SOIL DEGRADATION AND ITS RESPONSE TO HUMAN ACTIVITIES IN SUBTROPICAL HIGH-INTENSITY AGRICULTURAL SYSTEMS
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亚热带高强度集约农业土壤劣变及其对人类活动的响应

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ABSTRACT
Intensive agriculture-driven soil degradation has become a global environmental challenge, urgently requiring governance strategies that integrate farmer behavior with policy intervention to support sustainable development. In this study, matched soil experimental data and household survey responses were used to assess the status and degradation characteristics of key soil nutrient indicators, including soil pH, total nitrogen, ammonium nitrogen, nitrate nitrogen, available phosphorus, quick-acting potassium, organic carbon, and the C/N ratio. The effects of policy measures and farmers' behavioral practices on both individual soil nutrient indicators and the overall degree of soil degradation were empirically examined. Across 178 plots with an average management duration of 17.93 years, widespread soil acidification (mean pH = 4.535), nitrogen saturation effects, and other nutrient imbalances were identified. The application of restoration technologies was found to significantly reduce soil degradation, although the magnitude of improvement varied by nutrient type. Technical training and farmland transfer policies indirectly mitigated soil degradation by promoting the adoption of restorative practices. Furthermore, combinations of policy instruments demonstrated synergistic effects, compensating for the limitations of single-policy approaches. These findings highlight the need for policy frameworks that incorporate degradation-based targeted guidance, restoration subsidies, and standardized farmland transfer mechanisms. The study deepens understanding of the micro-level mechanisms linking farmer behavior with soil ecological processes and provides empirical evidence supporting progress toward the United Nations Sustainable Development Goal of achieving zero net land degradation.

摘要
集约农业造成的土壤劣变是全球性环境挑战，亟需从农户行为与政策干预视角探索有效治理路径，推动集约农业可持续发展。因此，本研究创新性地采用一对一匹配的土壤实验数据和农户调查数据，分析亚热带高强度集约农业的土壤 pH 值、全氮、铵态氮、硝态氮、有效磷、速效钾、有机碳和碳氮比等土壤养分指标状况及劣变特征，并实证检验政策措施与农户技术采纳行为对上述土壤养分指标及整体劣变程度的影响。研究发现，178 块平均经营年限达 17.93 年的集约经营样地普遍存在土壤酸化（pH 均值 4.535）和“氮饱和”效应等土壤养分结构性失衡问题。撒施生石灰和休耕等适合普通农户采纳的劣变土壤恢复技术能够显著缓解土壤劣变程度，且不同恢复技术对土壤养分指标具有差异化改善效应。技术培训和农地流转措施可通过影响农户的劣变土壤恢复技术采纳行为，间接改善集约农业土壤劣变程度。此外，不同的政策措施具有协同效应，联合施用可克服单一政策措施的局限性。这些发现意味着，根据高强度集约农业实际的土壤劣变程度为农户提供精确的指导至关重要。此外，应构建以土壤劣变治理为导向的补贴激励机制，并积极引导和规范农地流转市场发展。本研究在理论上丰富了农户行为与土壤环境互动的微观机制认知，为实现联合国可持续发展目标中的土地退化零增长贡献科学依据。

INTRODUCTION
Global population growth and surging food demand make intensive agriculture a vital means of ensuring food security *(Fan et al., 2023)*. However, agricultural soil degradation caused by over-intensification has become a significant challenge threatening global sustainability *(Amundson et al., 2015)*.

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Soil degradation, resulting from the influence of natural and human factors, is defined as a complex process involving the decline or irreversible compromise of soil productivity, environmental regulation capacity, and agricultural sustainability *(Guo et al., 2023)*.

Intensive agriculture is characterized by high-input land use and the heavy use of chemical fertilizers. Extended periods of intensive agricultural practices have caused soil acidification, nutrient disparities, and a significant reduction in microbial diversity and functional processes, consequently leading to serious ecological and environmental challenges. These issues pose a significant threat to the stability of regional ecosystems and sustainable socio-economic development *(Slijper et al., 2023)*. Effective governance of soil degradation caused by high-intensity agriculture is crucial for promoting the transition of agriculture towards sustainable intensification and reaching the sustainable development goals.

Scholars have extensively studied soil degradation from intensive farming, developing technologies such as topsoil replacement, ecological fertilization *(Wang et al., 2024)*, conservation tillage *(Pittelkow et al., 2015)*, substituting chemical with organic fertilizers *(Shi et al., 2024)*, and integrated fertilizer-residue management to restore soils *(Zhang et al., 2024)*. Proper use of such technologies improves soil biodiversity, boosts crop yield and quality, and restores degraded soil functions *(Dai et al., 2020)*. However, a significant gap remains between technological development and practical implementation. Farmers, as key implementers, consider more than technical efficiency *(Sulemana et al., 2014)*, but are also shaped by a range of internal factors, including their knowledge, financial situation, and risk attitudes *(Peng and Xu, 2024; Yue et al., 2025; Zhang et al., 2018)*, along with external influences like governmental policies, training programs, and market-based rewards *(Zhao et al., 2018; Cao et al., 2020; Vollebergh and Kemfert, 2005)*. A lack of understanding of regional soil nutrients and insufficient analysis of farmer behavior and policies lead to low adoption and limited restoration outcomes. This presents a paradox where high technological feasibility contrasts with low adoption rates.

