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Using Landsat imagery to map forest change in southwest China in response to the national logging ban and ecotourism development

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ABSTRACT

Forest cover change is one of the most important land cover change processes globally, and old-growth forests continue to disappear despite many efforts to protect them. At the same time, many countries are on a trajectory of increasing forest cover, and secondary, plantation, and scrub forests are a growing proportion of global forest cover. Remote sensing is a crucial tool for understanding how forests change in response to forest protection strategies and economic development, but most forest monitoring with satellite imagery does not distinguish old-growth forest from other forest types. Our goal was to measure changes in forest types, and especially old-growth forests, in the biodiversity hotspot of northwest Yunnan in southwest China. Northwest Yunnan is one of the poorest regions in China, and since the 1990s, the Chinese government has legislated strong forest protection and fostered the growth of ecotourism-based economic development. We used Landsat TM/ETM+ and MSS images, Support Vector Machines, and a multi-temporal composite classification technique to analyze change in forest types and the loss of old-growth forest in three distinct periods of forestry policy and ecotourism development from 1974 to 2009. Our analysis showed that logging rates decreased substantially from 1974 to 2009, and the proportion of forest cover increased from 62% in 1990 to 64% in 2009. However, clearing of high-diversity old-growth forest accelerated, from approximately 1100 hectares/year before the logging ban (1990 to 1999), to 1550 hectares/year after the logging ban (1999 to 2009). Paradoxically, old-growth forest clearing accelerated most rapidly where ecotourism was most prominent. Despite increasing overall forest cover, the proportion of old-growth forests declined from 26% in 1990, to 20% in 2009. The majority of forests cleared from 1974 to 1990 returned to either a non-forested land cover type (14%) or non-pine scrub forest (66%) in 2009, and our results suggest that most non-pine scrub forest was not on a successional trajectory towards high-diversity forest stands. That means that despite increasing forest cover, biodiversity likely continues to decline, a trend obscured by simple forest versus non-forest accounting. It also means that rapid development may pose inherent risks to biodiversity, since our study area arguably represents a "best-case scenario" for balancing development with maintenance of biodiversity, given strong forest protection policies and an emphasis on ecotourism development.

1. Introduction

Land cover and land use change are the main causes of biodiversity declines (Chapin et al., 2000; Foley et al., 2005; Vitousek et al., 1997), and old-growth forests are among the most threatened habitats globally. Old-growth forests are economically valuable for timber (Chazdon et al., 2009) and as agricultural land (Gibbs et al., 2010; Perfecto and Vandermeer, 2010), and they continue to disappear despite many efforts to protect them. Most of the remaining high-diversity old-growth forests are located in developing countries (Myers et al., 2000; Zimmerer et al., 2004), which are undergoing rapid development and population growth. High biodiversity often occurs in the same areas where people dwell (Naughton-Treves et al., 2005), and our understanding of how to balance livelihoods and conservation is still limited (Ferraro et al., 2011).

However, while old-growth deforestation continues, more and more countries have undergone a forest transition, i.e., a change in forest trajectory from decreasing to increasing forest cover (Meyfroidt and Lambin, 2011; Meyfroidt et al., 2010). Forest transition theory assumes that as a country develops, its forest trajectory

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follows an environmental Kuznets curve, i.e., the environment first worsens but then improves as incomes rise (Mather et al., 1999). While the opportunities of returning forests are substantial (Kauppi et al., 2006; Rudel, 2009; Rudel et al., 2005), increasing forest cover alone does not necessarily mean that biodiversity and natural ecosystems are on a pathway towards recovery. Secondary forests are not equal to old-growth forest in terms of biodiversity, carbon storage, and ecosystem service provision (Chazdon, 2008; Perfecto and Vandermeer, 2010; Rudel, 2009) and do not always return to high-diversity ecosystems (Chazdon et al., 2009).

As old-growth forests dwindle and new forests proliferate, two key challenges are to 1) identify effective protection strategies for remaining old-growth forests, and 2) understand the fate and implications of the increasing area of new forests. The key to both is to monitor forest change dynamics over broad spatial and temporal scales in response to different protection strategies, government policies, and economic development.

Remote sensing is a crucial tool for forest cover change mapping and monitoring. Mapping old-growth forest distribution (Congalton et al., 1993) and post-disturbance forest succession (Cohen et al., 1995; Fiorella and Ripple, 1993; Jakubauskas, 1996) have long been recognized as essential components of forest biodiversity assessment, and in recent years, multiple forest classes have been mapped even in extremely complex and little-studied environments (Helmer et al., 2000; Liu et al., 2002; Schmook et al., 2011).

However, detailed forest type classifications are usually performed for only a single time period, because there are formidable challenges associated with mapping change for multiple classes over several time-steps. First, using single-date classifications to detect change (i.e. post-classification change detection analysis) over multiple time-steps is problematic because errors multiply over each timestep (Kennedy et al., 2009). Composite change detection minimizes multiplicative error by stacking multi-date imagery together and classifying change directly. However, change classes typically have non-normal distributions. For example, even though deforested areas transition to grassland, agriculture, bare land, or shrub, all are included into a single “deforestation” class, and most classification techniques are ill suited to handle such complex class distributions.

Recently, non-parametric classification techniques, such as decision trees (Hansen et al., 2008; Potapov et al., 2011) have been tested for composite change detection because they can accommodate the non-normal and multi-modal distributions of multi-date imagery. The major disadvantage of non-parametric techniques for composite change detection is that they typically perform better with training datasets that provide a complete and representative sample of the classes (Pal and Mather, 2003). In composite change detection, overall change class numbers increase exponentially with each added land cover class, and adequate training data for rare land cover classes over multiple time-steps are difficult to acquire (Kennedy et al., 2009).

Support Vector Machines (SVM) are an alternative non-parametric classifier that offer particular promise for change detection of multiple forest classes because they can handle complex distributions of multi-temporal imagery (Huang et al., 2002), but they do not require training datasets that completely describe each class. SVM place hyperplanes to separate different classes, and only training points at the class boundaries are necessary for optimal hyperplane placement (Foody and Mathur, 2004). Therefore, SVM can perform effectively with a small sample of “mixed pixels” collected from purposefully selected locations (Foody et al., 2006).

Our overarching goal was to use remote sensing to map different forest types and forest loss in complex environments in order to understand processes affecting high-diversity forest types. Our study area was Diqing Prefecture of northwest (NW) Yunnan Province in the Himalayan mountains of southwest China, a global biodiversity hotspot (Myers et al., 2000) and rapidly developing region. Home to the most biologically diverse temperate forests in the world (Morell, 2008), and historically relatively undisturbed (Goodman, 2006), large expanses of NW Yunnan's old-growth forests were clear-cut by state logging companies from the 1960s through the 1990s to fuel China's national development (Harkness, 1998; Morell, 2008) and the logging industry dominated the local economy (Melick et al., 2007).

However, in response to catastrophic flooding along the Yangtze River, in 1998 the Chinese government instituted the National Forest Protection Plan (NFPP). One of the primary objectives of the NFPP was to ban logging of all forests in southwest China, except for small quotas allowed to local people for non-commercial uses (e.g. construction materials and fuelwood). Furthermore, since the 1990s China has invested heavily in reforestation programs (Liu et al., 2008) and ecotourism (Jenkins, 2009; Kolas, 2008). As a result, forest cover in SW China is increasing (Weyerhauser et al., 2005), but fine-scale studies indicate that old-growth forests continue to be logged (Melick et al., 2007; Xu and Melick, 2007; Zackey, 2007) and the ecological integrity of the new forests is unclear (Liu et al., 2008; Xu, 2011).

Using remote sensing to map forest change is a logical first step towards understanding the consequences of forest protection and economic development policies since the 1980s in SW China. However, remote sensing in the region is challenging. Because of the monsoonal climate, clouds cover the region during the growing season, but winter image analysis is challenged by snow cover, illumination effects from topography, and senescent vegetation. Furthermore, the collection of ground truth data is difficult because topography is extremely rugged and roads are few, aerial photos are not freely available, and different forest types are difficult to separate visually in either Landsat or high resolution imagery.

To overcome these challenges, and to understand complex processes of forest change in our study area, we used SVM, multi-temporal Landsat TM/ETM+ satellite imagery, purposefully selected ground truth data, and a combined post-classification and composite change detection technique to map multiple classes of forest cover and change in NW Yunnan from 1974 to 2009. Our specific objectives were to:

1. Map multiple forest classes and forest loss for the historical period (1974–1990), the decade before the logging ban (1990–1999) and the decade after the logging ban (1999–2009).
2. Assess the spatial and temporal patterns of logging in relation to geographic, demographic, and economic factors.
3. Determine overall forest cover change, and types of forest that have regenerated.

