Twenty-Five Years of Community Forestry: Mapping Forest Dynamics in Nepal

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Jefferson Fox, P.I.
Senior Fellow

Sumeet Saksena, Co-I
Senior Fellow

Kaspar Hurni, Co-I
Spatial Information Specialist

East-West Center
1601 East-West Road
Honolulu, Hawaii 96848
foxj@eastwestcenter.org
sakenas@eastwestcenter.org
kaspar.hurni@cde.unibe.ch

Jamon Van Den Hoek, Co-I
Assistant Professor

Alexander Smith
Ph.D. Candidate

Geography & Geospatial Science
Oregon State University
Corvallis, Oregon
jamon.vandenhoek@oregonstate.edu
smitale3@oregonstate.edu

Collaborators
Ram Chhetri, PhD
Pitamber Sharma, PhD
Resources Himalaya
Kathmandu Nepal
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Introduction and overview
This project sought to quantify the rate and extent of Nepal’s forest transition and identify significantly associated socioeconomic variables. The project has three overarching objectives: 1) Build a comprehensive database of changes in across Nepal since 1990; 2) Identify the physiographic and socioeconomic variables associated with tree-cover change and quantify their respective influences; and 3) Assess how foreign labor migration, remittances, community forestry and other variables correlate to tree-cover change across the country. We sought to realize our objectives at two nested scales: national and local community forests in the Middle Hills.

At the national scale, specific research objectives include:
1. Build comprehensive database of tree-cover change since 1990, and produce maps of tree-cover history (disturbance and recovery) at district and Village Development Committee (VDC) scales.
2. Integrate tree dynamics data with demographic and socioeconomic data from the Central Bureau of Statistics to identify physiographic and socioeconomic variables associated with tree dynamics at district and VDC scales.
3. Quantify correlations between the geographic distribution of economic migration and remittances with spatially explicit tree-cover dynamics.

At the local scale, specific research objectives include:
1. Identify a sample of sites mapped as showing tree regrowth or stagnation through this period for more intensive study.
2. Conduct focus group discussions and household interviews in these sample sites to document changes in tree management practices, and economic migration and remittance patterns.

Please note that unless we are refereeing to the forest department on known forest land we use the terms tree cover and forests interchangeably because in areas where trees have regrown on non-forest department land, i.e., on fallow agriculture land, we cannot distinguish between forests and tree cover.

Approach Adopted:
Multi-disciplinary, field and modeling approach in involving three teams: (1) building a comprehensive database of tree-cover change in Nepal over the last 25 years; (2) Identifying the physiographic and socioeconomic variables associated with tree-cover change and quantify their respective influences; (3) Field work team.

Accomplishments

Building a comprehensive database of tree-cover change in the Nepal over the last 25 years (Kaspar Hurni, Jamon Van Den Hoek, Alex Smith, and Jefferson Fox)

In year five we finalized the tasks related to the remote sensing components of this project and processed the tree-cover change data so that it can be used for the statistical and qualitative analysis with socio-economic and biophysical variables. In detail, we performed the following tasks:
1. Finalized image pre-processing routines and their evaluation, including publishing a manuscript on data pre-processing and developing of an on-line tool for conducting pre-processing routines (Kaspar Hurni, Jamon Van Den Hoek, and Jefferson Fox).


The availability of remote sensing big data and cloud computing services provides new opportunities for the preprocessing, analysis, and visualization of satellite images. But accessing and using such data and services is challenging and usually requires considerable expertise in remote sensing and scripting languages like JavaScript or Python. To lower this barrier, we developed a user-friendly online tool that requires only little user input to produce ready-to-use image composites. The tool can be found at: https://code.earthengine.google.com/21f27e216a68fa7ce0a96b9fd92a9f40

Use of Landsat and Sentinel data

The tool uses existing high-level remote sensing data products – Landsat “surface reflectance” and Sentinel “bottom of atmosphere” data – and performs a topographic correction for the Landsat data to remove any differences in the reflectance that result from illumination conditions (Sentinel bottom of atmosphere data available in Google Earth Engine has already been corrected for topographic illumination conditions). In addition, the tool applies a user-defined image composition strategy that deals with noise (e.g. clouds, haze, or shadows) and maximizes the amount of “valid pixels” in the output composite image.