Mulching technology, as a typical high-intensity production model, is widely applied in the management of bamboo groves for shoot production in subtropical regions. It relies on heavy fertilization and artificial covering to advance shoot emergence by over two months, boosting yield and farmer enthusiasm. Nevertheless, due to the common production issues among farmers, such as unscientific coverage and excessive use of chemical fertilizers, soil nutrient imbalances and acidification, among other soil degradation issues, have occurred. This not only degrades soil health but also threatens farmer livelihoods and sustainability *(Liu et al., 2018)*. In light of this, this study focuses on the Tianmu Mountain region of China, using mulched early-harvest Phyllostachys praecox shoot production as a case study. Based on 178 well-matched soil experimental datasets and household survey data, this study explores the impact of farmer behavior and policy measures on soil nutrient levels and degradation in highly-intensity agricultural settings. The results are intended to offer both theoretical insights and practical recommendations for crafting and executing policies to combat soil degradation in intensive farming systems.

Drawing from current literature, the main contributions of this study are highlighted in three aspects. First, taking the Tianmu Mountain region of China as the research area, 178 sample plots were selected using a stratified random sampling method, and a soil degradation evaluation framework based on the Analytic Hierarchy Process (AHP) was established. This framework accurately reveals the soil nutrient status and degradation characteristics of high-intensity intensive agriculture in the study area. Second, an analytical framework was constructed that incorporates natural factors, farmer behavior, and policy measures into a unified analysis of influencing factors, enabling a more in-depth examination of the drivers of soil degradation in intensive farming systems. Additionally, from the perspective of farmers' technology adoption, a differentiated portfolio of policy tools is proposed, providing a theoretical reference for the formulation of sustainable development policies for intensive agricultural systems in developing countries. Third, the study integrates soil experimental data with household survey data, addressing both the analytical requirements of soil science and the methodological needs of survey-based research. This innovative data fusion approach represents an exploratory attempt to combine experimental measurements with farmer-level behavioral data, producing interdisciplinary research evidence that supports both empirical rigor and policy relevance.

The structure of the remaining sections is arranged as follows: Section 2 outlines the materials and methods; Section 3 details the research findings; Section 4 provides the discussion; and Section 5 concludes the study with a summary of the main insights.

MATERIAL AND RESEARCH METHOD

Research Area

This research focused on the Tianmu Mountain region in China, situated at the center of the Yangtze River Delta economic zone. It encompasses two major administrative regions: Lin'an District of Hangzhou City and Anji County of Huzhou City, as shown in Fig. 1. The Tianmu Mountain region experiences a typical subtropical monsoon climate, marked by clear seasonal variations, where rainfall coincides with high temperatures, and the average annual temperature is 16.4 ℃. The landscape of this area is mainly hilly and mountainous, with the soil primarily consisting of subtropical red soil and yellow soil derived from Quaternary red clay, featuring deep soil layers and moderate organic content *(Chen et al., 2017)*.

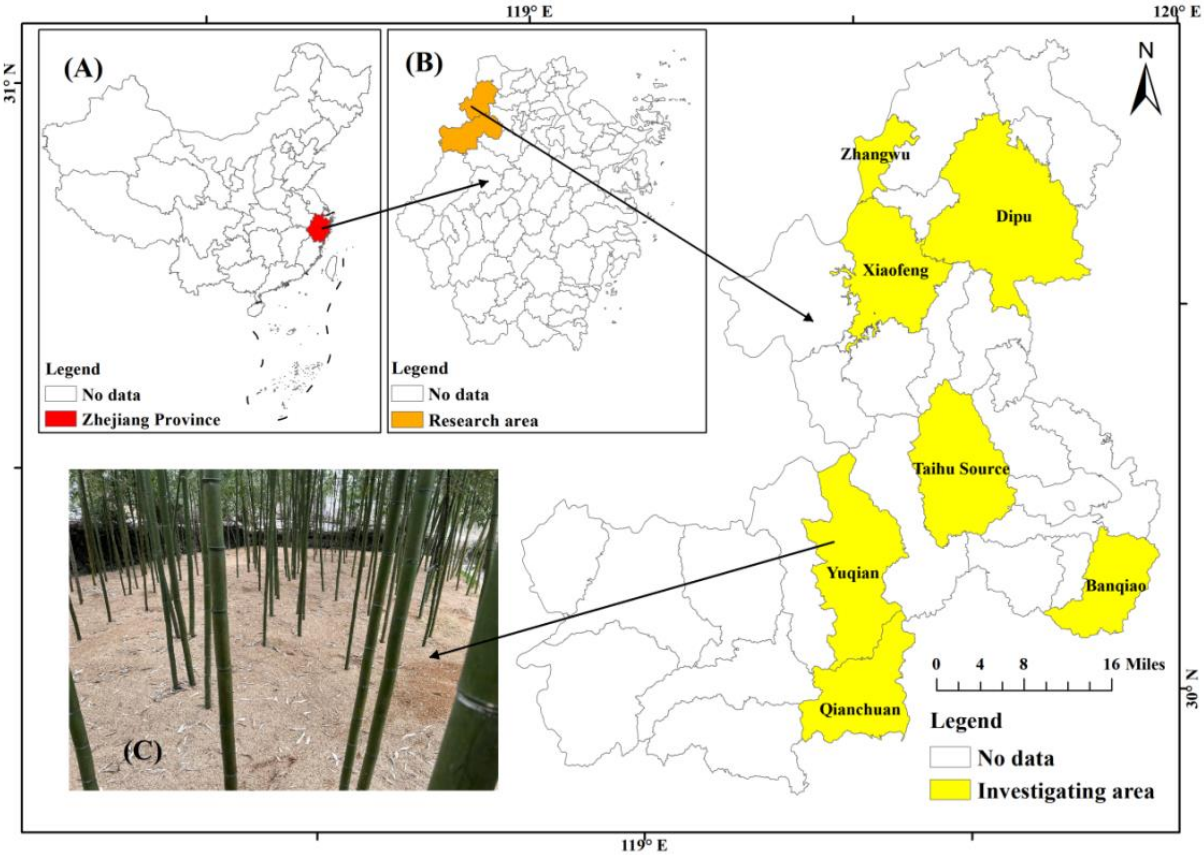

Fig. 1 - Location of the study areas

Note: The drawing review number is GS (2024) 0650.