2. Study region

Our study area (22,834 km²) was the Diqing Tibetan Autonomous Prefecture in the Hengduan Mountains of northwest (NW) Yunnan Province, bordering Tibet and Sichuan Province (Fig. 1a). Elevations in the study area range from 1500 to 6000 m above sea level (Fig. 1b), creating a large array of ecological niches in a relatively small area. Forest cover in our study area has been estimated at 60% (Weyerhauser et al., 2005), but the high-diversity old-growth forests, which are the primary conservation target in this biodiversity hotspot, are just a fraction of the total forest cover. The old-growth montane conifer and mixed forests are the most biologically diverse temperate forests globally (Morell, 2008). Over 7000 plant, 410 bird, and 170 mammal species have been documented in NW Yunnan, many of which are endemic to native old-growth forests (Chang-Le et al., 2007; Ma et al., 2007; Xu and Wilkes, 2004). Among the different land cover types, the old-growth forest community is richer in endemic, endangered and culturally useful species than any other land cover types (Anderson et al., 2005; Li et al., 2008; Ma et al., 2007; Salick et al., 2007; Wang et al., 2008; Wen et

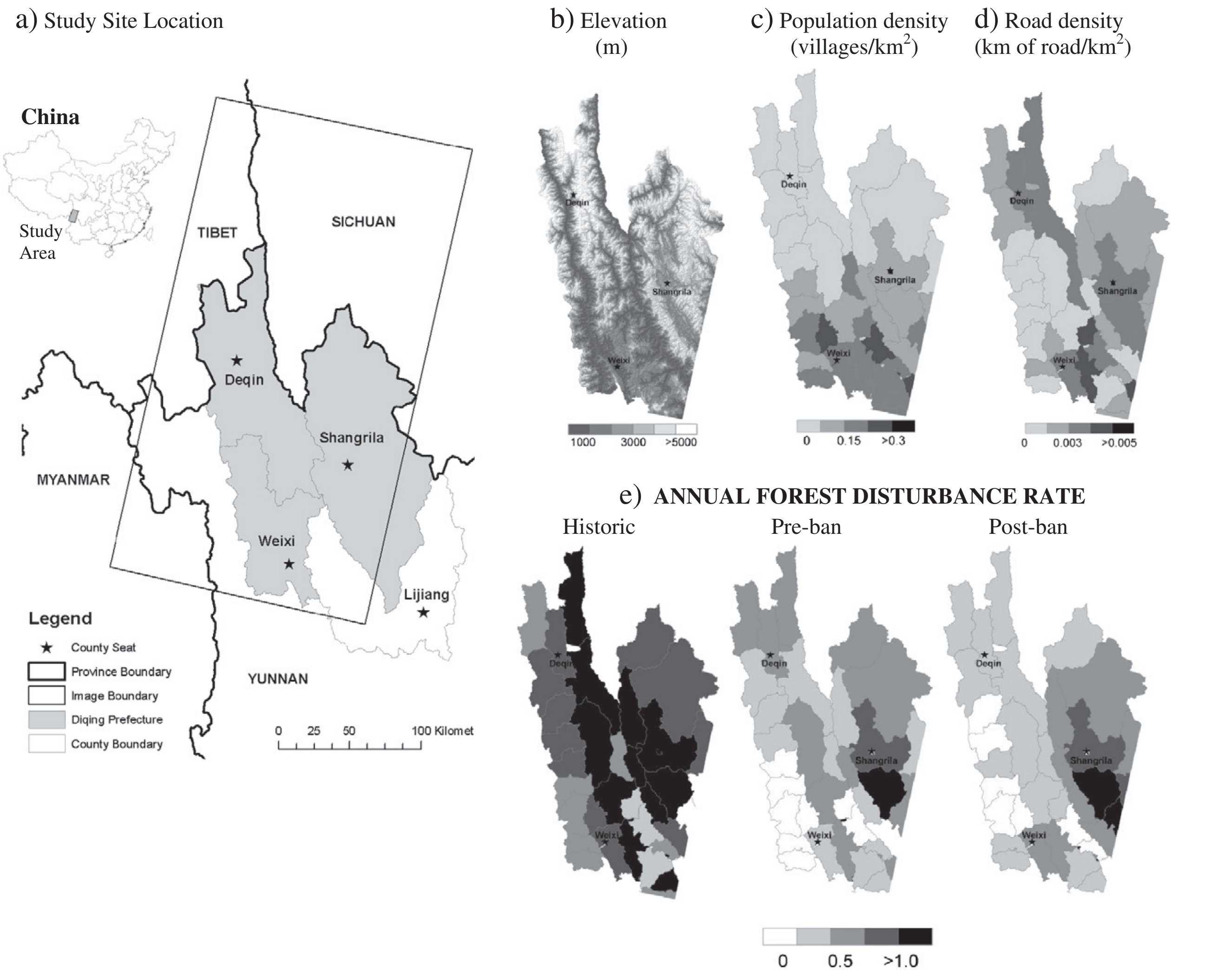

Fig. 1. Location of study area, and important spatial patterns in the study area. a) Location of study area, Diqing Prefecture, in Northwest Yunnan, China, b) elevation, c) population density, d) road density, and e) annual disturbance rate trends by township for the Historic (1974–1990), Pre-ban (1990–1999) and Post-ban (1999–2009) periods.

al., 2003), and is essential habitat to the endangered Yunnan snub-nosed monkey (Li et al., 2008; Wen et al., 2003), and to several rare species of pheasants (Wang et al., 2008).

NW Yunnan is also an UNESCO world heritage site because of its centuries-long history of indigenous subsistence cultures, including Tibetan, Lisu, Bai, Naxi, and Yi peoples. Historically, the region was sparsely populated (approximately 15 people/km^2), with a decreasing population gradient from the lower-elevation South to the higher, harsher-climate North (Fig. 1c). Most people live at a subsistence level, relying heavily on forests for their livelihoods. Forests are still the primary source of fuel for cooking, heating, and construction, and are intensively used for livestock grazing, hunting, food gathering, and traditional medicines. Old-growth trees are especially valuable to Tibetans, as large logs are required to construct traditional Tibetan houses.

NW Yunnan is one of China's poorest regions, making it a primary target of economic development programs since the 1980s, including the Great Western Development program in 1998, which emphasizes infrastructure development, ecological rehabilitation, foreign economic investment, and education throughout western China (Xu et al., 2006). Furthermore, tourism development in NW Yunnan's natural areas has been promoted as a strategy for both environmental protection and economic development (Li and Han, 2000; Wang and Buckley, 2010).

3. Methods

3.1. General approach

We used Landsat MSS/TM/ETM + images and a multi-temporal change classification technique to map forest cover and change in NW Yunnan from 1974 to 2009. We focused on the classification of forest cover loss and of three biologically distinct forest types. A field-derived training dataset and multi-temporal Landsat imagery (Fig. 2) enabled accurate classification of the three different forest classes. We performed a combination of composite and post-classification change detection, using multi-temporal imagery from four different time periods (1974, 1990, 1999 and 2009) to quantify land cover/land use change during three intervals (1974–1990, 1990–1999, and 1999–2009) (Fig. 3). One composite change classification mapped forest types and forest loss in the ‘Historic’ time period (1974–1990), and another mapped forest types and forest loss in both the ‘Pre-ban’, i.e., the decade before the logging ban (1990–1999), and ‘Post-ban’, i.e., the decade following the logging ban (1999–2009) periods. We then performed post-classification change detection from the two composite change classification to identify which types of forests were logged in the Pre-ban and Post-ban periods, and to measure what was the share of total forest

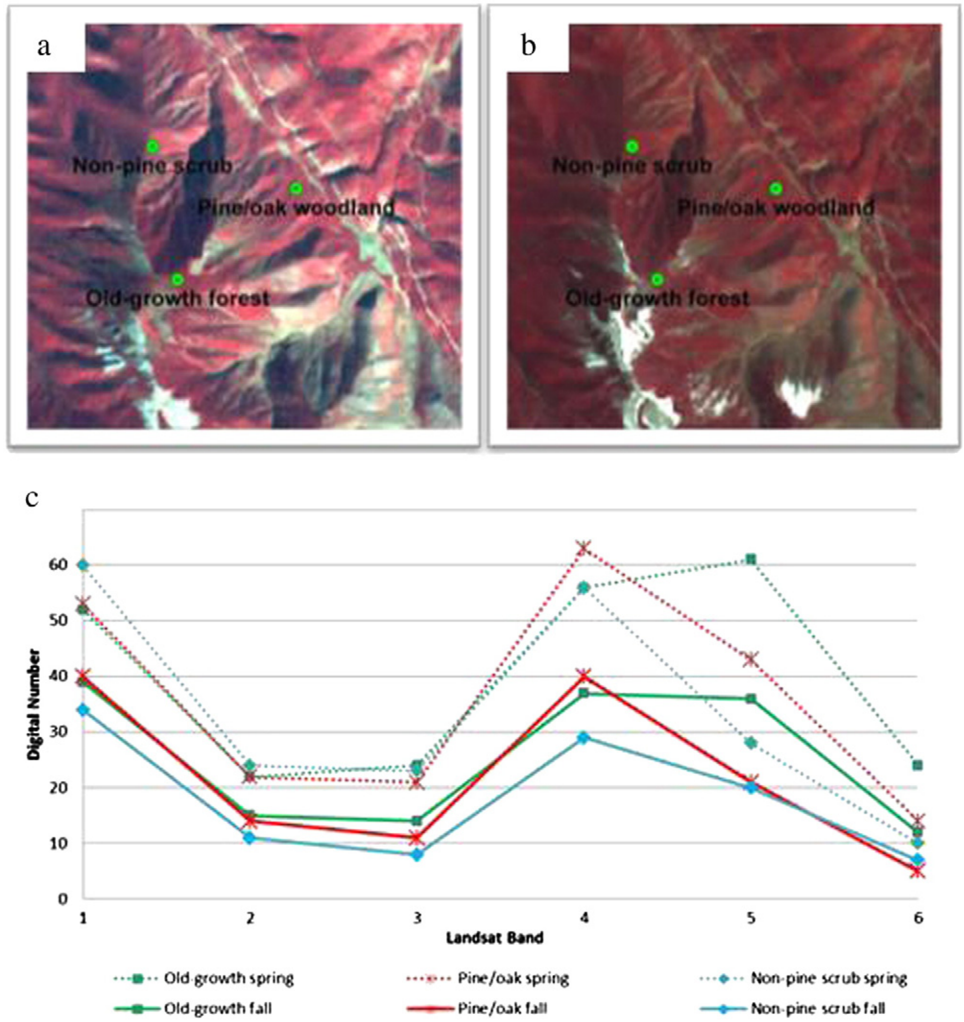

Fig. 2. Examples of how phenology was used to discriminate the different forest classes. Representative pixels from the three forest classes look similar under visual inspection on Landsat images from a) November 20, 1990 and b) April 13, 1991, but c) spectral plots (Landsat bands 1 to 6) show that different forest types vary in their response to winter drought, enabling discrimination between forest types with multi-temporal imagery.

