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Crop-raiding by wildlife and cropland abandonment as feedback from nature-based solutions: lessons from case studies in China and Nepal

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Abstract

Conservation efforts under the nature-based solutions (NbS) framework aim at better management of ecosystems and improvement of human well-being. Policies targeting forest-based livelihoods align well with the NbS principles, but their social-ecological outcomes are often confounded by complex human-environment interactions. In this study, we identify one major feedback effect of the ecosystem dynamic on people's livelihoods based on datasets collected from two study areas in China and Nepal. Our methodology integrates satellite remote sensing, household surveys, and statistical models to investigate households' cropland abandonment decisions under the influence of crop-raiding by wildlife. Results show that cropland parcels that have experienced crop-raiding are more likely to be abandoned in the following years. The more damage the crops have suffered on a given parcel, the more likely it is that the parcel will be abandoned. Parcels in proximity to natural forests, farther away from the house location, and with poorer access to paved roads bear a higher risk of being abandoned. These effects are robust and consistent after controlling for multiple parcel features and household characteristics at different levels and using the dataset from each study area separately. We conclude that policymakers need to consider this undesirable feedback of the ecological system to the livelihoods of local people to better achieve co-benefits for ecosystems and human society.

1. Introduction

Nature-based Solutions (NbS) are actions aimed at protecting, sustainably managing, and restoring ecosystems to confront societal challenges while benefiting both human well-being and biodiversity. This concept encompasses various ecosystem-based approaches like ecological restoration and green infrastructure to tackle issues such as climate change and food security (Cohen-Shacham *et al* 2019, Seddon *et al* 2020). Originating in the late 2000s, the NbS idea signifies a shift towards leveraging ecosystems proactively for societal benefits (Hanson *et al* 2020), marking a departure from traditional engineering methods. As a developing concept, NbS seeks an operational guide for broader application, emphasizing the need for a deeper understanding and solidifying its foundational principles (Cohen-Shacham *et al* 2016, Nesshöver *et al* 2017).

Under the NbS framework, policies have been initiated and practiced all over the world, aiming at simultaneously preserving ecosystems and their goods and services and providing benefits to human well-being. Examples of NbS-related initiatives for climate change mitigation include China's forest restoration/conservation policies and Nepal's community forestry program (Niraula and Pokharel 2016, Jin *et al* 2020, Fu *et al* 2021, Yu and Mu 2023). Since the late 20th century, China has implemented a series of ecological restoration projects, including the well-known Ecological Welfare Forest Program (EWFP) and Conversion of Cropland to Forest Program (CCFP) (Delang and Wang 2013). These programs subsidize participating rural households who secure ecosystem services through sustainable land-use management, including tree plantation on sloping cropland and logging bans in natural forests. Nepal was an early pioneer in promoting sustainable community forestry practices. Motivated by the degrading conditions of Himalayan forests, in 1978 the Nepalese government began an institutional shift toward decentralized governmental regulation, allowing local communities to directly access, monitor, and manage the forests that their livelihoods depended on (Acharya 2002). In both China and Nepal, an important goal of these programs is to alleviate poverty by improving the livelihoods of forest-dependent people. At the same time, local communities, especially socially marginalized communities, are empowered to grow, manage, and harvest forest resources.

Ecosystem conservation efforts are often confounded by complex socio-economic dynamics, leading to undesirable outcomes. A previous study found that China's forest restoration policy can induce unintended cropland abandonment (Zhang *et al* 2018b). The abandoned area may help strengthen ecological restoration, as they are more likely to be targeted by policymakers who aim to maximize conservation efforts (Newton *et al* 2021). However, cropland abandonment also threats food security with negative impacts on local livelihoods in the long term (Li *et al* 2023). Such an issue is not unique, as studies in Nepal have also observed prevalent abandonment of cropland in hilly areas where forests are abundant (Raj Khanal and Watanabe 2006, Bista *et al* 2021). According to the surveys in these studies, reported reasons of cropland abandonment include high cost of agricultural practices and low expected return. One major factor underlying reduced returns from agriculture pertains to crop-raiding by wildlife on croplands that abut natural forest (Chen *et al* 2019, Bista and Song 2022). Wild boar (*Sus scrofa*) is the most common wildlife species that invade cropland and cause crop damage in forest abundant areas in both China and Nepal, while other invasive species in Nepal include monkeys (*Macaca mulatta*) and deer (*Axis axis*), among others. Crop-raiding by wildlife is highly related to conservation efforts and has negative impacts on people's livelihoods such as influencing households' land-use decisions (Li and Von Essen 2021, Bashyal *et al* 2022). Cropland abandonment is a typical land-use decisions made by farm households and influenced by multiple factors (Prishchepov *et al* 2013, Subedi *et al* 2022, Guo *et al* 2023). Not only topographic properties (e.g. elevation) at the cropland location but also socio-economic characteristics of the household (e.g. labor availability) can influence the decision of abandoning cropland (Rey Benayas *et al* 2007). Cropland abandonment influenced by crop-raiding by wildlife can feature negative feedback from ecological restoration in the natural system to human livelihoods in the social system. Despite circumstantial evidence and observations linking crop-raiding and household land-use decisions, rigorous testing of their causal relationship is still lacking. Robust evidence of cropland abandonment driven by crop-raiding by wildlife can inform policymaking with a more comprehensive understanding of the social-ecological outcomes of NbS-related policies.

In this study, we ask whether and how crop-raiding in forest landscapes influences cropland abandonment as a feedback effect from the natural system to the social system. To answer this question, we use spatial data and household survey data to monitor the status (abandoned or cultivated) of cropland parcels and examine household land-use decisions on cropland abandonment with statistical models. The results can help better understand human-environment interactions within these complex adaptive systems and inform policymaking with NbS for sustainable environmental management.

