CHANGE DETECTION AND REMOTE SENSING METHODOLOGIES TO TRACK DEFORESTATION AND GROWTH IN THREATENED GLOBAL RAINFORESTS

by

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by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Area of Interest	AOI
Consistent Forest	CF
Consistent Non-Forest	CNF
Democratic Republic of the Congo	DRC
Digital Number	DN
Enhanced Thematic Mapper +	ETM+
Food and Agriculture Organization	FAO
Forest/Non-Forest	FNF
Hectares	ha
K-Nearest Neighbor	k-nn
Kilometer	km
Land Use/Land Cover	LULC
Landsat Ecosystem Disturbance Adaptive Processing System	LEDAPS
Meter	m
Middle Infrared	MIR
Moderate Resolution Imaging Spectroradiometer	MODIS
National Aeronautics and Space Administration	NASA
Normalized Difference Vegetation Index	NDVI
Near Infrared	NIR
Principle Components Analysis	PCA
Square Kilometer	sq km
Thematic Mapper	TM
Thermal Infrared	TIR
Transformed Divergence	TD
University of Maryland	UMD
United States Geological Survey	USGS
Vegetation Continuous Fields	VCF

ABSTRACT

CHANGE DETECTION AND REMOTE SENSING METHODOLOGIES TO TRACK DEFORESTATION AND GROWTH IN THREATENED GLOBAL RAINFORESTS

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This study describes, compares, and contrasts two forestry change detection methodologies for tracking deforestation and growth in three sites from 2000 to 2010. The three study areas include threatened forests in the Democratic Republic of the Congo (DRC), Indonesia, and Peru. The methodologies used in this study rely on freely available data including Landsat 5 and 7 Thematic Mapper (TM) and Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF). The two methods include conventional supervised signature extraction followed by a maximum likelihood classification and MODIS VCF guided Forest/Non Forest (FNF) Masking utilizing broad spatial resolution data to guide signature extraction. The process chain for each of these methods includes cloud masking of Landsat data, a threshold classification of MODIS VCF, training data or signature extraction, k- nearest-neighbor or maximum likelihood classification, analyst guided thresholding, and post-classification

image differencing to generate forest change maps. In addition to this research, two Forest/Non-Forest maps that are derived from these methods are compared and contrasted against a new global forest cover product called Landsat VCF. Comparisons of all methodologies was based upon an accuracy assessment via 500 validation pixels at each study area. Accuracy is evaluated in terms of both pixel counts and area proportions. Results of this accuracy assessment indicate that FNF Masking had the highest overall accuracy and was the best at labeling change. Conventional Supervised Classification had slightly lower overall accuracy but performed poorly when labeling change areas. Results indicate that Landsat VCF FNF maps had comparable accuracies to the previous two methods; however it was found that Landsat VCF substantially underestimates non-forested land cover and as a result overestimates forested land cover in all study areas.

INTRODUCTION

Deforestation has and continues to be a significant issue in global rainforests. Estimates indicate that over 10% of the world's tropical rainforest were destroyed between1990 and 2005. The majority of this loss occurred in the developing world including Africa, South America, and Southeast Asia. Additionally the amount of threatened tropical rainforest is also highest in these locations. Combined, the Amazon Basin, the Congo Basin, and Southeast Asia account for approximately one-third of the global forest area (Food and Agriculture Organization of the United Nations, 2011). Study areas were chosen in each of these three major rainforest locations including in the Democratic Republic of the Congo (DRC), Indonesia, and Peru. The forest area and rates of change for each of these countries can be seen in Table 1.

Country	Forest area (1,000 ha)				Annual Change Rate			
	1990	2000	2005	2010	1990-2000		2000-2010	
					1,000 ha/yr	%	1,000 ha/yr	%
DRC	160,363	157,249	155,692	154,135	-311	-0.20	-311	-0.20
Indonesia	118,545	99,409	97,857	94,432	-1,914	-1.75	-498	-0.51
Peru	70,156	69,742	68,742	67,992	-94	-0.14	-122	-0.18

Table 1: Total forest area and annual change rates from 1990 to 2010 for each country involved in this study (FAO, 2011).

Tracking change in these forests is also important for climate change science. It is estimated that tropical deforestation released between 1 and 2 billion tons of carbon per year in the 1990's. Furthermore, forest growth contributes to the sequestration and removal of carbon from the atmosphere and planting new forests could help in climatic stabilization. The measurement of carbon stocks and deforestation can also be linked and estimates can be made about the amount of carbon emissions that occur as a result of deforestation. The use of remotely sensed data is one of the primary methodologies when making such estimates (IPCC, 2006; Gibbs et al., 2007)

Consequently, the development of efficient forestry change detection tools and methodologies will become increasingly important. Tracking these forests through remote sensing is cost effective and saves the time of ground surveys (Muchoney and Haack, 1994). Tracking both loss and growth will allow stakeholders to make important conservation decisions relative to these pristine areas.

The objective of this study was to develop and test two change detection methodologies, evaluate the results, and compare the results against a new global product called Landsat Vegetation Continuous Fields (VCF). Each method was evaluated on overall accuracy and ability to track change. This was accomplished via an accuracy assessment and a comparison of methodologies. These two methods approach forestry change detection though the application of different techniques; however each method eventually standardizes study areas to simple forest/non-forest (FNF) maps. Post-classification image differencing is then used to extract areas of growth, loss, consistent forest, and consistent non-forest.

The first method employs analyst guided supervised signature extraction followed by a basic maximum likelihood classification. This methodology utilizes Landsat Thematic Mapper (TM) imagery and involves spectral signature extraction, signature evaluation via contingency testing and transformed divergence, followed by a maximum likelihood classification. Supervised signature extraction is both effective and widely used in numerous applications; however it has also been shown to be more time consuming and less efficient to implement (Erbek et al., 2004; Kozak et al., 2006). This methodology relies heavily on analyst guidance and meticulous signature extraction practices. Additionally, it is often challenging to transfer signatures across space and time. This is typically due to seasonality changes, spatial or spectral resolution differences, or varying Land Use/Land Cover (LULC) signatures at different spatial locations. This often means that the same signature extraction steps must be repeated to generate a good classification in multiple locations (Pax-Lenney et al., 2001).

The next method employs Moderate-resolution Imaging Spectroradiometer (MODIS) VCF to guide training data extraction from Landsat imagery. This methodology involves a standardized reclassification of MODIS VCF data, signature extraction via spatial overlay, followed by a k-nearest neighbor (k-nn) classification.

Three threatened areas were chosen for evaluation within the Democratic Republic of the Congo (DRC), Indonesia, and Peru. Immediately following this introduction, data and site locations will be described. Next a literature review will summarize relevant research and the methodologies will be discussed. Then the results of this study will be analyzed and examined for accuracy and compared against a Landsat VCF product. Finally conclusions will be drawn and further research will considered.

DATA

Three study areas were selected to analyze deforestation and growth rates in DRC, Indonesia, and Peru (Figures 1-3). Each site intersects a portion of pristine rainforest that is under threat of deforestation due to human expansion in the region. All sites are ~900 sq km in area and encompass about 1,000,000 Landsat pixels. These study areas were chosen because they feature mixtures of forest, urbanization, agriculture, and other land cover types. Theoretically, this research should be transferable to larger areas with more heterogeneous land covers.

The DRC area is comprised largely of dense intact rainforest and is located in the northeastern Congo Basin. In the southeast, the small town of Banalia is seated on the Banalia River. Several corridors, roadways, and small settlements are visible throughout the scene and deforestation is clearly visible from 2000-2010. This region was previously home to Maluku Steelworks, which was financed by the Zairian government in the 1970’s. However the project failed and there has been little documented economic expansion in the region since (Thomson, 2010). Hypothetically this shutdown may have slowed deforestation in the area. There is believed to be significant amounts of gold, iron, and other resources in the region, however due its remoteness and political instability, a thorough exploration has never been conducted (Eur, 2002).

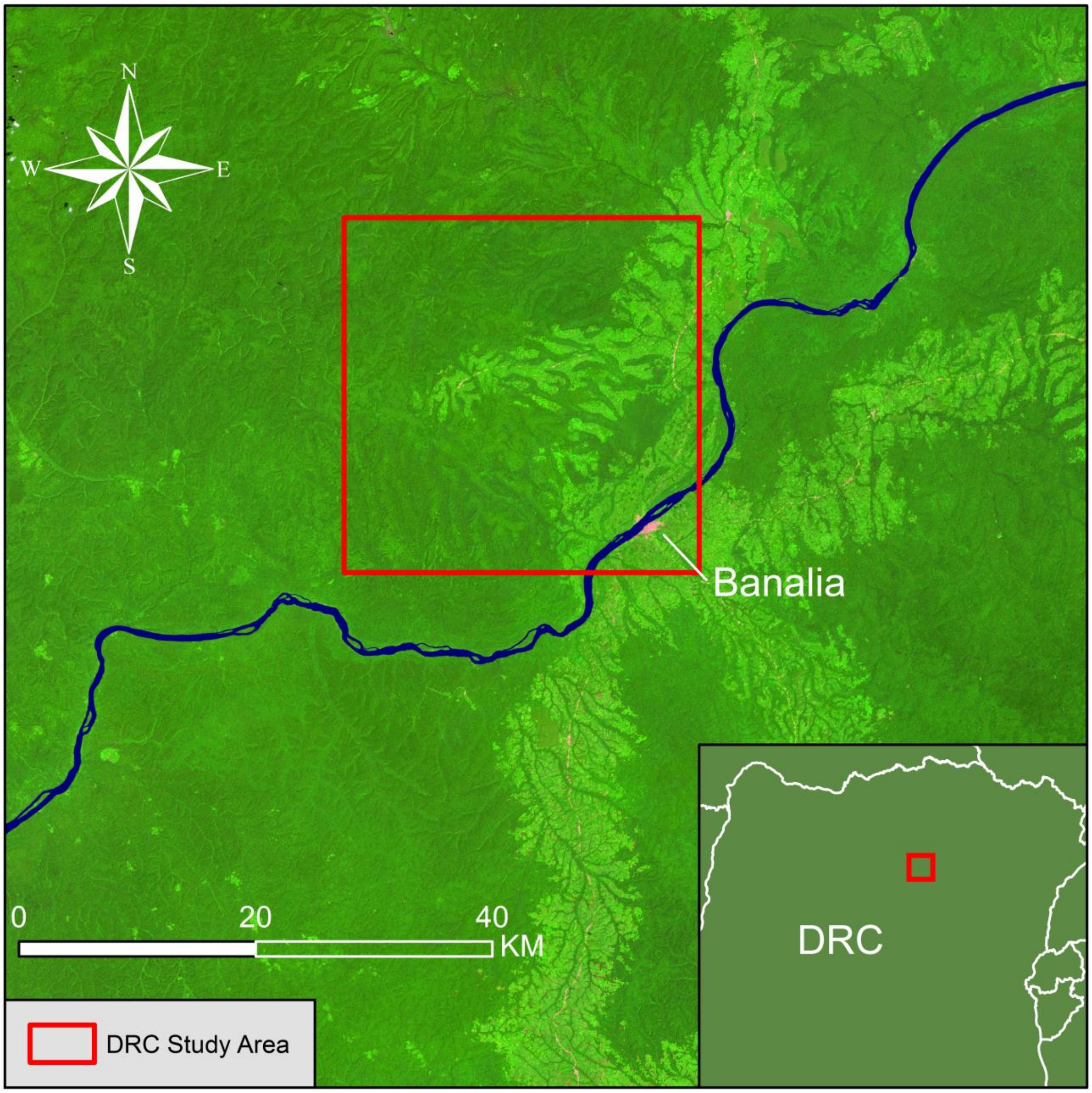

Figure 1: DRC Congo Basin Study Area- 2010 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The Indonesian study area is located just west of the Barisan Mountains on the island of Sumatra. The city of Putri Hijau is to the south-west of the site. Kerinci Seblat National Park is the largest protected area in Sumatra and intersects the north-eastern portion of the study area. This park has high biodiversity including the Sumatran tiger, elephant, and rhinoceros, among others. Some impressive vegetation can also be found in Kerinci Seblat including over 4,000 plant species including the largest flowers in the world which are commonly referred to as “corpse flowers” for their strong rotting scents (Margono et al., 2012). Previous research has shown that significant deforestation is occurring protected areas in Indonesia and that deforestation rates have likely been underestimated (Curran, 2004; Holmes, 2000). Based upon this information and considering the majority of the forest present in this study area is unprotected; this site should provide some excellent insight on how well the methods in this study track deforestation.