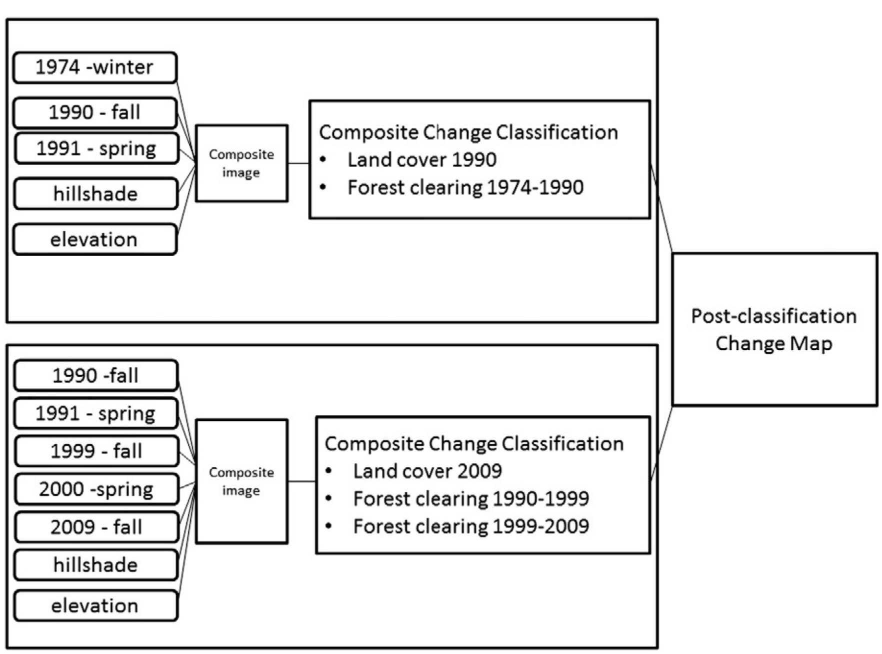

Fig. 3. Description of how multi-temporal imagery was used in a combined composite and post-classification change detection approach.

cover in 2009 that had been logged in the Historic period. The three forest types were:

(a) *Old-growth forests* represent the main target of biodiversity conservation in this region (Chang-Le et al., 2007; Ma et al., 2007; Xu and Wilkes, 2004). We define old-growth forests as the native, original forest vegetation community of this region. The old-growth forest community is composed of mixed evergreen and deciduous species, including fir (*Abies* spp.), spruce (*Picea* spp.), pine (*Pinus* spp.), larch (*Larix* spp.), evergreen oak (*Quercus* spp.), birch (*Betula* spp.) and rhododendron (*Rhododendron* spp.) with specific species composition highly related to topographic variability (Li and Walker, 1986). The vast majority of this category consists of the old-growth forest vegetation community in its climax state, but also includes this community in its secondary state, because the primary and secondary states are spectrally indistinguishable with our Landsat imagery because of the similarity in species composition.

(b) *Pine/oak woodlands* can occur naturally in NW Yunnan, and often colonize and persist in cleared areas after a disturbance (Li and Walker, 1986), but many pine forests have been planted after logging. In our study area, old-growth pine/oak woodlands are rare, and existing pine forests are typically homogeneous stands of young pines (*Pinus densata*) with oak shrub understory.

(c) *Non-pine scrub* represents a mix of deciduous and evergreen shrublands that regenerate and persist following logging. This forest type is especially common near villages and along roads, where forests are heavily used by livestock and people. Based on interviews with local people, many scrub forests have persisted for many decades after logging.

3.2. Satellite images

The study area is covered by two Landsat TM image footprints (path/row 132/040 and 132/041). We used a total of 14 images (Table 1), all from late October through early April, because cloud free images are not available during the growing season in this region due to the monsoonal climate. Images were obtained from the USGS Landsat archives and from the China and Thai International Ground Stations. We georeferenced all images to the Landsat 2000 GeoCover Dataset using ERDAS IMAGINE AutoSync, which was already orthorectified, and used a gap-filled Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) to account for relief displacement. Root mean square error for the georeferencing was less than 0.4 pixels (<12 m). Clouds and cloud shadows were masked manually from the images prior to all image analyses. We did not apply any other pre-processing of the images.

3.3. Field data

Field data for training and validation were collected during six months of field work, from September to November of 2008, and August to October of 2009. We sampled at least 40 locations for each land cover class to aid the interpretation of spectral subclasses during image analysis. The ground truth dataset consisted of 1573 polygons containing 93,300 pixels (Table 2). Due to the ruggedness of the study area, a random sampling design was not feasible. Ground truth data for uncommon classes, such as old-growth forests, required extensive trekking in remote locations. We hired local villagers to guide us to old-growth forests, alpine pastures, and areas of logging, and while trekking we conducted interviews with our guides about land use history and practices. We recorded land use and land cover observations and took photographs for an approximate 100×100 m area surrounding each GPS point (Justice and Townshend, 1981). We collected points for both “pure pixels” (i.e., homogeneous areas of a single land cover type), as well as “mixed pixels”, (i.e. areas were a mixture between land cover types prevails) to aid the SVM in hyperplane placement.

We supplemented field data with ground truth data from high resolution imagery available in Google Earth™, which covered approximately one-third of the study area, and the Landsat imagery. For the forest type classes, we relied entirely on field data, since these classes cannot be distinguished reliably based on visual inspection of single-date satellite imagery alone. For forest loss classes, approximately 60% of training data were derived from field data, and approximately 40% were selected by visual interpretation of the Landsat imagery. We identified forest loss classes in the field by visiting areas of past logging, and asking our local guide when the logging had occurred. Similarly, approximately 20% of the training areas for agriculture, grassland, sparse shrub, and bare/urban classes were collected from the high resolution imagery, and 80% in the field.

Table 2
The number of ground truth polygons and pixels in each class.

Land cover class	Polygons	Pixels
Old-growth forest	396	18,664
Pine/oak woodland	184	9713
Non-pine scrub	329	24,149
Deforestation — historic	51	5442
Deforestation pre-ban	85	3435
Deforestation post-ban	81	3970
Agriculture	141	5710
Grassland	98	2244
Alpine shrub expansion	41	1826
Sparse shrub	78	12,198
Bare/urban	45	2063
Other	44	3886
Total	1573	93,300

3.4. Change detection

We used Support Vector Machines (SVM), implemented in the software imageSVM (Janz et al., 2007), for our change detection. To train and validate our SVM, we used a random selection of approximately 1000 points from each class in our ground truth dataset. We performed a classification for the Historic period (1974–1990) by combining 1974 Landsat MSS images, ca. 1990 Landsat TM images, and elevation and hillshade from the DEM. The hillshade for the ‘Historic’ classification was calculated with a sun elevation angle of 34.04°, and a sun azimuth angle of 146.62° (corresponding to the November 19th 1990 Landsat TM image (Path/Row 132/40). For the ‘Historic’ classification, all images were resampled to the resolution of the MSS image (57 m pixels). We classified six classes, including the three forest types, a forest cover loss 1974–1990 class, agriculture and grassland, and other (bare/urban/snow/water).

Using the Landsat TM/ETM+ imagery from 1990, 1999, and 2009, we performed a second composite classification for the decade

Table 1
Images used for the analysis.

	Time period						
	ca. 1974	ca. 1990		ca. 1999		ca. 2009	Reference
Landsat Sensor	MSS	TM	TM	TM	ETM	TM	ETM
Acquisition date	1/5/1974	11/20/1990	4/13/1991	10/28/1999	4/13/2000	11/24/2009	12/25/2000

leading up to the logging ban (Pre-ban, 1990–1999), and the decade following the logging ban (Post-ban, 1999–2009). We stacked the five TM/ETM+ images along with elevation and hillshade data. The hillshade image for the Pre-ban and Post-ban classifications was derived using the image acquisition time of the October 28, 1999 image, Path/Row 132/40 (sun elevation = 41.87°, azimuth = 147.17°). One hillshade image was sufficient to represent shading caused by topography. For this classification, all images were resampled to a spatial resolution of 28.5 m. We classified the image stack into 11 classes, including three permanent forest types and forest loss classes in different periods (1990–1999 and 1999–2009), agriculture, grassland, alpine shrub expansion, sparse shrub, bare/urban, and other (snow/water) . To eliminate isolated misclassified pixels, we identified contiguous groups of pixels (using the 4-neighbor rule) and merged small patches (<2 pixels for the Historic classification and <6 pixels for the Pre-ban and Post-ban classification) into the largest neighboring patch (minimum mapping unit of 0.65 ha for the historic classification and 0.49 ha for the Pre-ban and Post-ban classification).

