“Agricultural intensification and forest cover change in South Asia: A panel econometric and ridge analysis”

AUTHORS	Bidyut Kumar Ghosh Suvayan Neogi

ARTICLE INFO	Bidyut Kumar Ghosh and Suvayan Neogi (2026). Agricultural intensification and forest cover change in South Asia: A panel econometric and ridge analysis. *Environmental Economics*, *17*(2), 15-28. doi:10.21511/ee.17(2).2026.02
DOI	http://dx.doi.org/10.21511/ee.17(2).2026.02
RELEASED ON	Friday, 10 April 2026
RECEIVED ON	Sunday, 19 October 2025
ACCEPTED ON	Friday, 30 January 2026

JOURNAL	"Environmental Economics"
ISSN PRINT	1998-6041
ISSN ONLINE	1998-605X
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
43	3	4

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Bidyut Kumar Ghosh (India), **Suvayan Neogi** (India)

AGRICULTURAL INTENSIFICATION AND FOREST COVER CHANGE IN SOUTH ASIA: A PANEL-ECONOMETRIC AND RIDGE ANALYSIS

Type of the article: Research Article

Received on: 19th of October, 2025
Accepted on: 30th of January, 2026
Published on: 10th of April, 2026

Bidyut Kumar Ghosh, Ph.D., Associate Professor, Manipal School of Commerce and Economics, Manipal Academy of Higher Education, Manipal, India. (Corresponding author)

Suvayan Neogi, Ph.D., Consultant, Centre for WTO Studies, Indian Institute of Foreign Trade, India.

Conflict of interest statement:
Author(s) reported no conflict of interest

Abstract

In the context of growing pressure on forest ecosystems arising from agricultural area expansion and intensification, expanding population, and climate variability, this study aims to identify and quantify the impacts of these changes on forest coverage in the South Asian region. Using a balanced panel dataset for 1990–2023, the analysis employs a regularized fixed-effects estimation to identify the key drivers of forest area change and assess variable importance.

The findings show that a 1% increase in agricultural value added is achieved at the cost of a 0.32% decrease in forest area, making it the most significant driver of forest loss. Use of inorganic fertilizer also exerts a strong negative influence, as forest cover is reduced by 0.18% for every additional percentage usage of fertilizer. Irrigation expansion has a similarly adverse effect, contributing to a 0.21% decline per 1% increase in irrigated area. Population density growth intensifies pressure on forests, with each additional 10 persons per km² corresponding to a 0.05% decrease in forest area. However, pasture share exhibits a positive association: a 1-percentage-point increase corresponds to a 0.14% rise in forest area, and cattle density also shows a modest but positive effect. The results indicate the presence of mixed livestock–forest systems and early forest-transition dynamics in some countries.

Overall, the findings demonstrate that the pattern of agricultural practices determines forest trajectories in South Asia, and achieving sustainability will require country-specific strategies that balance productivity growth with integrated land-use planning and long-term conservation goals.

Keywords deforestation, agriculture, panel data, ridge regression, livestock, forest cover, South Asia

JEL Classification C23, Q12, Q15, Q23, Q56

INTRODUCTION

Forest conservation and sustainable management are the most critical environmental challenges of the current century. Forests provide the ecological balance, carbon sequestration, climate regulation, biodiversity conservation, and hydrology system stability. These are important for planetary health and human health (FAO, 2020). However, the forest ecosystem is continuously threatened by human activities. Increasing land-use change due to agricultural area expansion, rapid population growth, and overall social and economic development are continuously pressing on the global forest landscape. At the same time, environmental variability and climate change collectively further alter forest integrity and resilience (Hansen et al., 2013; Pan et al., 2011).

These complex and interdependent forces shape the forest area dynamics and eventually produce a core scientific problem. Globally, agricultural land-use change remains the major driver of forest loss. This is particularly true in tropical and subtropical regions because the conversion of forests to cropland and pasture disrupts the forest ecosystems' functions and reduces biodiversity (Gibbs et al., 2010; Rosero-Añazco et al., 2025). However, agricultural resources themselves are multifaceted. Depending on how they are managed, permanent meadows and pasturelands may either slow down or accelerate the deforestation (Ma et al., 2023). At the same time, agricultural intensification through the increasing use of inorganic fertilizers (nitrogen, phosphorus, and potassium) to meet growing food demand further creates environmental externalities. Nutrient runoff, soil degradation, and depletion of groundwater are the direct outcomes of the increasing use of inorganic fertilizers. All these factors directly influence the forest area and overall forest health (Krasilnikov et al., 2022; Selim, 2020).

Regarding the impacts of livestock on forest health, the scholars are divided into two distinct categories. Scholars believe that livestock overall had negative impacts on forest structure and ecosystem functions through reductions in plant biomass and species abundance. However, the effects vary by livestock type, density, and region (Li & Jiang, 2021). On the other hand, growing livestock densities cause changes in vegetation structure and reduced fire frequency, particularly in tropical regions (Bernardi et al., 2019). Long-term cattle grazing can shift the ecological state of forest soils by modifying soil chemistry and biota. This helps in nutrient cycling and forest ecosystem functioning (Proesmans et al., 2022).

Growing rural population density and related demographic pressure are the major drivers of forest loss, as these will require direct land clearing for both agricultural and settlement expansion (Ryan et al., 2014).

Finally, the large-scale irrigation development increases the cultivable land area and results in substantial rural population density, which in turn puts negative pressure on the forest area (Boudot-Reddy & Butler, 2025). These agricultural and human pressures work alongside pervasive climatic stressors (Rajkumari & Hussain, 2025). Rising global temperatures, shifting precipitation regimes, and increased extreme weather events directly affect forest growth, species composition, and disturbance regimes. At the same time, these factors simultaneously alter agricultural productivity and land-use decisions (Seidl et al., 2017; Rosenzweig et al., 2014). Eventually, the forest area coverage emerges as the outcome of the interaction of economic, ecological, demographic, and climatic processes.

In this context, there is evidence of growing scholarship concerning forest area and biodiversity loss. However, most of them analyze these pressures separately. This limits the understanding of their combined and potentially synergistic effects on forest area trajectories (Hansen et al., 2013; IPCC, 2021). The scientific challenge, therefore, lies in exploring how these interconnected forces jointly influence forest cover and identifying the dominant factors shaping forest change in regions undergoing rapid agricultural transformation.

