The Centre for
Agricultural Research
& Development (CARD)

Assessing the effects of Land Registration on Climate-Smart Agriculture and Soil Investment Decisions: Machine learning informed lessons from Malawi's Chikwawa and Nkhotakota Districts

Technical Working Paper Series
202507002

NOVEMBER 2025

Assessing the effects of Land Registration on Climate-Smart Agriculture and Soil Investment Decisions: Machine learning informed lessons from Malawi's Chikwawa and Nkhotakota Districts

Patrick KAWAYE[#], Wongani CHIRWA[#], & Innocent PANGAPANGA-PHIRI[#a]

[#] Centre for Agricultural Research and Development (CARD), Bunda College, Lilongwe University of Agriculture and Natural Resources (LUANAR), P.O. Box 219, Lilongwe, Malawi
[a] Africa Centre of Excellence for Agricultural Policy Analysis (APA), Bunda College, Lilongwe University of Agriculture and Natural Resources (LUANAR), P.O. Box 219, Lilongwe, Malawi

Secure land tenure is widely recognized as a key driver of sustainable agricultural development. Yet, empirical evidence on how tenure security, particularly land registration, shapes farmers' soil investment decisions remain limited. This study applies Multivariate Bernoulli Mixture Models and machine learning approaches to investigate whether formal land registration influences patterns of climate-smart agriculture adoption and soil investment behaviour, while also identifying the socioeconomic and demographic factors that shape these decisions. The results reveal two distinct classes of soil investment behaviour, with registered farmers significantly more likely to adopt multiple practices, including soil amendments, conservation agriculture, and agroforestry. Land registration and education emerge as the strongest predictors of investment behaviour, whereas household income and age are closely linked to productivity outcomes. The findings suggest that land registration affects productivity indirectly, primarily by promoting investments in sustainable soil management. Beyond its role as a legal reform, land registration functions as a behavioural catalyst, nudging farmers toward practices that enhance soil health. These results underscore the value of integrating behavioural insights and advanced analytical methods into land policy design. Scaling up land registration programs could therefore play a critical role in improving soil quality, boosting agricultural productivity, and enhancing food security in tenure-constrained farming systems.

Keywords: Land registration, Climate-Smart Agriculture, Soil investment behavior, Multivariate Bernoulli Mixture model, Machine Learning models

Introduction

Secure land tenure is a cornerstone of rural development, particularly in Sub-Saharan Africa (SSA), where land remains the most critical productive asset for smallholder households (Pierri et al., 2025). Insecure tenure, characterized by fear of expropriation or unresolved disputes, acts as a critical disincentive for long-term investments in land improvement and restricts access to formal credit, ultimately constraining agricultural productivity and rural livelihoods (Mbudzya et al., 2022). To address these challenges, many countries in SSA, including Malawi, have turned to formal land registration programs as a policy lever to enhance tenure security and stimulate agricultural investment ((Erb et al., 2024; World Bank, 2014). Different countries across the African continent have prioritized formal land registration. In principle, such reforms aim to reduce disputes, safeguard property rights, which in turn acts as an incentive to drive adoption of sustainable soil management practices(World Bank, 2014). Malawi's recent land reform marks a significant policy shift, allowing customary land to be formally surveyed and registered, thereby providing farmers with legal certificates of ownership ((DAI Global, 2021).

Evidence from literature on the effects of titling on farm investment and yields remains mixed. Previous studies reported that land titling raises perceived tenure security and collateral value, but they often find little short-term change in measurable farm investments or output (Benjamin, 2020). For instance, a recent quasi-experimental study in Ghana found that although land certificates significantly increased land values, they did not lead to higher use of inputs or crop/livestock productivity; instead, households shifted labor toward non-farm activities (Agyei-Holmes, 2020). Such mixed findings suggest that the pathways by which land registration might "nudge" farmers toward greater soil conservation and higher yields are complex and context-dependent.

Prior studies across Ethiopia, Benin, China, India, and Vietnam demonstrate that land certification enhances farmers' perceived tenure security, increases adoption of long-term conservation practices, and often improves productivity (Tian et al, 2024; Holdenet al, 2016; Deininger et al, 2011). However, these studies didnt cover behavior patterns. Despite empirical evidence on the impact of land registration remain inconclusive, one key challenge lies in identifying the pathways through which land registration affects investment behavior and productivity outcomes (Erb et al., 2024). Traditional econometric models often impose restrictive assumptions and may fail to capture recursive and nonlinear interdependencies among variables (Wang et al., 2022). This paper unpacks how formal land registration influences farmers' soil investment decisions and ultimately their productivity. The paper addresses the following questions: (1) Do farmers have distinct behavior patterns based on land registration status? (2) Do socioeconomic factors influence farmers' behavior patterns in soil investment? (3) Does land registration lead to increased soil investment? (4) Is land registration associated with higher farm productivity? We address these questions using household data from smallholder farmers in Malawi, where formal land registration of customary land has recently been scaled up.