We randomly withheld 10% of the dataset for the accuracy assessment and 90% of the pixels were used for training. We classified the image stack a total of ten times, with a different random training dataset each time, and the final accuracy measures are derived from the mean error estimates of all ten classifications. The final classification was produced from 100% of the data points.

For accuracy assessment, from the confusion matrix we calculated an area-adjusted error matrix, including area-adjusted user, producer, and overall accuracies, that take into account the areal proportions of each class (Card, 1982). This is necessary to correct for potential bias due to the differences in the proportions of classes in the validation data and the true areal proportions of these classes in the map. We also adjusted the total area estimates from the classified map according to the bias correction, to produce an adjusted area coverage for each class, and then calculated 95% confidence intervals for these area estimates (Card, 1982; Cochran, 1977) to provide a more accurate and intuitive representation of error.

3.5. Analyzing logging rates and patterns

We compared forest change among the three different time periods, and at three different scales: the entire study area, county-level, and township-level. We used two different measures of forest disturbance. First, we calculated the number of hectares of forest loss. Second, we calculated an area and time-adjusted disturbance rate (Eq. (1))

$$ADR = \left(\left(D_j/FCB_j\right)/t\right) * 100 \quad (1)$$

where ADR is the annual disturbance rate, Dj is the number of pixels in the forest cover loss class for time period j, $FCBj$ is the total number of forest pixels at the beginning of time period j, and t is the number of years in time period j.

To understand the influence of humans on forest change patterns, we used spatial data on road networks, villages, and provincial and township boundaries, all digitized from 1:250,000 topographic maps from the late 1990s. We calculated township-scale village density (as a proxy for population density, which was not available), and road density (including national, provincial, county and village-level roads). Pearson correlation and multiple linear regression analyses were performed to determine the relationship between logging rates, village density, and road density during the three time periods. To understand the economic and demographic implications of NW Yunnan's rapid development, we gathered economic statistics from official Chinese sources, compiled at the scale of Diqing Prefecture. Data sources included the Yunnan Statistical Yearbooks, the Diqing Prefecture Statistics Bureau, the Diqing Tourism Bureau, and the Bank Loan Registration Information System of Diqing Prefecture. Economic data were corrected for inflation using the World Bank's GDP deflator values for China (World Bank 2011).

4. Results

4.1. Multiple forest class change detection

Area-adjusted overall accuracy (i.e., accuracy measures that are corrected for potential bias due to the differences in the proportions of classes in the validation data and the true areal proportions of these classes in the map (Card, 1982)) was 92% for the Historic classification and 93% for the Pre-ban and Post-ban classification (Table 3). Old-growth forests were mapped with an accuracy of at least 91% in both classifications. For the change (i.e. deforestation) classes, producer accuracies were lower than the user accuracies, representing a high error of omission, which means that our estimates of forest loss were conservative.

The lowest accuracies were the producer accuracies for the forest cover loss classes during the Historical (78%), Pre-ban (79%) and Post-ban (73%) periods. Accuracies from the raw confusion matrix for these change classes were much higher (ranging from 91 to 94%). However, when adjusting for potential areal biases, accuracies for classes with small areal proportions (e.g. a change class) can diminish dramatically even when just a few points of a smaller class are misclassified, because these pixels are frequently misclassified as a class with larger areal proportion (e.g. a no-change class), creating a high error of omission and a low producer accuracy. By generating area estimates for each class, and confidence intervals around those area estimates, a more accurate representation of error was provided (Table 3).

4.2. Logging rates and patterns

During the Historic period, 94,763 ± 6304 ha of forest were logged (95% confidence interval). Logging dropped dramatically during the Pre-ban (58,467 ± 4645 ha) and Post-ban (57,880 ± 5202 ha) periods. In the entire study area, the annual disturbance rate decreased

Table 3
Producer (PA) and user (UA) accuracies, adjusted areal extent and confidence intervals (CI) for each land cover class.

Class	PA	UA	Adj. area (ha)	± CI (ha)	± CI (%)
Historic classification					
Old-growth forest	93%	95%	566,233	11,976	2%
Pine/oak woodland	93%	89%	513,940	13,562	3%
Non-pine scrub	86%	86%	236,890	10,001	4%
Deforestation Historical	78%	95%	94,763	6304	7%
Agriculture and Grassland	89%	94%	226,072	7527	3%
Other	95%	93%	500,732	10,247	2%
Overall accuracy	92%				
Khat	0.92				
Pre-ban and post-ban classification					
Old-growth forest	91%	91%	501,165	12,435	2%
Pine/oak woodland	93%	92%	517,316	11,836	2%
Non-pine scrub	97%	90%	533,596	11,696	2%
Deforestation Pre-ban	79%	96%	58,467	4645	8%
Deforestation Post-ban	73%	95%	57,880	5202	9%
Agriculture	97%	98%	138,090	2600	2%
Grassland	92%	99%	68,710	3201	5%
Alpine shrub expansion	93%	99%	79,476	3153	4%
Sparse shrub	95%	97%	96,842	2850	3%
Bare/Urban	86%	95%	106,076	5215	5%
Other	97%	96%	392,733	6097	2%
Overall accuracy	93%				
Khat	0.93				

from 0.37% in the Historic period, to 0.29% and 0.27% in the Pre- and Post-ban periods, respectively.

The spatial pattern of logging changed over time. Multiple linear regressions to predict logging rates as a function of population and road density were significant during the Historic ($p=0.04$, Adj. $R^2=0.15$) and Pre-ban ($p=0.01$, Adj. $R^2=0.25$) periods, but not significant ($p=0.59$) during the Post-ban period. In univariate correlations of logging rates with either road or population density, logging rates were positively correlated with road density ($p=0.05$, $r=0.36$) during the Pre-ban period, and negatively correlated with village density during both the Historic ($p=0.01$, $r=-0.46$) and Pre-ban periods ($p=0.002$, $r=-0.53$). However, during the Post-ban period, there was no significant correlation between logging rates and road density ($p=0.46$) or logging rates and village density ($p=0.74$).

Logging rates decreased dramatically throughout the study area after the Historic period, except for the area around Shangrila City, where logging rates were consistently high in all three time periods (Fig. 1e). Furthermore, in Shangrila County, the area of old-growth forest cleared after the ban doubled compared to old-growth forest loss during the Pre-ban period (Fig. 4). Meanwhile, logging of other forest types (pine/oak woodlands and non-pine scrub), and in other counties, remained relatively consistent during the Pre- and Post-ban periods.

4.3. Forest cover and regeneration

Total forest cover (old-growth forest, pine/oak woodlands and non-pine scrub combined) increased in the study area from 62% in 1990 to 64% in 2009 (+50,000 ha) (Fig. 5a and b). This forest area increase represented mainly an increase in the non-pine scrub class (from 11% to 24%), while old-growth forests and pine/oak woodlands declined (from 26% to 20% and from 25% to 20%, respectively). Other land cover types remained fairly constant.

We summarized land cover in 1990–2009 for those pixels that were deforestation or non-pine scrub forest classes in the Historic period to understand trends in the regeneration (Fig. 6). Fourteen percent of the areas logged during the Historic period remained non-forested in 2009 (Fig. 5c). Of the areas where forest cover regenerated, only 14% had a species composition similar to the old-growth forest community, and 8% regenerated as pine/oak woodlands. The remaining 64% of the logged area regenerated as non-pine scrub. Similarly, only a small proportion of the non-pine scrub during the Historic period transitioned to either the old-growth forest community (8%) or pine forest (9%) as of 2009, and a substantial proportion (17%) lacked forest cover (Fig. 5d). The majority of the non-pine scrub in the Historic period remained as such in 2009 (66%). Furthermore, regeneration rates varied spatially. Areas with abundant old-growth forest (Fig. 7a) often had low rates of regeneration of the old-growth forest community (Fig. 7b).

4.4. Socioeconomic changes

Economic data indicated that there was rapid development since the logging ban in 1998, due to a rapidly developing tourism industry (Fig. 8a). In 1995, only 40,000 tourists visited Diqing Prefecture, but as of 2009, it received 5.3 million visitors annually. Income from tourism rose from 19 million RMB in 1995 to 5400 million RMB in 2009. Local government revenue increased 40-fold, from 11 million RMB in 1987 to 440 million RMB in 2009, and annual rural net incomes more than tripled from 661 RMB in 1989 to 2100 RMB in 2009 (Fig. 8b).

5. Discussion

5.1. Multiple forest class change detection

Remote sensing in our study area faces many obstacles, and our study represents the most detailed forest change detection analysis to date for SW China (Tuanmu et al., 2010; Vina et al., 2007, 2008; Willson, 2006). Image analysis is challenged by snow cover, strong illumination effects from topography, and senescent vegetation. The collection of ground truth data is difficult, and forest distribution and composition is extremely heterogeneous. We employed a range of techniques to overcome these obstacles. First, we used SVM to handle complex distributions of our land cover classes. Samples from a wide range of intra-image variability, including dramatic illumination effects and variable snow cover, were included in the training dataset to accommodate the multi-modal and non-normal distributions inherent in such a complex environment. Furthermore, in the field, we specifically identified training data in areas at the spectral boundaries of a class (e.g., 45% pine/oak woodlands and 55% old-growth forest) as input for the SVM. These “mixed pixels” were crucial to aid the SVM to identify precise hyperplanes between the classes.