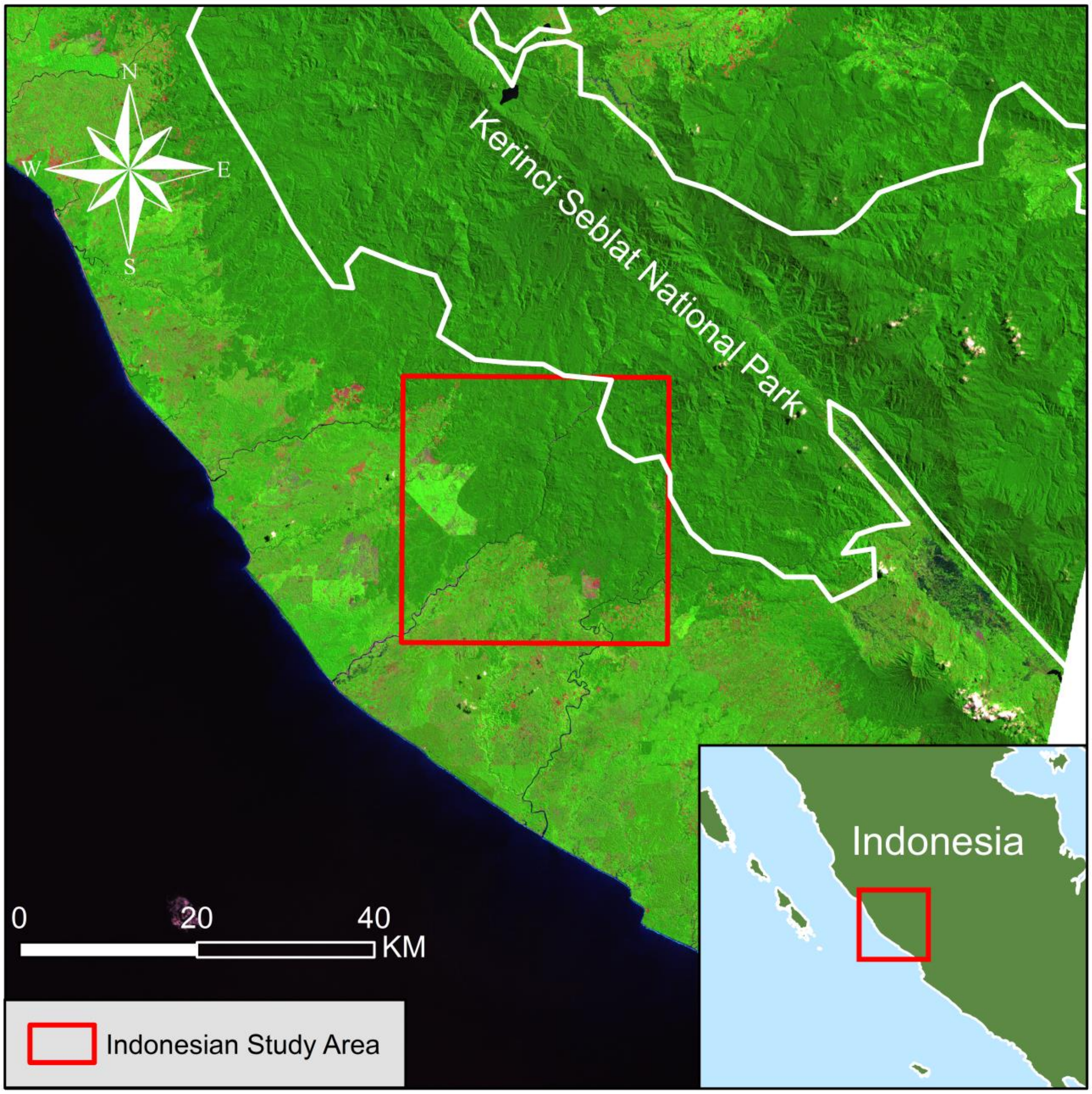

Figure 2: Indonesian Study Area- 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The Peruvian site encompasses the entirety of the protected area "Proyecto Infierno" and is situated just south of the city of Puerto Maldonado. The city is located in southern Peru amidst some of the most pristine rainforest in the world. Besides the urban center, a large agricultural area has been established and is partially incorporated in the study site. The construction of the Inter-oceanic highway through Puerto Maldonado is of particular concern for rainforest conservationists. The road is meant to connect the Atlantic with the Pacific running from Lima through the Amazon to the eastern Brazilian coast. It is hypothesized that this highway will bring about more destruction of the rainforest along its route and could disturb indigenous people along the Peruvian-Brazilian border. Recently in 2012 a major milestone was achieved in the construction of the highway: the completion of the Puente Continental Bridge. This bridge is the largest in Peru spanning 528 m over the Madre de Dios River through Puerto Maldonado. This bridge likely will open up the Amazon to greater expansions of the mining and timber industries in the region (Morrison and Forrest, 2013).

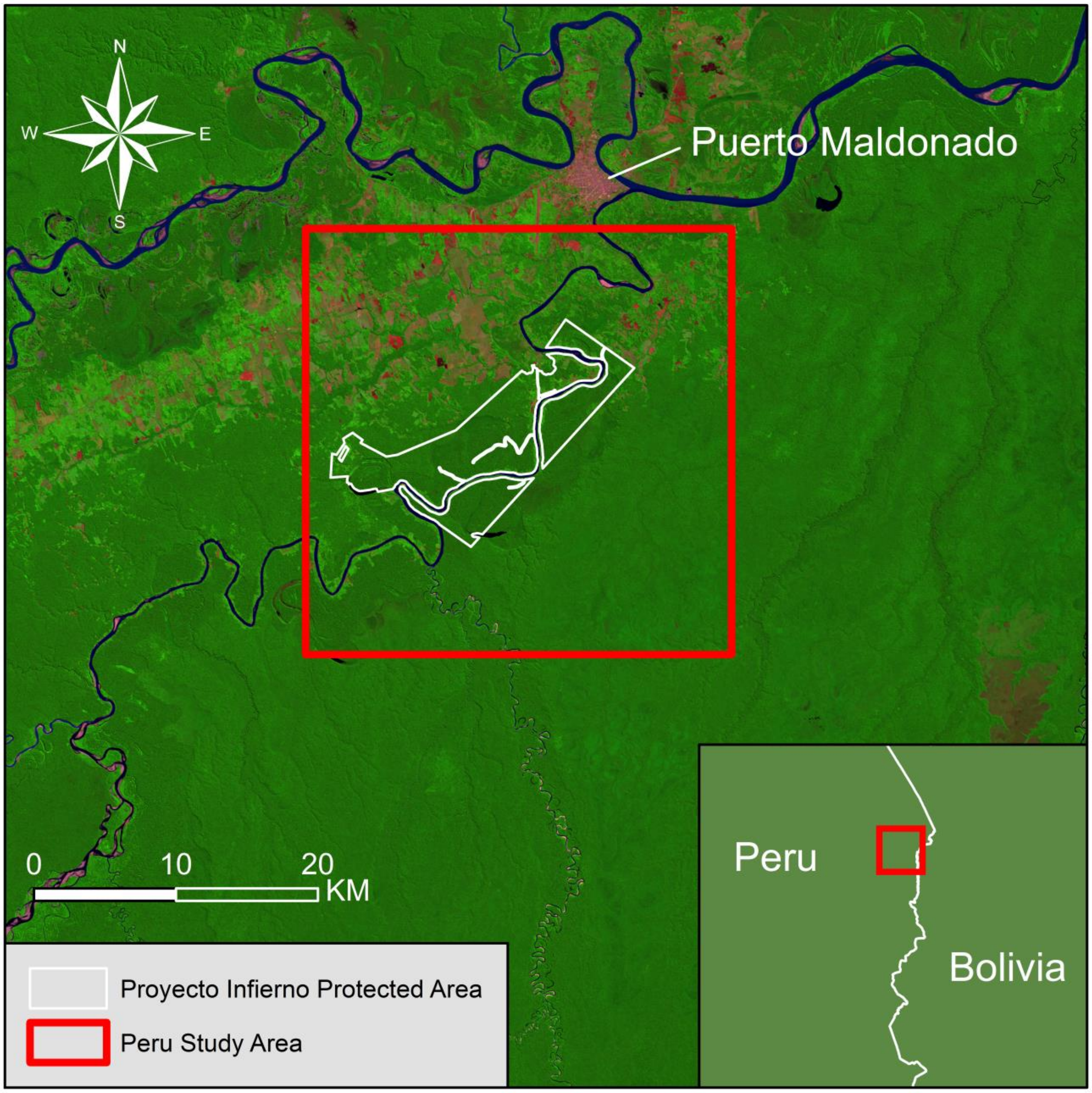

Figure 3: Peruvian Study Area- 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

Landsat Thematic Mapper (TM) 5 and Enhanced Thematic Mapper+ (ETM+) 7 were chosen as the primary data sources due to free cost and high spatial resolution of 30 m. Townshend and Justice (1988) recommend 30 m as the lowest spatial resolution when monitoring LULC change. Additionally, Landsat imagery has an expansive spectral resolution allowing for enhanced precision when identifying features. Six bands cover the visible, near infrared (NIR) and mid-infrared (MIR) portions of the electromagnetic spectrum. A seventh band covers the thermal infrared (TIR) portion of the spectrum and was not used in this study. Landsat has a footprint (area on ground for one image) of 183 km by 170 km and a temporal resolution of 16 days. Finding multiple acceptable scenes was particularly difficult in these areas due to typically high cloud cover as well as the scan-line corrector problem that has been exhibited in Landsat 7 data since 2003 (Table 2). Previous research indicates that Landsat imagery has been the standard when tracking change in tropical regions including South America, Central Africa, and Indonesia(Curran, 2004; Tucker and Townshend, 2000; Zhang et al., 2005).

