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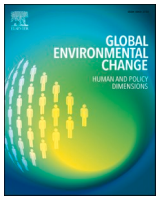

Precision justice in climate adaptation: Diagnosing asymmetric climate risk to target intersectional vulnerability – A Kenyan study with global implications

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ABSTRACT

Climate adaptation promises resilience, yet persistent disparities suggest that current investments fail to identify who remains most vulnerable and why. We introduce precision justice - a diagnostic framework centered on asymmetric climate sensitivity that distinguishes households suffering steep yield losses under adverse conditions from those able to benefit under favorable conditions. Applying this framework to 569 maize-producing smallholder households in Western Kenya, we identify a pronounced climate asymmetry trap. Female-headed households in the Lower Midland Zone show the most adverse profile: they exhibit high downside sensitivity and limited relative upside potential, and 57% have yields below the 1.8 t/ha threshold, compared with 0% in more advantaged strata. Their asymmetry ratio – the balance of upside gain to downside loss - is roughly 2.2, less than half that of male-headed households in the same zone. A secondary Rasch-based adoption-propensity measure suggests that implementation capacity may condition some climate-yield relationships, but this evidence is modest and treated as exploratory. These findings challenge universal adaptation models and show how downside-risk diagnostics can inform more precise financial protection, while capacity diagnostics can support better-matched extension. By diagnosing asymmetric risk at the intersection of gender and agroecology, precision justice offers a scalable framework for aligning climate finance with local vulnerability across the Global South.

1. Introduction

Environmental and ecological change is intensifying worldwide, placing the livelihoods and well-being of millions at risk. In response, significant global efforts and resources have been directed toward supporting adaptation initiatives in affected communities (Barnes et al., 2025). However, expansion in investment has not resolved underlying distributional inequities. Climate adaptation investments in low- and middle-income countries are expanding rapidly, yet persistent disparities suggest that these efforts often fail to reach the most vulnerable households (Garschagen and Doshi, 2022; Islam, 2022). Emerging adaptation debates increasingly warn that transferring climate risk management to individuals without recognizing unequal capacities may reinforce structural disadvantage (Parsons, 2026).

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In Sub-Saharan Africa, smallholder rainfed maize production – the backbone of food security for more than 300 million people - is increasingly exposed to rising temperatures and erratic rainfall (Badu-Apraku and Fakorede, 2017; Rezaei et al., 2023; Touch et al., 2025). Kenya's maize sector exemplifies this challenge: yields remain at roughly half of their potential despite sustained investment in climate-smart agriculture (Laub et al., 2023; van Ittersum et al., 2016), while projections of a 20% decline by 2050 underscore the urgency of addressing these risks (Rezaei et al., 2023). These persistent gaps suggest that the challenge is not only one of resource constraints, but also of how vulnerability is identified and addressed in existing analytical frameworks.

Current approaches tend to emphasize aggregate adoption and average outcomes but provide limited insight into how risk exposure varies across populations (Ahmed et al., 2025; Howard et al., 2024). As a result, they may overlook systematic differences in how households experience climate stress and benefit from adaptation interventions (Ngigi et al., 2017; Scognamillo et al., 2024). Consequently, substantial adaptation investments risk reinforcing the very inequalities they aim to reduce. More specifically, three limitations in contemporary adaptation frameworks hinder precise diagnosis of vulnerability.

First, although asymmetric risk metrics are well established in financial economics (Ang et al., 2006; Estrada, 2006; Sortino and Price, 1994; Sortino and Van Der Meer, 1991), their application to agricultural climate vulnerability remains limited - particularly in distinguishing adverse from favorable exposure across intersecting social dimensions such as gender and agroecology. Intersectionality infers the understanding that multiple dimensions of identity interact in ways that shape distinct experiences of disadvantage or advantage (Schill et al., 2026). Standard approaches, however, continue to rely on symmetric mean-variance formulations that obscure differential tail risk across populations (Markowitz, 1952; Rockafellar et al., 2006; Rockafellar and Uryasev, 2000, 2002).

Second, adaptive capacity is usually proxied using asset indices, binary adoption counts, or simple tallies, which inadequately capture the latent behavioral and cognitive dimensions that shape whether households can effectively implement complex technologies (Baker and Kim, 2004; De Ayala, 2009; Arndt et al., 2014; Cook et al., 2021). Third, and most critically, risk exposure and capacity are rarely integrated within a unified empirical framework. As a result, policymakers lack tools to identify households facing both elevated downside risk and constrained implementation capacity, increasing the likelihood of mismatches between standardized interventions and locally specific vulnerability profiles (Djoudi et al., 2016; Doss, 2018; Garschagen and Doshi, 2022).

Emerging paradigms – framing adaptation through justice, resilience, or development - are gaining momentum, echoing a broader diversity of local needs, knowledge systems, and lived experiences (Amorim-Maia and Olazabal, 2025). Recent research further suggests that climate responses and perceptions are socially structured and conditioned by unequal access to resources rather than determined solely by information or exposure (Mortell et al., 2026). This reinforces the need to examine adaptation through differentiated social positions rather than aggregate populations.

To advance this discourse, we introduce precision justice as a diagnostic framework centered on asymmetric climate sensitivity, measured through downside and upside yield responses to moisture stress. We complement this core risk diagnostic with a Rasch-based adoption-propensity measure, used as a secondary indicator of implementation capacity. Precision justice therefore requires diagnosing exposure asymmetry first, then examining whether capacity constraints further shape the ability to act on available adaptation options.

This framing motivates the central empirical questions of the study:

1. How do downside and upside climate sensitivities reveal asymmetric vulnerability among smallholder households?
2. How do these asymmetries vary across gender and agroecological strata?
3. How can a secondary implementation-capacity diagnostic support more targeted adaptation strategies?

We address these questions using two complementary diagnostics. First, asymmetric climate sensitivity is quantified through downside (β^{-}) and upside (β^{+}) coefficients adapted from financial risk analysis. Second, latent adoption propensity (θ) is estimated using Item Response Theory (IRT) as an exploratory indicator of implementation readiness, acknowledging that adaptive capacity is likely multidimensional (Baker and Kim, 2004; De Ayala, 2018; Embretson and Reise, 2013).