Second, multi-temporal imagery (Wolter et al., 1995) from late fall and early spring aided the separation of old-growth forest from the pine/oak woodlands and the non-pine scrub classes (Fig. 2). In southwest China, November through April is a period of extended drought, and the fact that different tree species respond differently to drought, was a crucial factor to discriminate forest types. The composite of the multi-temporal TM imagery from 1990 with the single winter MSS imagery from 1974 was essential to accurately classify different forest types during the historic period.

Finally, we combined two common approaches to multi-temporal change detection — composite and post-classification change detection techniques — to reduce multiplicative error. The “historical”

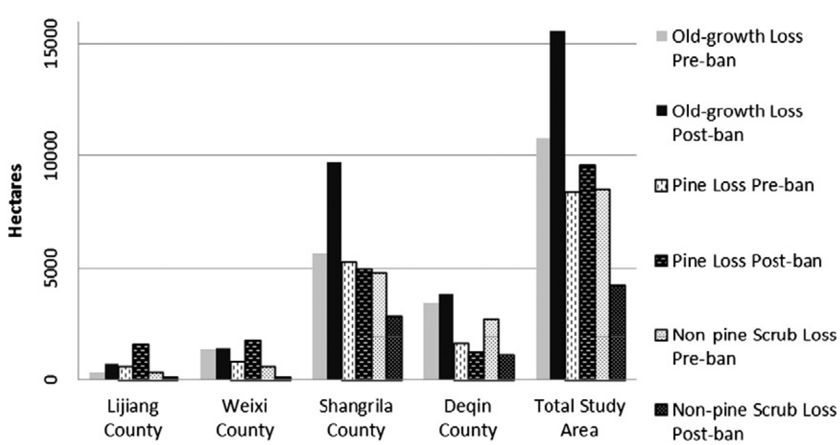

Fig. 4. Hectares of forest loss by forest type during the Pre-ban (1990–1999) and Post-ban (1999–2009) periods.

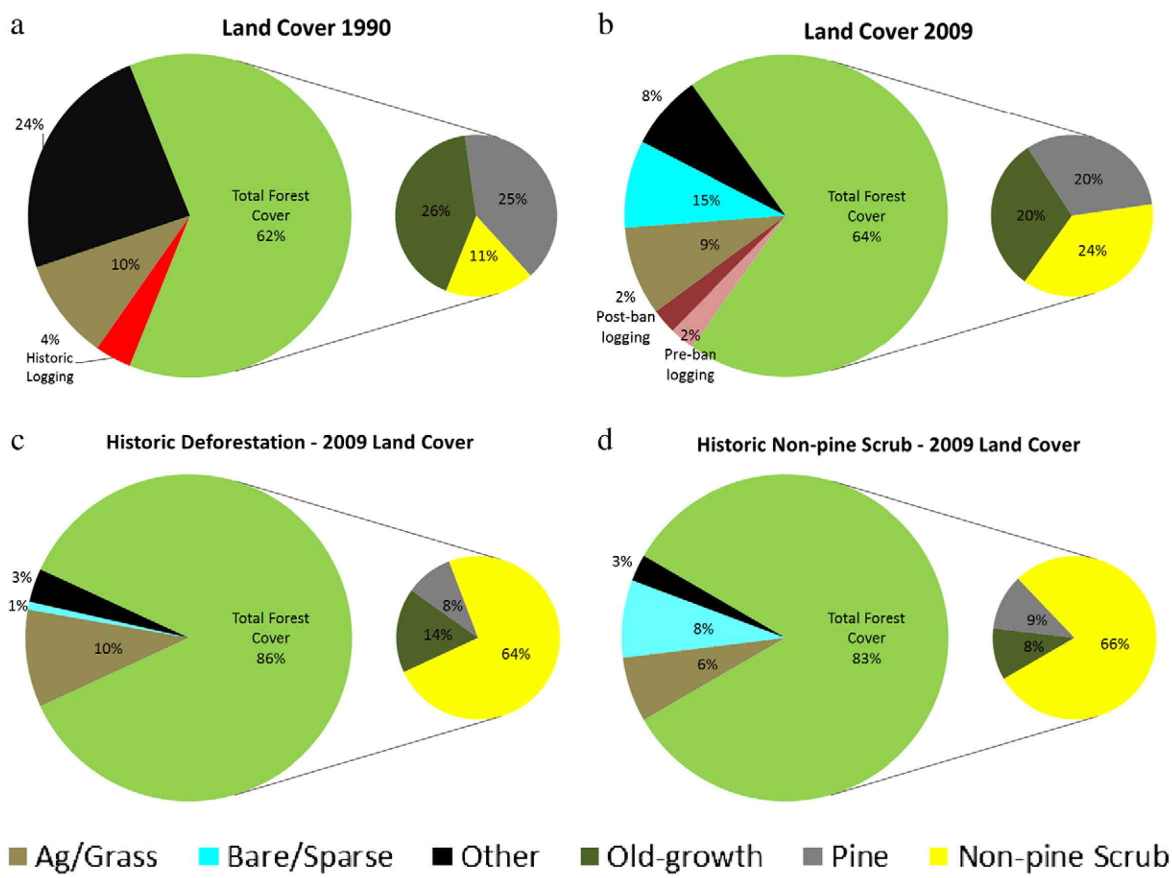

Fig. 5. Land cover distributions in a) 2009 and b) 1990 for the entire study area. The 2009 land cover of areas c) logged during the Historic period (1974–1990) and d) classified as secondary forest/shrub during the Historic period.

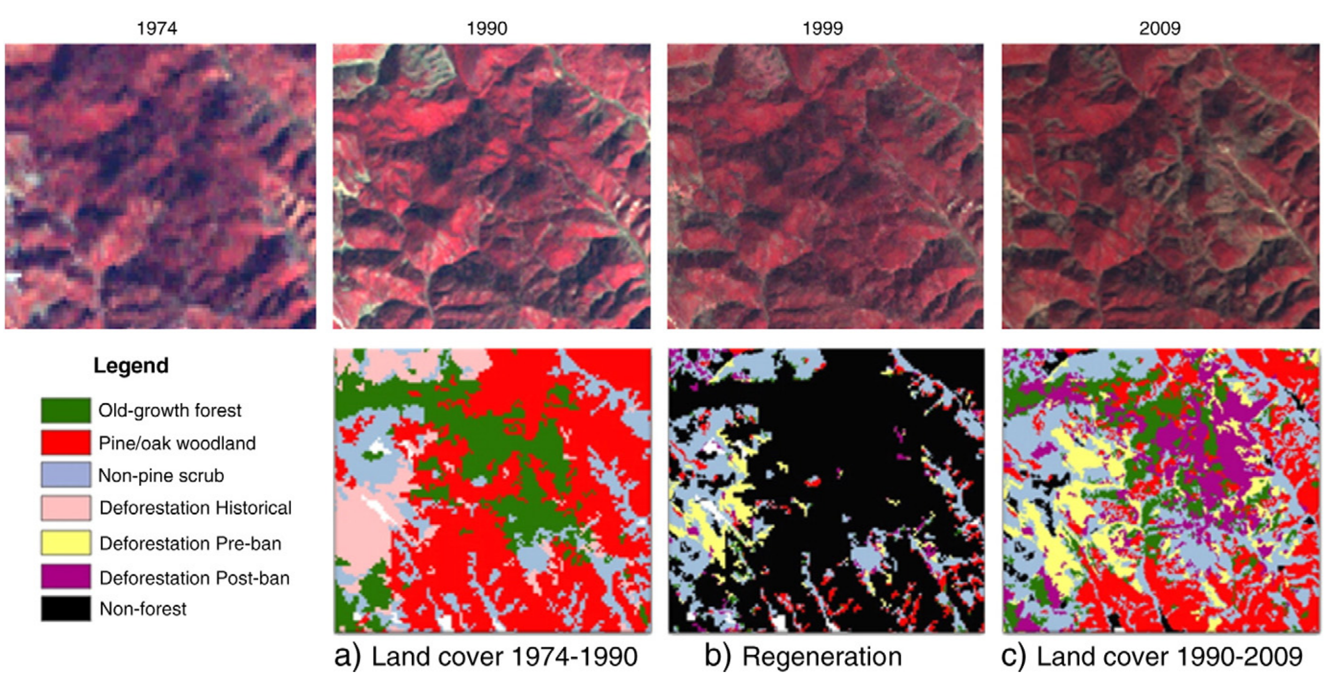

Fig. 6. A subset of the classifications for an area 8 km north of Shangrila that experienced intense logging during the Historic, Pre-ban and Post-ban periods. a) Logging activity and non-pine scrub surrounded a large patch of old-growth and pine forests during the Historic period. b) The composite classification from 1990 to 2009 for only those areas that were logged or non-pine scrub during the Historic period show that the majority of these areas regenerated as non-pine scrub. Exceptions include regenerating pine plantations and sites that continued to be logged. c) During the Pre-ban and Post-ban periods, the large patch of pine and old-growth forest from (a) experienced intense logging.