Topographic illumination correction

In mountainous areas, the varying illumination conditions resulting from slope, aspect, and the position of the sun lead to variations in the reflectance within the same land cover type. For example, the same forest type reflects differently on a sunlit slope than on a shaded slope. The tool reduces differences in solar irradiance related to slope and aspect and produces an
image which approximates reflectance values that would have been recorded over a flat surface.

Image composition

The tool creates a new, composite image by selecting the “best version” of each pixel from a series of multiple images. This function enables users to create image composites tailored to their study focus (e.g. covering a specific season) without facing trade-offs in the selection of individual images from the point of view of clouds and seasonality. The tool selects the most suitable pixel for the image composite based on multiple criteria:

1. Comparison of pixel reflectance based on user-defined criteria (e.g. focus on high greenness or low greenness)
2. Distance to clouds and cloud shadows (pixels further away from clouds are prioritized in the composite as they show less noise)
3. Distance to the “target day” of the composite (pixels closer to the target day are prioritized in the composite to reduce noise related to phenology)
4. Weights for the different years if the composition period spans multiple years (e.g. focus on recent images when the aim is to analyze recent land cover change)

Users can adjust parameters related to criteria 1, 3, and 4 according to their needs. This enables them to produce tailor-made image composites quickly and efficiently.
Using the tool

Image composites are based on data from either Landsat 4/5/7/8 (ca 1982 to present, pixel size of 30 m) or Sentinel 2 (ca 2015 to present, pixel size of 10 or 20 m). The tool visualizes the image composite within a few seconds, enabling users to check it and adjust their composition strategy if necessary. Users can then export the image composite to their Google Drive for offline use. Users need a Google Earth Engine account to be able to use the tool.

2. Evaluated the effect of topographic illumination correction (TIC) on long-term forest cover change estimates and paper for publication (Jamon Van Den Hoek, Kaspar Hurni, Alexander Smith, and Jefferson Fox)

Existing research does not capture the spatially and temporally variable effects of topographic illumination correction (TIC) on measurements of long-term tree-cover change, which are important for two reasons. First, since tree regeneration and loss commonly have distinct spatial patterns across a landscape’s sunlit and shaded slopes, especially in mountainous regions, this means that the effect of TIC on tree-cover change is spatially differentiated with respect to dominant drivers of change. Second, since tree-cover regeneration and loss typically have very distinct rates of change, the effect of TIC on net tree-cover change may be less evident in temporally aggregated (e.g., pentad or decadal) assessments. Absent this awareness, the effect of TIC on net tree-cover change cannot be decoupled from the pattern of tree-cover change, itself. Thus, the goal of our paper is to assess the variable effect of TIC on measurements of tree-cover change over time and space. With a Landsat time series-based case study in Nepal from 1992-2016, we had the following specific objectives:

1. Identify differences in tree-cover classification model accuracies using TIC and non-topographic illumination corrected (nonTIC) data;
2. Quantify differences in the areal distribution of inter-annual and long-term tree-cover change with TIC and nonTIC approaches; and
3. Assess differences in tree-cover conversion dynamics using TIC and nonTIC approaches.

