CSA4: $\hat{J} = -0.324$, −0.486 to −0.141). Strong positive complementarities are concentrated in Male-Headed Households in the Upper-Midland Zone (MHH-UMZ: CSA4-CSA5 $\hat{J} = 0.686$, 0.250–1.151; CSA5-CSA6 $\hat{J} = 0.524$, 0.031–1.090). In Female-Headed Households in the Lower-Midland Zones (FHH-LMZ), the strongest edge is a negative interaction between water harvesting (CSA2) and energy efficiency (CSA5: $\hat{J} = -0.727$, −1.386 to −0.203). Second, sequential analysis reveals distinct directed pathways. For FHH-LMZ, the only directed edge is CSA2 → CSA5, yet these practices are antagonistic. For MHH-LMZ, directed edges are CSA1 → CSA3 and CSA1 → CSA6, also with negative interactions. For MHH-UMZ, a self-reinforcing chain CSA3 → CSA4 → CSA5 → CSA6 aligns with positive complementarities. Cumulative probability of reaching CSA4 through the modeled sequence is 0.039 (0.024–0.059) for FHH-LMZ, 0.035 (0.026–0.045) for MHH-LMZ, and 0.056 (0.032–0.091) for MHH-UMZ – a disparity of about 1.6-fold between the most and least advantaged strata. The Intersectional Adoption Equity Index (IAEI) shows FHH-LMZ achieves 0.747 (0.349–1.384) of the reference group's cumulative

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adoption, while MHH-LMZ achieves 0.666 (0.361–1.154). Third, diagnostic counterfactual simulations applying MHH-UMZ transition probabilities yield modest and uncertain gains: FHH-LMZ cumulative CSA4 increases by 0.023 (−0.010 to 0.062), MHH-LMZ by 0.024 (−0.004 to 0.060); these gains are not statistically distinguishable from zero. We conclude that CSA scaling requires moving beyond one-size-fits-all bundling. Policy should, ex ante, first diagnose context-specific interaction patterns – positive synergies only in MHH-UMZ, antagonisms in FHH-LMZ and MHH-LMZ – address the structural barriers underlying negative interactions, and support the directed pathways identified for each stratum. The Bayesian-Ising framework offers a portable diagnostic toolkit for such context-specific analysis, with emphasis on adaptive learning given the substantial uncertainty surrounding equity metrics.

Nomenclature

Acronyms and abbreviations

CSA	Climate-Smart Agriculture
CSA1	Soil Management
CSA2	Water Harvesting
CSA3	Resilient Crops/Varieties
CSA4	Productive Agroforestry
CSA5	Renewable Energy
CSA6	Climate Information/Risk management
AEZ	Agroecological Zone.
FHH	Female-Headed Household
MHH	Male-Headed Household
LMZ	Lower-Midland Zone
UMZ	Upper-Midland Zone
IAEI	Intersectional Adoption Equity Index
SI	Supplementary Information
BCA	Bayesian Chain Analysis
DAG	Directed Acyclic Graph
ELPD	Expected Log Predictive Density
LRIN	Low-Rank Ising Network
PSIS	Pareto-smoothed importance sampling
LOO	Leave-One-Out cross-validation
KCSAS	Kenya Climate-Smart Agriculture Strategy
CAADP	Comprehensive Africa Agriculture Development Programme
ASAL	Arid and Semi-Arid Lands

1. Introduction

The stability of global food systems is increasingly jeopardized by climate change, with the Global South – particularly Low- and Middle-Income Countries (LMICs) – bearing a disproportionate share of its impacts (Gitz et al., 2016; UNICEF, 2021; World Health Organization, 2022). Nowhere is this vulnerability more acute than in sub-Saharan Africa (SSA), where rain-fed smallholder agriculture – the backbone of many economies and a primary source of livelihoods for millions – faces escalating risks from erratic rainfall, prolonged droughts, and rising temperatures (Serdeczny et al., 2017). Between October 2020 and early 2023, East Africa experienced five consecutive below-average rainy seasons, resulting in the most severe drought in four decades (Kimutai et al., 2025). In Kenya, these pressures are intensifying, with climate variability directly undermining livelihoods, exacerbating poverty, and threatening the stability of an economy heavily dependent on agriculture (D'Alessandro et al., 2015; Kipkemboi et al., 2021; Tomalka et al., 2020). Recent flooding and drought events have sharply highlighted a "hydroclimate whiplash" – the rapid swing between drought and extreme rainfall.

These challenges underscore an urgent need for agricultural adaptation (Cooper et al., 2008; Haile et al., 2020a,b). Within this context of compounded vulnerability, Climate-Smart Agriculture (CSA) has therefore emerged as a central pathway for building resilient agri-food systems. Defined by its pursuit of a "triple win," CSA seeks to simultaneously: (1) increase agricultural productivity and incomes; (2) enhance resilience and adaptive capacity to climate change; and (3) reduce greenhouse gas emissions where feasible (FAO, 2010; Lipper et al., 2014).

This integrated approach is particularly salient in Kenya, where national policies – including the Kenya Climate-Smart Agriculture Strategy (KCSAS), anchored in the Climate Change Act (RoK, 2016) – explicitly promote these objectives. These efforts align with broader continental and global frameworks, including: the African Union Agenda 2063 (environmentally sustainable, climate-resilient economies, agricultural modernization, and gender equality within the Comprehensive Africa Agriculture Development Program – CAADP); and the Sustainable Development Goals (SDGs) 2 (Zero Hunger), 5 (Gender Equality), 10 (Reduced Inequality and 13 (Climate Action). However, despite its conceptual appeal and policy support, the distribution of CSA adoption and its benefits remain uneven, raising critical questions about who adopts, who benefits, and under what conditions. As such, the scaling of CSA represents not only a national priority but also a broader development imperative.

The urgency of scaling CSA is further reinforced by the convergence of global constraints: a substantial climate finance gap, rising debt burdens across the Global South, and increasing scrutiny over whether international funding effectively reaches the most vulnerable. The operationalization of the Loss and Damage Fund at COP27, alongside the first Global Stocktake at COP28, has intensified pressure to allocate limited resources with demonstrable efficiency. In this context of fiscal constraint and heightened demand for value for money, merely documenting adoption gaps is insufficient. Instead, there is a need for diagnostic tools that can strategically target interventions to maximize gains in climate resilience, food security, and equitable development – particularly in contexts characterized by structural inequality (Parsons et al., 2026).

Despite a strong policy rationale and sustained investment, CSA adoption among African smallholders remains low and, critically, highly uneven – particularly among marginalized groups (Kassie et al., 2018; Njuki et al., 2022; Westermann et al., 2018; World Bank & CIAT, 2015). This pattern suggests that the central challenge is no longer solely the development of effective technologies, but rather, understanding and addressing the structural barriers that constrain equitable uptake. Evidence indicates that gender and agroecological conditions shape disparities in CSA adoption (Kerr et al., 2022; Kiptot & Franzel, 2012a; Ndiritu et al., 2014; Vizuete et al., 2025; Wollni & Andersson, 2014), with their intersection reinforcing existing power asymmetries and contributing to persistent inequities, including forms of elite capture (Mkupete & Davalos, 2025; Njuki et al., 2023; Persha & Andersson, 2014; Poulton & Kanyinga, 2014). However, existing approaches often fail to capture these intersecting constraints in a systematic and policy-relevant manner.

We argue that achieving the CSA “triple win” requires not only the adoption of individual practices, but also the effective implementation of context-specific practice combinations (Ellis & Tschakert, 2019; Wainaina et al., 2018), alongside an understanding of the sequential pathways that enable or constrain farmers – particularly marginalized groups – from assembling these combinations over time. This study is situated at this nexus, shifting the focus from documenting adoption rates to identifying the structural mechanisms that shape unequal uptake. To this end, we introduce a Bayesian-Ising ensemble framework that provides a unified diagnostic of adoption structure by jointly modeling co-adoption patterns (to identify practice complementarities) and sequential pathways (to reveal stage-specific bottlenecks), while explicitly accounting for intersectional heterogeneity.

This integrated workflow generates actionable equity metrics. The Ising network estimates synergistic complementarities ($\hat{J}$), identifying which practices form positive or negative associations. The Bayesian Chain Analysis (BCA) estimates sequential transition probabilities (P), revealing where marginalized groups exit adoption pathways. To capture structural disparities, we construct an Intersectional Adoption Equity Index (IAEI) by comparing adoption outcomes between intersectional strata, where values approaching 1 indicate equity and values approaching 0 indicate severe exclusion. Counterfactual simulations using g-computation translate these diagnostics into policy-relevant metrics, including equity gap closure (the remediable share of disparities), raw gain (absolute improvements in adoption), and equity weight (intervention efficiency across groups), thereby providing a quantitative bridge between structural diagnosis and targeted equity-sensitive intervention. This isolates the remediable share of structural constraints while holding initial access conditions fixed.

We acknowledge three design limitations that delimit the scope of our interpretive claims. First, the cross-sectional nature of the data captures adoption patterns at a single point in time, limiting causal inference on adoption pathways (although a structured sensitivity protocol is used to assess temporal stability). Second, binary adoption coding captures the extensive margin but not the intensity of practice implementation, potentially understating welfare differentials. Third, the findings are grounded in high-rainfall systems in Western Kenya; while the analytical framework is portable, the empirical results require validation in other agroecological contexts (e.g., arid and semi-arid regions) before broader generalization. These limitations inform a cautious interpretation of results and are addressed systematically in Section 4.7.

Nonetheless, this study makes a timely contribution by reframing the diagnosis of adoption inequities. We move beyond conventional approaches – such as binary and count models, switching regressions, and structural equation models applied in prior studies (for instance, Ndiwa et al., 2025; Tabe-Ojong et al., 2024; Wekesa et al., 2018) – which often rely on linear assumptions and obscure intersectional heterogeneity. We develop a unified diagnostic framework for identifying structural adoption constraints that jointly analyze synergistic co-adoption and sequential adoption pathways under an explicit intersectional lens. This enables three key advances, detailed in the following paragraph. Throughout the paper, we use standardized codes for CSA practices: CSA1 (soil management), CSA2 (water harvesting), CSA3 (resilient crops/varieties), CSA4 (productive agroforestry), CSA5 (renewable energy), and CSA6 (climate information and risk management). Plain-language descriptors are provided alongside these codes at their first mention in each major section to support readability.

First, we capture non-linear co-adoption structures using low-rank Ising networks (Fort, 2024; Marsman et al., 2022) showing that complementarities are stratified (context-specific synergy patterns) rather than universal. These patterns are not readily captured by standard models, yet crucial for designing targeted interventions that respect local interaction structures, rather than uniform, one-size-fits-all bundles. Second, we diagnose the underlying architecture of structural exclusion using Bayesian Chain Analysis (Heckerman, 2013; Heckerman et al., 1995), moving beyond static adoption gaps to quantify dynamic attrition – identifying the sequence points and transition probabilities at which marginalized groups exit adoption pathways. Third, by integrating these components, we operationalize a systems-based diagnostic framework (Jagustović et al., 2019; Scoones & Stirling, 2020; Tittonell, 2014) aligned with equity-oriented climate adaptation, and ground the analysis in the Capability Approach (Sen, 1999) and Elite Capture frameworks (Eriksen et al., 2021).

The Capability Approach distinguishes between access to resources (CSA technologies) and the capability to convert those resources into valued outcomes, such as resilience and food security. We therefore conceptualize low adoption not simply as a lack of access, but as a failure in the conversion process, shaped by intersecting structural barriers. Complementing this perspective, Elite Capture frameworks suggest that decentralized governance can disproportionately benefit already advantaged groups. Our framework operationalizes these concepts by identifying where conversion failures occur for marginalized groups and quantifying the concentration of synergistic advantages among more advantaged actors.

These diagnostic ambitions align closely with emerging priorities in climate risk management, including equitable adaptation, adaptation finance, and decision-support systems (Parsons et al., 2026). In parallel, a growing body of work applies the Capability Approach to assess hidden climate impacts; for example, (Some et al., 2026) quantify intangible flood costs and associated inequality burdens in Denmark. While such studies provide valuable insights into post-event (*ex post*) impacts, they are inherently retrospective and context-specific, limiting their ability to inform proactive targeting. Our contribution is complementary: rather than measuring hidden costs after impacts occur, we develop a prospective diagnostic framework that identifies, *ex ante*, the structural barriers – stratified complementarities and sequential attrition – that constrain equitable adoption of adaptation practices. In this way, the Bayesian-Ising ensemble responds directly to calls for actionable, forward-looking climate risk management.