Unlike many earlier studies, we utilized the Multivariate Bernoulli Mixture Model (MBMM) to classify farmer behavior into distinct soil investment profiles and employed a logistic regression followed by Machine Learning models to identify the socioeconomic and demographic factors shaping farmers decisions. The study aimed to provide new evidence from Malawi, to inform land reform policies to guide the design of effective interventions that incorporate institutional and cultural dynamics(Loconto et al, 2020). Our study builds on empirically testing the existence of distinct soil investment patterns among farmers due to formal land registration and reveals behavior determinants that would nudge farmers to engage in sustainable soil conservation practices. By integrating behavioral classification with predictive analytics, this study offers fresh insights for land policy, climate adaptation programming, and precision agriculture initiatives targeting tenure-constrained farming systems.

Literature Review

Land tenure security has long been recognized as a critical determinant of agricultural investment and productivity, particularly in rural, smallholder-dominated economies. Theoretically, secure land rights enhance farmers' perceived tenure security, reduce the risk of expropriation, increase the collateral value of land, and lengthen planning horizons all of which are expected to incentivize long-term investments in soil fertility and land improvement (Besley, 1995; Place & Migot-Adholla, 1998; Deininger & Jin, 2006). These linkages have informed land reform programs across sub-Saharan Africa, including Malawi, where customary tenure has historically lacked legal recognition (Ali et al, 2014). Empirical studies across African generally support a favorable association between land registration and soil-related investments. In Ethiopia, a low-cost land certification program led to significant increases in structural investments such as terraces and tree planting, with accompanying improvements in plot-level productivity (Holden et al, 2016; Holden, 2009). Similar results have been documented in other Ethiopian regions, where certification was found to increase manure application, soil conservation, and farmers' land management practice scores, though productivity effects were sometimes lagged or insignificant in the short term (Gedefaw et al, 2020; Tesfaye & Simane, 2023).

Evidence from Tanzania indicates that customary certificates of rights of occupancy (CCROs) improve soil management and yields (Stein, Maganga, & Odgaard, 2024). Outside Africa, studies from China and Vietnam suggest that titling facilitates crop rotation, organic fertilizer use, and environmentally friendly farming practices (Cheng et al., 2024; Zheng, 2024). Despite these positive associations, findings from Malawi remain mixed. Lawry et al. (2017) and Ali et al. (2019) reported that land registration outcomes are highly context-dependent, shaped by factors such as gender, plot quality, and institutional implementation. For example, randomized demarcation programs in Benin increased land investments on female-managed plots but did not yield immediate productivity gains (de la O Campos et al., 2023). Such evidence underscores the importance of examining behavioral mechanisms through which tenure reform alters farmer decision-making.

A key limitation of the existing literature remains on reliance on linear econometric models, which often fail to capture complex, recursive processes linking land registration, soil investment behavior, and productivity. Few studies rigorously test behavioral “nudge” mechanisms such as shifts in expectations or labor allocation (Tseng et al., 2020). Recent advances in machine learning (ML) offer opportunities to overcome these challenges. ML methods can model non-linear interactions and high-dimensional covariates without imposing restrictive assumptions (Wang et al., 2022; Southworth et al., 2024). Recursive ML frameworks, in particular, allow researchers to map sequential processes—such as how land registration influences soil investment decisions, which then shape productivity outcomes. Another critical research gap lies in the limited exploration of adoption patterns related to soil management practices, particularly through the lens of behavioral heterogeneity and non-traditional analytical tools (Qu et al., 2023). To address this limitation, this study employs a Multivariate

Bernoulli Mixture Model and ML techniques to investigate how formal land registration influences farmers' soil investment decisions and productivity outcomes. This dual approach not only deepens empirical understanding of the effects of tenure security but also advances methodological innovation by providing nuanced, data-driven insights for evaluating agricultural development interventions.

Methodology

Theoretical Framework

This study draws from classical property rights theory, which posits that secure tenure enhances landholders' incentives to invest in long-term productivity-enhancing practices (De Soto, 2000; Besley, 1995). Land registration is expected to reduce land-related disputes, improve tenure security, and facilitate market-based transactions such as land rental or collateralization (Feder & Nishio, 1997). These improvements in tenure security may, in turn, lead to increase on-farm investments, such as soil amendments, conservation structures, or agroforestry and ultimately improve agricultural productivity. However, empirical evidence on this pathway remains mixed, often limited by methodological challenges such as simultaneity, unobserved heterogeneity, and static estimation frameworks (Lawry et al., 2017; Mbudzya et al., 2022).

