Machine Learning to Analyze the Social-Ecological Impacts of Natural Resource Policy: Insights from Community Forest Management in the Indian Himalaya

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ABSTRACT

Machine learning promises to advance analysis of the social and ecological impacts of forest and other natural resource policies around the world. However, realizing this promise requires addressing a number of challenges characteristic of the forest sector. Forests are complex social-ecological systems (SESs) with myriad interactions and feedbacks potentially linked to policy impacts. This complexity makes it hard for machine learning methods to distinguish between significant causal relationships and random fluctuations due to noise. In this context, SES frameworks together with quasi-experimental impact evaluation approaches can facilitate the use of machine learning in forest policy and practice by providing guidance on the choice of variables while reducing bias in estimated effects. Here we combine an SES framework, optimal matching, and the Causal Tree machine learning algorithm to examine causal impacts of two community forest management policies (forest cooperatives and joint state-community partnerships) in Indian Himalaya. We find that joint forest management led to moderate vegetation growth, whereas cooperative forest management with similar biophysical and climatic factors led to improved growth while safeguarding grazing-based livelihoods. Stronger local institutions and secure tenure under cooperative management explain the difference. Our results show how a new direction for impact evaluation can be explored by using machine learning–based approaches to improve knowledge and policy relating to forest and other natural resource governance challenges.

Keywords: community forest management, forest livelihoods, machine learning, impact evaluation

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1. INTRODUCTION

Community-based forest management relies on the involvement of local communities in resource governance to improve social and ecological outcomes. National and international funding organizations spend millions of dollars every year to promote community participation in forest management [1,2]. Such initiatives include formation of local community institutions and downward transfer of forest resource tenure to enhance and protect forest resources [3–5]. Evidence of the success of such community-based interventions is mixed and highly heterogeneous [3,4,6]. Understanding how forest management policies perform, and which social and ecological contexts are more conducive for the success of these policies over the long term is critical to enhancing their effectiveness [7]. Recent machine learning–based approaches are especially promising for building such knowledge.

Machine learning methods rely on data to understand patterns and, therefore, have higher flexibility in their functional forms than typical econometric models. Such flexibility may help discover complex patterns and structures in the policy data that were not specified in the beginning [8–10]. Second, machine learning may enable translation of satellite data to social and ecological outcome measures by extracting and scaling meaningful signals to a broader study area based on a few sample locations. This capability of machine learning is of immense value for policy evaluation in areas where reliable data on social and economic indicators are limited [11,12]. Third, machine learning methods may help generate robust causal evidence on factors of interest and desired outcomes by complementing identification strategies adopted in econometrics [13–16].

So far, however, machine learning has had limited scope in forest policy and practice due in large part to limited sets of data observations, complexity of the social-ecological contexts, and reliance on data to predict patterns of interest rather than suggesting causal relationships. Contemporary forest programs often do not yield "big data" and lack granular-level data on features and related outcomes, restricting the utility of data-driven, machine learning prediction methods [17]. Furthermore, complex social-ecological systems (SESs) where forest programs are implemented present challenges in adequately capturing relevant interactions and feedbacks among social and ecological variables linked with the policy outcome [18–20]. The failure to capture full data variability linked to forest policies makes it difficult for machine learning algorithms to distinguish between significant patterns and random fluctuations due to correlated noise. Finally, the focus of machine learning is largely on data-driven prediction rather than on estimating causal impacts of natural resource policies as common in impact evaluation research [21–23].

Despite these challenges, we argue that integrating machine learning approaches with SES theories and econometric methods offers great potential to leverage data to evaluate the impacts of natural resource policies. In this study, we demonstrate the promise of such integration by analyzing the social-ecological impacts of different community forest management regimes in the Indian Himalaya. A recently developed decision-tree algorithm, Causal Tree (CT), provides opportunities for estimating heterogeneity in causal effects of policies [24]. We combine the CT algorithm, an SES framework (SES), and optimal matching to decipher the heterogeneous causal impacts and the associated social and biophysical variables and contexts that are more conducive to positive ecological outcomes of community forest management. Our findings are based on the evaluation of two community forest management regimes: cooperative forest management (CFM) and joint forest management (JFM) in Kangra District, Himachal Pradesh, India.