In addition to Landsat, MODIS VCF was used (Table 3). This product estimates woody vegetation, herbaceous vegetation, and bare ground proportions for the entire Earth (Hansen et al., 2003). The particular product used in this study estimates just woody vegetation in terms of a percentage. Therefore, each pixel has a value representing a percentage of woody vegetation ranging from 0-100 with water features masked out. MODIS VCF datasets were generated for the entire globe once annually. The data archives available for download currently range from 2000 to 2010. These data have a broad spatial resolution of 250m and the VCF dataset maps forests once a year. As such it is an excellent source for guiding training data extraction especially in forestry-change related projects (Dimiceli et al., 2011; Vermote et al., 2002, 1997). Validation assessments of these data have been conducted based on in-situ data at two sites in Maryland and three sites in Brazil. Overall these assessments indicate a Mean Absolute

Error in classification accuracy of 7.87% in Maryland and 9.40% in Brazil. The Root Mean Square Error was 9.47% in Maryland and 10.46% in Brazil (Townshend et al., 2011).

The final data product used in this study is Landsat VCF (Table 4). Landsat VCF was generated via the combination of MODIS VCF and Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospherically corrected Landsat imagery. The product also includes a water and cloud mask. Landsat VCF is generated by first masking out areas of non-forest and cropland in the MODIS VCF data layers. Next, Landsat imagery is rescaled to 250m spatial resolution and MODIS VCF is overlaid on top of the Landsat imagery. Training data is then generated and extracted from the Landsat imagery and a cubist regression tree is utilized to classify the Landsat imagery. The final product is similar to MODIS VCF and estimates woody vegetation proportions for the entire Earth with each pixel value ranging from 0-100. However, each pixel has a finer spatial resolution of 30m. Validation results of Landsat VCF data are comparable to MODIS VCF data with a Root Mean Square Error ranging from 8.6% to 11.9%. Landsat VCF is also an annual product and was created for two separate years: 2000 and 2005 (Sexton et al., 2013). However at present only the year 2000 data are available for download. As all FNF and change maps generated in this study were at 30 meter resolution, Landsat VCF data were used for accuracy comparison purposes.

Location	PathxRow	Satellite	Image Date
DRC	176x59	Landsat 7	12/13/2000
DRC	176x59	Landsat 5	12/17/2010
Indonesia	126x62	Landsat 5	5/13/2000
Indonesia	126x62	Landsat 5	7/9/2009
Peru	2x69	Landsat 5	7/27/2000
Peru	2x69	Landsat 5	7/23/2010

Table 2: Landsat imagery used in this study (Source: USGS GloVis).

Location	Path/Row	Image Dates
DRC	PN3536	2000 & 2010
Indonesia	ML4748	2000 & 2009
Peru	ML1920	2000 & 2010

Table 3: MODIS VCF data used in this study (Source: UMD and NASA).

Location	PathxRow	Image Date
DRC	176x59	2000
Indonesia	126x62	2000
Peru	2x69	2000

Table 4: Landsat VCF data used in this study (Source: UMD and NASA).

LITERATURE REVIEW AND METHODS

A literature review was conducted to evaluate several pre-processing strategies, data sources, and change detection methodologies. While forestry change detection is a common practice, this study evaluates change approaches that could improve upon already existing methodologies. Two methods were examined to evaluate their effectiveness at mapping deforestation and growth rates. These methods are described in the following section and illustrated in a method tree in Figure 4. Approach 1 was conducted in ERDAS Imagine while Approach 2 was conducted mostly in Linux utilizing the Food and Agriculture Organization's (FAO) Open Foris Toolkit. Post classification image differencing and all reclassifications were conducted in ArcGIS. The accuracy assessment portion of this study was conducted utilizing ArcGIS and GoogleEarth.

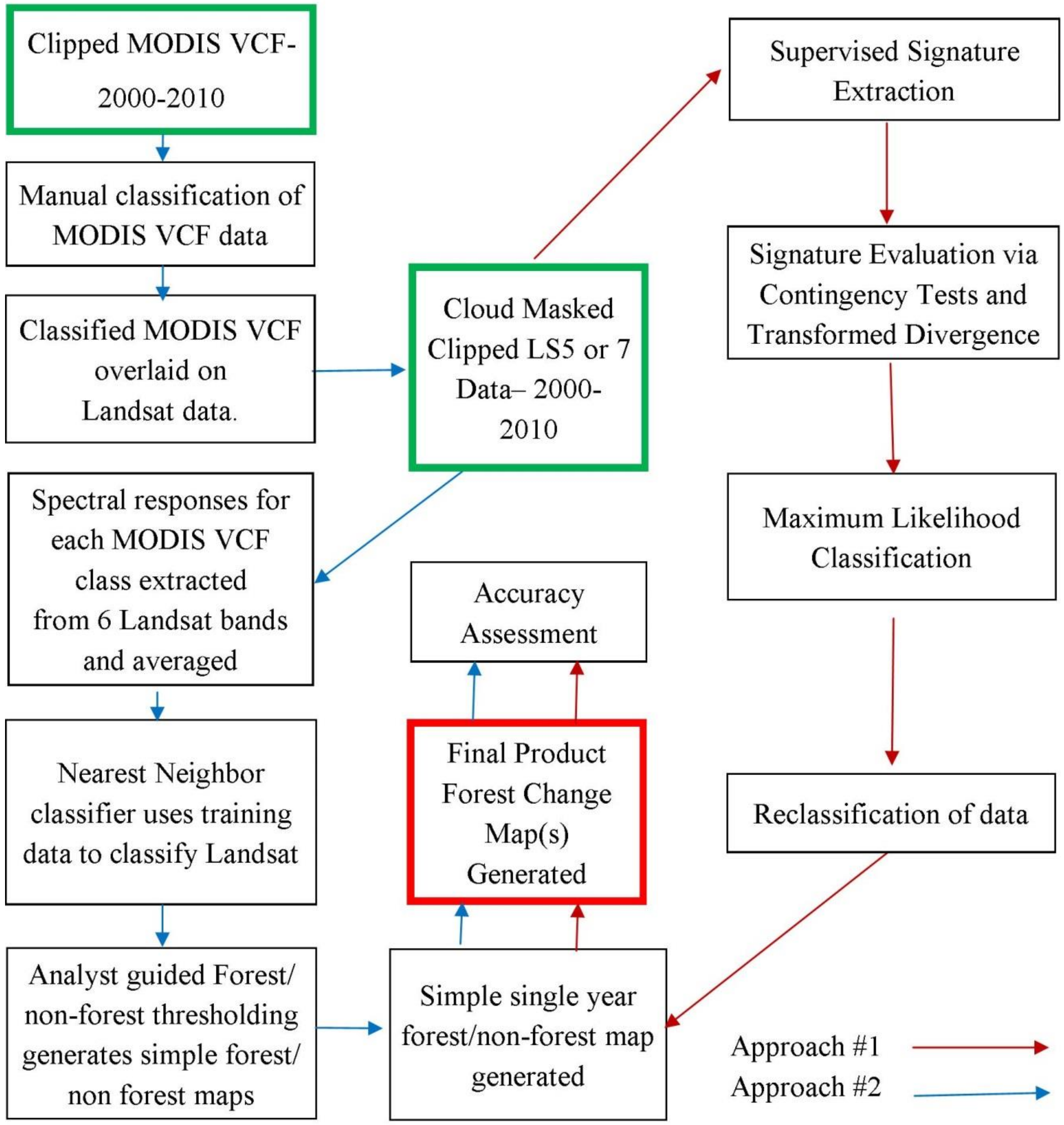

Figure 4: A methods tree showing the process for each approach. Inputs can be seen in green boxes, outputs can be seen in red.

Pre-Processing of Data

The pre-processing of data is extremely important when conducting change detection. In this study that included atmospheric corrections, cloud masking, georeferencing, and clipping datasets to the study areas. Multiple studies have shown that atmospheric conditions are often variable and must be corrected (Chavez, 1996; Masek et al., 2008, 2006; Vermote et al., 2002, 1997). It has been argued that atmospheric corrections are unnecessary for post classification image differencing change detection methodologies (Singh, 1989; Song et al., 2001). Previous research has shown that classification accuracies have remained consistent between both corrected and uncorrected imagery so long as the scales of both the training and classification data were consistent (Fraser et al., 1977; Kawata et al., 1990; Song et al., 2001).

However the uncorrected imagery in this study was determined to be quite hazy for the DRC 2000 scene and the DRC 2010 scene. As a result of the haziness, interpixel spectral signature variability between similar classes was determined to likely be quite high in these scenes. Consequently, it was determined that atmospheric correction of all scenes would enhance the quality of the results and ensure that each method was evaluated on a consistent basis. For these reasons, all imagery were corrected using the LEDAPS atmospheric correction system. These data are freely accessible and were downloaded from the USGS Earth Explorer website. All LEDAPS surface reflectance products were used in this study. This atmospheric correction methodology has previously shown excellent results in generating accurate surface reflectance values for mapping forest disturbance (Masek et al., 2008, 2006).

Cloud masking is necessary in imagery classification to reduce error and limit false misclassifications. Although the imagery chosen for this study appeared to be totally cloud free, this secondary step was completed to ensure all clouds were removed. In this study, cloud masking is accomplished via the fmask cloud masking algorithm developed by Zhu and Woodcock (2012). This free software analyzes all Landsat bands and masks out clouds, cloud shadows, and snow in any scene. The algorithm utilizes temperature, spectral variability, and brightness to produce a cloud probability mask with accuracies exceeding 96% (Zhu and Woodcock, 2012). Areas that were defined as clouds or cloud shadows were converted to no-data and removed from the imagery. However, after all scenes were cloud masked it was determined that no clouds were present.

All imagery were clipped to the respective 900 sq km areas utilizing the OpenForis toolkit oft-clip.pl tool. This tool clips and references all imagery ensuring that pixel locations remain consistently located over time. Additionally this tool resamples pixels with larger spatial resolutions to match the spatial resolution of the reference image. In this case, MODIS VCF data were resampled from 250 m per pixel to Landsat resolutions of 30 m per pixel. This was a required step for the Approach 2 methodology to work properly.