1. LITERATURE REVIEW

The investigation of drivers of forest area change requires simultaneous attention to multiple driving forces, as these forces act individually and interactively while shaping forest area over long periods of time. One common consensus of existing scholarly works is that deforestation in developing regions is primarily driven by land-use pressures arising from competing demands for cropland, pasture, and human settlement. The Food and Agriculture Organization assesses that agricultural activities are responsible for most of the forest conversion due to the growing demand for food production. This has been even more pronounced in the tropical and subtropical regions due to the interaction of ecological fragility with the rapid economic development (FAO, 2021). Empirical evidence suggests that rising per-capita demand for food is leading to substantial land clearing, especially when agricultural production is increased through intensive agricultural production practices (Lambin & Meyfroidt, 2011; Tilahun et al., 2022). The clearing of forest land for commodity crops,

http://dx.doi.org/10.21511/ee.17(2).2026.02

shifting cultivation, and permanent agricultural conversion plays as a central mechanism of ecosystem alteration (Geist & Lambin, 2002; Gibbs et al., 2010; Hansen et al., 2013). This agricultural expansion-driven deforestation can be relatively more aggressive in poorer economies, where the economic development is in the early stages due to low agricultural productivity, population pressure, weak institutional governance, and export-driven economic growth (Barbier & Burgess, 2001; Rudel, 1998; Tang et al., 2025; Tilman et al., 2011).

Further, an in-depth study of agriculture-driven deforestation suggests that agricultural land categories put different pressures on forests. Permanent meadows and pastures play a dual role in forest area change. While permanent meadows and pastures can buffer forests by stabilizing land use, they may also accelerate forest loss when expanded for commercial livestock production (DeLonge & Basche, 2018; Feurer et al., 2025). This dual role clarifies the need for refined assessments of how agricultural intensification and pastureland affect forest systems.

In connection with the pastureland, the livestock population reinforces this complexity further. Cattle production contributes to pasture expansion, soil disturbance, and vegetation removal, and slowly but steadily over a long time, it becomes an important driver of deforestation across multiple regions (Herrero et al., 2009; Lambin & Meyfroidt, 2011; Tilman et al., 2011). At the same time, grazing systems can alter forest structure and regeneration, with effects varying across landscapes (Li & Jiang, 2021). Further evidence is that livestock pressures interact in uneven and context-dependent ways with plantation forestry and pasture availability (FAO, 2021).

Increased inorganic fertilizer usage in the intensive crop production context also contributed to forest loss. It is widely known that fertilizers have played a pivotal role in global food production. However, this enhanced food production due to heavy usage of inorganic fertilizers came directly at the cost of nutrient runoff, soil degradation, and indirectly at the cost of loss of forest ecosystems adjacent to agricultural areas (Zhao et al., 2013). Even in managed forestry, fertilization has been found to alter ecological balances and downstream conditions (Binkley et al., 1999). Despite these insights, empirical evidence linking fertilizer intensity to forest outcomes remains limited at the large scale, and particularly in the South Asian context.

Climatic fluctuations add complexity to forest cover as they influence both forest conditions directly and indirectly by affecting agricultural practices. The forest resilience and species distribution are directly affected by rising earth surface temperatures, changed precipitation patterns, and growing other climatic disturbances such as fires, storms, and pest outbreaks (IPCC, 2021; Seidl et al., 2017). These changed climatic conditions also affect agricultural productivity, and their spillover effects will eventually lead to expanding agricultural land-use encroaching into forest areas (Bajželj & Richards, 2014). Growing climatic fluctuations through widespread drought- and heat-induced tree mortality undermine the global forest resilience (Allen et al., 2010). Empirical studies mostly acknowledge these dual impacts (direct climatic fluctuations and indirect through agriculture) on forest resilience. However, studies often fail to acknowledge these interaction effects of shared landscapes.

The socio-economic conditions enter into the biophysical relationship between climate and forest cover through their mediating role in further shaping the forest landscape. In principle, growing population density increases the demand for cultivable land. Higher irrigation requirements arising due to higher cultivable land can impact forest coverage in either way, depending on how the production system scales up (IPCC, 2022; Winkler et al., 2021). Governance quality, land tenure systems, and policy enforcement determine how effectively countries regulate land-use change, explaining why similar pressures produce divergent forest trajectories across regions (Curtis et al., 2018).

Lambin and Meyfroidt (2011) argued that land-use change, such as deforestation or forest recovery, results from complex, non-linear "land-use transitions" driven by interacting socio-ecological feedback and socio-economic shifts. This clearly underscores the need for the incorporation of non-linear patterns in the empirical studies, while most of the studies are linear in nature. Econometric approaches allow for linear causal inference and control for confounding factors (Wooldridge, 2010), unless specified exclusively. On the other hand, machine-learning techniques enable the automatic detection of nonlinearities and high-dimensional interactions (Athey, 2018; Hastie et al., 2009). The expansion of remote sensing technology and the availability of large-scale environmental datasets have facilitated the use of these combined tools in land-use studies (Mhanna et al., 2023; Yuh et al., 2023). Nevertheless, only a limited number of studies jointly evaluate agricultural intensification, livestock dynamics, climatic variability, and demographic pressures using integrated econometric–machine learning frameworks.

Thus, the existing empirical evidence has already advanced the study of the drivers of forest change. However, most studies have treated these determinants in isolation or within limited geographic and economic scopes. Additionally, there remains a critical gap for cross-country assessment over a long period of time, covering multidimensional drivers of forest change. To fill this gap, the current study makes a modest attempt at a data-driven hybrid econometric-machine learning approach to identify the drivers of forest area change in South Asia in a multidimensional setting.

We aim to quantify the combined effects of agricultural land use, fertilizer application, livestock systems, climatic variability, and socio-economic factors on forest area change in South Asia using a panel data setup. The primary objective is to investigate the empirical evidence to inform integrated land-use planning under changing environmental and economic conditions.

The specific objectives are to assess the complex pattern of impacts of agricultural land-use intensity, livestock population, climatic fluctuations, and socio-economic factors in shaping forest trajectories. To guide the analysis, we formulate the following hypotheses:

H1: *An increase in agricultural land use (quantified by cropland share and agricultural value added) and production intensity (measured by fertilizer use and irrigation coverage) is expected to reduce forest area through land conversion.*

H1a: *Intensification of existing farmland (via higher fertilizer intensity and irrigation) may partially offset forest loss by reducing the need for additional land conversion, exhibiting a land-sparing effect.*

H2: *Expansion and intensification of livestock systems (cattle density and pasture share) are expected to negatively affect forest cover through pasture expansion and encroachment into forested areas.*

H3: *Adverse climatic factors (growing surface temperature and precipitation fluctuations) are expected to reduce the forest cover by reducing forest resilience and altering growth conditions.*

H3a: *Socio-economic factors (higher population density and expanded irrigation coverage) will intensify deforestation by increasing demand for agricultural land and influencing land-use decisions.*

H4: *Econometric and machine learning techniques are expected to identify key determinants and their complex relationships more accurately. This hybrid approach should provide superior explanatory power compared to traditional single-method models.*

Therefore, we adopt a land-systems perspective and conceptualize forest area change as the result of interacting processes within shared landscapes. As direct indicators of land-use pressure that affect competition between cropland, pasture, and forest, we categorize the variables in this framework based on their functional roles: pasture share, irrigated area, agricultural value added, and fertilizer intensity. Cattle density directly affects pasture expansion in livestock systems, while increased grazing intensity brought on by higher cattle density and ensuing land degradation indirectly affects vegetation removal. Ecological stressors are also caused by climate variables such as temperature and precipitation variability. We consider population density and irrigation access as structural modifiers from the set of socioeconomic fac-

http://dx.doi.org/10.21511/ee.17(2).2026.02

tors. These structural modifiers can either quicken or slow the expansion of land use. Together, these factors form a complex system that determines the forest outcomes through the interaction of direct production incentives, indirect environmental conditions, and demographic pressures.

