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Scaling nature-based solutions for soil restoration in Malawi through adoption dynamics and soil carbon recovery

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Abstract

Land degradation, declining soil fertility, and increasing climate variability threaten the sustainability of Malawi's predominantly smallholder agricultural systems. Nature-based Solutions (NbS) offer a promising pathway for restoring soil health while enhancing climate resilience; however, integrated evidence linking adoption dynamics, biophysical outcomes, and institutional readiness remains limited. This study conducted a multi-zonal assessment across five agro-ecological zones in Malawi, operationalizing the IUCN Global Standard for NbS within a mixed-methods land-health monitoring framework. Household surveys (n = 89), laboratory analysis of 72 composite soil samples, key informant interviews, and policy review were combined with multivariate, hierarchical, and nonlinear modelling approaches. Overall NbS adoption was high (85.4%) but varied significantly across districts ($\chi^2 = 12.76$, $p = 0.026$). Education ($\beta = 0.47 \pm 0.18$, $p = 0.011$) and extension access ($\beta = 0.53 \pm 0.21$, $p = 0.008$) were the strongest predictors of adoption, while farm size and gender were not significant. Hierarchical modelling revealed substantial district-level heterogeneity in both baseline adoption and extension effectiveness. Soil analyses indicated multidimensional degradation pathways characterized by organic carbon depletion (mean SOC = 0.82 ± 0.27%) and emerging sodicity (ESP > 15% in 18% of samples). Principal Component Analysis identified fertility-depletion and sodicity-stress gradients explaining 69.6% of total variance. Quantile regression demonstrated heterogeneous soil carbon responses to NbS, with stronger gains among higher-performing farms. Logistic growth modelling showed nonlinear SOC recovery trajectories, with rapid early gains followed by asymptotic stabilization near agronomic thresholds. Farmers reported high perceived effectiveness of NbS (mean = 4.3/5), with significantly higher ratings among women and more experienced farmers. Policy analysis revealed strong conceptual alignment with NbS principles but limited institutional coherence, financing, and multi-scale monitoring capacity. The findings indicate that NbS adoption in Malawi is behaviourally accepted and ecologically consequential but context-dependent. Scaling success will depend on geographically adaptive extension strategies, differentiated soil-restoration pathways, sustained domestic financing, and institutionalized multi-level monitoring systems. The integrated monitoring workflow presented here provides a transferable framework for strengthening evidence-based NbS implementation across sub-Saharan Africa.

1. Introduction

Land degradation in sub-Saharan Africa is intensifying under the combined pressures of soil nutrient depletion, demographic expansion, and recurrent climate shocks. In Malawi, where smallholder agriculture dominates national food systems, declining soil organic carbon (SOC), persistent soil acidity in the highlands, and emerging sodicity in lowland systems are undermining productivity and long-term resilience. These structural constraints are compounded by increasing climate variability. In 2024, the Government of Malawi declared a national disaster across 23 districts following severe El Niño-induced drought, highlighting how climate extremes interact with pre-existing soil degradation to threaten food security and rural livelihoods (Government of Malawi, 2024).

Nature-based Solutions (NbS) have emerged globally as an integrative framework for addressing interconnected societal challenges, including climate adaptation, biodiversity loss, and sustainable food production. The IUCN Global Standard for Nature-based Solutions provides a structured framework of eight criteria and associated indicators to guide design, implementation, and verification of NbS interventions (IUCN, 2020). The updated edition further strengthens requirements for adaptive management, long-term monitoring, and institutional mainstreaming (Kapos et al., 2025). While NbS are conceptually appealing, their operationalization requires measurable outcomes and context-sensitive evaluation systems capable of linking ecological processes with behavioral and institutional dynamics.

Malawi's national development architecture increasingly aligns with these principles. Malawi Vision 2063 prioritizes agricultural productivity, commercialization, and climate resilience as pillars of inclusive growth (National Planning Commission [NPC], 2021). The Agriculture Land Resources Management Policy (2024) reinforces commitments to ecosystem restoration, soil conservation, and science-based land governance (Ministry of Agriculture [MoA], 2024). However, translating policy ambition into measurable restoration outcomes remains challenging. Monitoring systems often focus on activity indicators (e.g., trees planted, hectares under conservation agriculture) rather than biophysical recovery metrics such as SOC stabilization, pH normalization, or sodium reduction. This outcome–monitoring gap constrains adaptive management and limits evidence-based scaling.

From a biophysical perspective, soil degradation in Malawi follows multiple interacting pathways. Organic carbon depletion is widespread, particularly in the northern and central highlands, while southern lowlands exhibit emerging sodicity linked to irrigation mismanagement and evapotranspiration gradients (FAO, 2023; Zuza et al., 2023). Long-term conservation agriculture and agroforestry trials demonstrate potential gains in SOC and yield (Ngwira et al., 2022; Beedy et al., 2015), yet adoption intensity and effectiveness vary substantially across districts. Empirical studies increasingly show that adoption of sustainable practices is shaped not only by farm-level characteristics but also by education, extension quality, and social-institutional context (Mosha & Ngulube, 2025; Kassie et al., 2023). These findings suggest that NbS performance must be evaluated through multi-level analytical frameworks that integrate soil processes, farmer behavior, and institutional capacity.

Despite growing implementation of conservation agriculture, agroforestry, and integrated soil fertility management in Malawi, there is limited evidence linking (i) district-level adoption heterogeneity, (ii) multidimensional soil degradation pathways, and (iii) nonlinear soil recovery dynamics under NbS. Most existing assessments rely on linear modeling approaches and do not account for contextual clustering or heterogeneous treatment effects. Yet soil carbon accumulation is biologically constrained and typically follows nonlinear trajectories characterized by rapid early gains and asymptotic stabilization (Lal, 2004). Furthermore, adoption responsiveness may differ across districts due to variation in extension effectiveness, agroecological suitability, and institutional coherence.

This study addresses these gaps through a multi-zonal, mixed-methods assessment that operationalizes the IUCN NbS Standard within Malawi's agro-ecological landscape. The research integrates: (i)

laboratory-based soil diagnostics across representative agro-ecological zones; (ii) household survey data capturing adoption determinants and perceptions; (iii) hierarchical and machine-learning models to quantify contextual and nonlinear dynamics; and (iv) policy analysis assessing institutional readiness for scaling. Specifically, the study aims to:

1. Characterize multidimensional soil degradation pathways using multivariate analysis and cluster classification;
2. Quantify determinants and district-level heterogeneity in NbS adoption using hierarchical modeling;
3. Examine heterogeneous and nonlinear SOC recovery trajectories under NbS; and
4. Evaluate institutional alignment and monitoring readiness under the IUCN NbS framework.

By embedding farm-level biophysical and behavioral evidence within a standardized NbS evaluation architecture, this study provides an integrated framework for linking soil restoration outcomes with adoption dynamics and policy readiness. The findings contribute to strengthening evidence-based scaling of NbS in Malawi and offer a transferable methodological template for other sub-Saharan African countries confronting similar land degradation and climate-resilience challenges.

2. Materials and methods

2.1 Study design and conceptual framework

This study adopted a cross-sectional mixed-methods design to examine the applicability of the IUCN Global Standard for Nature-based Solutions (NbS) and the Land Health Monitoring Framework within Malawi's diverse agricultural and ecological systems. The design was grounded in a systems ecology perspective, which views land health as an emergent property shaped by interactions among biophysical, socio-economic, and policy subsystems.

The analytical framework integrated four tiers of assessment derived from the IUCN's hierarchical monitoring approach, soil, farm, landscape, and AEZ/national levels as summarised in Fig. 1. This stratification provided a coherent structure for linking micro-level soil data with macro-level policy and governance indicators. By aligning empirical data with the IUCN conceptual model, the study sought to assess both the technical applicability and the institutional readiness for implementing NbS as a land management paradigm in Malawi.

The mixed-methods design was chosen deliberately to enhance validity through triangulation. Quantitative analyses provided measurable indicators of land health, while qualitative insights from stakeholder interviews contextualized these findings within Malawi's agricultural governance system. This dual strategy allowed the study to not only test hypotheses statistically but also to explain the observed patterns through grounded narratives.

2.2 Study area and sampling framework

The study was conducted in six districts; Mzimba, Ntchisi, Lilongwe, Zomba, Chikwawa, and Karonga, each representing one of Malawi's five major Agro-Ecological Zones (AEZs). These zones vary in elevation, rainfall regime, soil type, and vegetation cover, offering an ecologically representative cross-section of the country's agricultural landscapes. Districts were selected purposively in consultation with the Ministry of Agriculture and IUCN Malawi. The inclusion of the districts was based on the coverage of areas where NbS interventions, such as conservation agriculture, agroforestry, and integrated soil fertility management, were either ongoing or recently completed by the Ministry of Agriculture and IUCN This implies that all the districts where NbS interventions have been not implemented, were excluded in each ecological zone.

Table 1
Villages in the sampled districts in respective Agro-Ecological Zones from which the study was conducted.

Agro-Ecological Zone (AEZ)	Sampled districts	Traditional Authority	Village
Lakeshore Plains	Karonga	Wasambo	Mung'ombwa
			Mwenyeshawane
Central Plateau	Lilongwe	Masumbakhumba	Phalaza
			Chasaza 1
		Kalolo	Mchepa
	Ntchisi	Kalumo	Khuwi
Shire Highlands	Zomba	Mwambo	Chibisa
		Mulumbe	Chitambala
Eastern Escarpment	Mzimba	Mzukuzuku	Chinjati
Southern Plains	Chikwawa	Mlilima	Dulansanje
		Katunga	Katunga

Within each district, villages and households were selected using stratified random sampling, stratified first by agroecological zone and second by intervention status (NbS versus non-NbS areas). The sampling frame consisted of 320 registered farmers, from which a sample of 89 was drawn using Cochran's finite population correction formula at a 95% confidence level and 5% precision. This yielded a statistically valid yet operationally feasible sample size. Random selection was implemented through digital randomization in Kobo Toolbox to minimize enumerator bias.

