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ORIGINAL ARTICLE

Interventions to control forest loss in a swidden cultivation landscape in Nan Province, Thailand

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Abstract

In tropical forest regions, swidden cultivation landscapes are experiencing land use transitions due to factors such as the introduction of cash crops, land tenure conflicts, and land use zoning for conservation. In northern Thailand, Nan Province, the introduction of maize as a cash crop in a landscape previously dominated by swidden cultivation has caused rapid forest loss. In the past decade, several land use interventions by government and non-government organizations were aimed at reducing forest loss and sustaining livelihoods of local communities. We analyzed how much of the recent forest loss was caused by new forest conversion *versus* a transition from swidden to permanent cultivation, and how effective are the recent land use interventions at conserving forests. We used classified Landsat images from 2000 to 2019 to understand land cover transitions and a matching technique based on the synthetic control method to evaluate the impact of project interventions on forest loss. We found that 20% of the land cover has undergone changes of which 41% were due to loss of forest, and 31% to swidden cultivation. Out of 55 villages with a land use intervention, only 3 have reduced forest loss as compared to their synthetic controls. Most of the villages with an intervention have similar rates of forest loss than their synthetic controls. Therefore, current land use projects have not yet contributed towards reduction in forest loss. Interviews with project leaders reveal that long-term funding, cooperation with local communities, and training and support of farmers to market new crops are key for successful interventions.

Keywords Swidden cultivation · Synthetic control · Forest loss · Remote sensing · And Cash crop

Introduction

Swidden cultivation—also referred to as shifting or slash-and-burn cultivation—is still a widely practiced form of agriculture in Latin America, Africa, and Southeast Asia (Heinimann et al. 2017). In this traditional agricultural practice, farmers clear forest plots mostly using slash-and-burn methods to cultivate them for about 1–3 years and then leaving them fallow for 5 to 20 years (Mertz et al. 2009). Swidden cultivation is widely thought to better maintain biodiversity, conserve soil and water, and maintain carbon storage compared to intensive agriculture (Bruun et al. 2009; Padoch and Pinedo-Vasquez 2010). Yet, a common narrative by governments is that swidden cultivation practices are primitive and harmful to the environment given the repeated forest clearing and its large land requirement (Fox et al. 2009). Therefore, governments and non-governmental organizations are constantly attempting to mitigate perceived problems related to swidden cultivation by promoting forest conservation using landscape zoning and agricultural intensification of cash crops, especially in Southeast Asian countries. For example, maize cultivation expanded in Laos, Vietnam, and Thailand (Vongvisouk et al. 2014; Yap et al. 2017; Belton and Fang 2022; Feng et al. 2021).

Swidden cultivation landscapes are complex, dynamic, and difficult to monitor (Kurien et al. 2019; Schmidt-Vogt et al. 2009). The global assessment by Van Vliet et al. (2012) found that the area under swidden cultivation increased or was stable in Central Africa, Madagascar, and Latin America, whereas it decreased in Southeast Asian countries. Various reasons may cause a transition out of swidden cultivation, such as the introduction of cash crops, land shortage due to population

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growth or encroachment of other land uses, changes in land tenure, or land use zoning for conservation (Van Vliet et al. 2012; Bruggeman et al. 2016). To be more resilient to market shocks, rural communities are adopting dual or composite economies, by mixing swidden cultivation and cash crop incomes (Mertz et al. 2013). Swidden cultivation is for subsistence while cash crop generates extra income to fulfill new lifestyle demands (Vongvisouk et al. 2014). The introduction of cash crops and monocultures of tree plantations may prevent the regrowth of natural forests, increase rates of deforestation, and shorten fallow periods (He et al. 2023).

Various land use interventions are aimed at reducing forest loss caused by cash crops expansion by promoting a sustainable intensification of agriculture and tree plantation (Furumo and Lambin 2021). However, it is difficult to estimate the effectiveness of such interventions at reducing forest loss given challenges related to both detection and attribution. Firstly, net forest loss is challenging to measure in swidden cultivation landscapes as additional forest clearing due to changes in cropping patterns is difficult to distinguish from the clearing of old fallows as part of the normal cultivation cycle (Chen et al. 2023). Secondly, it is challenging to attribute a change in forest loss to a specific land use intervention when it has been implemented at a local scale concomitantly with other policy and macro-economic changes that affect forest cover at a regional scale. Impact evaluation methods require a rigorous counterfactual to compare what actually happened with what would have happened in the absence of the intervention (Sills et al. 2015). Only then a causal relationship can be established, to directly attribute changes in outcome to a specific intervention. Studies have evaluated various interventions such as voluntary REDD + project in Brazilian Amazon forests and found an overestimation of reduced deforestation by using the quasi-experimental synthetic control method (Sharma et al. 2023). The same method has been used to estimate the impact of a Brazilian government program based on a blacklisting of municipalities with high deforestation rates (Damm et al. 2022; Sills et al. 2015).

Mountainous regions of Southeast Asia have faced major forest losses and agricultural field expansion in the last few decades. In Northern Thailand and Laos, maize has become one of the major cash crops and main reasons for forest loss in hilly landscapes (Vongvisouk et al. 2014; Yap et al. 2017). In this study, we analyzed land use transitions in Nan Province, Thailand, a landscape dominated by swidden cultivation where forest loss has been a major concern following a rapid transition to permanent maize cultivation as a monoculture. Nan is the second largest maize production province in Northern Thailand (Pongkijvorasin and Teerasuwannajak 2015).

This study addresses two issues. Firstly, there is a difference in understanding of the concept of forest loss between local communities in Nan Province and public authorities. During our initial field visits, local communities repeatedly stated that the transition away from swidden cultivation resulted in a shortening of the fallow cycle and therefore in a reduction in secondary forest areas rather than in new forest loss. Our first objective was to better characterize the nature of recent land use transitions in the province to evaluate the relative importance of net forest loss versus a shortening of the fallow cycle. We used remote sensing to understand the cycle of swidden cultivation based on a time series of Landsat images. Secondly, during our initial field visits, we identified several land use interventions by various state and non-state actors in Nan Province that were aimed at mitigating forest loss by promoting sustainable agricultural intensification and tree plantation. However, the effectiveness of these interventions is unknown. Our second objective was to evaluate the effectiveness of these various interventions in Nan Province. We developed a rigorous counterfactual for each land use intervention using the synthetic control method.

Study area

Nan Province is situated in Northern Thailand, along the border with Laos (Fig. 1a). The landscape is mountainous, with elevation ranging from 200 to 2300 m. The central part of Nan is a valley, referred to as lowlands, i.e. below 400 m, surrounded by undulating hills, referred to as upland, i.e., 400 to 800 m elevation, and highlands referred to as the mountain areas above 800 m (Fig. 1a) (HRDI 2023). The total area of Nan Province is 12,126.1 km^2, of which 15% is in lowlands and 85% in upland and highlands. The province is a major watershed, which supports water systems flowing South to the fertile plains of Thailand, all the way to Bangkok. Approximately 70% of the 893 villages are in lowlands and 30% in uplands and highlands. Nan's population is around 500,000, mostly farmers that used to practice swidden cultivation in uplands, with permanent agricultural fields in lowlands.

