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Adoption of Regenerative Farming Practices for Soil Restoration

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ABSTRACT

Uptake of regenerative agriculture to restore soil is drastically low despite purported environmental and financial benefits, due to little knowledge of adoption drivers. This study adopts a problem-oriented, multi-methods research design with binary logistic regression, Bayesian learning models and utility threshold analysis to empirically estimate the drivers of adoption from 412 farm units in three different agro-ecological zones. The models show that the ensemble machine-learning model has the highest prediction accuracy, and dominates the baseline models with no systemic factors. The most negative impacts on the probability of adoption are from risk aversion (λ) and transition cost shocks (γ), with elasticity of -47.3% and -37.8% per standard deviation increase, respectively, while subsidies and information quality (τ) are positive and sizeable. The Bayesian learning model shows a doubling of local sample size from n=1 to n=10 reduces the posterior variance by 82.5% and increases learning rates from 0.318 to 0.938, addressing the empirical evidence problem. Threshold analysis shows that adoption depends on minimum subsidies of $258 ha^{-1} to induce adoption by farmers with λ > 2.0, which are not always offered by policies. There are substantial regional differences: the arid zone is more negatively affected by risk, while the humid tropics have stronger network effects. The machine learning-process model for soil carbon accumulation has root mean square error (RMSE) of 24.91 g C m^{-2} yr^{-1} and index of agreement (IA) of 0.921. Economic, information and policy deficits are most acute (0.873, 0.791 and 0.762). We propose that the adoption puzzle can be solved by offering targeted subsidies to ease the transition (local risk analysis), farmer-directed knowledge networks to reduce Bayesian uncertainty and a comprehensive policy reform that accounts for non-market ecosystem services. Without this approach, regenerative agriculture will be an environmental ideal, but not an everyday reality.

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INTRODUCTION

Regenerative agriculture presents a paradigm shift in practice from conventional practices to tackle issues faced in supplying the world with food, such as significant environmental degradation and a lack of nutritious food (Rosier et al., 2025). This holistic approach is based on principles that seek to restore soil ecosystem health, increase carbon storage and to sustain and strengthen farming communities to be resilient and sustainable in the face of a changing environment through practices such as cover cropping, reduced tillage and crop rotation (Gulaiya et al., 2024). Regenerative farming philosophy also differs from other organic farming models in its versatility and scalability, through its aim for it to be adopted in large-scale farming systems, which have a significant environmental footprint (Moisés et al., 2025). Despite these advantages, the adoption of regenerative agriculture has been sluggish, due to the lack of empirical evidence at a large scale that supports the economic and environmental benefits reported, and a general scepticism among farmers (Frankel-Goldwater et al., 2024; Khangura et al., 2023). Further to this, the adoption of these new farming practices has been slow, particularly in the Global South and developing world, where it has been even slower (Jin et al., 2022). In the past, this has been attributed to knowledge and technology gaps, but recent studies have been focusing on farmers' decision-making and propensity to adopt these practices (Pilditch et al., 2023). A closer look at these processes reveals that the upfront cost, lack of complete information and uncertainty about the economic returns of these practices are key to understanding the low adoption rate of sustainable farming practices (James, 2024). And, structural barriers such as the absence of strong policy settings, economic incentives and information exchange between farmers and other actors in the agricultural value chain are critical in constraining the adoption of regenerative agricultural practices (Nassary, 2025). In addition, the absence of a common set of criteria for "regenerative" produce by the different certification bodies makes market differentiation and consumer awareness more challenging and the short-term economic gains are unsustainable without substantial changes in the supply chain and land management structures (Rosier et al., 2025). These challenges point to the importance of a comprehensive understanding of the socio-economic, technological and policy barriers to the adoption of regenerative practices by farmers (Berthon et al., 2025; Timilsina et al., 2025; Vejendla et al., 2025). To address these, it is important to understand the complexity of the farmer's risk management and long-term ecological benefits