Each sampled household constituted the primary sampling unit, and the head of household or principal decision-maker on land management was the key respondent. This approach ensured that responses reflected decision-making authority and actual management practices on the ground.

2.3 Document Review

We also carried out document review of different policies such as The National Forest Policy (2016), National Agriculture Policy (2010), National Land Policy (2002), and Environmental Management Policy (2004) and National Climate Change Management Policy).

Each policy was examined using a coding matrix structured around the eight IUCN NbS criteria and four land health dimensions (soil, ecosystem, society, and governance). Textual content was coded for both explicit references to NbS-related principles (e.g., “ecosystem restoration,” “landscape resilience”) and implicit alignment with NbS outcomes (e.g., “sustainable agriculture,” “integrated watershed management”). The policy review thus served both as a baseline for assessing institutional alignment and as a qualitative variable informing the discussion of governance readiness for NbS mainstreaming.

2.4 Soil sampling and laboratory analysis

Baseline biophysical data were collected from to provide empirical measures of land health. Within each selected village, composite soil samples were taken from both upland and lowland plots, ensuring representation of the primary toposequence in each AEZ. At each farm, five subsamples were collected from 0–40 cm depth using a zigzag transect pattern and combined into a single composite sample. A total of 72 composite samples were analyzed, corresponding to the number of unique farm plots included in the survey.

All soil analyses were performed at the Chitedze Agricultural Research Station Soil Laboratory, following standardized procedures. Soil pH was determined potentiometrically using a calibrated glass electrode. Soil Organic Carbon (OC) was quantified through the Walkley–Black dichromate oxidation method, while available phosphorus (P) was determined by the Murphy–Riley colorimetric method using UV spectrophotometry. Exchangeable bases (Ca^{2+}, Mg^{2+}, K^{+}, Na^{+}) were extracted with Mehlich-3 solution and measured using flame photometry and atomic absorption spectrophotometry (AAS).

2.5 Farmer household surveys

Quantitative socioeconomic and perception data were collected using a semi-structured digital questionnaire designed and administered through the KoBo Toolbox platform. The instrument captured demographic characteristics, land tenure, farming practices, knowledge and adoption of NbS, and perceptions of soil health and climate resilience.

The tools were pre-tested to refine language and ensure clarity. Enumerators were trained on both the content and ethics of data collection, including techniques for minimizing response bias. The final questionnaire included Likert-scale perception items measuring attitudes toward NbS effectiveness, environmental sustainability, and economic viability. Reliability analysis yielded a Cronbach’s alpha (α) of 0.83, indicating high internal consistency.

2.6 Key informant interviews

In-depth Key Informant Interviews (KIIs) were conducted with 17 stakeholders representing government ministries, research institutions, local NGOs, and international agencies. Participants were selected

purposively to ensure representation across policy, technical, and implementation domains. Each interview lasted between 40 and 45 minutes and followed a semi-structured guide aligned to the IUCN NbS criteria. Interviews were recorded with participant consent, transcribed verbatim, and analyzed using NVivo 14 qualitative software. Thematic saturation was reached after the 14th interview, indicating adequate coverage of perspectives.

2.7 Quantitative data analysis

All quantitative analyses were conducted using R (v4.3.1) and SPSS (v27). Data cleaning involved range, consistency, and normality checks. Outliers were detected using boxplot inspection. Descriptive statistics; means, standard deviations, and frequencies, were computed to summarize farmer demographics, soil characteristics, and adoption rates. For inferential analysis, one-way ANOVA tested mean differences in soil parameters (pH, OC, available P, ESP) across AEZs. Where significant, Tukey's Honest Significant Difference (HSD) post hoc tests were performed to identify specific inter-zone contrasts.

Independent samples t-tests were used to compare soil and adoption variables between intervention and non-intervention farmers, while Chi-square (χ^2) tests assessed the association between categorical variables such as gender and adoption. Binary logistic regression was used to identify determinants of NbS adoption, with education level, farm size, access to extension services, and gender as independent variables.

To explore relationships among soil parameters, Pearson's correlation coefficients (r) were computed, and multicollinearity was checked using Variance Inflation Factor (VIF < 5) thresholds. All tests were two-tailed with significance set at $p < 0.05$. Data visualization employed ggplot2 and corrplot packages in R to produce boxplots, regression fit plots, and correlation matrices illustrating soil health variability and adoption patterns.

2.8 Other statistical and modelling analyses

To comprehensively evaluate the biophysical, socioeconomic, and institutional determinants of NbS adoption and associated land-health outcomes, we applied complementary multivariate, hierarchical, machine-learning, causal pathway, and nonlinear forecasting techniques. These approaches were selected because NbS adoption and soil health are typically driven by correlated predictors, contextual clustering (e.g., districts), nonlinear interactions, and heterogeneous responses that are not adequately captured by single-equation linear models (Gelman & Hill, 2007; James et al., 2021). All analyses used primary data from 89 surveyed farmers and 72 farm soil samples.

2.8.1 Principal Component Analysis

Soil degradation is multidimensional and often expressed through correlated chemical indicators such as pH, OC, CEC, ESP). PCA was used to reduce collinearity, summarize soil variability into a smaller number of latent degradation syndromes, and provide interpretable composite gradients for subsequent

classification and modeling (Jolliffe & Cadima, 2016). The PCA was conducted on six soil parameters: pH, organic carbon (OC%), available phosphorus (P), exchangeable sodium percentage (ESP), cation exchange capacity (CEC), and total nitrogen. Variables were standardized using z-score transformation prior to analysis. Eigenvalue decomposition was performed on the correlation matrix, and components with eigenvalues > 1.0 were retained as a screening criterion, supported by interpretability and explained variance (Kaiser, 1960; Jolliffe & Cadima, 2016). Sampling adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity to confirm that correlations were sufficient for PCA (Kaiser, 1974; Bartlett, 1954).

2.8.2 K-Means Cluster Analysis

K-means clustering was used to group farms into soil condition classes based on similarity across the standardized indicators, enabling targeted recommendations and spatial prioritization (Hartigan & Wong, 1979; Jain, 2010). K-means was applied to standardized soil variables (n = 72 farms). The number of clusters (*k*) was selected using the elbow approach and silhouette diagnostics, which evaluate within-cluster cohesion and between-cluster separation (Kaufman & Rousseeuw, 1990). K-means + + initialization was used to improve stability and reduce sensitivity to poor starting centroids (Arthur & Vassilvitskii, 2007). Euclidean distance was used as the dissimilarity metric, consistent with standard k-means assumptions (Jain, 2010).

2.8.3 Hierarchical (Multi-Level) logistic regression

Farmers are nested within districts, violating independence assumptions and potentially inflating Type I error if clustering is ignored. Multi-level logistic regression accounts for district-level clustering and quantifies how much adoption variability is attributable to context, while estimating individual-level determinants (Gelman & Hill, 2007; Snijders & Bosker, 2012). To account for clustering of farmers within districts, multi-level logistic regression models were fitted with NbS adoption (binary) as the outcome.

$$logit(\pi_ij) = \beta_ + \beta_Education_ij + \beta_Extension_ij + \beta_FarmSize_ij + u_j$$

Where:

π_ij = probability of NbS adoption for farmer *i* in district *j*, β_0 = fixed intercept, β_1, β_2, β_3 = fixed-effect coefficients, u_0j = district-level random intercept, *i* = farmer index; *j* = district index. All parameters were estimated using Restricted Maximum Likelihood (REML). Marginal and conditional R^2 were computed to assess model fit. The Model fit and contextual clustering were summarized using the intra-class correlation coefficient (ICC) (Snijders & Bosker, 2012. The ICC was computed using the formula;

$$\frac{\sigma_u}{\sigma_u + \pi/3}$$

Where: σ^2_u = between-district variance and $\pi^2/3$ = variance of logistic distribution (≈ 3.29)

2.8.4 Random slopes model

To evaluate whether agriculture extension effectiveness varied across districts, a random slopes model was estimated.

logit(π_ij) = (β_0 + u_0j) + (β_1 + u_1j)Extension_ij + β_2Education_ij + β_3FarmSize_ij

Likelihood ratio tests compared random-intercept and random-slope specifications.

2.8.5 Random forest modelling

Adoption decisions may involve nonlinear relationships such as threshold effects of education and interactions such as extension × farm size. In this manner, parametric models can miss or mis-specify. Random forests were used to capture nonlinearities and interactions with strong predictive performance and robust internal validation via out-of-bag (OOB) error (Breiman, 2001; James et al., 2021). Random forest classification was fit to predict NbS adoption using 500 trees. OOB error was used as an internal cross-validation estimate (Breiman, 2001). Variable importance was assessed using impurity-based importance and permutation-based accuracy decreases, which summarize each predictor's contribution to predictive performance (James et al., 2021; Kuhn & Johnson, 2013).

2.8.6 Mediation Analysis

Beyond identifying predictors, the study aimed to test plausible mechanisms, specifically whether education influences productivity partly through NbS adoption (and related land-health improvements). Mediation analysis decomposes effects into direct and indirect components to quantify pathways consistent with the study's conceptual model (Hayes, 2018; Imai et al., 2010). The total effect of education (X) on productivity (Y) was decomposed into direct and indirect effects through a mediator as follows;

$$c = c\prime + (a \times b)$$

Where: c = total effect, c' = direct effect, a = effect of X on mediator M, b = effect of mediator M on outcome Y.