Nan has seven national parks. The first national parks were established in 1999 and most of the other ones were created after 2006. All the forests outside national parks are managed by the Royal Forest Department (Agarwal et al. 2022) as National Forests (Fig. 1b). The expansion of protected areas was associated with changes in national forest policy in Thailand. In the 1980s, Thailand forest experienced rapid deforestation and logging due to logging concession allocated to foreign companies, especially in northern Thailand. Subsequently, national forest conservation policies were reinforced. The Royal Forest Department began classifying all forests as protected areas, which greatly affected marginalized ethnic minorities living in mountainous areas, whose livelihoods directly depended on forests (Wong et al. 2007). Cases of forced resettlement were documented (Wong et al. 2007). This recent classification of forest reserves in northern Thailand is

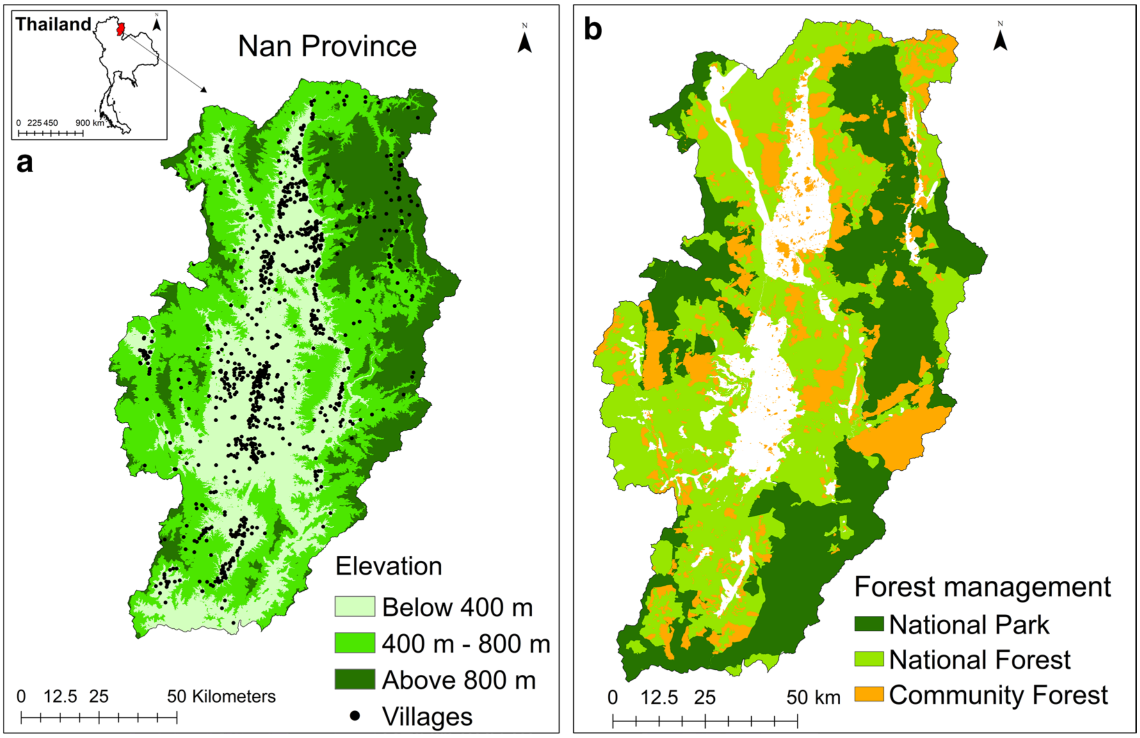

Fig. 1 **a** Study area map showing elevation range of lowlands, uplands, and highlands, as well as village locations of Nan Province; **b** map of National Park, National Forest, and Community Forest patches in Nan Province

still disputed today, especially since their stricter enforcement after the 2014 coup d'état. Similarly in Nan Province, National Parks and National Forests disproportionately cover upland and highland forests. However, the villages were established in and around forests well before the establishment of these parks and have traditionally managed forests through their customary laws and practices. Some of the ethnic groups are Lua, Khamu, Hmong, and Mien (Rossi 2012). Communities living in uplands and highlands still lack clear land tenure status, especially for land under swidden cultivation. This creates land use conflicts with government policies (Rossi 2012). Despite these conflicts, a recent study found 1950 community-managed forest patches in Nan Province that are well-conserved and better protected compared to National Parks and National Forests, highlighting the importance of local community involvement in forest protection (Agarwal et al. 2022). There are three types of community forests. "Watershed forests" are areas with a complete prohibition on logging but villagers are allowed to collect non-timber forest products. "Usable forests" are conserved but community members are allowed to use the forest under community rules. "Ritual forests" are used only for performing rituals according to community's beliefs (Sairorkham and Sakitram 2020).

Farmers in uplands and highlands are moving away from swidden to more permanent cultivation in response to a demand for maize. The expansion of maize was made possible by the micro-credit system, whereby farmers get a loan for maize hybrid seeds and fertilizers without presenting any collateral. Fixed price benefits from the government also supported maize as a cash crop (Ekasingh et al. 2007). However, in subsequent years, fluctuations of market prices of cash crops created a vicious cycle of debt for farmers. Nevertheless, farmers still preferred to grow maize as it is easy to cultivate, harvest, and sell thanks to middlemen and direct access to market (Yap et al. 2017). Moreover, there was often a lack of alternative crops with well-organized supply chains.

This land use transition has had a major impact on forest cover, soil erosion, and water systems downstream. Zeng et al. (2018a) estimated a 10% loss of forest between 2000 and 2017. Bruun et al. (2017) also found that the quality of soil deteriorated due to permanent maize production in uplands and highlands. With increasing attention on Nan's forest conditions, attempts to reduce maize production in Nan were made under the larger narrative of sustainable agricultural practices both by governmental and non-governmental organizations such as the Thai Royal family, local NGOs, corporations, and local communities (Rossi 2012).

Methods

Our method combines remote sensing with field interviews of key actors in Nan Province and econometric analyses.

Remote sensing analyses

To understand the pattern of swidden cultivation and changes in forest cover, we selected cloud-free images from Landsat 5 ETM for 2000, 2005, and 2009 and Landsat 8 OLI/TIRS for 2014 and 2019 with near anniversary dates (ESM Table 5). The selected images were from February and March, the months with the least cloud cover. We selected the year 2000 as the initial time period given limitations on data availability before 2000, as already noted by previous studies (Zeng et al. 2018b; Chen et al. 2023). High-resolution Google Earth images are available for ground reference for land cover after 2000. The other Landsat images were selected at 4-to-5-year intervals because they were the only cloud-free images available at near anniversary dates (Fig. 2).

We selected the blue, green, red, NIR, SWIR 1, and SWIR 2 spectral bands of Landsat 5 and 8. We also computed indices known to identify forest, agriculture, fallow land, plantation, and water: Normalized Difference Vegetation Index (NDVI) (Matsushita et al. 2007), Normalized Difference Moisture Index (NDMI) (Jin and Sader 2005), and Soil Adjusted Vegetation Index (SAVI) (Huete 1988). Slope and aspect were also computed based on the Shuttle Radar Topography Mission (SRTM) DEM data at a 30 m resolution.

Based on Google Earth imagery, representative areas of interests were identified and digitized for each time period. The Random Forest classifier—a highly robust pixel-based supervised classification method—was used to classify forests (i.e., canopy cover greater than 10%), agricultural lands, fallow/open lands (i.e., uncultivated and bare lands), and water body in Google Earth Engine (Agarwal and Nagendra 2020). A tree plantation class was added for the 2014 and 2019 classifications. During the 2019 fieldwork, geolocated ground observations were collected for tree plantations, along with information on the plantation scheme. As tree plantations had expanded in recent years and the improved spectral resolution of the Landsat 8 sensor reduced confusion with other classes, the plantation class was added on the 2014 and 2019 land cover maps.