The analysis is embedded within a distributive-procedural perspective on climate adaptation (Fraser, 2008, 2009; Schlosberg, 2007), drawing on the IPCC risk framework (Fuchs et al., 2024; Solomon, 2007), capabilities and entitlements (Devereux, 2001; Sen, 1983, 1999), and social vulnerability (Blaikie et al., 2014) and intersectionality perspectives (Crenshaw, 1989, 1991).

Applying this framework to data from 569 smallholder households in Kenya, we identify pronounced disparities across groups. Female-headed households in the Lower Midland Zone exhibit substantially higher downside sensitivity alongside a less favorable relative balance between upside and downside sensitivity, with 57% of households recording yields below the 1.8 t/ha threshold, compared with 0% in more advantaged groups. These patterns are not readily apparent in aggregate statistics. By diagnosing who is vulnerable (intersectional position), why they are vulnerable (asymmetric exposure), and how interventions can be targeted (β^{-}-calibrated protection), precision justice shifts adaptation policy from aggregate indices to empirically grounded, context-specific targeting. In this light, what matters is not average vulnerability, but how it is distributed - and how it can be precisely diagnosed and addressed.

The remainder of the paper is organized as follows. Section 2 outlines the study context, data, and empirical strategy. Section 3 presents the empirical results centered on the core asymmetric-risk diagnostic, while secondary implementation-capacity analyses are reported in the Supplementary Material. Section 4 discusses implications for adaptation policy. Section 5 concludes.

2. Methods

2.1. Study area and data

We conducted a cross-sectional survey of 569 maize-producing households in Western Kenya in September–October 2023, a region characterized by predominantly rainfed systems and socio-agroecological heterogeneity (Jaetzold, 2010; Jaetzold et al., 2006). A multistage stratified, purposive, and simple random sampling design was used to ensure representation across gender and agroecological zones (AEZs). Counties and sub-counties were purposively selected to capture variation in climate, soil, and market access, followed by random selection of villages and households within each stratum.

Survey respondents were drawn from either household heads or those responsible for key agricultural decisions. In male-headed households, the male head usually participated, although the spouse was interviewed when she played the central decision-making role or when the male head was unavailable. In contrast, female-headed households – whether de jure or de facto - were represented by the female head.

Data were collected using ODK-based questionnaires covering household demographics, farm management practices, and adoption of six climate-smart agriculture (CSA) practices. Ethical clearance was obtained from Kenya, National Commission for Science, Technology and Innovation - NACOSTI (License No: NACOSTI/P/23/28688). The distribution of the sample across strata is presented in Table 2. Because sub-counties in this region span multiple agroecological zones, households were sampled by village within zone rather than by sub-county (see

Supplementary Table A1 for the full village matrix). (See Figs. 1–3.) (See Table 1.) (See Tables 3–5.)

2.2. Analytical framework: precision justice as a distributive-procedural hybrid

The analytical strategy follows a diagnostic progression from identifying patterns of exposure to informing differentiated targeting. It centers on asymmetric climate sensitivity, captured by downside (β^-) and upside (β^+) coefficients that characterize how yields are associated with adverse and favorable moisture conditions. These metrics are examined across intersecting social and agroecological strata to reveal heterogeneous vulnerability profiles.

The framework is grounded in a distributive-procedural conception of precision justice, understood as an analytical lens rather than a new theory. The distributive dimension concerns how risks and resources are allocated across groups, while the procedural dimension relates to whether individuals are able to effectively utilize available intervention (Fraser, 2008, 2009; Schlosberg, 2007; Sen, 1983). In this context, β^- and β^+ serve as diagnostic indicators that can inform more differentiated approaches to financial protection, while θ provides a secondary check on implementation readiness.

The contribution of the framework lies in integrating asymmetric risk diagnostics with disaggregated, intersectional analysis. Drawing on downside risk from finance (Ang et al., 2006; Estrada, 2006; Sortino and Price, 1994), and intersectional perspectives from social science (Crenshaw, 1989, 1991), it provides a structured basis for examining how vulnerability varies across populations.

2.3. Stage 1: Descriptive stratification-identifying intersectional disparities

To characterize the empirical distribution of vulnerability, we examine yield outcomes and the share of households with yields below the 1.8 t/ha threshold across gender–AEZ subgroups. Yield distributions are visualized using kernel density estimates and boxplots for the four intersectional groups (FHH-LMZ, FHH-UMZ, MHH-LMZ, MHH-UMZ). The incidence, depth, and severity of below-threshold yields are assessed using the Foster-Greer-Thorbecke (FGT) class of measures (Alkire and Foster, 2011; Foster et al., 1984, 2010), defined as:

$$FGT_\alpha = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z - Y_i}{z}\right)^\alpha 1(Y_i < z)$$

where Y_i denotes maize yield (t/ha) for household i, z=1.8 t/ha is the subsistence threshold (Kang'ethe et al., 2020):

- FGT_0: incidence of below-threshold yields.
- FGT_1: depth of the yield shortfall
- FGT_2: severity of the yield shortfall

Table 2
Distribution of households across gender and agroecological strata.

Group	n	%
Whole sample	569	100
LMZ	461	81.0
UMZ	108	19.0
FHH	145	25.5
MHH	424	74.5
FHH-LMZ	116	20.4
FHH-UMZ	29	5.1
MHH-LMZ	345	60.6
MHH-UMZ	79	13.9

Note: Sub-counties in Western Kenya span multiple agroecological zones. For example, Kakamega County includes both Upper Midland Zone (Matungu) and Lower Midland Zone (Navakholo, Ikolomani) sub-counties; Bungoma County includes both Upper Midland Zone (Tongaren) and Lower Midland Zone (Bumula, Sirisia) sub-counties. Village-level sampling details are reported in Supplementary Table A1.

Uncertainty is assessed using bootstrap 95% confidence intervals based on 2000 resamples (Efron and Tibshirani, 1994).

To assess differences across groups, we estimate a two-way analysis of variance (ANOVA) with gender (female- vs. male-headed households) and AEZ (LMZ vs. UMZ), including their interaction. Effect sizes are reported using eta-squared (η^2) (Cohen, 1988), and pairwise comparisons are conducted using Tukey's Honestly Significant Difference (HSD) test (Tukey, 1949). Full ANOVA and Tukey results are reported in the Supplementary (Tables S1-S4).