2.8.7 Quantile Regression

NbS benefits may not be uniform across farmers; effects can differ across the distribution of soil improvement. Quantile regression estimates covariate effects at different points of the outcome distribution, supporting equity-sensitive inference and targeting (Koenker, 2005). Quantile regression assessed heterogeneous effects across the 25th, 50th, and 75th percentiles of soil organic carbon improvement. The regression was estimated using formula;

$$Q\tau\,(Y_i \mid X_i) = \beta\,(\tau) + \beta\,(\tau)X_i$$

Where: Qτ (Y_i | X_i) = conditional quantile at τ, τ = quantile (e.g., 0.25, 0.50, 0.75), and $\beta_0(\tau)$, $\beta_1(\tau)$ = quantile-specific coefficients

2.8.8 Logistic Growth Model for Soil Recovery

Understanding that policy planning requires interpretable forecasts of time-to-target for soil restoration. Logistic growth models was developed because they represent realistic recovery dynamics characterized by faster initial gains followed by saturation as soils approach an upper limit (Seber & Wild, 2003). This was calculated using formula;

$$OC\,(t)\ =\ \frac{L}{1\ +\ exp[-k(t\ -\ t\square)]}$$

Where: OC(t) = soil organic carbon at time t, L = upper asymptote (maximum attainable OC), k = growth rate parameter, t_0 = inflection point (time at L/2), and t = time in years. Model parameters were estimated using nonlinear least squares, and model fit was compared using Akaike Information Criterion (AIC).

2.9 Qualitative data analysis and integration

Qualitative data were analyzed through thematic analysis following Braun and Clarke's (2019) six-phase approach, familiarization, coding, theme development, review, definition, and reporting. Codes were generated inductively and later grouped into broader analytical categories such as *perceived benefits of NbS*, *barriers to adoption*, *policy coherence*, and *monitoring capacity*. Integration of quantitative and qualitative results followed a convergent parallel design, where both datasets were analyzed independently and merged during interpretation. This ensured that numerical trends such as adoption rates, soil health indices were interpreted through the lens of lived experiences and institutional contexts. The convergence enhanced interpretive validity and aligned the study with the IUCN's evidence-based NbS evaluation framework.

2.10 NbS Assessment

Existing agricultural and conservation projects in Malawi were evaluated against the eight criteria of the IUCN NbS Self-Assessment Tool (https://nbs-sat.iucn.org/). This provided a standardized metric to gauge the quality and comprehensiveness of NbS design and implementation.

3. Results

3.1. Farmer demographic and socio-economic characteristics

A total of 89 farmers were surveyed across six districts, representing five major Agro-Ecological Zones (AEZs) of Malawi. The gender distribution was balanced (51% male, 49% female). The mean age of respondents was 42.7 ± 9.5 years, with most falling in the 35–50 year range. Educational attainment varied significantly by gender (χ^2 = 8.17, p = 0.043), with 10% of women reporting no formal education compared to 3% of men. Farming was the primary occupation for 97% of respondents, though a small proportion (3%) supplemented income through petty trading. Landholding size averaged 1.26 ± 0.67 hectares, with no significant difference between male- and female-headed households (t = 1.24, p =

0.219). The high proportion of married farmers (94%) reflected the household-based nature of smallholder agriculture.

3.2. Understanding and adoption of nature-based solutions

Farmers' understanding of NbS was practical and experience-driven. The most cited interpretations associated NbS with manure use (32%), agroforestry (11%), and conservation agriculture (10%). Overall, 85.4% of respondents had adopted at least one NbS practice. Adoption differed significantly across districts (χ^2 =12.76, p = 0.026). Lilongwe exhibited the highest adoption (92%), followed by Chikwawa (88%), while Mzimba had the lowest (74%).

A binary logistic regression model identified education level (β = 0.47 ± 0.18, p = 0.011) and access to extension services (β = 0.53 ± 0.21, p = 0.008) as the strongest predictors of adoption (Table 2). Farm size and gender were not statistically significant predictors (p > 0.05).

Table 2
Farmer adoption and socioeconomic predictors of Nature-based Solutions

Variable	Mean ± SD / %	Test	Statistic	p-value	Interpretation
Adoption of ≥ 1 NbS	85.4%	χ^2	χ^2=12.76	0.026	Significant district variation
Education (years)	6.4 ± 2.3	β	0.47 ± 0.18	0.011	Higher education predicts adoption
Extension service access	71%	β	0.53 ± 0.21	0.008	Strong positive influence
Gender	—	β	0.14 ± 0.17	0.312	Not significant
Farm size (ha)	1.26 ± 0.67	β	0.11 ± 0.09	0.246	Not significant

3.3. Land health and soil quality status

3.3.1 Soil chemical Analysis

Soil chemical analysis revealed pronounced spatial variability in pH, organic carbon (OC), and exchangeable sodium percentage (ESP) across AEZs (Table 3). Mean soil pH ranged from 4.9 ± 0.3 in Mzimba to 5.8 ± 0.4 in Chikwawa, with highly significant inter-zone variation (F = 9.43, p < 0.001). Soils in the northern and central highlands (Mzimba, Ntchisi, Lilongwe) were predominantly acidic (pH < 5.7), while southern lowland soils (Zomba, Chikwawa) were moderately acidic to neutral.

Soil organic carbon averaged 0.82 ± 0.27%, below the agronomic threshold of 1% for most samples. Comparison between northern and southern zones indicated significantly lower OC in the north (t = 3.12, p = 0.002). Exchangeable sodium percentage exceeded 15% in 18% of samples, primarily in Zomba and Chikwawa, suggesting emerging sodicity problems. A strong negative correlation was detected between

OC and ESP (r = – 0.61, p < 0.01), indicating that sodium accumulation likely suppresses organic matter retention and microbial activity.

Table 3
Mean soil chemical properties across districts

District	pH ± SD	OC (%) ± SD	Avail. P (mg/kg) ± SD	ESP (%) ± SD	Interpretation
Mzimba	4.9 ± 0.3	0.71 ± 0.16	8.3 ± 2.1	10.4 ± 2.3	Strongly acidic, low OC
Ntchisi	5.2 ± 0.2	0.78 ± 0.21	10.1 ± 3.4	12.3 ± 3.1	Acidic, low OC
Lilongwe	5.3 ± 0.4	0.75 ± 0.18	11.5 ± 2.8	13.5 ± 3.7	Acidic, depleted OC
Zomba	5.6 ± 0.3	0.86 ± 0.24	12.9 ± 4.1	16.8 ± 1.9	Slightly sodic
Chikwawa	5.8 ± 0.4	0.95 ± 0.22	13.7 ± 3.8	15.1 ± 2.4	Neutral, sodicity emerging
Karonga	5.5 ± 0.3	0.89 ± 0.19	9.6 ± 2.9	13.2 ± 3.1	Slightly acidic
ANOVA	—	—	—	—	F = 9.43, p < 0.001

3.3.2 Multivariate soil degradation patterns and cluster-based soil classes

Principal Component Analysis (PCA) revealed that soil variability in the study landscape is structured along two dominant orthogonal gradients that together explain 69.6% of total variance. The first principal component (PC1) accounted for 46.7% of the total variance and was strongly positively associated with organic carbon (OC) and total nitrogen (N), and negatively associated with exchangeable sodium percentage (ESP). This axis represents a fertility–sodicity gradient, distinguishing soils with higher biological fertility from those exhibiting sodium-induced chemical and structural degradation. Farms positioned on the positive end of PC1 were characterized by relatively higher OC and N concentrations, indicative of improved soil biological function and nutrient retention, whereas those on the negative side reflected increased sodicity stress and diminished organic status.

Figure 3A shows PCA biplot of six soil indicators (pH, organic carbon [OC], available phosphorus [P], exchangeable sodium percentage [ESP], cation exchange capacity [CEC], and total nitrogen [N]). PC1 (46.7% of variance) represents a fertility–sodicity gradient contrasting high OC/N soils with sodium-affected soils, while PC2 (22.9%) reflects variability in chemical balance (pH and P availability). Arrows indicate variable loadings and direction of influence. In Fig. 3B, K-means clustering of farms projected in PCA space, identifying three soil degradation classes. Cluster 0 represents severely degraded soils (low

OC, lower pH), Cluster 1 represents moderately degraded or balanced soils, and Cluster 2 represents saline–sodic soils (high ESP, low OC). Stars denote cluster centroids. In Fig. 3C, radar plot of normalized cluster means illustrates distinct soil signatures for each class. Differences in OC and ESP primarily differentiate clusters, confirming the presence of multiple degradation pathways.

The second principal component (PC2), explaining 22.9% of the total variance, was primarily aligned with soil pH and available phosphorus (P). This dimension captures a soil chemical availability gradient, reflecting variability in acidity–alkalinity balance and phosphorus dynamics. Higher PC2 values corresponded to soils with more favorable chemical conditions for nutrient availability. Together, these two axes indicate that soil degradation in the study area is not unidimensional but structured around interacting biological and chemical processes. The PCA therefore provided a robust basis for dimensional reduction and subsequent classification.

Building on this multivariate structure, K-means clustering identified three distinct soil condition classes, clearly separated along the PCA axes. The first cluster represented severely degraded soils characterized by low OC, reduced nitrogen levels, and comparatively lower pH values. These soils occupy the negative region of PC1 and lower PC2 values, reflecting combined biological fertility depletion and chemical imbalance. This class likely represents systems subjected to prolonged nutrient mining and insufficient organic matter inputs.