Based on these theoretical foundations, we test three hypotheses:

1. **H1 (Synergy stratification):** Pooled analysis is expected to exhibit mixed or weak interactions, whereas stratified analysis may reveal positive complementarities concentrated in the most advantaged stratum (MHH-UMZ), particularly for CSA3-CSA4 and CSA4-CSA5 ($\hat{J} > 0.5$, with 95% credible intervals excluding zero), while other strata are anticipated to exhibit negative or negligible associations.
2. **H2 (Sequential attrition):** Transition probabilities are expected to vary across strata, with relatively lower cumulative CSA4 adoption probabilities in MHH-LMZ (potentially exceeding those observed in FHH-LMZ), yielding relatively low IAEI in the range of 0.3–0.4: indicative of substantial, though not extreme, inequity.
3. **H3 (Structural remediability):** Counterfactual simulations based on transition probabilities observed in MHH-UMZ are expected to substantially increase cumulative CSA4 adoption among more constrained groups (FHH-LMZ and MHH-LMZ), with gains potentially exceeding 100% and indicating a high degree of remediable structural disparity.

To address these hypotheses, the study is guided by two overarching questions:

1. What structural barriers – arising from the intersection of gender and agroecological conditions –constrain equitable CSA adoption among Kenyan smallholders?
2. How can an integrated analytical framework jointly diagnose synergistic practice bundling and sequential adoption pathways to inform policy-relevant levers:

(a) Bundled interventions targeting synergistic co-adoption.
(b) Sequenced support addressing gender-differentiated attrition points.
(c) Equity-focused governance diagnostics using real-time metrics (IAEI and equity gap closure) to mitigate elite capture in climate finance allocation.

Finally, in the Supplementary Information (Section S1B), we introduce the Precision Justice heuristic – a diagnostic lens that moves beyond identifying disparities to analyzing the structural configurations that produce them. Drawing on the Capability Approach and Elite Capture frameworks, the heuristic provides a theoretically grounded interpretation of stratified findings by distinguishing between strategic advantage (superior performance under favorable conditions) and structural dependency (where outcomes depend on configurations that are not uniformly accessible). Rather than assuming the linear scalability of "best practices," it reframes adaptation as a problem of system compatibility and configuration-dependence, emphasizing the need to reconfigure enabling conditions so that multiple viable pathways can emerge across diverse socio-ecological contexts. In doing so, it complements the economic rationale with a diagnostic focus on enabling investments, trade-offs, and adaptive governance, translating empirical and counterfactual results into policy-relevant insights. Grounded in the empirical findings, diagnostic methods, and equity metrics operationalized through the Bayesian-Ising ensemble – alongside extensive robustness checks – the heuristic is positioned as a portable, context-sensitive toolkit for diagnosis and policy dialogue rather than a prescriptive or empirically validated theory.

2. Methods

2.1. Study area and context

This study draws on a survey conducted between September and October 2023, covering 569 smallholder households in Kakamega and Bungoma counties in Western Kenya. The region is characterized by high population density and a strong reliance on rain-fed agriculture, making it particularly vulnerable to climate variability. The research design explicitly incorporates agroecological zone (AEZ) stratification, focusing on the Lower Midlands (LMZ; ~1,200–1,500 m above sea level, masl) and Upper Midlands (UMZ; ~1,500–1,800 masl) zones (Jaetzold, 2010; Jaetzold et al., 2006; Jaetzold & Schmidt, 1983). These zones differ in key biophysical conditions: the LMZ is characterized by less reliable rainfall and higher average temperatures, resulting in greater climate risk exposure and more marginal production conditions, whereas the UMZ benefits from more consistent precipitation and cooler temperatures.

By comparing female-headed households (FHH) and male-headed households (MHH) within and across these AEZs, the intersectional design enables analysis of how gender and biophysical disadvantage jointly shape adoption capabilities, while holding broader cultural and institutional contexts relatively constant. Survey respondents were either the household head or the individual identified as the primary decision-maker for agricultural activities. In male-headed households, this typically corresponded to the male head, although in some cases the spouse was interviewed if she was identified as the principal agricultural decision-maker or if the male head was unavailable. In female-headed households − both de jure and de facto (distinguishing between women recognized as heads due to the absence of a male partner and those managing daily affairs while a male head is temporarily absent; Aryal et al., 2019; Gebre et al., 2023) − the respondent was the female head.

A key limitation of this design is that, while it captures the perspective of the principal decision-maker, it does not account for intra-household differences in preferences or constraints between spouses. Accordingly, the gendered analysis reflects differences across household types rather than individual-level gender dynamics within households; this distinction is revisited in the limitations section. The core variables captured included: (i) Binary adoption of six CSA practices (sustainability transition indicators); and (ii) gender and AEZ binary dummies (equity stratifiers). Using a multi-stage stratified sampling approach, we sampled 569 smallholder households, as shown in Table 1.

2.2. *Climate Smart agriculture (CSA) practices*

This study considers six CSA practices relevant to smallholder systems in Western Kenya. For consistency, we use standardized codes throughout: CSA1 (soil management), CSA2 (water harvesting), CSA3 (resilient crops/varieties), CSA4 (productive agroforestry), CSA5 (renewable energy), and CSA6 (climate information and risk management).

CSA1 comprises sustainable soil and land management practices (mulching, composting, and soil-enhancing agroforestry) aimed at reducing erosion and improving soil fertility, corresponding to a land degradation neutrality indicator. CSA2 includes rainwater harvesting and efficient irrigation practices designed to manage rainfall variability, reflecting a water-use efficiency indicator. CSA3 captures the adoption of climate-resilient crops and livestock, such as drought-tolerant maize varieties and indigenous breeds, to stabilize yields and enhance resilience, corresponding to an agrobiodiversity resilience indicator. CSA4 focuses on biodiversity-enhancing and income-generating systems, including productive agroforestry and apiculture, contributing to ecosystem services and dietary diversity. CSA5 includes renewable energy technologies, such as biogas systems and improved cookstoves, which reduce deforestation pressures and lower labor burdens, particularly for women, corresponding to a decarbonization indicator. CSA6 captures the use of climate information services, mobile advisories, and insurance products to support risk management and decision-making, corresponding to a risk-mitigation indicator.

Agroforestry is coded using two distinct codes to reflect its functional roles. CSA1 captures soil-enhancing species (such as *Gliricidia sepium*), while CSA4 includes productive species such as avocado (*Persea americana*) and banana (*Musa spp*.) (Coe et al., 2014; Place et al., 2012). This distinction is consistent with the protective versus productive functions of agroforestry systems (Mbow et al., 2014) and reflects farmers' own cognitive differentiation between fertilizer and food trees (Kuyah et al., 2019). Evidence also suggests gender-differentiated adoption patterns, with women more likely to adopt productive species and men more likely to adopt soil-enhancing species (Kiptot et al., 2014; Kiptot & Franzel, 2012b). CSA intensity (CSANO) is defined as the unweighted sum of the six binary indicators. Separating CSA1 and CSA4 avoids conflating long-term soil benefits with more immediate income or dietary gains, thereby reducing the risk of misinterpreting adaptation strategies (van Noordwijk, 2020; van Noordwijk et al., 2018).

Binary adoption coding is motivated by both theoretical and empirical considerations. Theoretically, the Ising framework models adoption as a binary spin system, $\sigma_i \in \{-1, 1\}$, where the interaction parameter J_{ij} captures statistical dependence between practices at the extensive margin—that is, whether practices tend to be adopted jointly or whether adoption of one is associated with a reduced likelihood of adopting another. Positive interactions are consistent with complementarities, whereas negative interactions indicate substitutability or shared constraints suggesting that resource limitations may force trade-offs rather than complementarities. This formulation aligns with economic models of technology adoption as discrete choice under uncertainty (Feder et al., 1985; Foster & Rosenzweig, 2010).

Empirically, intensity measures (such as area under practice or investment levels) present several challenges: (i) recall bias in quantifying practice extent; (ii) lack of comparability across practices (for instance, kilograms of seed versus number of trees); and (iii)

Table 1
Multi-stage stratified random sample selection.

Western Kenya							
Kakamega			Bungoma				
Matungu (UMZ			Tongaren (UMZ)		Bumula (LMZ)		
Koyonzo (56)	Namamali (118)	Kabula (54)	Milima (28)	Ndalu (80)	Khasoko (54)	Bukusu (64)	Bumula (65)
UMZ: 108 (18.98%)					**LMZ:** 461 (81.02%)		
Male: 424 (74.52%) | **Female:** 145 (25.48%)							

zero-inflated and highly skewed distributions, which can destabilize estimation in smaller subgroups, particularly among female-headed households (Abay et al., 2021; Mouratiadou et al., 2021; Young et al., 2022). Nonetheless, binary coding obscures variation at the intensive margin. Sensitivity analyses using ordinal coding (0 = non-adopter, 1 = partial adopter, 2 = fuller adopter) are reported in the Supplementary Information and indicate that the main interaction patterns remain robust. If adoption intensity is positively associated with resilience outcomes, the analysis may therefore understate welfare differences across groups, as marginalized households may both adopt less frequently and at lower intensity. **Table S1.1** in the Supplementary Information provides additional detail on CSA practice definitions.

2.3. *Conceptual framework and analytical workflow*

Our analytical strategy is based on an ensemble framework that integrates two complementary approaches to diagnose the structure of CSA adoption. The workflow, summarized in Fig. 1, addresses two dimensions of the adoption process that are typically analyzed in isolation. First, the Low-Rank Ising Network (LRIN) models the simultaneous dimension, identifying patterns of co-adoption among CSA practices and revealing the latent structure of complementarities across social-ecological strata. Second, the Bayesian Chain Analysis (BCA) models the sequential dimension, estimating dominant adoption pathways and stage-specific transition probabilities. Both components are implemented under an intersectional stratification of gender and agroecology.

The outputs of these models are combined within an ensemble framework to provide a unified diagnostic of structural barriers, capturing both co-adoption structures associated with more advantaged groups and sequential attrition patterns affecting more constrained groups. This integrated approach enables a shift from identifying whether adoption gaps exist to explaining how such gaps are structurally reproduced through fragmented complementarities and disrupted adoption pathways. These dynamics are summarized through the Intersectional Adoption Equity Index (IAEI), which standardizes disparities in adoption outcomes across groups. Note, because the cumulative probability represents the joint adoption of all four practices in the modeled order, it is generally lower than the marginal adoption rate of any single practice. This provides a more conservative and structurally consistent measure of inequality.

2.3.1. *Intersectional adoption equity index (IAEI)*

The IAEI measures adoption equity as the ratio of adoption outcomes for a given group relative to a reference group:

$$IAEI(g) = \frac{P_{obs}(g)}{P_{ref}}$$

where $P_{obs}(g)$ denotes the observed adoption outcome for group g and P_{ref} corresponds to the reference group (here, MHH-UMZ). Values approaching 1 indicate equity, whereas values approaching 0 indicate increasing structural exclusion. For interpretive purposes, the following heuristic scale is used:

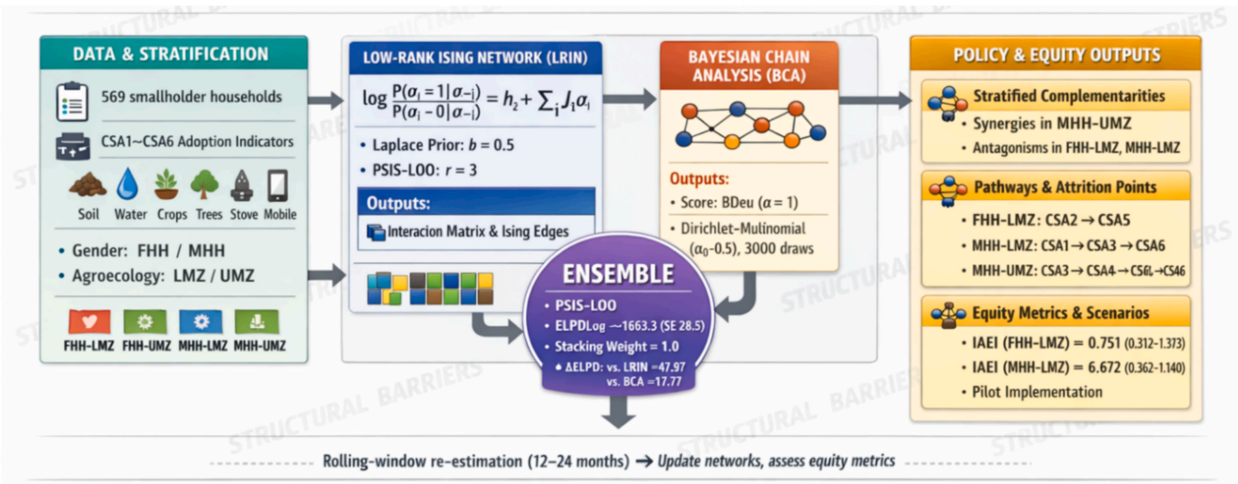

Fig. 1. Integrated workflow of the Bayesian-Ising ensemble for diagnosing structural disparities in CSA adoption. Data are stratified by gender and agroecological zone (AEZ). The Low-Rank Ising Network (LRIN) estimates pairwise complementarities ($\hat{J}$) using Bayesian nodewise logistic regression with Laplace priors; rank is selected via PSIS-LOO. The Bayesian Chain Analysis (BCA) models sequential adoption pathways using a score-based DAG with Dirichlet-multinomial CPTs. The ensemble combines both components, validated by PSIS-LOO (stacking weight = 1.0). Outputs include stratified complementarities, directed pathways, and equity metrics (IAEI, raw gain, gap closure) with 95% credible intervals. These inform policy levers: diagnose local synergy patterns, target stratum-specific pathways, and implement adaptive governance via rolling-window monitoring.

