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Assessment of Forest Degradation in Vietnam Using Landsat Time Series Data

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Abstract: Landsat time series data were used to characterize forest degradation in Lam Dong Province, Vietnam. We conducted three types of image change analyses using Landsat time series data to characterize the land cover changes. Our analyses concentrated on the timeframe of 1973–2014, with much emphasis on the latter part of that range. We conducted a field trip through Lam Dong Province to develop a better understanding of the ground conditions of the region, during which we obtained many photographs of representative forest sites with Global Positioning System locations to assist us in our image interpretations. High-resolution Google Earth imagery and Landsat data of the region were used to validate results. In general, our analyses indicated that many land-use changes have occurred throughout Lam Dong Province, including gradual forest to non-forest transitions. Recent changes are most marked along the relatively narrow interfaces between agricultural and forest areas that occur towards the boundaries of the province. One important observation is that the most highly protected national reserves in the region have not changed much over the entire Landsat timeframe (1972–present). Spectral changes within these regions have not occurred at the same levels as those areas adjacent to the reserves.

Keywords: forest degradation; land use change; Vietnam; Lam Dong Province; Landsat time series

1. Introduction

With a population of approximately 90.7 million and a population density of 293 people per square km, Vietnam is one of the most densely populated countries in Southeast Asia [1]. One of the challenges facing Vietnam, as well as other countries in the region, is to develop and enact land use and forest management policies that conserve natural forest ecosystems, while at the same time help to sustain wood and food production [2]. According to the Food and Agriculture Organization [3], approximately

42% of Vietnam's total land area was forested in 2010. The Vietnam Forest Administration estimates forest cover to be slightly lower (40% cover) [4]. Of the current forests in Vietnam, only 1% is considered to be primary forest (i.e., no clear visible indications of previous human activities or disturbance), whereas about 74% is natural secondary forest and about 25% is plantation forest. Between 1990 and 2010, forest area in Vietnam increased annually by 1.1% to 2.3%, although it has been noted that some provinces have experienced overall losses in forest cover over this same time period [4]. Table 1 summarizes some of the key forest statistics from Vietnam.

Table 1. Vietnam forest statistics [3,4]. Area values are in millions ha.

Total Area (Vietnam)	**32.9**
Forest area (1990)	9.4
Forest area (2000)	11.7
Forest area (2005)	13.1
Forest area (2010)	14.1
Forest area (2015)	14.8
Primary forest (2010)	1%
Secondary forest (2010)	76%
Planted forest (2010)	25%

It is very important to the Vietnamese government that current and comprehensive forest change information be readily available to the natural resource management community throughout Vietnam. The government has been proactive in implementing monitoring programs that use remotely-sensed imagery to monitor the forest changes. Such information is required for many decision-making processes, including land and forest use planning, assessing the success of forest protection policies, and enabling timely interventions when warranted. Monitoring of forest change is mandated by the Law on Forest Protection and Development [5], and the Policy on Payment for Forest Environment Services [6]. Standard forest inventories and monitoring activities are conducted regularly, and there is a recognized need to support technical activities to monitor the quality of forest ecological services. Improving capacity building, adding to the knowledge base regarding forest change, and improving forest change accuracy assessments are all part of this process. There is a strong desire by the Vietnamese government to accurately monitor Vietnam's forests, and as such, one of the main motivations behind the current project was to help determine effective operational approaches for monitoring forest conditions using remotely-sensed data.

The driving forces causing deforestation in Vietnam are varied [7], but in some areas, the process occurs gradually as a means to expand the boundaries of agriculture into forested areas. Within the Central Highlands region, which is the primary focus of the current study, the process usually involves selective harvesting of trees, planting of food crops in the gaps created by the opening of the forest canopy, and cutting additional trees until the forest is transformed into agricultural lands. This entire process can occur over multiple years. In Vietnam, we consider this gradual transition from forest to agriculture or to some other class as forest degradation. As discussed by [8], tropical forest degradation can range from minor to major impacts, and can include many non-sustainable harvesting activities. The identification and characterization of these subtle and gradual changes using remotely-sensed data can be challenging.

The overarching goal of this work was to explore the use of Landsat time series data for mapping and monitoring forest degradation in Vietnam. While there have been a number of studies that have made successful use of Landsat data and other sources of remotely-sensed imagery to assess Vietnamese forests (e.g., [9–12]) most of the studies have been primarily concerned with mapping forest cover and monitoring major deforestation events and trends, and have not focused on the relatively slow and subtle process of forest degradation. Forest degradation includes situations whereby selective tree harvest and slash and burn agriculture gradually changes forest state, and is of serious concern in Vietnam [13,14]. It can be easily overlooked or underestimated by remote sensing and forest inventory investigations [12]. It has been suggested by the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) [15] that assessments of forest degradation should be included in national forest monitoring systems that use remote sensing and ground-based approaches for conducting carbon inventory include assessments of forest degradation.

We were especially interested in the effectiveness of using dense Landsat time series data for monitoring forest degradation events over short time periods, such as between adjacent years. In general, the spatial, spectral and radiometric properties of Landsat data are particularly well-suited for providing landscape characterization and for monitoring degradation in tropical environments [16,17]. Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data have been systematically acquired for many parts of the globe since the launch of Landsat 5 in 1984, and now that the data are available at no cost via the Internet, the use of Landsat time series data for global monitoring applications is expanding. With the launch of Landsat 8, the acquisition of high quality 30-m resolution data has continued. It is also worth noting that recently there have been significant algorithmic improvements facilitating the analysis of landscape changes using time series data [18–21].

This study has three primary research objectives: (1) to explore different approaches for using Landsat time series data to map and monitor forest degradation in the Lam Dong Province of Vietnam; (2) to determine the spatial patterns of degradation-related changes occurring throughout the province; and (3) to assess the impact that two national parks have had on forest degradation both within and directly outside the parks.

2. Materials and Methods

2.1. Study Area

The area chosen for investigation was Lam Dong Province and adjacent areas in the southern portion of the Central Highlands of Vietnam (Figure 1). The area is covered by a single Landsat World Reference System 2 (WRS-2) path/row (124/52) (Figure 1). High quality cloud-free Landsat data are available from multiple years for the area. Most of these were acquired during the dry season, which for this region is from about December through April. According to the Vietnam Trade Promotion Agency [22], Lam Dong Province is home to about 1.2 million people representing about 40 ethnic groups. Much of the province is rural, although it does have two major cities: Da Lat City and Bao Loc City (Figure 2). The province has many natural forests on the boundaries of the province, while the more central portion is dominated by agriculture, including coffee, rice, cashews, and *Acacia* plantations.

There are two major national parks in the region: Cat Tien and Bidoup Nui Ba (Figure 1). Both parks are designated as "Category II National Parks" by the International Union for Conservation of Nature (IUCN). Category II parks are set aside to represent large natural areas for protecting natural biodiversity with their associated ecological structures and environmental processes, and are also intended in part to promote education and recreation. Cat Tien is mostly located at lower elevations, and is comprised of two separate sections located in three provinces (Lam Dong, Dong Nai and Binh Phuoc). This park, covering 71,920 ha, is one of the largest national parks in Vietnam, and was designated a Biosphere Reserve Zone in 2001 [23]. The topography of Cat Tien is characterized by steep hills in some areas, and flat areas in others, and the dominant vegetation is broadleaf forest. The park was sprayed with herbicides during the Vietnam War (1965–1973), and was logged directly afterwards [24]. Bidoup Nui Ba National Park consists of high elevation montane forests, dominated by middle mountain evergreen closed forest, evergreen coniferous open forest, and evergreen coniferous-broad-leaved mixed forest [25]. It is comprised of 64,800 ha in the "core zone" and 32,300 ha in the "buffer zone" [26]. The park was converted from nature reserve to national park status in 2005. Both Cat Tien and Bidoup Nui Ba parks are important for preservation of the region's biodiversity [24,25]. Both parks are experiencing stress from various anthropogenic factors. Cat Tien

Park is located in a densely populated area and the people living within the park and along the park boundaries are impacting the area largely through farming and grazing activities. Bidoup Nui Ba Park degradation is primarily from limited forest encroachment through agricultural activities.