2. DATA AND METHODS

We use the Causal Tree estimator coupled with optimal matching to evaluate heterogeneous causal impacts of CFM and JFM regimes. The research findings are based on a study of 202 Forest Management Regions (FMRs) for a period of 14 years (2002 to 2016) in Kangra District (figure 1). For this study, the treatment group includes all FMRs that were under CFM and JFM between 2002 and 2006. The treatment group for CFM consists of 15 FMRs where CFM was implemented. In the case of JFM, the treatment group consists of 38 FMRs where JFM was implemented.

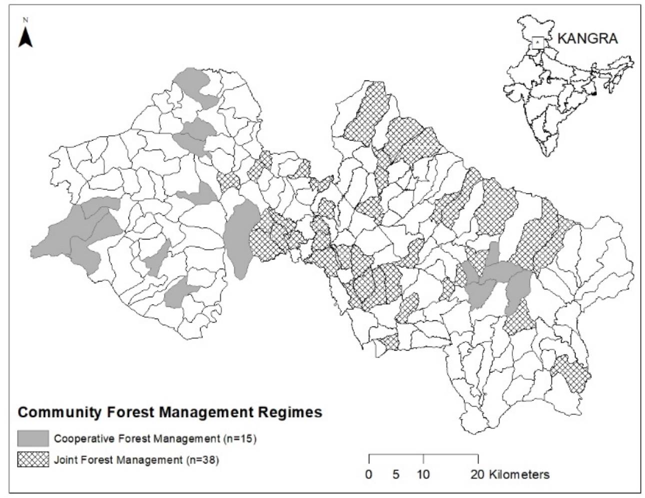


Figure 1. Community forest management regimes in the study area.

CFM, in this case known as Kangra Forest Cooperative Societies Scheme, was launched by the state government in several FMRs during the 1940s and 1950s to promote sustainable forest management by preventing deforestation and soil erosion [25–27]. A forest cooperative society, registered as a co-proprietary body of village landowners, was formed in each village covered under the scheme. The state government gave secure property rights to cooperatives for several forests in each FMR, and members of the cooperatives received a certain percentage of the revenue from these forests as a share of the profits from sale of forest products [25]. Government support for these cooperatives dwindled after 1973, but they continue to exist and derive minor income from sale of fodder, cooperative assets (buildings, schools, meeting halls, etc.), and fines imposed on locals for forest-related offenses.

JFM (a Forest Development Agency program funded by the national government) was the flagship community participatory initiative for forests in India starting in the 1990s [28–30]. In the early 2000s, the state government started JFM interventions in several of our study FMRs to involve communities in forest regeneration and protection mainly to attract donor funding in forest management. The focus of this program was to encourage local communities in afforestation programs to enhance green cover and to meet local livelihood needs. Communities were organized in the form of JFM committees (with a member from each village household) to raise and protect plantations on public lands [26,28,30,31]. However, such committees did not receive any secure forest property rights or revenue from their forests and instead received wages for plantation works only during the limited program period (approx. 5 years)[25].

We expect CFM regimes to improve long-term ecological outcomes at the FMR level through collective action due to the strong institutional tenure of forest cooperatives. Members of forest cooperatives formed under CFM may supply labor, resources, and information to other members and forest officials, and may lead the way to sustainable use of forest resources through mutual monitoring and enforcement of rules [32,33]. On the other hand, due to the transient nature of village institutions and absence of secure forest tenure over forests in JFM, we expect those interventions to have a lower favorable impact on long-term ecological outcomes than CFM schemes.