To capture the behavioral dimension of investment decisions, this study further draws on the Theory of Planned Behavior (TPB), which argues that farmers' decisions are shaped by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). Under TPB, land registration may strengthen positive attitudes toward soil investment by lowering perceived risks of expropriation, alter social norms through visible formalization of rights within communities, and enhance perceived control by enabling farmers to access credit or extension services. Similarly, nudging theory suggests that institutional interventions such as issuing certificates or public recognition of rights, can serve as behavioral cues that "nudge" farmers toward sustainable practices without coercion, particularly in contexts where traditional incentives alone may be insufficient (Thaler & Sunstein, 2008).

Beyond static frameworks, methodological extensions emphasize the importance of dynamic decision-making and learning processes. Farmers continuously update their beliefs about the security of their tenure and the returns to soil investment based on past experiences, policy enforcement, and peer learning (Galiani & Schargrodsky, 2010). Such adaptive behavior implies recursive feedback: investments improve land productivity and visible claims, which in turn reinforce perceived security, creating a virtuous cycle; conversely, weak enforcement or delayed benefits may generate disinvestment traps. Theoretically, this perspective resonates with behavioral models, which posit that tenure security can function as a psychological "nudge," shaping farmers' risk perceptions and intertemporal choices ((Tseng et al., 2020; Erb et al., 2024). In this sense, land registration may encourage long-term soil investments primarily among farmers who perceive future returns as both attainable and secure.

Finally, institutional theory highlights the mediating role of both formal and informal institutions in shaping how land registration translates into investment outcomes (North, 1990). Formal institutions determine the credibility of registration systems, while informal norms, such as customary authority and community trust, govern local enforcement. Path dependence in land policy implementation and variations in institutional capacity can explain heterogeneous outcomes across regions (Boone, 2014). Moreover, social norms influence how rights are exercised within households and communities, mediating the extent to which women, youth, or marginalized groups benefit from registration. By integrating these perspectives, this study acknowledges that the impact of land registration on soil investment is not uniform but contingent on behavioral, institutional, and methodological dynamics. This broader framework provides a richer basis for explaining the mixed empirical findings in the literature and for identifying heterogeneity in farmers' responses to land policy reforms.

Empirical Strategy

The study used a Multivariate Bernoulli Mixture Model (MBMM) and Machine Learning (ML) techniques to analyze farmers' soil investment behavior following established approaches in mixture modeling and predictive analytics (Hsu, 2024, Zhou, 2025, Saeed, 2013) . The first step involved the application of the MBMM to classify farmers into distinct behavioral groups based on the joint adoption of multiple soil management practices. This approach was chosen because it allows for the identification of unobserved heterogeneity and clustering of farmers into latent classes that reflect unique adoption profiles (Sun et al, 2007). The second step involved linking class membership to land registration status and socioeconomic variables using multinomial logistic regression. This stage examined the extent to which formal registration, education, household income, and demographic factors predict membership in particular soil investment behavior classes. The robustness of the classification and regression results was assessed by comparing alternative specifications of the MBMM and cross-validating classification accuracy.

The third step used machine learning models, specifically Random Forest and XGBoost algorithms, to predict both soil investment behavior and productivity outcomes. Permutation Importance analysis was carried out for the Random Forest model to identify the most influential predictors, while SHAP (Shapley Additive Explanations) values were used for the XGBoost model to provide both global and local interpretability of predictor effects (Lundberg & Lee, 2017). These methods were selected because they provide model-agnostic and robust approaches for uncovering nonlinear relationships and complex interactions among explanatory variables. The integration of MBMM with machine learning ensured that both behavioral patterns and predictive determinants were rigorously examined. This combined approach was appropriate for the study because it enabled the detection of latent heterogeneity in soil investment decisions and provided robust insights into the pathways through which land registration influences both farmer behavior and productivity.

Household Survey

The study was conducted in the Nkhotakota and Chikwawa districts of Malawi (Fig. 1). Nkhotakota lies along the shores of Lake Malawi in the Central Region, situated between longitudes 12°00’ E and 12°30’ E and latitudes 12°30’ S and 13°00’ S. The district has an estimated population of 81,064 farming households (MoA, 2024). Agriculture is the mainstay of the local economy, with farmers primarily engaged in the cultivation of rice, cassava, maize, and groundnuts, alongside small-scale fishing activities along Lake Malawi. The area has a tropical climate characterized by unimodal rainfall, usually between November and April, averaging 1,000–1,500 mm annually. Chikwawa District is located in the Southern Region of Malawi, situated between longitudes 34°30’ E and 35°15’ E and latitudes 16°00’ S and 16°45’ S. The district has a population of 95,970 farming households (MoA, 2024).

Agriculture is the main source of livelihood, with households cultivating maize, sorghum, millet, and cotton, and engaging in livestock production. Due to its location in the Shire Valley, the district experiences semi-arid conditions with average annual rainfall of about 700–1,000 mm, making it more vulnerable to recurrent droughts and floods. The districts were purposively selected to represent areas where land registration programs have been implemented and areas without. Within each district, enumeration areas (EAs) were randomly selected from a national sampling frame maintained by the National Statistical Office (NSO). The selection ensured representation of various agroecological zones and customary tenure regimes. From each EA, eligible farming households were identified through household listing then a random sample was drawn from the list. Data were collected from a total sample of 506 households.