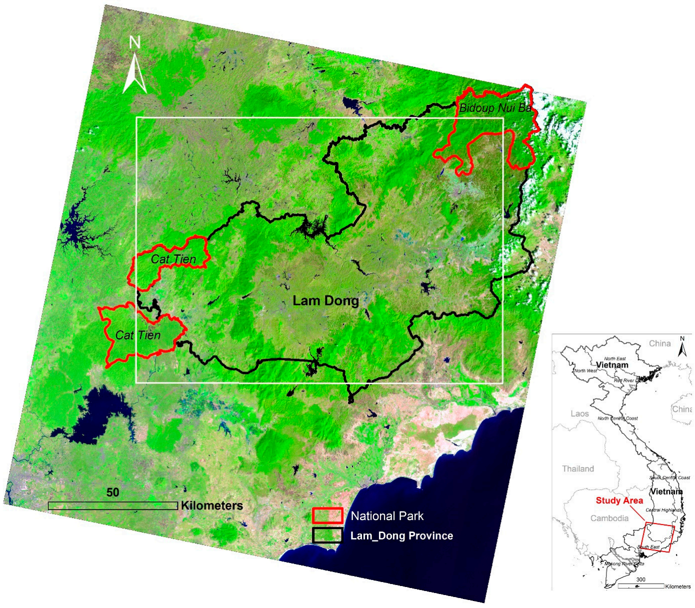

Figure 1. Boundary of Lam Dong Province superimposed on Landsat imagery. The boundary locations of two national parks within the region are also shown on the image in red. The white box indicates the area shown for many of the following figures. This image, as well as the following "green" images, were produced using a red green blue (RGB) composite of Landsat's shortwave infrared 1, red, and green bands in the order of red, green and blue.

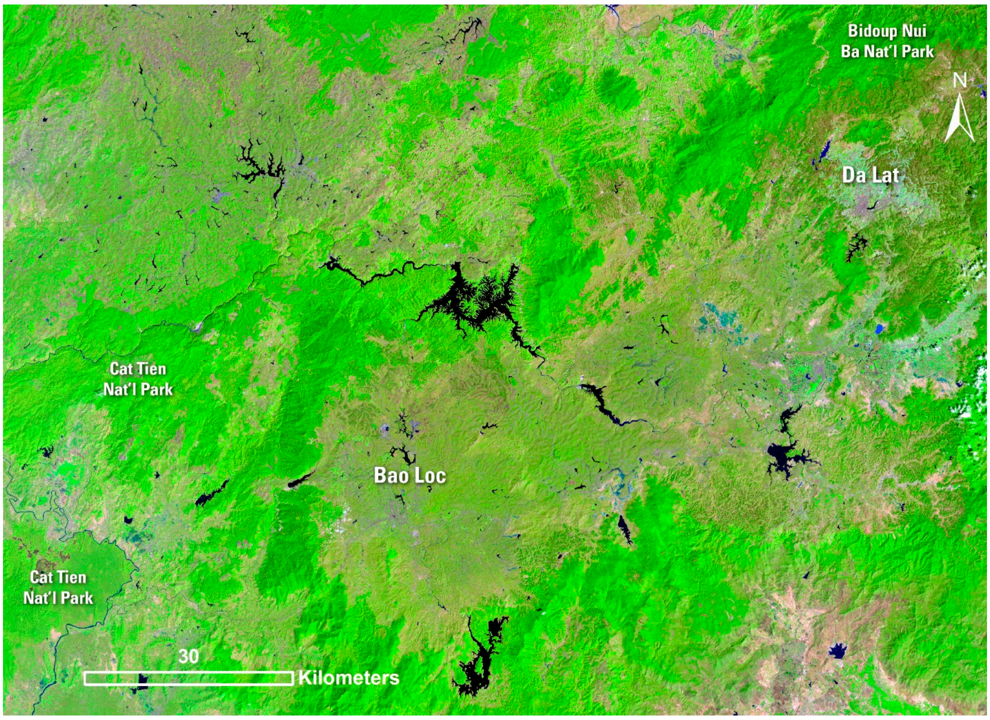

Figure 2. Location of a few key features of interest in the study region.

2.2. Field Trip

Over the period 4–9 August 2014, we visited Lam Dong Province, which is located north of Ho Chi Minh City. The main purpose of the visit was for us to familiarize ourselves with forest conditions and land use throughout the region. The trip involved visiting various locations that represented both healthy and mostly undisturbed conditions as well as conditions where significant degradation and land use change activities are taking place. We took many photographs with Global Positioning System locations during the trip, and used these photographs to help interpret imagery during later stages in the investigation. Figure 3 shows some representative photographs from this trip associated with a portion of a Landsat image.

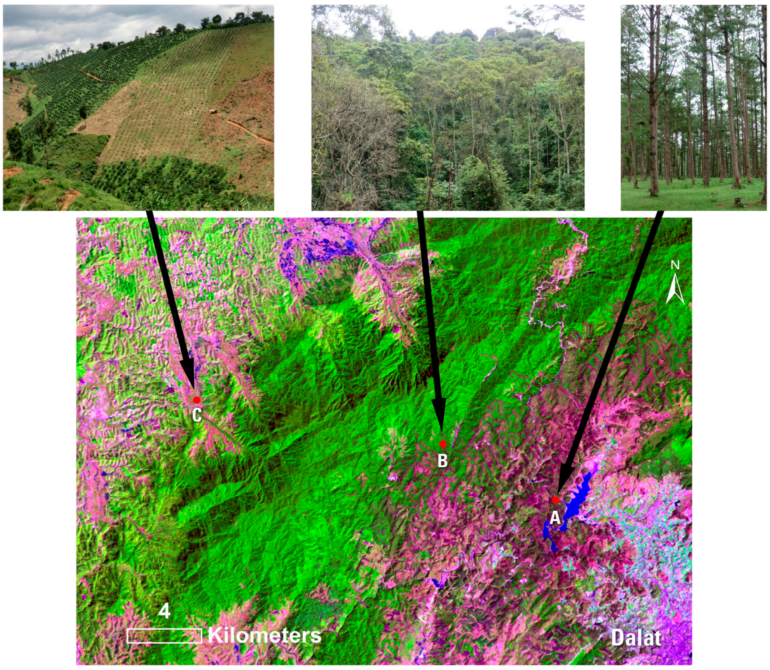

Figure 3. Field photos showing several representative land cover types in study area, and their location on Landsat imagery. A = Conifer (pine) forest; B = Mature broadleaf forest; C = Coffee plantation.

2.3. Baseline Imagery

The various steps taken in this study are summarized in the flow chart in Figure 4. Most of the imagery that we used was acquired during the 2001–2014 time frame from Landsats 5, 7 and 8. In some cases, we obtained imagery from older time periods to help provide context for understanding the changes taking place, and hence included Landsat 5 data from the 1980s and 1990s, and some imagery from the Multispectral Scanner System (MSS) time period (Landsat 1 data from 1973). Landsat 5, 7 and 8 data used in the study were atmospherically corrected and referenced to Universal Transverse Mercator coordinates, and clouds were masked out using Fmask [27]. Landsat 5 and 7 data were processed by the Landsat Ecosystem Disturbance Adaptive Processing System [28]. Landsat 8 images were processed by the Landsat 8 Surface Reflectance (L8SR) system [29]. All Landsat imagery used in the study were obtained from the US Geological Survey Earth Resources Observation and Science Observation data archive [30].

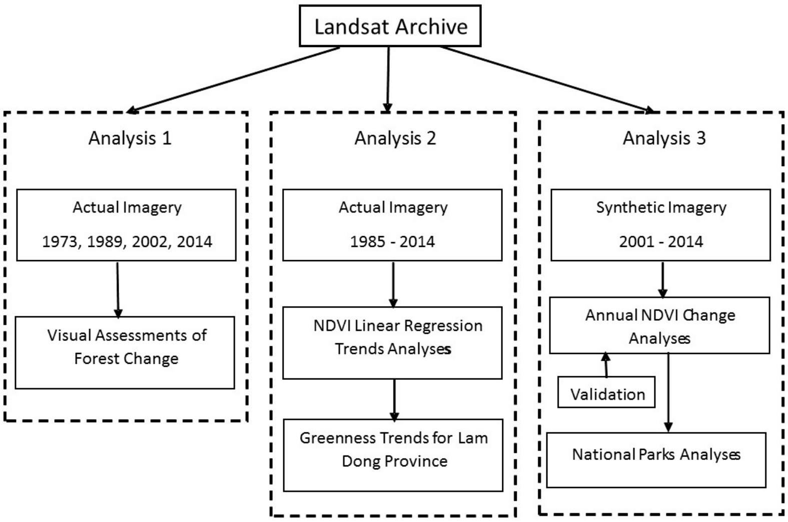

Figure 4. Flow chart summarizing the major steps taken during the investigation. NDVI: Normalized Difference Vegetation Index.

2.4. Synthetic Imagery

We used several approaches to analyze forest changes throughout the study area, with one involving the development of what is termed "synthetic images". The advantage to using synthetic images are two-fold: (1) images can be developed for any date desired, even when no images were acquired then, which can help to normalize data among years and facilitate comparisons; and (2) clear and seamless image data can be developed for areas even when there are clouds obscuring the desired information. These synthetic images were generated using Landsat data derived using the Continuous Change and Detection Classification (CCDC) algorithm [21,31]. The CCDC algorithm estimates time series models and uses the models to predict expected observations and to detect deviations from expected conditions. The time series models are comprised of harmonic models [32,33] that account for the seasonality of the time series for each pixel, and a slope component that can be used to assess trends. For many investigations, the algorithm is used for detecting location and magnitude of major spectral changes that have occurred during the time period, but in this study we were more interested in using it for developing seamless image data to be used for further analyses. This was accomplished through an approach developed by Zhu et al. [34].