Moreover, additional descriptive metrics, including tail risk measures and inequality indicators (Gini coefficients), are used to further characterize variation in vulnerability across groups.

2.4. Stage 2: Asymmetric climate risk quantification (β^-, β^+)

Standard risk metrics assume symmetric yield responses, which may obscure differences in how adverse and favorable conditions are associated with outcomes. To capture potential asymmetries, we adapt downside and upside sensitivity measures from financial risk analysis to characterize how yields are associated with local climate variability.

Given the cross-sectional design, β^- and β^+ are interpreted as spatial conditional associations between yields and climate conditions across households and locations, rather than temporal responses or causal effects. We estimate these by comparing yields across households experiencing different moisture regimes (adverse vs. favorable SPEI-3 DJF values) within the same agroecological zone.

This approach mitigates confounding from soil heterogeneity and temperature variation because: (i) AEZ stratification controls for soil type, elevation, and base biophysical conditions (Jaetzold, 2010), and (ii) SPEI standardization accounts for evaporative demand in its calculation, isolating moisture availability.

Thus, β^- reflects yield sensitivity to adverse moisture conditions across space (drier vs. wetter locations within the same AEZ), while β^+ reflects sensitivity to favorable moisture conditions across space - not "bad years" versus "good years" for the same household (Lobell et al., 2009; Lobell and Asseng, 2017; Lobell and Burke, 2010; Lobell and Di Tommaso, 2025).

Selection of climate indices: We use the Standardized Precipitation–Evapotranspiration Index at a 3-month accumulation (SPEI-3), which captures combined effects of precipitation and evaporative demand (Vicente-Serrano et al., 2010). Based on maize phenology in Western Kenya (Marcos-Garcia et al., 2024; Mumo and Yu, 2020; Ojara et al., 2022), we select the SPEI-3 for December–February (DJF), representing mid- to late-season moisture conditions. Preliminary screening using non-parametric methods (random forest permutation importance and univariate generalized additive models) indicates that this index is among the most relevant climate correlates of yield variation. Variance inflation factors (VIF < 2) suggest limited multicollinearity (Hair et al., 2013). Full screening results are reported in the Supplementary (Tables S11–S14).

Piecewise specification (McGee and Carleton, 1970): For each household i, the climate index C_i is decomposed into negative and positive components:

$$C_i^- = \min(C_i, 0), C_i^+ = \max(C_i, 0)$$

We then estimate the following piecewise linear model for each subgroup s:

$$Y_i = \alpha_s + \beta_s^- C_i^- + \beta_s^+ C_i^+ + \varepsilon_i$$

where β_s^- captures the association between yields and adverse conditions, and β_s^+ captures the association with favorable conditions.

To improve robustness, we estimate the model using Huber regression (Huber, 1992) and compute 95% confidence intervals via bootstrap

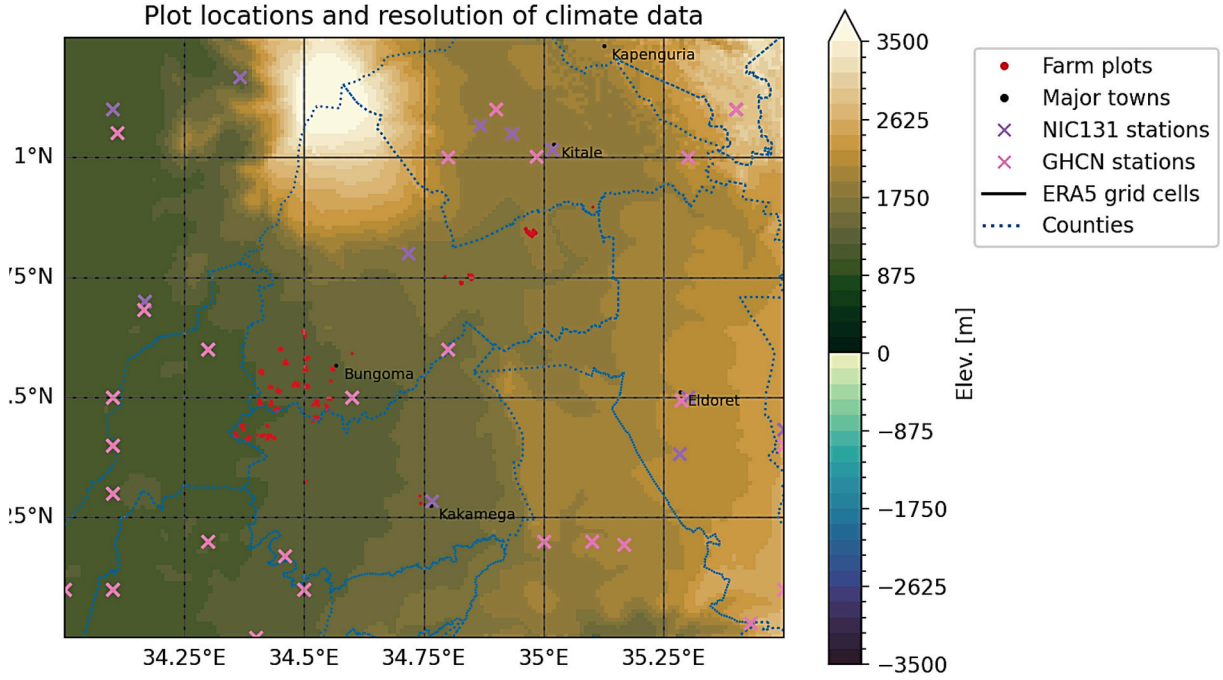


Fig. 1. Study area and sampling distribution across agroecological zones in Western Kenya. The study includes 569 maize-producing smallholder households sampled from Kakamega and Bungoma counties in Western Kenya. Households were stratified by agroecological zone (Lower Midland Zone [LMZ] and Upper Midland Zone [UMZ]) and by household-head gender to support intersectional analysis. Sampling locations and climate-data resolution are shown spatially. Detailed village-level sampling information is reported in the Supplementary Material.

with 1000 resamples (Efron and Tibshirani, 1994). Results are reported for subgroups with sufficient sample size and stable estimates; less stable estimates are presented in the Supplementary (Table S15). The Huber-robust regression for the piecewise asymmetric beta estimation is possible because the same climate index (SPEI-3 DJF) has both negative and positive values in the sample (except in the UMZ, where it is always negative). The piecewise regression model decomposes the index into two separate variables - downside component and upside component - which are entered simultaneously. The coefficient for the downside component (β^-) estimates the yield response when the index moves from zero to more negative (drier); the coefficient for the upside component (β^+) estimates the yield response when the index moves from zero to more positive (wetter).