We collected all available Landsat Surface Reflectance images over Nepal from 1992-2016. After harmonizing Landsat 5, 7, and 8 data and removing cloudy and hazy images, we had 1,893 remaining images for our analysis. We performed band-wise topographic illumination correction (TIC) on each of these images following Hurni, Van Den Hoek, and Fox (2019); this became our TIC time series, which we compared to the nonTIC time series. For both time series, we built annual peak greenness composites and ran LandTrendr to construct pixel-level linear interpolations across each time series. To characterize topographic illumination (IL) conditions, we used the SRTM 30m DEM and measured the mean IL across all images. IL ranges from zero to one and is equivalent to the cosine of the solar incidence angle, which is based on a location’s slope and aspect and the sun’s position at the time of image acquisition. We collected training data across Nepal at forested and non-forested sites, extracted TIC and nonTIC spectral values as well as topographic variables at each training site, and built two Random Forest classifiers based on the TIC and nonTIC training data. We ran these classifiers on annual imagery from 1992-2016 to map tree/non-tree cover, measured differences in classifier model accuracy, calculated differences in inter-annual and long-term tree-cover change, and gauged the effect of TIC on long-term tree-cover dynamics (i.e., tree-cover gain, loss, stable non-tree, stable tree).

First, we found a consistently small decrease in mean metric values at non-forest (NF) sites after TIC was applied (mean=-4.1%) while forest (F) sites had negligible change (mean=-0.05%). The decline in mean metric values at NF sites means that F and NF metric values are slightly more similar with TIC, which may signal a slightly reduced ability to separate F and NF in a TIC classification. Considering the standard deviation of metrics across F sites, 9 out of 13 spectral metrics saw a decreased standard deviation by 18-35% with TIC, which is expected. Across various assessments of classifier model performance, TIC yielded a positive but small improvement on classification accuracy (Table 1). These show that TIC brings modest gains in accuracy. Similar gains in accuracy were seen in the OOB Score (1.53%), Accuracy Score (0.83%), F1 Statistic (1.37%), Precision (1.18%), Recall (1.5%), and Jaccard Score (1.9%). The ROC AUC Score was the only metric that declined with TIC (-0.39%), however, this decline is considerably smaller in magnitude compared to the other metric increases.

Table 1. Comparison of model accuracies (%) for nonTIC and TIC models with respective 95% confidence intervals.

<table>
<thead>
<tr>
<th></th>
<th>nonTIC</th>
<th>TIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>OOB Score</td>
<td>90.11</td>
<td>91.64</td>
</tr>
<tr>
<td>Accuracy Score</td>
<td>85.73 (+/- 14.93)</td>
<td>86.56 (+/- 15.42)</td>
</tr>
<tr>
<td>F1 Statistic</td>
<td>79.72 (+/- 18.37)</td>
<td>81.09 (+/- 18.03)</td>
</tr>
<tr>
<td>Precision</td>
<td>83.95 (+/- 25.66)</td>
<td>85.13 (+/- 25.34)</td>
</tr>
<tr>
<td>Recall</td>
<td>77.75 (+/- 22.88)</td>
<td>79.25 (+/- 21.94)</td>
</tr>
<tr>
<td>Jaccard Score</td>
<td>67.22 (+/- 24.78)</td>
<td>69.12 (+/- 24.60)</td>
</tr>
<tr>
<td>ROC AUC Score</td>
<td>93.42 (+/- 12.36)</td>
<td>93.03 (+/- 12.96)</td>
</tr>
</tbody>
</table>
Second, we found that both nonTIC and TIC models show a steady expansion of tree cover across Nepal from 1992-2016 but differ in their estimates of annual net tree-cover change (Fig. 1). The nonTIC model estimates a tree-cover net gain of 29,960 km² (an average of 1,248 km²/year) while the TIC model estimates a lower net gain 28,076 km² (an average of 1,170 km²/year). The nonTIC model thus overestimates the TIC estimate of net tree-cover gain by 1,884 km², which corresponds to 1.3% of Nepal’s land mass or 5.2% of Nepal’s tree cover in 1992. In both models, all IL strata show tree-cover expansion over time with the better illuminated strata (6-10) showing more rapid expansion than the less illuminated strata (1-5) (Fig. 2a-b). The effect of TIC on detecting tree-cover extent and change is thus not only spatially variable with respect to illumination conditions (i.e., IL strata), these results show that the effect is also non-stationary given the particularly acute rate of tree-cover change in Nepal in the mid-1990s that was more concentrated in moderately illuminated IL strata.