Approach 1: Conventional Supervised Classification

The first method utilized a maximum likelihood decision rule to classify analyst extracted spectral signatures. This methodology involves spectral signature extraction, signature evaluation, followed by a maximum likelihood decision tree classification. Multiple signatures for each land cover type were chosen via an analyst guided supervised extraction process. Areas of interest (AOI) polygons were drawn over known LULC categories and spectral properties were extracted for each AOI. Each potential signature was then saved for evaluation. Classes varied over each study site; however they all included Forest, Agriculture, Urban, Water, Bare Earth, Open Land, and Recently Deforested Areas. The number of initial spectral signatures collected per site ranged between 30 and 40. This included at a minimum 10 signatures associated with forest cover. The number of signatures associated with non-forest classification types varied per site and year based upon variability within the site.

Following initial signature collected, signature evaluation began. Signature evaluation is an important step in assessing the quality of spectral signatures. Signatures were evaluated by Transformed Divergence (TD) and contingency testing. Transformed Divergence is a common signature evaluation practice that provides information on signature spectral separability. This separability is derived from the means and covariance matrices of each spectral signature and measures the statistical distance between a signature and all other signatures in the classification. This information provides an insight about the likelihood of a correct classification using these signatures. Values of TD are on a continuum ranging from 0 to 2000 (Richards, 2012). Generally, a TD value of 1,500 or greater indicates acceptable separability between signatures (Latty and Hoffer, 1981). However due to the abundance of signatures collected, this study was more stringent and utilized a cutoff value of 1,700.

Signature separability was evaluated only across different FNF classes, since low separability between different spectral signatures of the same FNF class would not affect the classification accuracy. Signatures were analyzed using Microsoft excel. Any signature that was determined to be of low quality or low spectral separability from other classification types was removed. This study tried to conserve as many signatures as possible through this process. Signatures that intersected multiple other signatures were removed first. Signatures that only intersected one other signature were closely examined and then only removed if there were multiple other acceptable signatures of a similar classification type. For example this would include removing a water signature that had poor separability from a forest signature if there were already multiple water signatures still being utilized elsewhere in the classification.

After signatures of poor quality were removed, contingency testing was utilized as the next step in signature evaluation. This second tier of contingency testing was utilized to ensure that all spectral signatures truly were of acceptable quality. Contingency testing generates a contingency matrix via a quick maximum likelihood classification of the pixels within the training AOIs. The contingency matrix then shows what percentage of pixels are classified as expected. If each signature is of acceptable quality the percentage of correctly identified pixels in each class should approach 100%.

Contingency data from the same FNF classes were combined and once again signature accuracy was only evaluated across FNF classes. Additionally, a base minimum overall classification error goal was set at 2.5%. This threshold was required to be reached by all contingency testing for each image signature evaluation to be termed "completed". During the first round of contingency testing the overall accuracy was recorded, however ignored until further signature evaluation was explored. During this exploration process, each signature in each class was cross compared against one another in terms of classification accuracy. Any signature that misidentified greater than 2% of its pixels as another signature type was highlighted. Spectral signatures that misclassified multiple other signatures were removed. If no misclassifications were revealed and the overall classification error was below 2.5%, signature evaluation was termed "completed" for that scene.

Upon any signature removal, contingency testing was re-run and reevaluated based upon the new results. If the overall classification error was lower than 2.5% and also lower than the original overall classification error, signature extraction was termed to be complete. If overall classification error was under 2.5% but higher than the original classification error, more signatures were gathered using supervised signature extraction methods and both TD evaluation and contingency testing were restarted. If the overall classification error remained above 2.5% other signatures showing the greatest amount of pixel misidentification was once again highlighted and removed. This process was repeated until an acceptable signature set was generated for each image that had a classification error of less than 2.5%.

Once signature evaluation was concluded, and an appropriate grouping of high quality signatures existed, a maximum likelihood decision rule classification was executed. Initial research showed that the maximum likelihood decision rule has been used in many LULC classifications. Additionally this methodology has often been used as a baseline to which other methods are compared (Erbek et al., 2004; Hagner and Reese, 2007; Miller and Yool, 2002). Consequently, the maximum likelihood classification is an excellent choice for comparison to other forest change detection methodologies. This approach generated a multi-class data layer for each site that was then converted to simple FNF classes using a reclassification tool.

Approach 2: MODIS VCF Guided Forest/Non-Forest Masking

The second method incorporated an analyst classified MODIS VCF data layer to extract Landsat spectral signatures to train and execute a k-nearest neighbor (k-nn) classification of Landsat data. MODIS VCF data were automatically reclassified via analyst thresholding into ten or eleven distinct percentage based classes. Each class value was broken at every tenth place utilizing the MODIS VCF digital numbers (DN) ranging from 0-100. An eleventh class was generated if the scene had water pixels which are pre-masked as a DN value of 200. This classification can be seen in Table 5.

Class Number	DN Values
1	0 - 10
2	11 - 20
3	21 - 30
4	31 - 40
5	41 - 50
6	51 - 60
7	61 - 70
8	71 - 80
9	81 - 90
10	91 - 100
11	200

Table 5: The reclassification table used to generate a new classified MODIS VCF data layer.

The second step in the process overlaid the newly created VCF data layer on the Landsat imagery. The spectral values for every Landsat pixel that intersect with each particular VCF class were extracted and stored. This includes values for Landsat spectral bands 1, 2, 3, 4, 5, and 7. An example of this overlay process can be seen in Figure 5.

These values are then averaged for each band for each class. Thus each VCF class has six average Landsat spectral responses associated with them. An example of average Landsat spectral responses can be seen in Table 6. These data are then used to train a k-nn classifier to generate a classified Landsat image. The classified Landsat image has the same defined classes as the classified MODIS VCF data. Each Landsat pixel was classified into a respective group by a majority vote based upon their relationship with neighboring Landsat pixels. K-nn classification systems have been previously used to effectively classify imagery in forestry applications at broader scales in Europe. This classification has been shown to be highly effective in forest mapping exhibiting accuracies greater than 80% (Finley and McRoberts, 2008; Franco-Lopez et al., 2001; McRoberts et al., 2007, 2002; Pekkarinen et al., 2009). The classified Landsat scene for each study area was then grouped into simple FNF based on the classification.

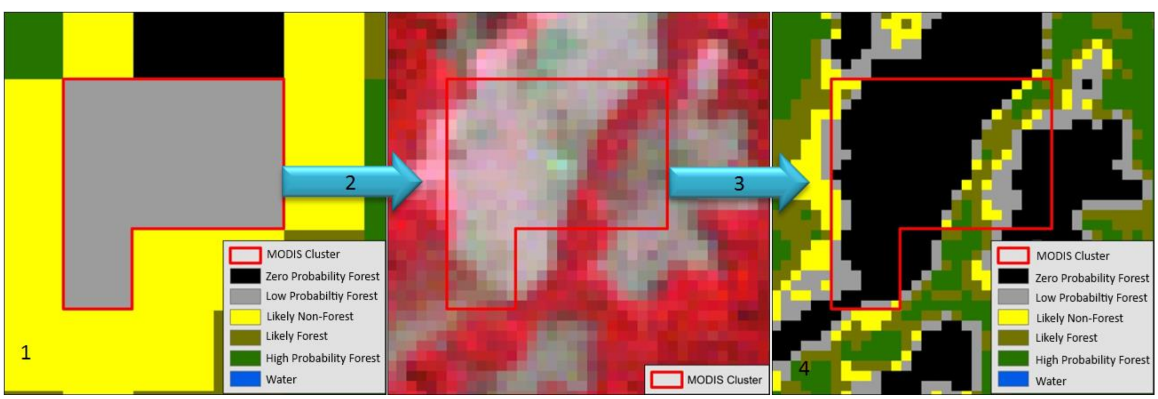

Figure 5: An example of the MODIS VCF Guided FNF Masking Process Chain. Classified MODIS VCF (1) is used to guide extraction of averaged Landsat signatures for each band for each MODIS Cluster (2). These data are then used to train a k-nearest neighbor (3) classifier which then classifies Landsat into respective classes (4).

Class Number	Landsat Bands					
	Band 1	**Band 2**	**Band 3**	**Band 4**	**Band 5**	**Band 7**
1	403.8	747.4	732.4	3035.2	2023.1	1036.4
2	354.6	658.4	600.3	3155.9	1923.2	930.3
3	318.8	583.9	516.4	3074.7	1689.6	778.9
4	290.4	525.1	439.8	3105.2	1659.2	742.2
5	264.1	469.9	375.1	3094.8	1590.6	686.2
6	243.4	421.5	327.1	2950.7	1466.1	619.6
7	226.6	386.8	288.5	2862.3	1355.1	548.3
8	212.7	357.2	258.1	2696.2	1240.2	485.4
9	208.9	348.3	248.8	2628.6	1207.3	469.7
10 (Water)	417.1	691.1	808.2	1692.2	571.5	279.0

Table 6: An example of average Landsat surface reflectance spectral responses from Peru 2000 to each MODIS VCF cluster for each band.

Furthermore, the combination of broad and fine spatial resolution data have been shown to be successful when classifying forest landscapes (Bodart et al., 2011; Hansen et al., 2008; Lindquist, 2012; Pekkarinen et al., 2009; Portillo-Quintero et al., 2012; Raši et al., 2011). These studies have shown that coarse spatial resolution imagery such as MODIS can be used to assist classifiers and generate FNF maps at higher spatial resolutions with accuracies between 80-90%. Previous research combining k-nn and multi-spatial resolution imagery focused on multiple study areas and used multiple Landsat scenes to generate results. Comparatively, the research in this study focuses on just a portion of one Landsat scene for each site and may evaluate the effectiveness of these methods in smaller areas. Other research has utilized high and middle spatial resolution data mixed with random or systematic sampling in an attempt to derive accurate estimates of LULC and forest change (Duveiller et al., 2008; Lindquist, 2012; Portillo-Quintero et al., 2012). However Tucker and Townshend (2000) argue that sampling is often ineffective if only a small portion of the total study area is included in the sampling schema. This research does not use a sampling approach as it was unnecessary in study areas of this size. Furthermore deriving estimates of the precise amount of forest change occurring in a location was not the ultimate goal of this study.

Change Detection Methodologies

There are various change detection methodologies currently in use today. The majority of these methods are imagery based and rely upon remote sensing data. The most common imagery based change detection techniques include principle component analysis (PCA), image differencing, and post-classification image differencing (Lu et al., 2004; Singh, 1989). Other common change detection techniques include Vegetative Index differencing, Tasseled-Cap analysis, Change Vector Analysis, and Artificial Neural Networks. The PCA methodology helps to enhance differences between images by reducing spectral complexities down to a few principle components. This method has previously been used in forest change research and other LULC change studies(Muchoney and Haack, 1994; Singh, 1989). Image differencing is also used regularly in change detection. In this method one image is subtracted from another resulting in a map that highlights areas of change. Although this method is simplistic, it requires precise analyst thresholding to generate accurate areas of change. A detailed change matrix cannot be generated without appropriate thresholding(Lu et al., 2004; Singh, 1989).