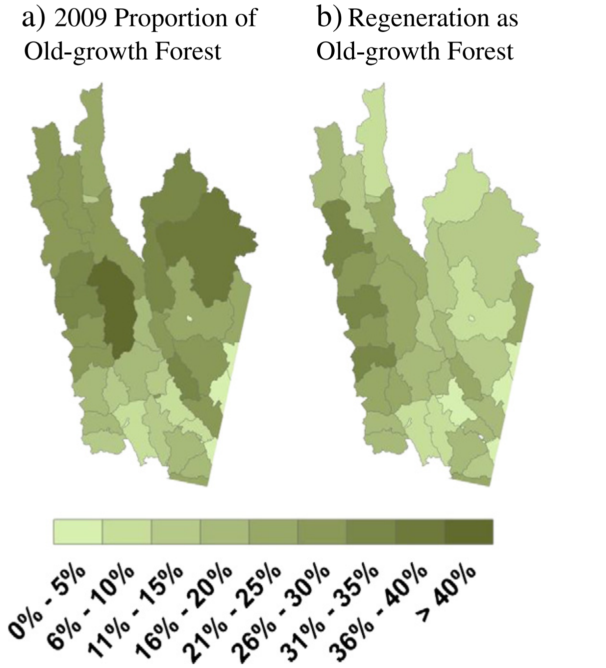

Fig. 7. Patterns of (a) current proportion of old-growth forest on the landscape and (b) relative rates of regeneration as old-growth forest.

classification gave us the baseline maps necessary to compare logging rates for different forest types during the Pre- and Post-ban time periods, but we reduced much of the cumulative error that would have resulted from a pure post-classification change detection methodology.

Despite the high level of accuracy achieved by our classifications, there are uncertainties in our estimates. First, it is possible that

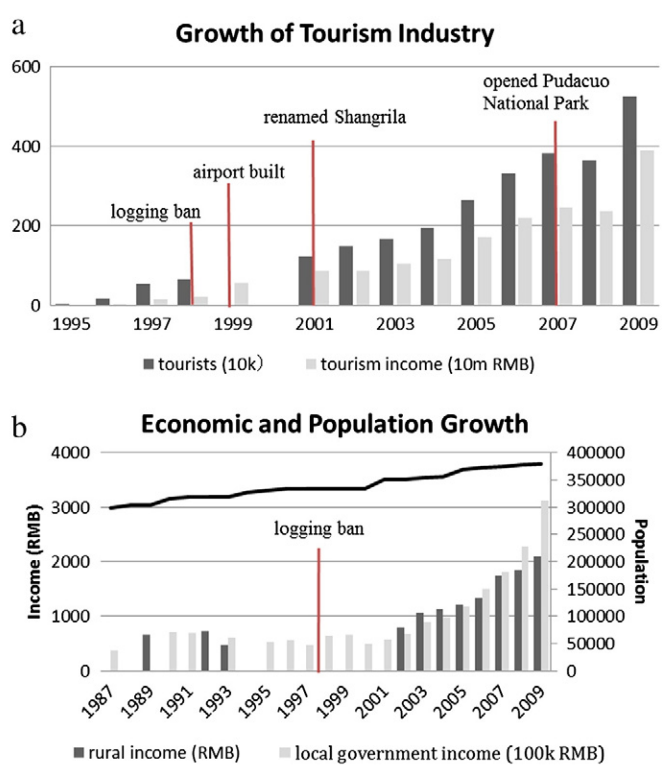

Fig. 8. a) Economic development and population growth, and b) growth of the tourism industry in Diqing Prefecture.

classification accuracies were overestimated because our ground truth dataset was not random, possibly resulting in spatial autocorrelation among the pixels within polygons. On the other hand, accuracy was underestimated to some degree because we purposefully included "mixed pixels" in our training and validation dataset to aid SVM in hyperplane placement. These points were often classified inaccurately, even though in the field the appropriate classification is ambiguous.

Second, forests in this region are extremely heterogeneous and we had to limit our classification scheme to just three forest types to achieve a balance between classification accuracy and thematic detail. Third, our classification could not discriminate logging from other forest disturbances (insects and fire), which are not frequent events in our study area, but do occur in isolated patches. In addition, selective logging is not well captured in our land cover classifications. Finally, during post-classification processing we eliminated small, isolated patches to remove noise, and small patches of logging may have been falsely removed. Selective and small-scale logging do occur in our study area, and further research is necessary to quantify the extent and consequences of these logging practices.

5.2. Logging patterns

The logging patterns that emerged from our satellite image analysis reflect NW Yunnan's turbulent history since the mid 1900s, and highlight its consequences for old-growth forest and biodiversity conservation. Our analysis confirmed that logging was indeed intense throughout the study area during the Historic period (1974–1990) (Fig. 1b). Logging rates decreased dramatically during the Pre-ban period (1990–1999), and during the Post-ban period (1999–2009), logging was reduced even further. Thus, our analysis indicates that the bold forest protection policies that China implemented were successful and increased forest cover in our study area.

However, substantial logging still occurred despite the logging ban. Approximately 60,000 ha was logged in each of the Pre-ban and Post-ban periods, and the spatial distribution of logging changed dramatically. We expected that areas with high road density would have high rates of logging (Chomitz and Gray, 1996; Cropper et al., 2001). Surprisingly, this was the case during the Historic and Pre-ban periods, but not in the Post-ban period. Village and road density had some predictive value for logging rates during the Historic and Pre-ban periods, but not during the Post-ban period, indicating that the processes influencing regional-scale patterns of logging changed.

For example, most logging during the Historic and Pre-ban periods was performed by state logging companies. Easily accessible areas (i.e. along major roads) were already logged in high-population density areas, but abundant old-growth forests remained along major roads in low population density areas, which explains the positive correlation of logging with road density and the negative correlation of logging with village density during these early periods. After the logging ban, state-sponsored logging companies disbanded, and logging was only allowed by local people for non-commercial use. Logging and population/road density became divorced (i.e. relationships became insignificant) during the Post-ban period because logging became concentrated in a "hotspot" around Shangrila.

Old-growth forest logging accelerated in the Post-ban period around the city of Shangrila most likely because of high demand for old-growth timber due to rapid ecotourism-based economic development. Local and national government officials responded to the logging ban by initiating the development of NW Yunnan into one of the premiere ecotourism destinations in China (Jenkins, 2009; Kolas, 2008; Morell, 2002). Shangrila City is the tourism "gateway" into NW Yunnan, and transformed since the 1980s from a backwater town into a one of the premiere tourist destinations in China (Jenkins, 2009; Kolas, 2008; Morell, 2002). The region's only airport (built in 1999) is located 5 km outside of Shangrila City. In 2007, China's flagship National Park Pudacuo (Jieng, 2008), was established just 30 km from Shangrila City.

The development of Shangrila resulted in a growing demand for tourism accommodations (Fig. 8a) and a growing population (Fig. 8b). From 2002 to 2007, new tourism-based businesses received 2.3 billion RMB in government loans. Shangrila's tourism industry capitalizes on both the natural beauty of the region, and on Tibetan culture (Jenkins, 2009). Therefore, much of the new construction for tourists (guesthouses, tourist attractions, restaurants, and vacation homes) uses a Tibetan architecture style (Kolas, 2008). In addition, increasing wealth resulted in more — and larger — traditional Tibetan-style houses for local families. Villagers reported to us that each new Tibetan house requires between 50 and 100 trees, and that the primary sources of timber were the old-growth spruce and fir forests around Shangrila City. Among 23 houses that we visited, those built after 2001 had, on average, central pillars with an average diameter of 79 cm, while pillars in those built before 2001 were only 51 cm in size. These data are too limited to be representative, but indicate potential effects of increasing wealth. In addition to construction materials, each household needs 10–30 m^3 of fuelwood/year (Xu and Wilkes, 2004). Higher demand for firewood due to the increasing number of households, and the restaurants and guesthouses of the tourism industry, thus likely accelerated forest cover loss around Shangrila.

Increased logging rates were likely not a result of increasing demand for wood products in other parts of China, as we did not encounter logging camps or logging trucks, and export of timber to the rest of Yunnan is strictly prohibited and enforced by logging checkpoints. Instead, the increasing demand for old-growth timber in Shangrila is due to the rapidly growing tourism industry and the increasing income levels of the local people. Research in the Wolong Giant Panda Reserve in neighboring Sichuan Province similarly revealed accelerated forest cover loss following reserve implementation, due to tourism, a growing population, and greater wealth (Liu et al., 2001).

Ecotourism, or nature-based tourism, is expanding around the world because it offers a strategy to wed sustainable economic development with environmental protection (Balmford et al., 2009; Karanth and DeFries, 2011). However, what constitutes true ecotourism, and the consequences of ecotourism for biodiversity conservation, is still a matter of great debate (Kirkby et al., 2010; Nash, 2009; Sims, 2010; Wang and Buckley, 2010; Yu et al., 1997). In Shangrila, the tourism industry encompasses a wide range, including nature, adventure, ethnic, and protected area tourism. We used the term "ecotourism" to represent this wide range because, first, appreciation of nature is undeniably the primary attraction of Shangrila. Second, and perhaps more importantly, Shangrila's tourism industry is branded as ecotourism, i.e., both the producers (advertisers, local businesses, and tour guides) and consumers (i.e. tourists) believe that they engage in ecotourism. As such, it is particularly noteworthy that our result showed continued deforestation.