- IAEI ≈ 1.0: Equity
- IAEI ≈ 0.7–0.9: Mild inequity
- IAEI ≈ 0.4–0.6: Moderate inequity
- IAEI ≈ 0.2–0.4: Substantial inequity
- IAEI < 0.2: Severe inequity

The inverse of the index provides an alternative interpretation in terms of relative likelihood:

$$IAEI_{(g)}^{-1} = \frac{P_{ref}}{P_{obs}(g)}$$

which reflects how much more likely the reference group is to achieve a given adoption outcome compared to group g. Empirical estimates of the IAEI and associated uncertainty intervals are presented in Section 3.

2.3.2. Economic grounding of model parameters

The analytical framework operationalizes core economic concepts related to technological complementarities, sequential adoption constraints, and equity in resource allocation. First, the Ising interaction parameters ($\hat{J}$) capture technological complementarities in the sense of supermodularity (Barrett, 2021; Barrett et al., 2020; Milgrom & Roberts, 1990; Topkis, 1998), whereby the marginal returns to adopting one practice increase with the adoption of another. Positive interactions are therefore consistent with complementarities and reflect economies of scope in farm-level innovation portfolios (Chavas & Nauges, 2020), while negative interactions indicate substitutability or shared constraints.

Second, transition probabilities (P) characterize sequential adoption dynamics shaped by multiple economic mechanisms. These include liquidity constraints, which limit adoption of capital-intensive practices (Feder et al., 1985; Karlan & Valdivia, 2011); transaction costs, reflecting information frictions and missing markets for risk-management technologies (De Janvry et al., 1995; Jack, 2013; Sadoulet & De Janvry, 1995); and learning externalities, whereby adoption is influenced by social networks and knowledge diffusion (Conley & Udry, 2010; Foster & Rosenzweig, 1995). Together, these mechanisms align with broader frameworks emphasizing the interaction between external constraints, innovation characteristics, and household capabilities in shaping adoption pathways (Zabala et al., 2025).

Finally, the equity weight metric derived from counterfactual simulations provides an indication of relative prioritization across groups. While conceptually related to the shadow price of equity – capturing the marginal effort required to improve adoption outcomes for disadvantaged groups – these estimates should be interpreted cautiously given uncertainty in the underlying adoption gains. Robust cost-effectiveness analysis would require dedicated cost data collected alongside adoption outcomes (Alene & Manyong, 2007).

The following sections detail how these complementarities ($\hat{J}$) and transition dynamics (P) are estimated through the Low-Rank Ising Network (LRIN) and Bayesian Chain Analysis (BCA) components of the framework.

2.4. Low-rank Ising network: Simultaneous dependence structure

We model the co-adoption of climate-smart agriculture (CSA) practices using a Bayesian nodewise pseudo-likelihood approximation to the Ising model, which provides a computationally tractable representation of pairwise conditional dependencies (Chen et al., 2016; Meinshausen & Bühlmann, 2006; Ravikumar et al., 2010; Shojaie, 2021). This approach is particularly suitable for stratified analysis with limited sample sizes, where full likelihood estimation is infeasible due to the intractable partition function (Marsman et al., 2015, 2022; Park et al., 2022).

For each binary CSA indicator $\sigma_j \in \{0,1\}$, we estimate a nodewise logistic regression of the form:

$$\log\frac{P(\sigma_j = 1|\sigma_{-j})}{P(\sigma_j = 0|\sigma_{-j})} = h_j + \sum_{i\neq j}\beta_{ji}\sigma_i$$

where h_j is a node-specific intercept and β_{ji} represents the conditional dependence of practice j on practice i. This pseudo-likelihood formulation avoids direct evaluation of the Ising partition function while retaining interpretable pairwise interactions.

To ensure sparsity and numerical stability – particularly in small subsamples – we assign independent Laplace (L_1) priors to the nodewise regression coefficients (Park & Casella, 2008):

$$p(J_{ij}|\lambda) = \frac{\lambda}{2}\exp(-\lambda|J_{ij}|), i \neq j$$

In implementation, this corresponds to a Laplace distribution with scale parameter $b = 0.5$, implying $\lambda = 2$. This weakly informative prior encourages shrinkage of small coefficients toward zero without imposing overly strong regularization. Sensitivity to this prior choice is examined in Supplementary Table S2.4.

Posterior inference was performed using the No-U-Turn Sampler (NUTS) as implemented in PyMC (Salvatier et al., 2016). We ran four independent Markov chains with 1500 warm-up iterations and 1500 post-warm-up draws per chain, targeting an acceptance rate of 0.95. Convergence was assessed using the potential scale reduction factor $\widehat{R} < 1.0$ and effective sample sizes, which generally exceeded 400 for key parameters in the final specification.

A symmetric interaction matrix J was constructed by averaging reciprocal nodewise coefficients, $J_{ij}=(\beta_{ij}+\beta_{ji})/2$, yielding an undirected representation of pairwise dependence.

To recover the dominant low-dimensional structure and reduce estimation noise, we applied a low-rank projection to each posterior draw of the symmetrized interaction matrix. Posterior means and 95% credible intervals were then computed from these projected draws. The optimal rank r was selected using Pareto-smoothed leave-one-out (LOO) cross-validation (Vehtari et al., 2017), comparing candidate ranks $r \in \{1, 2, 3, 4, 5\}$. In the empirical application, rank r=3 yielded the highest expected log predictive density (ELPD).

For reporting, we classify an interaction as "credible" if its 95% posterior credible interval excludes zero. This criterion is used solely for interpretative emphasis; all estimated interactions are retained in posterior summaries.

2.5. Bayesian chain analysis (BCA): mapping sequential pathways

Sequential adoption dynamics are modeled using a score-based Bayesian network approach with Dirichlet-multinomial estimation of conditional probability tables (CPTs). This framework allows for probabilistic representation of adoption pathways while accommodating sparse data and stratified analysis (Heckerman, 2013; Heckerman et al., 1995; Moglia et al., 2018; Scutari & Denis, 2021).

We impose an order constraint reflecting the logical progression of CSA practices (CSA1 → CSA2 → …), reducing the search space and ensuring interpretability. Network structure is learned using hill-climbing optimization under the Bayesian Dirichlet equivalent uniform (BDeu) score with an equivalent sample size parameter $\alpha = 1$ and a sparsity-inducing edge penalty of 1.2 subtracted for each edge added.

For each node i with parent configuration j, we estimate CPTs using a symmetric Dirichlet prior:

$\theta_{ij\cdot} \sim Dirichlet(\alpha_0,\ldots,\alpha_0)$,

with $\alpha_0 = 0.5$, yielding posterior distributions:

$$\theta_{ij\cdot} | n_{ij\cdot} \sim \mathrm{Dirichlet}\left(\alpha_0 + n_{ij1}, \cdots, \alpha_0 + n_{ijK_i}\right).$$

We drew 3000 posterior samples from the Dirichlet posterior for each CPT, thereby generating a full distribution of transition probabilities. Uncertainty was propagated through all subsequent calculations, including counterfactual simulations.

Counterfactual simulations are conducted using g-computation (Hernán & Robins, 2010; Robins, 1986), replacing CPTs of disadvantaged groups with those of the reference group for non-root nodes while holding initial conditions fixed. This yields diagnostic estimates of remediable structural constraints rather than causal treatment effects.

2.5.1. Counterfactual simulation and uncertainty propagation

To quantify remediable structural constraints, we implement counterfactual simulations using g-computation. These simulations are interpreted as diagnostic rather than causal estimates of specific interventions. For each disadvantaged group, we replace the conditional probability tables (CPTs) of non-root nodes with those of the reference group (MHH–UMZ), while holding the root node distribution fixed. This isolates the role of sequential constraints from differences in initial access. Joint adoption probabilities are computed via the factorization:

$$P(CSA_1, \cdots, CSA_k) = \prod_{i=1}^{k} P(CSA_i | P_a(CSA_i))$$

Counterfactual outcomes are obtained by recursively substituting CPTs along the adoption pathway. Uncertainty is propagated by repeating simulations across posterior draws of the CPTs, yielding full posterior distributions for all derived quantities. Summary statistics (means and 95% credible intervals) are reported in the Results section.

2.5.2. Adoption gaps to policy signals

We derive four metrics from counterfactual simulations to translate structural diagnostics into policy-relevant indicators.

First, equity gap closure (EGC) measures the proportion of the adoption gap that can be reduced by removing structural constraints:

$$EGC = \frac{Counterfactual - Baseline}{Reference - Baseline}$$

Second, Raw gain (Δ) captures absolute change in adoption:

Δ= Counterfactual − Baseline.

Third, equity weight (EW) reflects the relative effort required to achieve marginal improvements in adoption outcomes, defined as the inverse of the raw gain:

$$\mathrm{EW} = \frac{1}{\Delta}$$

Finally, equity-adjusted benefit (EAB) combines magnitude and equity considerations:

$$EAB = \Delta \times (1 - IAEI)$$

All metrics are computed for each posterior draw, allowing uncertainty to be propagated and summarized using posterior distributions. Detailed estimates are presented in the Results and Supplementary Information.

2.6. Ensemble validation

We evaluate model performance using Pareto-smoothed importance sampling (PSIS) LOO cross-validation (PSIS-LOO) (Vehtari et al., 2017). Predictive performance is summarized using the Expected Log Predictive Density (ELPD). To assess the contribution of each component, we compute stacking weights for the ensemble model (Ising + BCA), defined as:

$$\widehat{w} = \arg \max_{w} \frac{1}{n} \sum_{i=1}^{n} log \left(\sum_{m=1}^{M} w_m p_m (y_i | y - i) \right)$$

subject to $w_m \geq 0$ and $\sum_{m=1}^{M} w_m = 1)$ where $p_m(y_i|y - i)$ are the LOO predictive densities from model m (Yao et al., 2018).

Comparisons of ELPD across models are used to evaluate whether the ensemble improves predictive performance relative to individual components. Robustness checks are conducted to assess sensitivity to prior specification, regularization, and estimation choices, with results reported in the Supplementary Information.

2.7. Reproducibility, implementation, and limitations

All analyses were implemented in Python. Initial development and pilot testing were conducted in a standard Python 3.14.3 environment to verify analytical logic, script structure, and output generation. For the final revision and reproducible execution, the workflow was standardized in an Anaconda environment (Anaconda Distribution 2025.12–2), which provides more stable dependency management and improved compatibility across the libraries required for Bayesian inference, graphical modeling, and posterior diagnostics. This transition ensures version control, minimizes package conflicts, and facilitates full replication by reviewers and future users.

The final analytical pipeline relies on core Python libraries, including pandas (McKinney, 2010) and numpy (Harris et al., 2020) for data handling; pymc (Salvatier et al., 2016) for Bayesian estimation; arviz (Kumar et al., 2019) for posterior diagnostics and leave-one-out model comparison; scipy (Virtanen et al., 2020) and statsmodels (Seabold & Perktold, 2010) for supporting statistical routines; networkx (Hagberg et al., 2007) for graph operations; and matplotlib (Hunter, 2007) and seaborn (Waskom, 2021) for visualization.

2.7.1. Main analysis script

The core workflow – including nodewise Bayesian Ising estimation, low-rank projection, score-based Bayesian network learning, Dirichlet-multinomial conditional probability table sampling, and counterfactual g-computation – is implemented in a single script, *closer_bayesian_csa_pipeline_fixed.py*. This script accompanies a minimalist corresponding input dataset and can be executed within the packaged environment specified in the replication materials. It contains the analytical dataset used for estimation, variable definitions and coding rules, the full analysis script with execution instructions, and the complete set of output tables and figures in the results section, including all IAEI and equity metric computations. The package enables full reproducibility of the estimation pipeline within the specified Anaconda environment without additional configuration and will be deposited in a public Zenodo repository once data restrictions are lifted. In the meantime, a contextual dataset is provided to facilitate replication of the analytical workflow.