2. Materials and methods

2.1. Description of study areas

We selected two study areas from two countries, China and Nepal, to investigate the impacts of crop-raiding by wildlife on the abandonment of cropland parcels (figure 1). Both countries adopted NbS for forest restoration and conservation programs to address pressing ecological and environmental problems. China implemented the CCFP and EWFP for soil and water conservation (Song *et al* 2018). Nepal has practiced Community Forestry for over four decades, significantly improving its forest condition and supporting the livelihoods of forest-dependent peoples (Bista *et al* 2021, Ojha *et al* 2022). The study area in China is Tiantangzhai Township, which is located in the western Anhui Province. Tiantangzhai forms part of Tianma Nature Reserve, which preserves the largest area of natural secondary mixed broadleaf forests in the Dabie Mountains in eastern China (Han *et al* 2011). The township covers an area of 189 km^2, with an elevation range of 400–1700 m above mean sea level. Although households conduct diverse livelihood activities (e.g. raising livestock, out-migration, local off-farm employment), agricultural practice is the predominant livelihood. Each household farms several cropland parcels that are located in different places surrounding the house location. Two major types of cropland parcels are paddy land for growing rice and dryland for growing potatoes, corn, and beans, among other crops. Both CCFP and EWFP

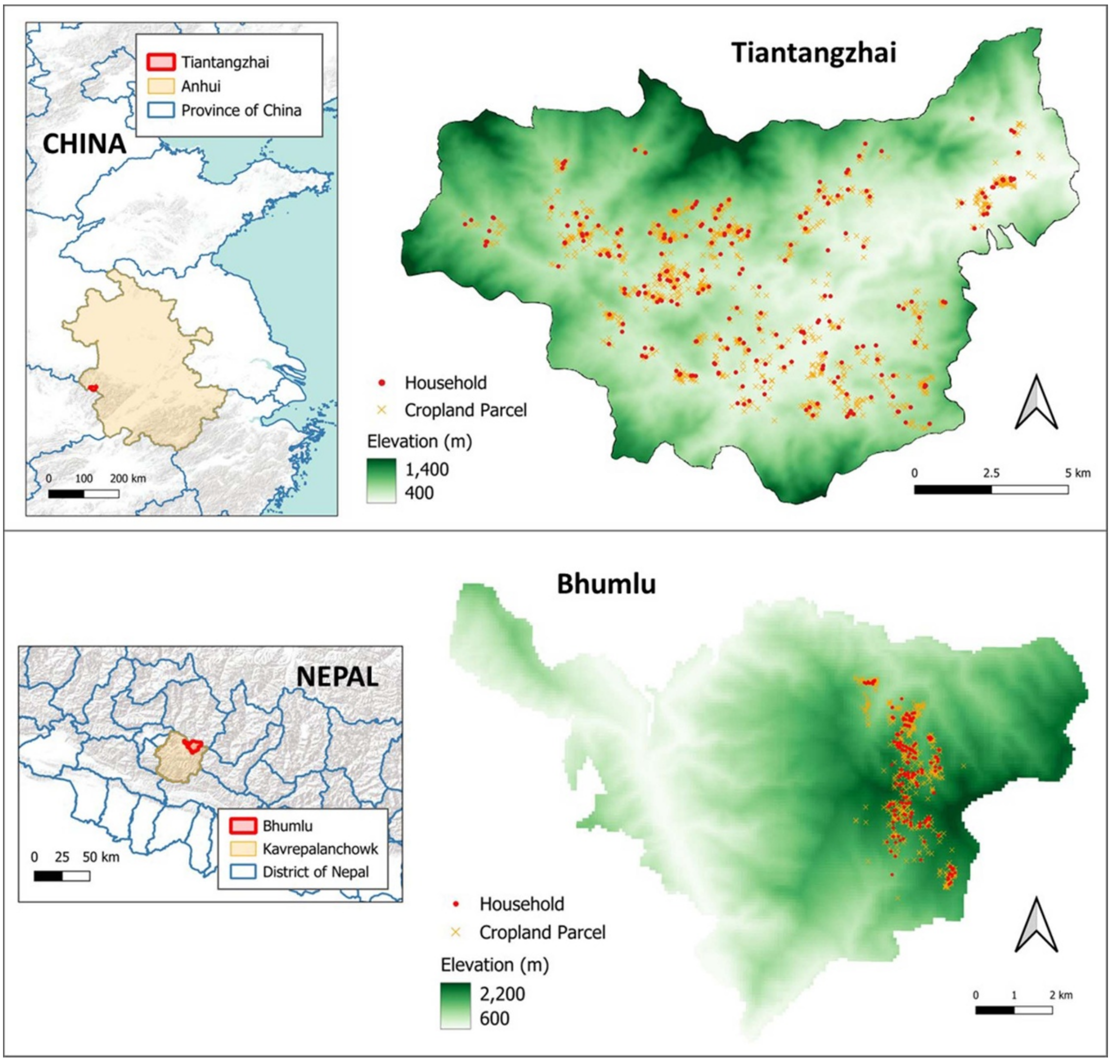

Figure 1. Study areas: Tiantangzhai Township in Anhui Province, China (upper panel); Bhumlu Municipality in the Kavrepalanchowk District, Nepal. The background of country boundaries is ESRI Terrain base map. Elevation maps for the two study areas in the insets are based on Shuttle Radar Topography Mission digital elevation data.

were implemented in the study area, converting some cropland parcels to planted forests and protecting the existing natural forests in large patches (Song *et al* 2018). In recent years, cropland abandonment following rural out-migration has been widespread in the study area (Zhang *et al* 2018a, 2018b). Meanwhile, the regeneration and greening of forest cover are accompanied by the increasing activities of wildlife, leading to crop raiding (Chen *et al* 2019).

The second study area is located in Bhumlu Municipality in Kavrepalanchowk District in Nepal, which is characterized by a subtropical highland climate or a temperate oceanic climate with dry winters. The Bhumlu municipality spans an area of 91.4 km^2, with the elevation ranging from 600 to 2200 m above mean sea level. Forest cover dominates the landscape. In addition to cropland cultivation, raising cattle within the forest landscape is also a major livelihood activity. Cropland can be divided into two types, bari, which is mainly for growing rainfed crops such as maize, and khet, which is often irrigated for growing rice and hence is more productive. Thus, bari is similar to dryland while khet is similar to paddy land. Communities in Bhumlu have been practicing Community Forestry since 1978 (Acharya 2002, Gurung *et al* 2004, Thoms 2008), a community-based natural resource management program that involves forest management practices for sustainable forest management and local livelihood support (e.g. fuelwood provision). Similar to the study area in China, Bhumlu has also witnessed cropland abandonment (Bista *et al* 2021) and human-wildlife conflicts due to crop-raiding by wild animals (Bista and Song 2022).