Data Collection

Questionnaire survey data

To obtain representative household data, a three-stage stratified random sampling method was used. In the first stage, 7 townships were randomly selected from the townships (towns or subdistricts) within the study area; in the second stage, the number of sample villages randomly selected from each town was determined based on the proportion of villages in each town, resulting in a total of 30 sample villages; in the third stage, the number of sample households randomly selected from each sample village was determined based on the proportion of households engaged in forest land mulching technology in each sample village, resulting in a total of 181 households being selected.

The interviewee was the primary individual responsible for agricultural production activities within the household. The questionnaire mainly covered basic information about the person in charge, basic information about the household, production status, and the adoption status of soil restoration technologies. To guarantee the reliability and validity of the questionnaire, pilot surveys were conducted on November 8, 2021, and December 29, 2021, with large-scale farms in Hailong Village, Qianchuan Town, and Qianmao Village, Yuqian Town, within the research area. The questionnaire was revised and improved based on the findings from these pilot surveys. After finalizing the formal questionnaire, the team conducted field research from January to February 2022, administering questionnaire interviews and collecting data from the sample households, ultimately obtaining 178 valid questionnaires.

Soil experimental data

To ensure precise correspondence between soil data and household survey data, the largest and most representative plot currently cultivated by each sampled household was selected as the soil sampling site. During the field investigation, soil samples were collected from a depth of 0–30 cm across 178 plots using a five-point sampling method conducted by the research team. The collected samples were thoroughly homogenized, debris was removed, and each sample was sealed in a pre-labeled airtight bag for transport to the laboratory. Soil analysis was conducted following the procedures outlined in *Gao et al. (2025)*, measuring soil pH, total nitrogen, ammonium nitrogen, nitrate nitrogen, available phosphorus, quick-acting potassium, organic carbon, and the carbon-to-nitrogen (C/N) ratio, among other nutrient indicators. Duplicate samples and quality control samples were included for all measurements, with analytical precision controlled within 5%. The spatial distribution of soil samples and sampling plots is presented in Table 1.

Table 1

Samples and sample plots distribution

	Qianchuan Town	Taihu Source Town	Banqiao Town	Yuqian Town	Zhangwu Town	Xiaofeng Town	Dipu Town	Total
Number of sample villages	5	6	2	5	6	4	2	30
Proportion of sample villages (%)	16.6%	20.0%	6.7%	16.6%	20.0%	13.3%	6.7%	100%
Number of soil samples (plots)	38	35	12	27	34	22	10	178
Proportion of soil samples (plots)	21.3%	19.7%	6.7%	15.2%	19.1%	12.4%	5.6%	100%

Soil Degradation Evaluation Method

Soil evaluation methods used by scholars can be divided into qualitative and quantitative types *(Murage et al., 2000)*. Qualitative methods are highly subjective, while quantitative methods are data-dependent and require an ordered soil nutrient evaluation standard. Soil degradation in intensive agriculture is manifested as both a lack of certain soil nutrients and an excessive accumulation of others. Due to the nonlinear nature of nutrient imbalance, it is impossible to construct an ordered soil nutrient evaluation standard, which means quantitative evaluation methods relying on ordered soil nutrient standards are not applicable for evaluating the degradation of intensive agricultural soils. Therefore, this study primarily uses the Analytic Hierarchy Process (AHP) to construct an evaluation system for the degree of soil degradation in intensive agriculture. When evaluating soil degradation, it is first necessary to select effective soil nutrient evaluation factors *(Qiao et al., 2022)*. The main manifestations of soil degradation in intensive agriculture include soil acidification and imbalances in nitrogen, phosphorus, and potassium nutrients, as well as the accumulation of soil organic carbon due to mulching operations *(Li et al., 2013)*. Therefore, this study selects soil pH, ammonium nitrogen, nitrate nitrogen, available phosphorus, available potassium, and soil organic carbon as indicators to evaluate the degree of soil degradation, with the degradation type being soil fertility degradation.

The evaluation criteria developed in this study were determined through two rounds of evaluation by 12 experts, including 4 professional farmers, 4 senior technical experts, and 4 related researchers. Soil nutrient levels were assigned degradation scores according to their relevance for intensive agricultural production and management, with scores ranging from 1 to 5. The higher the value, the higher the degree of degradation of soil nutrients. The first round of evaluation mainly determines the ranking of degradation assignment. In the second round, experts independently constructed evaluation standards without discussion, and the average values were used to establish the soil nutrient degradation evaluation criteria for intensive agriculture. Evaluation criteria for soil nutrient degradation in intensive agriculture are shown in Table 2.

Table 2

Evaluation criteria for soil nutrient degradation in intensive agriculture

Soil pH value	Ammonium nitrogen (mg·kg^{-1})	Nitrate nitrogen (mg·kg^{-1})	Available phosphorus (mg·kg^{-1})	Quick-acting potassium (mg·kg^{-1})	Organic carbon (g·kg^{-1})	Nutrient index degradation value
<4.5	<15	<10	<5	<30	<24	5
4.5-5.5	15-30	10-20	5-15	>400	24-48	4
>7.5	>150	>120	15-25	30-60	48-72	3
5.5-6.5	100-150	80-120	>50	160-400	72-96	2
6.5-7.5	30-100	20-80	25-50	60-160	96-120	1

The application of AHP generally involves four steps. First, constructing the hierarchical structure model. The soil degradation evaluation system is divided into a goal layer and a criterion layer, as shown in Fig. 2.

After developing the judgment matrix and estimating the approximate eigenvector values, the indicator weights were obtained through matrix solving. (Due to space limitations, the judgment scale table (Table A1) and the formula used to estimate the approximate eigenvector values are provided in Appendix A.)