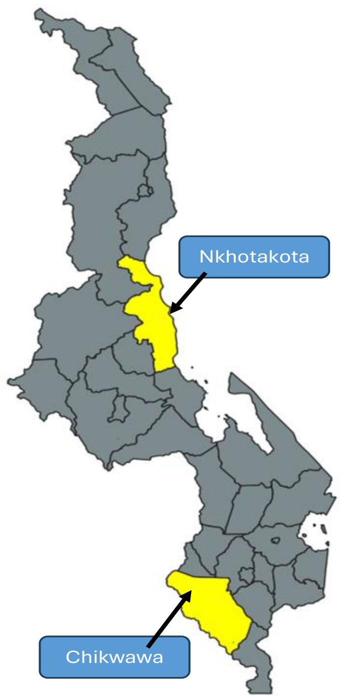


Fig 1 Map showing study areas

Data Collection

Data for this study were collected during the 2024/2025 cropping season using the World Bank Survey Solutions platform on tablets. Enumerators received comprehensive training covering ethical considerations, mock interviews, and piloting procedures. Interviews were conducted in local languages at respondents’ homes at convenient times and typically lasted 45–60 minutes. To ensure data quality, the Survey Solutions platform incorporated built-in checks, including skip logic, range validations, and GPS verification, complemented by daily supervisor reviews. The questionnaire comprised four modules: (i) household demographics and assets, (ii) land tenure and registration, (iii) production, costs, and marketing, and (iv) soil and water management, climate/advisory services, and food security/nutrition. Key socio-demographic and institutional variables included the sex and age of the household head, education, household size and composition, group membership or leadership roles, income sources, and ownership of durable and agricultural assets. Land-related information captured ownership, number and size of parcels, registration status, document type, demarcation, acquisition history, perceived tenure security, rights, and transaction constraints.

Aligned with the study's behavioral focus, perceptions and attitudes toward land registration and soil investment were measured using multi-item statements on five-point Likert scales, covering topics such as the perceived advantages of registration, challenges of unregistered land, protection from eviction, and confidence in authorities. Adoption of soil and water conservation practices, including vetiver strips, terraces, contour/ridge bunds, infiltration pits, crop rotation and intercropping with legumes, mulching, minimum tillage, and residue management, was recorded as binary variables, with intensity or quantity measured where applicable. Similarly, the use of soil amendments, such as organic and inorganic fertilizers, lime, biochar, and manure mixtures, was documented to capture investment levels in soil fertility management.

Results and Discussion

Socioeconomic Characteristics of Farming Households

A total of 506 farmers were included in the primary analysis, comprising 234 non-registered and 272 registered farmers (Table 1). Compared to their registered counterparts, a slightly higher proportion of non-registered farmers were male (81.5% vs. 79.8%; p = 0.617). Registered farmers were more likely to be married monogamously (73.9% vs. 70.9%; p = 0.021) and to have attained primary education (71.7% vs. 59.4%; p = 0.003). Although farming was the main occupation for the majority in both groups, the share was marginally lower among registered farmers (88.2% vs. 88.9%; p = 0.007). Registered farmers also exhibited stronger institutional participation, with a significantly higher proportion belonging to farmer organizations (39.9% vs. 29.5%; p = 0.015). Household characteristics further revealed that registered farmers had slightly larger household sizes (5.6 vs. 5.2 persons; p = 0.014) and more years of formal education (5.9 vs. 4.9 years; p = 0.006). Income differentials were also evident: registered farmers reported higher total and agricultural incomes (MWK 862,653 and MWK 534,880, respectively) compared to non-registered farmers (MWK 651,804 and MWK 278,501), with the difference in agricultural income being statistically significant (p = 0.047). The number of land parcels was similar across the two groups (mean = 2; p = 0.699), and no significant differences were observed in farmer age (mean 55.0 vs. 54.8 years; p = 0.170) or total income (p = 0.228).

Table 1: Characteristics of Registered and Non-Registered farmers

Characteristics	Description	No Reg. (%)	Yes Reg. (%)	Total (%)	Test p-value
Gender	1=Male	81.50	79.80	80.60	0.617
Marital status	1=Married	70.90	73.90	72.50	0.021
Education level	1=Primary	59.40	71.70	66.00	0.003
Main occupation	1=Farmer	88.90	88.20	88.50	0.007
Member of farmer org.	1=Yes	29.50	39.90	35.00	0.015
Age	Years	78.40	55.00	65.80	0.170
Household size	Number	5.20	5.60	5.40	0.014
Education	Years	4.90	5.90	5.40	0.006
Total income	MWK	651,804.00	862,653.00	765,146.00	0.228
Income_agri	MWK	278,501.00	534,880.00	416,083.00	0.047
Parcels_no	Number of plots	2.00	2.00	2.00	0.699