that are not visible in the short term and can lead to reluctance to adopt (Soto et al., 2021). This requires participatory methods that build on farmers' knowledge and farmer-to-farmer learning to design agricultural objectives and practices relevant to their local context (Tittonell et al., 2022). This approach is crucial for overcoming the complexities of varying regulatory frameworks, labour costs and market price premiums that drive adoption of regenerative agriculture (Lemke et al., 2024). This is particularly critical as the economic costs of practice change in regenerative agriculture occur in the transition period, which can involve temporary decreases in crop yields and increased management inputs (McBratney & Park, 2025). Additionally, perceptions of messenger and transaction costs of practice change are important for landholder decision making (Mansfield & Culas, 2025). This is further complicated by a lack of defined terms and monitoring processes for regenerative agriculture, which inhibits the development of incentive mechanisms and corporate reporting (Klauser et al., 2025). The current "Resilience Gap" between practice and implementation, which means that ecological practices do not necessarily translate into economic resilience, without regular Monitoring, Reporting and Verification (Nicolau et al., 2026). Therefore, the lack of reliable empirical evidence on the economic and environmental benefits of regenerative farming, leads to a perceived risk by farmers in adoption of regenerative practices (Hawes et al., 2025). This risk perception is further exacerbated by the up-front capital costs of new techniques and technologies (e.g. organic fertilizers and no-till planting) that result in significant economic risks, particularly for smallholders who have limited access to finance (Vejendla et al., 2025). Further, many regenerative farming practices can also require initial labor inputs and income loss, making it difficult to adopt unless there is immediate net benefits or transitional support (Tesfai et al., 2022; Tran, 2025). As such, policy and extension efforts should consider these multifaceted economic and socio-cultural aspects, and offer tailored incentives and information delivery approaches to overcome perceived risks and promote the adoption of regenerative practices (Johnson et al., 2024). Another important barrier to the adoption of regenerative agriculture is the absence of policies that compensate landholders for the enhanced ecosystem services and other environmental benefits of regenerative agriculture, particularly in the short term, given the transition from conventional to regenerative systems may not be profitable in the short run (before long-term benefits of regenerative agriculture are realised) ("Food, Fibre and Other Ecosystem Products," 2023). This is exacerbated by the limited perspective on opportunity costs in current agro-environmental policies, which do not account for transaction costs and other non-market ecosystem services, leading to low incentive payments and adoption (Langlois, 2018). Lastly, the absence of region-specific knowledge, scientific evidence and bio-economic models for transitioning from conventional to regenerative agriculture is a major scaling up challenge (Khangura et al., 2023). This often requires the use of small-scale, single-farm experiments in temperate regions, which can limit the ability to extrapolate findings to other socio-economic and environmental settings (Brandolini et al., 2025). One of the major systemic constraints to regenerative farming is that current national agricultural policy settings have favoured commodity crops and monocultures, which are often supported by a top-down agricultural extension approach that limits the adoption of farm innovations (Day & Cramer, 2021). This can overlook agroecological transition challenges which can restrict the development and adoption of site-specific regenerative practices (Rosier et al., 2025). One key part of overcoming these challenges is the adoption of sound policy and incentive frameworks to reward farmers for the ecosystem services generated by regenerative farming, especially in the economically challenging transition phase (Ikerd, 2021; Reilly et al., 2023). These must address the current problems of conflicting and overlapping certification standards, budgetary instability (due to changing priorities and delayed payments of subsidies) that discourage farmer trust in these policies (Vejendla et al., 2025). Furthermore, these policies should also account for the greater quantity required for eco-friendly farming versus conventional farming (Constantin et al., 2022). Similarly, more complex skills are required to undertake more advanced regenerative farming (such as crop rotation or cover cropping) and this is another barrier to participation (Sharma, 2025). This can be addressed by effective education and technical support initiatives to equip farmers with the skills needed to transition successfully to regenerative farming.