For each pixel, the CCDC algorithm is capable of predicting Landsat surface reflectance for any desired date through the estimation of these time series models. The algorithm makes use of all available data for given periods of time, and works best when dense time series information exists. There were about 140 Landsat scenes available for the region between 2000 and 2014, with most years having six or more scenes with less than 25% cloud cover. Based on our experiences with the CCDC, this number is high enough for CCDC to work effectively for our study. Conversely, there are relatively few images available prior to the year 2000, with significant gaps in coverage occurring during the early and late 1990s, which preclude the algorithm's effective implementation prior to 2000. Using the CCDC, we generated synthetic images for 1 January from 2000 through 2014 using the "simple" model, which fits each pixel to a pixel-specific and time-specific sinusoidal curve (defined by the intra- and inter-annual spectral patterns each pixel's reflectance values through time). If there are abrupt changes that occur in the pixel's time series, as detected through differencing predicted and observed Landsat observations, with differences being larger than a chosen threshold, then a break in the time series is identified. Otherwise, the pattern is assumed to be consistently and annually sinusoidal, with similar patterns from year to year (resulting in no noticeable difference between adjacent years for a given pixel) or gradual changes (the pattern is either gradually increasing or gradually decreasing for any given band, resulting in a slight difference between adjacent years for a given pixel). Figure 5A,B shows examples of synthetic images generated for 1 January 2014 and 2000. Figure 5C is an actual image from 2014, and is temporally most comparable to the synthetic image in Figure 5A. While there are some general color and tone differences between the two image products, the information portrayed is very similar between the two. It should be noted that there are more complicated models that could have been used to generate the synthetic images, but these run the risk of "overfitting" the data, which can yield spurious results, especially if there are a relatively limited number of available data sets for curve fitting.

We also used standard Landsat scenes (i.e., non-synthetic images) for some assessments. The reason for this, in part, is that there were some assessments that we wished to conduct using the Landsat images dating back to 1984. While there were not enough image data sets for conducting CCDC-related analyses from 1984 to 2000, the older data sets were useful for providing longer-term overviews on the land cover changes taking place throughout the region.

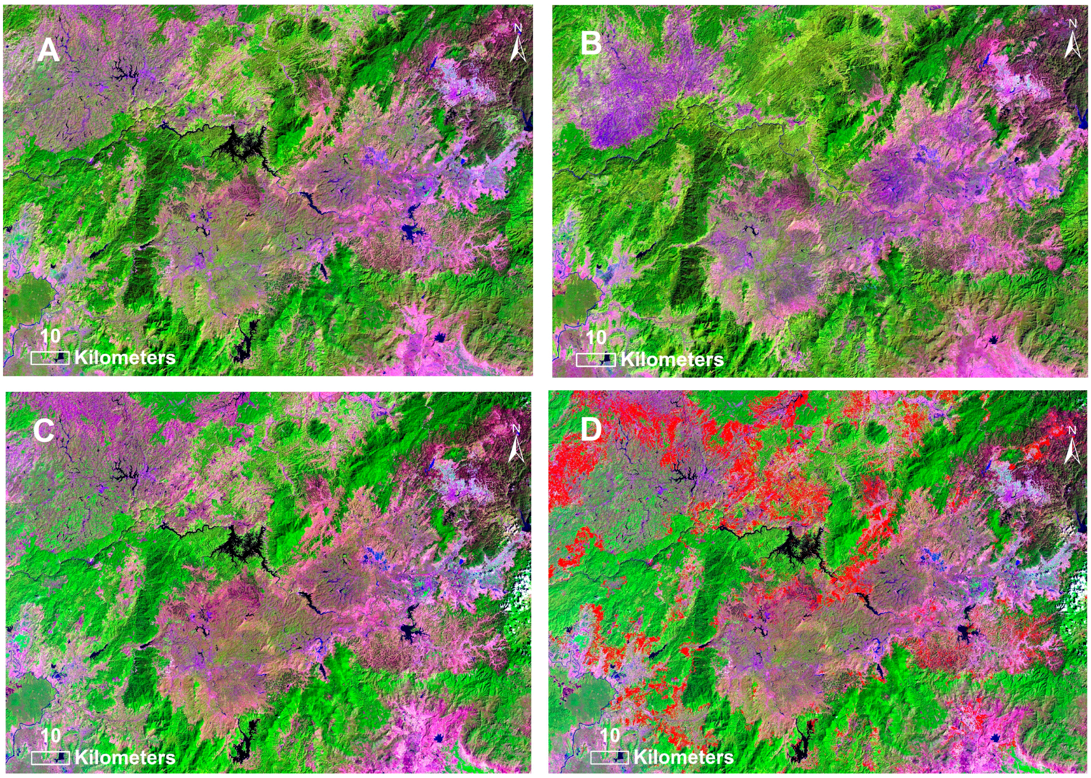

Figure 5. Landsat imagery showing a portion of Lam Dong Province (same area as shown in Figure 2). (**A**) = Synthetic image, January 2014; (**B**) = Synthetic image, January 2000; (**C**) = Actual image, 15 February 2014; (**D**) = Global forest change product showing forest loss from 2000 through 2014 in red [35] overlain onto 15 February 2014 image.

2.5. Image Analyses

We conducted three types of analyses in this study: (1) simple visual comparison of imagery dating back to 1973 to provide broad overall context regarding the forest changes that have taken place throughout the region; (2) assessments of greenness trends over 29 years using linear regression; and (3) assessments of annual differences using synthetic imagery from 2001 to 2014. For Analysis 1, we used four actual data sets (1973, 1989, 2002, 2014); for Analysis 2 we typically used one actual image data set for each year (when available) from 1987 to 2014; and for Analysis 3, we used a data stack of 14 synthetic images, with each image depicting 1 January for the years 2001 through 2014. For the second and third analyses, we focused primarily on image data stacks comprised solely of the Normalized Difference Vegetation Index (NDVI), defined as (NIR − Red)/(NIR + Red), with NIR referring to the near-infrared band, and Red referring to the red band. The NDVI is a widely used index that has been shown to be useful for many land cover and land use change applications. The three analyses provide different sets of information, with the first providing broad overviews of the changes that have taken place throughout the region since the early 1970s, the second providing information about 20+ year trends in greenness, and the third providing information about annual changes in greenness over the past decade.

Previous studies have found that linear regression employed using multi-temporal image stacks has provided useful information on gradual changes taking place across a landscape [36,37]. Consequently, for this project and for Analysis 2, we generated linear regression relationships on a pixel by pixel basis between time (x variable) and the vegetation index value (y variable) for all pixels. As a general rule, and for the NDVI index used in this study, regression models with negative slope values indicate decreases in greenness or vegetation cover. Pixels that have a slope approaching zero indicate static conditions, and represent "no change". Models with positive slope values indicate where vegetation growth is increasing.

Simple differencing of vegetation index data sets (Analysis 3) was done to indicate where changes have taken place over selected time periods. Using the NDVI images derived from the synthetic images, differences were generated between adjacent years to assess changes over short time periods. This type of information can have value for resource managers who are interested in where degradation events are actively occurring.

Actual thresholds were set interactively by analysts based on their knowledge, experience, and image interpretation. When the defined threshold is too low, there are many areas of known stability that will show a high degree of "speckling", generally interpreted as spurious change. Conversely, if the threshold is too high, there will not be enough change depicted. Determining the appropriate threshold to be used involves selecting the value that is a "compromise" between too much and too little change, as determined using visual inspection of the imagery. This approach has the advantage of enabling the analysts to help guide the change detection process through the use of their knowledge of the area. Use of the same threshold throughout the study ensures consistency of results for comparative purposes.