Change detection in this study was accomplished via post-classification image differencing where the 2010 FNF Mask is subtracted from the 2000 FNF Mask. This visualization shows areas of forest growth, loss, consistent forest, and consistent non-forest. Post-classification image differencing minimizes atmospheric effects and environmental differences between images (Lu et al., 2004). This was particularly important considering this study encompassed multiple study areas. These areas contain a variety of tree species and each image has varying atmospheric conditions. Thus post-classification was an obvious choice. Overall twelve FNF maps were differenced to generate six forestry change maps, two for each site. Detailed statistics are then extracted from these visualizations so growth and loss can be evaluated in terms of area and percentages.

Comparison to Landsat VCF

The results of both Approach 1 and 2 were compared against thresholded Landsat VCF datasets. As there is currently only a single year of Landsat VCF data available; only basic FNF maps from 2000 were compared against the Landsat VCF 2000 dataset. Landsat VCF data were thresholded at the same levels used in Approach 2; FNF Masking. This means that any value greater than 60 was declared as forest and any value under 60 was declared as non-forest. There was one exception to this rule; the Landsat VCF dataset for the DRC study area was thresholded at a value of 70. It was determined that thresholding the DRC dataset at 60 created a map that grossly overestimated forestation. It was determined that comparisons between Approaches 1 and 2 at the DRC site would have proved to be of little value. No Landsat VCF change maps were generated nor can they be compared at this moment. The comparison between FNF maps was based on the accuracy assessment methodologies described in the following subsection.

Accuracy Assessment

The final step of this process and one of the most critical is an accuracy assessment. A map without an accuracy assessment ultimately holds little value to the creator or any other potential user.

The generation of a reference dataset is required for an accuracy assessment. This dataset displays ground truth information that was used to validate change maps and FNF maps. Landsat pixels were used as the validation sample unit. Five-hundred random sample points were generated and stratified amongst the four classes based on the change maps at each study area. The location of these points was stratified as follows: 200 for consistent forest, 100 for consistent non-forest, 100 for forest growth, and 100 for deforestation. A Landsat pixel that intersected with a point was used as a validation pixel.

The change map generated from Approach 2 MODIS VCF Guided FNF Masking was utilized to simplify sample point stratification. Although the Approach 2 change map was utilized to generate validation pixels, when labeling these pixels it was unknown as to which strata the pixel belonged. Additionally, AOIs that were utilized in the spectral signature extraction process for Approach 1 were unlabeled and unknown when generating the reference dataset. This is considered to be good practice and should have little bias (Olofsson et al., 2013a). The validation pixels were then labeled via the visual interpretation of Landsat data with assistance from Google Earth. Imagery from 2000 and

2009/2010 were interchanged quickly to allow for labeling. The reference dataset was labeled as Consistent Forest (CF), Consistent Non-Forest (CNF), Growth, or Loss. This also enabled reference datasets for the 2000 and 2009/2010 FNF maps to be generated as each of the previously described labels can be termed either Forest or Non-Forest for each year.

Contingency matrices were the primary method utilized for evaluating accuracy in this study. An error matrix or contingency table is recommended as the standard for reporting accuracies (Congalton, 1991; Olofsson et al., 2013b). Such a table allows for the calculation of various descriptive statistics including overall map accuracy, producer accuracy, user accuracy, and a Kappa statistic for each map. In addition to the standard contingency matrix, an additional matrix was generated describing accuracy in terms of area proportions. Describing error in terms of map area allows for the estimation of an area based margin of error for each class type. This allows for additional descriptive statistics to be generated including an error adjusted area for each class and a standard error area adjustment that presents a 95% confidence interval for this data. A contingency table allows for greater insight into map accuracy and shows where a map is strongest and weakest when discriminating between multiple LULC types.

Each LULC map class type is listed furthest left column and the second most upper row of each portion of Table 7. Each LULC map class has a number of correctly identified pixels that are displayed along the diagonal of the chart. In the upper most portion of Table 7 correctly classified pixel counts can be seen for each class and are 196, 86, 78, and 50 respectively. Misclassified pixels are in the non-diagonal potions of the chart and display the various confusions between classes. Producer accuracy describes "error of omission" and is categorized as the exclusion of a sample unit that should have been included in the class. Errors of omission are displayed in columns. Producer accuracy for each class is calculated by dividing the number of correctly identified pixels by the number of correctly identified pixels plus all errors of omission. This generates a percentage value ranging from 0-100%. User accuracy can be defined as an "error of commission" and is categorized as the inclusion of a sample unit that should have been excluded from the class. Errors of commission are displayed in rows. User accuracy for each class is calculated by dividing the number of correctly identified pixels by the number of correctly identified pixels plus all errors of commission. This generates a percentage value ranging from 0-100%. Overall map accuracy is then calculated by dividing the number of correctly classified sample units for every class by the total amount of known sample units.

A traditional contingency matrix typically includes a Kappa statistic as well. The Kappa statistic is a measure of statistical agreement and indicates whether the results described in the contingency matrix are significantly better than a random result (Congalton, 1991). Kappa is expressed as a score that ranges from 0 to 1. A score of 0 indicates no agreement, low accuracy, and that the results were likely random. A score of 1 indicates complete agreement and high accuracy.

Peru FNF Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	196	0	2	2	**98.0%**	62043.5	68.9%
CNF	6	86	5	3	**86.0%**	18829.4	20.9%
Loss	20	2	78	0	**78.0%**	5621.4	6.3%
Growth	44	5	1	50	**50.0%**	3505.7	3.9%
Producer's Accuracy	**73.7%**	**92.5%**	**90.7%**	**90.9%**		**Kappa Statistic**	**0.740**
Overall Accuracy					**82.0%**		

Peru FNF Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	67.6%	0.0%	0.7%	0.7%	**98.0%**	62043.5	64599.2 ± 1628.2
CNF	1.3%	18.0%	1.1%	0.6%	**86.0%**	18829.4	16481 ± 1331.7
Loss	1.3%	0.1%	4.9%	0.0%	**78.0%**	5621.4	5981.7 ± 1292.5
Growth	1.7%	0.2%	0.0%	2.0%	**50.0%**	3505.7	2938.2 ± 1143.2
Producer's Accuracy	**94.1%**	**98.3%**	**73.3%**	**59.7%**		**Kappa Statistic**	**0.835**
Overall Accuracy					**92.4%**		

Table 7: An example accuracy assessment contingency matrix. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

In addition to the traditional elements found in a contingency matrix, this matrix has been augmented to include map area for each class and the weight of that class. Map area was calculated in hectares for each class and documented in the second column from the right. This was accomplished utilizing the ArcGIS area calculator feature that utilizes the map projection and the number of pixels in each class to calculate the map areas for each class. Weight is the proportion of the overall area that each class represents. In the example dataset one can see that the CF class has the highest amount of area associated with it, giving it the largest weight of 68.9%. Weights data always add up to 100%. When evaluating error in terms of just pixel counts, all error is weighted the same. However, this error is not weighted the same on the map or in the actual landscape. To illustrate this, one should note the discrepancy between the total number of sample counts and the weight of each class. For example the CF class has 40% of the sample units for this map; however it represents 68.9% of the area. Conversely, the Growth class has 20% of the sample units for this map; however it represents just 3.9% of the area. The number of sample units utilized for each class is highly unproportional to the areas of each different map class. This discrepancy shows how sample counts cannot be used to calculate appropriate accuracies and actual LULC areas (Olofsson et al., 2013b).

Thus, describing the error matrix in terms of estimated area proportion instead of sample counts enhances the descriptive qualities of the matrix and provides a more informative analysis of error within a change map. This is important for tracking the amount of change in area in a landscape and accounting for the amount of error that may be associated with LULC change (Olofsson et al., 2013b). Tracking accuracy in terms of area proportions is easily accomplished utilizing some basic math. For each element in each class, the pixel count value is multiplied by the class weight and then divided by the sum of all pixel counts in the row. For example, the correctly classified number of CF pixels in the upper portion of Table 7 is 196. The value of 196 is multiplied by the weight (68.9%) and then divided by the sum of correctly classified pixels and all errors of commission for the class (row data). This generates an estimated area proportion percentage of 67.6%. This percentage represents the correctly classified amount of total map area that falls in the CF class. In the same row one can see that 0.7% of the map area associated with the CF class has been misclassified as Loss. This math is repeated for all elements within the upper portion of Table 7 and the results of this math can be seen in the lower portion of Table 7. This generates a new table indicating estimated area proportion for all classes.

User, producer, and overall accuracy can now be recalculated utilizing the previously described calculations based upon estimated area proportion. Producer and overall accuracy often changes based upon these recalculations, however user accuracy does not change. This is due to the influences of weighting. Producer accuracy and overall accuracy changes as it now accounts for errors of omission that possess different weights based upon map area. User accuracy remains consistent as errors of commission all have the same weight for each class. Additionally a new Kappa statistic can be generated utilizing these data that provides a more accurate evaluation of statistical agreement and map accuracy (Olofsson et al., 2013b).

The final descriptive statistics that can be calculated from area adjusted estimates includes an error adjusted area estimate and a ~95% confidence interval that is termed standard error. Error adjusted area estimates simply account for all weighted error present in the data. These values are generated by excluding all weighted commission errors and including all weighted omission errors. For example the error adjusted area estimate for the CF class in Table 7 is calculated by summing the correctly classified area proportion (0.6756) and all omission area proportions. This sum is then multiplied by the total map area (90,000 ha). This generates an error adjusted area estimate of approximately 64,600 ha. Standard error provides a ~95% confidence interval in terms of area for the error adjusted area estimate. This value is generated utilizing both sample counts and area proportion. The equation utilizes all elements for each class including correctly identified pixels and both commission and omission errors. The equation also accounts for weight. This generates a standard error area proportion estimate that is multiplied by total map area to generate a standard error area estimate. Finally, this value is multiplied by 1.96 (rounded to 2) to generate a ~95% confidence interval for all classes (Olofsson et al., 2013b). One should note that error adjusted area values are still dependent upon overall map accuracy. Although these values are likely closer to what actual LULC is in this region than baseline map area, these estimates and the standard error estimates still may contain a large amount of error.

Accuracy assessment results for all change maps were generated utilizing the methodologies described above. Methodologies were compared and contrasted based upon these results. Additionally, an accuracy assessment was generated for the Landsat VCF FNF map and the year 2000 FNF maps that were generated utilizing approaches 1 and 2. This once again allows for these methods to be compared and contrasted. Finally a combined accuracy assessment that is based upon the summed pixel count data and area proportions was generated. This allowed for a simplified method comparison across all study areas. The same was done for comparisons to Landsat VCF and the year 2000 FNF maps for approaches 1 and 2.

RESULTS AND DISCUSSION

The next sections present the findings of the research. All methods were duplicated for each of the three study areas. The methodology included Conventional Supervised Classification, MODIS VCF Guided FNF Masking, and then a comparison of simple 2000 FNF Maps from Approaches 1 and 2 to thresholded Landsat VCF FNF maps. This set of consistent methodology allows for a detailed analysis of the results and a comparison of results across the study areas.