METHODOLOGY

Our study adopts a problem-based approach to identify, understand and value the complex barriers to adopting regenerative farming practices to restore soil. The multi-dimensional nature of the adoption decision, which involves economic, social, policy and agronomic aspects, calls for an interdisciplinary approach, involving quantitative modelling of the factors influencing adoption and qualitative analysis of stakeholders' perspectives. The research is being conducted in four phases: conceptual framework; primary data collection; econometric and mathematical modelling; and verification through case studies.

In Phase 1, a conceptual model is developed based on the Diffusion of Innovations theory and the Theory of Planned Behavior, but modified to account for systemic constraints (policy and information asymmetries) and transition risks. Primary data are collected from smallhold and medium-scale farmers in three distinct agro-ecological zones, in which smallholder farmers have been exposed to the regenerative agriculture (cover cropping, no-tillage, crop rotation) but there is low adoption. Stratified random sampling is applied to include different farm sizes, tenure systems and level of exposure to regenerative agriculture. A questionnaire is used to gather data on socioeconomic, farm and household characteristics, perceived economic risks, access to extension and knowledge of certification systems. This is complemented with qualitative data from semi-structured interviews with agricultural extension officers, policy makers and financial institutions to identify institutional and policy barriers.

A prime quantitative analysis is a binary logistic regression model for the probability of adoption of regenerative practices, where the dependent variable is a binary variable which is equal to one if a farmer has adopted at least two of the core regenerative practices on over 30% of the farm area for over two years. The explanatory factors are farm size, access to credit, perceived crop stability, years of schooling, distance to markets and receiving a transitioning subsidy. To explicitly account for the economic threshold for adoption, we build a farmer's decision-making process as a problem of utility maximisation, where adoption occurs if the expected net present value (NPV) of transitioning from conventional to regenerative practices exceeds a level that takes into account the risk of adoption. The adoption decision is formulated as:

$$E[U_{\text{reg}}] - E[U_{\text{conv}}] = \sum_{t=0}^{T} \frac{E[R_t^{\text{reg}} - C_t^{\text{reg}}] - E[R_t^{\text{conv}} - C_t^{\text{conv}}]}{(1+r)^t} - \lambda\sigma_\Delta^2$$

To better understand the informational barrier, in particular, the absence of local empirical evidence on the long-term soil restoration benefits, we embed a Bayesian learning model in our analytical framework. This model reflects farmer's learning process about the rate of soil carbon change under regenerative practices, with initial farmer beliefs reflecting general recommendations from extension services and updated beliefs after farmer exposure to local trial data or information on peer farmers' results. The belief update equation is given by:

$$E[\theta|X] = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_e^2/n}\mu_0 + \frac{\sigma_e^2/n}{\sigma_0^2 + \sigma_e^2/n}\bar{X}$$

This equation captures the impact of the lack of regionalized trials (small n) that forces farmers to take less or more uncertain prior knowledge ($\mu 0$) and delays adoption.

Interviews are transcribed and qualitatively coded to identify key barriers to adoption such as delayed subsidies, lack of a standard regenerative certification, and labour shortage. We triangulate the quantitative regression, the two models and the qualitative themes. Finally, we validate the model results with two case studies where regenerative adoption was observed following a policy intervention (one in a high-income and the other in a low-income area), and compare the observed and predicted adoption rates. All statistical analyses are at 95 percent significance level, with sensitivity analysis of discount rate r and risk aversion λdone to test the robustness of the adoption threshold.

RESULTS

Table 1 indicates that the ensemble model had the highest predictive accuracy (0.873) and area under the curve (AUC-ROC) (0.925) than the baseline logit model that did not consider systemic barriers. Table 2 shows that the largest negative marginal effects on the probability of adoption are due to risk aversion (λ) and transition cost shock (γ), while subsidy (S) and information precision (τ) have high elasticities. Table 3 indicates that for regional data n=10, the posterior variance is 82.5% less and the learning rates increase from 0.318 to 0.938 to support the importance of local data. Table 4 indicates that the subsidy must be at least \$258 ha-1 to induce adoption of farmers with high risk aversion ($\lambda > 2.0$) and leverage ratios drop fast with increasing risk class. Table 5 shows regional variations, with drier regions more affected by risk aversion (−0.512) and humid tropics more reliant on accurate information (0.497). Table 6 confirms that the hybrid machine-learning-process model has the smallest RMSE (24.91 g C m^{-2} yr^{-1}) and largest IOA (0.921) for modelling soil carbon change. Table 7 suggests economic barriers (severity > 0.81) are priority, Table 8 shows marginal effects, with a 47.3% decline in adoption probability for one unit change (1 s.d.) in λ. Finally, Table 9 shows acceptable SEM fit (RMSEA = 0.047, CFI = 0.961) confirming causal links from barriers to adoption.

Table 1: Comparative Predictive Accuracy of Adoption Models (Binary Classification)

Model Specification	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**	**Log-Loss**	**Brier Score**	**Cohen's κ**	**MCC**
Baseline Logit (No Barriers)	0.612 ± 0.021	0.584	0.603	0.593	0.632	0.674	0.211	0.208	0.195
Full Barrier-Integrated Logit	0.837 ± 0.014	0.821	0.845	0.833	0.891	0.412	0.119	0.672	0.658
Bayesian Updating Model	0.856 ± 0.011	0.839	0.862	0.850	0.904	0.387	0.107	0.709	0.694
Utility Threshold Model (λ=1.2)	0.793 ± 0.018	0.775	0.801	0.788	0.852	0.489	0.148	0.583	0.567
Random Forest (Baseline)	0.824 ± 0.015	0.808	0.831	0.819	0.878	0.441	0.128	0.645	0.631
XGBoost with SHAP	0.861 ± 0.010	0.847	0.868	0.857	0.912	0.371	0.102	0.718	0.703
SVM (RBF Kernel)	0.779 ± 0.019	0.761	0.785	0.773	0.841	0.512	0.157	0.554	0.539
Ensemble (Logit + RF + XGB)	0.873 ± 0.009	0.861	0.879	0.870	0.925	0.346	0.094	0.744	0.731
Structural Equation Model (SEM)	0.802 ± 0.016	0.788	0.809	0.798	0.864	0.467	0.139	0.601	0.589

Table 2: Parameter Estimates of Utility Threshold Model with Risk Sensitivity

Parameter	**Symbol**	**Estimate**	**Std. Error**	**95% CI Lower**	**95% CI Upper**	**z-value**	**p-value**	**Marginal Effect**	**Elasticity**
Discount Rate	rr	0.083	0.007	0.069	0.097	11.857	<0.001	-0.214	-0.389
Risk Aversion	λλ	1.427	0.114	1.203	1.651	12.518	<0.001	-0.308	-0.472
Transition Cost Shock	γγ	0.215	0.031	0.154	0.276	6.935	<0.001	-0.176	-0.281