A year 2000 forest/non-forest mask derived from methods similar to those described in [38] was used to mask out low forest cover pixels. Six of the most cloud-free Landsat TM and ETM+ images from the year 2000 were acquired and cloud masked. The forest/non-forest masks were then created for each image using a Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation continuous fields (VCF) data layer to extract spectral signatures from the Landsat imagery [39,40]. MODIS VCF values range from 0–100 and depict the likelihood a pixel is forested. These values were binned into groups of 10 and assigned a class value ranging from 1 (least likely forested) to 10 (most likely forested). The MODIS VCF mask was then clipped and resampled to Landsat extent and spatial resolution. An average spectral response for every cloud-free Landsat pixel in a scene in each of the ten classes was collected for each of the six Landsat bands in the visible to Shortwave Infrared (SWIR) portions of the electromagnetic spectrum. This information was then used to train a k-nearest neighbor classifier that is parameterized with a k-value = 1, an equal neighbor-weighting scheme and the Euclidean distance metric. This process was repeated six times, once for each of the six Landsat scenes. The output of this process was six forest maps, with values ranging from 1 (least likely forested) to 10 (most likely forested). These maps were then averaged together to produce a composite and optimal forest mask with minimal cloud cover. An optimized threshold value was derived by comparing the forest mask with high-resolution and Landsat imagery. The threshold was empirically derived via analyst guidance and visually matching the forest mask extent to observed forest extent in the imagery. Any value above the threshold was masked as forest; any value below the threshold was masked as non-forest. The year 2000 forest mask was used because it represents a good baseline from which to develop the post-2000 change assessments. This was the mask employed for validation of results described below.

For some of the image products shown, we used a year 2000 VCF tree cover data set developed at the Global Land Cover Facility at the University of Maryland [40] to mask out low forest cover pixels. This dataset contains estimates of the percentage of ground in each 30 m pixel covered by woody vegetation greater than five meters in height [41]. This approach was used when we wished to visually compare our results with the forest change products developed with the University of Maryland Global Forest Change Dataset [35]. Such comparisons were done to help validate our data sets and to check consistency between the products between the two studies. Lack of consistency between the two sets of products would be of concern, and would call into question the accuracies of at least one of the sets of change products.

Digital elevation model (DEM) data were analyzed in conjunction with the trends data for Lam Dong Province. The DEM data that were used had 30-m spatial resolution, and were from the Advanced Spaceborne Thermal Emission and Reflection (ASTER) Global Digital Elevation Model V002 [42]. The ASTER data were obtained from the Land Processes Distributed Active Archive Center at the United States Geological Survey Earth Resources Observation and Science Center, Sioux Falls, South Dakota. For the study, data were binned into 11 elevation classes: 0–200 m, 201–400 m, 401–600 m, and so on through class 11 (2001–2200 m). Mean NDVI slope values derived from the 1985–2014 trend analysis for each elevation class were then derived for each elevation class.

2.6. Validation Points

One of our goals in this project was to assess the value and utility of Landsat time series data for assessing changes related to forest degradation, and during the course of the investigation, we obtained validation points for assessing accuracies of some of the products. Our goal was not necessarily to achieve maximum classification accuracy, which generally requires much iterative refinement work to yield increasingly improved results, but to generate products that would be appropriate for capturing the major trends occurring throughout the region. The validation was intended to ensure that these data sets had sufficient accuracies for these purposes.

Three separate groups of points were used to create an accuracy assessment consisting of 263 points that were visually interpreted as forest or non-forest from 2000 to 2014. From the 263 points, an initial 125 points were created from a stratified random sample of forest cover maps. Areas of persistent forest, persistent non-forest, and forest change were all sampled. Next, a secondary simple random sample of 100 points was generated. Finally, a 38-point sample was manually generated that specifically targeted areas of obvious forest change according to the University of Maryland Global Forest Change Dataset [35]. For the purposes of the study, plantations and other woody agroforestry crops that appeared to be mature and above 5 m in height were considered forest. Each point was first interpreted using all available high-resolution imagery from Google Earth. All points for the years 2000 and 2007 that lacked high resolution imagery were then visually interpreted using the most cloud free Landsat scenes from each respective calendar year. Points that could not be visually interpreted accurately as forest, non-forest, or fell in mixed landcovers were discarded. Samples that depicted forest growth were also removed, as tracking growth was not the purpose of this study and forest growth was not depicted in the final output products. As multiple interpretations occur at each of the 263 points over the 2000–2014 timeframe, a total of 1169 visual interpretations were collected for validation. The validation approach employed multiple image data sets, and was similar in concept to the TimeSync method [43].

2.7. National Park Change Analysis

Understanding patterns and trends of degradation change can help natural resource managers determine whether or not changes in their management approaches are warranted. As part of this project, we were interested in the utility of our change products for addressing applications questions of practical significance. As such, we compared the inter-annual changes (i.e., disturbances) taking place within Cat Tien and Bidoup Nui Ba National Parks (Figure 1), and in their surrounding regions.

After obtaining the Geographic Information Systems (GIS) boundaries of these parks, we assessed the changes taking place through calculating the percentage of pixels that underwent a decrease in NDVI between adjacent years between 2001 and 2014 for both parks. A pixel was considered to have been degraded if it decreased by 0.02 NDVI units or more between adjacent years. If a previously degraded pixel then increased in value during the next pair of adjacent years, then it would no longer be considered degraded for that latter time period. The premise behind this is that NDVI will drop following disturbance events, and will remain stable between adjacent years if no change has taken place. While the actual value may seem quite low, because we were assessing degradation changes, which are relatively subtle, we felt that using such a low value was justified. Regardless, the same threshold value was used for tabulating changes for all pairs of adjacent years enabling consistent comparisons among study areas. Once we calculated the changes taking place within the two national parks between each adjacent pair of years from 2001–2014, we generated 3-km boundaries around the national parks, and conducted the same type of change assessment for the areas within the "buffer zones" but excluding the areas within the national parks. We created a series of binary maps, one for each adjacent pair of years, which depict where degradation occurred from one year to the next. We then calculated the percentage of pixels for four areas of interest (e.g., the two national parks and their associated "buffer zones") showing amount of degradation for each pair of adjacent years, and graphically compared results from within the parks with those from the buffer zones as an indication of the effectiveness of the park reserve system for protecting the forests.

3. Results and Discussion

3.1. Qualitative Image Assessments

Data sets representing four time periods (1973, 1989, 2002 and 2014) are shown for the western part of the study area (Figure 6). The area shown includes a portion of Cat Tien National Park. These were processed to mimic false color infrared photography whereby red indicates the presence of dense green vegetation. Much of this area is just to the west of Lam Dong Province, but provides clear indication and overview of the types of changes occurring throughout the region over the previous several decades. From the 1973 data set, it can be seen that much of the region was forested. Much forest clearing took place between 1973 and 1989 throughout much of the region, although Cat Tien National Park was maintained in a mostly undisturbed state over the timeframe. Since 1989, the area that had previously been cleared has become increasingly vegetated. This is especially apparent in the southeastern portion of the imagery, as inferred by the degree of red (related to the greenness in the vegetation) in the images. Much of the increase in greenness is related to maturing agroforestry, including maturation of coffee vegetation within the plantations.

These general observations of forest transitions are consistent with the trends observed by other Vietnam land cover studies [10,44,45]. A major shift from net deforestation to reforestation occurred throughout Vietnam during the 1990s, with reforestation occurring at a higher rate than deforestation during this time. In [44] it was observed that the reforestation occurred both as a function of natural forest regeneration and an increase in plantation forests. While we see much evidence of extensive reforestation through an increase in planted forests, we see only limited natural forest regeneration throughout Lam Dong Province. It is interesting that planted forests were considered to be almost nonexistent until the 1980s, and that they increased to reach approximately 7–8% of forest cover of Vietnam by 2005 [44]. This implies that a major shift in land use occurred in Vietnam from the 1970s to present, with the earlier period marked by extensive forest extraction activities and clearing for agriculture, and the later period dominated by extensive agroforestry activities and marginal agricultural areas reverting to forests [46]. We should note that we did observe areas, especially north of the western portion Lam Dong Province, where extensive deforestation has been occurring throughout the 2000s (visible in the upper left part of Figure 7), but this was not as apparent throughout much of Lam Dong.