The second cluster comprised moderately degraded or relatively balanced soils. These farms occupied intermediate positions along both PC1 and PC2, indicating moderate organic carbon levels, balanced pH, and intermediate ESP values. This class reflects transitional systems where degradation is present but not severe, suggesting greater responsiveness to restoration interventions.

The third cluster was defined by elevated ESP and comparatively lower OC, consistent with saline–sodic conditions. These soils were distinctly separated from the other groups along the fertility–sodicity gradient. The dominance of sodium-related indicators suggests structural instability and impaired nutrient dynamics, requiring targeted remediation strategies distinct from those appropriate for simple fertility depletion.

Normalized cluster profiles further highlighted the mechanistic differentiation among groups. Organic carbon strongly discriminated severely degraded soils from moderately degraded systems, while ESP was the principal distinguishing variable for the saline–sodic cluster. Cation exchange capacity showed comparatively less variability across clusters, suggesting that underlying mineralogical properties may be relatively stable, while chemical degradation processes vary substantially.

3.3.3 Heterogeneous and temporal dynamics of soil organic carbon recovery under NbS

To better understand both the distributional heterogeneity and long-term recovery dynamics of soil organic carbon (SOC) under, we integrated quantile regression analysis with nonlinear trajectory

forecasting. Quantile regression revealed a positive association between baseline SOC and percentage SOC improvement across all conditional quantiles (Q25, Q50, Q75) (Fig. 4). However, the magnitude of response differed substantially across the distribution. The slope of the upper quantile (Q75) was steeper than that of the median (Q50) and lower quantile (Q25), indicating that farms experiencing larger improvements exhibited stronger responsiveness to baseline SOC conditions.

The increasing spread between Q25 and Q75 across baseline SOC levels indicates that variability in restoration outcomes widens over time, reinforcing the need for targeted support strategies. Quantile regression illustrating differential relationships between baseline SOC and percentage SOC improvement following NbS implementation is shown in Fig. 4. The 25th (Q25), 50th (Q50), and 75th (Q75) conditional quantiles are shown, representing small, median, and large improvement responses, respectively. Dashed lines indicate quantile-specific regression slopes, and points represent observed farm-level responses. All quantiles demonstrate a positive association between baseline SOC and subsequent improvement; however, the slope for the upper quantile (Q75) is markedly steeper than for Q50 and Q25. This pattern indicates heterogeneous treatment effects, with larger gains observed among farms in the upper improvement distribution. The divergence between quantile slopes suggests that NbS benefits are not uniformly distributed across the response spectrum, highlighting potential equity and targeting implications for soil restoration interventions

To evaluate long-term restoration potential, SOC dynamics were modelled using a logistic growth framework and compared with a linear trend projection. The logistic model predicts rapid early increases in SOC following NbS adoption, followed by diminishing marginal gains as SOC approaches an agronomic threshold of 1.0%. This saturation pattern reflects ecological constraints on soil carbon accumulation and provides a more realistic representation of biophysical recovery than constant linear growth.

Under the base scenario, SOC progresses from a baseline of approximately 0.82% toward the 1.0% threshold within the modelled implementation window. While the linear projection eventually surpasses the logistic curve in later years, it does so by assuming unrealistically constant accumulation rates. In contrast, the logistic trajectory accounts for biological limits and thus provides more conservative long-term projections.

Prediction intervals and alternative growth-rate assumptions demonstrate that while the direction of SOC improvement is robust, the timing of threshold attainment is sensitive to implementation intensity. Optimistic scenarios achieve the agronomic threshold earlier, whereas pessimistic assumptions delay recovery. Nevertheless, all modelled scenarios exhibit monotonic upward trends, reinforcing the structural resilience of NbS-driven SOC improvement.

3.4. District-level adoption patterns, determinants of NbS uptake, and farmer perceptions of effectiveness

Adoption of Nature-based Solutions (NbS) varied significantly across districts ($\chi^2 = 12.76$, $p = 0.026$), with an overall national adoption rate of 85.4%. Lilongwe recorded the highest adoption rate, followed by Zomba and Chikwawa, all exceeding the national average. Karonga was slightly below the mean, while Mzimba and Ntchisi exhibited comparatively lower adoption levels. These geographic differences suggest that institutional support, agroecological suitability, and local implementation dynamics may shape district-level uptake patterns.

Binary logistic regression analysis further identified key determinants of NbS adoption. Extension access ($\beta > 0$, $p = 0.008$) and education level ($\beta > 0$, $p = 0.011$) emerged as significant positive predictors of adoption probability, indicating that knowledge dissemination and human capital play central roles in behavioral uptake. In contrast, farm size and gender were not statistically significant predictors ($p > 0.05$), suggesting that structural farm characteristics alone do not explain adoption decisions once informational and educational factors are accounted for. These findings underscore the importance of strengthening extension systems and farmer education in scaling NbS interventions.

Farmer perceptions of soil health improvements and NbS effectiveness were consistently high, with a mean rating of 4.3 ± 0.6 on a 5-point Likert scale. Female farmers reported significantly higher perception scores (4.5 ± 0.5) compared to male farmers (4.1 ± 0.7), indicating a meaningful gender difference in perceived benefits ($t = 2.62$, $p = 0.011$). Additionally, farmers with more than 10 years of agricultural experience expressed greater confidence in NbS effectiveness ($F = 4.87$, $p = 0.010$), suggesting that experiential knowledge reinforces perceived intervention value. Qualitative narratives from Key Informant Interviews corroborated these quantitative findings, frequently citing improved yields, reduced soil erosion, enhanced soil structure, and increased moisture retention as observable benefits.

3.5 Multi-level evidence of district-level variation in NbS adoption dynamics

Hierarchical logistic regression results (Fig. 6) reveal substantial district-level heterogeneity in both baseline adoption propensity and the effectiveness of agricultural extension services. Together, the random intercept and random slope estimates demonstrate that NbS adoption dynamics are strongly shaped by contextual geographic factors.

District-specific random intercept estimates ($\beta \pm 95\%$ CIs) indicate deviations in baseline probability of NbS adoption relative to the overall mean (Fig. 6A). The vertical dashed line at zero represents the grand mean intercept across all districts. Positive deviations reflect adoption-facilitating contextual environments after controlling for individual-level covariates (education, extension access, and farm size), whereas negative deviations indicate adoption-constraining conditions. Lilongwe exhibits the strongest positive contextual effect, followed by Zomba and Chikwawa, suggesting supportive institutional or agroecological environments. Karonga shows a modest positive deviation. In contrast, Ntchisi and Mzimba display negative random intercepts, indicating context-specific barriers to adoption.

Confidence intervals overlapping zero suggest limited statistical certainty for some districts, whereas non-overlapping intervals indicate statistically meaningful contextual influence.

In addition to baseline differences, district-specific random slope estimates (β ± 95% CIs) illustrate significant variation in the effectiveness of agricultural extension services on NbS adoption (Fig. 7B). The vertical reference line at zero represents the average extension effect across districts. Positive coefficients indicate districts where extension services increase adoption probability more strongly than the overall mean, while negative coefficients indicate weaker or potentially counterproductive extension effects. Substantial heterogeneity is observed. Ntchisi and Mzimba exhibit the largest positive slope deviations, suggesting that extension services are particularly effective in increasing adoption likelihood in these contexts. Lilongwe and Zomba demonstrate moderate positive responsiveness, whereas Chikwawa shows a comparatively smaller effect. In contrast, Karonga displays a negative deviation, indicating weaker extension impact relative to the overall average.

Confidence intervals overlapping zero suggest limited statistical certainty in some districts, whereas intervals clearly above or below zero indicate meaningful variation in extension responsiveness. Overall, the combined random intercept and random slope evidence demonstrates that NbS adoption is shaped not only by individual farmer characteristics but also by district-level contextual factors and geographically heterogeneous extension effectiveness. These findings underscore the importance of district-specific extension strategies and context-sensitive policy implementation rather than uniform national programming.

3.5 Policy environment for Nature-based Solutions in Malawi

Malawi's policy environment demonstrates substantial commitment to the principles of sustainable land management, though challenges persist in translating these intentions into practice. The review of national and sectoral policy documents revealed that most frameworks recognize the role of ecosystem services and climate-resilient agriculture in achieving national development goals. The Agriculture Land Resources Management Policy (2024), the National Agriculture Policy (2010), and the National Climate Change Management Policy (2016) all emphasize the restoration of degraded ecosystems, the integration of conservation agriculture, and the promotion of sustainable soil fertility management as key drivers of agricultural transformation.

However, analysis across documents showed varying degrees of policy coherence. While several policies share common objectives around land restoration and ecosystem resilience, their implementation mandates often overlap across ministries, leading to fragmented accountability. Soil and water conservation responsibilities are distributed among the Departments of Land Resources Conservation, Environmental Affairs, and Water Resources, resulting in limited coordination and inconsistent monitoring approaches. This fragmentation weakens the ability to track cumulative progress on land health and hinders cross-sectoral synergy at the district level.

Institutional stakeholders expressed concern over limited financing mechanisms for long-term restoration. Public expenditure data show that less than three percent of agricultural budgets from 2018 to 2024 directly targeted land restoration or ecosystem management. Many restoration and NbS initiatives remain donor-driven, with limited domestic co-financing or sustainability plans beyond project cycles. The establishment of the Malawi Green Growth Platform in 2023 provides an important opportunity to mobilize climate finance and private-sector investment, yet operational guidelines for assessing and reporting NbS outcomes are still in development.