2. METHOD

The study uses a panel dataset of six South Asian countries (Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka) over a period of more than two decades (1990–2023). We have excluded Afghanistan and the Maldives from the study due to the unavailability of data. The data for forest area and agricultural variables were collected and compiled from FAOSTAT, and socio-economic and climate indicators were sourced from the World Bank's World Development Indicators.

To address the feature interactions and complexity, we have adopted two complementary analytical techniques. A fixed-effects panel regression is employed to establish directional relationships and isolate within-country variation over time. This method will minimize confounding from unobserved structural differences across countries. The science of forest change processes, however, frequently exhibits nonlinearities, threshold effects, and heterogeneous responses that conventional regression techniques may miss. Consequently, we adopted machine-learning interpretability tools (Accumulated Local Effects plots) to identify nonlinear patterns and determine country-specific contribution structures to enhance the explanatory power of the econometric model. This hybrid approach of integrating econometrics and machine learning enables the capture of both the causal mechanisms of land-use drivers and the complex, high-dimensional interactions.

After the initial visualization of data, we estimate all three possible model specifications: pooled ordinary least squares (OLS), fixed-effects (FE), and random-effects (RE) for the specified regression framework. We use a set of tests for correctly identifying the optimal panel regression model: the *F*-test for fixed versus pooled OLS, the Breusch–Pagan Lagrange Multiplier test for random effects, and the Hausman test for fixed versus random effects. Fixed effect panel regression emerged as the winner. Diagnostic tests on the winning model (FE) revealed substantial multicollinearity among agricultural and socio-economic predictors, as well as heteroscedasticity and autocorrelation within the panel. This necessitates robust variance estimation.

To address the multicollinearity problem, we apply regularization-based alternatives. We have tried all three regularization techniques: ridge, lasso, and elastic net. Lasso and elastic net methods eliminated key covariates due to their sparsity-inducing penalties. Therefore, we consider the ridge regression as the preferred approach, as it stabilizes coefficient estimates by shrinking them toward zero while retaining all predictors. All variables were standardized before estimation.

In the subsequent step, unobserved heterogeneity specific to each country was addressed using the within-country fixed-effects transformation:

$$X_{it}^{within} = X_{it} - \ddot{X}_i, Y_{it}^{within} = Y_{it} - \ddot{Y}_i \quad (1)$$

Here, overbars $\left(\overline{X_i}, \overline{Y_i}\right)$ denote the country means. Ridge regression was subsequently implemented on these transformed variables:

$$\hat{\beta}_{ridge} = \arg\min_{\beta} || Y^{within} - X^{within}\beta ||^2 + \lambda || \beta ||_2^2 \quad (2)$$

The regularization parameter was selected using cross-validation. Approximate analytical standard errors were then computed using:

$$\mathrm{Var}\left(\hat{\beta}_{ridge}\right) \approx \hat{\sigma}^2 (X^\top X + \lambda I)^{-1} X^\top X (X^\top X + \lambda I)^{-1} \quad (3)$$

Residual variance was estimated using effective degrees of freedom. This enables the calculation of *t*-statistics and *p*-values for hypothesis testing for population inference.

Finally, to interpret the contribution of each predictor for each country and year, feature contributions were computed as follows:

$$\mathrm{Contribution}_{i,t,j} = \hat{\beta}_j \left(X_{j,it} \ddot{X}_{j,i} \right) \quad (4)$$

The contributions were aggregated to generate country-level profiles. We use Accumulated Local Effects (ALE) plots for visualizing country-specific variable contributions to forest cover change over the range of covariates. All analyses were conducted in Python using pandas, stats models, and scikit-learn, and figures were generated with matplotlib.

3. RESULTS

The forest cover as a percentage of the total land of six South Asian countries (India, Pakistan, Bangladesh, Nepal, Sri Lanka, and Bhutan) over the period 1990–2022 are displayed in Figure 1. The time series plots reveal notable disparities among these countries. The forest areas have shown a gradual expansion in India and Nepal. This could be attributed to reforestation initiatives and improved forest management. Bhutan shows a steep rise in the mid-1990s. Thereafter, it follows a gradual elevation in subsequent years. However, there is no empirical evidence on what causes this steady afforestation in Bhutan. On the other hand, Pakistan exhibits a continuous decline in forest cover throughout the study period. Bangladesh maintained a stable forest during the latter part of the last century. But it failed to maintain and experienced a substantial reduction after 2000. Sri Lanka experienced continued decreases in forest areas until 2010. Only a minor recovery is noticed toward the end of the study period. This cross-country heterogeneity in the relative forest area highlights the diverse socio-ecological and policy factors influencing forest dynamics in South Asia.

The summary statistics of the forest area (% of total area) along with its potential drivers are presented in Table 1. The summary statistics of these variables are calculated considering all six countries together over the study period. The forest cover across six countries ranges from less than 5% to over 70%. This highlights South Asia's diverse ecological conditions and land-use histories. Pasture shares are even more dispersed (ranging from approx. 6% to 81%). It is clearly indicative of varying degrees of reliance on livestock and grazing-based systems. This is further pronounced in the substantial heterogeneous cattle density. Spanning over a range of 58 to 1912, the cattle density pattern exhibits significant heterogeneity and indicates the existence of smallholder-oriented areas to zones with concentrated livestock populations. Finally, the observed variations in NPK fertilizer use, agricultural value added, irrigation area, manure nitrogen, rainfall deviations, and population density reflect distinct agricultural intensification patterns, demographic pressures on the land, and diverse climatic conditions across the sample. These descriptive results and the heterogeneous forest areas change across the countries support the application of panel data methods that can capture within-country changes over time while accounting for unobserved heterogeneity.