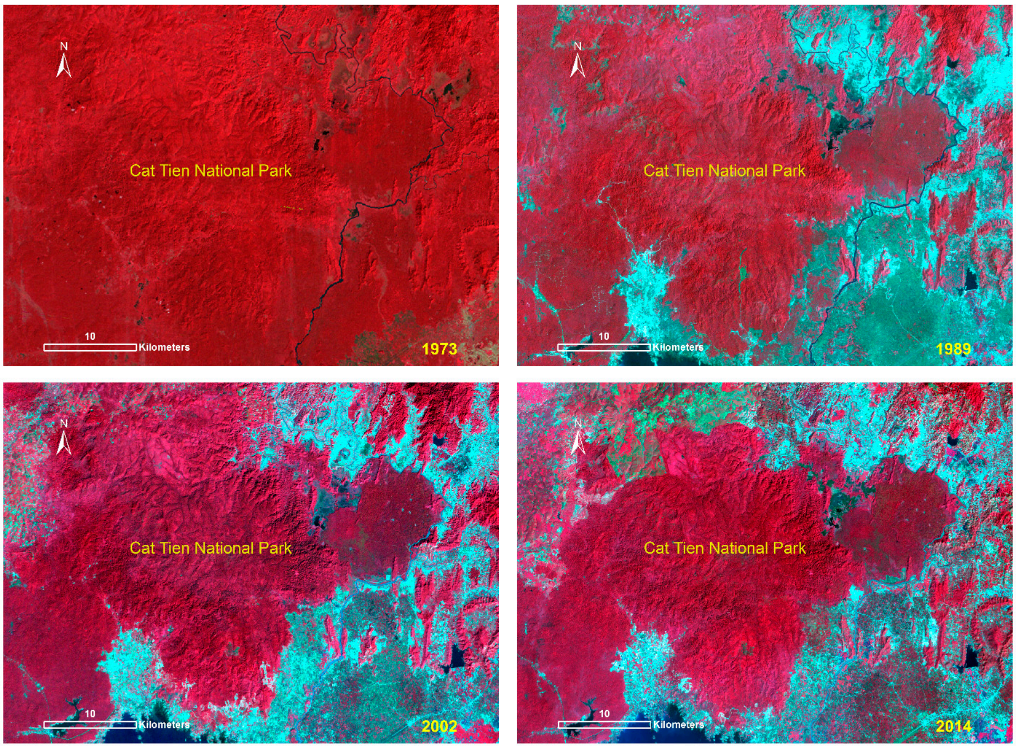

Figure 6. Landsat false color composites from different epochs. All images were produced using near-infrared, red, and green bands in the order of red, green, and blue. The 1973 image is from Landsat 1 Multispectral Scanner System (bands 4-2-1), 1989 imagery is from Landsat 5 (bands 4-3-2), 2002 imagery is from Landsat 7 (bands 4-3-2), and the 2014 image is from Landsat 8 (bands 5-4-3).

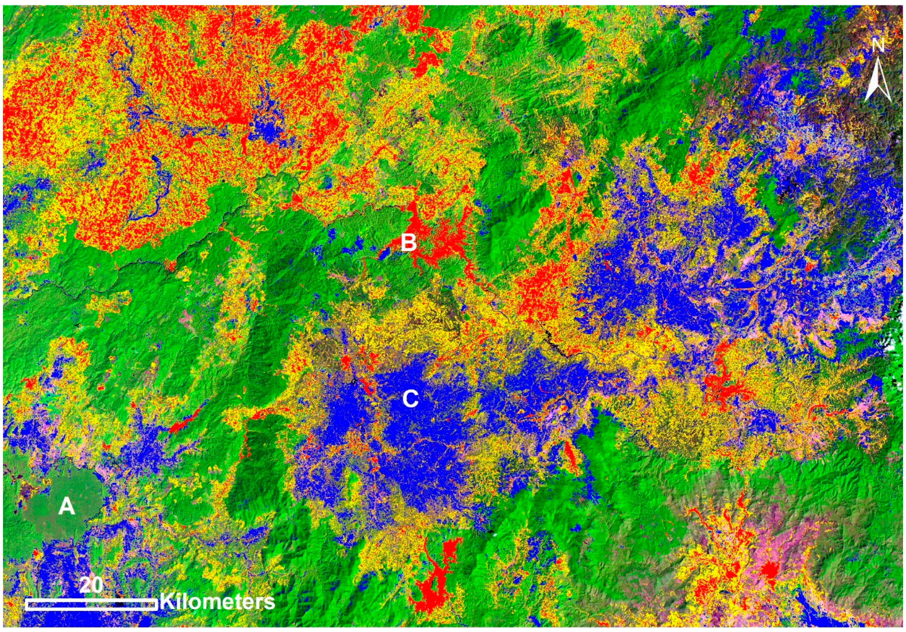

Figure 7. Normalized Difference Vegetation Index (NDVI) trend image based on regression analysis generated using 1985–2014 time series data. Red indicates where NDVI shows major decrease in greenness, whereas yellow shows moderate decrease in greenness. Blue indicates where greenness increased. A = Mature forest (no increases or decreases in NDVI) associated with Cat Tien National Park. B = Area transformed from forest to reservoir. C = Area of greening related to agroforestry.

It is noteworthy that a number of other investigations have noted increased greenness trends that have occurred throughout Southeast Asia [47–49]. These studies offered various explanations as to why the satellite data showed increases in greening, including climate and land use changes. In our study, the changes throughout southern Vietnam are largely related to changes in land cover and land use (e.g., deforestation followed by greening caused by agroforestry). Consistent with the land cover and use trends described by others [10,44,46], we note that the greening that we are observing in Vietnam was not linear for the duration of the time period 1973–2014 (i.e., there were decreases in vegetation cover over much of the region from 1973 to 1989, followed by increasing vegetation cover from 1989 to 2014). Developing an understanding of when and where major land cover and land use events have taken place is critical to our interpretations of greenness trends. This understanding can be effectively accomplished using historical and fine resolution imagery provided by Landsat.

3.2. Trend Analyses Using Time Series from 1985 to 2014

A Normalized Difference Vegetation Index (NDVI) regression trend image generated using actual (i.e., non-synthetic) imagery (1985–2014 slope of NDVI versus time; Figure 7) shows variable spatial trends of changes throughout the study region over the previous 29 years. In this image, red indicates where NDVI shows major decrease in the "slope" of NDVI (i.e., greenness) versus time, whereas yellow shows moderate slope changes in NDVI. Blue indicates where NDVI increased. No forest mask was employed for this test. Areas that are not red, blue or yellow (i.e., areas where the actual imagery can be seen and is usually green) represent areas that did not show slope changes (i.e., neither increases or decreases in NDVI) over the time period, and mostly represent mature forests. For the most part, yellow indicates areas where relatively recent forest degradation and loss have occurred, whereas the red areas indicate where forest degradation occurred at an earlier time interval. It is noteworthy that the patterns of degradation are primarily along the edges of the forest, which is consistent with our knowledge of how agriculture has been expanding into these areas through the gradual removal of trees over the past several decades.

While this image provides a broad overview of the changes that have taken place throughout the region over the 1985–2014 timeframe, it needs to be recognized that it is only capturing the time versus index changes that are linear in nature. Thus, any area that decreased in greenness, such as through the deforestation process, and then increased in greenness, such as through increased agroforestry processes, may not be adequately captured using this approach. That being said, the overall patterns that are visualized in Figure 7 are very consistent with what we know about the changes that have been taking place through the region over this 29-year period. Using all Lam Dong Province pixels, we ascertained that about 39% showed evidence of decreasing greenness based on the 1985–2014 regression results (i.e., decreasing NDVI slope), whereas about 62% showed evidence of greening (i.e., increasing NDVI slope). Using values that were plus or minus one standard deviation from the mean as cutoff values, roughly 10% showed what appeared to be significant decreases in greenness, and roughly 10% showed significant increases. Thus, most the pixels showing increases or decreases in greenness were within one standard deviation of the mean, with substantially more being in the "increasing greenness" category than the "decreasing greenness" category.

The greenness trends for the Lam Dong Province vary as a function of elevation (Figure 8). Not only does average NDVI slope increase with increasing elevation, but the variance decreases with increasing elevation. The higher elevations in the Lam Dong Province tend to be forested, whereas the lower elevations tend to have more variable land uses, including more agriculture, so it might be expected that average NDVI might be higher at the higher elevations. However, it is unclear why greenness trends would be increasing at these higher elevations. It is possible that the forests at these high elevations, which are largely secondary, are still maturing. If so, they may be producing more foliage over time, which increases greenness. It should be emphasized that these increases in greenness are relatively subtle, and it is unclear what these changes mean from an ecological and biophysical standpoint.

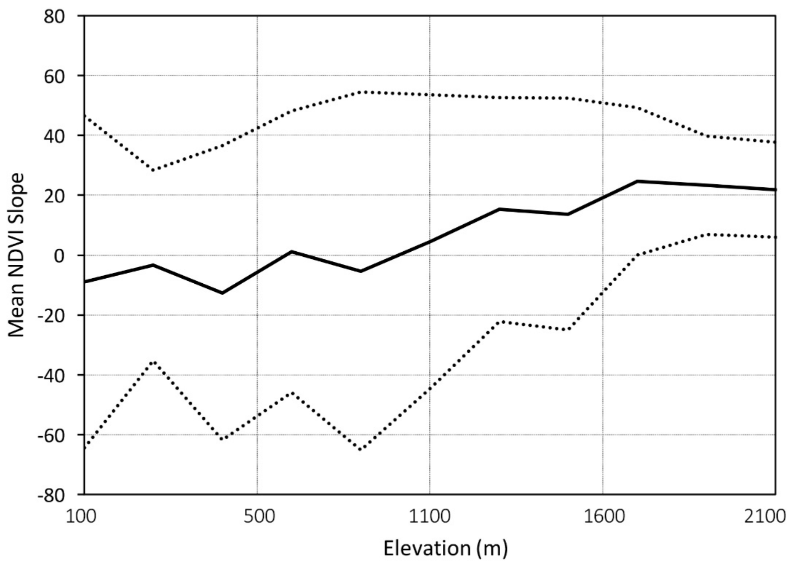

Figure 8. Mean Normalized Difference Vegetation Index (NDVI) slope (plus and minus one standard deviation) versus elevation. Mean NDVI slope values were calculated for each of 11 elevation classes (0–200 m, 201–400 m, etc.), with the exception of a small percentage of pixels in the northern and western portion of the Lam Dong Province where imagery was lacking to conduct the regression analysis, all pixels in the province were used. NDVI slope values are ×10,000 per annum.