3.6 Applicability of the IUCN Nature-Based Solutions frameworks

Application of the IUCN Global Standard for Nature-based Solutions to Malawi's agricultural landscapes revealed high conceptual relevance but moderate readiness for full implementation. The evaluation of the eight IUCN criteria showed that the country is well-positioned in terms of policy alignment and recognition of societal challenges but faces institutional and technical limitations in adaptive management and long-term sustainability.

Among the eight criteria, those related to addressing societal challenges and ensuring biodiversity benefits demonstrated the highest levels of applicability, as they align closely with Malawi's development priorities under Vision 2063. Land degradation, soil fertility loss, and declining biodiversity are well recognized as interconnected challenges, and current policies and programs address them within the broader framework of climate-smart agriculture and sustainable land use. In contrast, criteria related to adaptive management and mainstreaming NbS into financial and institutional systems were rated as less applicable due to limited integration of monitoring data into planning cycles and the absence of permanent funding mechanisms to sustain NbS beyond pilot projects.

Mapping Malawi's existing data systems against the IUCN's four land-health monitoring levels; soil, farm, landscape, and AEZ/national, revealed uneven capacity across scales. Soil and farm-level indicators such as pH, organic carbon, and exchangeable sodium percentage are routinely measured through agricultural extension and research programs. However, higher-level indicators capturing landscape connectivity, ecosystem service valuation, and socio-economic co-benefits remain underdeveloped. This gap highlights the need for capacity development in environmental accounting, geospatial analysis, and long-term data curation.

Stakeholder consultations confirmed strong conceptual support for the IUCN framework, with most respondents viewing it as a valuable tool for unifying ecological and socio-economic monitoring. Nevertheless, only a minority believed that existing institutional arrangements could operationalize the full framework without external technical support. Respondents emphasized the importance of simplifying indicators for local application and piloting the framework within selected districts before national rollout.

The review indicate that Malawi has a robust policy foundation and institutional awareness of NbS but lacks harmonized monitoring systems, sustainable funding, and adequate technical capacity for large-scale operationalization. The IUCN framework provides a practical roadmap for building these capacities, offering both diagnostic and implementation guidance for integrating NbS into Malawi's land restoration and agricultural planning processes. Strengthening institutional coordination, investing in long-term monitoring, and establishing dedicated financing streams would significantly enhance the applicability and sustainability of NbS across the country's diverse agroecological zones.

4. Discussion

4.1 Adoption dynamics: The central role of education and extension

The high overall adoption rate of NbS (85.4%) reflects strong behavioral acceptance of soil-restorative practices across agro-ecological zones, exceeding typical adoption rates for conservation agriculture in sub-Saharan Africa (30–60%) (Knowler & Bradshaw, 2007; Kassie et al., 2013). Education and extension access significantly increased adoption probability, consistent with diffusion of innovation theory emphasizing the role of knowledge and institutional support in behavioral change (Rogers, 2003). Education enhances farmers' ability to evaluate long-term soil benefits (Asfaw et al., 2012; Teklewold et al., 2013), while extension services reduce uncertainty and information barriers (Feder et al., 1985). The non-significance of farm size suggests that NbS adoption in this context is knowledge-driven rather than capital-dependent, underscoring the importance of human capital in scaling sustainable land management practices.

4.2 Geographic heterogeneity and contextual effects

Significant district-level variation in adoption rates and hierarchical model estimates confirms that NbS uptake is context-dependent rather than uniform. Random intercept variation demonstrates that baseline institutional, socio-economic, and agroecological environments shape adoption likelihood beyond individual characteristics. Such contextual heterogeneity is widely documented in agricultural technology adoption studies, where local infrastructure, governance quality, and agroecological suitability influence outcomes (Pannell et al., 2006; Meijer et al., 2015). Furthermore, random slope heterogeneity reveals that extension effectiveness varies geographically. In some districts, extension significantly amplifies adoption probability, while in others the marginal effect is weaker. This supports arguments that extension impact is mediated by local institutional capacity, trust networks, and agroecological compatibility (Anderson & Feder, 2007). Uniform national extension strategies may therefore produce uneven results unless tailored to district-specific contexts.

4.3 Soil Degradation Pathways: Fertility Depletion and Sodicity Stress

Soil chemical analysis revealed persistent acidity and organic carbon depletion across northern and central highlands, alongside emerging sodicity in southern lowlands. The average SOC level (0.82%) falls below the agronomic threshold of 1%, indicating structural vulnerability of smallholder systems. Organic carbon is widely recognized as a key determinant of soil structure, nutrient retention, and microbial activity (Lal, 2004; Lehmann & Kleber, 2015). The strong negative correlation between SOC and exchangeable sodium percentage (ESP) suggests that sodium accumulation suppresses organic matter stabilization, potentially through dispersion-induced structural breakdown and reduced microbial functioning (Qadir et al., 2001). PCA identified two dominant degradation pathways: (i) organic matter and nutrient depletion, and (ii) sodicity-driven stress, patterns consistent with dryland systems experiencing fertility decline and salinization (FAO & ITPS, 2015). These findings imply the need for differentiated NbS strategies, including organic amendments for carbon-depleted soils and chemical or drainage interventions for sodic systems.

4.4 Heterogeneous recovery and nonlinear soil carbon dynamics

Quantile regression results indicate that SOC improvement under NbS is heterogeneous, with larger gains observed among farms in the upper improvement distribution. This suggests differential responsiveness, potentially linked to baseline soil condition, management intensity, or extension quality. Heterogeneous treatment effects are increasingly recognized in agricultural impact evaluations (Wooldridge, 2010; Koenker, 2005).

The logistic growth modeling further demonstrates that SOC accumulation follows a biologically constrained trajectory characterized by rapid early gains and diminishing returns as equilibrium approaches. This pattern aligns with ecological carbon sequestration theory, which predicts asymptotic stabilization rather than indefinite linear accumulation (Lal, 2004; Paustian et al., 2016). Importantly, uncertainty analysis shows that while improvement direction is robust, threshold attainment timing depends on implementation intensity. This underscores the importance of sustained support mechanisms to avoid stagnation before agronomic targets are reached.

4.5 Perception, gender, and experiential knowledge

Farmer perceptions of NbS effectiveness were overwhelmingly positive, with mean ratings above 4.3/5. Positive perception is a well-established predictor of sustained adoption and practice maintenance (Meijer et al., 2015). The higher perception scores among female farmers are particularly noteworthy, as gendered differences in environmental stewardship and soil management priorities have been observed in smallholder systems (Doss & Morris, 2001; Fisher & Carr, 2015). The stronger confidence among experienced farmers suggests that long-term exposure reinforces recognition of ecological benefits. Experiential learning has been shown to strengthen resilience-based agricultural transitions (Pretty, 1995). The alignment between quantitative ratings and qualitative narratives (yield improvement, erosion reduction, improved structure) strengthens the credibility of perceived benefits.

4.6 Policy coherence, financing gaps, and institutional fragmentation

Malawi's policy environment reflects strong rhetorical alignment with sustainable land management principles. However, fragmented institutional mandates and limited budget allocation (< 3% dedicated to restoration) constrain operationalization. Similar challenges in policy coherence and inter-ministerial coordination have been reported across sub-Saharan Africa (Reed et al., 2017). Reliance on donor-driven financing reduces sustainability of restoration programs. Long-term soil restoration requires sustained investment and integrated monitoring frameworks (FAO & ITPS, 2015). The Malawi Green Growth Platform offers a potential institutional anchor for scaling NbS, provided that clear monitoring standards and financing mechanisms are established.

4.7 Applicability of the IUCN NbS global standard

The evaluation against the IUCN Global Standard indicates strong conceptual alignment but moderate institutional readiness. The challenges identified, monitoring gaps, financing constraints, and limited cross-scale integration, mirror findings from other NbS implementation contexts globally (IUCN, 2020). Malawi demonstrates readiness at soil and farm monitoring levels but limited integration at landscape and national scales. Bridging this gap will require investment in environmental accounting, geospatial monitoring, and adaptive governance structures. The IUCN framework offers a structured pathway for institutional strengthening and harmonized monitoring across agroecological zones.

4.8 Implications for scaling NbS

Scaling NbS in Malawi requires moving beyond pilot projects toward integrated, system-level implementation. Although adoption is high, sustained scaling depends on stronger institutional, financial, and technical support. Extension and farmer education remain central, as adoption is knowledge-driven rather than capital-intensive. Enhancing extension capacity and expanding learning platforms can reduce variability in implementation quality.

Given marked district-level heterogeneity, scaling strategies must also be geographically tailored, incorporating local agroecological and institutional contexts. Interventions should be differentiated by soil degradation pathway, with organic amendments prioritized in carbon-depleted systems and chemical or water management strategies applied in sodic soils. Sustainable domestic financing mechanisms are equally critical to reduce dependence on donor-funded cycles and ensure long-term continuity. Finally, multi-scale monitoring systems must be institutionalized to track nonlinear soil recovery dynamics and support adaptive management.