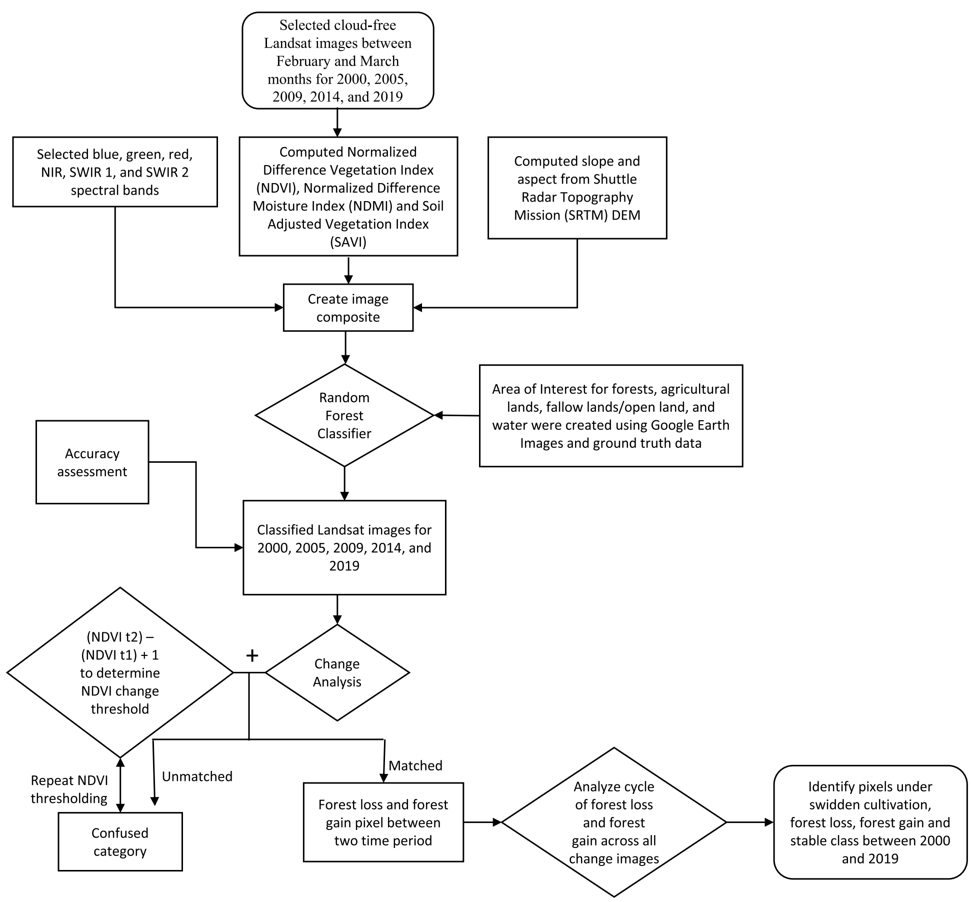

Fig. 2 Flowchart of remote sensing method

Around 350 points were generated randomly for accuracy assessment based on the proportion of land cover under each class in the 2019 classification (Congalton 1991). Approximately 100 points covered forests and fallows and 50 covered agriculture, water, and plantations. Classification accuracy was assessed using Google Earth images of the corresponding time periods.

We used the hybrid change detection method to avoid the propagation of classification errors into the land cover change analysis. With this method, we combined NDVI thresholding with change analysis from classified images to detect forest loss and forest gain. Firstly, NDVI subtraction of two time periods was used to identify areas with vegetation loss and gain, using the formula: (NDVI t_2) – (NDVI t_1) + 1, where t_2 is the later year and t_1 is the earlier year (Singh 1989). The result provides the distribution of change values, from − 1 to 3. The values on either side of the distribution of NDVI difference values, beyond threshold values, represent vegetation loss and gain (ESM Table 6). The above analysis was conducted using the ENVI software. The validity of the threshold values was carefully verified across the landscape using ground truth data and Google Earth images. As we used atmospherically corrected surface reflectance, the thresholding values remained consistent across the landscape.

Secondly, the change pixels identified based on these thresholds were used to mask the classified images from both time periods to identify "from-to" change categories. If the change category from the NDVI difference image and the post-classification comparison were in agreement, then the change pixels were identified under this change category. If the two change maps produced divergent results, then the pixels were kept under a "confused" change category and reanalyzed. Although the number of pixels in the "confused" category was small, we repeated the thresholding process using Google Earth images as reference points.

The pixels under the "confused" category were overlaid on the NDVI images. Their change category was then determined based on their NDVI values, according to the thresholds shown on ESM Table 7, which were derived from areas of known change. Even though the number of pixels in the "confused" category was low, the method decreased the propagation of misclassification errors into change images. The final change image integrating all time periods identifies sequences of change, such as forest loss to forest gain, forest gain to forest loss, and forest loss with land remaining fallow. The method has identified pixels under forest loss (L) and forest gain (G) categories in four change images, i.e., between 2000 and 2005, 2005 and 2009, 2009 and 2014, and 2014 and 2019. The change images were reclassified to contain only forest loss and forest gain classes. In a final step, pixels under the following sequences were identified as swidden cultivation: G-G-L-G, G-G-L-L, G-L-G-G, G-L-G-L, G-L-L-G, L-G-G-L, L-G-L-G, L-G-L-L, L-L-G-G, and L-L-G-L (Fig. 2).

Field interviews

In the recent decade, various land use interventions were aimed at reducing farmers' dependency on the commercial demand for maize by providing an alternative source of livelihood. We interviewed project leaders of approximately 40 such interventions using the snowball sampling method, of which 13 projects were selected as they were initiated at least 3–4 years before our study and covered one or more villages with large numbers of household participating. Semi-structured interviews were conducted with project and village leaders and were linked to the results of our remote sensing analyses at the village level. Our questions included: when the project started, what was the intervention, how the project was implemented, how many households joined the project, and what was the purpose and motivation behind the initiative. We also asked about funding, marketing strategies, farmers' interests, upscaling of the project to other villages, and challenges of implementing the project. Each interview took around 2 h including translation from Thai to English. We also collected data on village boundaries and overlaid them on our forest cover change maps to measure the impact of the interventions on forest loss.

Interventions were categorized based on the organization that initiated the projects: (1) Royal family, (2) government, (3) NGO, (4) community, (5) corporation.

Synthetic control method

The synthetic control method helps design a comparative study based on a systematic, transparent, and rational selection of comparative units, especially for small sample sizes (Sills et al. 2015). The method compares the occurrence of an intervention on units of interest, called treatment, to similar units without the interventions, called control. The units are compared with the careful selection of counterfactual variables. This includes consideration of the time of intervention as one of the important factors to ensure that the trends were mostly similar between treatment and control units before the intervention. Aggregation of control units in a synthetic control is performed based on the weighted average that best represents or resembles the treatment unit. We used the "synth" package in R version 3.6.2 (Abadie et al. 2011). The method estimates the counterfactual outcome of a treatment (i.e., a project intervention in this case) by constructing a synthetic control based on the weighted combination of comparison units. The method matches the treatment pre-intervention characteristics. The difference between the treatment and synthetic control therefore provides an estimate of the intervention impact.