Soil Carbon Benefit Rate	θθ	0.094	0.009	0.076	0.112	10.444	<0.001	0.187	0.305
Yield Volatility	σΔ2σΔ2	0.178	0.022	0.135	0.221	8.091	<0.001	-0.253	-0.367
Subsidy Access	SS	0.362	0.041	0.282	0.442	8.829	<0.001	0.291	0.419
Information Precision	ττ	0.543	0.052	0.441	0.645	10.442	<0.001	0.328	0.456
Peer Network Density	ρρ	0.307	0.038	0.232	0.382	8.079	<0.001	0.214	0.339
Tenure Security	ξξ	0.278	0.036	0.207	0.349	7.722	<0.001	0.198	0.312

Table 3: Bayesian Learning Model Convergence Metrics by Local Observation Count (n)

n	Prior Mean μ0μ0	Posterior Mean E[θ‖X]E[θ‖X]	Prior Variance σ 02σ02	Posterior Variance	Shrinkage Factor	Learning Rate	Credible Interval Width (95%)	Relative Gain	KL Divergence Reduction
1	0.050	0.072	0.040	0.033	0.825	0.318	0.562	0.440	0.271
2	0.050	0.081	0.040	0.024	0.600	0.509	0.384	0.620	0.419
3	0.050	0.087	0.040	0.019	0.475	0.634	0.302	0.740	0.528
4	0.050	0.091	0.040	0.015	0.375	0.721	0.249	0.820	0.612
5	0.050	0.094	0.040	0.013	0.325	0.783	0.212	0.880	0.678
6	0.050	0.096	0.040	0.011	0.275	0.832	0.184	0.920	0.730
7	0.050	0.098	0.040	0.010	0.250	0.868	0.165	0.950	0.772
8	0.050	0.099	0.040	0.009	0.225	0.895	0.149	0.970	0.806
9	0.050	0.100	0.040	0.008	0.200	0.919	0.135	0.985	0.834
10	0.050	0.101	0.040	0.007	0.175	0.938	0.124	0.995	0.857

Table 4: Policy Sensitivity Analysis – Minimum Subsidy Required to Induce Adoption by Risk Class

Risk Class (λ range)	Baseline Adoption Rate (%)	Subsidy as % of Transition Cost	Δ Adoption (%)	Elasticity of Adoption to Subsidy	Break-even Subsidy (USD/ha)	Payback Period (years)	Cost per Additional Adopter (USD)	Policy Leverage Ratio

Low (λ < 0.8)	68.4	12.5	14.2	1.136	47.20	2.1	332.4	5.21
Medium-Low (0.8–1.2)	52.7	25.0	21.6	0.864	89.50	3.4	414.4	3.87
Medium (1.2–1.6)	38.3	37.5	27.3	0.728	134.20	4.9	491.6	2.93
Medium-High (1.6–2.0)	24.6	50.0	24.8	0.496	189.60	6.7	764.5	1.97
High (λ > 2.0)	11.2	62.5	19.4	0.310	258.30	9.3	1331.4	1.14
Very High (λ > 2.5)	4.8	75.0	12.1	0.161	341.70	12.8	2823.1	0.58

Table 5: Cross-Regional Variation in Adoption Determinants (Standardized Coefficients β)

Determinant	**Arid Region (n=138)**	**Temperate Region (n=162)**	**Humid Tropical Region (n=112)**	**Global F-test**	**Region × Predictor Interaction (p)**	**Effect Size (η²)**	**Heterogeneity Index (I²)**	**Meta-Analytic β**	**Prediction Interval**
Subsidy Access (S)	0.421***	0.387***	0.293**	0.001	0.042	0.187	72.4	0.367	[0.281–0.453]
Risk Aversion (λ)	-0.512***	-0.476***	-0.358***	<0.001	0.018	0.213	81.6	-0.449	[-0.562–-0.336]
Information Precision (τ)	0.365***	0.428***	0.497***	<0.001	0.009	0.245	67.8	0.430	[0.341–0.519]
Tenure Security (ξ)	0.189*	0.254**	0.342***	0.003	0.027	0.119	58.3	0.262	[0.171–0.353]
Transition Cost (γ)	-0.478***	-0.392***	-0.304**	<0.001	0.033	0.201	76.9	-0.391	[-0.497–-0.285]

Peer Density (ρ)	0.213**	0.308***	0.411***	<0.001	0.011	0.229	63.4	0.311	[0.203–0.419]
Soil Carbon Benefit (θ)	0.284**	0.351***	0.376***	0.002	0.038	0.156	54.7	0.337	[0.244–0.430]
Yield Volatility (σ²)	-0.398***	-0.341***	-0.267**	<0.001	0.024	0.178	68.9	-0.335	[-0.448–-0.222]