2.2. Data sources

We used data collected from multiple sources, including satellite images, GIS spatial datasets, and household and land surveys.

2.2.1. Satellite images and geospatial datasets

We leveraged satellite images and other ancillary geospatial datasets (table S1) to classify the status of cropland parcels (abandoned or cultivated) following the years of household surveys. Satellite data include images collected from RapidEye, PlanetScope, and Sentinel-2 satellites. RapidEye Earth observation provides imagery at a five-meter resolution, with spectral bands in blue, green, red, red edge, and near-infrared (NIR) wavelength ranges. Sentinel-2 satellite constellation carries sensors comprising four bands at 10 m, six bands at 20 m, and three bands at 60 m spatial resolution. PlanetScope satellites provide four-band (blue, red, green, and NIR) data with global daily coverage at a spatial resolution resampled to 3 m. Ancillary geospatial datasets include Shuttle Radar Topography Mission, digital elevation data (Farr *et al* 2007), forest cover, and road network data. In Tiantangzhai (China), we took advantage of the land-use and land-cover map generated in previous work (Zhang *et al* 2020) to depict forest cover (polygon vector) and delineate the paved road network (polyline vector). In Bhumlu (Nepal), we obtained the road dataset of the Nepal road network from the Humanitarian Data Exchange and the forest extent dataset from the European Commission Joint Research Centre (Bourgoin *et al* 2023).

2.2.2. Household and land surveys

We collected crop raiding data at the cropland parcel level and socio-economic data of the parcel owner households in both study areas. The surveys in Tiantangzhai and Bhumlu were conducted during the summers of 2013 and 2018, respectively, collecting cross-sectional data mostly reflecting the crop raiding status in the past 12 months preceding the survey. During the surveys, we carefully clarified the concepts and practical meanings for each question to ensure information consistency. For example, cropland abandonment was defined as farmers cease to grow crops on land parcels without any intension to re-cultivate it in the foreseeable future, which differs from the term 'fallow' (temporary) representing a land management strategy. In both study areas, the survey teams recorded the number of cropland parcels managed by each interviewed household and their biophysical characteristics (e.g. parcel area, whether abandoned, whether experienced crop-raiding by wildlife). Following the interviews, the teams also obtained the geolocation of each parcel using a hand-held GPS unit in addition to the house location. With these coordinates, we were able to derive biophysical and geographic variables at the parcel and household locations (e.g. elevation, the distance between the house and each parcel). The Tiantangzhai sample includes 250 households with 1196 parcels, and the Bhumlu sample includes 214 households and 545 parcels. Detailed descriptions of the sampling procedures and surveys can be found in previous publications (Song *et al* 2018, Bista *et al* 2021). For the 1196 parcels in Tiantangzhai, we delineated the parcel polygons from previous work (Zhang *et al* 2023). In Bhumlu, however, we had tracked only the centroids of the parcels. Thus, we generated circular buffers surrounding the centroids based on the parcel areas reported during the interview. We performed sensitivity analyses of the classification and modeling results to different sizes of the circular buffers, specifically multiplying the circular radius by a resizing factor of 0.5, 0.7, 0.9, 1.0, 1.1, 1.3 of 1.5.

2.3. Classification of cropland parcels

One challenge of using cross-sectional data is that parcels that had been abandoned do not contain information on crop-raiding by wildlife at the survey time, while crop damage by wildlife only applied to those still under cultivation. To address this issue, we selected a subset of the parcels that were still under cultivation at the time of the surveys and used satellite images to identify the cropland parcels that had been abandoned since the survey times. To facilitate image processing with improved consistency, we adopted the automatic adaptive signature generation (AASG) method, which identifies and selects stable pixels as the training sample for image classification (Gray and Song 2013). AASG requires three input layers, including a reference satellite image, a land-cover/land-use map corresponding to the reference image, and a target image to be classified. Using the Tiantangzhai study area as an example, the classification algorithm based on RapidEye and PlanetScope imager [3] is as follows. We first defined the 2013 image encompassing the township as the reference image and aimed to classify the images of each year during 2014–2018. All the initial 1196 cropland parcels were traced for their status (abandoned or cultivated) for each pixel within the parcels in the reference image. After deriving the normalized difference vegetation index (NDVI) bands for both reference and target images, the difference between the two NDVI bands was generated, and the associated histogram was plotted (figure 2). The histogram of NDVI difference shows a normal distribution shape for each image pair (figures S1 and S2), based on which key AASG parameters (mean: μ; standard deviation: σ) were derived to determine the stable pixels (table S2). Any pixel with a value of NDVI difference falling within the interval of $\mu \pm 0.5^*\sigma$ would be labeled as a stable pixel (figure S3) and used as training (and validation) points to classify the cropland pixels in the target image. About 75% of the stable points were used as training points while the remaining were retained as validation points. The Random Forest classifier was used to classify each target image individually during 2014–2018. A parcel would be regarded as being abandoned in a single year if more than half of the

[3] RapidEye and PlanetScope data are not freely available to the public but can be requested free of charge by university-affiliated students for education and research purposes. The first Sentinel-2 satellite was launched in 2015, which was two years later than the base year of analysis in Tiantangzhai.