To identify land use interventions that are effective at slowing forest loss, we examined 13 projects in 55 villages of Nan Province as treatment groups. These projects were chosen because they were initiated at least 3–4 years before 2019 and covered more than one village, with large numbers of household participating (Fig. 3). We also identified 145 villages without any intervention (Fig. 3), as a control group.

The synthetic control method considers prior information available for matching counterfactual variables that minimize differences in pretreatment characteristics between the treatment and control units. As the focus of the study is on the effectiveness of land use interventions in slowing forest loss, we considered counterfactual variables related to land use, such as elevation mean, elevation range, slope mean, aspect mean, population of the village, distance to nearest road, and initial forest areas in the villages (Agarwal et al. 2022). The topographic variables were computed based on the SRTM DEM data at a 30 m resolution. Population data were collected during the interviews. The road data were collected from the GIS department of Hug Mung Nan Foundation, Nan Province. The nearest neighbor method was used to calculate distance to nearest road. Our Landsat image classification of 2000 was used to calculate initial forest area.

The method uses all the non-project villages and matches the counterfactual variable with the project village. An iterative procedure like boot strapping helps minimize the mean squared prediction error. We analyzed the projects based on their starting year, as a greater impact on forest cover is expected for older projects, while recent projects are less likely to already show a detectable impact on forest cover change.

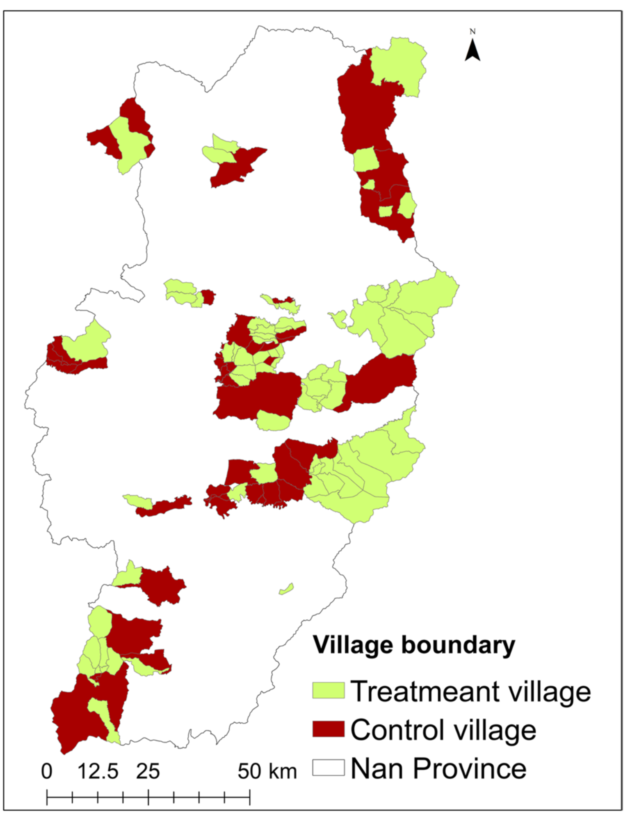

Fig. 3 Map of selected treatment and control villages

Results

Remote sensing analyses

The overall accuracy of individual classifications is greater than 91% for all images (Table 1). Figure 4 shows the successive land cover maps (Fig. 4a–e) and land cover changes (Fig. 4f–i). Clearing of both primary forests and forest fallows as part of swidden cultivation systems are major causes of land cover changes (Fig. 4j). About 80% of the Nan landscape remained unchanged between 2000 and 2019 (Fig. 5a and ESM Table 8), of which more than 80% was forest cover (Fig. 5b and ESM Table 8). Among the remaining 20% land area, most of the changes were due to forest loss (41%) followed by swidden cultivation (31%), while plantations (18%) and forest gain (10%) contributed less to land cover changes (Fig. 5c). The forest loss area has declined between 2014 and

Table 1 Overall accuracy of individual classifications

Year	Class	Producer accuracy	User accuracy	Kappa	Overall accuracy
2000	Forest	99.1	89	85.40	92.60
	Agriculture	85.7	100		
	Fallow land	73.1	96.6		
	Water	93.9	100		
2005	Forest	98.6	88.8	84.10	91.50
	Agriculture	88.2	83.3		
	Fallow land	75.4	100		
	Water	84.3	100		
2009	Forest	98.9	87.7	86.30	91.78
	Agriculture	83.3	88.2		
	Fallow land	82.5	100		
	Water	86	97.7		
2014	Forest	99.3	89.7	89.70	92.91
	Agriculture	76.9	90.9		
	Fallow land	94.5	95.4		
	Water	84.8	100		
	Plantation	77.3	94.4		
2019	Forest	94	90.9	89	91.50
	Agriculture	100	74.5		
	Fallow land	84.4	97.4		
	Water	92.6	100		
	Plantation	90.7	92.5		