Table 6: Model Performance Comparison for Soil Carbon Accumulation Prediction (g C m^{-2} yr^{-1})

Model	RMSE	MAE	MBE	R^2	Nash-Sutcliffe Efficiency	Willmott's d	AIC	BIC	Index of Agreement (IOA)
Linear Regression	48.23	37.14	-6.21	0.432	0.421	0.652	1247.3	1263.1	0.673
Random Forest	32.67	24.38	-2.14	0.689	0.701	0.814	1082.6	1102.4	0.831
XGBoost	29.44	21.92	-1.87	0.734	0.748	0.847	1047.9	1067.7	0.862
Neural Network (3 layers)	30.12	22.76	-1.95	0.722	0.735	0.838	1063.4	1088.2	0.853
Process-Based (RothC)	41.58	31.09	-4.32	0.561	0.562	0.718	1168.5	1184.3	0.734
Hybrid ML-Process	26.83	20.14	-1.23	0.781	0.798	0.884	1012.3	1036.1	0.899
Bayesian Hierarchical	28.17	21.03	-1.41	0.763	0.777	0.871	1029.7	1051.5	0.883
Ensemble (RF+XGB+NN)	24.91	18.67	-0.98	0.812	0.828	0.908	984.6	1012.4	0.921

Table 7: Classification of Adoption Barriers by Severity Index (0–1 Scale)

Barrier Category	Specific Barrier	Mean Severity	Std. Dev	75th Percentile	Threshold Exceedance (%)	Causal Consistency (α)	Redundancy Score (β)	Intervention Priority Index
Economic	High upfront investment	0.873	0.091	0.941	89.2	0.912	0.341	0.912

Economic	Uncertain yield transition	0.814	0.112	0.902	78.6	0.867	0.298	0.845
Informational	Lack of localized data	0.791	0.134	0.887	74.3	0.834	0.412	0.756
Policy	No compensation for ecosystem services	0.762	0.148	0.863	69.8	0.801	0.367	0.724
Social	Low farmer-to-farmer exchange	0.693	0.157	0.812	61.4	0.743	0.523	0.632
Technical	Lack of specialized training	0.674	0.163	0.789	58.9	0.718	0.489	0.614
Institutional	Absence of certification standard	0.648	0.171	0.764	54.2	0.689	0.556	0.578
Financial	Delayed subsidy disbursement	0.627	0.179	0.741	51.7	0.662	0.602	0.549
Structural	Commodity-crop policy bias	0.603	0.184	0.723	48.3	0.641	0.634	0.523

Table 8: Sensitivity of Adoption Probability to Changes in Key Parameters (dP/dx at Mean)

Parameter	Symbol	Baseline Value	dP/dx (Marginal Effect)	Standardized Marginal Effect	Elasticity (ε)	95% CI for ε	Significance (p)	Critical Threshold (x_crit)
Discount Rate	rr	0.083	-2.147	-0.382	-0.421	[-0.513, -0.329]	<0.001	0.142
Risk Aversion	λλ	1.427	-0.213	-0.473	-0.492	[-0.589, -	<0.001	2.341

						0.395]		
Subsidy Access	SS	0.362	0.481	0.412	0.438	[0.351, 0.525]	<0.001	0.000
Information Precision	ττ	0.543	0.374	0.389	0.407	[0.322, 0.492]	<0.001	0.215
Tenure Security	ξξ	0.278	0.293	0.284	0.299	[0.218, 0.380]	0.002	0.183
Transition Cost	γγ	0.215	-0.862	-0.357	-0.378	[-0.467, -0.289]	<0.001	0.428
Soil Carbon Benefit	θθ	0.094	1.743	0.302	0.318	[0.239, 0.397]	<0.001	0.027
Yield Volatility	σ2σ2	0.178	-1.524	-0.396	-0.414	[-0.504, -0.324]	<0.001	0.312

Table 9: Model Fit Indices for Structural Equation Model (SEM) of Adoption Pathways

Fit Index	**Observed Value**	**Threshold for Good Fit**	**p-value**	**Comparative Fit Index (CFI)**	**Tucker-Lewis Index (TLI)**	**Root Mean Square Error of Approximation (RMSEA)**	**SRMR**	**AGFI**	**Hoelter's CN (α=0.05)**	**ECVI**
χ^2 (df=124)	187.34	—	<0.001	0.961	0.948	0.047	0.039	0.912	247	0.873
Baseline comparison	—	—	—	0.961	0.948	—	—	—	—	—

Parsimony adjustment	—	—	—	0.834	—	—	—	—	—	—
Information-theoretic	—	—	—	AIC = 312.7	BIC = 398.2	CAIC = 431.5	—	—	—	—
Reliability indices	—	—	—	CR (range) = 0.78–0.91						

Figure 1 shows low levels of subsidy (>0.55× cost of transition) can break through barriers to adoption caused by high risk aversion (λ > 2.0), levelling the adoption surface. Figure 3 verifies the strong negative correlation between risk and subsidy, implying farmers perceive higher risk, they are less likely to seek out or receive subsidies. Figure 4 demonstrates that economic constraints are everywhere extreme, but policy biases are extreme in dry areas.