Farmers behavior in soil investment based on tenure security

Results from the Multivariate Bernoulli Mixture Model (MBMM) revealed two distinct behavioral classes of farmers based on soil investment patterns among both registered and non-registered groups (Fig. 2). Among registered farmers, Class 1 accounted for 58% of the sample and exhibited a high propensity to invest across all four soil management practices—soil conservation (Pr = 1), conservation agriculture (Pr = 0.8534), agroforestry (Pr = 0.7174), and soil amendments (Pr = 0.9262). Class 2 (42%), by contrast, displayed markedly lower adoption probabilities, particularly for agroforestry (Pr = 0.1135) and conservation agriculture (Pr = 0.2058), indicating limited engagement in soil-enhancing investments. For non-registered farmers, Class 1 (48%) demonstrated strong adoption probabilities for soil conservation (Pr = 0.9969), conservation agriculture (Pr = 0.8586), and agroforestry (Pr = 0.8488), with full adoption of soil amendments (Pr = 1), suggesting a subset highly committed to sustainable soil management. Conversely, Class 2 (52%) showed low probabilities across all practices, especially soil conservation (Pr = 0.3435) and soil amendments (Pr = 0.2828), reflecting weak investment behavior.

Overall, the MBMM results indicate clear behavioral segmentation, with one class consistently characterized by strong engagement in sustainable soil practices. Interestingly, while registration appears to enhance adoption intensity, some non-registered farmers in Class 1 exhibited comparable or even higher adoption rates in specific practices (e.g., agroforestry and soil amendments), suggesting that land registration interacts with, but does not solely determine, soil investment behavior.

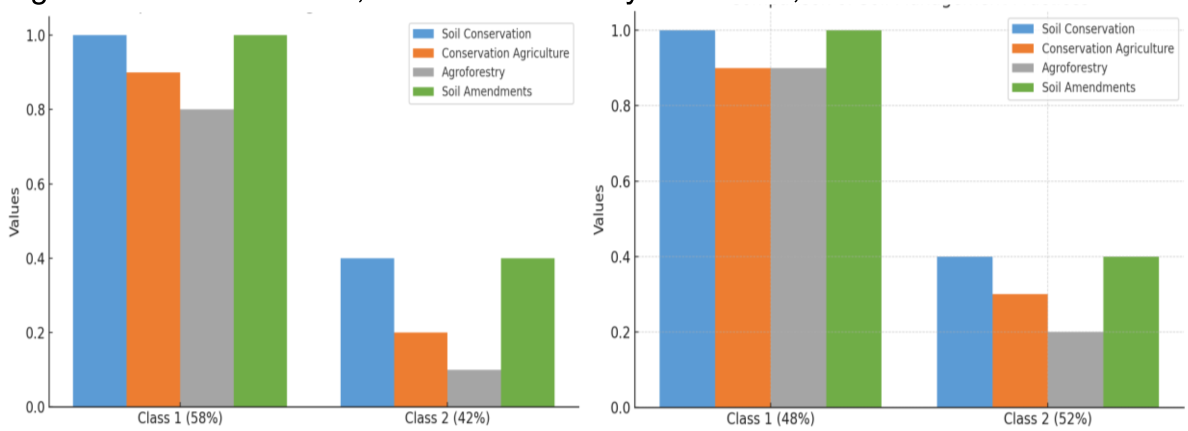
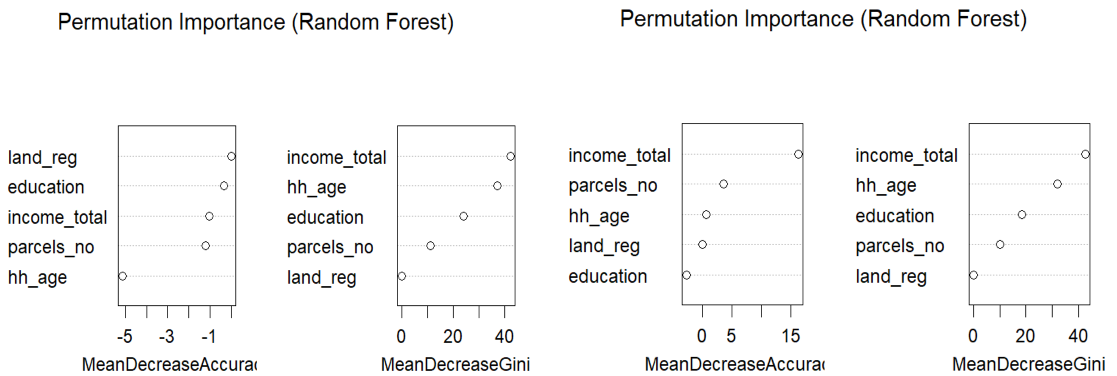