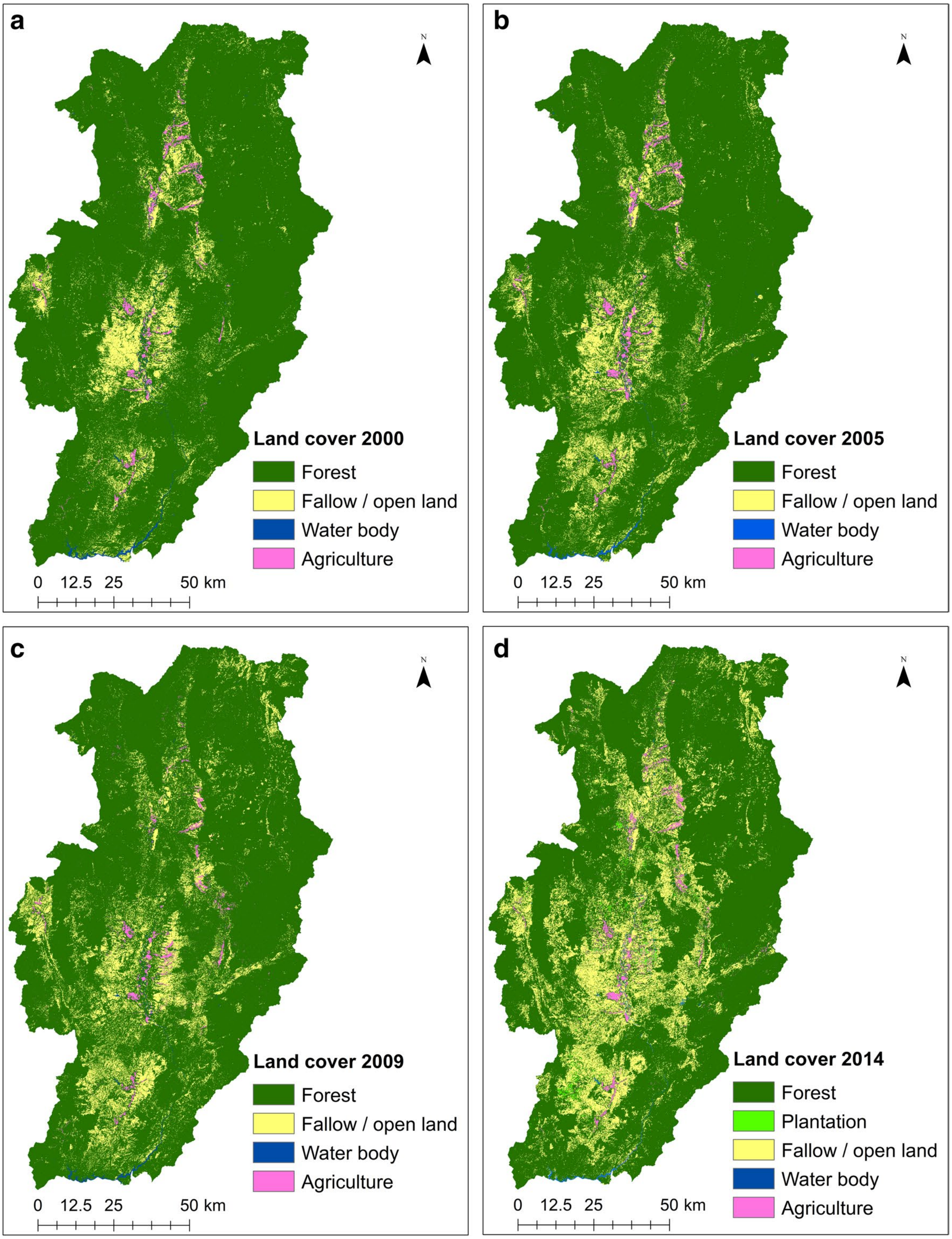

Fig. 4 Land cover classes: **a** 2000, **b** 2005, **c** 2009, **d** 2014, and **e** 2019; forest loss and forest gain between **f** 2000 and 2005, **g** 2000 and 2009, **h** 2009 and 2014, and **i** 2014 and 2019; **j** land cover change classes between 2000 and 2019

2019, with an increase in tree plantations (Fig. 5d and ESM Table 8). On Landsat 5 ETM images from 2000, 2005, and 2009, it was difficult to distinguish tree plantations from forests. Therefore, the tree plantation class was only added for Landsat 8 OLI/TIRS images from 2014 and 2019. The land cover change matrix shows that 1103.15 km^2 and 430.69 km^2 are transitioning between forest and fallow/open land between 2000 and 2019 (Table 2).

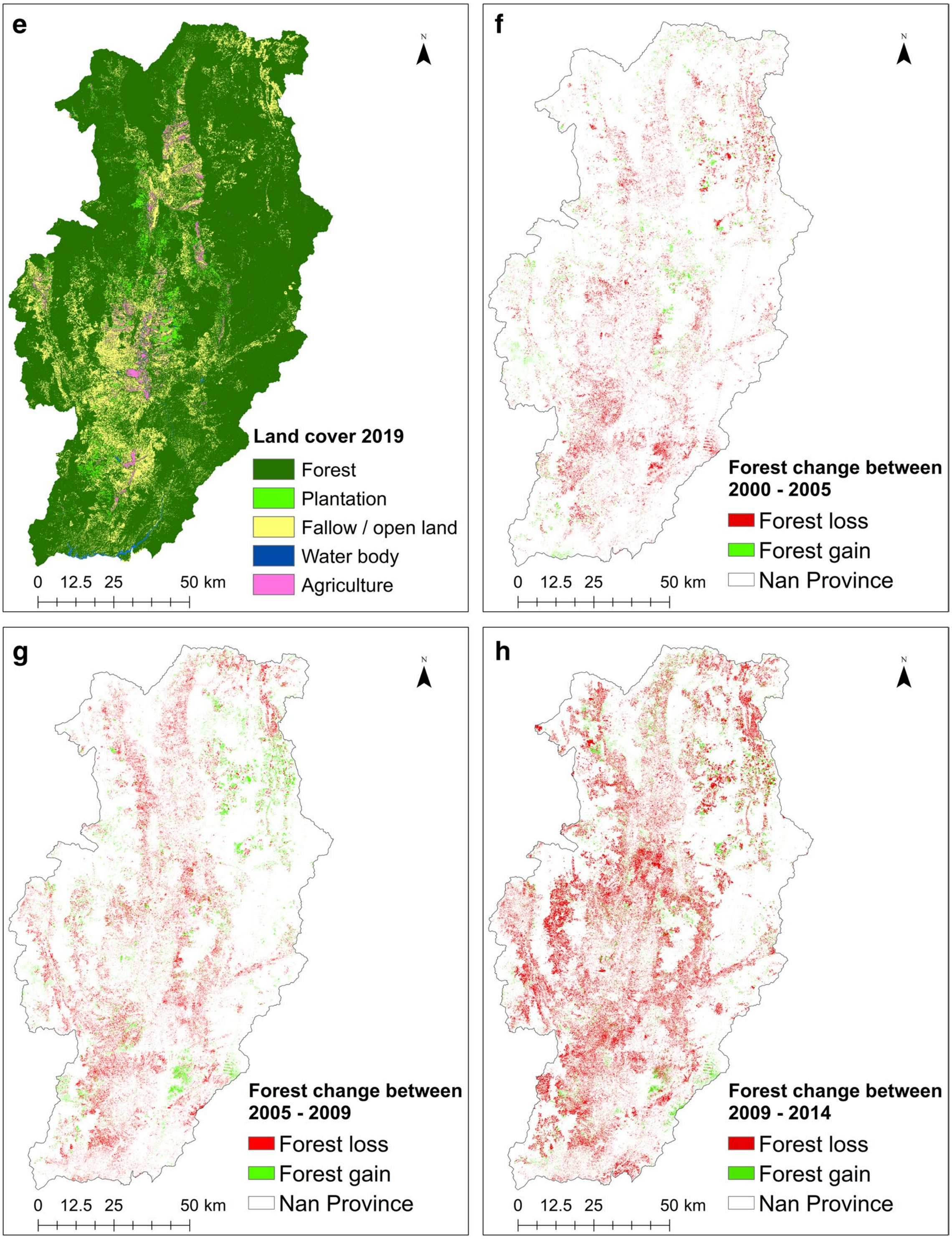

Fig. 4 (continued)

Evaluation of project interventions

We divided the intervention outcomes into four categories based on the forest loss trajectory in the project villages measured by our remote sensing analyses as compared to their synthetic control: (1) forest loss decreased by at least 5% after project implementation and was lower than the synthetic control, (2) forest loss remained similar to the synthetic control, (3) forest loss remained constant after project implementation (i.e., it had not increased or decreased by