Democratic Republic of the Congo

The first study area under evaluation was located in the DRC. The following sections discuss the findings of Approaches 1 and 2 and a comparison of these approaches against Landsat VCF.

Approach 1: Conventional Supervised Classification

Following signature extraction a maximum-likelihood classifier was applied to the 2000 and 2010 Landsat imagery. A simple reclassification then generated two basic FNF maps. A change map was subsequently generated using post-classification image differencing (Figure 6). An initial visual assessment reveals that this map likely is over-estimating consistent non-forest. Additionally there is a large amount of speckling of both growth and loss in the northwestern and southwestern areas of what is likely consistent forest. Actual loss and growth appears to be focused around areas of consistent non-forest. This indicates both human expansion and forest re-growth in the study area.

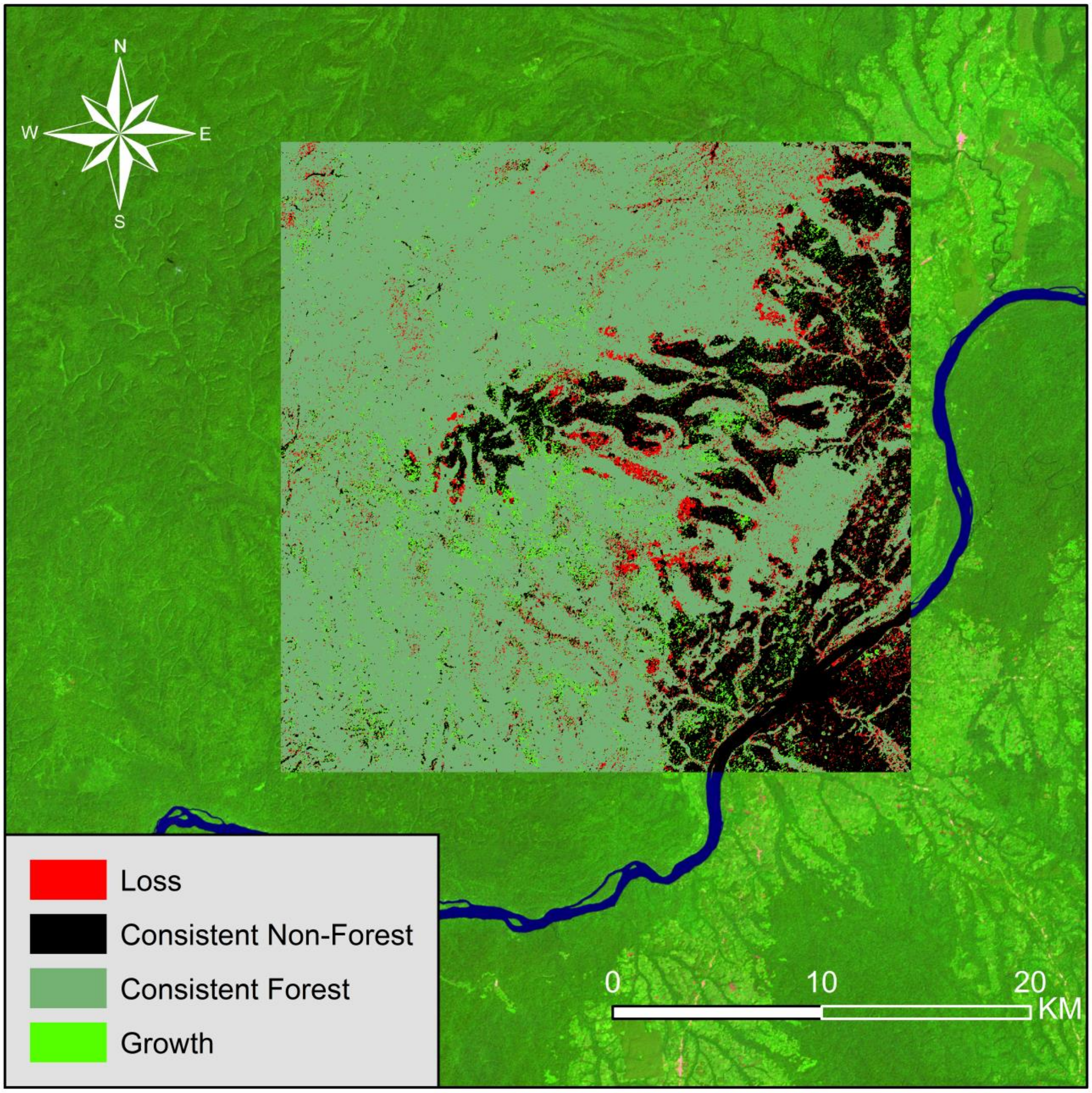

Figure 6: The 2000-2010 Conventional Supervised Classification change map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

An accuracy assessment was generated for this site based upon 500 reference pixels (Table 8). The overall accuracy of this map based solely upon pixel counts is 72%. Based upon user accuracy this map's sole strength is in estimating consistent forest. The consistent forest class has only has three commission errors and exhibits a user's accuracy of 98.4%. However, every other class exhibits large amounts of commission error and low user accuracies. User accuracies for these three classes range from 58.4% to 33.3%. From a producer's perspective this map's strength was in the consistent non-forest class. The accuracy assessment revealed a producer's accuracy of 96.8% for CNF classes with just 5 omission errors. The CF class performs moderately well exhibiting a producer's accuracy of 78.3% but has 51 omission errors. Both the loss and growth classes exhibit low producer's accuracies of 31% and 17% respectively. The Kappa statistic of 0.572 is average and indicates that the change map could be improved upon. Based upon an assessment of the pixel count data, this map is of moderate quality and has several key weaknesses that lower its value.

DRC Conventional Supervised Classification Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	184	1	0	2	**98.4%**	62581.5	68.7%
CNF	25	149	39	42	**58.4%**	19105.9	20.9%
Loss	10	3	18	0	**58.1%**	5145.0	5.7%
Growth	16	1	1	9	**33.3%**	4250.8	4.7%
Producer's Accuracy	**78.3%**	**96.8%**	**31.0%**	**17.0%**		**Kappa Statistic**	**0.572**
Overall Accuracy					**72.0%**		
DRC Conventional Supervised Classification Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	67.6%	0.4%	0.0%	0.7%	**98.4%**	62581.5	67629.3 ± 1811.2
CNF	2.1%	12.3%	3.2%	3.5%	**58.4%**	19105.9	12153.9 ± 1500.6
Loss	1.8%	0.6%	3.3%	0.0%	**58.1%**	5145.0	6067 ± 1305.1
Growth	2.8%	0.2%	0.2%	1.6%	**33.3%**	4250.8	5233.1 ± 1516.5
Producer's Accuracy	**91.1%**	**91.9%**	**49.2%**	**27.1%**		**Kappa Statistic**	**0.664**
Overall Accuracy					**84.7%**		

Table 8: The accuracy assessment of the 2000-2010 Conventional Supervised Classification change map generated for the DRC study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

The lower portion of Table 8 displays the accuracy of the map based upon area proportions. Each of the pixel counts have been weighted by the percentage of total map area that they represent. This allows for correctly classified data and errors of commission and omission to be characterized as a percentage of map area instead of less informative pixel counts. Due to this weighing change overall accuracy shifts to 84.7%.

User accuracies always remain consistent across each class. The reason for this is because pixel counts that are representative of errors of commission carry the same area weight as correctly identified pixels. Conversely, producer's accuracy often always changes as errors of omission are weighted differently across classes compared to correctly identified pixels. For this approach, in this study area, producer's accuracy increases for all classes except for the CNF class which dips slightly to 91.9%. The CF class producer's accuracy improves to 91.1% due to over 68.7% of the area being categorized as CF. As pixel counts for CF classes are now weighted more strongly than other classes, accuracy now improves. Loss and Growth accuracies also improve to 49.2% and 27.1% due to CNF, Loss, and Growth classes all having lesser overall weights. Kappa also shifts slightly upward to a score of 0.664 which still indicates some room for improvement and moderate statistical agreement. Overall this map still possesses high inaccuracies for CNF, Loss, and Growth, and likely holds little end value for a potential user.

This table also includes error adjusted area and standard error. Overall these data suggest that the map likely has underestimated CF, Loss, and Growth, while overestimating CNF. Standard error numbers indicate a ~95% confidence interval of the Error Adjusted Area estimates. Standard error ranges from ± 1305 to 1811ha indicating a fairly precise classification of error. One should note that Error Adjusted Area values are still dependent upon overall map accuracy. Although these values are likely closer to what actual LULC is in this region than baseline map area, the map still contains roughly 15.3% error.

Approach 2: FNF Masking

Following the k-nn classification of 2000 and 2010 Landsat imagery a simple reclassification then generated two basic FNF maps. A change map was subsequently generated using post-classification image differencing (Figure 7). An initial visual assessment reveals that this map appears to be quite accurate. This change map has some speckling in consistent forest areas; however appears to be more accurate than the Conventional Supervised Classification change map.