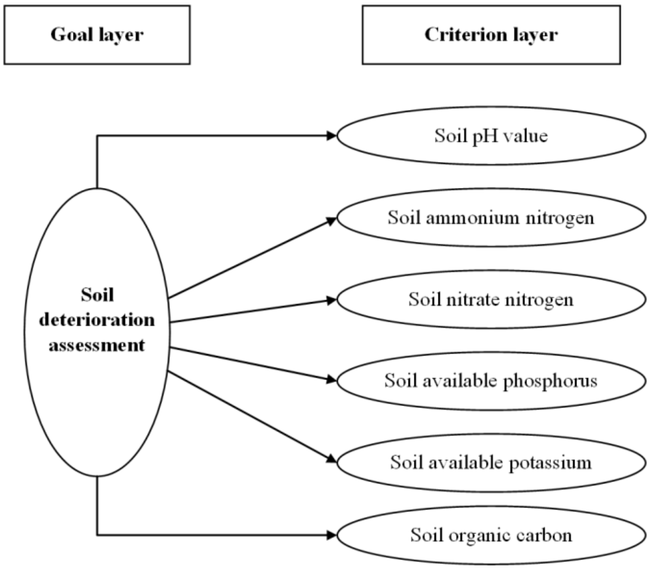

Fig. 2 - Structural model for rating soil degradation in intensive agricultural systems

The weight values of each soil nutrient indicator were calculated using the weights and average scores obtained from the AHP. The hierarchical evaluation results for soil degradation in intensive agricultural systems are presented in Table 3. The indicators ranked by weight (from highest to lowest) are as follows: soil pH (41.822%), available potassium (19.412%), available phosphorus (12.580%), soil organic carbon (12.580%), ammonium nitrogen (6.803%), and nitrate nitrogen (6.803%). The consistency index (CI) value was 0.023. Based on the weighted product of each soil nutrient indicator and its corresponding degradation value, the final soil degradation scores for all 178 intensive agricultural plots were determined.

Table 3

Hierarchical analysis results

Items	Eigenvector	Weight value (%)	Maximum eigenvalue	*CI* value
Soil pH value	3.107	41.822	6.113	0.023
Ammonium nitrogen	0.505	6.803		
Nitrate nitrogen	0.505	6.803		
Available phosphorus	0.935	12.580		
Quick-acting potassium	1.442	19.412		
Organic carbon	0.935	12.580		

As shown in Table 4, the consistency check produced a maximum eigenvalue of 6.113. Using the corresponding Random Index (*RI*), where the relevant RI value is 1.25, the consistency ratio was calculated as $CR = CI/RI = 0.018 < 0.1$.

Table 4

Consistency test results

Maximum eigenvalue	*CI* value	*RI* value	*CR* value	Consistency test results
6.113	0.023	1.250	0.018	Pass

Empirical Analysis Framework

Variable Selection

Soil degradation is a multi-dimensional, multi-level process that requires comprehensive indicators to assess its severity and specific indicators to identify its types. This study established a two-tier system of dependent variables: the first tier evaluated the degree of soil degradation (scale 1-5) using the AHP, where a score ≤1 indicates no degradation, 1-2 slight, 2-3 moderate, 3-4 severe, and 4-5 extremely severe degradation. The second tier comprised eight continuous soil nutrient indicators: pH, total nitrogen, ammonium nitrogen, nitrate nitrogen, available phosphorus, available potassium, organic carbon, and ratio of carbon to nitrogen.

The explanatory variables primarily included five soil restoration techniques suitable for ordinary farmers in intensive agriculture production, as well as three policy measures. Based on field investigation, five soil restoration measures suitable for ordinary farmers were selected: applying organic fertilizer instead of chemical fertilizer, soil testing and formula-based fertilization, spreading lime, adding topsoil, and fallowing. Based on policy practices in the study area, this study identified three primary policy tools, technical training, technical subsidies, and farmland circulation measures. Among them, technical training is mainly achieved through training farmers on agricultural technical procedures such as soil testing and formula fertilization technology. Technical subsidies are primarily granted to farmers who adopt soil restoration technology as a form of direct economic compensation. The implementation of farmland circulation measures is relatively complex, relevant departments have established regulations and systems for circulation trading platforms, contract signing, term agreements, and dispute arbitration. In addition, to control for other factors that may affect soil nutrients and the degree of degradation, this study added variables such as topographical characteristics, current conditions of the sample plots, soil types, and management duration.

Table 5 displays the descriptive statistics for the explanatory variables. The mean adoption rates among sample farmers for organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technology, spreading lime, adding topsoil, and fallowing techniques is 0.747, 0.303, 0.320, 0.371, and 0.455, respectively. Farmers show notable variations in the adoption rates of various restoration techniques. In terms of policy participation, 45.50% of farmers participated in technical training, but only 9.60% had received technical subsidies, indicating that the coverage of subsidy policies is relatively limited. 37.10% of farmers had transferred land into their operations, reflecting the activity level of land circulation. In terms of natural conditions, 96.07% of the sample plots are flat land, and 3.93% are sloping land. 76.97% of the sample plots were mulched at the time of sampling, while only 23.03% were not mulched. 61.80% of the sample plots had soil primarily composed of sand particles, while 38.20% had soil primarily composed of clay particles.