The outcomes of these two management regimes are measured using the NDVI (Normalized Difference Vegetation Index), a proxy for vegetation growth [34]. We calculated NDVI as an average value of NDVI (mean, annual) for FMRs for the period between 2011 and 2016. We expect a temporal lag of 5 to 9 years between the start of community-based forest management regimes (CFM and JFM) and their outcomes in the form of improved vegetation growth. Planted seedlings or protected natural regenerated areas need more than five years to make substantial improvement in NDVI values (higher values suggest tree cover[1]); therefore, the ability of CFM or JFM institutions to influence long-term vegetation growth will depend on how well they monitor and protect such areas and other forests over a longer period of time (e.g. 5–9 or more years).

We used a four-step approach to evaluate the heterogeneous causal effects of CFM and JFM:

Step 1: Identify SES variables relevant to ecological outcomes under study (tables 1 and S1) based on prior scholarship on SES frameworks as suggested in common property research.
Step 2: Identify theoretically grounded indicators for the variables (tables 1 and S1) based on secondary data from publicly available secondary social and spatial datasets.
Step 3: Use optimal matching to construct matched treated and control groups for use in the Causal Tree estimator to reduce the risk of bias of possible confoundedness due to the observational nature of the study.
Step 4: Use indicators in the Causal Tree algorithm to estimate heterogeneous impacts and suggest plausible causal pathways

Table 1. Social-ecological system variables related to long-term ecological outcomes (Normalized Difference Vegetation Index, mean annual) in forest management regions (FMRs) in Kangra, Himachal Pradesh, India.

Variable	**Indicators**	**All FMRs (n = 202)**	**CFM FMRs (n = 15)**	**JFM FMRs (n = 38)**
Sub-system 1: Actors				
1. Users	Number of households	1080	1987	764
	Number of villages	13	16	9
	Number of cultivators	317	469	239
	Number of marginal people	1067	2175	765
2. Socioeconomic conditions	Number of literate people	3685	6930	2560
	Number of unemployed people	1011	1537	823
	Economic activity (1–63, values)	5.05	7.15	3.62
	Road density (km/km^2)	1.11	1.12	0.95
3. Importance of resource	Number of smallholdings	921	785	1083
Sub-system 2: Governance				
4. State afforestation programs	Area planted (ha)	80.48	6.45	5.09
	Broadleaf sp. planted (%)	38.36	42.76	38.14
	Number of nurseries	0.27	0.33	0.37
Sub-systems 3 &4: Resource Units and Resource System				
5. Mobile animals	Number of grazing animals	4970	5528	5358
6. Size of resource system	Forest beat area (ha)	1756.14	2487.08	1742.02

[1] FMRs in our study area usually do not have very high NDVI values, so we do not expect NDVI saturation to be an issue for the analysis.

		Tree cover (ha)	1037.7	1014.58	1100.83
		Crop acreage (ha)	41.44	58.56	34.66
		Grass acreage (ha)	16.47	11.85	17.83
		Bare land acreage (ha)	0.97	0.06	1.9
7.	System productivity	Soil depth (cm)	95.1	100	88.16
		Total carbon (Kg C m-2)	7.58	6.87	7.92
		Total organic carbon (% weight)	1.36	1.16	1.48
		Available soil water capacity (mm)	99.58	123.33	80.92
		Baseline vegetation/NDVI (-1 to 1)	0.5	0.49	0.5
8.	Location	Altitude (m)	874.79	658.79	1099.6
Interactions (I)					
9.	Conflict among users	Number of forest fires	1.96	0.24	0.1
Outcomes (O)					
10.	Ecological performance	NDVI (-1 to 1)	0.5	0.51	0.53
Related ecosystems (ECO)					
11.	Climatic factors	Temperature (degree Celsius)	18.26	19.68	16.15
		Precipitation (mm)	77.09	78	76.65
		Land surface temperature (Kelvin)	297.05	29.8	29.6

Note: All values are averages for the full study period (2002–2016); CFM, cooperative forest management; JFM, joint forest management. Further details on these variables and their sources can be found in the supplementary Information, table S1.