Fig 2 (a) MBMM Plot for land registered and (b) Plot for non-land registered farmers

The results of a Permutation Importance Analysis from the Random Forest model, comparing two complementary measures of feature importance: Mean Decrease Accuracy (left panel) and Mean Decrease Gini (right panel) are presented in Figure 3. The left panel, which assesses how much model accuracy declines when each feature is randomly permuted, identifies land registration status and education as the most influential predictors. Both variables produce the largest reductions in accuracy (approximately −5), indicating that the model relies heavily on them for correct classification. Household income and number of farm parcels have moderate effects on predictive accuracy, whereas age of the household head contributes minimally, suggesting limited predictive influence. In contrast, the right panel depicts importance based on Mean Decrease Gini, which reflects each feature's contribution to improving node purity during tree construction. Under this measure, household income emerges as the most significant variable (above 40), followed by age of the household head, implying these features frequently generate effective data splits. Education and number of farm parcels show moderate Gini importance, while land registration ranks lowest, despite being among the most critical variables for predictive accuracy. This divergence illustrates the distinct insights provided by the two metrics: Mean Decrease Accuracy captures a feature's contribution to overall model performance, whereas Mean Decrease Gini highlights its role in structuring decision rules. Collectively, these results underscore that land registration and education are pivotal for predictive precision, while income and age primarily shape the model's internal decision architecture.



Registered farmers (3a) **Non-Registered farmers (3b)**

Fig 3: Permutation Importance analysis for a Random Forest model

Figure 4 presents a SHAP (Shapley Additive Explanations) summary plot that visualizes the contribution of each feature to XGBoost model's predictions. On the vertical axis, features are ranked by their importance, with household total income appearing at the top as the most influential, followed by age and education of the household head then number of parcels and land registration status at the bottom. The horizontal axis represents SHAP values, indicating how much each feature, for a given observation, pushes the prediction toward either class 1 (positive SHAP values) or class 0 (negative SHAP values). Each dot represents a single observation, with its position on the x-axis indicating the size and direction of the feature's impact and its color reflecting the actual value of the feature, ranging from low (dark purple) to high (red/orange). The plot reveals that household income has the widest spread of SHAP values, meaning it has the greatest and most consistent impact on model predictions. High income values tend to increase the probability of being in class 1, while low income values lower it. Similarly, age exerts a strong influence, with older household heads generally pushing predictions higher. Education shows moderate importance, where higher levels tend to increase prediction values. In contrast, number of farm parcels shows a weaker and more mixed influence, with no consistent directional effect based on value. Finally, land registration status exhibits minimal influence, with SHAP values clustered tightly around zero, indicating it contributes very little to the model's output.