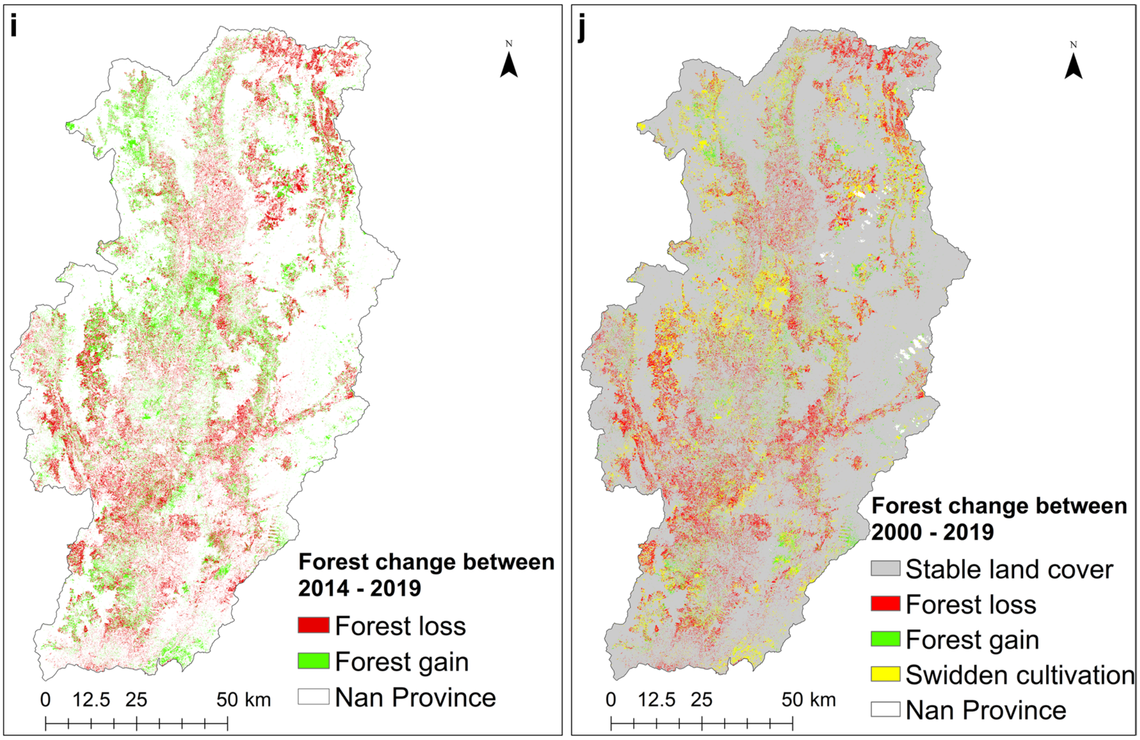

Fig. 4 (continued)

more than 5%) but was lower than the synthetic control, (4) forest loss has increased after project implementation and was higher than the synthetic control (Table 3 and Fig. 6).

Most of the studied project interventions were focused on tree plantation and providing livelihood support to local communities through agroforestry and improved crop and vegetable production, except for the eco-tourism and bamboo check dam projects. These small dams made of local bamboo control soil erosion and retain rainwater. This allows farmers to grow successive crops on their plots. It thus indirectly reduces the need to convert forests (Table 4). All these projects aimed at enabling farmers to generate sufficient income from limited land areas while sparing land for forest (Table 4). Only three of the projects included supply chain interventions in the form of support for commercialization of new agricultural products (ESM Table 9).

The Highland Research and Development Institute (HRDI), Phu Fha Royal project, and Pidthong are Royal initiatives supported by government funding. These projects were well-funded and had multiple centers across the landscape, with higher levels of community engagement observed in villages with project centers compared to those without. In contrast, projects initiated and run by government agencies, such as the Nan Farmer Council, Sister Aid project, and Eco-tourism projects in Khun Sathan and Si Nan National Park, experienced lack of long-term commitment by project officers at the local level. Interviews revealed that government officers had not followed up after providing saplings. NGOs and community-based projects demonstrated more significant engagement with the local community, although they regularly struggled to secure funding opportunities (ESM Table 9). These projects operated on a smaller scale compared to Royal and government initiatives. In some cases, sub-district officers secured corporate funding for plantation projects and maintained good community engagement but faced challenges in ensuring a continuous flow of funding.

Despite all the efforts from various project interventions, our analysis shows that only 3 of the studied villages have experienced a decrease in forest loss more rapidly than their synthetic control (Table 3). These successful villages were part of the HRDI and Joko projects (Fig. 6 and ESM Fig. 10). Sixteen villages have at least maintained constant forest loss, which is lower than their synthetic control. Twenty-two villages have exhibited forest loss similar to their synthetic control, indicating that the project interventions had no significant impact on reducing forest loss in these villages. Twelve of the villages have seen an increase in forest loss, surpassing their synthetic control. These results show heterogeneity within the same project, indicating variance across villages in terms of their response to a similar intervention (ESM Figs. 7–12).

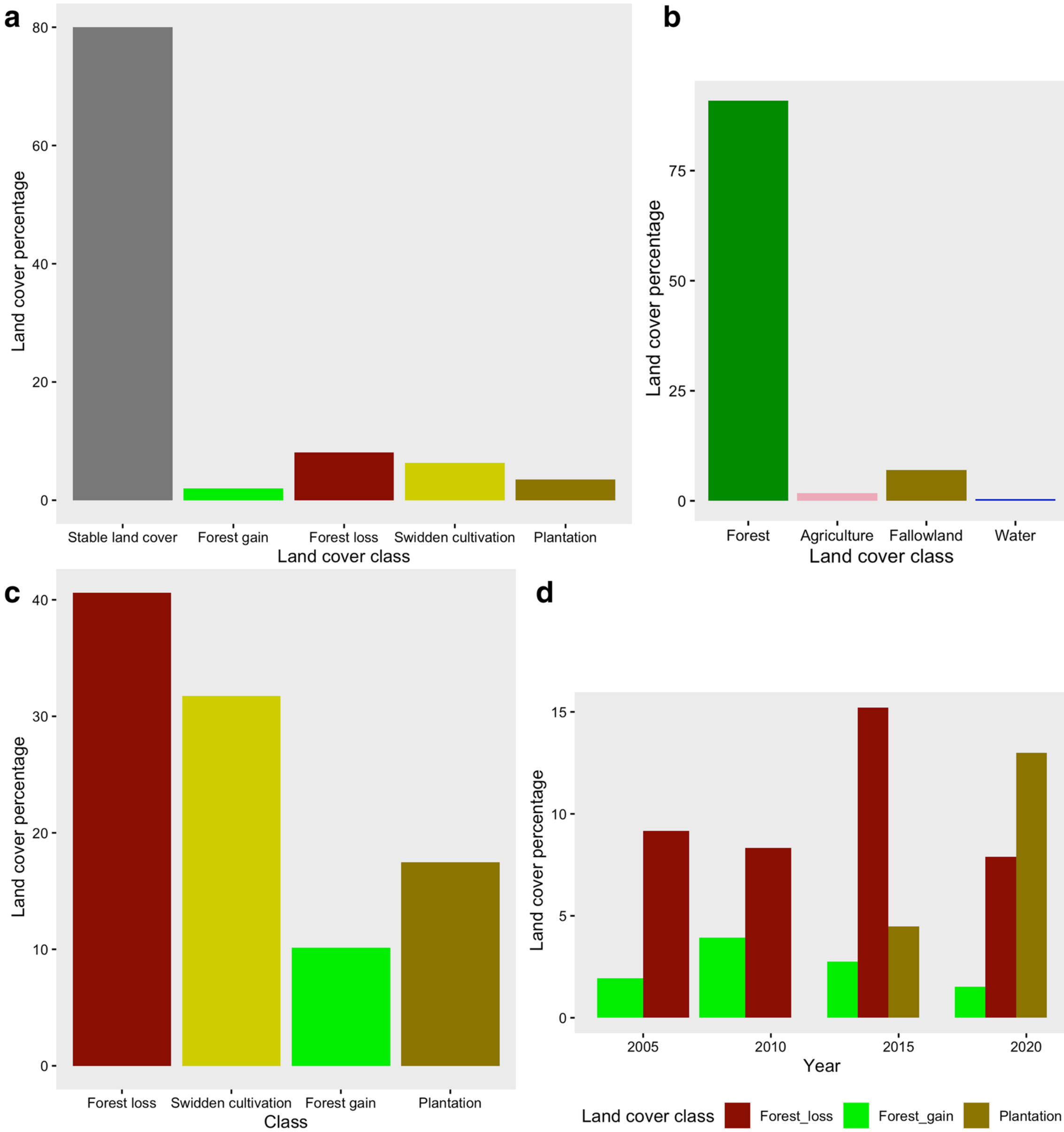

Fig. 5 **a** Percentages of change and no-change categories on land cover change map for 2000–2019. **b** Percentages of no-change land cover classes for 2000–2019. **c** Percentages of change land cover classes for 2000–2019. **d** Percentages of change land cover classes at the different time periods