5. Conclusions

This study provides integrated evidence that NbS adoption in Malawi is both behaviorally accepted and ecologically consequential, yet contextually heterogeneous. Adoption rates are high overall (85.4%), but

significant district-level variation demonstrates that uptake is shaped by localized institutional and agroecological conditions. Education and extension access emerged as the strongest predictors of adoption, underscoring the central role of human capital and knowledge systems rather than structural farm characteristics such as land size. Soil analyses confirm multidimensional degradation pathways characterized by organic carbon depletion and sodicity stress. Importantly, SOC recovery under NbS follows a nonlinear trajectory, with rapid early gains and eventual stabilization consistent with ecological carbon dynamics. Quantile regression results reveal heterogeneous improvement patterns, indicating that NbS benefits are not uniformly distributed but vary according to baseline conditions and contextual responsiveness. Farmer perceptions of NbS effectiveness are overwhelmingly positive and reinforced by experiential knowledge and gender-differentiated responses. However, institutional fragmentation, limited dedicated financing, and inconsistent monitoring frameworks constrain long-term scaling. While Malawi's policy architecture aligns conceptually with sustainable land management principles, operational coherence and cross-scale integration remain limited. Thus, NbS adoption in Malawi is not constrained by farmer willingness but by contextual variation, extension heterogeneity, and institutional capacity gaps. Scaling success will depend on geographically adaptive strategies, sustained investment, and integrated monitoring systems that bridge farm-level gains with national restoration targets.

6. Recommendations

Scaling NbS in Malawi requires strengthening institutional and knowledge systems to match the demonstrated farmer willingness to adopt. Extension approaches should be tailored to district-specific agroecological and institutional contexts, recognizing the observed heterogeneity in both baseline adoption and extension effectiveness. Continuous training of extension personnel, coupled with structured performance monitoring, would improve consistency and quality of implementation across regions.

Investment in farmer education and knowledge dissemination platforms remains fundamental. Expanding farmer field schools, community-based learning networks, and digital advisory services can accelerate knowledge diffusion, particularly among less-experienced farmers. Given that adoption is knowledge-driven rather than capital-intensive, strengthening human capital is likely to yield sustained scaling gains. Interventions should also be differentiated according to soil degradation pathways. Organic amendments, residue management, and agroforestry practices are particularly appropriate for carbon-depleted soils, while sodic systems require targeted chemical and water management interventions. Context-sensitive targeting will enhance ecological effectiveness and reduce resource inefficiency.

Long-term soil monitoring systems must be institutionalized to track nonlinear recovery trajectories and support adaptive management. Integrating geospatial monitoring tools and standardized soil health indicators across district and national levels would improve accountability and evidence-based planning.

Declarations

Clinical trial number

Not applicable.

Consent to Participate:

Informed consent was obtained from all participants involved in the study prior to data collection. Participation was voluntary, and all respondents were informed about the purpose of the study, the confidentiality of the information provided, and their right to withdraw from the study at any stage without any consequences.

Ethics approval:

The study protocol was approved by the Malawi University of Science and Technology Research Ethics Committee (MUSTREC) (Approval No. P.11/2025/405). MUSTREC is registered with the United States Office for Human Research Protections (OHRP) as an International Institutional Review Board (IRB00012588; FWA00029630).

Accordance

The study was conducted in accordance with the ethical principles approved by the MUSTREC and all applicable institutional and national guidelines governing research involving human participants.

Consent to publish:

Not applicable

Funding Declaration: not applicable

Author Contribution

W.M. conceived and designed the study, developed the methodology, conducted the formal analysis and modelling, interpreted the findings, and drafted the original manuscript. I.M. contributed to study design, field investigation, data collection, and manuscript review. J.N. contributed to methodological development, interpretation of environmental and land-health findings, and critical revision of the manuscript. C.K.M. contributed to socioeconomic data interpretation, qualitative analysis, and manuscript review. B.K. contributed to data curation, quantitative analysis, and visualization. J.K. and G.K. contributed to field investigation, soil and land-resource assessment, and interpretation of soil-health findings. M.M. contributed to soil laboratory analysis, validation, and interpretation of soil chemical data. T.T. contributed to the Nature-based Solutions framework, policy and institutional analysis, and interpretation of the findings within the IUCN NbS context. J.R. contributed to conceptualization of the Nature-based Solutions assessment, interpretation of the IUCN Global

Standard, and critical review of the manuscript. All authors reviewed and approved the final version of the manuscript.