2.7.2. Supplementary robustness script

To generate the extensive set of supplementary robustness checks (Tables S2.4-S3.16 and associated figures), we provide a separate script, *final_bayesian_robustness_pipeline_v4.py*. This script is designed to be placed in the same folder as *closer_bayesian_csa_pipeline_fixed.py*, from which it dynamically imports the core functions (nodewise fitting, low-rank projection, BDeu DAG learning, Dirichlet-multinomial CPT sampling, and uncertainty propagation). By reusing these functions, the robustness checks remain fully consistent with the main analysis while allowing for faster execution (using fewer MCMC draws for diagnostic purposes). The script produces all Supplementary Tables And Figures referenced in the **Supporting Information** and, like the main script, is fully documented and executable within the same Anaconda environment.

This implementation enables a unified diagnostic of adoption structure that conventional regression-based approaches cannot readily provide. Specifically, the framework identifies conditional complementarities among CSA practices, traces sequential attrition points across adoption pathways, and propagates uncertainty through counterfactual equity metrics. The contribution is therefore both substantive and computational: the Bayesian-Ising ensemble functions as a portable diagnostic toolkit for structurally informed climate adaptation analysis.

Several limitations bound the interpretation of the results. First, the cross-sectional design captures adoption patterns at a single point in time and does not permit definitive causal inference on adoption sequences; counterfactuals should therefore be interpreted as diagnostic simulations rather than causal predictions. Second, binary adoption coding captures the extensive margin but not the intensity of implementation, which may lead to conservative estimates of welfare disparities if marginalized households also adopt at lower intensity. Third, self-reported adoption may be subject to recall and social desirability biases, potentially attenuating estimated complementarities. Fourth, smaller strata yield wider credible intervals, although the direction and substantive interpretation of the main contrasts remain stable across uncertainty bounds. Finally, the empirical findings are grounded in the high-rainfall systems of Western Kenya; while the analytical framework is portable, the observed configuration of complementarities and adoption pathways is context-specific and requires validation in other agroecological settings. We return to this in the Discussion.

Taken together, the Bayesian-Ising ensemble should be understood as a reproducible and extensible diagnostic framework for identifying structural barriers to climate adaptation under inequality. While empirical results are context-bound, the analytical logic is designed for adaptation and replication across diverse settings.

3. Results

3.1. Sample characteristics and descriptive patterns

The analytical sample comprised 569 households, stratified by gender of the household head (female-headed, FHH; male-headed, MHH) and agroecological zone (low- to medium-rainfall zone, LMZ; upper medium-rainfall zone, UMZ). The largest stratum was MHH-LMZ (n = 345), followed by FHH-LMZ (n = 116), MHH-UMZ (n = 79), and FHH-UMZ (n = 29) (Table 1). The total number of adopted Climate-Smart Agriculture (CSA) practices (CSANO count) was moderate and similar across groups, with means ranging from 2.05 (MHH-LMZ) to 2.21 (FHH-UMZ) and overlapping confidence intervals (full descriptive statistics are available in the replication package). Omnibus tests confirmed no statistically significant differences in CSA count between the four strata (Kruskal-Wallis: $\chi^2 = 0.81$, $p = 0.846$; ANOVA: $F = 0.61$, $p = 0.606$) nor between pooled female- and male-headed households (Mann-Whitney: $U = 32105.5$, $p = 0.394$; Welch t-test: $t = 0.53$, $p = 0.599$) (full test results are available in the replication package). All pairwise post-hoc comparisons were non-significant after Bonferroni correction, indicating that overall adoption intensity did not differ by gender or AEZ.

3.2. Marginal adoption probabilities

Marginal adoption probabilities for each of the six CSA practices varied across subgroups (Figs. 2a and 2b; standard errors and 95% confidence intervals are provided in the replication package). CSA1 (minimum tillage) was the most widely adopted practice across all groups (0.759–0.836). CSA6 (crop rotation) was the least adopted (0.000–0.063). CSA5 (legume intercropping) showed the largest relative variation: adoption among FHH-UMZ (0.310, 95% CI [0.142, 0.479]) was more than double that in FHH-LMZ (0.147, [0.082, 0.211]) and MHH-LMZ (0.130, [0.095, 0.166]). Adoption of CSA2, CSA3, and CSA4 was moderate with overlapping confidence intervals across groups.Fig 3.Fig 4.Fig 5a.Fig 5b.Fig 5c.

3.3. Adoption profiles and co-occurrence

The top 15 adoption profiles (binary vectors indicating which practices were adopted) are shown in Supplementary Fig. 2. The most common profile was “100000” (adoption of CSA1 only), observed in 105 households. The second most common was “101000” (CSA1 and CSA3), with 97 households. Profiles involving CSA1 in combination with CSA3 or CSA4 were frequent, while profiles including CSA5 or CSA6 appeared less often.

Co-occurrence of at least three practices (triad) was high across all strata, ranging from 96.6% (FHH-UMZ) to 99.1% (FHH-LMZ),

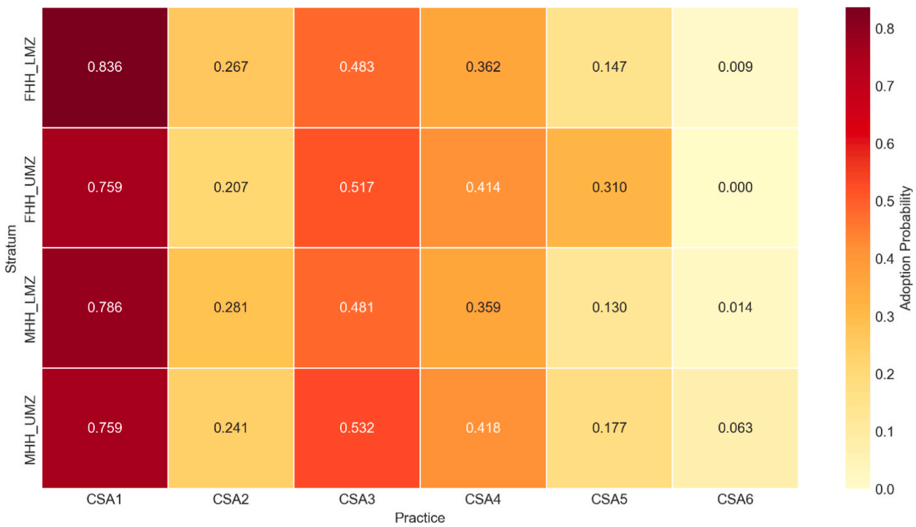

Fig. 2a. Marginal adoption probabilities of six CSA practices by stratum. Probabilities are sample proportions.

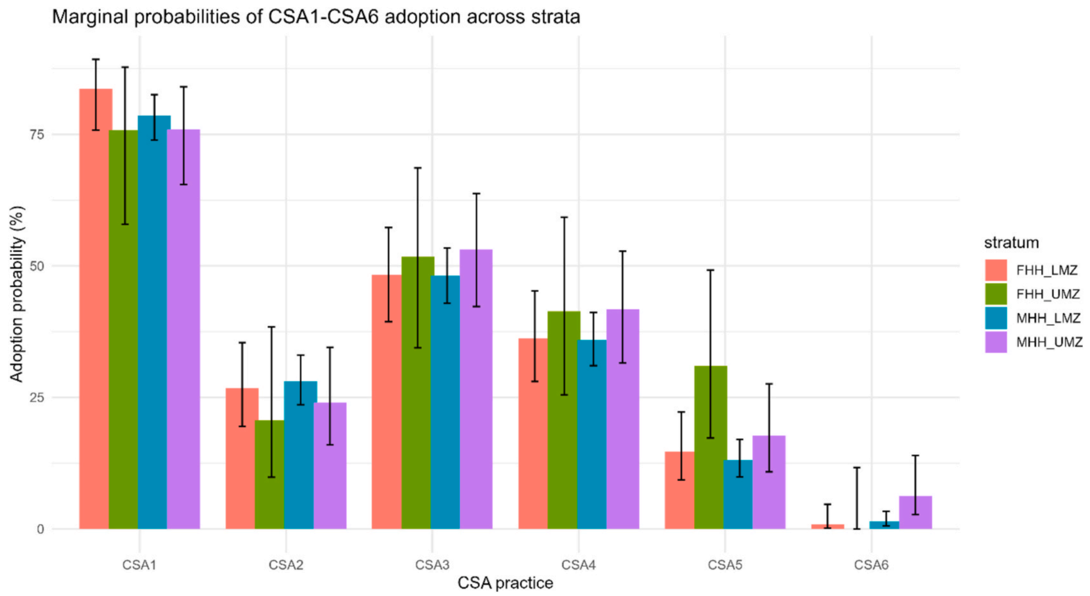

Fig. 2b. Marginal probabilities of CSA-CSA6 adoption across strata with confidence intervals.

indicating that most households adopt a bundle of at least three CSA practices (Supplementary Table S2.1). However, the proportion adopting all six practices was low, ranging from 11.3% (MHH-LMZ) to 24.1% (MHH-UMZ). The highest proportion of full adoption was observed in MHH-UMZ, suggesting that complete adoption bundles are more common in the upper medium-rainfall zone, especially among male-headed households.

3.4. Network structure of CSA adoption

3.4.1. Pooled ising network

The pooled Ising model revealed a mixture of negative and positive pairwise associations (Table 2; the full posterior mean matrix is available in the replication package). Negative edges were concentrated around CSA1: CSA1-CSA3 (−0.385, 95% CI [−0.577, −0.199]) and CSA1-CSA4 (−0.324, 95% CI [−0.486, −0.141]), indicating that adoption of minimum tillage was associated with lower adoption of these complementary practices. Positive edges were observed between CSA4-CSA5 (0.253, 95% CI [0.036, 0.450]) and between CSA5-CSA6 (0.348, 95% CI [−0.037, 0.761]), though the latter did not reach statistical significance.Table 3.Table 4a. Table 4b.

3.4.2. Stratified Ising networks

Substantial heterogeneity in pairwise interactions was evident across the four strata (Table 4; full interaction matrices are provided in Supplementary Tables S2.3a–d).

Key findings include:

FHH-LMZ: Strong negative interactions involving CSA2-CSA5 (−0.727, 95% CI [−1.386, −0.203]) and CSA1-CSA4 (−0.392, 95% CI [−0.749, −0.015]). A positive interaction between CSA4 and CSA5 (0.157) was present but not statistically significant.

FHH-UMZ: Negative interactions among CSA3-CSA4 (−0.155), CSA3-CSA5 (−0.217), and CSA1-CSA3 (−0.199), but none reached statistical significance at $\alpha = 0.05$. Positive interactions (for instance, CSA2-CSA3, 0.248) were also non-significant.

MHH-LMZ: Negative interactions dominated, particularly CSA1-CSA6 (−0.649, 95% CI [−1.267, −0.080]), CSA1-CSA3 (−0.297, 95% CI [−0.541, −0.035]), CSA1-CSA4 (−0.279, 95% CI [−0.526, −0.004]), and CSA2-CSA3 (−0.257, 95% CI [−0.440, −0.063]). No positive interactions reached significance.

MHH-UMZ: Consistently positive and often significant interactions, especially CSA4-CSA5 (0.686, 95% CI [0.250, 1.151]), CSA5–CSA6 (0.524, 95% CI [0.031, 1.090]), CSA3-CSA4 (0.460, 95% CI [0.114, 0.798]), CSA2-CSA4 (0.406, 95% CI [0.024, 0.795]), and CSA3-CSA5 (0.390, 95% CI [0.026, 0.737]). This pattern suggests that in the upper medium-rainfall zone, male-headed households tend to adopt complementary practices together, whereas in other strata interactions are predominantly negative or neutral.

3.4.3. Model selection for Ising

Rank selection for the Ising model indicated that a model with rank 3 provided the best predictive performance based on expected log pointwise predictive density (ELPD_LOO), with a negligible improvement for higher rank. Rank 3 achieved the lowest ELPD_LOO (−1710.8), and higher ranks did not meaningfully improve fit (ΔELPD < 0.1 for rank 5). This supports the use of a low-dimensional structure to capture pairwise dependencies among CSA practices.