Discussion

We found that new areas of forest have been encroached between 2000 and 2019, as only 31% of observed land cover changes was due to swidden cultivation and 41% to additional forest loss. However, forest loss has reduced significantly between 2014 and 2019, and tree crop plantations have expanded. Such trends were also observed in other parts of the

Table 2 Land cover change matrix between 2000 and 2019

		Land cover area (km^2) in 2019				
	Land cover class	Forest	Agriculture	Fallow/open land	Water body	Plantation
Land cover area (km^2) in 2000	**Forest**	**9443.42**	113.68	1103.15	2.78	195.16
	Agriculture	43.85	**64.12**	31.51	0.16	5.30
	Fallow/open land	430.69	90.40	**476.99**	0.66	72.69
	Water body	19.98	2.14	4.20	**25.00**	0.20

Table 3 Number of villages in the different categories of forest loss change

Agency	Project	Decreased forest loss and lower than synthetic control	Forest loss similar to synthetic control	Forest loss constant but lower than synthetic control	Increased forest loss and higher than synthetic control
1. Royal family	a) Highland Research and Development Institute (HRDI)	1	8	6	1
	b) Phu Fha Royal project		1	4	1
	c) Pidthong		1		3
2. Government	a) Nan Farmer Council				2
	b) Sister Aid project				1
	c) Eco-tourism projects		1	1	1
3. NGO	a) Tree Bank project		1		1
	b) Joko	2	3		
	c) Bamboo Check Dam		1		
4. Community	a) The Monk project		1		
	b) Khun Naiyana Tee Kawong project			1	
	c) Cap and Foot on the Mountain			1	
5. Cooperate	a) Nam Phang Model		5	3	2

world, where government policies emphasized tree plantations instead of forest regeneration (Fleischman 2014; Heilmayr et al. 2016). Overall, Nan Province has faced high rates of forest loss between 2009 and 2014, confirming previous studies (Zeng et al. 2018b). Here, we teased apart areas that have undergone forest cover changes due to swidden cultivation and new agricultural encroachments in forest areas, which is essential for the design of interventions to control forest cover changes.

After comparing the outcome of various land use interventions in Nan Province to their synthetic control, we found only three villages with projects that have been successful at reducing forest loss. Most villages have similar rates of forest loss as compared to their synthetic control. Thus, most projects have not yet contributed to reduce forest loss beyond the general trend of Nan Province. In 16 villages, projects were able to stabilize the rate of forest loss. By contrast, in twelve villages, forest loss had increased after the initiation of the project.

The majority of the projects focused on providing saplings for cultivating fruits, vegetables, bamboo, and coffee. Only two projects focused on providing water supply to highland villages by creating check dams and constructing pipelines for farms. Only a few projects also provided support to the farmers for selling their products by linking them to the market (HRDI and Phu Fha Royal projects). Projects aimed at providing alternative livelihoods to farmers do provide benefits to local communities, but they have not yet been transformative. Some farmers remain trapped in a vicious cycle of debt associated with maize cultivation (Rossi 2012). While plantation-based projects offer a long-term strategy for alternate livelihood support, they do not provide immediate solutions to help farmers develop new sources of income that are sufficient to meet subsistence needs and repay debts.

Santika et al. (2017) studied community-based forest management projects in Indonesia and found that, with good community support and leadership, they were able to conserve their indigenous forests. The role of local leadership was also mentioned in our interviews; however, we mainly interviewed project and community leaders, thus creating a strong selection bias. Some projects used payments for ecosystem services for incentivizing villagers to initiate and maintain tree plantations. Although maintaining long-term funding for community-based, small-scale projects is challenging, good leadership qualities and efforts enabled to raise funds from various organizations and sustain financial help for their community. The study by Kahsay and Medhin (2020) in Ethiopia highlights the importance of educating community leaders and frequent elections for forest outcome. Other projects could not be sustained because of lack of funding. In our study, Royal and government projects maintained more long-term, constant funding than other initiatives. As a result, they provided better incentives to local communities for participating to their projects. Even though the impact of most of these projects is not yet visible on the ground in terms of reducing forest loss, studies have shown that positive impact on the local community's economies could lead to sustainable forest conservation outcomes on the long term (Sills et al. 2020; Agarwal et al. 2017). A case study on Namibia's communal conservancies by Turpie and Letley (2021) also showed that communities co-operate better provided there is external financial support with a careful involvement of trustworthy local organizations.

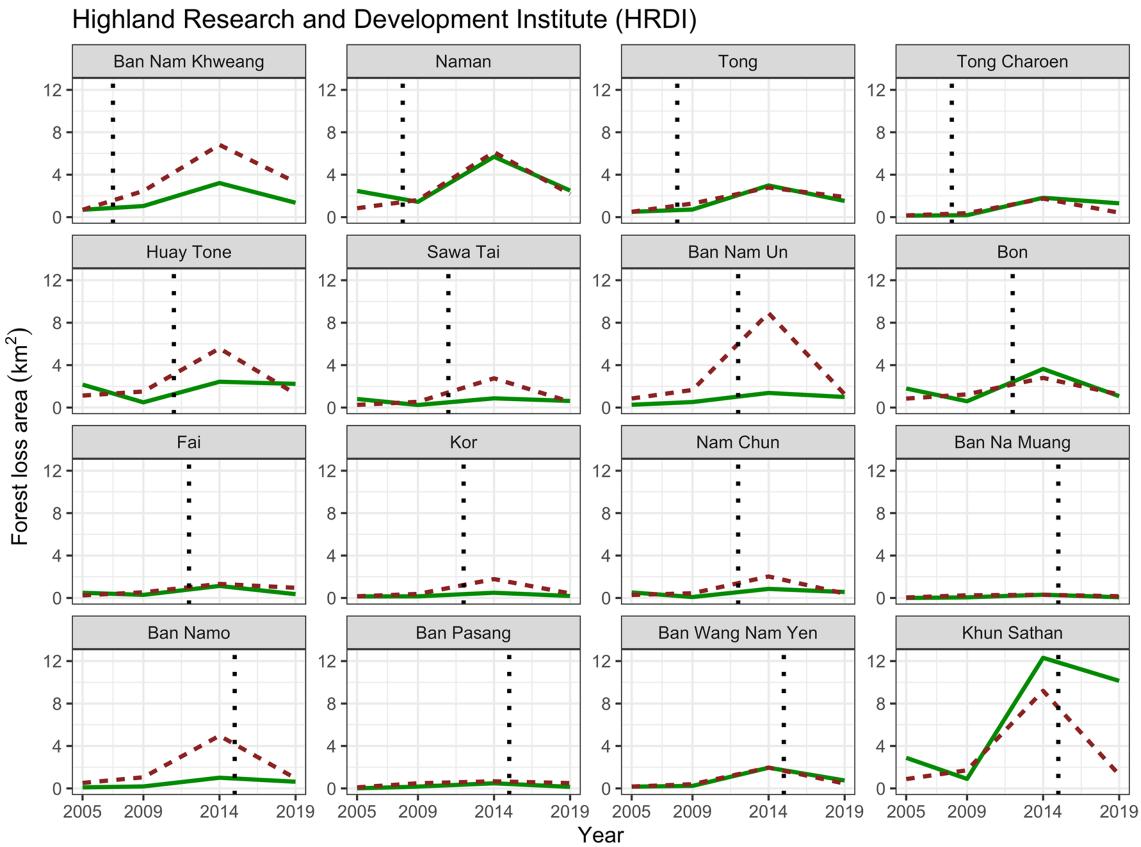

Fig. 6 Time trend of forest loss area for villages with the Highland Research and Development Institute (HRDI) project: treatment (green line) *versus* synthetic controls (red dashed line). The dotted black lines are the project start dates