5.3. Forest cover trends

While old-growth forests declined, forest area overall increased from 62% in 1990 to 64% 20 years later. However, only a fraction (20%) of deforested or non-pine scrub areas during the Historic period returned to either pine/oak woodlands or the old-growth forest vegetation community (Fig. 5c and d). This is not to say that with time and appropriate forestry management, the non-pine scrub forests in our study area could not potentially return to the original vegetation community, but we did not observe this. No information is available about successional trajectories of Shangrila forests, but in general, regeneration to climax forest in temperate regions takes centuries to thousands of years, much slower than the observed rate of old-growth forest clearing around Shangrila. Furthermore, our field observations indicated that land use intensity was high in regenerating areas, inhibiting the regeneration of the original vegetation community. Likewise, our remote sensing results suggest that non-pine scrub may not be in a process of natural succession, since we observed small proportions of regeneration to pine or vegetation communities typical of old-growth forests in those areas that were non-pine scrub forest from 1974 to 1990.

The assumption of forest transition theory is that increasing forest cover indicates that environmental conditions are improving (Mather et al., 1999), but here we show that increasing forest cover alone does not necessarily mean that biodiversity and natural ecosystems are on a pathway towards recovery (Meyfroidt and Lambin, 2011). We observed that secondary and scrub forests are a growing proportion of forests in our study area, which is similar to many countries around the world (Chazdon, 2008; Grau et al., 2008). Yet, most studies showing shifts in forest trajectory have not distinguished between primary and secondary forest types, even though the value of regrowing forests, in terms of species habitat and ecosystem services, is far lower than that of old-growth forests (Chazdon, 2008; Meyfroidt and Lambin, 2008; Perfecto and Vandermeer, 2010). Land use largely determines whether the forests regrowing after harvest will eventually recover to a high-diversity ecosystem (Chazdon et al., 2009), but unfortunately, land use intensity in secondary forests is not included in forest transition theory (Meyfroidt et al., 2010; Perfecto and Vandermeer, 2010). Likewise, forest transitions and increasing forest cover may be only due to monoculture plantations with little biodiversity value (Rudel, 2009) or result in more intense land use of surrounding forests, with potentially negative effects on overall biodiversity (Perfecto and Vandermeer, 2010). Furthermore, countries experiencing a forest transition may simply export their ecological footprint elsewhere (Mayer et al., 2005; Meyfroidt and Lambin, 2009; Meyfroidt et al., 2010).

6. Conclusions

Our results highlight that forest monitoring must incorporate multiple forest classes to assess forest change in the context of the conservation of biodiversity and ecosystem services. Simple forest versus non-forest cover assessments in areas with remaining unprotected old-growth forests are inadequate to understand the implications of protection and development strategies for high-diversity forest types, and can obscure important environmental degradation processes. This represents a major challenge for the remote sensing community, because error and complexity increases when multiple dates or multiple classes are examined via change detection. We used multi-temporal imagery, carefully selected training data with SVM and a combination post-classification and composite classification technique to reduce error and accurately detect change in multiple forest classes in a complex environment.

One of the primary objectives of the NFPP is to ban commercial logging of all forests in southwest China, and allow only small quotas for local consumption. Our results show that, overall, China's forest protection policies effectively reduced forest loss in NW Yunnan. Logging decreased over most of the landscape, and forest cover increased. However, the logging ban was trumped in areas of rapid economic development, as old-growth forest loss accelerated due to a growing ecotourism industry. Ecotourism has expanded rapidly in developing countries around the world (Balmford et al., 2009; Karanth and DeFries, 2011), because it offers a strategy to wed sustainable economic development with environmental protection. However, our results show that even in Shangrila — an arguably best-case-scenario with strong institutions, well-funded environmental protection efforts, and strong government policies aimed at forest protection — the negative impacts of ecotourism-based economic development on the environment outweighed conservation efforts. As tourism development continues to expand into previously remote and little-visited regions, the negative impacts observed near Shangrila City in the last decade may soon follow unless steps are taken to mitigate the threats that development poses.

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References

Anderson, D., Salick, J., Moseley, R. K., & Xiaokun, O. (2005). Conserving the sacred medicine mountains: A vegetation analysis of Tibetan sacred sites in Northwest Yunnan. *Biodiversity and Conservation*, *14*, 3065–3091.

Balmford, A., Beresford, J., Green, J., Naidoo, R., Walpole, M., & Manica, A. (2009). A global perspective on trends in nature-based tourism. *PLoS Biology*, *7*.

Card, D. (1982). Using known map category marginal frequencies to improve estimates of thematic map accuracy. *Photogrammetric Engineering and Remote Sensing*, *48*, 431–439.

Chang-Le, M., Moseley, R. K., Wen-Yun, C., & Zhe-Kun, Z. (2007). Plant diversity and priority conservation areas of Northwestern Yunnan, China. *Biodiversity and Conservation*, *16*, 757–774.

Chapin, F., Zavaleta, E., Eviner, V., Naylor, R., Vitousek, P., Reynolds, H., et al. (2000). Consequences of changing biodiversity. *Nature*, *405*, 234–242.

Chazdon, R. (2008). Beyond deforestation: Restoring forests and ecosystem services on degraded lands. *Science*, *320*, 1458–1460.

Chazdon, R. L., Peres, C. A., Dent, D., Sheil, D., Lugo, A. E., Lamb, D., et al. (2009). The potential for species conservation in tropical secondary forests. *Conservation Biology*, *23*, 1406–1417.

Chomitz, K. M., & Gray, D. A. (1996). Roads, land use, and deforestation: A spatial model applied to belize. *World Bank Economic Review*, *10*, 487–512.

Cochran, W. (1977). *Sampling techniques* (3rd ed.). New York: Wiley.

Cohen, W. B., Spies, T. A., & Fiorella, M. (1995). Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, USA. *International Journal of Remote Sensing*, *16*, 721–746.

Congalton, R. G., Green, K., & Teply, J. (1993). Mapping old-growth forests on national forest and park lands in the Pacific-northwest from remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, *59*, 529–535.

Cropper, M., Puri, J., & Griffiths, C. (2001). Predicting the location of deforestation: The role of roads and protected areas in North Thailand. *Land Economics*, *77*, 172–186.

Ferraro, P. J., Hanauer, M. M., & Sims, K. R. E. (2011). Conditions associated with protected area success in conservation and poverty reduction. *Proceedings of the National Academy of Sciences of the United States of America*, *108*, 13913–13918.

Fiorella, M., & Ripple, W. J. (1993). Determining successional stage of temperate coniferous forests with Landsat satellite data. *Photogrammetric Engineering and Remote Sensing*, *59*, 239–246.

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science*, *309*, 570–574.

Foody, G. M., & Mathur, A. (2004). Toward intelligent training of supervised image classifications: Directing training data acquisition for SVM classification. *Remote Sensing of Environment*, *93*, 107–117.

Foody, G. M., Mathur, A., Sanchez-Hernandez, C., & Boyd, D. (2006). Training set size requirements for teh classification of a specific class. *Remote Sensing of Environment*, *104*, 1–14.

Gibbs, H. K., Ruesch, A. S., Achard, F., Clayton, M. K., Holmgren, P., Ramankutty, N., et al. (2010). Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proceedings of the National Academy of Sciences of the United States of America*, *107*, 16732–16737.

Goodman, J. (2006). *Joseph F. Rock and his Shangri-La.* : Caravan Press.

Grau, H. R., Gasparri, N. I., & Aide, T. M. (2008). Balancing food production and nature conservation in the Neotropical dry forests of northern Argentina. *Global Change Biology*, *14*, 985–997.

Hansen, M. C., Stehman, S. V., Potapov, P. V., Loveland, T. R., Townshend, J. R. G., DeFries, R. S., et al. (2008). Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 9439–9444.

Harkness, J. (1998). Recent trends in forestry and conservation of biodiversity in China. *China Quarterly*, 911–934.

Helmer, E. H., Brown, S., & Cohen, W. B. (2000). Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery. *International Journal of Remote Sensing*, *21*, 2163–2183.

Huang, C., Davis, L., & Townshend, J. (2002). An assessment of Support Vector Machines for land cover classification. *International Journal of Remote Sensing*, *23*, 725–749.

Jakubauskas, M. E. (1996). Thematic mapper characterization of lodgepole pine seral stages in Yellowstone National Park, USA. *Remote Sensing of Environment*, *56*, 118–132.

Janz, A., vander Linden, S., Waske, B., & Hostert, P. (2007). imageSVM — A user-oriented tool for advanced classification of hyperspectral data using Support Vector Machines. In I. Reusen, & J. Cools (Eds.), *EARSeI SIG Imaging Spectroscopy* Bruges, Belgium.

Jenkins, M. (2009). Searching for Shangri-La. *National Geographic*.

Jieng, G. -H. (Ed.). (2008). *Planning of Shangri-La Pudacuo National Park Establishment and Management. (in Chinese)*. Kunming: Yunnan People Publication.

Justice, C., & Townshend, J. (1981). Integrating ground data with remote sensing. In J. Townshend (Ed.), *Terrain Analysis and Remote Sensing* (pp. 38–58). Boston, USA: Allen and Unwin.