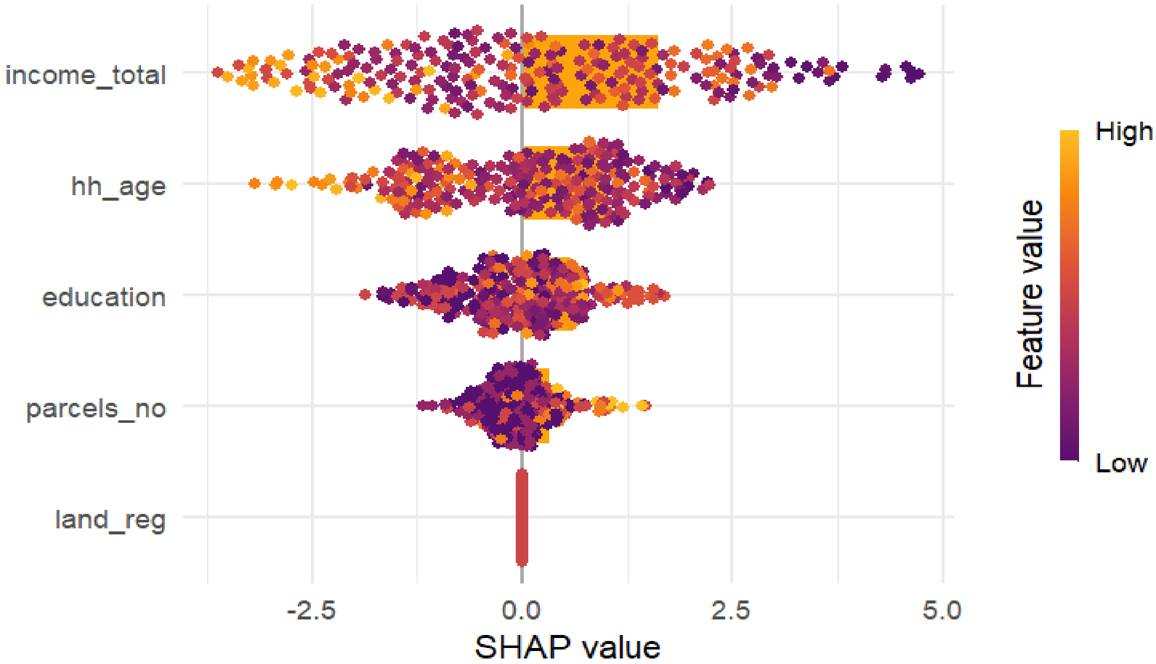


Fig 4 Shapley Additive Explanations (SHAP) importance values plot

Figure 5 illustrates the SHAP summary plot, which visualizes the relative contribution of each input feature to the model's predictions. On the horizontal axis are the SHAP values, representing the magnitude and direction of each feature's effect on the predicted outcome, while the vertical axis lists the input features ranked by their overall importance. Each point corresponds to a single observation in the dataset. The color gradient, ranging from red to yellow, indicates the sign and intensity of the SHAP value, with red representing strong negative contributions and yellow denoting positive contributions to the prediction. The wider or denser the spread of colors along the horizontal axis, the greater the variability and influence of that feature on the model's output. In essence, features occupying larger red or yellow regions have higher SHAP values, meaning they exert a stronger impact on the prediction results across the sample. This visualization thus provides an interpretable, feature-level explanation of how each variable drives differences in the model's predicted soil investment behavior.

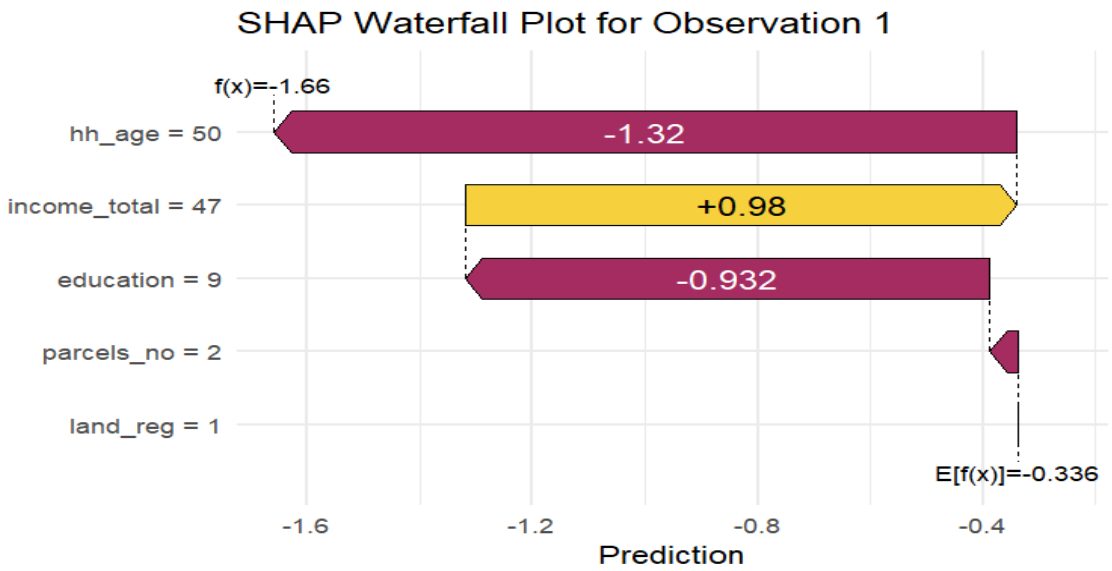


Fig 5: Prediction model performance

Conclusion and Policy Implications

This study examined how formal land registration influences farmers' soil investment behavior and productivity outcomes in Malawi, employing a Multivariate Bernoulli Mixture Model and Machine Learning techniques. The analysis provided new empirical evidence on how tenure security, proxied by land registration, interacts with socioeconomic and demographic factors to shape heterogeneous patterns of soil investment among smallholder farmers. Results revealed that land registration and education were the most significant predictors of soil investment behavior. Registered farmers were more likely to adopt multiple sustainable soil management practices, including soil amendments, conservation agriculture, and agroforestry, than their non-registered counterparts. In contrast, household income and the age of the household head were more strongly linked to productivity outcomes rather than investment behavior itself, suggesting that land registration enhances productivity indirectly through its effect on soil management decisions. These findings highlight that land registration serves not merely as a legal reform but as a behavioral catalyst that motivates farmers to adopt long-term, sustainability-oriented soil practices.

From a policy perspective, scaling up land registration programs should remain a key national priority, integrated with livelihood and agricultural development initiatives to reinforce tenure security and stimulate sustained investment in soil health. To maximize impact, registration efforts must be complemented by farmer education and capacity-building programs aimed at improving knowledge of sustainable soil management practices. Strengthening institutional frameworks, transparency, and enforcement mechanisms is also critical to maintain trust in land governance systems. Finally, the use of demonstration farms, participatory learning platforms, and community-based awareness campaigns can effectively showcase the long-term economic and environmental benefits of soil investments under secure land tenure, thereby accelerating adoption and supporting Malawi's broader goals of agricultural transformation and climate resilience.