2.5. Stage 3: Secondary implementation-capacity diagnostic

As an exploratory secondary indicator, we estimate a Rasch-based adoption-propensity score (θ) using the six CSA practices. Because θ is not the primary inferential focus of this manuscript, its validation diagnostics and exploratory climate-yield buffering analyses, including alternative 2PL results, are reported in the Supplementary Material (Section S2.2, Tables S6-S10, Figs. S5-S7). In the main manuscript, θ is retained only as a secondary implementation-capacity diagnostic for framing and policy interpretation.

The Rasch model was selected over the 2-parameter logistic model due to greater stability and interpretability of θ scores, despite some items exhibiting weak or inconsistent discrimination. The resulting θ scores are standardized (mean = 0, SD = 1) and range from −2.30 to 4.08. Construct validity was assessed by examining correlations between θ and external variables not included in the IRT estimation, including household head education, household size, fertilizer use, and dietary diversity. Spearman rank correlations are reported in Supplementary Table S10. Positive associations with education and input use are consistent with interpreting θ as a proxy for implementation readiness, while remaining distinct from conventional proxies such as wealth or education.

2.6. Robustness checks and limitations

Analyses not central to the core asymmetric-risk framework are reported in the Supplementary. These include: (i) full ANOVA results with effect sizes and Tukey HSD pairwise comparisons; (ii) robustness checks for asymmetric sensitivity estimates using ordinary least squares, median quantile regression, and ridge regression; (iii) machine learning validation using random forest models with cross-validation; and (iv) exploratory generalized additive models examining climate–yield relationships. These analyses provide additional context and reinforce the consistency of the main findings.

All analyses were implemented in Anaconda with Python 3.10 and R 4.2. The full code and data (subject to ethical restrictions) are available in the supplementary materials.

Limitations: The cross-sectional design captures associations rather than temporal dynamics; accordingly, β^- and β^+ are interpreted as spatial conditional relationships rather than causal effects. The IRT specification assumes a single latent dimension, while some item characteristics suggest multidimensionality; we therefore interpret θ as a parsimonious summary of adoption propensity rather than a comprehensive measure of adaptive capacity.

3. Results

Our analytical strategy follows a sequential diagnostic logic. Stage 1 identifies distributional disparities across gender-AEZ strata. Stage 2 quantifies asymmetric climate sensitivity (β^-/β^+) as spatial conditional associations. This progression links exposure and intersectional position into a coherent diagnostic framework.

3.1. Descriptive stratification: intersectional disparities in yield and below-threshold yield incidence

We operationalize intersectionality descriptively through stratification (gender × AEZ), rather than through formal interaction effects, given the cross-sectional design and sample size constraints. Maize

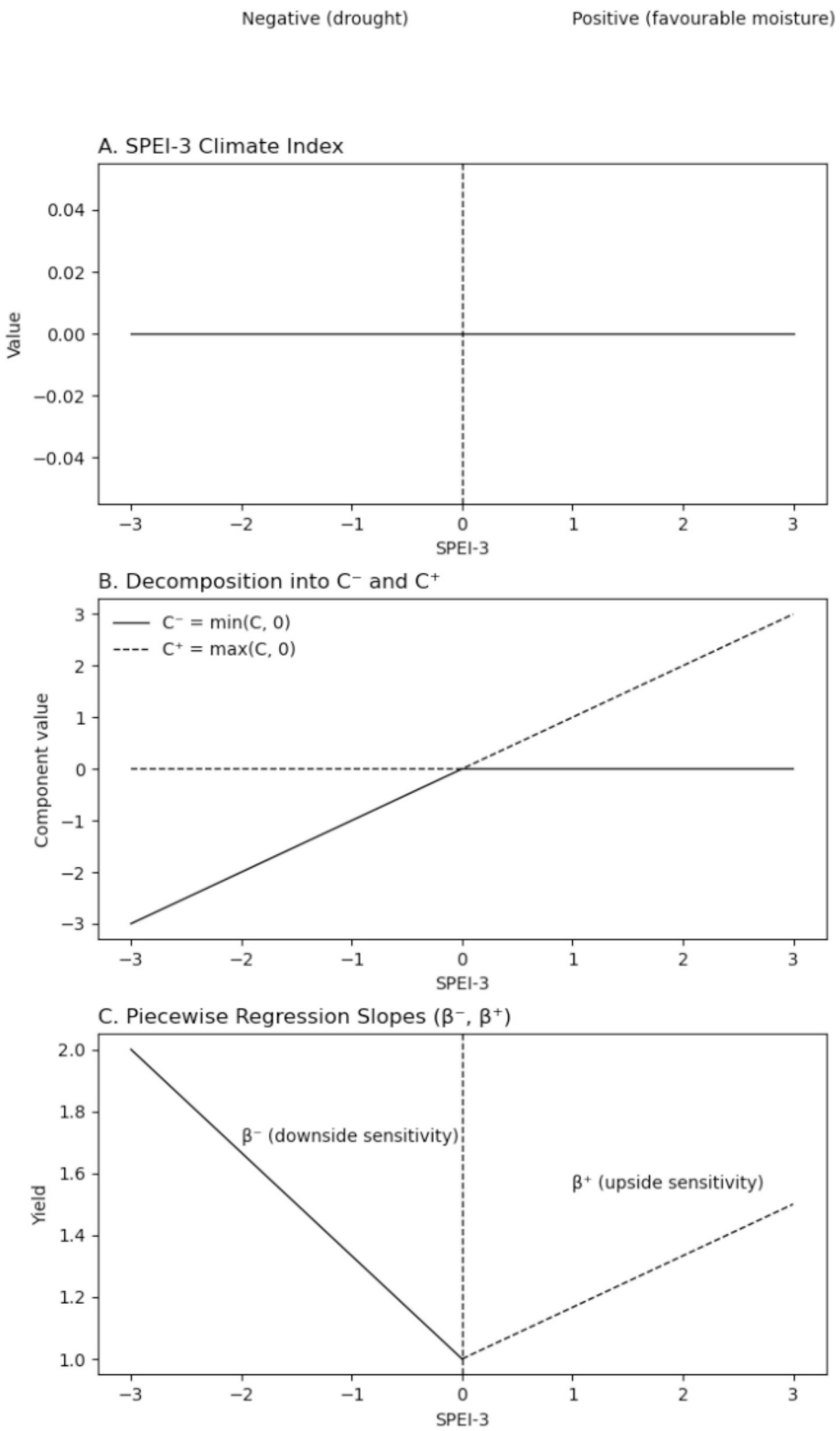
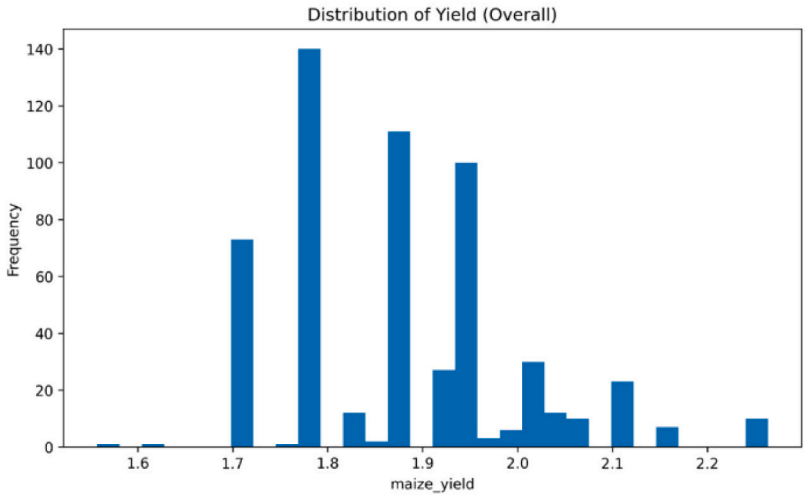