2.1. CAUSAL TREE ESTIMATOR

Causal Tree is a decision tree–based approach derived from machine learning methods to recursively partition units under study into smaller groups so as identify heterogeneous treatment effects [24]. The method builds on CART (Classification and Regression Trees) with the difference that Causal Tree focuses on estimating conditional average treatment effects rather than predicting outcomes. In an 'honest' approach [24], the algorithm does not use the same information for selection of the model structure as for estimation given this model structure. It does so by splitting the sample into two parts, one part for constructing the tree (including the cross-validation) and a second part for estimating treatment effects within leaves of the tree. The honest approach is used to guarantee consistency or asymptotic (large sample) normality of predictions [24].

Causal Tree is based on the assumption that assignment to the treatment (CFM or JFM) is randomized. In the case of observational studies, this assumption is hard to fulfill, as treated FMRs have not been randomly assigned to CFM or JFM interventions. For this analysis, we use optimal matching to create treatment and control groups to remove bias from simple comparisons of treated and control units, and then use the matched treated and control groups in a Causal Tree algorithm (in R) to calculate the heterogeneous causal effects of CFM and JFM interventions.

The tuning parameter for the causal tree function is to have a minimum number of treated and control observations per leaf to calculate treatment effect within each leaf. In the splitting function, there is a restriction on the set of potential split points. Later in the splitting process, the covariate values within each leaf and each treatment group are rescaled to ensure that the same number of treatment and control observations are moved from the right leaf to the left leaf when moving from one potential split point to the next. The causal function uses a minimum of five cross-validation samples as another tuning parameter to produce the best-fitted predictive model of heterogeneous treatment effects [24].

Causal Tree specification in this study uses an honest Causal Tree (CT) splitting rule with fit as cross-validation method. We used 5-fold cross-validation with a discrete splitting option. The treatment probability is set as propensity = 0.5 for the CT splitting rule. Complexity parameter (cp) and normalized cross-validation error for CFM and JFM are given in Supplementary Information (see table S2). For the tree selection, a complexity parameter corresponding to the minimum cross-validation error is chosen. Thereafter, the prune () function is used to trim the selected tree by removing the branches that make use of features with low importance. The pruning is done to increase the predictive performance of the tree by reducing overfitting. The resultant tree is then used to understand the heterogeneous treatment effects of management regimes under study [35].

2.2. OPTIMAL MATCHING

This study uses optimal matching to create a matched control group for the treated FMRs for use in the causal tree algorithm [36, 37]. This matching-based identification strategy is a quasi-experimental methodology to evaluate various programs and policies [36, 38, 39]. Here we use a number of background covariates for matching treated (with community-based management) and control groups (without community-based management) to obtain a counterfactual for the treated FMRs under intervention. The counterfactual (or control group) for the treated FMRs (with CFM or JFM) is created based on matching observable variables related to the assignment of intervention or vegetation outcome so as to reduce selection bias due to confoundedness. Optimal matching creates matched control groups for FMRs under CFM and JFM interventions from the available control donor pool of FMRs in Kangra District. For a treated group of 15 FMRs, optimal matching creates a control group of 75 FMRs out of 187 available control FMRs (out of the 202 total FMRs). In the case of JFM, for a treated group of 38 FMRs, optimal matching creates a control group of 152 FMRs out of 164 available control FMRs (out of 202 FMRs). The covariate balance is given in the Supplementary Information (< 0.25 standardized t diff as threshold; see table S3).