Third, we found that nonTIC and TIC showed slight differences in measures of tree-cover conversion, i.e., Never Forest, Always Forest, Regenerated Forest, and Lost Forest (Fig. 3). TIC estimates of Never Forest and Always Forest exceeded nonTIC estimates by 1.4% (1067 km²) and 2.4% (744 km²), respectively. The TIC model detected a slightly more stable landscape than the nonTIC model, as the nonTIC model measured 4.6% (1637 km²) more Regenerated Forest and 3.6% (174 km²) more Lost Forest than the TIC model. Considering tree-cover conversions across IL strata, Never Forest pervades the lowest (1-3) and highest (7-10) IL strata while Always Forest dominates IL strata 4-5 (Fig. 4a). Both nonTIC and TIC models measured Regenerated Forest at 10-30% in each IL stratum with the most Regenerated Forest in IL strata 6-8. In contrast to national-level tree conversion trends that show TIC capturing more tree-cover stability (principally due to the very large areas of IL strata 8-10), these IL stratum-level views of tree conversion show that TIC has a highly variable effect on both tree-cover stability and regeneration.
Our results thus show the various effects of TIC in classifier model accuracy, annual tree-cover extent, inter-annual and long-term net tree-cover change, and tree-cover conversion dynamics (i.e., stability, regeneration, loss). The results of this study offer a comprehensive assessment of the effects of TIC on time series analysis of mountainous tree-cover change with broad import for remote sensing scientists, national forest managers, and international forest cover and carbon monitoring efforts.


3. Finalized correlation of socio-economic and biophysical variables with changes in tree cover (Sumeet Saksena, Jefferson Fox, Hanpei Zhang, Anna Kato, Kaspar Hurni, Alex Smith, Jamon Van Den Hoek, Pawan Kanel, and Faisal Qamar)
The team finalized modeling tree cover using a large suite of biophysical and socio-economic data based on new RS estimates of tree cover. Considering that most coupled natural-human systems are complex, the team felt it best to use modern machine learning approaches. Specifically we chose to use Random Forests (RF). In these models, we also incorporated the effects of spatial clustering. This entailed inclusion of an auto-covariance term in regular regression models using Augustin et al.’s (1996) method: values of the auto covariate depend on the values of the response variable in the neighborhood. We chose to model as the dependent variable the percentage tree cover in 2001 and 2011. That is, we used a panel design for the Random Forest modeling with VDCs being the set of units in the panel. The main aim of the modeling exercise was to examine the association of tree cover with migration and community forestry. However, the models need to control for the potential influence and confounding of other known and hypothesized drivers of tree-cover change. We relied mainly on international literature to identify the socio-economic and biogeophysical drivers of tree-cover change. We assembled a large set of potential predictors. This set was pruned on the basis of data availability and issues related to multicollinearity. Though it is known collinearity is not prohibited in machine learning models such as random forests, we nevertheless excluded variables whenever correlations were higher than 80%.

Table 2 shows the results of the Random Forest model. The table lists the main factors driving tree-cover change in terms of relative rankings. This modeling approach indicates that population density is one of the key drivers of change, more so than either migration or community forestry or protection efforts. An advantage of the Random Forest models over the traditional regression models is that they enable us to examine the partial dependence between the outcome variable and the predictors. Figures 5 to 9 show the dependence of percentage tree cover and migration, community forestry, literacy rate, village wealth index, and road density. In most cases, we gained valuable insights into these relationships. They are nonlinear, non-monotonous, and they have thresholds, tipping points and saturation effects. Previous studies of the impact of migration on tree-cover change did not explore these aspects of the association.
Table 2: Random Forests model of the percentage tree cover, ranking of predictor influence