Fig. 2. Construction of the asymmetric climate-sensitivity diagnostic. Panel A shows the standardized SPEI-3 moisture index for December–February (DJF). Panel B illustrates decomposition of the climate index into negative (dry) and positive (wet) components used in piecewise estimation. Panel C presents the conceptual derivation of downside (β^{-}) and upside (β^{+}) climate sensitivity coefficients. Downside coefficients capture yield responses under adverse moisture conditions, whereas upside coefficients capture responses under favorable moisture conditions.

yields varied markedly by agroecological zone, while differences by gender were minimal. The Lower Midland Zone had a mean yield of 1.85 t/ha (SD = 0.094), compared to 2.02 t/ha (SD = 0.123) in the Upper Midland Zone. Within each AEZ, yields were similar across gender groups: LMZ female-headed = 1.835 t/ha and male-headed = 1.850 t/ha; UMZ female-headed = 2.020 t/ha and male-headed = 2.024 t/ha.

A two-way ANOVA showed a strong main effect of AEZ ($F = 271.5$, p

Panel A.



Panel B.

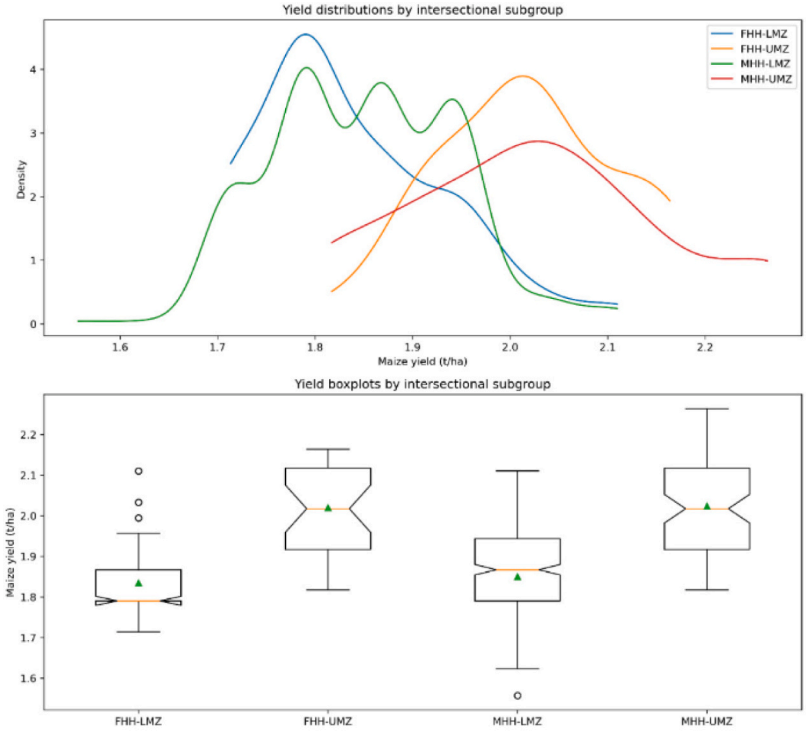


Fig. 3. Yield distribution and intersectional disparities in maize production outcomes. Panel A presents the overall distribution of maize yield among sampled households. Panel B shows yield distributions across gender × agroecological strata (female-headed households [FHH] and male-headed households [MHH] within Lower Midland Zone [LMZ] and Upper Midland Zone [UMZ]). Female-headed households in the LMZ exhibit a lower yield central tendency and a higher share of households with yields below the 1.8 t/ha threshold, consistent with subsequent asymmetric-risk diagnostics. Yield is expressed in tons per hectare (t/ha).

Table 1
Precision justice framework linking climate asymmetry, implementation capacity, and adaptation targeting.