Reference

Ali, D.A., Deininger, K., & Goldstein, M. (2014). “Environmental and gender impacts of land tenure regularization in Africa: Pilot evidence from Malawi.” Journal of Development Economics, 138, 269–286. https://doi.org/10.1016/j.jdeveco.2013.12.009

Besley, T. (1995). “Property rights and investment incentives: Theory and evidence from Ghana.” Journal of Political Economy, 103(5), 903–937. http://dx.doi.org/10.1086/262008

DAI Global. (2021). “Malawi’s land governance is headed in the right direction.” DAI Global Developments. https://dai-global-developments.com/articles/malawis-land-governance-is-headed-in-the-right-direction

Deininger, K., & Jin, S. (2006). “Tenure security and land-related investment: Evidence from Ethiopia.” European Economic Review, 50(5), 1245–1277. https://doi.org/10.1016/j.euroecorev.2005.02.001

Deininger, K., Ali, D. A., & Alemu, T. (2011). Impacts of land certification on tenure security, investment, and land market participation: evidence from Ethiopia. Land Economics, 87(2), 312-334.https://doi.org/10.3368/le.87.2.312

Erb, K., Matej, S., Haberl, H., & Gingrich, S. (2024). Sustainable land systems in the Anthropocene: Navigating the global land squeeze. One Earth, 7(7), 1170-1186. https://doi.org/10.1016/j.oneear.2024.06.011

Feder, G., & Nishio, A. (1997). The benefits of land registration and titling: Economic and social perspectives. Land Use Policy, 15(1), 25-43. https://doi.org/10.1016/S0264-8377(97)00039-2

Holden, S. T., & Ghebru, H. (2016). Land tenure reforms, tenure security and food security in poor agrarian economies: Causal linkages and research gaps. Global Food Security, 10, 21-28.https://doi.org/10.1016/j.gfs.2016.07.002

Lawry, S., et al. (2017). “The impact of land property rights interventions on investment and agricultural productivity in developing countries.” World Development, 95, 357–372. https://doi.org/10.1080/19439342.2016.1160947

Lundberg, S., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. In *Advances in neural information processing systems 30* (pp. 4765–4774). Neural Information Processing Systems Foundation. https://doi.org/10.48550/arXiv.1705.07874

Mbudzya, J. J., Gido, E. O., & Owuor, G. (2022). Effect of land tenure security on agricultural productivity among small scale farmers in Kenya: a conditional mixed processes analysis. Cogent Food & Agriculture, 8(1). https://doi.org/10.1080/23311932.2022.2139805.

Pierri, F. M., Anseeuw, W., & Campolina, A. (2025). Land tenure for resilient and inclusive rural transformation. Global Food Security, 44, 100835. https://doi.org/10.1016/j.gfs.2025.100835

Place, F., & Migot-Adholla, S.E. (1998). “The economic effects of land registration on smallholder farms in Kenya: Evidence from Nyeri and Kakamega districts.” Land Economics, 74(3), 360–373. https://doi.org/10.2307/3147118

Shiferaw, B., Okello, J. J., & Reddy, V. R. (2009). Challenges of adoption and adaptation of land and water management options in smallholder agriculture: Synthesis of lessons and experiences. In Rainfed agriculture: Unlocking the potential (pp. 164–183). https://www.researchgate.net/publication/266064557_Challenges_of_Adoption_&_Adaptation_of_Land_and_Water_Management_Options_in_Smallholder_Agriculture_Synthesis_of_Lessons_&_Experiences

Southworth, J., Smith, A. C., Safaei, M., Rahaman, M., Alruzuq, A., Tefera, B. B., Muir, C. S., & Herrero, H. V. (2024). Machine learning versus deep learning in land system science: A decision-making framework for effective land classification. Frontiers in Remote Sensing, 5, 1374862. https://doi.org/10.3389/frsen.2024.1374862

Tian, C., Luo, Y., & Teng, Y. (2024). Land certification, tenure security and off-farm employment: Evidence from China. Land Use Policy, 147, 107328.https://doi.org/10.1016/j.landusepol.2024.107328

Tseng, T., Robinson, B. E., Bellemare, M. F., BenYishay, A., Blackman, A., Boucher, T., Childress, M., Holland, M. B., Kroeger, T., Linkow, B., Diop, M., Naughton, L., Rudel, T., Sanjak, J., Shyamsundar, P., Veit, P., Sunderlin, W., Zhang, W., & Masuda, Y. J. (2020). Influence of land tenure interventions on human well-being and environmental outcomes. Nature Sustainability, 4(3), 242-251. https://doi.org/10.1038/s41893-020-00648-5

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. Science of The Total Environment, 822, 153559. https://doi.org/10.1016/j.scitotenv.2022.153559