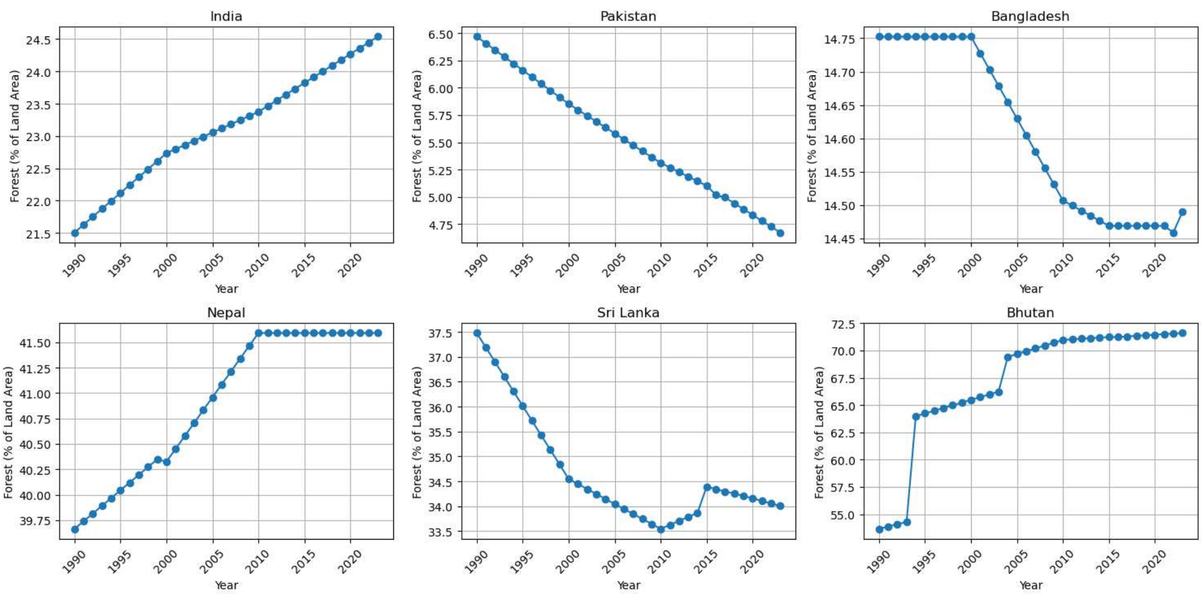

Figure 1. Forest percentage over years in select south Asian countries

http://dx.doi.org/10.21511/ee.17(2).2026.02

Table 1. Descriptive statistics of variables

Variable	Mean	Std	Min	25%	50%	75%	Max
pasture_pct	26.92	24.78	5.71	6.43	14.42	43.19	80.51
forest_pct	31.01	20.2	4.67	14.6	29.04	41.12	71.61
cattle_density	603.01	566.9	58.36	186.5	487.52	654.5	1912.29
npk	100.74	73.99	0	37.57	98.94	146.48	353.35
temp_change	0.6	0.45	-0.51	0.31	0.56	0.94	1.81
agri_va	21.62	9.31	6.88	13.11	21.1	28.42	43.88
manure_n	5.066298e+08	7.508884e+08	292355.761273	1.264481e+07	1.284779e+08	5.717041e+08	2.352655e+09
rain_dev	5.85	236.48	-715.99	-101.84	6.51	109.89	730.94
irrig_area	14,939.36	23,141.73	27	570	2,079.45	19,165.00	75,500.00
pop_density	375.59	355.24	11.87	174.44	287.6	395.98	1,301.26

Before estimating the primary model, specification tests were conducted to decide the right panel estimation framework. The F-test strongly rejects pooled OLS in favor of a fixed-effects (FE) specification ($F = 41.09$, $p < 0.001$), and the Breusch–Pagan LM test rejects pooled OLS for random effects ($LM = 76.82$, $p < 0.001$). The Hausman test yields an inconclusive outcome ($\chi^2 = 6.93$, $p = 0.7319$), which is not uncommon in panels with few cross-sectional units and multiple regressors. Given the likelihood that unobserved country-specific factors correlate with the regressors, the fixed-effects model remains the most theoretically appropriate and econometrically robust choice (Wooldridge, 2010), especially in short panels where random-effects assumptions may not hold reliably.

Variance Inflation Factors (Table 3) show large multicollinearity among multiple predictors, particularly agricultural value added (log_agri_va) and population density (log_pop_density), both of which exceed VIF values of twelve. The pastureland share (pasture_pct) also shows an elevated VIF, suggesting overlapping information with other agricultural variables. To mitigate the resulting instability in coefficient estimates, regularization methods were implemented. Of the methods (lasso, elastic net, and ridge regression) evaluated, ridge regression demonstrated superior performance by retaining all theoretically necessary variables and reducing variance inflation. Grid search optimization identified $\alpha = 1.53$ as the optimal penalty parameter.

Table 3. Variance Inflation Factors (VIF) for FE model predictors

Feature	VIF
log_agri_va	12.27
log_pop_density	12.09
pasture_pct	4.54
log_manure_n	3.35
log_irrig_area	3.21
log_cattle	3.01
temp_change	2.56
cropland_pct	2
log_npk	1.57
rain_dev	1.14
const	1

The ridge-regularized fixed-effects model results are shown in Table 4. Agricultural value added shows a strong, highly significant negative (–2.405, $p < 0.0001$) effect on forest cover. The negative and statistically significant estimate of agricultural value added is consistent with the established land-conversion theory – the negative pressure of the expansion of agricultural activities on forest land. The irrigated area also exhibits a strong statistically significant (–0.713, $p < 0.0001$) negative effect. It implies that irrigation expansion often occurs on previously cleared land for cultivation. Heavy inorganic fertilizer use is also resulting in

Table 2. Model selection in panel data analysis

Test	Statistic	p-value	Decision
F-test (FE vs Pooled OLS)	41.09	0	Reject Pooled OLS; FE preferred
LM Test (RE vs Pooled OLS)	76.82	0	Reject Pooled OLS; RE preferred
Hausman Test (FE vs RE) *	6.93	0.7319	Inconclusive; rely on the F-test and context due to the small entity compared to the features
Final Model Choice	–	–	Fixed Effects (FE) selected

a reduction in forest area. The estimated negative coefficient of −0.417 ($p = 0.0004$) underscores the relationship between fertilizer-driven intensification and forest loss. Cropland share, as expected, is imposing a negative effect (–0.089) on forest land area. However, this is not statistically significant after controlling for other factors. This is possibly due to overlapping variance with other agricultural variables. So, three complementary agricultural expansion factors (agricultural value added, irrigation coverage, and increased fertilizer usage) jointly reinforce pressures on forest ecosystems. The forest cover decline in South Asia is not driven by a single agricultural factor in isolation, but rather by the cumulative and interacting effects of agricultural growth strategies that include cultivated land expansion and intensive production systems. Additionally, population density (–0.845, $p = 0.0033$) contributes to deforestation pressures and appears to be a key driver of deforestation in developing regions. This further confirms the demographic–land–use nexus in which population growth increases demand for food, settlement, and rural infrastructure, thereby intensifying pressure on land resources. To meet the rising food demand, agricultural systems expand horizontally through land conversion and vertically through intensified production practices. The intensive production eventually requires expanded irrigation coverage and heavy fertilizer use. Manure application shows a negative but statistically non-significant (–0.213, $p = 0.204$) association with forest cover, which may reflect its secondary role compared to synthetic fertilizers or its dual function in both intensive and extensive farming systems.