3.3. Images Depicting Forest Degradation Occurring over Different Time Periods

A series of images in Figure 9 depicts the progression of degradation across the region from 2001 to 2014. As discussed earlier, this time period has dense Landsat coverage, and we would expect the annual synthetic images generated from this time period to be reliable for indicating changes over short time frames, such as between adjacent years. In this study, the synthetic images were developed to represent 1 January of each year from 2001 to 2014. The first image (Figure 9; upper left) shows a composite indicating where degradation events occurred annually between years 2001 and 2006. While there are multiple ways of displaying such events from dense time series data, in this case red areas indicate a composite of annual changes developed using adjacent years of imagery for a five-year time period. Thus, any area that indicated a drop in NDVI (i.e., 0.02) between any pair of adjacent years (i.e., between 2001 and 2002, 2002 and 2003, 2003 and 2004, 2004 and 2005, or 2005 and 2006) is depicted as red. The second image (Figure 9; upper right) was generated similarly, except that the time period has been expanded to cover 2001–2010 (i.e., using nine pairs of adjacent years of NDVI difference images, and representing changes over a ten year time period). Figure 9 (lower left) depicts the degradation changes occurring over the entire 14-year time period (as measured using 13 pairs of adjacent years of NDVI difference images). The last image (Figure 9; lower right) shows the changes that occurred over the three separate epochs (i.e., 2001–2006, 2006–2010, and 2010–2014) in one image.

From Figure 9, it is clear that various areas within the region are being differentially impacted by forest degradation. While most of the changes observed are occurring along the forest-agricultural zone interfaces, more marked changes are occurring in the northwestern portions of the images outside of Lam Dong Province. The major red feature at “B” in the lower two images of Figure 9 represents a previously forested area that was converted into a reservoir in 2010. It is noteworthy that most of the interior forest regions, which includes the Cat Tien National Park (A) show little evidence of degradation events. The data set that depicts overall forest change (Figure 9; lower left image) is quite similar to that of the 2000–2014 global forest change product (Figure 5D) [35]. The global forest change data were produced using different methods and different data sets, and the consistency between data sets gives us additional confidence that the results from our study are valid. That being said, there are some significant differences between the data sets, such as the area where the reservoir was built, which is not depicted as a change in the global forest change data.

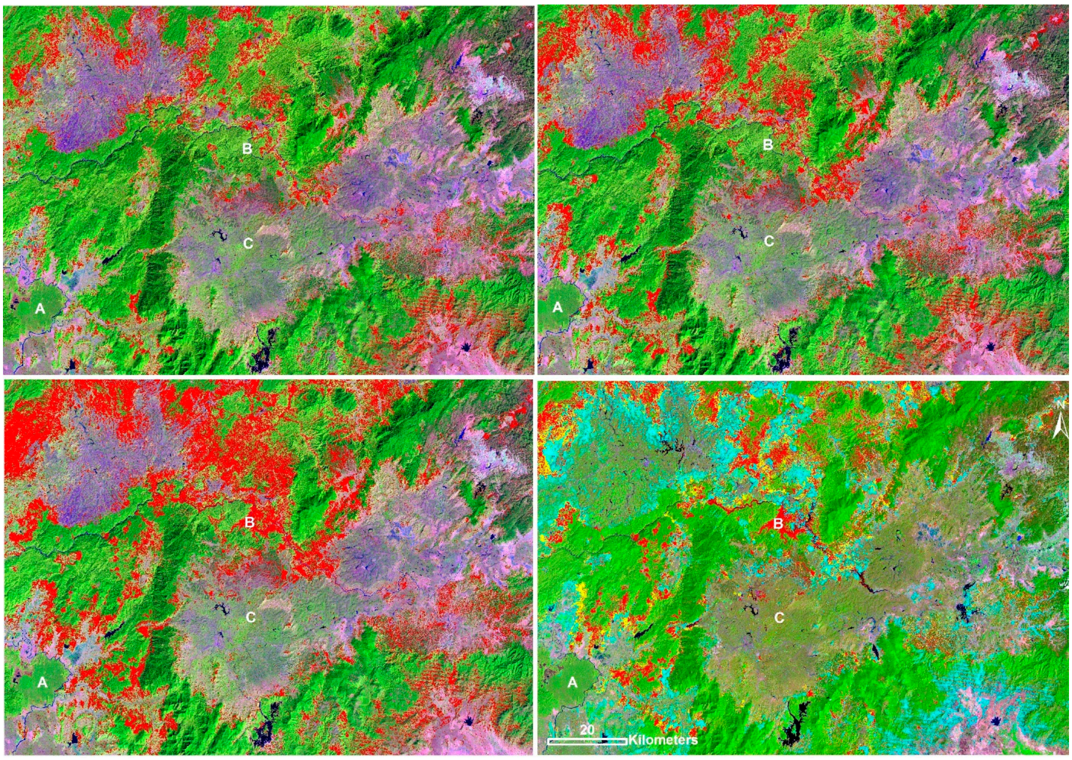

Figure 9. Images depicting forest degradation occurring over different time periods. Upper left image = Degradation changes from 2001 to 2006 (in red); Upper right image = Degradation changes from 2001 to 2010 (in red); Lower left image = Degradation changes from 2001 to 2014 (in red); Lower right image = Degradation changes by epoch, with turquoise representing changes from 2001 to 2006, yellow representing changes from 2006 to 2010, and red being changes occurring from 2010 to 2014. Areas denoted by letters A, B and C are described in the Figure 7 caption.

3.4. Validation

A total of 263 pixel locations were used to validate all products generated in this study. We conducted the validation using multiple time periods, and used a total of 1169 visual interpretations collected across 2000–2014 for these locations. The visual interpretations were derived from all available high resolution (2000–2014) and Landsat imagery (2000 and 2007 only). We present contingency matrices of the NDVI-derived products. For this exercise, we validated forest/non-forest maps for the years 2000, 2007, and 2014 (forest map validation; Table 2). We also validated forest change products that depict persistent forest, persistent non-forest, and forest degradation or loss from 2000–2007, 2007–2014, and 2000–2014 (forest change validation; Tables 3–5). Finally, we validated the forest and forest change product for all years of study from 2000–2014 using all 1169 visual interpretations collected (average forest map accuracy; Table 6). During the development of these change products, we used consistent threshold values for delineating forest degradation from year to year.

Overall accuracies for the three forest/non-forest maps from 2000, 2007 and 2014 ranged from 83.0 to 93.0%. Producer's accuracy values ranged from 86.3 to 92.9% for forest vegetation, and from 80.9 to 85.1% for non-forested areas. User's accuracy values were comparable, with values for forest ranging from 78.8% to 93.9%, and values for non-forest ranging from 86.5% to 90.5%. Statistically, these validation datasets indicate that the method was effective at delineating forest and non-forest land covers. We have the most confidence in the use of the forest/non-forest map as a forest mask in 2000 because we used imagery from this year for its development. It can be seen from the tables that accuracies generally declined between 2000 and 2007, and even more so in 2014. Because we developed our change products sequentially starting in 2000 and ending in 2014, it is likely that some of the errors in the tables represent error propagation through the time series. Regardless, the latter accuracy values are very acceptable for providing an overview regarding the changes taking place through the region. The approach that we used for this exercise, which involved the thresholding the difference images between adjacent years, provides a simple and effective way to create classification change images that unambiguously show where change has occurred on an annual basis.

The forest change validation accuracies for the three change maps (Tables 3–5) were quite similar and showed consistency over time, ranging from 84.2% to 84.7%. Producer's accuracy values ranged from 86.8% to 93.1% for persistent forest areas, and from 81.5% to 92.5% for persistent non-forest areas. User's accuracy values were similar for persistent forest areas ranging from 81.3% to 86.4%, and values for persistent non-forest areas ranged from 81.7% to 92.5%. Ultimately, the 2000 to 2014 validation slightly underestimated forest loss, sometimes confusing it with persistently forested areas. The producer's accuracy was 72.9% and user's accuracy for the forest loss class was 81.4%. Generally, it appears that given a longer timeframe, accuracies for detecting forest loss and degradation improve. It should also be noted that the change data set accuracies tended to be lower for the 2000–2007 time frame than for the 2007–2014 time frame. In part, we think that this might be related to the sources of the validation imagery. We tended to use mostly Landsat imagery for validating the 2000–2007 changes, and high resolution imagery for validating the 2007–2014 changes. While we believe that most of the errors encountered were image-based, it should be noted that there were likely at least some errors in the validation data.