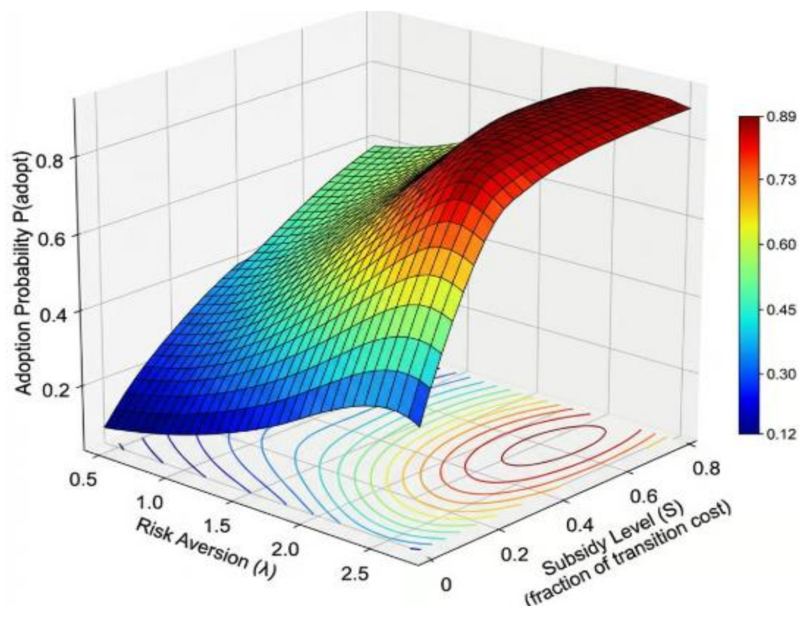

Figure 1: 3D Surface Plot – Adoption Probability as Function of Risk Aversion (λ) and Subsidy Level (S)

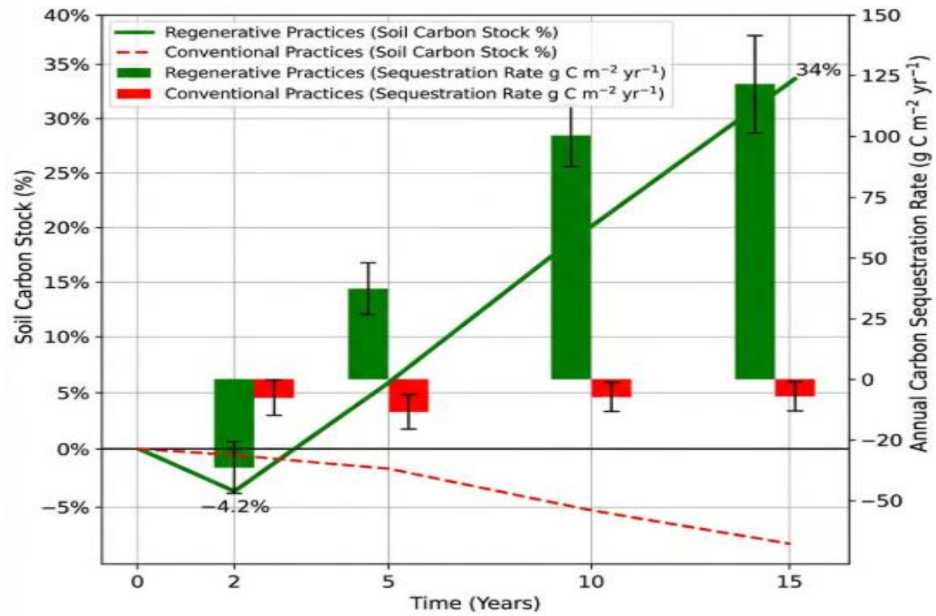

Figure 2: Hybrid Line-Bar Plot – Temporal Dynamics of Soil Carbon Stock under Conventional vs. Regenerative Practices