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

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Figures

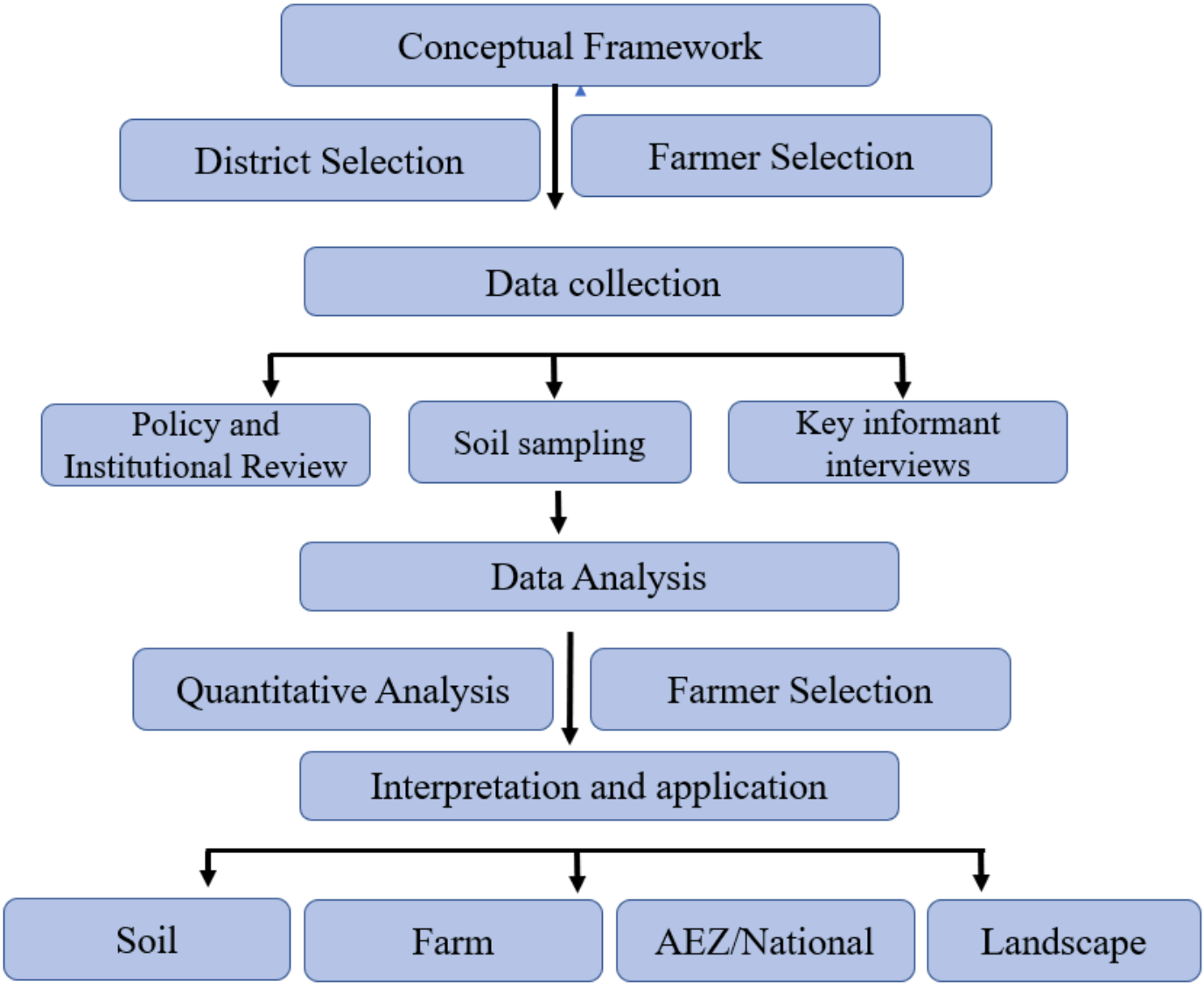

Figure 1

Conceptual framework for the study

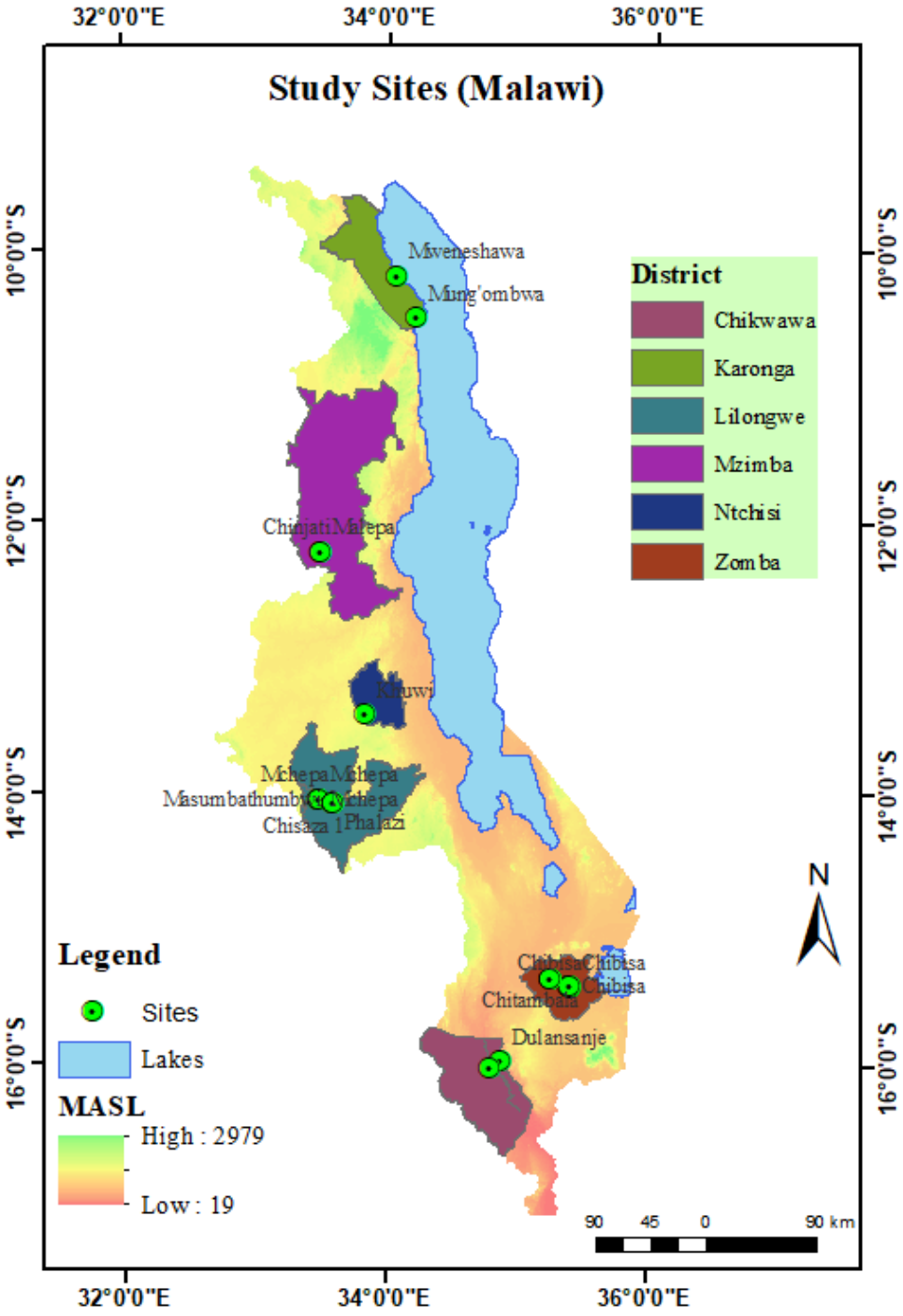

Figure 2

Map of Malawi showing villages and sampled districts from which the study was conducted



Figure 3

Figure 2: Some agroforestry trees in Malawi. A = *Rhus typhina*, B = *Tephrosia vogelli* (Picture credit; W. Mbewe, 2024)

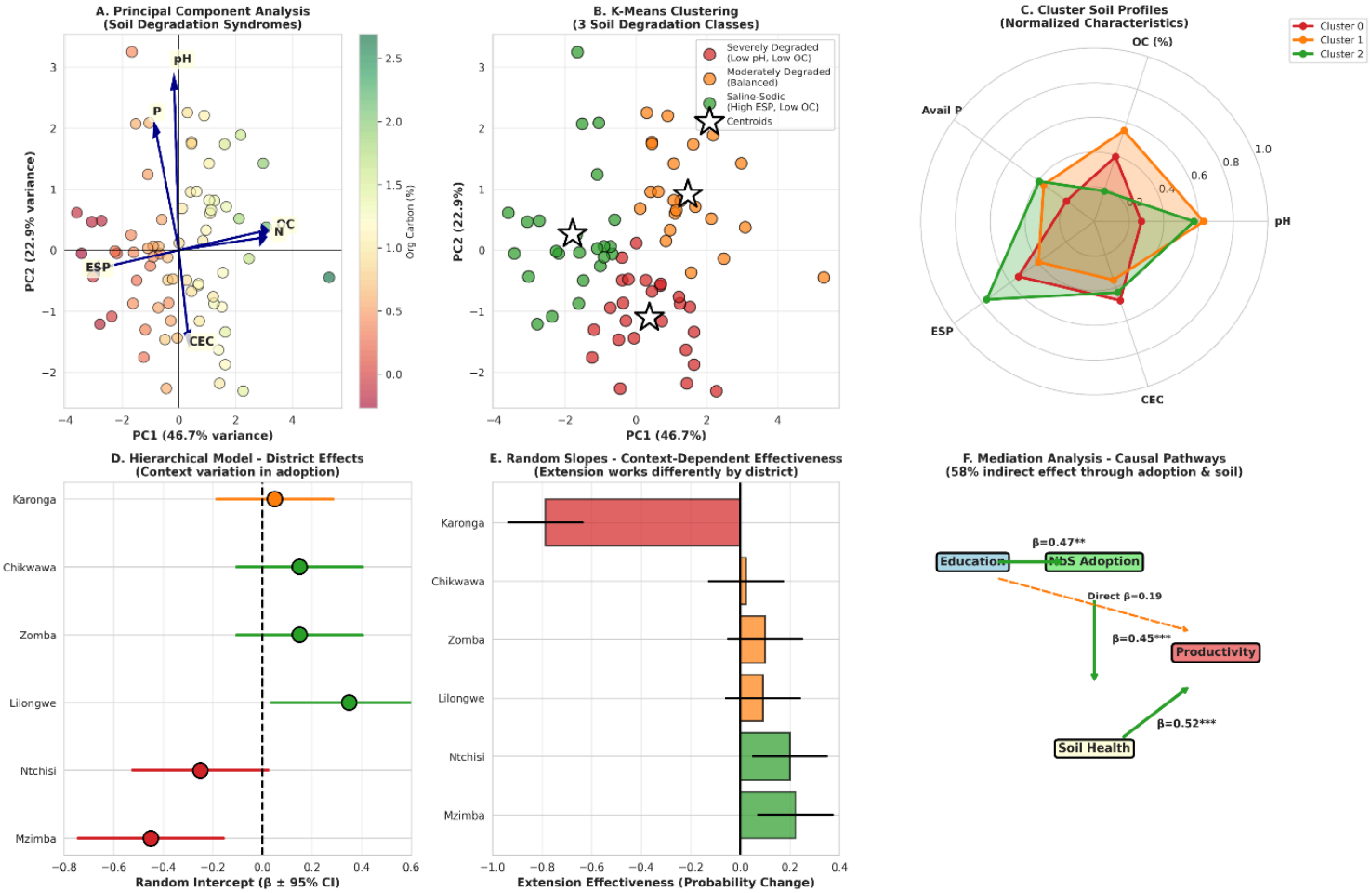

Figure 4

Figure 3: Multivariate characterization and classification of soil degradation patterns across sampled farms

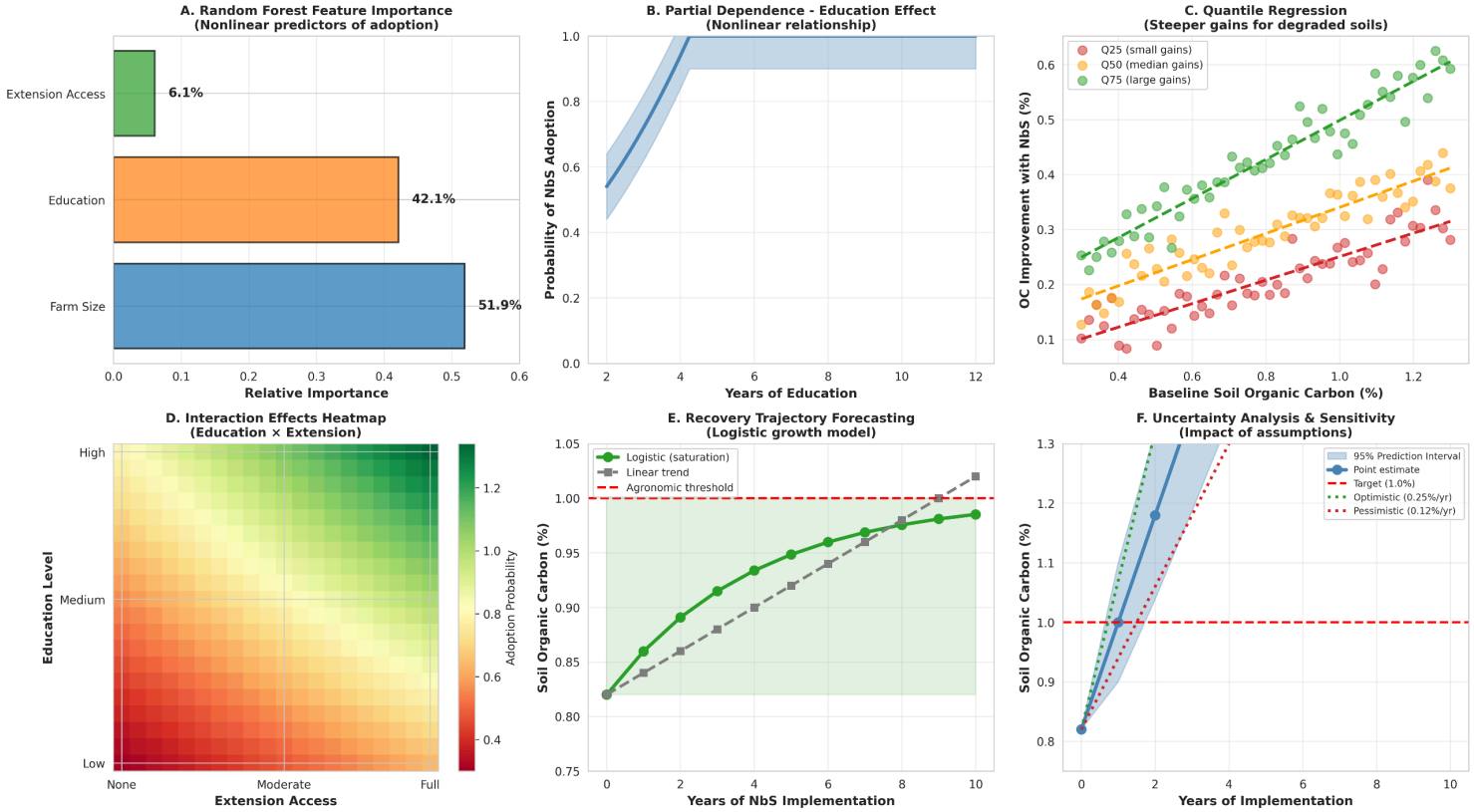

Figure 5

Figure 4: Quantile regression analysis of SOC improvement following NbS implementation.