Surprisingly, the proportion of pastureland (pasture_pct) shows a large, significant positive effect (+995, $p < 0.0001$) on forest area change. This finding differs markedly from classical deforestation trajectories observed in regions such as the Amazon. Cattle density also exhibits a marginally positive effect (0.269, $p = 0.073$). This is consistent with regional land-use systems in South Asia, where multifunctional landscapes and silvopastoral practices frequently permit grazing alongside tree cover. The climatic fluctuations measured through temperature and rainfall deviations, however, do not exhibit statistically significant effects. This implies that short-term climatic fluctuations exert less influence than land-use drivers at the regional scale.

The coefficient of cattle density is found to exert a marginally positive effect (log_cattle 0.269, $p = 0.073$). The finding reflects that in South Asia countries with a predominance of smallholder and mixed-use land systems, cattle grazing coexists with wooded landscapes, village woodlots, or secondary forests without causing large-scale forest clearing.

With a within-R^2 of 0.685, the model explains a substantial proportion of the changes in forest cover across countries and over time. The estimated model highlights the crucial role of agricultural and demographic factors, both value added and infrastructure, as persistent threats to forest health in South Asia. The surprising results for pasture and livestock underscore the need to consider aggregate relationships in the context of spatial policy, local variations, and potential compatibility between livestock and forests in certain settings. The best use of ridge regression (with $\alpha = 1.53$, chosen via grid search) enables retention of all theory-driven covariates and simultaneously

Table 4. Ridge regression results for forest area determinants

Predictor	Coefficient	Std. Error	t-value	p-value
log_npk	−0.417	0.117	−3.57	0.0004
temp_change	0.145	0.147	0.98	0.326
log_agri_va	−2.405	0.286	−8.42	< 0.0001
log_manure_n	−0.213	0.167	−1.28	0.204
rain_dev	−0.131	0.1	−1.31	0.192
log_irrig_area	−0.713	0.163	−4.38	< 0.0001
log_pop_density	−0.845	0.284	−2.98	0.0033
pasture_pct	0.995	0.188	5.29	< 0.0001
cropland_pct	−0.089	0.129	−0.69	0.489
log_cattle	0.269	0.149	1.8	0.073
$\alpha = 1.53$		Within-R^2 = 0.685		

http://dx.doi.org/10.21511/ee.17(2).2026.02

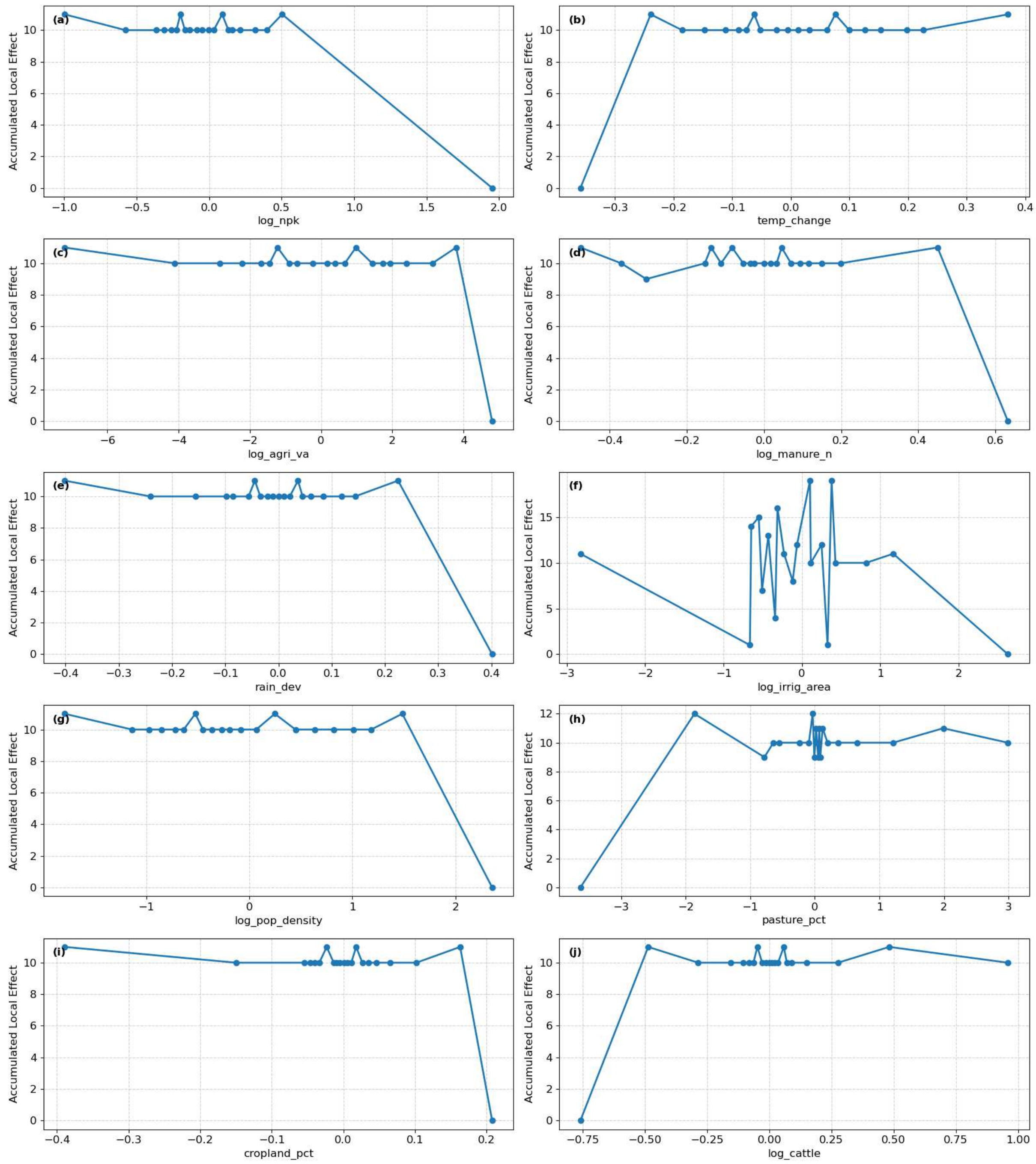

Figure 2. Accumulated local effects plot

mitigates overfitting and instability due to collinearity. Thus, the regularized panel regression provides policy-relevant effect sizes across all principal drivers, such as land use, socio-economic, and environmental dimensions.