3. RESULTS AND DISCUSSION

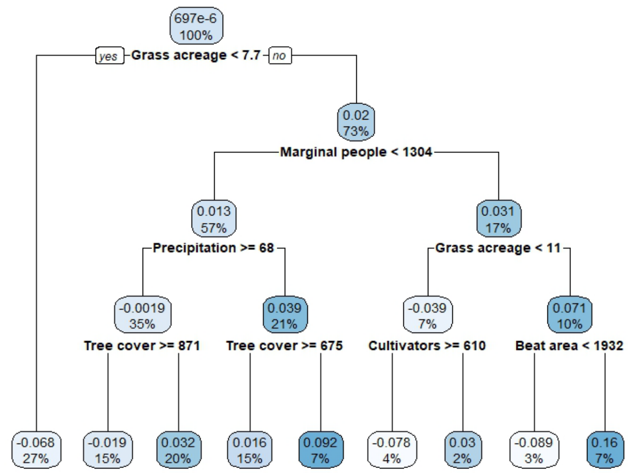
Results show that both CFM and JFM have led to an increase in vegetation growth during the study period (2011-2016). However, their impacts vary depending on the contextual social and ecological factors.

3.1. CAUSAL EFFECTS OF COOPERATIVE FOREST MANAGEMENT

Figure 2(a) and table 2(a) show the heterogeneous causal effects for CFM and the various causal pathways that have led to positive average treatment effects of the policy on long-term vegetation growth. Complexity parameters and cross-validation relative error for CFM are given in table S2 (a) and figure S1). We selected a Causal Tree with complexity parameter corresponding to minimum cross-validation error in order to maximizing predictive power without “overfitting” (size of tree = 15) [24].

Under CFM, forest cooperatives have durable tenure over their forests. Secure tenure is expected to improve local livelihoods due to improved access to biomass (e.g. for energy needs) and lower cost of sustainable forest management due to higher local participation in the protection and management of forests [40–42]. Moreover, durability of institutional tenure has been shown to be positively related to improved forest condition [43].

a. Causal Tree: Cooperative forest management (CFM)



b. Causal Tree: Joint forest management (JFM)

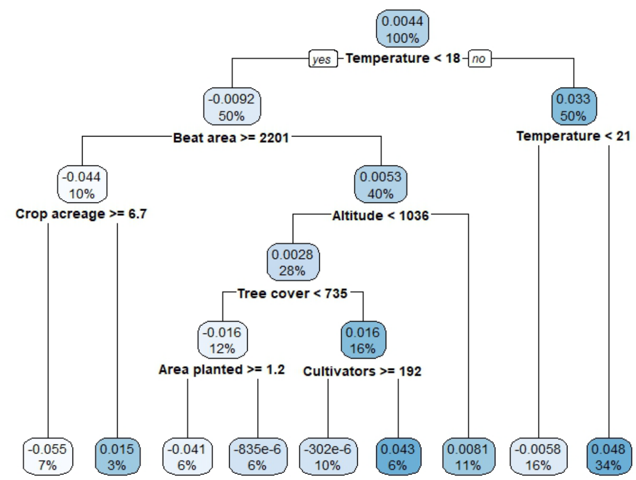


Figure 2. Causal Tree: heterogeneous causal impacts.

Our results confirm these prior findings and show that the impact of secure tenure is conditional on local social and ecological contextual factors (table 2(a)). CFM leads to a positive impact on vegetation growth in the medium to long term (5 to 9 years after intervention), especially when members of the cooperatives have greater access to grazing areas (> 7.7 ha, first causal pathway, 18th to 100th percentile). These grazing areas provide community institutions with a regular source of income through grass auctions and provide grazing resources to support local livestock-based livelihoods. This result shows the criticality of protecting alternative livelihoods while striving for improved vegetation cover, even when local institutions have secure tenure over their forests.

Table 2. Heterogeneous causal impacts of cooperative forest management (CFM) policy on NDVI.

Causal pathways	Predictor I	Predictor II	Predictor III	Predictor IV	Conditional average treatment effects
a. Conditions associated with positive impacts					
I	Grass acreage (>= 7.7 ha)[a]				0.02
II	Grass acreage (>= 7.7 ha)	Number of marginal people [2] >= 1304[b]			0.03
III	Grass acreage (>= 7.7 ha)	Number of marginal people >= 1304	Grass acreage (>= 11 ha)		0.07
IV	Grass acreage (>= 7.7 ha)	Number of marginal people >= 1304	Grass acreage (>= 11 ha)	Forest beat area >= 1932 ha[c]	0.16
b. Conditions associated with negative impacts					
I	Grass acreage (< 7.7 ha)				-0.07
II	Grass acreage (< 11 ha)	Number of cultivators >= 610[d]			-0.08