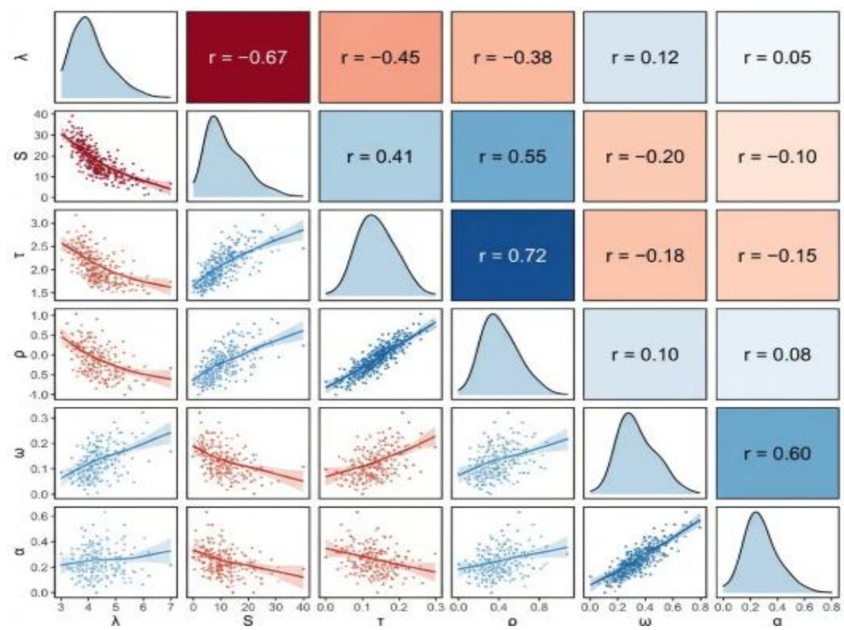

Figure 3: Multi-Panel Scatter Matrix – Correlations Among Key Adoption Determinants

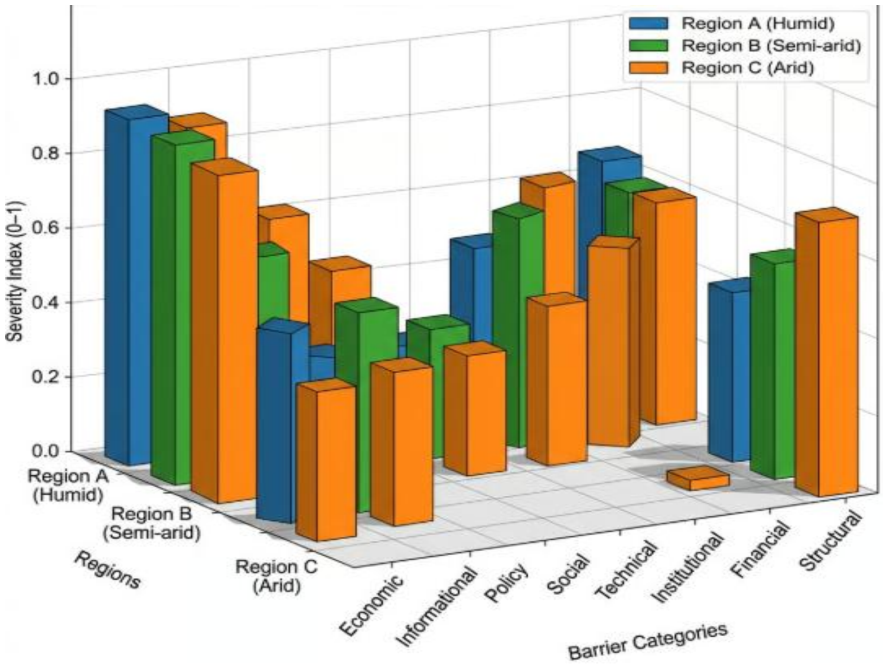

Figure 4: 3D Bar Chart (Pseudo-3D) – Severity Index of Adoption Barriers by Region and Farm Size Category