Some projects initiated by government agencies were under-performing due to a low involvement and lack of regular follow-up by officials. Well-funded interventions also require continuing, long-term support to communities (Handberg and Angelsen 2019). Farmers need training to learn new techniques as well as support in the initial stages to accelerate adoption of new practices. Large-scale government-initiated projects need to develop a closer connection with local communities to have an impact on the ground (To et al. 2012). Payments for ecosystem services seem to work better when payments act to strengthen an already existing land use system (Turpie and Letley 2021).

Farmers are adopting a composite agricultural system, where they continue with the swidden cultivation system for their subsistence while also adopting cash crops, agroforestry, or organic farming (Vongvisouk et al. 2014). We found similar patterns of dual economies. The project leaders mentioned that changing farmers' crop allocation from maize to fruit trees, coffee or bamboo is challenging because of a lack of initial investment, alternative livelihood support, training, and knowledge of market demand, as well as the long lag time between tree crop plantation and the first harvest. Moreover, the supply chains for higher value crops as alternative to maize were generally lacking. Therefore, most farmers involved in these projects adopted new land uses for only less than one-fourth of their farmland, while continuing to grow maize or maintaining their swidden cultivation. Interviews also revealed that, initially, few farmers participated to new projects but, as the interventions progressed, a growing number of farmers joined as they became aware of the benefits. We found no evidence to support the notion that the land use interventions had led to such significant new income generation that it stimulated more economic activity and therefore more forest clearing, in a rebound effect.

A key lesson is that the success of interventions to reduce forest loss driven by marginal smallholder farmers requires sufficient external resources over a sufficient period of time to ensure a sustained community engagement. In our study, community engagement was found to be higher in villages with HRDI centers as compared to villages without such centers. Yet, community engagement without profitable alternative land uses made possible by an environment supporting a transition and by well-organized supply chains is not sufficient. In that

Table 4 Description of the project interventions

Name of project	Description
Royal initiatives	
Highland Research and Development Institute (HRDI)	Project to develop people's livelihood conditions in highlands. Improves livelihood conditions by enabling people to earn more money on less land area so that the remaining land can be reforested. HRDI have stable income source and established village-level centers
Phu Fha Royal project	Project to help farmers to grow diverse fruits and vegetables. Farmers get support to market and package their products. Project supported by government funding and have established village-level centers
Pidthong	Initial project focus was to provide water supply to farmers by building check dams and pipelines. Later it also provided them with saplings/seedlings of bamboo, vegetables, fruit trees. Projects have funding source from government agencies and have many village centers
Government initiatives	
Nan Farmer Council	Program to provide fruit tree saplings to farmers. Government funded projects for plantations
Sister Aid project	The Agriculture Department of Nan Province provided fruit tree saplings to farmers and trained them for maintaining the trees
Eco-tourism projects	Villages close to Khun Sathan and Si Nan National Park have eco-tourism projects from the Forest Department
NGO initiatives	
Tree Bank project	The Tree Bank Foundation from Bangkok and volunteers from Nan provided saplings to farmers and payments for managing the trees
Joko (Rice field exchange project)	Khun Samruay Padpol initiated the Joko learning center to educate farmers about rice varieties, protect seedlings of rice and vegetables, and encourage people to exchange their highland plots with lowland rice fields
Bamboo Check Dam	Nan Hospital and volunteers from other organizations helped farmers solve water shortage issues to grow multiple crops in the same field and reforest the remaining land
Community initiatives	
The Monk project (Monk Khun Pra Karu Sujit)	The Buddhist monk Khun Pra Karu Sujit motivates communities to manage their community forests and conducts tree ordination. He provides farmers with saplings and facilitates training for organic farming and other agricultural practices
Khun Naiyana Tee Kawong project	The village leader Khun Naiyana Tee Kawong received the Globe Award for her efforts in sustainably managing forests, the environment and villages. She promotes the management of community forests to protect forests and use resources sustainably
Cap and Foot on the Mountain	Khun Phet Chaipong, head of Palaeyo sub-district, promotes forest gain of the heads and foots of mountains with wild trees, and allocates middle slopes for fruits, bamboos, rice and vegetables. He links farmers and donors, who pay farmers for 5 years for maintaining trees
Corporate initiative	
Nam Phang Model	A major Thai agribusiness company (Charoen Pokphand Group Co., Ltd.) provides fruit tree saplings to farmers and trains them for maintaining the trees

respect, our study highlights the importance of estimating at frequent intervals impacts of various interventions through rigorous evaluation methods that include counterfactual analyses.

Limitations in our remote sensing analyses prevented the identification of different fallow ages and the separation of old secondary forests from primary forests, which are sources of uncertainty in our estimates of swidden cultivation. A more detailed classification would have required time series of detailed ground information. Moreover, we could only analyze Landsat data at 5-year intervals due to persistent cloud cover in the study region. A denser time series would have also increased the reliability of the identification of pixels under swidden cultivation. However, we did capture pixels that experienced forest loss and gain at 5-year intervals. Addition of social and economic variables such as income, religion, ethnicity, or adoption of specific farming practices could have further strengthened the synthetic control analysis. However, some of these variables display little variance across neighboring villages. Distance to roads provides a good proxy for the remoteness of villages, which influences access to social and economic opportunities.

Conclusion

Most recent land use interventions in Nan Province did not reduce forest loss beyond the trend observed in other, similar villages, despite the growing environmental issues caused by forest clearing for cropland expansion. This can be explained by three factors. Firstly, most of the projects were initiated only less than a decade ago and have yet to show a detectable impact on forest loss. The first iterations with these interventions may not have the intended effects, especially on a reduction of forest loss which may take years to materialize. The large-scale adoption of new land use practices also takes time as a group of pioneers experiments with the practices on a small part of their farm before these practices are scaled up. Secondly, most projects are focused on providing livelihood support to local communities as a pre-condition for the diffusion of forest-friendly land uses. Hence, the impact of these interventions may not be readily reflected on forest loss. Thirdly, the supply chains to commercialize alternative agriculture products were lacking. Overall, a sustained engagement of the local community and inflow of funds over several years are important factors for the success of these interventions.

Interventions have been initiated and supported by the Thai government, civil society organizations, leaders of local communities, and a large private company but success of these intervention depends on people being involved in decision-making processes rather than just having to comply with top-down land use prescriptions. A major factor underlying land use decisions by rural communities is their expectation for welfare improvements including health, education, transportation, and social networks. Finding sustainable markets for farmers' produces is also key for their long-term participation to new land use projects.

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Author contribution Shivani Agarwal: conceptualization, methodology, data collection, analysis, and writing. Eric Lambin: conceptualization, methodology, writing, and editing.

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Declarations

Conflict of interest The authors declare no competing interests.

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