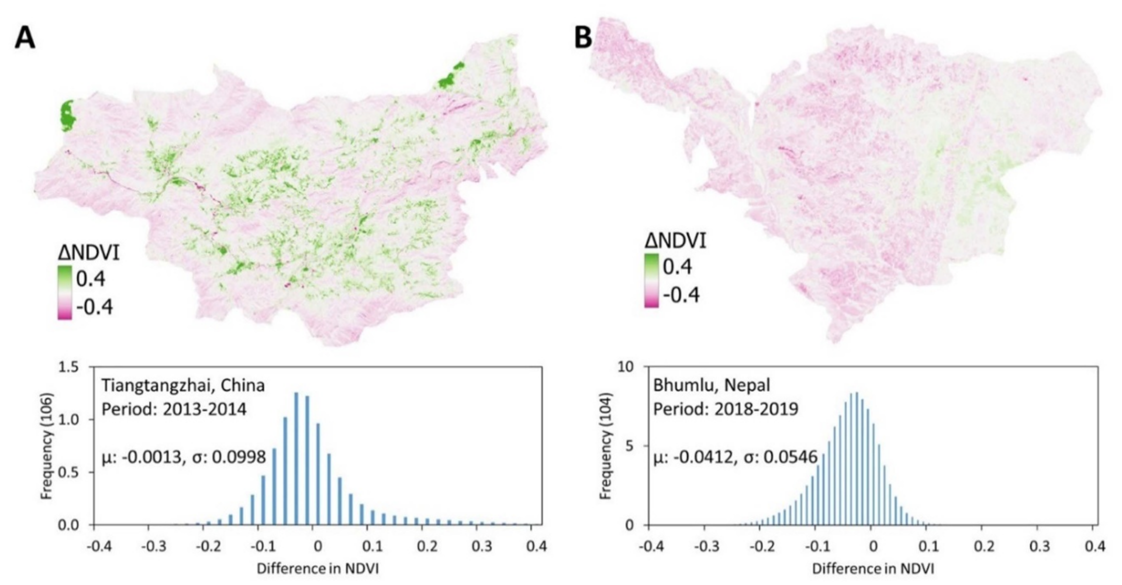

Figure 2. Illustration of AASG classification based on histograms of NDVI difference over the study areas. (A) Tiantangzhai, China. (B) Bhumlu, Nepal.

pixels within the parcel were classified as abandoned areas. Accuracy was also assessed at the parcel level. In each study area, 10% of the parcels were randomly selected and visually interpreted in Google Earth to determine whether they had been abandoned during the years since the survey times. Confusion matrices at both pixel and parcel levels were constructed based on the validation points and sampled parcels.

2.4. Multilevel analysis for cropland abandonment

We constructed multilevel mixed-effects regression models (Guo and Zhao 2000) to examine the impacts of crop-raiding by wildlife on household land-use decisions on cropland abandonment. Multilevel models can capture the variance at a higher level, providing a more accurate estimation of the fixed effects at different levels (Pan and Bilsborrow 2005). In this case, for example, households make decisions on whether to abandon a cropland parcel depending on both parcel features and household characteristics, while parcels managed by the same household may bear more similar risks of being abandoned than those managed by different households. Model specification is as follows,

$$\log\left(\frac{P\left(y_{ij}=1\right)}{1-P\left(y_{ij}=1\right)}\right)=\alpha+\beta x_{ij}+\ldots+\gamma z_j+\ldots+\mu_j+\varepsilon_{ij}. \quad (1)$$

In this equation, y denotes the status of cropland parcel i ($0=$ cultivated, $1=$ abandoned) managed by household j; x and z denote parcel-level and household-level explanatory variables, respectively; α is the intercept, while β and γ are fixed effects to be estimated corresponding to parcel and household variables, respectively; ε and μ are random effects at the parcel and household levels, respectively. The outcome variable is in a binary format, indicating whether a parcel had been abandoned at least once based on satellite image classification. The key explanatory variables include whether the parcel was raided by wildlife (0/1) and the percentage of crop damage due to crop-raiding by wildlife (0.0–1.0), which is at the parcel level (table 1). Based on theoretical understanding and empirical knowledge (Lambin *et al* 2001, Rindfuss *et al* 2004, Rey Benayas *et al* 2007, Zhang *et al* 2018b), the models control for a variety of parcel features (e.g. elevation, slope, distance to nearest forest) and household characteristics (e.g. livelihood activities), allowing random effects at both parcel and household levels. The variable, 'off-farm livelihood', was computed as the ratio of the total income from off-farm activities to the unit price of rice in the local area (2.4 Yuan/kg in Tiantangzhai and 46 NPR/kg in Bhumlu based on the surveys) to represent the household's purchasing power. We fitted the models for each of the key variables relating to crop-raiding by wildlife separately for the dataset from each study area. In addition, we pooled the data from both study sites with the same model specification and included a dummy variable that indicates the study area (0: Tiantangzhai, 1: Bhumlu). The inclusion of the dummy variable at the intercept captures only the systematic differences (e.g. the mean size of the cropland managed by households) between the two study sites, but it cannot reflect the difference in terms of the influence of the explanatory variables (e.g. different influencing directions of the same variable across regions). Regarding the key variables in this study, the effects

Table 1. Description and statistical summary of variables for modeling cropland abandonment.

Variable Description	Mean	SD	Min	Max	Mean	SD	Min	Max
Parcel Level	Tiantangzhai, China ($N = 969$)				Bhumlu, Nepal ($N = 421$)			
If the cropland parcel was abandoned (1 = yes, 0 = no)	0.13	0.33	0	1	0.22	0.42	0	1
If experienced crop-raiding by wildlife (1 = yes, 0 = no)	0.26	0.43	0	1	0.41	0.49	0	1
Percentage of crop damage due to crop-raiding by wildlife (0–1)	0.10	0.19	0	1	0.08	0.09	0	0.75
Parcel area (ha)	0.11	0.07	0.01	0.47	0.26	0.18	0.03	1.53
Parcel type (1 = dryland, 0 = paddy-land)	0.40	0.49	0	1	0.20	0.40	0	1
Elevation at parcel location (100 m)	6.37	0.79	4.09	8.79	17.48	1.89	13.05	20.76
Slope at parcel location (degree)	7.21	3.76	0.36	22.30	21.05	6.94	2.80	42
Distance to nearest natural forest (100 m)	0.10	0.15	0	1.49	0.35	0.47	2.55	176.76
Distance to nearest main road (100 m)	0.97	0.97	0.04	5.89	0.71	0.62	0	4.01
Distance to house location (100 m)	2.70	3.42	0.09	43.38	2.03	3.69	0	33.96
Household Level	Tiantangzhai, China ($N = 239$)				Bhumlu, Nepal ($N = 212$)			
Age of head	52.63	9.63	31	78	50.74	13.43	23	84
Gender of head (1 = female, 0 = male)	0.05	0.21	0	1	0.11	0.32	0	1
Education of head	6.92	2.75	0	14	3.96	3.64	0	12
Number of household member (non-migrant)	3.11	1.46	0	9	3.96	1.76	1	10
Number of migrants	1.46	1.29	0	7	1.66	1.86	0	8
Elevation at house location (100 m)	6.43	0.98	4.05	8.75	17.62	1.83	12.03	20.41
Area of land under cultivation (ha)	0.34	0.23	0	1.93	0.52	0.37	1.1	2.23
Area of abandoned cropland (ha)	0.08	0.12	0	0.74	0.21	0.40	3.31	44.60
Amount of fuelwood collected (1000 kg)	8.9	5.83	0	36.25	0.37	0.20	0	1.28
Purchasing power of income from off-farm work (ton of rice)	1.16	2.09	0	15.18	0.03	0.03	0	0.15

of crop-raiding by wildlife on land-use decisions in one study area may significantly differ from that in the other. Furthermore, there exist differences of general biophysical and socio-economic contextual factors, which may also exhibit higher-level clustering features among households, namely households in one study areas may have distinct behavior limited by the surrounding social and natural environments. To address these issues, we also generated interactions terms between the study area dummy variable and each explanatory variable and included them in the model.