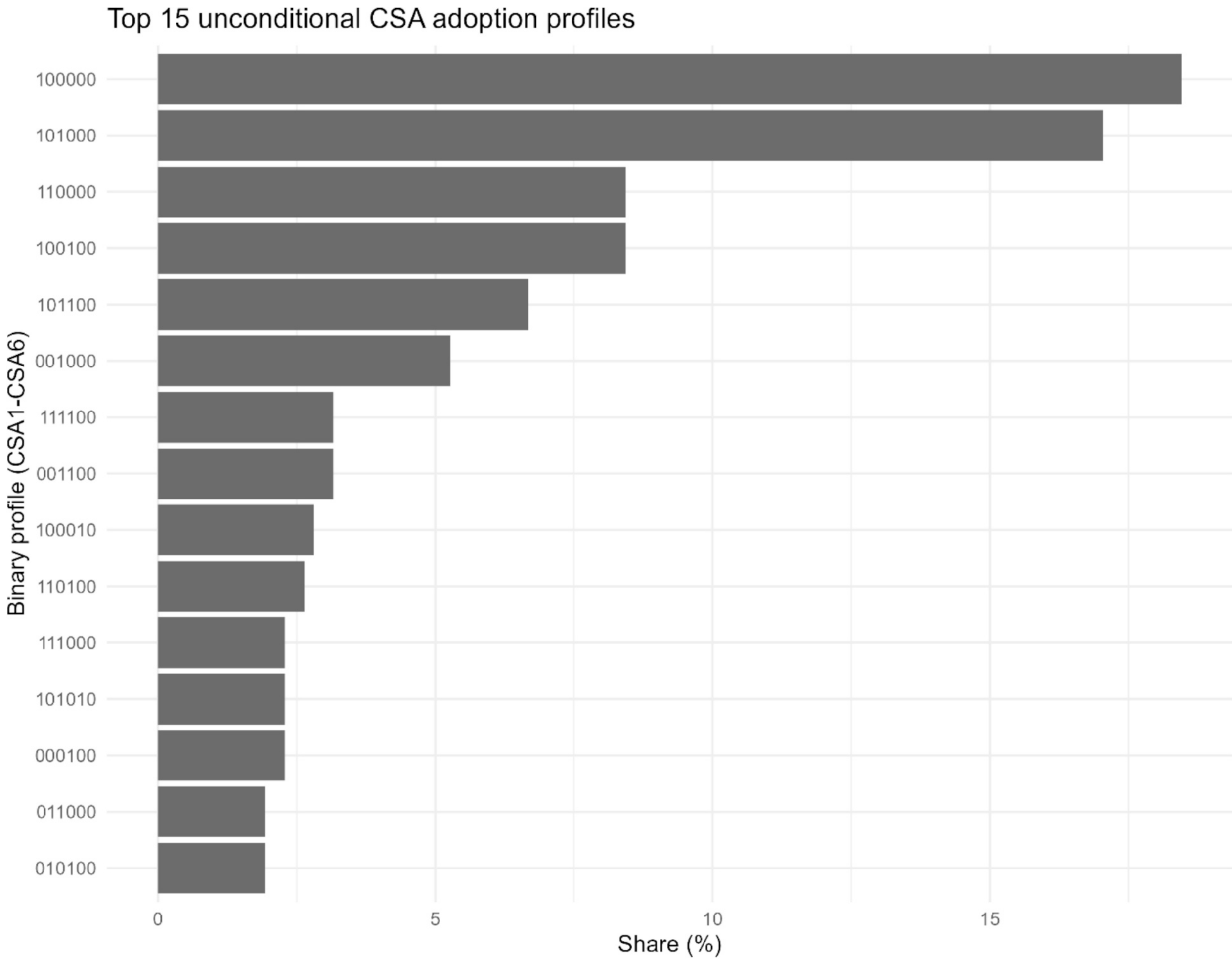

Fig. 3. Top 15 unconditional (portfolios) CSA adoption profiles.

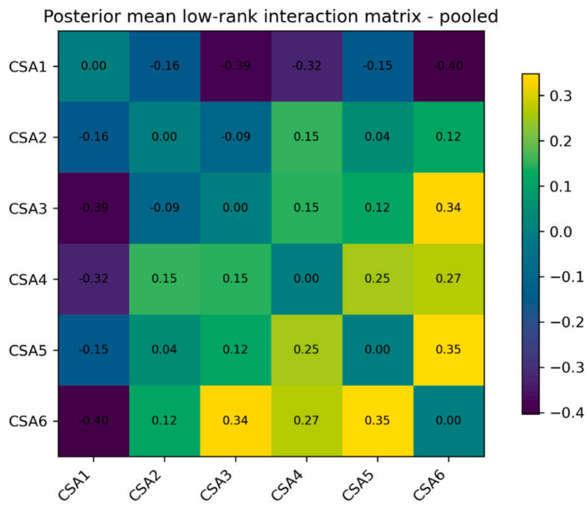

Fig. 4. Posterior mean interaction matrix. Entries represent estimated pairwise interaction parameters ($\hat{J}$) from the low-rank Ising model. Positive values indicate complementarities (co-adoption tendencies), while negative values indicate antagonisms (substitution or mutual exclusivity between practices). Diagonal elements are set to zero by construction. The matrix is symmetric, reflecting undirected conditional dependence between CSA practices.

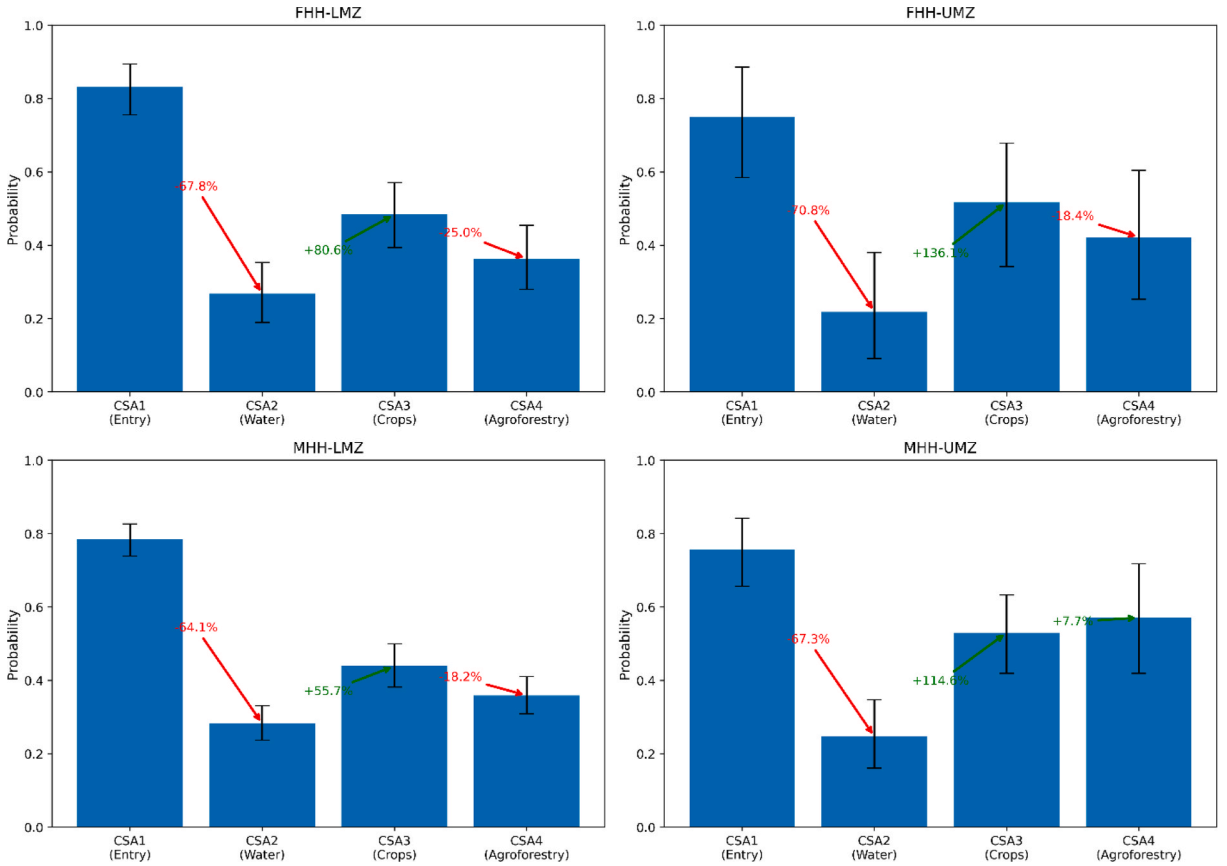

Fig. 5a. Sequential adoption pathways by stratum with 95% credible intervals. Bars represent conditional adoption probabilities at each stage of the CSA sequence, with vertical error bars indicating 95% credible intervals. Arrows denote proportional changes between stages, where red arrows indicate declines (attrition) and green arrows indicate increases (complementarity). A pronounced drop between CSA1 and CSA2 is observed across all strata, indicating a common structural bottleneck. This is followed by strong recovery between CSA2 and CSA3, suggesting conditional complementarity once initial constraints are overcome. Final-stage transitions vary across groups, with male-headed households in the upper midland zone approaching structural parity, while female-headed households continue to face residual barriers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.5. Directed relationships from Bayesian networks

Bayesian network analysis identified directed dependencies that imply potential causal ordering (Table 5). In the pooled dataset, CSA1 was a driver of CSA3 and CSA4 (csa1 → csa3, csa1 → csa4). Stratified networks revealed distinct pathways:

No directed edges involving CSA1 were retained in the MHH-UMZ network, reinforcing the contextual nature of adoption sequences.

3.6. Sequential adoption and equity implications

Transition probabilities for the sequential adoption model are reported in provided in the replication package (see glossary guide in the supplementary)s. These probabilities reflect the likelihood of adopting a practice given adoption of preceding practices in the directed chain and were used to compute counterfactual adoption of CSA4 under an intervention targeting this practice.

The inequality-adjusted equity impact (IAEI) and related metrics are presented in Table 6. For FHH-LMZ, the IAEI was 0.747 (95% CI [0.349, 1.384]), indicating that the intervention would close only about three-quarters of the gap relative to the reference group (MHH-UMZ). The gap closure estimate for this group was 1.357 (95% CI [−2.529, 4.460]), reflecting high uncertainty. Raw gains in CSA4 adoption were modest (0.023 for FHH-LMZ, 0.024 for MHH-LMZ) and not statistically distinguishable from zero for either group. Equity weights—which quantify the relative value placed on improving adoption among disadvantaged groups—were large and imprecisely estimated, consistent with the heterogeneity in baseline adoption and network structures. The reference group (MHH-UMZ) showed an IAEI of 1.0 by definition, with zero raw gain.

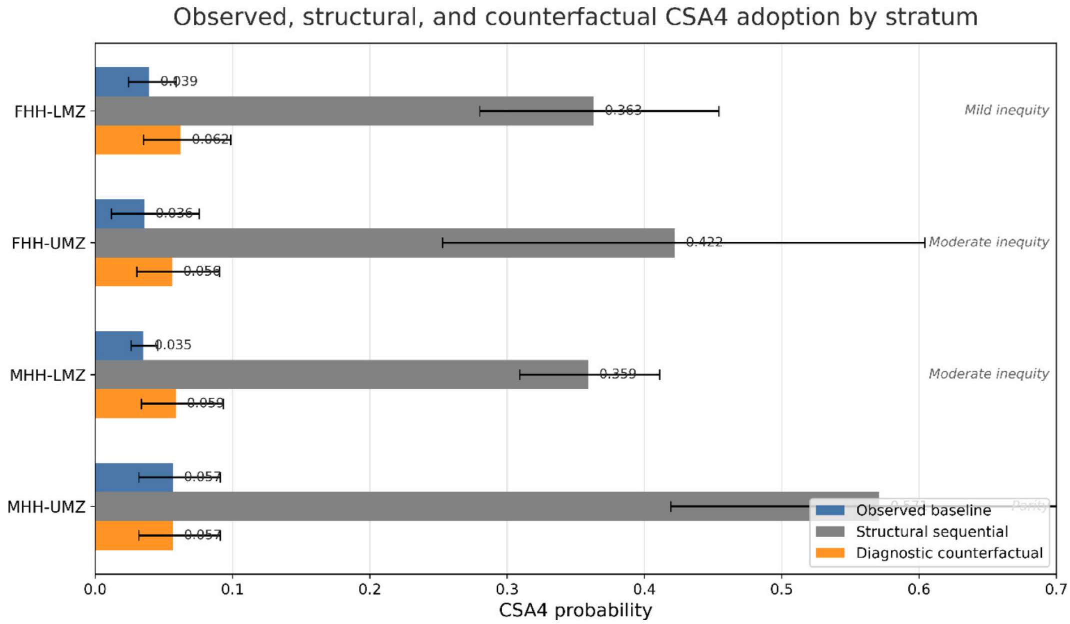

Fig. 5b. Observed, structural (sequential), and counterfactual CSA4 adoption probabilities by stratum. Bars represent the cumulative probability of adopting CSA4 under three scenarios: observed basesline (realized outcomes), structural sequential probability (predicted adoption under observed transition pathways), and diagnostic counterfactual (adoption under removal of identified pathway constraints). Error bars denote 95% credible intervals. Across all strata, observed adoption is substantially lower than the structural benchmark, indicating binding constraints along the adoption pathway. Counterfactual gains are positive but modest relative to the structural gap, suggesting that targeted interventions partially alleviate, but do not fully eliminate, systemic barriers. Panel annotations indicate equity classification based on the Integrated Adoption Equity Index (IAEI), linking outcome disparities to underlying structural inequalities.