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Nepal</th>
<th>Terai</th>
<th>Middle Hills</th>
<th>Himalaya</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (test set) %</td>
<td>95</td>
<td>97</td>
<td>91</td>
<td>91</td>
</tr>
<tr>
<td>Terrain Roughness index</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>15</td>
</tr>
<tr>
<td>Compound Topographic Index</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>12</td>
</tr>
<tr>
<td>Population density</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Elevation</td>
<td>4</td>
<td>3</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Spatial autocorrelation</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Aridity</td>
<td>6</td>
<td>14</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Road density</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Solar radiation</td>
<td>8</td>
<td>12</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>Distance to highway</td>
<td>9</td>
<td>15</td>
<td>20</td>
<td>13</td>
</tr>
<tr>
<td>Accessibility</td>
<td>10</td>
<td>6</td>
<td>11</td>
<td>17</td>
</tr>
<tr>
<td>Percentage houses in community forestry</td>
<td>11</td>
<td>9</td>
<td>21</td>
<td>25</td>
</tr>
<tr>
<td>Terrain northness</td>
<td>12</td>
<td>8</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Water bodies density</td>
<td>13</td>
<td>24</td>
<td>15</td>
<td>5</td>
</tr>
<tr>
<td>Literacy</td>
<td>14</td>
<td>18</td>
<td>13</td>
<td>9</td>
</tr>
<tr>
<td>Year</td>
<td>15</td>
<td>26</td>
<td>12</td>
<td>26</td>
</tr>
<tr>
<td>Distance to protected areas</td>
<td>16</td>
<td>16</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Village Wealth Index</td>
<td>17</td>
<td>11</td>
<td>17</td>
<td>22</td>
</tr>
<tr>
<td>Female land ownership</td>
<td>18</td>
<td>21</td>
<td>14</td>
<td>18</td>
</tr>
<tr>
<td>Female headed households</td>
<td>19</td>
<td>23</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td>Topographic Position Index, landscape scale</td>
<td>20</td>
<td>10</td>
<td>24</td>
<td>14</td>
</tr>
<tr>
<td>Streams density</td>
<td>21</td>
<td>20</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>Percentage migrants</td>
<td>22</td>
<td>22</td>
<td>16</td>
<td>11</td>
</tr>
<tr>
<td>Terrain Eastness</td>
<td>23</td>
<td>17</td>
<td>23</td>
<td>24</td>
</tr>
<tr>
<td>Topographic Position Index, intermediate scale</td>
<td>24</td>
<td>19</td>
<td>26</td>
<td>21</td>
</tr>
<tr>
<td>Female owned houses</td>
<td>25</td>
<td>25</td>
<td>22</td>
<td>23</td>
</tr>
<tr>
<td>Topographic Position Index, local scale</td>
<td>26</td>
<td>13</td>
<td>25</td>
<td>20</td>
</tr>
<tr>
<td>Percentage protected area</td>
<td>27</td>
<td>27</td>
<td>27</td>
<td>27</td>
</tr>
</tbody>
</table>
Fig 5: Partial dependency of Tree Cover on % migrants (belts: 1 = Terai, 2 = Middle Hills, 3 = Himalaya)
Fig 6: Partial dependency of Tree Cover on % houses that are members of community forestry groups (belts: 1 = Terai, 2 = Middle Hills, 3 = Himalaya)
Fig 7: Partial dependency of Tree Cover on village wealth index (belts: 1 = Terai, 2 = Middle Hills, 3 = Himalaya)

Fig 8: Partial dependency of Tree Cover on literacy rate (belts: 1 = Terai, 2 = Middle Hills, 3 = Himalaya)
Fig 9: Partial dependency of Tree Cover on road density (belts: 1 = Terai, 2 = Middle Hills, 3 = Himalaya)