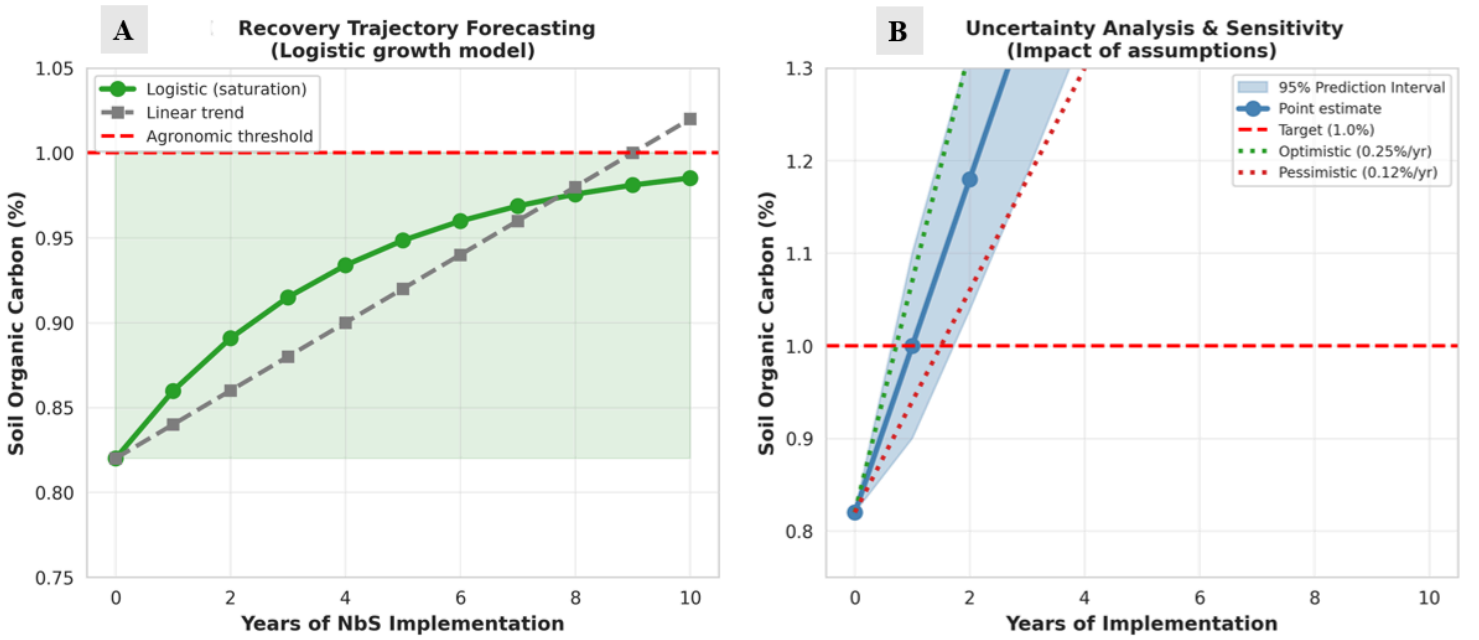

Figure 6

Figure 5: SOC recovery trajectories under NbS and associated uncertainty analysis.

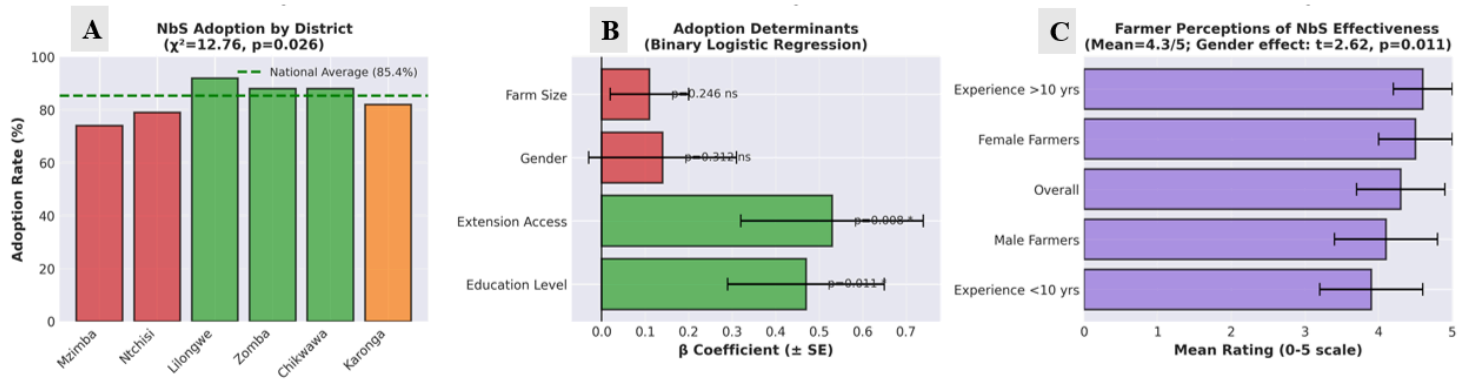

Figure 7

Figure 6: District variation, determinants, and perceived effectiveness of NbS

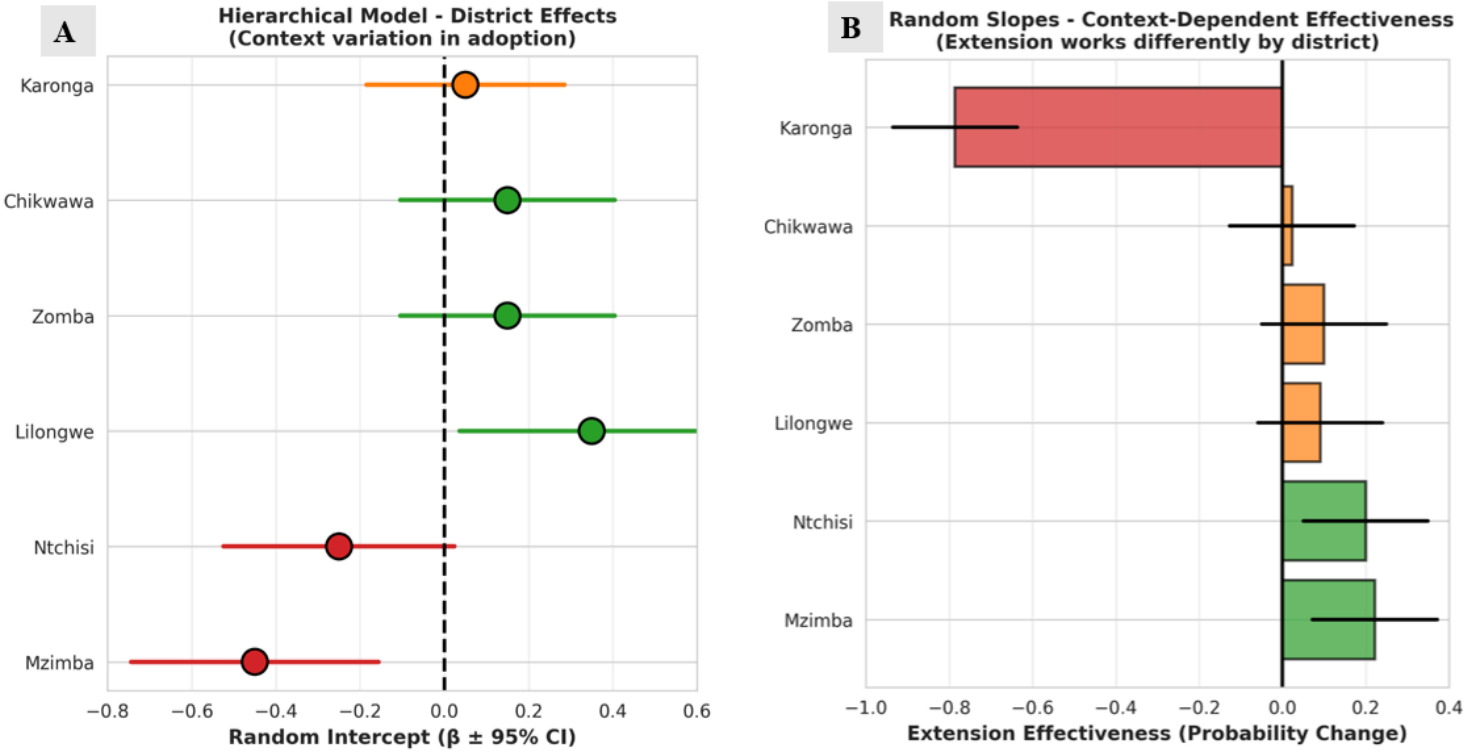

Figure 8

Figure 7: Context-dependent variation in NbS adoption across districts. Figure A shows district-level random intercepts from a hierarchical logistic model showing deviations in baseline adoption probability relative to the overall mean (vertical dashed line). Figure B shows district-specific random slopes illustrating heterogeneity in the effect of agricultural extension on adoption. Points represent coefficient estimates with 95% confidence intervals.