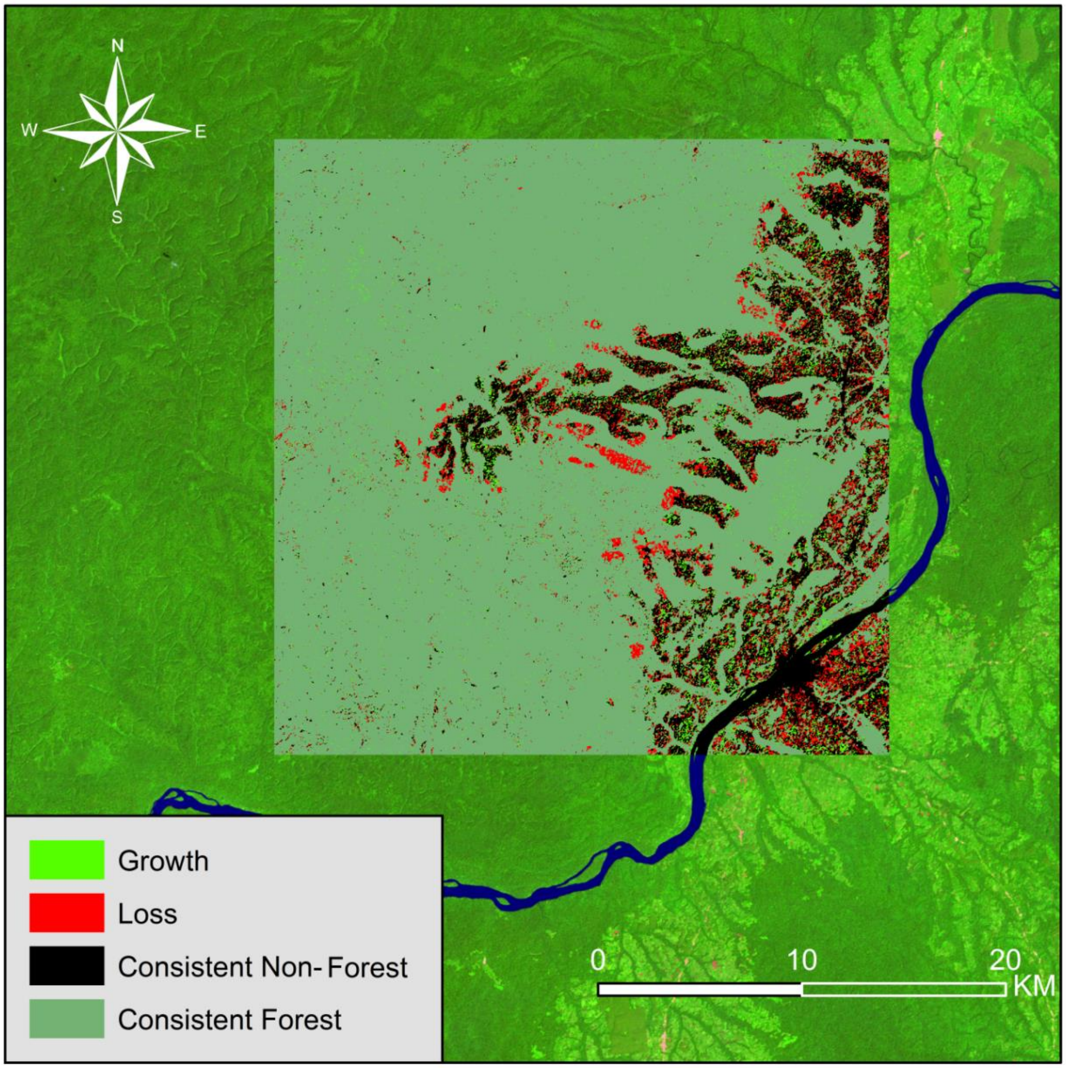

Figure 7: The 2000-2010 FNF Masking change map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

An accuracy assessment was generated for this site based upon the same 500 reference pixels utilized in Approach 1 (Table 9). The overall accuracy of this map based solely upon pixel counts is 79.2%. User accuracy for both CF and CNF classes was high at 98.5% and 94% respectively. The CF class had just 3 errors of commission and the CNF class had 6 commission errors. User's accuracies for the Loss and Growth classes were substantially lower at 57% and 48%. Producer's accuracies were quite high for most classes. The Loss and Growth classes have the highest producer's accuracies of 98.3% and 90.6% with few errors of omission in each class. The CF class had a producer's accuracy of 83.8% and the CNF class had the lowest producer's accuracy of 61%. The Kappa statistic of 0.705 indicates satisfactory agreement, however lower than excellent. Based upon an assessment of the pixel count data, this map is of above average quality but has several key weaknesses that lower its' value.

The second portion of Table 9 displays the accuracy of the map based upon area proportions. Due to this weighing change overall accuracy shifts by nearly 15 points to 93.9%. User's accuracies remains consistent and producer's accuracies improve for the CF (97.4%) and CNF (79.6%) classes while dropping slightly for the Loss (93.9%) and Growth (72.5%) classes. The CF class producer's accuracy once again improves due to nearly 80% of the area being categorized as CF. As pixel counts for CF classes are now weighted more strongly than other classes, accuracy improves. As the CNF class is weighted less than the CF class, this results in a producer's accuracy improvement. Lesser weighting of the Loss and Growth classes also maximizes omission errors present in the data, thus lowering producer's accuracies for both classes. The Kappa statistic improves to 0.821 which indicates strong agreement and an excellent classification. Overall this change map is quite accurate for the CF and CNF classes; however accuracy for areas of change remains quite low for this method.

DRC FNF Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	197	1	0	2	**98.5%**	72502.7	79.6%
CNF	4	94	1	1	**94.0%**	10785.1	11.8%
Loss	8	33	57	2	**57.0%**	2900.9	3.2%
Growth	26	26	0	48	**48.0%**	4894.7	5.4%
Producer's Accuracy	**83.8%**	**61.0%**	**98.3%**	**90.6%**		**Kappa Statistic**	**0.705**
Overall Accuracy					**79.2%**		

DRC FNF Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	78.4%	0.4%	0.0%	0.8%	**98.5%**	72502.7	73351.2 ± 1397.5
CNF	0.5%	11.1%	0.1%	0.1%	**94.0%**	10785.1	12730.4 ± 1025.7
Loss	0.3%	1.1%	1.8%	0.1%	**57.0%**	2900.9	1761.4 ± 360.4
Growth	1.4%	1.4%	0.0%	2.6%	**48.0%**	4894.7	3240.3 ± 1157.9
Producer's Accuracy	**97.4%**	**79.6%**	**93.9%**	**72.5%**		**Kappa Statistic**	**0.821**
Overall Accuracy					**93.9%**		

Table 9: The accuracy assessment of the 2000-2010 Conventional Supervised Classification change map generated for the DRC study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

The lower portion of Table 9 also includes error adjusted area and standard error. Overall these data suggests that the map likely has underestimated CNF while overestimating both Loss and Growth. When accounting for the Standard Error confidence interval, the CF class appears to be quite accurate. Standard error numbers indicate a ~95% confidence interval of the Error Adjusted Area estimates. The Loss class had the smallest standard error value and the CF class had the largest. These data range from ±360 ha to ±1397 ha indicating a fairly precise classification for most classes and an extremely precise classification for the Loss class.

Comparison of Approaches 1 and 2

A comparison of Approaches 1 and 2 in the DRC study area indicates that the FNF Masking approach outperformed Conventional Supervised Classification. Overall accuracy was higher for the FNF Masking change map in terms of both pixel counts and area proportions. Additionally the Kappa statistics were also higher for the FNF Masking change map. FNF Masking change map user accuracies were higher for the CNF and Growth classes. The CF and Loss classes were about even for both change maps at ~98% and ~58% respectively. Combined, this indicates that the FNF Masking map had fewer errors of commission indicating a lower amount of false-positive classifications of LULC.

Producer’s accuracies varied across all classes and methods. The FNF Masking methodology provided higher producer accuracies for the CF, Growth, and Loss classes. The Conventional Supervised Classification change map outperformed the FNF Masking map in terms of producer’s accuracy for only the CNF class. This indicates fewer omission errors in three of the four classes for the FNF Masking map. This signifies that fewer misclassifications of LULC are present in the FNF Masking map and that the Conventional Classification map is prone to underestimation. Error adjusted area estimates are also fairly varied. The Approach 2 change map estimates that consistent forest was likely more prevalent in this study area than estimates derived from the

Approach 1 change map. Consistent non-forest is about even for both maps at roughly ~12,000 ha. Loss and Growth estimates are substantially higher for the Approach 1 change map versus the Approach 2 change map. The standard error values are smaller for Approach 2 versus Approach 1 values indicating a more precise classification for the FNF Masking methodology.

When evaluating these maps in terms of change assessment in the study site; Approach 2: FNF Masking significantly outperforms Approach 1: Conventional Supervised Classification. Approach 2 has a higher overall accuracy and has fewer errors of commission and omission. Additionally areas of actual change are more accurate in this map as areas of loss and growth are more accurately and precisely classified. Error adjusted area estimates are likely more accurate for the FNF Masking map due to fewer omission errors and a higher overall accuracy.

Comparison to Landsat VCF

The 2000 Landsat VCF data layer for the DRC study site was converted via a simple reclassification to a basic FNF map (Figure 8). Any value under 70 was reclassified to Non-Forest and any value greater than or equal to 70 was classified as forest. Water was naturally classified as non-forest. Comparisons were drawn to the 2000 Conventional Supervised Classification FNF map (Figure 9) and the 2000 FNF Masking FNF map (Figure 10). This analysis was conducted via an accuracy assessment utilizing the same 500 points from Approaches 1 and 2. Instead of CF, CNF, Loss, and Growth the reference dataset was converted to state whether or not the 2000 LULC at each point was either Forest or Non-Forest.

The DRC Landsat VCF FNF map appears to be of moderate quality and locating an appropriate threshold was difficult to achieve for an equal balance of accurate forest and non-forest. Based upon a simple visual interpretation, the Landsat VCF map appears to be overestimating forest in this study area in comparison to the Approach 1 and 2 FNF maps. However there is still some speckling of Non-Forest in areas of obvious forest, particularly in the northwest and southwest. Conversely the Conventional Supervised Classification map appears to be overestimating non-forest throughout the entire map. This is particularly noticeable around the southeastern portion of this map and around the town of Banalia. Non-forest speckling in the western forest is quite prevalent in the Approach 1 map. The Approach 2 FNF Masking map appears to have the best balance of forest and non-forest. It may be slightly underestimating non-forest in some areas, notably in the eastern portion. This map exhibits the least amount of non-forest speckling in the west.

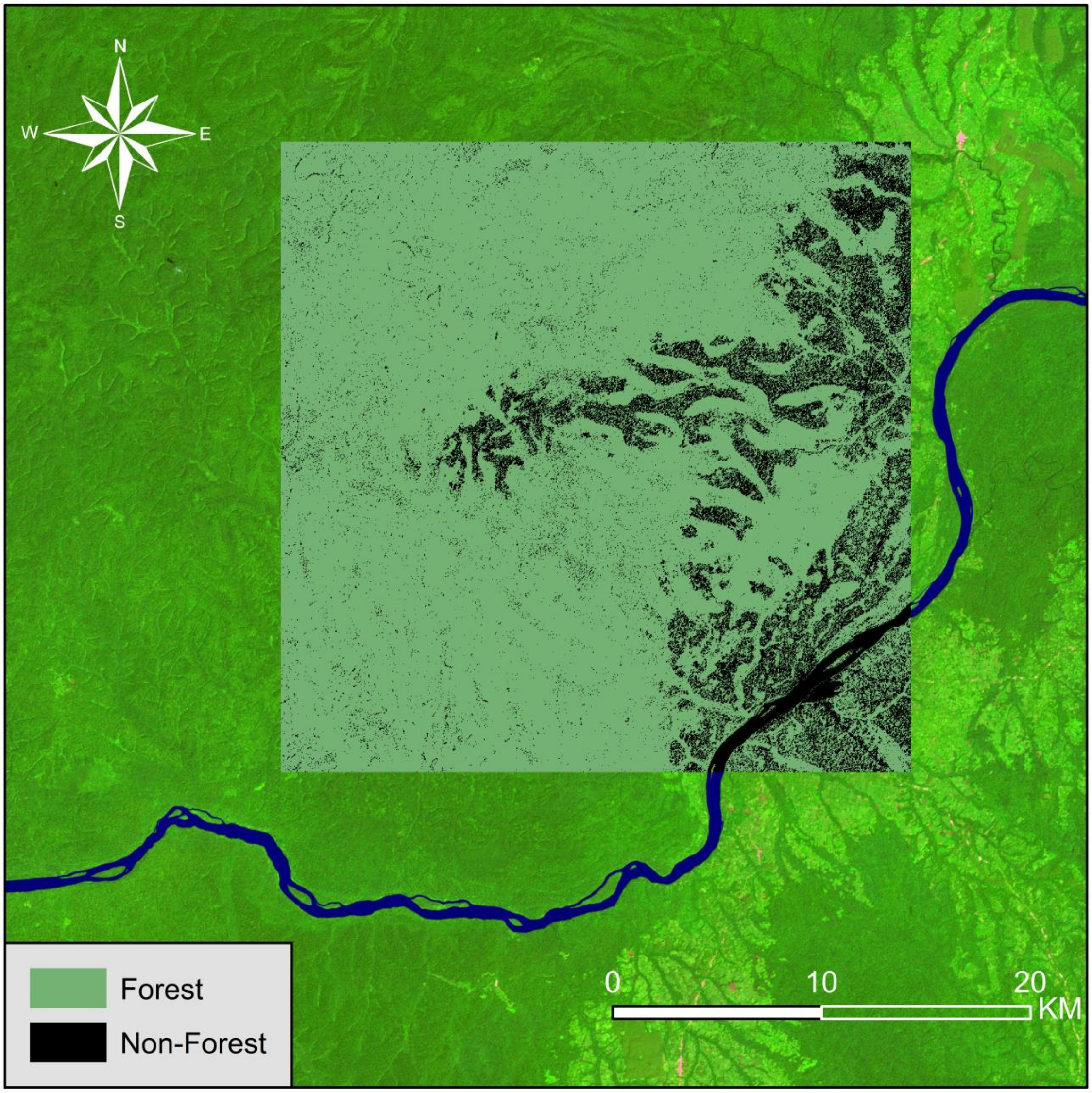

Figure 8: The 2000 Landsat VCF FNF map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