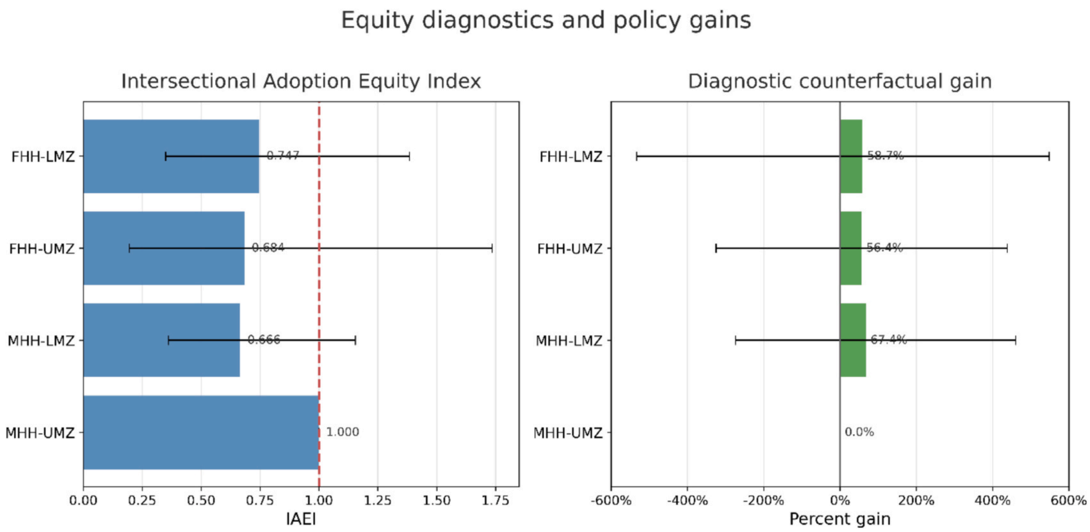

Fig. 5c. Intersectional Adoption Equity Index (IAEI) and diagnostic counterfactual gains in CSA4 adoption. The left panel presents IAEI values by stratum with 95% credible intervals, where the dashed vertical line at 1 denotes parity. Values below unity indicate inequity in adoption outcomes relative to the reference group (MHH-UMZ). The right panel shows percentage gains in CSA4 adoption under the diagnostic counterfactual scenario, with error bars reflecting uncertainty intervals. Results indicate that while all disadvantaged groups experience positive gains, the magnitude of improvement is insufficient to close structural equity gaps, as reflected by IAEI values remaining below parity. Together, the panels demonstrate that policy-relevant gains are constrained by deeper pathway dependencies and intersectional inequalities.

Table 2
Descriptive statistics by gender-agroecological stratum.

group	n	Mean	sd	se	median	min	max	q25	q75	ci_low	ci_high
FHH-LMZ	116	2.1	0.83	0.08	2	1	4	2	2	1.95	2.25
FHH-UMZ	29	2.21	1.11	0.21	2	1	5	1	3	1.8	2.61
MHH-LMZ	345	2.05	0.88	0.05	2	1	5	1	3	1.96	2.15
MHH-UMZ	79	2.19	1.34	0.15	2	1	6	1	3	1.89	2.49

Notes: n denotes sample size. Values are reported by gender–agroecological strata (FHH = female-headed households; MHH = male-headed households; LMZ = lower-midland zone; UMZ = upper-midland zone). Means are presented with standard errors (SE) and 95% confidence intervals (CI), indicating estimation precision and the range of plausible population values, respectively. Standard deviation (SD) reflects within-group variability. Median, minimum, maximum, and quartiles (q25, q75) summarize the distribution. Confidence intervals are computed as mean $\pm$ 1.96 $\times$ SE.

Table 3
Pooled Ising network edge strengths with 95% credible intervals.

Edge	$\hat{J}$	95% CI
CSA1–CSA2	–0.155	[–0.361, 0.039]
CSA1–CSA3	–0.385	[–0.577, –0.199]
CSA1–CSA4	–0.324	[–0.486, –0.141]
CSA1–CSA5	–0.153	[–0.381, 0.068]
CSA1–CSA6	–0.403	[–0.746, –0.049]
CSA2–CSA3	–0.088	[–0.273, 0.112]
CSA2–CSA4	0.153	[–0.031, 0.309]
CSA2–CSA5	0.038	[–0.197, 0.271]
CSA2–CSA6	0.118	[–0.196, 0.490]
CSA3–CSA4	0.146	[–0.027, 0.310]
CSA3–CSA5	0.118	[–0.093, 0.350]
CSA3–CSA6	0.337	[–0.021, 0.739]
CSA4–CSA5	0.253	[0.036, 0.450]
CSA4–CSA6	0.268	[–0.039, 0.533]
CSA5–CSA6	0.348	[–0.037, 0.761]

Note: Edge strengths ($\hat{J}$) are posterior means from the low-rank Ising model (rank = 3). Credible intervals are based on posterior draws and reflect uncertainty in the conditional associations. Positive values indicate complementarity; negative values indicate substitutability or shared constraints.

Table 4a
Selected stratified Ising edge strengths with 95% credible intervals.

Group	Edge	$\hat{J}$	95% CI	Interpretation
FHH-LMZ	CSA2–CSA5	–0.727	[–1.386, –0.203]	Strong negative
FHH-LMZ	CSA1–CSA4	–0.392	[–0.749, –0.015]	Credible negative
MHH-LMZ	CSA1–CSA6	–0.649	[–1.267, –0.080]	Strong negative
MHH-LMZ	CSA1–CSA3	–0.297	[–0.541, –0.035]	Credible negative
MHH-LMZ	CSA1–CSA4	–0.279	[–0.526, –0.004]	Credible negative
MHH-LMZ	CSA2–CSA3	–0.257	[–0.440, –0.063]	Credible negative
MHH-UMZ	CSA4–CSA5	0.686	[0.250, 1.151]	Strong positive
MHH-UMZ	CSA5–CSA6	0.524	[0.031, 1.090]	Positive
MHH-UMZ	CSA3–CSA4	0.460	[0.114, 0.798]	Strong positive
MHH-UMZ	CSA2–CSA4	0.406	[0.024, 0.795]	Positive
MHH-UMZ	CSA3–CSA5	0.390	[0.026, 0.737]	Positive

Note: Edges are selected where the 95% credible interval does not contain zero. For each stratum, only the most informative interactions are shown; full matrices are in Supplementary Tables S2-3a–d. Positive (negative) values indicate conditional complementarities (substitutability) after accounting for other practices.

3.7. Ensemble validation

Ensemble validation using leave-one-out cross-validation (LOO) demonstrated that the combined Ising + Bayesian chain ensemble outperformed both individual models (Table 7). The ensemble achieved the lowest expected log pointwise predictive density (ELPD_LOO = − 1663.3, SE = 28.5) and received a stacking weight of 1.0, indicating it was the optimal combination. Both the Ising network only (ΔELPD = − 47.97) and the Bayesian chain only (ΔELPD = − 17.77) performed worse, confirming that the ensemble captured complementary aspects of the adoption process. Fig. 6a provides a visual comparison of predictive performance based on posterior log-likelihood draws, consistent with the PSIS-LOO model comparison reported in Table 7.Fig. 6b..

Table 4b
Model comparison across low-rank Ising specifications using expected log predictive density (ELPD).

Rank	Model	ELPD	SE	ΔELPD vs best
1	Low-rank Ising (k = 1)	−1739.23	30.39	−28.42
2	Low-rank Ising (k = 2)	−1720.30	30.19	−9.49
3	Low-rank Ising (k = 3) − Best	−1710.82	30.02	0.00
4	Low-rank Ising (k = 4)	−1713.86	30.07	−3.04
5	Low-rank Ising (k = 5)	−1710.90	30.52	−0.08

Notes: ELPD denotes expected log predictive density, with higher (less negative) values indicating better predictive performance. SE represents the standard error of the ELPD estimate. ΔELPD vs best is calculated relative to the top-performing model. Models differ by the rank (k) of the low-rank Ising approximation, where higher k allows more complex dependence structures. Predictive performance improves substantially from k = 1 to k = 3, after which gains plateau, with k = 3 achieving the highest ELPD. The negligible difference between k = 3 and k = 5 (ΔELPD = –0.084) indicates that higher-rank models do not provide meaningful improvements in predictive accuracy. This pattern suggests that a three-dimensional latent structure is sufficient to capture the dependence structure in CSA adoption, supporting a parsimonious specification.

Table 5
Directed Bayesian network edges by stratum.

Group	Directed edges
Pooled	csa1 → csa3, csa1 → csa4
FHH-LMZ	csa2 → csa5
MHH-LMZ	csa1 → csa3, csa1 → csa6
MHH-UMZ	csa3 → csa4, csa4 → csa5, csa5 → csa6

Note: Directed acyclic graphs (DAGs) were learned using a score-based hill-climbing algorithm with the BDeu score (α = 1). Edges represent conditional dependencies consistent with a partial order (earlier practices can influence later ones). Pooled DAG includes only csa1 → csa3 and csa1 → csa4.

Taken together, the figures reveal that adoption disparities are not primarily driven by differences in entry into CSA, but by structural bottlenecks and pathway dependencies that limit progression, resulting in persistent equity gaps even under counterfactual improvement scenarios.

Summary of key findings.

- Adoption intensity did not differ significantly across gender or AEZ, but the composition of adopted practices varied.
- Most households adopted at least three practices, but full adoption of all six was rare (11–24%), with MHH-UMZ showing the highest complete adoption.
- The pooled Ising network revealed negative associations of CSA1 with CSA3 and CSA4, and positive complementarities between CSA4 and CSA5.
- Stratified networks showed that positive, significant complementarities were concentrated in MHH-UMZ, while other strata exhibited predominantly negative or weak interactions.
- Bayesian network directed pathways differed by stratum, with FHH-LMZ showing a single edge csa2 → csa5, MHH-LMZ showing csa1 → csa3 and csa1 → csa6, and MHH-UMZ showing a chain csa3 → csa4 → csa5 → csa6.
- Equity-adjusted metrics indicated that raw gains from a hypothetical intervention targeting CSA4 were modest and uncertain, with wide confidence intervals for all groups except the reference.
- Ensemble modeling combining Ising and Bayesian chain approaches outperformed either model alone, justifying the integrated framework.

These results underscore that CSA adoption is characterized by context-specific interdependencies and directed pathways, and that one-size-fits-all bundling or sequencing strategies are unlikely to be effective. Policy interventions should be tailored to the specific network structures and transition bottlenecks observed in each gender-AEZ stratum.

4. Discussion

This study set out to diagnose the structural barriers to equitable Climate-Smart Agriculture (CSA) adoption in Kenya. By integrating a Bayesian-Ising ensemble with an intersectional lens, we move beyond documenting adoption gaps to examining the mechanisms through which they are reproduced. The results show that both complementarities and adoption pathways are stratified: positive interactions are concentrated in the most advantaged stratum (male-headed households in the Upper Midlands, MHH-UMZ), while other strata exhibit weak or negative associations. The discussion synthesizes these findings to address the study's research questions, clarify the contributions to theory and method, and derive policy implications, while maintaining caution given the cross-sectional design and the uncertainty reflected in the credible intervals.

Table 6

Sequential adoption probabilities and equity metrics with 95% credible intervals.