3. Results

3.1. Classification results of cropland abandonment

The AASG-based classification of abandoned cropland parcels shows generally satisfactory accuracy in both study areas (figure 3, tables S3 and S4). Based on the stable points, we successfully generated the map of abandoned areas within the parcel boundaries, most of which overlap with non-cropland areas (e.g. shrubs, trees, grass) based on visual evaluation of fine resolution satellite images (figure 3). Although

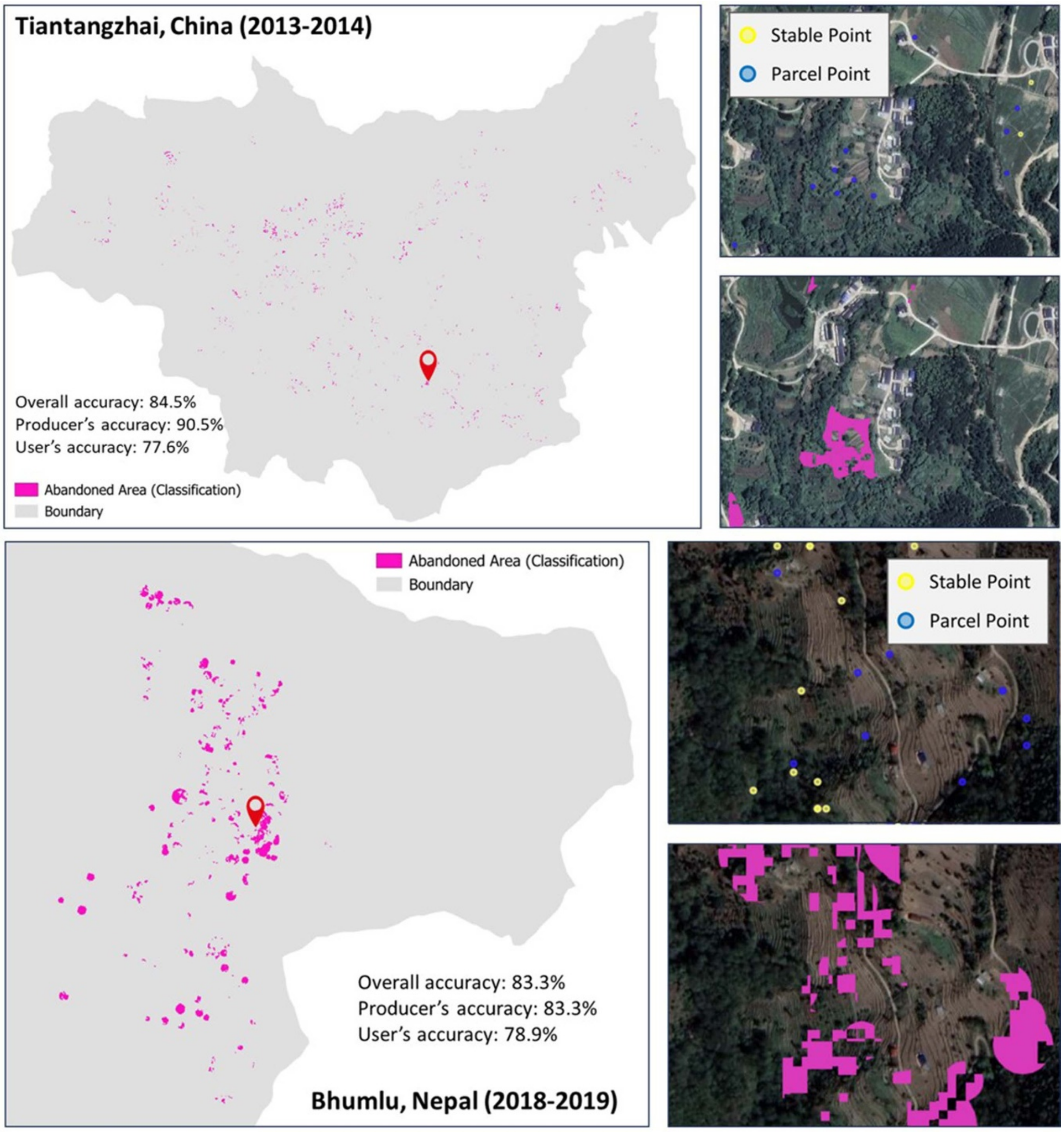

Figure 3. Parcel points, AASG-identified stable points, and classified abandoned area within cropland parcels. Upper panel: Tiantangzhai, China (2013–2014). Lower panel: Bhumlu, Nepal (2018–2019). Overall accuracy corresponds to both abandoned and cultivated parcels, while producer's accuracy and user's accuracy correspond to abandoned parcels. Base map is from Google Earth Engine. The pinpoints in red mark the locations of the zoomed-in areas showing the classification results. QuickMapServices Google Satellite 2016.

annual pixel-level accuracy is comparatively low, ranging from 60.7% to 81.8% (table S3), parcel-level accuracy reaches nearly 85% (table S4), demonstrating that most parcels have been correctly classified as either being abandoned or under cultivation. In both study areas, at the parcel level, the producer's accuracy (83.3%–90.5%) is higher than the user's accuracy (77.6%–78.9%) for abandoned parcels, suggesting that more parcels are correctly classified as being abandoned relative to the reference parcels that are regarded as actually abandoned (lower level of omission error). In Tiantangzhai (China), cropland abandonment is more prevalent in the central-western part of the study area with relatively high elevation, compared to the eastern part. In Bhumlu (Nepal), cropland abandonment is ubiquitous throughout the study area.