[a] Value of 7.7 ha is 17th percentile on the total distribution of grass acreage in the study area (202 FMRs).
[b] Value of 1304 is 74th percentile on the total distribution of marginal population in the study area.
[c] Value of 1932 ha is 71th percentile on the total distribution of areas of forest beats in the study area.
[d] Value of 610 is 87th percentile on the total distribution of number of cultivators (farmers) in the study area.
Note: Predictors I, II, III, IV are ranked as per their importance in achieving the best performance predictive CT algorithm (with minimum cross-validation error and optimal level of complexity).

We find that CFM policy led to a favorable long-term ecological outcome even in the presence of a higher number of marginal people in FMRs (causal pathways II–IV, 74th to 100th percentile). Marginalized populations are expected to have higher forest dependence due to their heavy reliance on local forest resources for subsistence needs such as grazing and collection of fuelwood, fodder, and small timber. However, CFM policies appear to moderate such forest dependence, leading to positive long-term vegetation growth as found in other studies in the region [25–27].

Finally, we find that the ecological performance of CFMs was much better in the context of FMRs with larger grass acreage, a marginalized population, and larger overall area (71st to 100th percentile) (causal pathway IV). This finding is likely due to better availability of resources with increased FMR size, which may help distribute pressure of the local users on the forests.

Several contextual social and ecological factors were not conducive to CFM success (table 2(b)). Despite the presence of strong forest tenure, low availability of grazing lands in the FMRs (1st to 17th percentile) can reverse the positive effects of tenure over long-term social and ecological outcome trajectories. This result indicates that local participation in forest improvement and protection efforts is unlikely in the absence of sufficient grazing lands. This unfavorable impact of CFM on vegetation growth further intensifies with the increase in number of cultivators (farmers). Higher numbers of cultivators likely means greater dependence on forests for subsistence needs and, in turn, increased pressures on forests resulting in decreased vegetation growth [32,44].

3.2. CAUSAL EFFECTS OF JOINT FOREST MANAGEMENT

Table 3 shows the causal impacts of JFM using Causal Tree. Causal Tree with a complexity parameter corresponding to minimum cross-validation error is chosen for analysis to maximize the predictive power of the tree and to avoid “overfitting” (size of tree = 9) (table S2(b) and figure S2) [24].

JFM policy also led to favorable long-term vegetation growth, but the magnitude of impact on ecological outcomes is lower than with CFM. Moreover, the social and ecological contexts that are conducive to long-term vegetation growth are different from those of CFM. JFM policy resulted in favorable vegetation growth in FMRs having high temperatures (47th to 100th percentile) (table 3(a)). The reason for this finding is that JFM targeted mainly the higher temperature low hills and plains of the study region to maximize the likelihood of the success of desired forest plantation species such as teak (*Tectona grandis*), bamboo (*Dendrocalamus strictus*), khair (*Acacia catechu*), and shisham (*Dalbergia* sp.).

[2] Number of marginal people represents individuals belonging to the Scheduled Caste category. This official category is designated by the government as historically disadvantaged and socially and economically marginal for affirmative action.

Different social and ecological contexts were conducive to the higher level of growth found in JFM in higher temperature areas. For example, JFM implemented in medium-sized FMRs situated at low to moderate elevations with high baseline tree cover were more likely to experience favorable vegetation growth (figure 3(a)). This may be because of good soil depth and more acreage for extending vegetation cover. Regions with higher baseline tree cover indicate more monitoring and supervision from forest agencies that further help vegetation growth in these areas. Previous vegetation cover may also positively influence vegetation growth [44].