Group	P(CSA1)	P(CSA2|CSA1)	P(CSA3|CSA1-2)	P(CSA4|CSA1-3)	Baseline P (CSA4)	Counterfactual P (CSA4)	IAEI	Equity Interpretation	Gap Closure	Raw Gain	Equity Weight
FHH-LMZ	0.832 [0.756, 0.894]	0.268 [0.190, 0.353]	0.484 [0.394, 0.571]	0.363 [0.280, 0.454]	0.0392[0.0241, 0.0590]	0.0622[0.03495, 0.09863]	0.747 [0.349, 1.384]	Mild inequity	1.357[–2.529, 4.460]	0.0230[–0.01026, 0.06221]	74.8[–533.4, 547.9]
FHH-UMZ	0.750 [0.585, 0.886]	0.219 [0.091, 0.380]	0.517 [0.342, 0.678]	0.422 [0.253, 0.604]	0.0358[0.0118, 0.0755]	0.0560[0.03045, 0.09060]	0.684 [0.195, 1.735]	Moderate inequity	1.057 [–0.7939, 2.713]	0.0202[–0.02637, 0.06210]	100.4 [–325.4, 438.3]
MHH-LMZ	0.785 [0.739, 0.826]	0.282 [0.237, 0.331]	0.439 [0.382, 0.500]	0.359 [0.309, 0.411]	0.0350 [0.02613, 0.04531]	0.0586[0.03366, 0.09340]	0.666 [0.361, 1.154]	Moderate inequity	1.127 [–0.2286, 2.650]	0.0236 [–0.003701, 0.05968]	26.9[–274.3, 460.1]
MHH-UMZ	0.756 [0.657, 0.842]	0.247 [0.161, 0.347]	0.530 [0.419, 0.633]	0.571 [0.419, 0.718]	0.0565 [0.03162, 0.09090]	0.0565[0.03162, 0.09090]	1.000 [1.000, 1.000]	Reference / parity	—	0.000[0.000, 0.000]	—

Notes: Transition probabilities (*P*) are means from posterior Dirichlet draws; 95% credible intervals are reported in the supplementary materials. Baseline cumulative P(CSA4) is the product of the four transition probabilities in the modeled sequence: P(CSA1) × P(CSA2|CSA1) × P(CSA3|CSA1, CSA2) × P (CSA4|CSA1, CSA3). Counterfactual P(CSA4) is obtained by applying the MHH–UMZ transition probabilities to the disadvantaged strata while retaining their own P(CSA1). IAEI = Baseline P(CSA4) ÷ P(CSA4) of the reference group (MHH–UMZ). Equity interpretation categories: Mild inequity (IAEI 0.7–0.9), Moderate inequity (IAEI 0.4–0.6). Gap closure = (counterfactual – baseline) ÷ (reference – baseline); values > 1 indicate overshoot. Raw gain = counterfactual – baseline. Equity weight = 1 ÷ raw gain. Point estimate only; confidence intervals are extremely wide, as shown in Table 6). The wide confidence intervals around raw gains, gap closure, and equity weight are discussed in the main text and should be considered when interpreting these metrics. Wide intervals are 95% credible/confidence intervals derived from posterior draws (bootstrap for equity metrics) indicate substantial uncertainty; these should be interpreted with caution and not used for precise cost-effectiveness claim.

Table 7
Ensemble model validation via Pareto-smoothed leave-one-out cross-validation.

Model	ELPD_LOO	SE	ΔELPD vs ensemble	Stacking_weight
Ising + BCA Ensemble	–1663.266	28.471	0.000	1.000
Ising network only	–1711.235	30.105	–47.969	0.444
Bayesian Chain only	–1681.033	30.434	–17.767	0.556

Note: ELPD_LOO = expected log pointwise predictive density (higher is better). ΔELPD is the difference relative to the best-performing model (ensemble). Stacking weights are the optimal convex combination of the two individual models; the ensemble receives a weight of 1.0, indicating it dominates predictive performance.

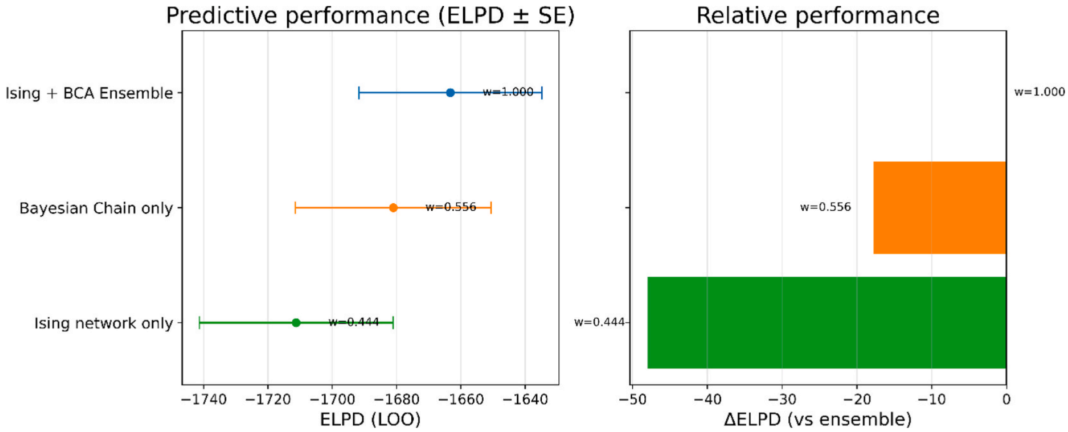

Fig. 6a. Predictive performance, relative comparison, and model contribution weights. The left panel presents expected log predictive density (ELPD) estimated via leave-one-out cross-validation, with error bars indicating standard errors. The right panel shows ΔELPD relative to the ensemble model (set to zero), illustrating the performance loss of alternative specifications. Colors distinguish models: ensemble (blue), Bayesian chain (orange), and Ising network (green). Stacking weights (w) indicate each model's contribution to the ensemble predictive distribution. The ensemble (stacking weights) achieves the highest predictive performance (w = 1.000), while the Bayesian chain model contributes slightly more than the Ising model (w = 0.556 vs 0.444), highlighting the importance of sequential adoption dynamics alongside structural complementarities. The consistency of performance differences relative to uncertainty supports the robustness and complementary value of the ensemble approach.

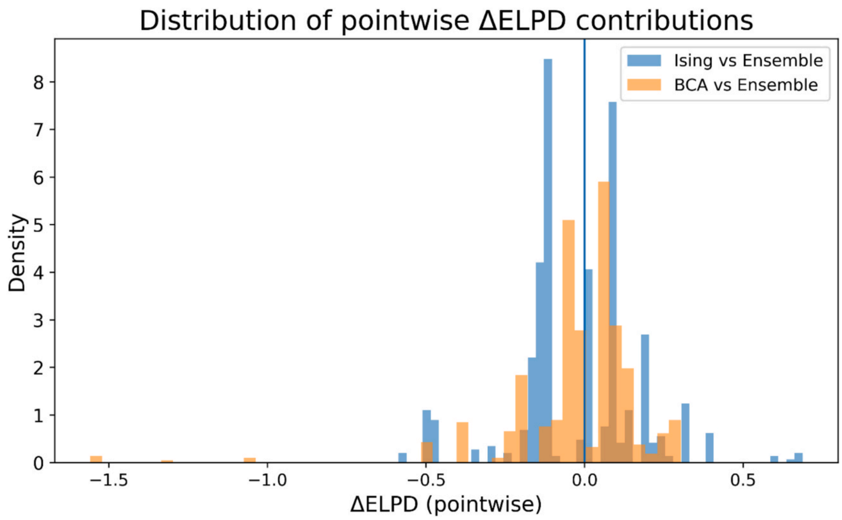

Fig. 6b. Distribution of pointwise predictive performance differences (ΔELPD). The figure shows the distribution of observation-level differences in expected log predictive density (ΔELPD) between component models and the ensemble. Negative values indicate observations for which the ensemble provides better predictive performance. The distribution is predominantly centered at or below zero for both models, indicating that ensemble gains are broadly distributed rather than driven by a small subset of observations. The wider dispersion for the Ising model reflects its inability to capture sequential dependencies, while the Bayesian chain model exhibits a narrower distribution, consistent with its closer aggregate performance. These results confirm that the ensemble improves predictive accuracy across the majority of observations.

4.1. Structural inequities as systemic conversion failures

Our first research question asked what fundamental structural barriers – shaped by gender and agroecological zone – impede equitable adoption. The results indicate that the central barrier is not simply initial access, but a failure in converting early adoption into progression along the broader pathway toward resilience. This pattern is consistent with the Capability Approach (Drèze & Sen, 1990; Sen, 1999), which distinguishes access to resources from the capability to convert those resources into valued outcomes.

Although a high proportion of female-headed households in the Lower Midlands (FHH-LMZ) adopt foundational soil management (CSA1; 83.6%), only 3.9% (95% CI: 2.4–5.9%) achieve the cumulative sequential outcome of reaching CSA4 through the modeled pathway. Male-headed households in the same zone (MHH-LMZ) show a similarly low completion rate of 3.5% (95% CI: 2.6–4.5%) despite 78.6% adopting CSA1. By contrast, the reference stratum (MHH-UMZ) reaches 5.6% (95% CI: 3.2–9.1%). These patterns suggest substantial attrition along the pathway, particularly in the Lower Midlands. However, the confidence intervals caution against treating differences across disadvantaged strata as definitive rank orderings.

The intersectional pattern is important. The most constrained group is not female-headed households per se, but male-headed households in the more marginal agroecological zone, closely followed by female-headed households in the same zone. This implies that agroecological disadvantages are at least as important as headship status in shaping progression along the adoption pathway. More broadly, the results suggest that equity in CSA should not be conceptualized only in terms of who adopts an initial practice, but also in terms of who is able to sustain movement through a sequence of interrelated practices. This aligns with Doss (2018), who argues that gendered productivity gaps are often misattributed to individual characteristics rather than structural constraints; and with (Agarwal, 1994) on how land tenure insecurity systematically limits women's ability to invest in long-term agricultural improvements.

This interpretation aligns with emerging evidence that studies focusing only on uptake may miss the more consequential question of pathway completion and sustained use (Birhanu & Jensen, 2023; Ragasa, 2012; Thompson et al., 2022). In this sense, the observed disadvantage is less about whether households enter the system and more about whether they can navigate it successfully once they do.

4.2. Stratified complementarities and the role of structural advantage

The stratified Ising results show that positive complementarities are concentrated in MHH-UMZ, with significant interactions for CSA3-CSA4 ($\hat{J} = 0.460$, 95% CI: 0.114–0.798) and CSA4-CSA5 ($\hat{J} = 0.686$, 95% CI: 0.250–1.151). By contrast, FHH-LMZ exhibits a strong negative interaction for CSA2-CSA5 ($\hat{J} = -0.727$, 95% CI: –1.386 to –0.203), while MHH-LMZ shows predominantly negative associations, including CSA1-CSA6 ($\hat{J} = -0.649$, 95% CI: –1.267 to –0.080) and CSA2-CSA3 ($\hat{J} = -0.257$, 95% CI: –0.440 to –0.063).

This distribution of complementarities suggests that synergistic bundling is not a universal property of CSA adoption. Rather, it appears to depend on social and agroecological conditions that are more favorable in the advantaged stratum. This pattern is consistent with literature showing that households with stronger access to credit, extension, information, and complementary inputs are better positioned to capture the compound benefits of multiple practices (Bezner Kerr et al., 2019; Fisher & Carr, 2015; Mudege et al., 2017). Quisumbing & Pandolfelli (2010) emphasize that women's differential access to agricultural inputs and services is a key driver of gendered adoption gaps. (Eriksen et al., 2021) further argue that structural vulnerability, not just exposure, determines adaptation outcomes. At the same time, the magnitudes of the positive interactions are moderate rather than extreme, and the credible intervals do not justify overly strong claims about deterministic "success bundles.".

The Bayesian Chain Analysis helps clarify the structural basis of these disparities. Directed pathways differ across strata. In FHH-LMZ, the only directed edge is CSA2 → CSA5, yet the Ising network indicates that these practices are negatively associated. In MHH-LMZ, the directed edges CSA1 → CSA3 and CSA1 → CSA6 are likewise paired with negative interactions. In MHH-UMZ, by contrast, the chain CSA3 → CSA4 → CSA5 → CSA6 is reinforced by positive complementarities among later-stage practices. Taken together, these findings suggest that the same practice may occupy very different roles across contexts: a gateway in one stratum, a bottleneck in another, and part of a reinforcing bundle in a third. This heterogeneity implies that uniform sequencing or bundling strategies are unlikely to perform well across groups.

Counterfactual simulations reinforce the need for caution. Applying MHH-UMZ transition probabilities to disadvantaged strata yields modest gains: FHH-LMZ increases from 0.0392 to 0.0622 ($\Delta = 0.023$, 95% CI: –0.010 to 0.062), and MHH-LMZ from 0.0350 to 0.0586 ($\Delta = 0.024$, 95% CI: –0.004 to 0.060). Because the credible intervals include zero, these gains are not statistically distinguishable from no effect. Similarly, equity gap closure estimates are highly imprecise. The most defensible interpretation is therefore not that the full gap is remediable, but that structural reforms may improve outcomes, albeit with uncertain magnitude.

4.3. The equity-efficiency nexus: A cautious interpretation

The equity metrics derived from the counterfactual analysis were intended to assess whether structurally targeted interventions might simultaneously advance equity and improve the efficiency of scarce climate investments. The results suggest that such an interpretation remains plausible in principle but cannot be established confidently with the present data.