To complement the fixed-effects ridge regression results, we apply Accumulated Local Effects (ALE) plots for the main covariates to identify how the ridge regression model translates covariates into predicted forest loss. The resulting plots are shown in Figure 2 (panels a–j). As expected with a linear specification, most variables show monotonic relationships, though irregularities appear at the distributional tails where data are sparse. Fertilizer use (panel a), agricultural value added (panel c), irrigation expansion (panel f), and population density (panel g) all display downward slopes at high-

http://dx.doi.org/10.21511/ee.17(2).2026.02

er values, consistent with their roles as strong drivers of deforestation. Cropland share (panel i) shows the sharpest decline, underscoring the land-use trade-off with forests, though its estimated coefficient lost significance in the multivariate setting. By contrast, pasture extent (panel h) and cattle density (panel j) yield flat profiles, aligning with the regression results. Climatic predictors, temperature change (panel b), and rainfall deviation (panel e) show weaker and less consistent profiles, suggesting that land-use pressures dominate direct climate signals in shaping forest outcomes. Overall, as a visual complement to the regularized panel regression estimates, the ALE plots show the directional influence of predictors while highlighting areas where the fitted model is less stable (e.g., at the extremes of the data distribution).

The country-specific feature contribution plot (Figure 3) shows that the L2-regularised fixed effects model consistently assigns a prominent positive contribution from pasture percentage in Nepal, Bhutan, Sri Lanka, and India, and marginally in Pakistan. This pattern does not represent direct causal country-specific coefficients but rather the average influence of pasture percentage as estimated by the penalized model, shaped by the distribution and covariation of predictors across countries. The model-based positive contributions across multiple South Asian countries suggest that higher pasture proportions are associated with greater forest area in the fitted model. While counter to classical frontier deforestation narratives, this association may reflect the influence of silvopastoral systems, forest transition processes, or regional policy effects as articulated in Forest Transition Theory (FTT). These attributed effects are still model artefacts, driven by both the country covariate patterns and L2 shrinkage. It should be used as hypothesis generators, not as definitive evidence of causal effects or policy impacts, without further, explicit interaction modelling or causal analysis.

Unlike in frontier landscapes, the positive or negligible effect of cattle density, particularly relative to pasture area, indicates that the structure of land use (extensive versus integrated systems) has a greater impact on forest outcomes than the number of animals alone. In South Asia, mixed, smallholder, or silvopastoral systems weaken the traditional association between livestock and deforestation, promoting forest conservation by allowing cattle to graze among trees or on regenerating former croplands.

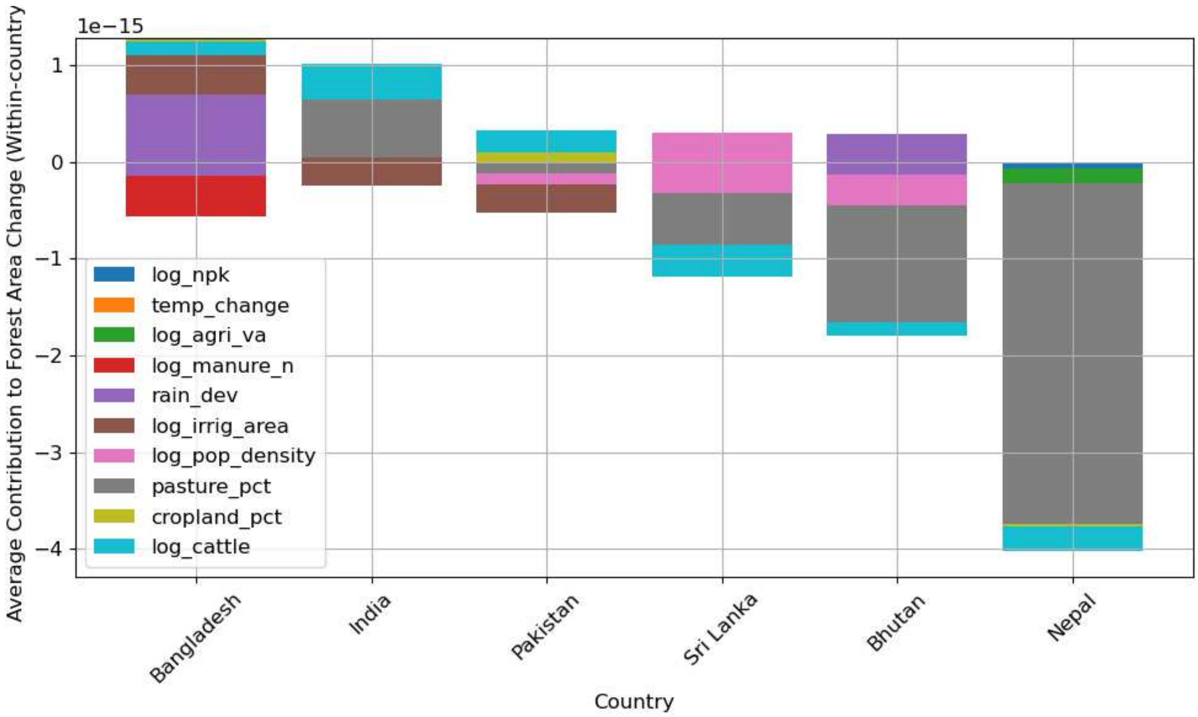

Figure 3. Country-specific feature contribution

http://dx.doi.org/10.21511/ee.17(2).2026.02

4. DISCUSSION

The results provide several aspects of the drivers of forest area change in South Asia. The results reveal both confirmations and departures from conventional deforestation theorems. The strong negative association between agricultural value added and forest cover aligns with the established deforestation trajectories. The estimated model identifies agriculture as a primary driver of global forest loss (FAO, 2021; Gibbs et al., 2010; Hansen et al., 2013). The magnitude of the estimated relationship in the current study exceeds estimates from sub-national or plot-level analyses. This can be due to national-level data aggregation and the inclusion of covariates such as fertilizer use and irrigation infrastructure. The inclusion of these covariates further intensifies the pressure on forest areas.

Although manure nitrogen does not exhibit a significant effect, its negative direction is consistent with the prevalence of mixed-intensive production systems in the region. The significant negative coefficient for population density corroborates previous research connecting demographic pressures to land scarcity and the expansion of cultivated areas (Curtis et al., 2018).

The most distinctive result is the significant positive association between the proportion of pasture and forest cover. This finding contrasts with patterns observed in frontier regions, such as the Amazon, where pasture expansion is a primary driver of deforestation. Instead, the observed pattern aligns with the Forest Transition Theory (Mather & Needle, 1998; Rudel et al., 2005). The Forest Transition Theory posits that forest recovery may occur when agricultural intensification, rural outmigration, or economic diversification reduces pressure on marginal lands. In South Asia, the widespread adoption of silvopastoral systems integrating trees, shrubs, and livestock (Nair, 2011) also contributes to this positive relationship. The estimated results of the current study suggest that pasturelands in South Asia frequently coexist with, or actively support, ecological restoration efforts rather than driving forest loss. The marginal positive and significant effect of cattle density underscores this distinctiveness of land-use configurations in South Asia. This is consistent with empirical observations from certain Indian states and Bhutan, where community forestry, agroforestry, and silvopastoral practices have led to greater overall tree cover alongside livestock-based livelihoods. Statistically insignificant coefficients of climatic variables suggest that anthropogenic land-use decisions outweigh climate variability at this level of aggregation. This does not necessarily imply that climate change is inconsequential for forest health. Instead, it shows that annual national data may be too coarse to detect ecological responses that occur over longer horizons or at finer spatial scales. This is consistent with findings in earlier large-scale assessments (Seidl et al., 2017; IPCC, 2021).