Core component	Role	Operationalization	Diagnostic question	Policy implication
Asymmetric exposure	Core diagnostic	Downside (β^{-}) and upside (β^{+}) climate sensitivity	How is climate risk distributed across the yield distribution?	β^{-}-calibrated insurance: align protection with downside exposure
Intersectional stratification	Core diagnostic	Gender × agroecological zone (AEZ)	Who suffers steep losses in drought yet gains little in optimal seasons?	Target hidden vulnerability hotspots invisible in aggregate data
Adoption propensity	Secondary diagnostic	Rasch θ score	What is a household's capacity to utilize complex adaptation technologies?	Match extension complexity to demonstrated implementation readiness
Precision justice synthesis	Integrating lens	Risk × capacity	Where are the sharpest disparities hidden by aggregate analysis?	Differentiated adaptation portfolios

Table 3
Yield outcomes and vulnerability across gender–agroecological strata.

Group	n	Mean yield (t/ha)	SD	CV (%)	FGT_0 (headcount)	FGT_1 (gap)	FGT_2 (severity)
Whole sample	569	1.880	0.122	6.5	0.380	0.00798	0.00035
LMZ whole	461	1.846	0.094	5.1	0.469	0.00985	0.00044
UMZ whole	108	2.023	0.123	6.1	0.000	0.000	0.000
FHH–LMZ	116	1.835	0.097	5.3	0.569	0.01121	0.00045
MHH–LMZ	345	1.850	0.093	5.0	0.435	0.00940	0.00043
FHH–UMZ	29	2.020	0.093	4.6	0.000	0.000	0.000
MHH–UMZ	79	2.024	0.134	6.6	0.000	0.000	0.000

Note: CV = coefficient of variation. FGT indices use a threshold of 1.8 t/ha. Parentheses for FGT_0 contain 95% bootstrap confidence intervals (2000 resamples). No UMZ households fell below the threshold; consequently, FGT_0 is zero for these groups.

Table 4
Asymmetric climate sensitivity across household groups. Downside (β^-) and upside (β^+) coefficients estimated using the SPEI-3 December–February moisture index.

Group	n	β^- (dry) [95% CI]	β^+ (wet) [95% CI]	Ratio $\beta^+/\lvert\beta^-\rvert$
Whole sample	569	−0.48*** [−0.55, −0.41]	1.57*** [0.40, 2.48]	3.3
FHH only	145	−0.52*** [−0.64, −0.40]	0.67 [−1.32, 2.69]	1.3
MHH only	424	−0.47*** [−0.56, −0.38]	1.79*** [0.55, 2.80]	3.8
LMZ whole	461	−1.47*** [−1.91, −0.99]	4.12*** [2.77, 5.61]	2.8
FHH-LMZ only	116	−2.10*** [−2.70, −1.56]	4.55*** [2.22, 7.08]	2.2
MHH-LMZ only	345	−0.72*** [−0.93, −0.51]	4.03*** [3.24, 4.82]	5.6

Note: Bootstrap 95% confidence intervals (1000 replicates) shown in brackets. *** indicates $p < 0.01$ based on bootstrap success. Coefficients represent spatial conditional associations between yield and the 5-year average SPEI-3 DJF index, estimated separately for negative (dry) and positive (wet) values. The Upper Midland Zone is omitted because SPEI-3 DJF values were uniformly negative, preventing estimation of an upside slope.

Table 5
Conceptual shift from aggregate vulnerability metrics to precision justice diagnostics.

Previous approach	Precision justice approach
Vulnerability indices that average across groups	Stratified diagnostics that expose intersectional traps (β^-, β^+)
Symmetric risk metrics (mean–variance)	Asymmetric risk metrics (β^-, β^+) that capture differential exposure
Adoption counts as proxy for capacity	Latent capacity measurement (θ) that reveals behavioral constraints, used as secondary diagnostic
Universal policy packages	Tailored bundles matched to β^- profiles and intersectional position
Outcome-focused justice (who gets what)	Process-oriented justice (how capacity is built and how decisions are made)

< 0.001, $\eta = 0.325$), while neither gender ($F = 1.81$, $p = 0.179$) nor the gender × AEZ interaction ($F = 0.20$, $p = 0.652$) was statistically significant. Tukey HSD comparisons indicated significant differences between LMZ and UMZ groups ($p < 0.001$), with no significant gender differences within zones ($p > 0.4$). Full ANOVA and Tukey results are reported in Supplementary Tables S1–S4.

Below-threshold yields were concentrated in the LMZ. Overall, 46.9% of LMZ households had yields below the 1.8 t/ha threshold, compared with 0% in the UMZ. Within the LMZ, the share of female-headed households below the threshold was 56.9%, compared with 43.5% among male-headed households ($p < 0.05$, bootstrap test). The depth and severity of yield shortfalls followed similar patterns.

3.2. Asymmetric climate risk: the core diagnostic

To assess differential exposure to adverse and favorable moisture conditions, we estimated a piecewise linear model of yield against the 5-year average SPEI-3 for December–February (DJF), separating negative (dry) and positive (wet) values. Because the SPEI-3 October–December index lacked positive variation in the sample, the DJF index was used for both components. Agronomically, DJF coincides with the grain-filling stage of the short-rains maize crop in Western Kenya; positive values indicate above-average moisture during this critical period, while negative values indicate deficit.

In the full sample, $\beta^- = -0.48$ [−0.55, −0.41] and $\beta^+ = 1.57$ [0.40, 2.48]. The ratio $\beta^+ / |\beta^-| = 3.3$ indicates stronger yield responses under favorable conditions relative to adverse conditions at the aggregate level.

In the Lower Midland Zone, the magnitude of both coefficients increased: $\beta^- = -1.47$ [−1.91, −0.99] and $\beta^+ = 4.12$ [2.77, 5.61], yielding a ratio of 2.8. Within the Lower Midland Zone, female-headed households exhibit steep yield gradients across the moisture continuum: severe penalties in locations with adverse moisture regimes ($\beta^- = -2.10$ [−2.70, −1.56]) relative to those with favorable regimes ($\beta^+ = 4.55$ [2.22, 7.08]), yielding an asymmetry ratio of 2.2. This spatial asymmetry pattern indicates that households in drier micro-locations within the same agroecological zone suffer disproportionate yield penalties that are not offset by proportional gains in wetter micro-locations.

In the Upper Midland Zone, SPEI values were uniformly negative, preventing estimation of an upside coefficient. This indicates that moisture conditions in the UMZ did not span the positive range required for piecewise estimation.