The Intersectional Adoption Equity Index (IAEI) indicates relative disadvantage for both FHH-LMZ and MHH-LMZ, with point estimates of 0.747 (95% CI: 0.349–1.384) and 0.666 (95% CI: 0.361–1.154), respectively. These values are below 1, but the uncertainty intervals are wide and, in some cases, include parity. Likewise, the raw gains from the counterfactual simulations are modest and imprecise.

The same caution applies to the equity weight metric. Although designed to reflect the relative effort associated with improving adoption outcomes across groups, its posterior intervals are too wide to support strong claims about intervention efficiency or about the relative return to targeting more marginalized groups. Hallegatte et al. (2018, 2020) argue that climate adaptation investments must be prioritized based on both vulnerability and cost-effectiveness, but our results suggest that such prioritization requires much more precise estimates than the current data allow. Garschagen & Doshi (2022) similarly note that adaptation finance often fails to reach the most vulnerable because targeting mechanisms are insufficiently diagnostic. The current evidence therefore does not resolve the equity-efficiency trade-off. Rather, it shows that structurally targeted interventions may hold promise, but that the empirical basis for ranking such interventions remains weak without stronger precision and, ideally, direct cost data.

The policy implication is not that equity and efficiency are unrelated, but that they should be treated as questions for adaptive experimentation rather than settled conclusions. In this sense, the framework is more useful as a tool for screening and monitoring than for making high-confidence optimization claims.

4.4. Triangulated evidence for structural exclusion

The interpretation above would be less persuasive if the observed inequalities could plausibly be attributed to model artifacts, unstable measurement choices, or idiosyncratic sample composition. Our validation exercises reduce, but do not eliminate, these concerns.

Temporal stability checks, using split-sample re-estimation, indicate that the main adoption sequence patterns are relatively stable across sample splits ($\Delta\hat{J} \leq 0.02$; Supplementary Table S3.4). Latent-confounder perturbations, applied as heterogeneous normal noise to the posterior mean interaction matrix, suggest that unobserved variables are unlikely to reverse the sign of the core network structure, with a sign-consistency rate of 100% (Supplementary Table S3.5). Ordinal coding sensitivity checks, where a stricter adoption definition (practice adopted only if the household's total adoption count exceeds the median) is used, show that moving beyond binary coding does not materially alter the sign or rank order of the main interaction patterns; the core triad's sign consistency is preserved for one of the three edges, and the all-edge Spearman rank correlation, while not high, indicates that the qualitative structure remains recognizable (Supplementary Tables S3.6, S3.6a). Dirichlet pooling stabilizes conditional probability tables in sparse strata, reducing CPT variance by 57–59% for FHH-LMZ and FHH-UMZ without altering substantive interpretation (Supplementary Table S3.13).

The analytical framework is explicitly designed for portability, and replication in other regions is encouraged (Supplementary Tables S3.9, S3.15). As Tittonell & Giller (2013) argue, yield gaps in African smallholder systems are often poverty traps that are structurally reproduced; our findings are consistent with that diagnosis. Taken together, these checks support the interpretation that the observed disparities are not reducible to a single modeling assumption. At the same time, robustness should not be equated with certainty. The validation results strengthen confidence in the qualitative pattern of structural inequality, but they do not eliminate uncertainty regarding the size of specific counterfactual gains or the exact ranking of disadvantaged strata.

4.5. Policy levers: Addressing antagonisms and supporting context-specific pathways

The combined results point to three policy implications. The first is that policy should diagnose local interaction structures before promoting bundles. The second is that interventions should address the specific transition bottlenecks identified within each stratum. The third is that governance systems should monitor these dynamics adaptively rather than assume that a fixed package will work everywhere.

4.5.1. Diagnose local synergy structures before promoting bundles

The Ising results show that positive complementarities are not universal. In MHH-UMZ, later-stage practices such as CSA4-CSA5 and CSA5-CSA6 display moderate positive interactions, suggesting scope for bundled support. In FHH-LMZ and MHH-LMZ, however, many of the relevant interactions are negative. This means that policy should not assume that the same "resilience bundle" can be scaled across all strata. Instead, the first step should be to diagnose where antagonisms exist and what generates them.

For example, the strong negative interaction between CSA2 and CSA5 in FHH-LMZ suggests that water harvesting and energy efficiency may be in tension, potentially because of labor requirements, capital costs, or seasonal trade-offs. In such a context, promoting the bundle without first addressing the underlying incompatibility risks low uptake or incomplete pathway progression. Thornton et al. (2018) emphasize that adaptation strategies must be tailored to local contexts and gender dynamics; our findings provide a concrete empirical basis for such tailoring.

4.5.2. Target stratum-specific pathways rather than generic sequences

The Bayesian networks identify different directed pathways across strata. In FHH-LMZ, the only directed edge is CSA2 → CSA5. In MHH-LMZ, the main directed edges are CSA1 → CSA3 and CSA1 → CSA6. In MHH-UMZ, the pathway CSA3 → CSA4 → CSA5 → CSA6 is more coherent and better aligned with positive complementarities.

These differences imply that interventions should be pathway-specific. For FHH-LMZ, the practical challenge is not simply to promote CSA2 and CSA5, but to make them jointly feasible. For MHH-LMZ, policy should focus on reducing the tensions linking soil management to resilient crops and risk management. For MHH-UMZ, the policy problem is different: existing complementarities may be leveraged more effectively through coordinated support for later-stage bundling. The broader lesson is that pathway design should be conditional on local adoption architecture rather than assumed ex ante. Doss & Meinzen-Dick (2020) highlight that land tenure security is a foundational enabling condition; without it, even well-targeted pathways may fail to generate sustained adoption.

4.5.3. Embed equity audits within adaptive governance

Because the equity metrics remain uncertain, policy design should avoid presenting the results as a definitive targeting algorithm. Instead, the Bayesian-Ising ensemble is better understood as an adaptive governance tool. Used iteratively, it can help monitor whether interventions are changing interaction structures, transition probabilities, and relative disadvantage over time.

This suggests a role for equity audits within county agricultural planning and climate finance delivery. Metrics such as the IAEI, gap closure, and raw gain can provide standardized signals for identifying groups that warrant closer policy attention, but they should be interpreted alongside local qualitative evidence and continuous monitoring. Chambers (1997) long ago argued for participatory, context-sensitive approaches; our framework can be embedded in such processes to provide quantitative diagnostics that complement local knowledge. For financing mechanisms such as the Green Climate Fund, Adaptation Fund, or Loss and Damage architecture, the main contribution of the framework is diagnostic discipline: it can help ensure that targeting decisions are informed by structurally specific evidence rather than broad assumptions about vulnerability.

4.6. Methodological legacy: A portable diagnostic toolkit

Our second research question asked how a novel analytical framework can inform more effective and equitable policy. A central contribution of this study is therefore methodological. The Bayesian-Ising ensemble integrates two dimensions that are often treated separately in adoption research: simultaneous dependence among practices and sequential progression through an adoption pathway.

Conventional approaches such as count models, multivariate probit, and structural equation models can be informative, but they do not readily capture both synergy and sequencing while preserving intersectional heterogeneity. Bayesian networks have increasingly been used in agricultural adoption research to model conditional dependencies and pathway structures (Gambelli & Bruschi, 2010; Khanal et al., 2019; MacPherson et al., 2025). Our framework extends this literature by combining Ising-based co-adoption structure, Bayesian chain analysis, and equity-oriented diagnostics within a unified stratified design. Jagustović et al. (2019) and Scoones & Stirling (2020) advocate for complex systems perspectives in sustainability science; our framework operationalizes such perspectives by modeling emergent synergy and path dependence.

The key value of the framework is portability. The specific empirical findings reported here are context-bound, but the analytical workflow can be replicated elsewhere to identify context-specific complementarities, bottlenecks, and pathway disparities. In that sense, the framework should not be read as prescribing a universal model of CSA adoption, but as offering a diagnostic toolkit for identifying where and how structural barriers emerge.

4.7. Limitations and strategic research frontiers

While the framework addresses several methodological gaps, important limitations remain.

4.7.1. Temporal dynamics and causal inference

The cross-sectional design identifies structured patterns in adoption, but it cannot establish causal sequence formation or show how those pathways evolve under shocks or policy change. The counterfactuals should therefore be interpreted as diagnostic simulations, not causal forecasts. Future work using panel data could extend the framework toward rolling-window or time-varying analysis, allowing equity audits to track whether pathway constraints change over time. Literature affirms how poverty traps in agriculture require longitudinal designs to capture dynamics; our framework is intended as a foundation for such future studies (Barrett & Carter, 2013; Carter & Barrett, 2006; Jensen et al., 2024).

4.7.2. Adoption intensity and economic valuation

Binary coding was necessary for the present framework, but it obscures meaningful variation in implementation quality and intensity. Future work should integrate graded or ordinal adoption structures to assess whether complementarities differ at higher levels of implementation and whether intensity changes the estimated welfare consequences of pathway completion. Michler et al. (2019) and Suri (2011) illustrate the importance of accounting for selection and intensity in technology adoption; our ordinal sensitivity checks suggest binary findings are robust, but intensity likely matters for welfare outcomes.

4.7.3. Measurement error in self-reported adoption

Self-reported adoption may be subject to recall and social desirability bias. Such error would likely attenuate estimated complementarities and transition probabilities, making the present findings conservative. Future studies would benefit from validation subsamples, field observation, georeferenced verification, or other objective adoption measures. Abay et al. (2021) and Carletto et al. (2015) emphasize the need for improved measurement in agricultural surveys; our sensitivity checks help, but full validation remains a priority.

4.7.4. Geographical generalizability

The empirical results are grounded in Western Kenya's high-rainfall systems and should not be generalized mechanically to arid and semi-arid regions. The framework itself is portable, but its empirical outputs are context-specific. Replication in ASAL counties would be especially valuable for testing whether the observed adoption architecture changes under different biophysical and institutional conditions. Jellason et al. (2022) and Vetter, 2005) highlight the distinct dynamics of dryland systems; our framework could be applied there to generate comparative insights.

4.7.5. Alignment with farmer perceptions and local priorities

The patterns identified by the ensemble are statistically robust, but they may not fully coincide with farmer-preferred bundles or locally legitimate intervention pathways. Future research should therefore combine the present diagnostics with qualitative and participatory approaches to identify whether statistically constrained pathways also align with lived priorities and local perceptions of feasibility. Dossou-Yovo et al. (2024) and Long (2003) illustrate the value of integrating local knowledge with formal modeling.

Nonetheless, this study makes four main contributions. First, it provides quantitative evidence that complementarities and adoption pathways are stratified rather than universal. Second, it operationalizes a capability-based interpretation of adoption by distinguishing entry into the system from progression through it. Third, it bridges complex systems thinking and policy diagnostics by linking co-adoption structure, sequential attrition, and equity metrics. Fourth, it contributes to climate finance debates by offering a framework for uncertainty-aware targeting under structural inequality. The contribution is therefore not simply to show that disadvantage exists, but to provide a way of diagnosing how it is organized and where policy may need to intervene.

4.8. Conclusion

This study shows that complementarities and adoption pathways in CSA are stratified rather than universal. Positive interactions are concentrated in the most advantaged stratum (MHH-UMZ), while disadvantaged strata exhibit weak or negative associations and substantially lower rates of cumulative pathway completion. The main contribution of the Bayesian-Ising ensemble is therefore diagnostic: it shifts attention from whether adoption gaps exist to how they are organized through interaction structures and sequential bottlenecks. Three conclusions follow. First, complementarities are context-specific. Policies should diagnose local interaction structures before promoting bundles, rather than assuming that a single package can be scaled across heterogeneous settings. Second, equity should be understood not only in terms of access to initial practices, but also in terms of the capability to progress along a broader adoption pathway. Third, while counterfactual diagnostics suggest that structural reforms may improve outcomes, the gains are modest and uncertain and therefore do not justify strong claims about remediability or efficiency advantage. Although the study is grounded in Western Kenya's high-rainfall systems, the broader analytical framework is portable. As climate adaptation finance increasingly emphasizes targeting, accountability, and equity, there is a growing need for tools that can diagnose structural barriers rather than merely describe symptomatic adoption gaps. The Bayesian-Ising ensemble is offered in that spirit: not as a universal prescription, but as a reproducible diagnostic framework for identifying where climate adaptation systems are most likely to exclude, stall, or reinforce advantage.

CRediT authorship contribution statement

Denis Momanyi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Job K. Lagat:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Jiqin Han:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Robert A. Marchant:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **George M. Ogendi:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Hermann Lotze-Campen:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Stefan Sieber:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Denis Momanyi reports financial support was provided by Foundation Fiat Panis Project No. 2023/06. Denis Momanyi reports financial support was provided by World Wildlife Fund Russell E. Train Education for Nature Program (EFN) #EF14201. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2026.100828.

Data availability

Data will be made available on request.

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