Country-level decompositions reinforce the unevenness of forest transitions in South Asia. Nepal shows strong signs of forest recovery alongside agricultural intensification. Sri Lanka and Bhutan face persistent pressure from agricultural expansion. India and Bangladesh display mixed dynamics shaped by policy interventions, technological change, and demographic pressures. These contrasts underline the need to interpret aggregate coefficients within specific institutional and ecological contexts.

In summary, the findings confirm the central role of agricultural development pathways in shaping forest trajectories in South Asia. It also identifies the land-use configurations, such as silvopastoral practices, which challenge conventional expectations. Unlike in frontier deforestation regions, certain areas of South Asia are experiencing or nearing forest transition phases, although the magnitude and direction of these transitions differ considerably across countries. These insights are consistent with, yet extend, previous studies that highlight the necessity of integrated land-use strategies to balance agricultural productivity with forest conservation.

CONCLUSION

This study identifies the principal drivers of forest area change in South Asia by employing an integrated empirical framework that combines fixed-effects ridge regression with model-agnostic feature interpretation. The analysis provides new insights into the influence of agricultural intensification, livestock systems, demographic pressures, and climatic fluctuations on forest outcomes in the region. The findings reveal that agricultural value added, irrigation expansion, and fertilizer use consistently reduce forest cover. In contrast, pastureland and, to a lesser extent, cattle density are associated with higher forest cover in several countries. Differing from the classical agriculture-led deforestation, the study suggests land-use transitions with evolving production systems, changing rural landscapes, and new forms of integrated land management.

Firstly, the study claims that agricultural development remains the primary driver of forest reduction, indicating that growth in primary production sectors continues to exert significant land-use conversion pressures. Second, the findings confirm the positive association between pasture systems and forest cover in multiple countries, suggesting that mixed and silvopastoral land uses can coexist with forest recovery. This underscores the need to understand regional land-use configurations rather than relying on uniform relationships observed in other tropical regions. Third, the regional country-specific heterogeneity demonstrates that national forest trajectories are shaped by distinct country-specific institutional, ecological, and socio-economic contexts, rather than by a single regional pattern.

As a future scope, more detailed, sub-national analyses are required to clarify local forest-transition processes. Further research should also examine the long-term interactions among climate change, agricultural adaptation, and forest resilience using high-resolution spatial datasets and causal identification strategies. In addition, evaluating the effectiveness of silvopastoral and agroforestry practices across diverse environments would enhance understanding of how integrated land-use systems contribute to both ecological restoration and rural livelihoods.

The study concludes that, with the right mix of agricultural intensification, technological advancement, and effective management, global food needs in 2050 can be met without significantly expanding into natural ecosystems or forests. It emphasizes that farmland expansion need not be the primary strategy; instead, improving yields and boosting efficiency should drive future production gains.

AUTHOR CONTRIBUTIONS

Conceptualization: Bidyut Kumar Ghosh, Suvayan Neogi.
Data curation: Bidyut Kumar Ghosh, Suvayan Neogi.
Investigation: Suvayan Neogi.
Methodology: Bidyut Kumar Ghosh, Suvayan Neogi.
Software: Bidyut Kumar Ghosh, Suvayan Neogi.
Supervision: Bidyut Kumar Ghosh.
Validation: Bidyut Kumar Ghosh, Suvayan Neogi.
Visualization: Suvayan Neogi.
Writing – original draft: Bidyut Kumar Ghosh, Suvayan Neogi.
Writing – review & editing: Bidyut Kumar Ghosh, Suvayan Neogi.

REFERENCES

1. Allen, C. D., Macalady, A. K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D. D., Hogg, E. H. (Ted), Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J.-H., Allard, G., Running, S. W., Semerci, A., & Cobb, N. (2010). A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *Forest Ecology and Management*, *259*(4), 660-684. https://doi.org/10.1016/j.foreco.2009.09.001
2. Athey, S. (2018). The impact of machine learning on economics. In *The economics of artificial intelligence: An agenda* (pp. 507-547). University of Chicago Press. Retrieved from https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/impact-machine-learning-economics
3. Bajželj, B., & Richards, K. (2014). The positive feedback loop

http://dx.doi.org/10.21511/ee.17(2).2026.02

between the impacts of climate change and agricultural expansion and relocation. *Land, 3*(3), 898-916. https://doi.org/10.3390/land3030898