**Summary**

Overall, a few biogeophysical factors (such as elevation, terrain roughness index and aridity) were discovered to be the most important predictors of tree cover. Among the socio-economic drivers of change found population density to be one of the most influential factors. Across all belts an increase in population density was associated with lower tree cover. The second most important anthropogenic driver was road density. In the Middle Hills and the Himalaya, tree cover was found to first increase with increasing road density and then decrease. In the Terai, road density consistently decreased tree cover. The relationship between level of migration and tree cover was found to vary across the belts. In the Middle Hills the curve has an inverted U-shape. In the Terai tree cover was found to decrease with level of migration and it was the opposite in the Himalaya. Where the influence of community forestry is concerned we found that by ignoring outliers, tree cover increased with community forestry participation rates in the Terai and the Middle Hills. It was the opposite in the Himalaya. Literacy rate has a remarkably consistent pattern in all the three belts. That is, greater literacy is associated with higher tree cover. In the Terai and Middle Hills we found that an increase in wealth is associated with higher tree cover, in the Himalaya the opposite was observed.
4. Finalized Nepal fieldwork and submitted a paper for publication and prepared a second paper (Ram Chhetri, Phanwin Yokying, and Jefferson Fox)

Ram Chhetri spent 3 months in Hawaii analyzing field data collect and writing a paper summarizing project results. This study sought to summarize differences in forest cover, land use, demographic and socioeconomic characteristics between a survey of six sites in Sindhu Palchok and Kabhre Palanchok Districts in the Middle Hills that Chhetri conducted in 1992 with a survey he conducted of the same six sites in 2017. The study also sought to correlate changes observed in the 1992 and 2017 surveys with changes in forest cover in the same six sites based on the results from this project. Finally, the project sought to examine differences between households with and without migrants in the 2017 survey and to seek insights into how land use is changing in response to migration and other factors, and the implications these changes hold for the future of trees and agriculture in the six sites. Chhetri and Fox conclude with two major findings. First, forest and tree cover has increased tremendously; farmers are less reliant on forests and forest products for their livelihoods, and there is no reason to believe that this trend will reverse. Stable and perhaps even regenerating forest cover will be part of Nepal’s landscape for the near future. Second, farmers are farming less land but this does not mean the end of agriculture. In these six sites, which sit on the edge of Kathmandu valley, we find that farmers have found crops that have commercial value, and with the development of road infrastructure, they have developed value-added chains for marketing their goods in Kathmandu and other nearby towns. Occupational multiplicity, where households create a nexus of activities, some farm and other non-farm, some highly commoditized and other quasi-subsistence, some on the farm and others elsewhere may offer a very stable situation for these villages.


Dr. Phanwin Yokying used the Nepal Labour Force Survey (NLFS, 2010), a nationally representative survey carried out by Nepal’s Central Bureau of Statistics to capture seasonal variations in employment. This paper aims to examine the effects of out-migration on work time of left-behind children, working-age individuals, and elderly people in rural areas of Nepal. Results show that migration increases work time of the left-behind individuals, especially among boys and women. In particular, the left-behind boys along with working-age and elderly women allocate more time towards agriculture, while elderly women increase the time spent on domestic and care work. We also find that the left-behind males and females from all age cohorts spend more time fetching water and collecting firewood. We conclude that migration generates a loss in household labor supply, increasing workload and responsibilities in labor-intensive and low-paying activities among those who remain at home.


5. Used Nepal forest cover time series data to support Alex Smith’s PhD dissertation research (Alex Smith, Jamon Van Den Hoek)

The availability of novel, long term yearly land cover data sets, such as the forest cover data generated for this project, opened the door to new analytical possibilities in the social sciences. My research built on one of this project's primary deliverables - a long term (1988-2016), nation-wide tree-cover change data set for Nepal. I used the tree-cover change data to answer three questions: 1) How did the implementation of decentralized forest management
(i.e. community forest management) operate at the scale of the individual community forest affect forest change between 1988-2016? 2) How did migration driven land-use changes operated on private land at the forest patch level to drive forest change between 1988-2016? And 3) how did forest change patterns varied between areas inside and outside community forest management across time?