Karanth, K. K., & DeFries, R. (2011). Nature-based tourism in Indian protected areas: New challenges for park management. *Conservation Letters*, *4*, 137–149.

Kauppi, P. E., Ausubel, J. H., Fang, J. Y., Mather, A. S., Sedjo, R. A., & Waggoner, P. E. (2006). Returning forests analyzed with the forest identity. *Proceedings of the National Academy of Sciences of the United States of America*, *103*, 17574–17579.

Kennedy, R. E., Townsend, P. A., Gross, J. E., Cohen, W. B., Bolstad, P., Wang, Y. Q., et al. (2009). Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. *Remote Sensing of Environment*, *113*, 1382–1396.

Kirkby, C. A., Giudice-Granados, R., Day, B., Turner, K., Velarde-Andrade, L. M., Duenas-Duenas, A., et al. (2010). The market triumph of ecotourism: An economic investigation of the private and social benefits of competing land uses in the Peruvian Amazon. *PLoS One*, *5*.

Kolas, A. (2008). *Tourism and Tibetan culture in transition. A place called Shangrila.* New York, NY.

Li, D. Y., Grueter, C. C., Ren, B. P., Long, Y. C., Li, M., Peng, Z. S., et al. (2008). Ranging of *Rhinopithecus bieti* in the Samage Forest, China. II. Use of land cover types and altitudes. *International Journal of Primatology*, *29*, 1147–1173.

Li, W., & Han, N. (2000). Ecotourism management in China's nature reserves. *Ambio*, *30*, 62–63.

Li, X., & Walker, D. (1986). The plant geography of Yunnan Province, Southwest China. *Journal of Biogeography*, *13*, 367–397.

Liu, J. G., Li, S. X., Ouyang, Z. Y., Tam, C., & Chen, X. D. (2008). Ecological and socioeconomic effects of China's policies for ecosystem services. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 9477–9482.

Liu, J., Linderman, M., Ouyang, Z., An, L., Yang, J., & Zhang, H. (2001). Ecological degradation in protected areas: The case of Wolong Nature Reserve for Giant Pandas. *Science*, *292*, 98–101.

Liu, Q. J., Takamura, T., Takeuchi, N., & Shao, G. (2002). Mapping of boreal vegetation of a temperate mountain in China by multitemporal Landsat TM imagery. *International Journal of Remote Sensing*, *23*, 3385–3405.

Ma, C. L., Moseley, R. K., Chen, W. Y., & Zhou, Z. K. (2007). Plant diversity and priority conservation areas of Northwestern Yunnan, China. *Biodiversity and Conservation*, *16*, 757–774.

Mather, A. S., Needle, C. L., & Fairbairn, J. (1999). Environmental kuznets curves and forest trends. *Geography*, *84*, 55–65.

Mayer, A. L., Kauppi, P. E., Angelstam, P. K., Zhang, Y., & Tikka, P. M. (2005). Importing timber, exporting ecological impact. *Science*, *308*, 359–360.

Melick, D., Yang, X., & Xu, J. (2007). Seeing the wood for the trees: How conservation policies can place greater pressure on village forests in southwest China. *Biodiversity and Conservation*, *16*, 1959–1971.

Meyfroidt, P., & Lambin, E. F. (2008). Forest transition in Vietnam and its environmental impacts. *Global Change Biology*, *14*, 1319–1336.

Meyfroidt, P., & Lambin, E. F. (2009). Forest transition in Vietnam and displacement of deforestation abroad. *Proceedings of the National Academy of Sciences of the United States of America*, *106*, 16139–16144.

Meyfroidt, P., & Lambin, E. (2011). Global forest transition: Prospects for an end to deforestation. *Annual Review of Environmental Resources*, *36*, 1–29.

Meyfroidt, P., Rudel, T. K., & Lambin, E. F. (2010). Forest transitions, trade, and the global displacement of land use. *Proceedings of the National Academy of Sciences of the United States of America*, *107*, 20917–20922.

Morell, V. (2002). China's Hengduan Mountains. *National Geographic* (pp. 98–113)..

Morell, V. (2008). Letting 1000 forests bloom. *Science*, *320*, 1442–1443.

Myers, N., Mittermeier, R., Mittermeier, C., da Fonseca, G. A. B., & Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, *403*, 853–858.

Nash, S. (2009). Ecotourism and other invasions. *Bioscience*, *59*, 106–110.

Naughton-Treves, L., Buck, M., & Brandon, K. (2005). The role of protected areas in conserving biodiversity and sustaining local livelihoods. *Annual Review of Environmental Resources*, *30*, 219–252.

Pal, M., & Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, *86*, 554–565.

Perfecto, I., & Vandermeer, J. (2010). The agroecological matrix as alternative to the land-sparing/agriculture intensification model. *Proceedings of the National Academy of Sciences of the United States of America*, *107*, 5786–5791.

Potapov, P., Turubanova, S., & Hansen, M. C. (2011). Regional-scale boreal forest cover and change mapping using Landsat data composites for European Russia. *Remote Sensing of Environment*, *115*, 548–561.

Rudel, T. K. (2009). Tree farms: Driving forces and regional patterns in the global expansion of forest plantations. *Land Use Policy*, *26*, 545–550.

Rudel, T. K., Coomes, O. T., Moran, E., Achard, F., Angelsen, A., Xu, J. C., et al. (2005). Forest transitions: Towards a global understanding of land use change. *Global Environmental Change — Human and Policy Dimensions*, *15*, 23–31.

Salick, J., Amend, A., Anderson, D., Hoffmeister, K., Gunn, B., & Zhendong, F. (2007). Tibetan sacred sites conserve old growth trees and cover in the easter Himalayas. *Biodiversity and Conservation*, *16*, 693–706.

Schmook, B., Dickson, R. P., Sangermano, F., Vadjunec, J. M., Eastman, J. R., & Rogan, J. (2011). A step-wise land-cover classification of the tropical forests of the Southern Yucatan, Mexico. *International Journal of Remote Sensing*, *32*, 1139–1164.

Sims, K. R. E. (2010). Conservation and development: Evidence from Thai protected areas. *Journal of Environmental Economics and Management*, *60*, 94–114.

Tuanmu, M. -N., Vina, A., Bearer, S., Xu, W., Ouyang, Z., Zhang, H., et al. (2010). Mapping understory vegetation using phenological characteristics derived from remotely sensed data. *Remote Sensing of Environment*, *114*, 1833–1844.

Vina, A., Bearer, S., Chen, X. D., He, G. M., Linderman, M., An, L., et al. (2007). Temporal changes in giant panda habitat connectivity across boundaries of Wolong Nature Reserve, China. *Ecological Applications*, *17*, 1019–1030.

Vina, A., Bearer, S., Zhang, H., Ouyang, Z., & Liu, J. (2008). Evaluating MODIS data for mapping wildlife habitat distribution. *Remote Sensing of Environment*, *112*, 2160–2169.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science*, *277*, 494–499.

Wang, C. H., & Buckley, R. (2010). Shengtai Anquan: Managing tourism and environment in China's Forest Parks. *Ambio*, *39*, 451–453.

Wang, W., Ren, G. P., He, Y. H., & Zhu, J. G. (2008). Habitat degradation and conservation status assessment of gallinaceous birds in the Trans-Himalayas, China. *Journal of Wildlife Management*, *72*, 1335–1341.

Wen, X., Ding, W., Cui, L. W., Zhou, R. -L., & Zhao, Q. -K. (2003). Habitat degradation of *Rhinopithecus bieti* in Yunnan, China. *International Journal of Primatology*, *24*, 389–398.

Weyerhauser, H., Wilkes, A., & Kahrl, F. (2005). Local impacts and responses to regional forest conservation and rehabilitation programs in China's northwest Yunnan province. *Agricultural Systems*, *85*, 234–253.

Willson, A. (2006). Forest conversion and land use change in rural northwest Yunnan, China: A fine-scale analysis in the context of the 'big picture'. *Mountain Research and Development*, *26*, 227–236.

Wolter, P., Mladenoff, D., Host, G., & Crow, T. (1995). Improved forest classification in the Northern Lake States using Multi-Temporal Landsat Imagery. *Photogrammetric Engineering and Remote Sensing*, *61*, 1129–1143.

Xu, J. (2011). China's new forests aren't as green as they seem. *Nature Australia*, *477*.

Xu, J., & Melick, D. (2007). Rethinking the effectiveness of public protected areas in southwestern China. *Conservation Biology*, *21*, 318–328.

Xu, J., & Wilkes, A. (2004). Biodiversity impact analysis in northwest Yunnan, southwest China. *Biodiversity and Conservation*, *13*, 959–983.

Xu, J. T., Yin, R. S., Li, Z., & Liu, C. (2006). China's ecological rehabilitation: Unprecedented efforts, dramatic impacts, and requisite policies. *Ecological Economics*, *57*, 595–607.

Yu, D. W., Hendrickson, T., & Castillo, A. (1997). Ecotourism and conservation in Amazonian Peru: Short-term and long-term challenges. *Environmental Conservation*, *24*, 130–138.

Zackey, J. (2007). Peasant perspectives on deforestation in southwest China: Social discontent and environmental mismanagement. *Mountain Research and Development*, *27*, 153–161.

Zimmerer, K., Galt, R., & Buck, M. (2004). Globalization and multi-spatial trends in the coverage of protected-area conservation (1980–2000). *Ambio*, *33*, 520–529.