Note on the asymmetry ratio ($\beta^+/|\beta^-|$): This ratio quantifies the balance between yield gains under favorable moisture and losses under adverse moisture. A ratio > 1 indicates that, on average, a one-unit increase in wetness yields a larger response than a one-unit decrease in dryness. However, the smaller ratio for FHH-LMZ households (2.2 versus 5.6 for MHH-LMZ) reflects a less favorable balance between downside and upside sensitivity. This difference is driven primarily by the substantially greater downside magnitude among FHH-LMZ households, despite broadly similar absolute favorable-moisture coefficients. This imbalance reflects structural constraints that prevent them from fully benefiting from favorable conditions, thereby reinforcing persistent vulnerability.

3.3. The intersectional asymmetry trap

The sharpest vulnerability profile appears among female-headed households in the Lower Midland Zone. This group combines three adverse features: (i) the highest share of households with yields below the 1.8 t/ha threshold in the sample (56.9%), (ii) the steepest downside sensitivity ($\beta^- = -2.10$), and (iii) the lowest asymmetry ratio (2.2) relative to male-headed households in the same zone (5.6). The lower asymmetry ratio is driven primarily by the much steeper downside sensitivity of FHH-LMZ households, despite broadly similar absolute favorable-moisture coefficients. This relative disadvantage – high

downside, limited upside - is the asymmetry trap.

If one examined only the overall sample, the system would appear resilient (ratio 3.3). Disaggregation reveals that the most vulnerable group experiences a much steeper downside association relative to its favorable-moisture response. This explains why uniform policies often fail them - they face a fundamentally different risk profile. The beta diagnostics provide a basis for designing targeted interventions, such as insurance triggers calibrated to specific downside sensitivity.

Exploratory analyses of whether Rasch-based adoption propensity (θ) is associated with variation in climate-yield relationships are reported in the Supplementary Information (Section A; Figs. A2-A3; Table A8).

4. Discussion and policy implications

In this study, β^- and β^+ are interpreted as diagnostic indicators of spatial conditional associations rather than structural parameters or causal effects. Our findings suggest the need to reconsider how climate resilience is conceptualized within the human dimensions of global environmental change. Rather than a uniform capacity that can be enhanced through technology alone, resilience appears to vary systematically with asymmetric risk exposure across populations. By integrating directional climate sensitivity measures and disaggregated analysis across gender and agroecological strata, we move beyond aggregate perspectives to examine how vulnerability differs across groups.

4.1. Asymmetric risk and the limits of mean-based adaptation

Standard risk assessments, typically based on symmetric sensitivity measures, implicitly assume that yield responses to adverse and favorable conditions are balanced. Our results suggest that this assumption may not hold across all groups. Disaggregated estimates of β^- and β^+ indicate that female-headed households in the Lower Midland Zone are associated with substantially larger yield losses under adverse conditions ($\beta^- = -2.10$ [−2.70, −1.56]), despite a favorable-moisture coefficient broadly comparable to that of male-headed households in the same zone ($\beta^+ = 4.55$ [2.22, 7.08]), yielding an asymmetry ratio of 2.2.

This pattern is consistent with the possibility that negative shocks have disproportionately larger effects for vulnerable groups, while gains during favorable conditions are comparatively constrained. Such asymmetries align with perspectives emphasizing how constraints in access to resources and recovery capacity can shape vulnerability (Blaikie et al., 2014; Sen, 1983) and may be associated with precautionary or low-return strategies under risk (Iddrisu et al., 2022; Newman and Tarp, 2018; Nkegbe et al., 2014).

These findings point to limitations of uniform risk management approaches. Index-based insurance schemes that rely on common trigger thresholds may not reflect differences in downside exposure across groups. The β^- metric provides a basis for considering more differentiated approaches to risk protection. Groups with higher downside sensitivity may require more responsive trigger thresholds, while groups with lower downside sensitivity may be adequately served by standard thresholds. Such a β^--informed approach illustrates how diagnostic measures of downside exposure can inform the calibration of financial protection mechanisms in ways that better reflect observed heterogeneity in vulnerability.

It should be noted that the upside coefficient (β^+) was estimated from the positive part of the DJF index (because the OND index lacked positive variation), meaning it captures favorable moisture during the grain-filling window rather than the planting stage originally intended; this does not alter the finding of pronounced asymmetry.

4.2. Precision justice as a diagnostic framework

Recent climate adaptation scholarship argues that adaptation governance is increasingly shifting from collective protection toward individualised responsibility, raising concerns that market-driven adaptation systems may reinforce existing inequities and undermine climate justice objectives (Parsons, 2026). In this context, precision justice extends these debates by providing an empirical diagnostic framework that identifies how vulnerability is unevenly distributed across intersecting social and agroecological positions.

Precision justice draws on three established strands of literature. First, entitlements and capabilities. Devereux (2001) and Sen (1983) emphasize that vulnerability arises from constraints in accessing and converting resources, rather than aggregate scarcity alone. The downside sensitivity metric (β^-) captures variation in exposure to adverse outcomes across groups, while the latent capacity measure (θ) serves as a secondary implementation-capacity indicator. Together, these measures provide a structured way to examine how exposure and response capacity vary across populations, while acknowledging that capabilities are only partially observed (Nussbaum, 2011).

Second, distributive and procedural justice (Fraser, 2008, 2009; Schlosberg, 2007) incorporate both how risks and resources are distributed across groups and whether individuals are able to effectively utilize available interventions. In this framework, β^- and θ provide diagnostic indicators that can inform more differentiated approaches to risk protection and extension, without prescribing a single implementation model.

Third, intersectionality perspectives (Crenshaw, 1989, 1991) highlight how vulnerability varies across overlapping social and ecological contexts. Our results indicate that disparities are more pronounced when gender and agroecological dimensions are considered jointly, underscoring the value of multi-dimensional diagnostics. While gender and agroecological zone each show limited association with yield outcomes when considered separately, their interaction reveals more pronounced disparities. In particular, female-headed households in the Lower Midland Zone are associated with higher downside sensitivity, with 57% of households recording yields below the 1.8 t/ha threshold, despite comparable levels of CSA adoption. These patterns are not readily apparent in aggregate indicators, illustrating the limitations of mean-based assessments of vulnerability (Calvin et al., 2023; IPCC, 2023).