Through statistical comparison between the two study areas, the proportion of abandoned areas based on image classification is higher in Bhumlu than in Tiantangzhai, which is consistent with the situation prior to the survey times (figure 4). Specifically, the proportions of abandoned cropland are 9.8% and 15.5% in Tiantangzhai (2013–2018) and Bhumlu (2018–2023), respectively; the area proportions of abandoned cropland before the survey times are 18.0% and 29.5% in Tiantangzhai and in Bhumlu, respectively. Thus, there is less abandoned land than there was prior to the surveys. Overall, about 72.2% of the cropland area remains under cultivation in

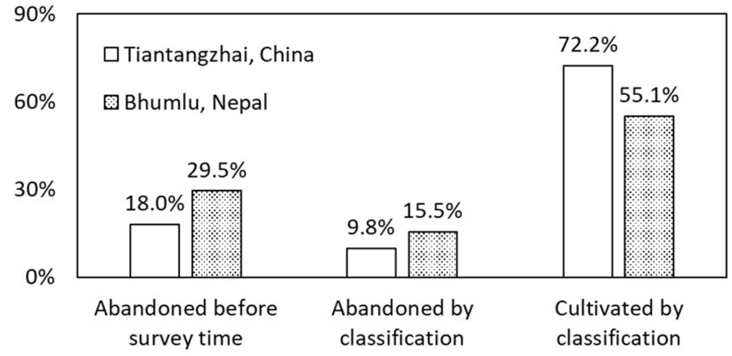

Figure 4. Proportions of areas for abandoned cropland before the survey times, abandoned cropland by classification, and cropland under cultivation by classification.

Tiantangzhai, but only 55.1% in Bhumlu based on the classifications. Dividing the parcels into the three groups (abandoned prior to survey times, abandoned after survey, and cultivated after survey), we also compared variables regarding crop-raiding by wildlife and topographic/geographic features. In both study areas, cropland parcels classified as abandoned experienced more crop-raiding and a higher percentage of crop damage by wildlife (figure S4). Note that parcels abandoned before the survey times do not suffer from crop-raiding because there were no crops to be raided at the survey times. For topographic and geographic variables, mean elevations are similar for the three parcel groups but mean slopes and mean distances to the nearest forests show more differences (figure S5). Parcels abandoned before and after the survey times generally have steeper slopes and shorter distances to the nearest forest, compared with those under cultivation through the entire study period, which is more prominent in Bhumlu than in Tiantangzhai.

3.2. Statistical summary of variables

Parcel-level and household-level variables both show similarities and differences between the two study areas (table 1). For the parcels that were under cultivation at the survey times, about 13% and 22% had been abandoned in Tiantangzhai (2013–2020) and Bhumlu (2019–2023), respectively, based on satellite image classification. Among these sampled parcels, 26% and 41%, respectively, experienced crop-raiding by wildlife at the survey times according to the survey. The mean percentage of crop damage estimated by the household is relatively low (including those with no crop-raiding or zero damage), which ranges from 8% to 10% in both areas. Compared with parcels in Tiantangzhai, parcels in Bhumlu have a much larger mean area, located in places with higher elevations and steeper slopes. For geographic variables, parcels in Tiantangzhai are closer to the nearest forest and slightly more accessible from the house locations as well as the paved roads, compared to those in Bhumlu.

Regarding household-level variables, household heads have mean ages of 52.6 and 50.7 in Tiantangzhai and Bhumlu, respectively. In both study areas, the proportions of female heads are low (5%–11%). The heads in Tiantangzhai receive nearly 7 yr of education on average, which is higher than those in the other study area where the average is nearly 4 years. The mean household size (3–4 persons on average) and the number of migrants (1–2 persons on average) are similar in the two study areas. In terms of cropland use, both total areas of cropland under cultivation and abandoned are larger in Bhumlu than those in Tiantangzhai. Households in Tiantangzhai consume 8900 kg of fuelwood per year, which is much more than those in Bhumlu, which consume only 370 kg per year. The purchasing power with off-farm income for local rice is much higher in Tiantangzhai than that in Bhumlu.

3.3. Results from multilevel regression models

By using the datasets from both study areas, we fitted two separate models, one including the key explanatory variable indicating whether a parcel experienced crop-raiding by wildlife and the other including the variable representing the percentage of crop damage by wildlife. Through a multilevel mixed-effects modeling approach, which controls for parcel features, household characteristics and study areas, we found that the binary variable of the crop-raiding incident has a statistically significant effect on households' decisions on cropland abandonment in Tiantangzhai (China), while the continuous variable of the degree of crop damage by wildlife has a statistically significant effect in both Tiantangzhai (China) and Bhumlu (Nepal) (table 2). By including the dummy variable of the study area at the intercept and slopes of the explanatory variables (i.e. interactions terms), the estimated effects are consistent with those in models where datasets of the two study areas are fitted separately (table S5). Specifically, when a parcel experienced crop-raiding by wildlife, the likelihood of being abandoned increases by 40.2% (10% significance level) during the following years in Tiantangzhai, but the effect is not statistically significant in Bhumlu. For every additional 10% more damage of crops by

Table 2. Results of multilevel mixed-effect models for cropland abandonment.