We found two main causal pathways where JFM policies had negative impacts on long-term vegetation growth (table 3(b)). JFM did not perform well in FMRs that experienced low temperatures even when these regions were large. This finding suggests failure of JFM strategies to trigger vegetation growth in colder mountainous areas where local and migratory grazing is common—often resulting in loss of vegetation [45]. Even regions with more area under crops experienced loss of vegetation, which shows the inability of the JFM regime to manage agriculture-related dependence on the forests.

Table 3. Heterogeneous causal impacts of joint forest management (JFM) policy on NDVI.

Causal pathway	Predictor I	Predictor II	Predictor III	Predictor IV	Conditional average treatment effects
a. Conditions associated with positive impacts					
I	Temp >= 18 °C				0.03
II	Temp < 18 °C	Forest beat area < 2201 ha			0.005
III	Temp < 18 °C	Forest beat area < 2201 ha	Altitude < 1036 m		0.003
IV	Temp < 18 °C	Forest beat area < 2201 ha	Altitude < 1036 m	Tree cover >= 735 ha	0.02
b. Conditions associated with negative impacts					
I	Temp < 18 °C				-0.009
II	Temp < 18 °C	Forest beat area >= 2201 ha			-0.04
III	Temp < 18 °C	Forest beat area >= 2201 ha	Crop acreage >= 6.7 ha[e]		-0.06

[a] Value of 18 °C is 47th Percentile on the total distribution of temperature in the study area (202 FMRs)

[b] Value of 2201 is 76th Percentile on the total distribution of areas of forest beats in the study area

[c] Value of 1036 m is 80th Percentile on the total distribution of elevation values in the study area

[d] Value of 735 ha is 33th Percentile on the total distribution of tree cover acreage in the study area

[e] Value of 6.7 ha is 6th Percentile on the total distribution of crop acreage in the study area

Note: Predictors I, II, III, IV are ranked as per their importance in achieving the best performance predictive CT algorithm (with minimum cross-validation error and optimal level of complexity)

4. CONCLUSION

The Causal Tree algorithm has the potential to evaluate the causal impacts of forest policies and to suggest contextual factors that are conducive to the success of these policies in achieving improved social and ecological outcomes. Our results indicate that both CFM and JFM have led to favorable long-term vegetation growth but this effect is heterogeneous and varied in direction and magnitude based on contextual factors.

CFM and JFM followed different pathways to achieve long-term vegetation growth. CFM, due to its more robust institutions coupled with secure forest tenure, appears to follow a socially beneficial path to achieve higher vegetation growth. Such positive ecological change has occurred without harming existing livestock-based livelihoods, as causal pathways to such growth include a minimum acreage under grass in the FMRs. The continuation of strong incentives to maintain forests, including sale of grass from the protected forestlands, has helped local community institutions to mobilize people to protect them. By contrast, biophysical attributes of FMRs were the dominant contextual factors facilitating positive policy impacts on vegetation growth. Moreover, JFM had a lower magnitude of impact on ecological outcomes than CFM.

Our findings support previous research [19,46,47] showing that the strength and durability of community institutions and tenure are key predictors in explaining long-term social and ecological outcomes. Understanding how contextual differences shape the outcome trajectories of forest policies through machine learning–based approaches can inform policy makers and practitioners to design targeted and effective policy interventions in the field of forest conservation and management. For example, future community-based plantation programs in the Indian Himalaya would do well to provide alternative grazing options to forest communities and facilitate secure rights over forests to foster positive long-term vegetation growth trajectories.

To the best of our knowledge, this study is the first application of machine learning in impact evaluation research in the context of natural resource governance. Our experience underscores the need for future applications of machine learning algorithms in this field to carefully consider the data-generating process, use social and economic theories to guide the choice of variables and regularization or tuning parameters, and to clearly list all the factors to increase credibility of the chosen algorithm. Machine learning may also be more useful in cases where the prime objective is to test the predictability and performance of the impacts of forest policies based on certain social and economic theories. The Causal Tree algorithm, as shown in this work, demonstrates significant potential to extend machine learning capabilities in econometric studies within the broad field of environmental and natural resource policy.

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