Table 5

Explanatory variable name, meaning and descriptive statistics

Variable	Variable description	Mean	SD	Median	Min	Max
Organic fertilizer instead of chemical fertilizer	1=Yes; 0=No	0.747	0.436	1.000	0.000	1.000
Soil testing and formula fertilization technology	1=Yes; 0=No	0.303	0.461	0.000	0.000	1.000
Spreading lime	1=Yes; 0=No	0.320	0.468	0.000	0.000	1.000
Adding topsoil	1=Yes; 0=No	0.371	0.484	0.000	0.000	1.000
Fallowing	1=Yes; 0=No	0.455	0.499	0.000	0.000	1.000
Topographical characteristics	1= flat land; 0= sloping land	0.961	0.195	1.000	0.000	1.000
Plot conditions	1= mulched; 0= Non-mulched	0.770	0.422	1.000	0.000	1.000
Soil types	1= Sandy Soil; 0= Clay Soil	0.618	0.487	1.000	0.000	1.000
Management duration	Management Duration (Until 2022)	17.978	9.148	16.000	2.000	50.000
Technical training	1=Yes; 0=No	0.455	0.499	0.000	0.000	1.000
Technical subsidies	1=Yes; 0=No	0.096	0.295	0.000	0.000	1.000
Farmland circulation	1=Yes; 0=No	0.371	0.484	0.000	0.000	1.000

Note: The observation count for all variables is 178.

Model construction

Given that the degree of soil degradation in high-intensity agricultural systems is an ordinal, multi-category variable, an ordered Logit (OLogit) model was constructed to assess the influence of farmers' adoption of restoration technologies on the extent of soil degradation. The model is expressed as follows:

$$Degradation = \alpha_0 + \alpha_1 Techgy_i + \alpha_2 Nature + \eta_k + \varepsilon_i \quad (1)$$

In the formula, $Degradation_i$ represents the degree of soil degradation, $Techgy_i$ represents the farmer's adoption behavior of five soil restoration technologies, including applying organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technologies, spreading lime, adding topsoil, and fallowing.

$Nature_i$ represents natural factor variables such as topographical characteristics, sample plot conditions, soil types, and management duration. η_k represents fixed effects at the township level, α_1 and α_2 are the coefficients to be estimated, and ε_i represents the random error term.

Since all eight intensive agricultural soil nutrient indicators are continuous variables, a multiple linear regression model was employed to explore the impact of farmers' technology adoption behavior on different soil nutrient indicators.

The model is as follows:

$$Nutrient_i = \beta_0 + \beta_1 Techgy_i + \beta_2 Nature_i + \eta_k + \varepsilon_i \quad (2)$$

In the formula, $Nutrient_i$ represents nutrient indicators such as soil pH, total nitrogen, ammonium nitrogen, nitrate nitrogen, available phosphorus, available potassium, soil organic carbon, and ratio of carbon to nitrogen. $Techgy_i$ represents the five farmers' behavior to adopt soil restoration technologies, including applying organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technologies, spreading lime, adding topsoil, and fallowing. η_k represents fixed effects at the township level, β_2 and β_3 represent the coefficients to be estimated, and ε_i represents the random error term.

Policy measures are the primary means for the restoration of degraded soil, making it essential to carry out an empirical analysis of the effects and mechanisms of policy implementation. Since policy measures may affect soil nutrients by regulating farmers' behaviors *(Zhang et al., 2023)*, the empirical analysis takes farmers' adoption of soil restoration technologies as the dependent variable and construct a binary Logit model.

$$Techgy_i = \varphi_0 + \varphi_1 Policy_i + \eta_k + \varepsilon_i \quad (3)$$

In the formula, $Techgy_i$ represents the adoption of organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technology, spreading lime, adding topsoil, and fallowing, all of which are categorized as binary variables. $Policy_i$ denotes the policy measures variable, encompassing three policy tools: technical training, technical subsidies, and farmland circulation measures. φ_1 denotes the coefficient of interest, η_k represents the fixed effects at the township level, and ε_i represents the random error term.

RESULTS

Soil Nutrient Status and Degradation Characteristics of Sample Plots

The nutrient status and degree of soil degradation of the sample plots are shown in Fig. 3 and Table 6. The average duration of intensive management for the 178 sample plots is 17.93 years, indicating that the soil exhibits typical characteristics of intensive agriculture.

Firstly, soil acidification is a serious issue. The mean soil pH of the sample plots is 4.535, with a median of 4.410, significantly lower than the suitable soil pH range (5.5 - 6.5) for bamboo growth, indicating a pronounced acidification trend. This result aligns closely with the trend of soil acidification observed in intensive agricultural regions globally *(Raza et al., 2020)*, indicating a widespread environmental issue stemming from high-intensity farming practices.

Secondly, long-term imbalanced fertilization with nitrogen fertilizers led to excessive accumulation of nitrogen in the soil, resulting in a structural imbalance of nitrogen, phosphorus, and potassium nutrients. The average values of total nitrogen, ammonium nitrogen, and nitrate nitrogen in the soil samples are 1.544 g/kg, 46.548 mg/kg, and 73.157 mg/kg, respectively. The content of total nitrogen in the soil far exceeds the rich level standard in China's soil nutrient classification criteria (>1.0 g/kg). The mean values of available phosphorus and quick-acting potassium are 24.872 mg/kg and 252.444 mg/kg, respectively. Intensive management practices, accompanied by excessive nitrogen fertilizer inputs, leads to a "nitrogen saturation" effect in soil, resulting in severe imbalances in the soil N, P, and K ratios.

Thirdly, the phenomenon of abnormal organic carbon enrichment is significant. The average organic carbon content in the sample plots' soil is 37.350 g/kg. Based on the grading criteria outlined in the Second National Soil Census in China, the organic carbon content in the sample plots' soil has reached extremely high levels. This phenomenon is primarily due to the large input and decomposition of organic mulch materials in the forest land mulching.

However, the high soil organic carbon content did not lead to an improvement in soil quality; instead, it caused an imbalance in the ratio of carbon to nitrogen, with an average of 35.586, far exceeding the ideal range of 20-30, and the highest value even reaching 130.42.