1. How did community forest management affect tree cover between 1988 and 2016?

I used the forest cover data set and community forest boundary data from eight user groups to measure forest cover at the community forest user group level beginning prior to the establishment of the user groups until the present. I assessed the conservation impact of decentralized forest management by linking the community forest user group level forest cover data with changes in management. These changes in management were recorded through interviews and focus groups with forest users and managers identifying the direct impact of policy changes related to the introduction of community forestry on forest cover, (harvest restrictions, forest monitoring, resource use and forest management/restoration efforts). Finally, I assessed the impact of changing forest condition and socioeconomic factors on the effectiveness of decentralization by linking the community forest level forest cover data with data on changes in forest resource use and valuation over time. Data on changes in forest resource use and valuation were obtained by acquiring detailed evidence from interviews and focus groups on how changes in forest condition and socioeconomic factors moderated or enhanced the effectiveness of forest management decentralization across time as measured by forest resource availability, forest resource value, availability of alternative income sources, and availability of alternatives to forest resources.

Two main conclusions were drawn from this analysis. First, all 8 community forests recognized improvement in forest cover that could be directly attributed to initial changes in forest management that were the result of forest decentralization. Second, long-term improvements in forest condition, as well as broader socioeconomic factors in Nepal, led to decreasing demand for forest resources and declining investment in forest conservation.

2. How did migration driven land-use changes affect tree cover on private land 1988-2016?

I used the forest cover data set and community forest boundary data from three community forest-user groups to identify and measure areas of afforestation on private lands. I evaluated patterns and drivers of land abandonment and afforestation on these lands by linking the forest cover change data from privately held land to oral histories of land use and land management. These histories were obtained by collecting detailed data from interviews with landowners and tenants on historic and current land use and land cover and the social and ecological factors that motivated those changes. Finally, I evaluated pathways of forest change across time by linking long term forest change data from private land with interview data on the long term effect of land abandonment and afforestation to examine: 1) local social and ecological systems and 2) how these systems changed and interacted over time. Data on land abandonment and afforestation driven changes in local social ecological systems were obtained by recording detailed evidence from interviews and focus groups with private landowners and tenants. These interviews focused on historic patterns of land use and land cover change as well as how those changes fed back on each other to drive future changes in local social and ecological systems.
Two main conclusions were drawn from the analysis of the forest change data from areas under private ownership and the interviews on changes in land management, use and function following land abandonment and afforestation. First, the majority of land that was abandoned had historically been under cultivation. Abandonment typically occurred when land owners switched to non-farm income generating activities followed a few years later by a switch to non-farm income generating activities by tenant farmers. Afforestation followed within 5-10 years. Second, while initial land abandonment and the subsequent afforestation were almost exclusively driven by migration from farming areas, later waves of land abandonment were often the result of environmental changes that made farming increasingly unsustainable. While migration driven abandonment is still common, human wildlife conflict is increasingly noted as a driver of both land abandonment and a factor that would prevent a return to cultivation in the future.

3. How did forest change patterns differ inside and outside community forests across time?

I combined community forest boundary and watershed boundary data to map all areas under community forest management. I followed the same process for all areas outside community forest management in Charnawati Watershed, Dolakha District Nepal. I then quantified spatial and temporal patterns in forest cover between areas inside and outside community forest management by overlaying the forest cover data with the Charnawati watershed land management data and extracting the yearly forest cover for each category of land management, (community forest management vs. private management). Finally, I compared spatial and temporal trends in forest cover change with existing interview data from community forest managers and users as well as private landowners and tenants.

Preliminary results from a small sample of community forest-user groups support the initial hypothesis that two separate forest transitions have been occurring in Nepal over the past 30 years. Afforestation in areas under community forest management, initially driven by local shortages in forest resources, began in the late 1980s-early 1990s and plateaued in late 2000-early 2010s. In contrast, afforestation in areas outside community forest management, typically driven by migration, started in the mid to late 1990s and has continued through 2016.