Average forest map accuracy (Table 6) was created using visual interpretations of all available high-resolution imagery in Google Earth and all of the Landsat visual interpretations from 2000 and 2007. This validation product represents the average accuracy of forest and non-forest maps over time from 2000 to 2014. The derived overall accuracy is 86.6%. Producer's accuracy for forested areas was 89.0%, and 84.2% for non-forested areas. User's accuracy values were again similar for forested (84.8%) and non-forested (88.5%) areas. Ultimately, these results indicate that this method is effective at mapping forest and non-forested land covers with minimal over and under classification of each class.

Table 2. Forest map validation. Validation was done with points visually interpreted using Landsat imagery from the 2000, 2007, and 2014 NDVI-derived forest maps. Areas are classified as forest or non-forest. Overall accuracy using this approach was 93.0%.

Year	Class	Reference Total	Classified Total	Number Agreement	Producer's Accuracy	User's Accuracy
2000	Forest	161	165	155	96.3%	93.9%
2000	Non-forest	67	63	57	85.1%	90.5%
2007	Forest	123	130	112	91.1%	86.2%
2007	Non-forest	94	87	76	80.9%	87.4%
2014	Forest	76	80	63	82.9%	78.8%
2014	Non-forest	100	96	83	83.0%	86.5%

Table 3. Forest change validation; 2000–2007. Validation was done using annual NDVI forest change dataset derived from points visually interpreted using Landsat and high-resolution imagery. If areas classified as forest in 2000 showed decreases in NDVI values during adjacent year periods afterwards (e.g., between 2001 and 2002, 2003 and 2004, and so on through 2007), then the change areas were classed as forest loss. Areas that did not show changes in the forested or non-forested areas were classed as persistent forest or persistent non-forest. Overall accuracy using this approach was 84.4%.

	Persistent Forest	Persistent Non-Forest	Loss	User's Accuracy
Persistent forest	108	7	10	86.4%
Persistent non-forest	1	44	3	91.7%
Loss	7	3	16	61.5%
Producer's accuracy	93.1%	81.5%	55.2%	

Table 4. Forest change validation; 2007–2014. Validation was done using annual NDVI forest change dataset derived from points visually interpreted using Landsat and high-resolution imagery. If areas classified as forest in 2007 showed decreases in NDVI values during adjacent year periods afterwards (e.g., between 2008 and 2009, 2010 and 2011, and so on through 2014), then the change areas were classed as forest loss. Areas that did not show changes in the forested or non-forested areas were classed as persistent forest or persistent non-forest. Overall accuracy using this approach was 84.7%.

	Persistent Forest	Persistent Non-Forest	Loss	User's Accuracy
Persistent forest	59	6	4	85.5%
Persistent non-forest	7	49	4	81.7%
Loss	2	1	25	89.3%
Producer's accuracy	86.8%	87.5%	75.8%	

Table 5. Forest change validation; 2000–2014. Validation was done using 2000–2014 annual NDVI forest change dataset derived from points visually interpreted using Landsat and high-resolution imagery. If areas classified as forest in 2000 showed decreases in NDVI values during adjacent year periods afterwards (e.g., between 2001 and 2002, 2003 and 2004, and so on through 2014), then the change areas were classed as forest loss. Areas that did not show changes in the forested or non-forested areas were classed as persistent forest or persistent non-forest. Overall accuracy using this approach was 84.2%.

	Persistent Forest	Persistent Non-Forest	Loss	User's Accuracy
Persistent forest	61	3	11	81.3%
Persistent non-forest	1	37	2	92.5%
Loss	8	0	35	81.4%
Producer's accuracy	87.1%	92.5%	72.9%	

Table 6. Average forest map accuracy. Validation of the 2000–2014 annual NDVI forest change dataset was derived from all points from 2000 to 2014 visually interpreted using Landsat and high-resolution imagery. Areas are classified as forest or non-forest for each year of study. Overall accuracy using this approach was 86.6%.

Class	Reference Total	Classified Total	Number Agreement	Producer's Accuracy	User's Accuracy
Forest	582	611	518	89.0%	84.8%
Non-forest	587	558	494	84.2%	88.5%

It is also worth noting that even though the visual interpretation classes are very basic (i.e., forest versus non-forest) there were a number of points that were difficult to characterize. This was often due to complex management practices such as agroforestry, where points were located on edges between cleared areas and forest, and other times when deciduous forests exhibited leaf on to leaf off variations throughout the seasons. If a visual interpretation was too uncertain, these points were omitted. Additionally, multiple images were used to ensure that visual interpretations were as accurate as possible, and the consistent accuracies of each of the products over time indicate that the visual interpretations likely were correct. However, some misclassification of validation points likely occurred, as is common in most studies.

Accuracy matrices provide an important type of information that enable users to evaluate the quality of the various classification data sets generated. There is also value in augmenting such evaluations with other sources of information. Simple qualitative assessments can be very useful to users and producers of the data as part of the evaluation process. As an example, in this study we made a simple visual comparison of the products that we generated with the global forest change product [35]. The high level of consistency between the two efforts helps support our contention that the products that we generated have good quality. In addition, we had first-hand knowledge through our field work (as well as second-hand information with those who know the region well) that the forest changes are taking place very gradually throughout the region primarily at the forest edges.

We observed this in our change products, and on a general basis, field information is consistent with what we found. It should be pointed out that while the field visit provided good information for generating broad overviews and understanding of the region, we did not feel that the information could readily be incorporated into quantitative validation assessments. Rather, the information was used: (1) to help familiarize ourselves with the conditions and types of changes occurring throughout Lam Dong; (2) to provide us with an understanding of where the changes are occurring and what the driving forces of the changes are; and (3) to provide us with a basis for helping to define the threshold values that we used for generating the change products. We should also note that we rarely found changes located in areas where we did not suspect major changes to be occurring, such as in the national parks. We believe that in addition to formal accuracy assessments, that it is important to conduct these other qualitative assessments to ensure that the products "make sense" and are consistent with our knowledge of the region.

3.5. Forest Changes within and Surrounding Protected Areas

The analyses that we conducted within and surrounding the two national parks of the region indicate that relatively little change has occurred in these protected areas from 2001 through 2014 as compared to those areas directly outside the national parks in the "buffer areas" (Figures 10 and 11). For these comparisons, we assessed the annual percentage change data, as estimated using NDVI change information determined using adjacent years of imagery, for areas within the parks and within the buffer areas. For the case of Cat Tien National Park, annual change for the area within the park ranged from about 0.0% to 0.5% change, compared with 0.2% to 3.6% annual change just outside the park (Figure 10). The changes associated with Bidoup Nui Ba National Park were considerably lower, ranging from near 0.0% to 0.1% change within the park, and near 0.0% to near 0.6% change within the buffer zone (Figure 11). We are not certain about what caused the inter-annual variation within these graphs, nor are we certain how much artifacts in the image processing methods that were used impacted results. Nonetheless, there are two main observations that can be made from this portion of the study. The first is that the buffer areas consistently exhibit more changes than the areas within the parks, implying that the parks are having a positive impact on helping to preserve the integrity of the regions within the parks themselves. The second observation is that there is considerably more land cover and land use change surrounding Cat Tien National Park than Bidoup Nui Ba National Park. The former is at a lower elevation, and the overall area is more conducive to agricultural activities and human-induced land cover change than is the region surrounding Bidoup Nui Ba Park. While there are a number of studies that have demonstrated the value of national parks for preserving habitat and biodiversity [50], this is not always the case [51]. It is noteworthy that for these two parks, the protection status of these parks is having the desired impacts.

There have been several other studies that have assessed the effectiveness of national parks and other protected areas for stabilizing land cover trends. In general, it has been documented that when viewed globally, protected areas tend to improve management effectiveness, implying that their protected status helps to preserve their conservation value [52]. However, there are many cases of "paper parks", which may have very limited value, and each park needs to be evaluated separately to determine whether it is achieving its conservation objectives. In a study of the Bach Ma National Park, located in Central Vietnam, it was determined that significant land cover changes occurred inside and outside the park [45]. The changes occurred just prior to establishment of the park but leveled off soon afterwards. In a separate study in the Tam Dao National Park Region in Northern Vietnam [53], use of land cover data sets derived from different time periods were effectively used for modeling future conditions and helping land resource managers to plan and prioritize accordingly.