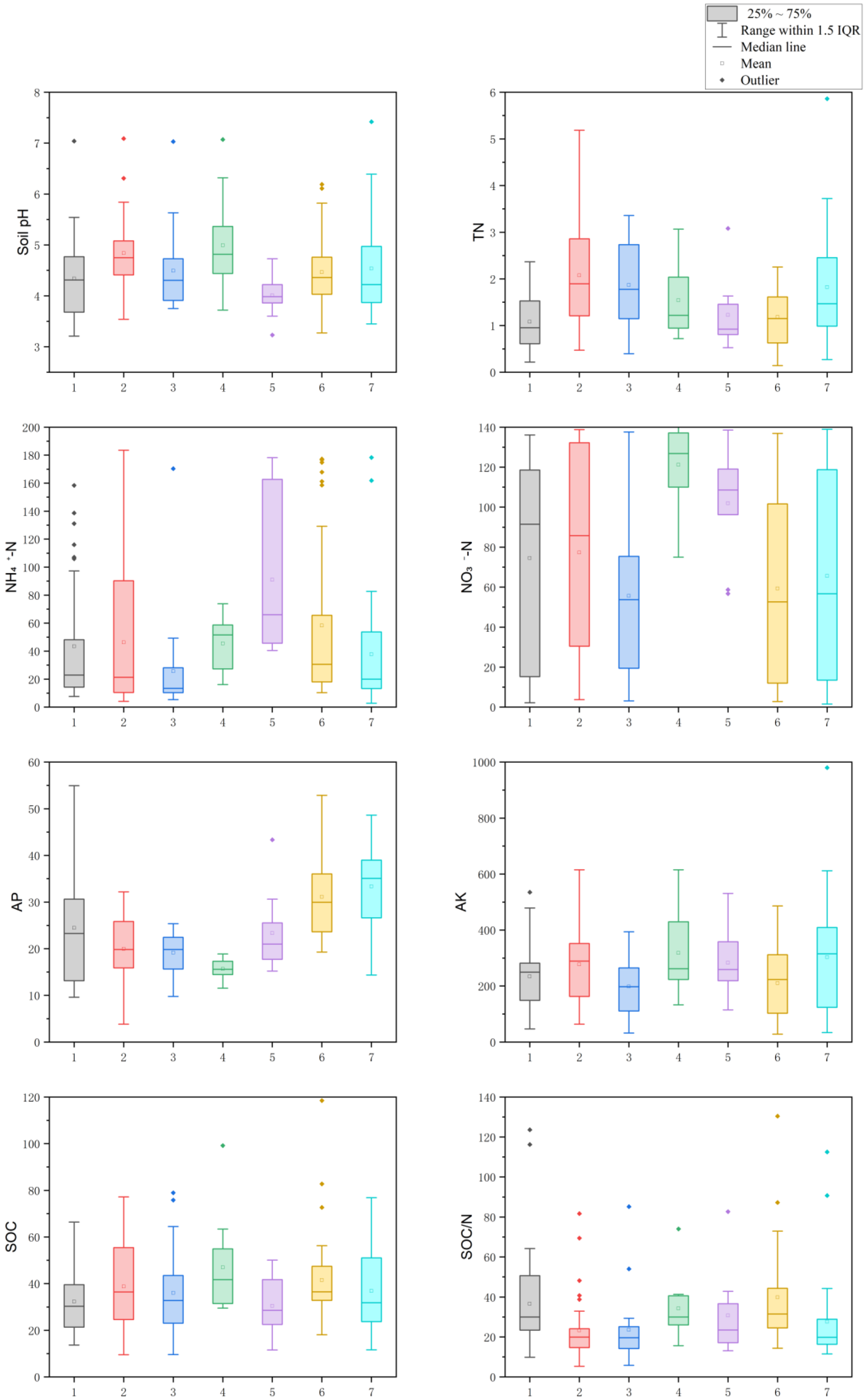

Fig. 3 - Boxplot of soil physicochemical properties in the sample plots

Table 6

Nutrient status and degree of soil degradation of the sample plots

	Mean	SD	Median	Min	Max
Degree of soil degradation	3.921	0.536	4.000	2.000	5.000
Soil pH value	4.535	0.791	4.410	3.210	7.420
Total nitrogen (g/kg)	1.544	0.973	1.394	0.142	5.860
Ammonium nitrogen (mg/kg)	46.548	47.929	27.248	2.750	183.550
Nitrate nitrogen (mg/kg)	73.157	48.028	77.590	1.513	140.139
Available phosphorus (mg/kg)	24.872	10.129	23.328	3.830	54.950
Quick-acting potassium (mg/kg)	252.444	144.268	251.500	28.000	980.000
Organic carbon (g/kg)	37.350	17.410	34.088	9.552	118.477
Ratio of carbon to nitrogen (SOC/N)	35.586	64.194	24.358	5.350	130.42

Impact of Farmers' Technology Adoption on Soil Degradation and Nutrient Dynamics in Intensive Agricultural Systems

The collinearity diagnostics reveal that the variance inflation factors (VIF) for all models in Table 7 are below 1.04, well under the critical threshold of 10, suggesting a minimal likelihood of multicollinearity among the variables. Fig. 4 shows the technical adoption rates of five soil restoration technologies, among which the technical adoption rate of fallow is the highest. Columns (1) - (9) of Table 9 present the estimated results of the impacts of five soil restoration technologies on different soil nutrients and degrees of degradation. The estimation results show that the estimated coefficients for spreading lime and fallowing regarding soil degradation are -1.401 and -1.630, respectively, both significantly negative at the 1% level. This indicates that after controlling for topographical characteristics, management duration, and township-level fixed effects, households adopting spreading lime and fallowing practices significantly reduce the degree of soil degradation in intensive agriculture. Among these, the estimated coefficient of organic fertilizer instead of chemical fertilizer on available phosphorus in the soil is 3.519, showing a significant positive effect at the 5% level.