Variable	Coef. (S.E.)	O.R.	Coef. (S.E.)	O.R.
If experienced crop-raiding by wildlife (1 = yes, 0 = no)	0.402 (0.219) *	1.495	N/A	N/A
Percentage of crop damage due to crop-raiding by wildlife (0–1)	N/A	N/A	0.824 (0.412) **	2.279
Parcel area (ha)	−1.091 (1.598)	0.336	−1.072 (1.603)	0.342
Parcel type (1 = dryland, 0 = paddy-land)	−0.135 (0.221)	0.873	−0.166 (0.224)	0.847
Elevation at parcel location (100 m)	−0.07 (0.418)	0.933	−0.053 (0.421)	0.948
Slope at parcel location (degree)	0.042 (0.028)	1.043	0.039 (0.028)	1.040
Distance to nearest natural forest (100 m)	0.295 (0.723)	1.344	0.263 (0.725)	1.301
Distance to nearest main road (100 m)	0.211 (0.09) **	1.235	0.213 (0.09) **	1.238
Distance to house location (100 m)	−0.095 (0.052) *	0.909	−0.095 (0.052) *	0.909
Age of head	0 (0.011)	1.000	−0.002 (0.011)	0.998
Gender of head (1 = female, 0 = male)	−0.138 (0.643)	0.871	−0.143 (0.643)	0.867
Education of head	−0.016 (0.044)	0.984	−0.019 (0.044)	0.981
Number of household member (non-migrant)	0.045 (0.087)	1.046	0.046 (0.087)	1.047
Number of migrants	−0.084 (0.096)	0.920	−0.075 (0.096)	0.928
Elevation at house location (100 m)	0.081 (0.414)	1.084	0.075 (0.417)	1.078
Area of land under cultivation (ha)	−0.359 (0.496)	0.698	−0.334 (0.5)	0.716
Area of abandoned cropland (ha)	0.839 (0.906)	2.313	0.819 (0.905)	2.268
Amount of fuelwood collected (1000 kg)	−0.011 (0.019)	0.989	−0.011 (0.019)	0.989
Purchasing power of income from off-farm work (ton of rice)	−0.209 (0.083) **	0.812	−0.204 (0.083) *	0.815
Study Area (0 = Tiantangzhai, 1 = Bhumlu)	−3.694 (2.401)	0.025	−3.985 (2.423)	0.019
Interaction with Study Area: If experienced crop-raiding by wildlife (1 = yes, 0 = no)	−0.14 (0.37)	0.869	N/A	N/A
Interaction with Study Area: Percentage of crop damage due to crop-raiding by wildlife (0–1)	N/A	N/A	1.957 (1.463)	7.076
Interaction with Study Area: Parcel area (ha)	0.836 (1.88)	2.308	0.809 (1.882)	2.245
Interaction with Study Area: Parcel type (1 = dryland, 0 = paddy-land)	0.575 (0.447)	1.777	0.645 (0.45)	1.905
Interaction with Study Area: Elevation at parcel location (100 m)	0.284 (0.448)	1.329	0.28 (0.451)	1.323
Interaction with Study Area: Slope at parcel location (degree)	0.054 (0.037)	1.056	0.058 (0.037)	1.059
Interaction with Study Area: Distance to nearest natural forest (100 m)	−5.2 (1.259) ***	0.006	−5.113 (1.26) ***	0.006
Interaction with Study Area: Distance to nearest main road (100 m)	0.233 (0.251)	1.262	0.242 (0.253)	1.273
Interaction with Study Area: Distance to house location (100 m)	0.13 (0.064) *	1.139	0.129 (0.064) **	1.137

(Continued.)

Table 2. (Continued.)

Variable	Coef. (S.E.)	O.R.	Coef. (S.E.)	O.R.
Interaction with Study Area: Age of head	−0.006 (0.018)	0.994	−0.006 (0.018)	0.994
Interaction with Study Area: Gender of head (1 = female, 0 = male)	0.302 (0.782)	1.353	0.356 (0.784)	1.428
Interaction with Study Area: Education of head	−0.061 (0.066)	0.941	−0.062 (0.066)	0.939
Interaction with Study Area: Number of household member (non-migrant)	−0.103 (0.131)	0.902	−0.125 (0.132)	0.883
Interaction with Study Area: Number of migrants	0.054 (0.135)	1.056	0.043 (0.135)	1.044
Interaction with Study Area: Elevation at house location (100 m)	−0.133 (0.441)	0.876	−0.132 (0.444)	0.876
Interaction with Study Area: Area of land under cultivation (ha)	0.324 (0.643)	1.383	0.347 (0.648)	1.414
Interaction with Study Area: Area of abandoned cropland (ha)	−0.608 (0.964)	0.544	−0.568 (0.964)	0.567
Interaction with Study Area: Amount of fuelwood collected (1000 kg)	0.726 (0.832)	2.067	0.8 (0.833)	2.225
Interaction with Study Area: Purchasing power of income from off-farm work (ton of rice)	1.252 (5.355)	3.497	2.074 (5.421)	7.956
Constant	−1.829 (1.088) *	0.161	−1.764 (1.092)	0.171
Log likelihood	−504.9		−503.1	
Wald chi2(37)	127.8		130.2	
Prob > chi2	0.000		0.000	

Note: Coef. Denotes coefficient; S.E. denotes standard deviation; O.R. denotes odds ratio; N/A denotes not applicable. The number of observations: 1390, and the number of groups is 451. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

wildlife, the likelihood of being abandoned increases by 8.24% and 28.8% in Tiantangzhai (5% significance level) and Bhumlu (10% significance level), respectively. These results suggest that households' land-use decisions on cropland abandonment tend to be more influenced by the extent to which crops have been damaged by wildlife rather than the occurrence of crop-raiding. It is the loss of crops to be harvested that incurs high opportunity costs and subsequently facilitates the decision to abandon the parcel, which is as expected.

The multilevel analysis also suggests that parcel features play a more critical role than household characteristics in affecting cropland abandonment, as more parcel-level variables have significant effects, which is consistent in both study areas. For example, parcels in locations with steeper slopes, closer to natural forests, and farther away from paved roads are more likely to be abandoned. These results are in line with expectations based on theoretical and empirical understanding, such as the shading effect of tree crowns (Bista *et al* 2021) and poor accessibility to the agricultural market (Meyfroidt *et al* 2016). After controlling for these confounding factors, the effects of the key explanatory variables regarding crop-raiding by wildlife remain statistically significant, suggesting the robust estimation of their effects on cropland abandonment.

According to sensitivity analysis to buffer size in the Bhumlu study area, the classification results for the abandoned parcels and the estimated effects of crop-raiding by wildlife are generally as expected (figure S6). The parcel-level classification accuracy remains high (78% or above). As the buffer size increases from small to large values (0.5–1.5), more cropland parcels tend to be classified as abandoned. This is because more areas that are natural land-cover types (ground truth) are included in larger buffers, gradually dominating the pixels within the buffer and resulting in the apparent abandonment. Based on the regression results, the estimated effects and their significance levels are stable when the scaling factor is within a relatively small range (e.g. 0.9–1.1), suggesting that the results are robust for the selected buffer size, which are based on reported parcel areas during the survey. On the one hand, the effect of crop-raiding severity fluctuates with increasing buffer sizes, which is due to the influence of various land-cover types surrounding the parcels. The effect, on the other hand, becomes stronger and more significant with reduced buffer sizes, which nevertheless bears risk of introducing more uncertainty from the geolocations of the parcels. Overall, these results strengthen the robustness and reliability of the estimated effects of crop-raiding by wildlife on cropland abandonment.