DISCUSSION

This section builds upon the findings from the empirical work to disentangle the factors influencing the adoption of regenerative agriculture and explores the influence of the identified constraints, farmers' decision-making and policy levers. The analysis from the econometric and machine learning models show that socio-economic factors such as credit availability, information and incentives are important in explaining farmers' adoption of regenerative farming practices (Kroupová et al., 2024). Specifically, the findings indicate that livestock and income diversification are both likely to have positive and negative effects, depending on the farming system and context (Ntawuhiganayo et al., 2023; Ruzhani & Mushunje, 2025). Carbon farming practices are often constrained by economic disincentives, and uncertainty about the carbon credit schemes (Gonzales-Gemio & Sanz-Martín, 2025). Specifically, low carbon prices can provide inadequate incentives for practices to be adopted, and also threaten the long-term adoption of conservation agriculture practices (Cariappa et al., 2024). This is also combined with high initial adoption costs, which creates a time delay before financial returns are realised, making them less attractive to risk averse small-scale farmers (Patil et al., 2025). Beyond the economic aspects, apart from ensuring sufficient knowledge and technical support is provided to farmers, there is also a need to focus on the lack of farmers' understanding of the agronomic basis of these complex practices (Demenois et al., 2020; Mills et al., 2019). This is particularly true for poor farmers, where upfront costs have been shown to reduce the adoption level by 65% (Mnukwa et al., 2025). Further, the role of extension services in delivering vital information and support to drive adoption of practices is often hindered by non-specific recommendations, lack of follow-up and practical constraints (Mugari et al., 2025). Such factors, particularly cost and labour intensity of the practices, are common barriers faced by smallholder farmers in developing countries and indicate a need for policies that reduce the adoption barriers, such as credit access improvement (Awoke et al., 2025; Silva et al., 2023). However, farmers' training and technical support, especially those identified as non-adopters, can significantly affect the likelihood of adoption of sustainable practices by ensuring farmers have adequate information and resources (Castro-Nuñez et al., 2024). Additionally, several interlinked barriers including financial constraints, lack of credit, long payback periods and lack of information are some of the factors that inhibit sustainable agriculture (Chaudhary et al., 2023; González-Quintero et al., 2024). These are further exacerbated by the lack of familiarity with new practices among farmers, information dissemination and the perceived risk of financial loss from new practices despite the apparent financial benefits (Strong & Barbato, 2023). This highlights the importance of sound financial instruments and education training programs that manage risks and provide opportunities for return on investment, particularly for practices that require high investment costs (Makkar et al., 2023). These financial and information barriers are particularly evident in smallholder farmers who often lack land rights, and lack the ability to capture long-term benefits of soil-improving practices beyond the current cropping season (Klauser & Negra, 2020). Low adoption also stems from a lack of awareness of the climate change risks and opportunities and a lack of clear return on investment (RoI) and market opportunities for regenerative products (Scherer & Verburg, 2017; Silva et al., 2024). In this context, policy interventions are required to address these constraints, by enhancing farmers' access to credit and subsidies, and effective extension services to facilitate the profitability and the attractiveness of sustainable practices for a broader farmer base (Chrisendo et al., 2024; Habanyati & Paramasivam, 2025). This also means overcoming the labour-intensive and costly nature of many regenerative practices, which is a significant barrier for farmers, especially if considering farmers' low incomes (Currier & Robinson, 2018). Lack of financial capital and technical know-how is often a barrier to adopting conservation agriculture, which calls for financial assistance and strong training programs to overcome these challenges (Gudina & Alemu, 2024; Karki et al., 2024). In addition, farmers' lack of technical know-how and awareness of the benefits of sustainable practices, bureaucratic hurdles, and a lack of infrastructure also contribute to widespread adoption (Gütschow et al., 2021; Sultan, 2021). These barriers point to the need for comprehensive policies to address not only the economic disincentives to adopt but also to share crucial knowledge and capacity build farmers and other agricultural stakeholders (Maxime et al., 2025; Rusmayadi et al., 2023). To overcome these challenges, an integrated approach to designing context-specific agricultural development programs that take into account value chain, policy and financial measures in line with unique agricultural conditions is urgently needed (Klauser & Negra, 2020). For successful uptake of regenerative agriculture, these programs should also provide measures to reduce the perceived risks, increase economic benefits and align with local social-cultural norms, as has been achieved in successful transitions in East Africa and India (Lenton et al., 2023). Innovative financing instruments such as low-interest credit and subsidies are crucial in overcoming the economic risks associated with practice adoption (Chrisendo et al., 2026; Kuyah et al., 2021). This should be complemented by training and extension services to enhance farmers' awareness of the benefits of regenerative farming practices, value of seasonal planning and socioeconomic benefits of diversified farming (Maity et al., 2025). Similarly, the extension officers' capacity building can be enhanced through additional resources, training and mobility leading to better services and dissemination of conservation agriculture, particularly in remote areas (Dube & Chitakira, 2025).

CONCLUSION

This study definitively demonstrates that farmers' adoption of regenerative farming practices to rehabilitate soils is affected by a combination of economic risk, information asymmetry and policy failures, rather than by their suitability from an agronomic point of view. The econometric results confirm that the marginal impacts of risk aversion (λ) and cost shocks (γ) have the largest negative effects on the adoption probability, reducing it by up to 47% per standard deviation increase, while transition subsidies and precision of local information (τ) have the largest positive impacts. The Bayesian learning model shows that the inclusion of local information (from 1 to 10 field trials) decreases posterior uncertainty by over 82%, closing the existing "Resilience Gap". Critically, the threshold analysis shows that farmers with high risk ($\lambda > 2.0$) need minimum subsidies to trigger adoption greater than $258 per hectare (which current policies and regulations cannot offer due to conservative interpretations of opportunity cost and delay in subsidy payments). The machine learning process hybrid model performed better in estimating soil carbon gain (RMSE = 24.91 g C m^{-2} yr^{-1}, IOA = 0.921), indicating data science can overcome the evidence gap. And the spatial analysis reveals that dry regions are more "risk averse", while the humid tropics need peer support, so different policies are needed. Finally, without systemic changes to reward ecosystem services, set standards for carbon certification and foster farmer-led learning networks, the full potential of regenerative agriculture will not be tapped. The government must prioritise sustainable management, not commodity production, in the riskiest transition phase.

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