The estimated coefficient of soil testing and formula fertilization technology on soil pH is 0.192, indicating a significant positive effect at the 10% level. Soil testing and formula fertilization technology has a significant negative impact on total nitrogen, nitrate nitrogen, quick-acting potassium, and organic carbon in the soil, with coefficient values of -0.277, -21.097, -37.893, and -5.727, respectively. The estimated coefficient of spreading lime on soil pH is 0.296, with a positive relationship confirmed at the 5% significance level. The addition of topsoil has a significant negative impact on soil ammonium nitrogen and quick-acting potassium, with estimated coefficients of -31.307 and -58.295, respectively.

Fallowing positively influences soil organic carbon, with a coefficient of 8.780. The estimation results indicate that spreading lime and fallowing can significantly reduce the degree of degradation in intensive agricultural soils. In intensive agricultural systems, lime is a direct and effective acidification corrective agent, and moderate production cessation is more conducive to restoring soil ecological functions than continuous external inputs. Among these, soil testing and formula fertilization technology, along with spreading lime, could significantly improve the acidification trends in intensive agricultural soils.

The use of organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization, and adding topsoil could significantly address the structural imbalance of soil nutrients in forest land mulching production. Fallowing could effectively increase soil organic carbon content but do not further improve the soil ratio of carbon to nitrogen.

Among the other variables, topographical characteristics significantly influenced the degree of soil degradation. Compared to sloping land, flat land exhibits a higher degree of soil degradation (with a coefficient value of 3.917, $p < 0.01$), primarily due to the ease of mechanized operations and higher levels of intensive management in flat areas. The current mulching condition of the sample plots significantly influenced several soil indicators. In mulched sample plots, levels of nitrate nitrogen and available potassium increase significantly, as does soil organic carbon content. Extended periods of intensive management significantly affect soil nutrients, leading to a decrease in nitrate nitrogen and available potassium as the duration of management increases.

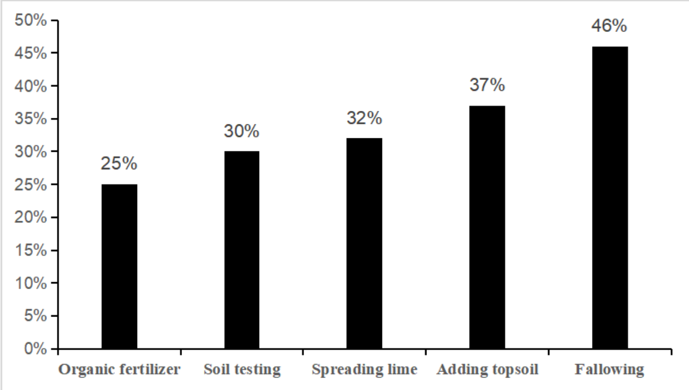

Fig. 4 - Technical adoption rate of soil restoration technologies

Table 7

Estimation results of impact factors on soil nutrients and degree of degradation in high-intensity agriculture

	Degree of soil degradation	Soil pH value	Total nitrogen	Ammonium nitrogen	Nitrate nitrogen	Available phosphorus	Quick-acting potassium	Organic carbon	SOC/N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Organic fertilizer	-0.862 (0.556)	0.102 (0.099)	0.269 (0.177)	7.355 (8.304)	3.682 (6.916)	3.519** (1.677)	26.890 (21.802)	3.134 (2.902)	-0.530 (9.056)
Soil testing	-0.015 (0.501)	0.192* (0.113)	-0.277* (0.141)	-7.149 (8.565)	-21.097*** (7.109)	-1.938 (1.373)	-37.893* (21.577)	-5.727** (2.709)	-9.961 (11.745)
Spreading lime	-1.401*** (0.478)	0.296** (0.126)	-0.086 (0.204)	11.548 (9.464)	0.421 (7.960)	-0.278 (1.408)	34.987 (29.811)	2.621 (3.299)	3.497 (5.644)
Adding topsoil	-0.290 (0.507)	0.060 (0.107)	-0.001 (0.172)	-31.307*** (8.926)	-0.059 (7.501)	-1.416 (1.469)	-58.295** (24.149)	-4.342 (3.192)	-14.148 (8.921)
Fallowing	-1.630*** (0.629)	-0.011 (0.103)	0.128 (0.164)	-11.262 (8.436)	2.762 (8.341)	-1.678 (1.649)	3.386 (23.437)	8.780** (3.829)	22.173 (20.680)
Topography	3.917*** (0.791)	-0.913** (0.446)	0.461* (0.260)	9.636 (10.283)	9.273 (13.910)	-4.940 (3.227)	-36.806 (38.329)	10.378** (5.236)	-0.199 (8.608)
Plot conditions	0.960 (0.634)	-0.948*** (0.166)	-0.054 (0.238)	-1.658 (10.302)	45.592*** (9.414)	-2.292 (2.044)	73.678** (35.061)	9.375** (4.140)	23.860 (22.987)
Soil types	0.424 (0.413)	0.027 (0.098)	-0.156 (0.149)	-4.558 (7.471)	-8.112 (7.233)	-0.190 (1.507)	-2.095 (21.677)	-3.837 (2.942)	4.097 (7.541)
Management duration	0.016 (0.021)	-0.006 (0.006)	-0.009 (0.008)	0.268 (0.401)	-0.651* (0.364)	-0.061 (0.083)	-3.501*** (1.198)	0.008 (0.136)	0.262 (0.226)
Site_FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.341	0.550	0.317	0.292	0.439	0.463	0.308	0.253	0.183
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Note: ***、** and * indicate significance at the 1%, 5%, and 10% levels; the figures in parentheses represent standard errors. The standard errors of the regressions have been clustered at the individual level. Since policy measures do not directly affect soil nutrient indicators or the degree of degradation, they have not been included in the empirical analysis of influencing factors.*