4. Discussion

This study provides evidence of the negative impacts of crop-raiding by wildlife on cropland abandonment by rural households. Households tend to abandon parcels where crops have been severely damaged by wildlife, particularly those located in rough terrain, in proximity to natural forests, and with poor access to paved roads. This major finding is consistent with datasets compiled from two representative study areas in China and Nepal, both having been practicing forest policies with favorable outcomes (Lu *et al* 2018, Oldekop *et al* 2019). In line with the literature (Chen *et al* 2019, Li and Von Essen 2021, Kc *et al* 2023), our results suggest that crop-raiding by wildlife can be a concomitant phenomenon associated with ecosystem conservation efforts, compromising rural people's livelihoods. Crop-raiding devalues cropland parcels by reducing crops available to be harvested by rural households and increasing the cost of agricultural activities through labor and financial expenses for prevention measures (Hua *et al* 2016, Pandey and Bajracharya 2016).

Our findings advance the theoretical understanding of the dynamics of complex systems, featuring a typical human-environment relationship in the land system (Rindfuss *et al* 2004, Brondízio and Moran 2013, Müller and Munroe 2014). Forest regeneration and greening under the conservation policies strengthen the habitat for wildlife and increase biodiversity, but they also potentially bring undesirable risk to the natural resource-based livelihoods of the local communities (Giefer and An 2020, Bashyal *et al* 2022). Crop-raiding represents a linkage between the ecosystem and human society, through which wildlife damages crops that rural farmers depend upon (Chen *et al* 2019, Bista and Song 2022). In response to these challenges, farmers take adaptive measures to prevent further loss from crop-raiding. When farmers perceive that the prevention costs outweigh the expected return of crop harvesting for a given parcel, they would cease growing crops and subsequently abandon the parcel. During the interview, farmers mentioned that the prevention measures were not effective in protecting crops being raided or damaged by wildlife. On the one hand, the abandonment poses potential issues for food production which supports agriculture-centered livelihoods (Li *et al* 2018, Ojha *et al* 2022, Guo *et al* 2023). On the other hand, abandoned land is often in proximity to natural forests, enhancing ecological recovery (Queiroz *et al* 2014), and contributing to larger contiguous areas of natural landscape. For instance, previous research suggests that farmers are more willing to retire parcels that have experienced crop-raiding and enroll them in a reforestation program, namely the *Conversion of Cropland to Forest Program* (Chen *et al* 2019).

The methodology designed in this research offers alternative perspectives of examining households' land-use decisions on cropland abandonment in relation to crop-raiding by wildlife under NbS conservation efforts. Previous research that relies on cross-sectional datasets can be challenged by endogenous issues when examining correlations between factors and outcomes. In this case, for example, the household and land survey cannot obtain the information on crop-raiding by wildlife on cropland parcels at the survey time that had been abandoned before the survey time (e.g. parcels abandoned ten years ago) (Bista *et al* 2021). Meanwhile, for parcels still under cultivation at the survey time, it would be difficult to anticipate households' future land-use decisions regarding whether to abandon them or not. To address this challenge, we leveraged remotely sensed satellite data and the advanced AASG algorithm (Gray and Song 2013, Zhang *et al* 2020, Leblanc *et al* 2021) to classify cropland parcels in the following years of the survey time. The combination of remote sensing tools and survey datasets can facilitate the monitoring of land-use change and improve the cost-effectiveness (e.g. reducing costs of following-up household and land surveys) of testing the associated factors such as crop-raiding by wildlife.

The scope of this research was to test the hypothesis that crop-raiding by wildlife affects land-use decisions on cropland abandonment. We did not use data specific to animal behavior or how animals respond to forest dynamics. A major assumption, well supported by previous studies, is that wildlife activities are strongly related to forest changes that occur in response to NbS policy interventions (Chen *et al* 2019, Bista and Song 2022). Other underlying factors may also be at play. For example, although Nepal's forest cover increased from 26% in 1992%–45% in 2016 in response to changes in forest policies (Fox 2023), this did not necessarily translate into improved biodiversity conservation. Monocultures of economically valuable tree species are limited in their capacity to support wildlife diversity, and may even drive wildlife into cultivated lands for water and food sources (Agetsuma 2007). From a methodological standpoint, the classification errors resulting from the classification of satellite images may affect the regression models, introducing bias when estimating the fixed effects (Alix-García and Millimet 2023). A follow-up *in-situ* land survey may improve the confidence of the classified results. Future research would benefit from estimates of the share of food production loss due to crop-raiding by wildlife in order to better quantify the cost and benefits relating to food security and forest conservation, better informing policymakers with trade-offs and synergies embedded in NbS.

5. Conclusion

In this study, we investigated cropland abandonment due to crop-raiding by wildlife, which is a critical interaction between ecosystem dynamics and human well-being, especially in a mixed agricultural and forested mosaic. Our methodology integrates satellite remote sensing, household surveys, and statistical models in order to test the hypothesis of household land-use decisions influenced by crop-raiding. We applied this analytical framework in two rural areas from two countries (China and Nepal) and found consistent outcomes using the datasets from both study sites. Households tend to abandon cropland parcels that have experienced crop-raiding incidents by wildlife. The greater extent to which the crops grown on the parcel have been damaged, the higher the likelihood the parcel would be abandoned in the following years. Household decisions about cropland abandonment are more influenced by the extent of crop damage by wildlife than the occurrence of crop-raiding. Our study identifies a major feedback mechanism from the natural system to the human system within the complex adaptive system in the forest landscape setting. Crop-raiding by wildlife should be considered and internalized when practicing NbS to minimize the trade-offs between ecosystem conservation and rural livelihood improvement, as well as to enhance the efficiency and effectiveness of environmental policies.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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