This shift moves adaptation policy beyond "one-size-fits-all" approaches toward a more stratified, diagnostic perspective that aligns resource allocation with observed patterns of vulnerability. By rendering both distributional and procedural dimensions empirically tractable, precision justice provides a structured basis for more targeted and potentially more equitable adaptation strategies.

Our findings also align with emerging intersectionality debates in climate justice, which argue that vulnerability is relational and non-additive rather than attributable to isolated identities (Schill et al., 2026). Consistent with this perspective, the present study shows that vulnerability among Kenyan smallholders is not adequately captured by gender or agroecological position independently. Instead, the pronounced vulnerability observed among female-headed households in the Lower Midland Zone reflects the interaction of social and ecological disadvantage. Precision justice operationalises this intersectional logic by linking it to measurable asymmetries in climate sensitivity.

Furthermore, recent climate scholarship similarly argues that climate responses and perceptions are socially structured rather than purely informational. Among vulnerable agricultural workers, climate risk recognition itself has been shown to co-vary with social position and access to resources (Mortell et al., 2026). Consistent with this broader perspective, the present study finds that vulnerability among Kenyan smallholders is not uniformly distributed but emerges through intersecting social and agroecological positions.

4.3. From risk diagnosis to differentiated policy

Translating diagnostic insights into practice requires attention to the

institutional and structural conditions that shape vulnerability. Rather than prescribing a single policy model, our results point to several areas where more differentiated and context-sensitive approaches may be considered. This finding aligns with recent calls to resist the individualisation of climate risk and to retain adaptation as a collective responsibility rather than assuming uniform adaptive capacity across populations (Parsons, 2026).

First, gender-responsive financial services may benefit from incorporating measures of downside exposure (β^-) into risk assessment frameworks. Integrating climate risk indicators with alternative screening approaches could help align credit access with exposure, particularly for groups facing higher downside risk.

Second, capacity-aware extension systems could move beyond uniform technology dissemination toward more adaptive forms of support. Diagnostic indicators such as θ may help inform how extension services tailor recommendations to differing levels of adoption readiness, while remaining responsive to local constraints and institutional capacities. However, given the modest and exploratory nature of the θ evidence in this study, any extension-matching recommendations should be treated as provisional and tested empirically.

Third, land tenure and institutional conditions remain central to enabling longer-term adaptation investments. Secure tenure can influence incentives to adopt more resource-intensive or longer-horizon practices, particularly among marginalized groups. Our findings are consistent with the view that such structural factors interact with both risk exposure and adaptive capacity.

Taken together, these considerations illustrate how linking financial protection to downside exposure (β^-) and aligning support mechanisms with observed heterogeneity in capacity (θ) can inform more differentiated approaches to adaptation. While implementation will depend on context-specific institutional conditions, this perspective provides a structured basis for considering how climate adaptation strategies may be made more targeted and inclusive.

4.4. Limitations and future research directions

This study identifies consistent patterns of asymmetric risk and intersectional variation in vulnerability, but several limitations suggest directions for further research.

First, the cross-sectional design captures associations between climate conditions, yields, and adoption patterns, but does not allow assessment of dynamic adaptation processes or causal mechanisms over time. In addition, limited variation in some climate indicators – for example, the absence of positive SPEI values in parts of the Upper Midland Zone - constrains the estimation of upside responses. These limitations point to the value of longitudinal datasets that capture a broader range of climatic variability.

Second, the Item Response Theory approach provides a useful summary of adoption patterns, but the presence of misfit and negative discrimination for some practices suggests that CSA adoption may not be fully captured by a single latent dimension. Future work could explore multi-dimensional or multi-group IRT models to examine whether adoption is better represented by multiple latent traits and whether measurement properties vary across gender or agroecological contexts.

Third, extending the analysis to longitudinal settings would allow examination of how asymmetric risk and adaptive capacity interact over time. Applying similar diagnostic approaches to other resource-dependent systems (such as fisheries and pastoralism) could help assess the generalizability of these patterns. Empirical evaluation of targeted adaptation approaches informed by diagnostic indicators would provide further insight into their effectiveness and feasibility in practice.

5. Conclusion

This study shows that climate vulnerability is not uniform but varies systematically with differences in risk exposure and structural conditions. By integrating asymmetric climate sensitivity (β^-/β^+) with disaggregated analysis across gender and agroecological strata, we move beyond aggregate assessments to examine how vulnerability differs across populations. Our findings indicate that aggregate indicators can obscure substantial disparities. Female-headed households in more fragile agroecological zones are associated with higher downside sensitivity and a less favorable balance between downside and upside sensitivity, alongside a higher share of households with yields below the 1.8 t/ha threshold. These patterns are consistent with the presence of an "asymmetry trap," characterized by comparatively steep downside exposure relative to favorable-moisture responses, with implications for both risk management and long-term resilience.

These results suggest the importance of moving beyond uniform approaches toward more differentiated adaptation strategies. In this context, precision justice provides a diagnostic and operational perspective for linking risk exposure to policy-relevant interpretation. This includes considering how financial protection mechanisms may be informed by downside exposure (β^-), and how extension and support systems may be aligned with observed heterogeneity in adoption patterns (θ). More broadly, the framework offers a structured basis for translating disaggregated diagnostics into more targeted and potentially more equitable adaptation approaches. While implementation will depend on context-specific socio-ecological and institutional conditions, this perspective contributes to ongoing efforts to better align climate adaptation strategies with the diverse realities of vulnerability across the Global South. Effective climate adaptation requires not more resources, but better and more equitable alignment between risk, capacity, and support. If vulnerability is uneven, adaptation cannot remain uniform.

CRediT authorship contribution statement

Denis Momanyi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Job K. Lagat:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Investigation, Conceptualization. **Jiqin Han:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Formal analysis. **Robert A. Marchant:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Formal analysis. **George M. Ogendi:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Conceptualization. **Hermann Lotze-Campen:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Stefan Sieber:** Writing – review & editing, Writing – original draft, 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. Denis Momanyi reports financial support was provided by World Wildlife Fund. 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.gloenvcha.2026.103237.

Data availability

Data will be made available on request.

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