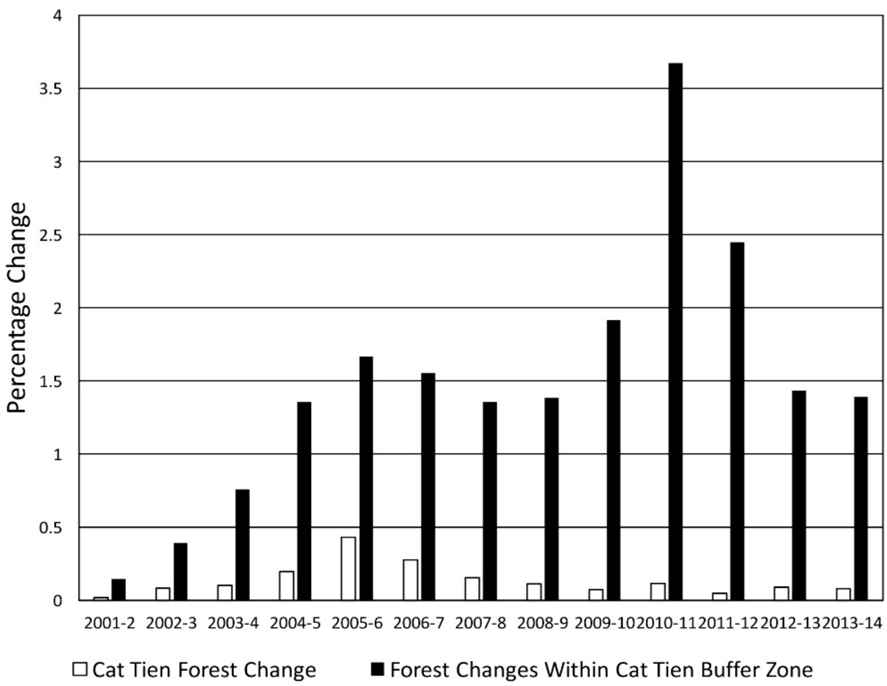

Figure 10. Comparison between forest change due to disturbance in Cat Tien National Park and buffer zone regions. Disturbance changes represent loss of greenness as determined using NDVI difference threshold values between adjacent years.

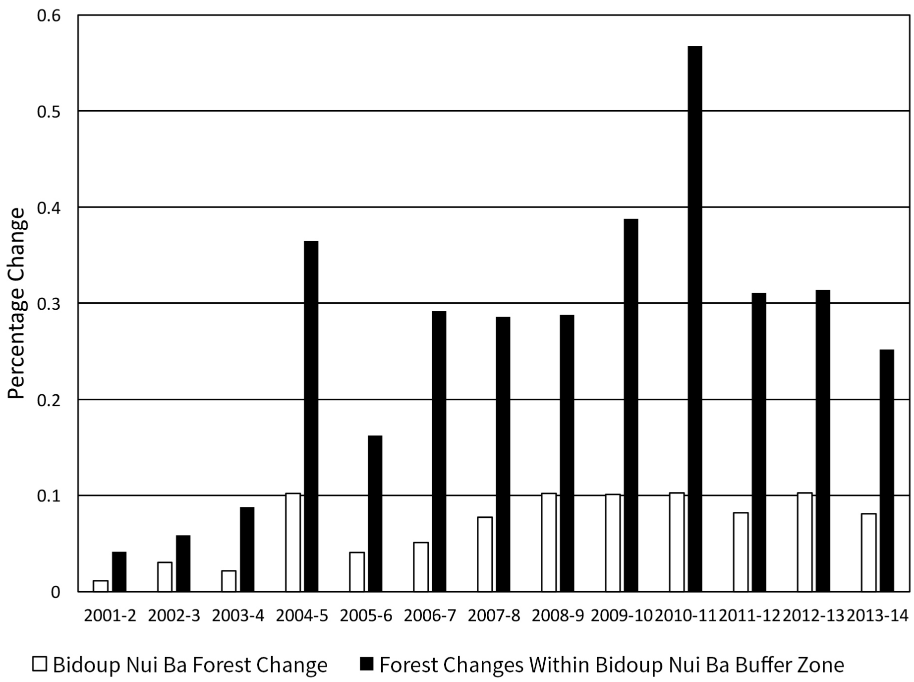

Figure 11. Comparison between forest change due to disturbance in Bidoup Nui Ba National Park and buffer zone regions. Disturbance changes represent loss of greenness as determined using NDVI difference threshold values between adjacent years.

It is important that we understand land-use change around protected areas, as the changes directly surrounding these areas can reduce their effective size and limit their ability to conserve biodiversity due to the potential that land-use change can alter ecological processes and the ability of organisms to move among protected areas [54]. Within some countries such as the United States, it appears that many land use changes have been and will continue to occur in the areas surrounding protected areas because they are considered to be desirable locations to live, and many boundary areas risk losing much of their natural vegetation as a function of urbanization [55,56]. It is unclear to which this is a major threat and of long-term concern to the two national parks analyzed in this investigation. While we noticed marked differences between the land changes occurring in the buffer zones as compared with the regions within the park boundaries, the rates of change were much higher surrounding Cat Tien Park as compared with Bidoup Nui Ba Park, implying higher relative risk of potential long term adverse effects. The differences in rates of change between the two park buffer areas can likely be attributed in part to the different geographies of the parks, as well as the differences in the external population pressures nearby. As discussed by others [54–56], understanding regional land-use dynamics is critical for effective management and planning of protected lands, and likely need to be analyzed on a case-by-case basis taking into consideration a wide variety of local factors. Based on the results from this study, we do not see evidence that either park is currently under major conservation threats from external influences. However, it is important to note that the parks are relatively small in size and could be considered as vulnerable to external forces. As such, they will require constant vigilance in order to ensure that their current status does not degrade.

4. Conclusions

There have been many studies over the years that have documented the suitability of Landsat data to track changes in forest ecosystems. However, transforming these types of studies into processes so that we can actively monitor areas on an annual basis whereby many of the changes occurring are "subtle" or "gradual" (e.g., forest degradation) has proven extremely difficult. The Vietnamese government is motivated to monitor their forests frequently (e.g., annually), and this project helps to move towards that direction. Overall, we believe that this study provides options regarding ways to conduct monitoring in Vietnam, and also provides contextual information on where and when the changes are taking place. While not part of this study, we anticipate that with the launch of Sentinel-2, there will be many additional satellite image sets appropriate for assessing forest degradation in Vietnam in the foreseeable future. Sentinel-2 has higher spatial resolution than Landsat (10/20 m for most of the bands vs. 30 m for TM, ETM+ and Operational Land Imager (OLI) sensors), and this improved resolution will likely be very appropriate for detecting the gradual degradation events typical throughout Vietnam.

There are a number of main conclusions that we can draw from this study. Firstly, from a technical side, this project makes effective use of dense time series data and synthetic imagery for detecting changes. Synthetic images have a number of advantages over using more traditional imagery, including facilitating year by year detection of changes. Use of synthetic images has not been widely employed by other investigators, but appears to be very effective for mapping year to year changes. Secondly, many of the changes being detected are rather gradual in nature, and fall into the broad category of "forest degradation". Many investigators have had difficulties in mapping and monitoring these types of changes. Many of the changes taking place in Vietnamese forests are related to this degradation process, which tend to be much more difficult to map and monitor than outright deforestation. This study demonstrates the feasibility of mapping and monitoring these types of changes using dense time series. Thirdly, developing operational approaches for large area monitoring has never been easy. Using long-term time series approaches, while gaining in popularity, is an area of active investigation by many researchers. We recognize that many of the approaches that we used in this study are relatively simple, but we would also like to emphasize that such approaches can have merit because they can be relatively straightforward to implement. Finally, one important conclusion that we obtained from this study was that the most highly protected national reserves in the region (Cat Tien and Bidoup Nui Ba National Parks) have not changed much over the entire Landsat timeframe (1972–present).

Forest degradation changes within these regions have not occurred at the same levels as those areas directly outside the reserves. In general, the patterns that we found in the change imagery are very instructive, and provide good indications of where and when changes are gradually taking place throughout the region. The more that we know about the patterns and rates of change occurring throughout a region, the more that we can project likely changes into the future, and the more likely it is that natural resource managers will be able to respond appropriately.

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Author Contributions: J.E.V., K.V.P., D.X.L. and M.C.W. conceived and designed the study, K.V.P. organized and led the field trip through Lam Dong Province, H.T.D. and L.V.H. assisted with field activities and sampling design, J.E.V. and H.S. conducted the image analyses, and J.S. conducted the validation work. J.E.V. was the principal writer of the paper, with the other authors contributing to it. The work in this report was sponsored by SilvaCarbon, which is a technical cooperation program that seeks to enhance our ability to monitor and manage forest and terrestrial carbon.

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