4. Barbier, E. B., & Burgess, J. C. (2001). The economics of tropical deforestation. *Journal of Economic Surveys, 15*(3), 413-433. https://doi.org/10.1111/1467-6419.00144
5. Bernardi, R. E., Staal, A., Xu, C., Scheffer, M., & Holmgren, M. (2019). Livestock herbivory shapes fire regimes and vegetation structure across the global tropics. *Ecosystems, 22*(7), 1457-1465. https://doi.org/10.1007/s10021-019-00349-x
6. Binkley, D., Burnham, H., & Lee Allen, H. (1999). Water quality impacts of forest fertilization with nitrogen and phosphorus. *Forest Ecology and Management, 121*(3), 191-213. https://doi.org/10.1016/S0378-1127(98)00549-0
7. Boudot-Reddy, C., & Butler, A. (2025). Watering the seeds of the rural economy: Evidence from groundwater irrigation in India. *The World Bank Economic Review*, *39*(3), 571-591. https://doi.org/10.1093/wber/lhae041
8. Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science, 361*(6407), 1108-1111. https://doi.org/10.1126/science.aau3445
9. DeLonge, M., & Basche, A. (2018). Managing grazing lands to improve soils and promote climate change adaptation and mitigation: A global synthesis. *Renewable Agriculture and Food Systems, 33*(3), 267-278. https://doi.org/10.1017/S1742170517000588
10. FAO. (2020). *The State of the World's Forests*. Food and Agriculture Organization. Retrieved from https://www.fao.org/state-of-forests/en/
11. FAO. (2021). *COP26: Agricultural expansion drives almost 90 percent of global deforestation*. Food and Agriculture Organization. Retrieved from https://www.fao.org/newsroom/detail/cop26-agricultural-expansion-drives-almost-90-percent-of-global-deforestation/en
12. Feurer, M., Markovic, J., Starke, M., Wilkes-Allemann, J., & Wolf, O. (2025). Drivers of deforestation and forest degradation between 1990 and 2023 – A global meta-analysis. *Environmental Science & Policy, 173,* Article 104242. https://doi.org/10.1016/j.envsci.2025.104242
13. Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation: Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience, 52*(2), 143-150. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2
14. Gibbs, H. K., Ruesch, A. S., Achard, F., Clayton, M. K., Holmgren, P., Ramankutty, N., & Foley, J. A. (2010). Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proceedings of the National Academy of Sciences, 107*(38), 16732-16737. https://doi.org/10.1073/pnas.0910275107
15. Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science, 342*(6160), 850-853. https://doi.org/10.1126/science.1244693
16. Hastie, T., Tibshirani, R., & Friedman, F. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer.
17. Herrero, M., Thornton, P. K., Gerber, P., & Reid, R. S. (2009). Livestock, livelihoods and the environment: Understanding the trade-offs. *Current Opinion in Environmental Sustainability, 1*(2), 111-120. https://doi.org/10.1016/j.cosust.2009.10.003
18. IPCC. (2021). *IPCC Sixth Assessment Report Working Group 1: The Physical Science Basis*. Intergovernmental Panel on Climate Change. Retrieved from https://www.ipcc.ch/report/ar6/wg1/
19. IPCC. (2022). *Climate Change and Land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Cambridge University Press. Retrieved from https://www.ipcc.ch/site/assets/uploads/sites/4/2022/11/SRCCL_Full_Report.pdf
20. Krasilnikov, P., Taboada, M. A., & Amanullah. (2022). Fertilizer use, soil health and agricultural sustainability. *Agriculture, 12*(4). https://doi.org/10.3390/agriculture12040462
21. Lambin, E. F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences, 108*(9), 3465-3472. https://doi.org/10.1073/pnas.1100480108
22. Li, B. V., & Jiang, B. (2021). Responses of forest structure, functions, and biodiversity to livestock disturbances: A global meta-analysis. *Global Change Biology, 27*(19), 4745-4757. https://doi.org/10.1111/gcb.15781
23. Ma, S., Wang, L.-J., Jiang, J., & Zhao, Y.-G. (2023). Direct and indirect effects of agricultural expansion and landscape fragmentation processes on natural habitats. *Agriculture, Ecosystems & Environment, 353,* Article 108555. https://doi.org/10.1016/j.agee.2023.108555
24. Mather, A. S., & Needle, C. L. (1998). The forest transition: A theoretical basis. *Area, 30*(2), 117-124. https://doi.org/10.1111/j.1475-4762.1998.tb00055.x
25. Mhanna, S., Halloran, L. J. S., Zwahlen, F., Asaad, A. H., & Brunner, P. (2023). Using machine learning and remote sensing to track land use/land cover changes due to armed conflict. *Science of The Total Environment, 898,* Article 165600. https://doi.org/10.1016/j.scitotenv.2023.165600

26. Nair, P. K. R. (2011). Agroforestry systems and environmental quality: Introduction. *Journal of Environmental Quality, 40*(3), 784-790. https://doi.org/10.2134/jeq2011.0076

27. Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S., & Hayes, D. (2011). A large and persistent carbon sink in the world's forests. *Science, 333*(6045), 988-993. https://doi.org/10.1126/science.1201609

28. Proesmans, W., Andrews, C., Gray, A., Griffiths, R., Keith, A., Nielsen, U. N., Spurgeon, D., Pywell, R., Emmett, B., & Vanbergen, A. J. (2022). Long-term cattle grazing shifts the ecological state of forest soils. *Ecology and Evolution, 12*(4), Article e8786. https://doi.org/10.1002/ece3.8786

29. Rajkumari, R., & Hussain, S. (2025). A systematic literature review of land use and land cover dynamics in Manipur, India. *Discover Geoscience, 3*(1), Article 115. https://doi.org/10.1007/s44288-025-00198-3

30. Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., & Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences, 111*(9), 3268-3273. https://doi.org/10.1073/pnas.1222463110

31. Rosero-Añazco, P., Zhu, A., Cuesta, F., Speelman, E., & Hofstede, G. J. (2025). What is behind land use change in tropical forests? From local relations to global mining concessions. *Ecology and Society, 30*(1), Article art29. https://doi.org/10.5751/ES-15646-300129

32. Rudel, T. K. (1998). Is there a forest transition? Deforestation, reforestation, and development. *Rural Sociology, 63*(4), 533-552. https://doi.org/10.1111/j.1549-0831.1998.tb00691.x

33. Rudel, T. K., Coomes, O. T., Moran, E., Achard, F., Angelsen, A., Xu, J., & Lambin, E. (2005). Forest transitions: Towards a global understanding of land use change. *Global Environmental Change, 15*(1), 23-31. https://doi.org/10.1016/j.gloenvcha.2004.11.001

34. Ryan, S. J., Palace, M., Hartter, J., Diem, J. E., Chapman, C. A., & Southworth, J. (2014). Population pressure and global markets drive a decade of forest cover change in Africa's Albertine Rift. *arXiv*. https://doi.org/10.48550/ARXIV.1409.7280

35. Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M. J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T. A., & Reyer, C. P. O. (2017). Forest disturbances under climate change. *Nature Climate Change, 7*(6), 395-402. Retrieved from https://www.nature.com/articles/nclimate3303

36. Selim, M. M. (2020). Introduction to the integrated nutrient management strategies and their contribution to yield and soil properties. *International Journal of Agronomy*. https://doi.org/10.1155/2020/2821678

37. Tang, C., Long, Y., Tang, Y., & Mao, Y. (2025). Impact of economic growth and agricultural expansion on forest cover in ASEAN: New evidence for forest transition theory. *Forest Policy and Economics, 178,* Article 103576. https://doi.org/10.1016/j.forpol.2025.103576

38. Tilahun, D., Gashu, K., & Shiferaw, G. T. (2022). Effects of agricultural land and urban expansion on peri-urban forest degradation and implications on sustainable environmental management in Southern Ethiopia. *Sustainability, 14*(24). https://doi.org/10.3390/su142416527

39. Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences, 108*(50), 20260-20264. https://doi.org/10.1073/pnas.1116437108

40. Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications, 12*(1), Article 2501. https://doi.org/10.1038/s41467-021-22702-2

41. Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

42. Yuh, Y. G., Tracz, W., Matthews, H. D., & Turner, S. E. (2023). Application of machine learning approaches for land cover monitoring in northern Cameroon. *Ecological Informatics, 74,* Article 101955. https://doi.org/10.1016/j.ecoinf.2022.101955

43. Zhao, B., Wang, S., Dong, X., Wang, J., Duan, L., Fu, X., Hao, J., & Fu, J. (2013). Environmental effects of the recent emission changes in China: Implications for particulate matter pollution and soil acidification. *Environmental Research Letters, 8*(2), Article 024031. https://doi.org/10.1088/1748-9326/8/2/024031

http://dx.doi.org/10.21511/ee.17(2).2026.02