Influence Mechanism of Policy Measures

Table 8 outlines the analytical findings on the relationship between policy instruments and the adoption of soil restoration technologies by farmers. The collinearity diagnostic results indicate that the variance inflation factor (VIF) for all models in Table 8 is less than 1.01, suggesting a very low probability of multicollinearity among variables. The regression results reveal that technical training and farmland circulation measures exhibit significant technology dissemination effects, while the technology subsidy policy does not show significant results, demonstrating clear heterogeneity among policy tools. Specifically, technical training significantly influenced farmers' adoption of organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technology, and spreading lime, with coefficient values of 0.708, 1.279, and 1.095 respectively. Transferred land also significantly influences farmers' adoption of organic fertilizer instead of chemical fertilizer, spreading lime, and adding topsoil, with coefficient values of 0.854, 0.671, and 0.992 respectively. The estimation results indicate that among the implemented policy measures in the study area, technical training and farmland circulation measures promoted farmers' adoption of soil restoration technologies, while technology subsidies do not produce significant results. Additionally, technical training and farmland circulation measures have significant impacts on different types of technologies, and the combined implementation of different policy measures has a synergistic effect.

Table 8

Effects of policy measures on farmers' adoption of soil restoration technologies

	Organic fertilizer (1)	Soil testing (2)	Spreading lime (3)	Adding topsoil (4)	Fallowing (5)
Technical training	0.708* (0.427)	1.279*** (0.387)	1.095*** (0.391)	0.307 (0.382)	0.373 (0.344)
Technology subsidies	-0.389 (0.658)	-0.241 (0.570)	0.679 (0.542)	0.731 (0.514)	-0.435 (0.561)
Farmland circulation measures	0.854**(0.431)	0.550(0.386)	0.671*(0.402)	0.992**(0.405)	-0.067 (0.331)
Site_FE	Y	Y	Y	Y	Y
R-squared	0.144	0.211	0.261	0.254	0.125
Prob>F	0.000	0.000	0.000	0.000	0.000

*Note: ***、** and * indicate significance at the 1%, 5%, and 10% levels; The figures in parentheses represent standard errors. The standard errors of the regressions have been clustered at the individual level.*

CONCLUSIONS

This study is based on 178 matched soil experimental data sets and farmer questionnaire data from the Tianmu Mountain area in China, uncovering the soil nutrient status and degradation characteristics of intensive subtropical agriculture. Utilizing econometric models, this study empirically examines the impact of policy measures and farmers' behavior in adopting soil restoration technologies on soil nutrient indicators such as soil pH, total nitrogen, ammonium nitrogen, nitrate nitrogen, available phosphorus, quick-acting potassium, organic carbon, and ratio of carbon to nitrogen, as well as the degree of soil degradation. The results show that:

(1) The mean soil pH of the 178 intensive agricultural sample plots is 4.535, with a median of 4.410, indicating a pronounced soil acidification characteristic. The excessive nitrogen fertilizer application associated with intensive agriculture has resulted in a "nitrogen saturation" effect in the sample plots, leading to structural imbalances in soil N, P, and K ratios.

(2) In general, spreading lime and fallowing can significantly reduce the degree of soil degradation in intensive agriculture, resulting in a decrease in soil degradation scores by 1.401 and 1.63, respectively. In terms of specific nutrient indicators, soil testing and formula fertilization technology can effectively mitigate the acidification trend in intensively managed bamboo forests. The use of organic fertilizer instead of chemical fertilizer, soil testing and formula fertilization technology, and adding topsoil can significantly address nutrient imbalances in forest land mulching production. Meanwhile, fallowing effectively boosts soil organic carbon content but does not enhance the ratio of carbon to nitrogen.

(3) Technical training and farmland circulation measures can improve soil nutrient status by influencing farmers' behavior in adopting soil restoration technologies, effectively alleviating soil degradation. Furthermore, different policy measures significantly impact different types of technologies, suggesting that their combined implementation produces a synergistic effect.

The conclusions highlight the need to incentivize farmers to adopt soil restoration technologies, improve policy effectiveness, and enhance the synergy of supporting measures in managing soil degradation in high-intensity subtropical agriculture. Due to limited soil data, future research should include longitudinal and cross-regional studies to improve the generalizability and accuracy of the findings.

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APPENDIX A.

Table A1

Judgment scale table

Judgment scale（B_{ij}）	Meaning
1	B_i and B_j are equally important
3	B_i is slightly more important than B_j
5	B_i is significantly more important than B_j
7	B_i is strongly more important than B_j
9	B_i is extremely more important than B_j
2、4、6、8	Intermediate value between two adjacent judgment scales above

The root method was used to estimate the approximate eigenvector values in the judgment matrix. The eigenvectors were then normalized to obtain the weight vector. The maximum eigenvalue of the judgment matrix was subsequently determined, and can be expressed as follows:

$$W_i = \frac{(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}, ij = 12kn \tag{A1}$$

$$W = (W_1, W_2, \ldots, W_n)T \tag{A2}$$

$$A \cdot W = \lambda_{max} \cdot W \tag{A3}$$

where A is the original judgment matrix and W is the calculated weight vector.

Third, the hierarchy was subjected to overall ranking and consistency testing. To account for potential random deviations in the judgment matrix, the consistency ratio (CR) was calculated to evaluate whether the matrix meets the required consistency standard.

$$CI = \frac{\lambda_{max} \text{-n}}{\text{n-1}} \tag{A4}$$

$$CR = \frac{CI}{RI} \tag{A5}$$

If CR < 0.1, the judgment matrix passes the consistency test. The test results are shown in Table A2.

Table A2

Average random consistency index *RI* standard values

Matrix order	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

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