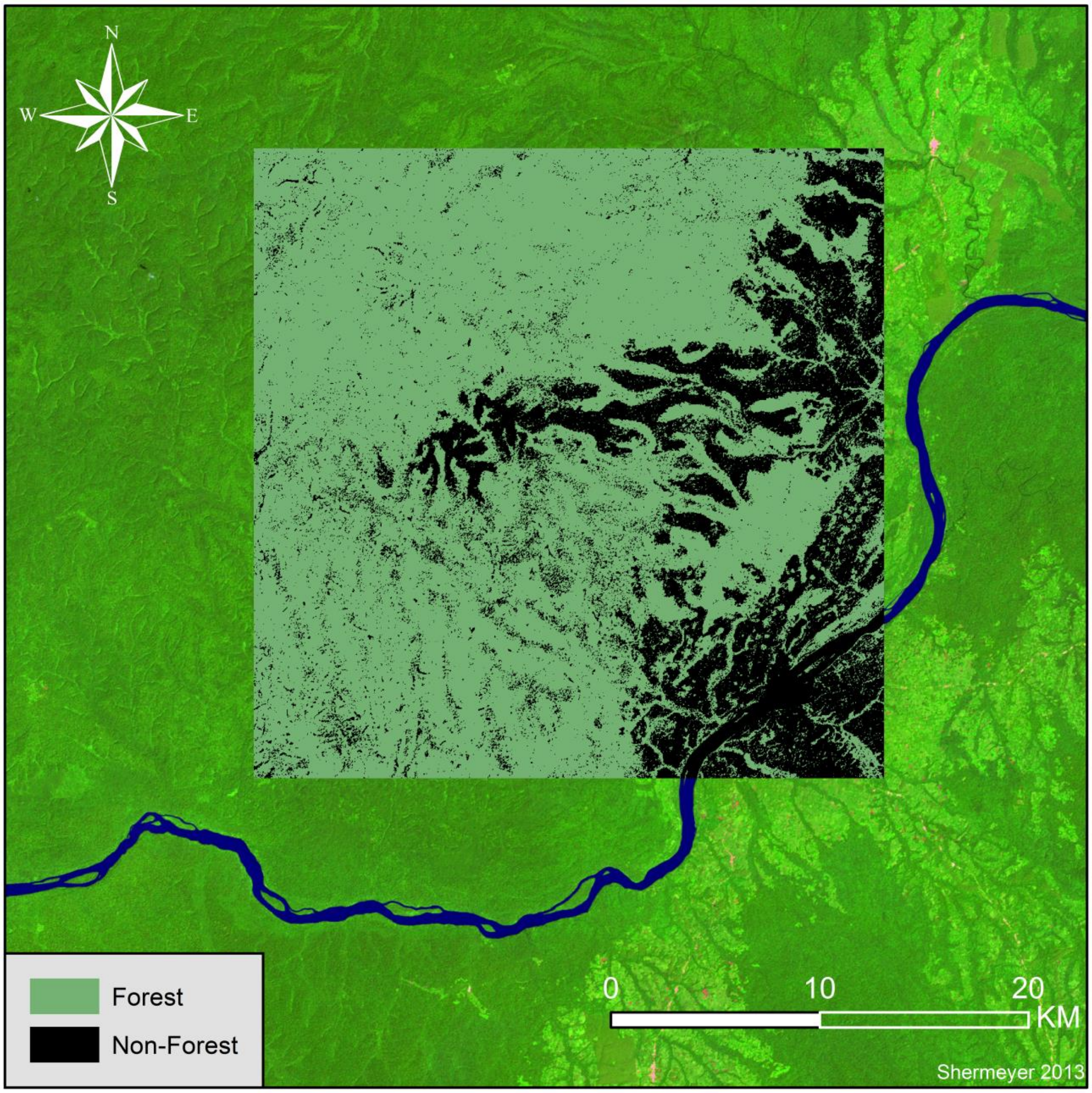

Figure 9: The 2000 Conventional Classification FNF map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

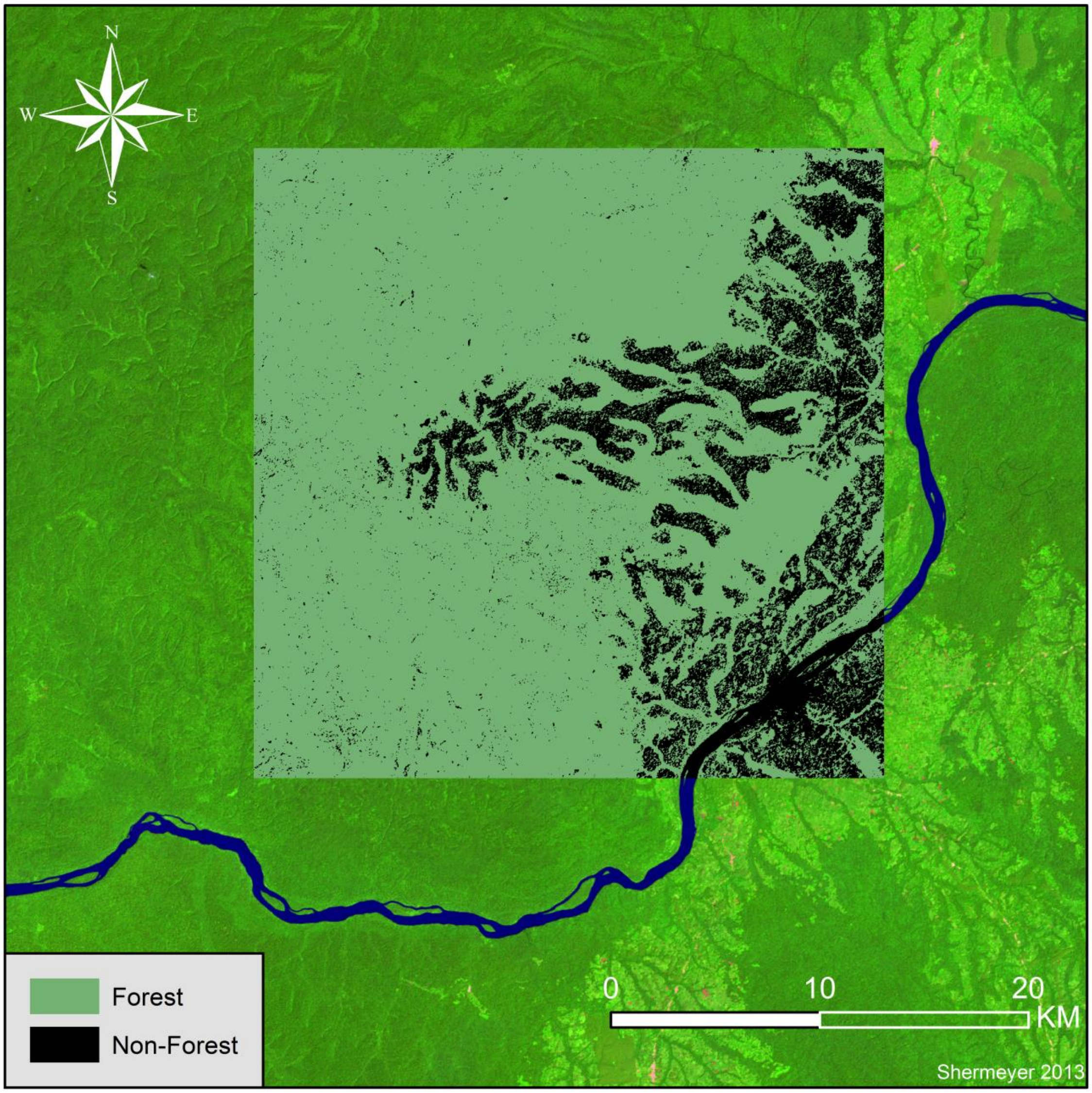

Figure 10: The 2000 FNF Masking FNF map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The accuracy assessment was generated for each FNF map based upon the same 500 reference pixels utilized in Approach 1 and Approach 2 (Tables 10-12). Overall accuracies based upon both pixel counts and area proportions were once again relatively high and changed only a small amount for the area proportion part of the assessment.

Based upon pixel counts the FNF Masking map had the highest overall accuracy and Landsat VCF remained the lowest. When evaluating area proportions, the Conventional Supervised Classification map had the highest overall accuracy and Landsat VCF remained the lowest. User accuracies were varied across all maps with each map holding its own strengths and weaknesses. The Conventional Supervised Classification map had the highest user accuracy for Forest at 97.2 % followed by the FNF Masking map at 87.3%. Landsat VCF had the lowest user accuracy for forest at 80.2%. This indicates that errors of commission were highest in Landsat VCF and that it is overestimating the forest classification. Conversely Landsat VCF had the highest user accuracy for non-forest at 86.2% followed by FNF Masking at 84.5%. User accuracy for the Conventional Classification map dropped substantially for non-forest classification to 71.3%. Commission error for the Conventional Classification was highest and indicates the map is over-classifying non-forest LULC.

DRC 2000 Landsat VCF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	275	68	**80.2%**	78172.6	85.8%
Non-Forest	18	139	**88.5%**	12910.7	14.2%
Producer's Accuracy	**93.9%**	**67.2%**		**Kappa Statistic**	**0.632**
Overall Accuracy			**82.8%**		

DRC 2000 Landsat VCF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	68.8%	17.0%	**80.2%**	78172.6	64155 ± 3434.3
Non-Forest	1.6%	12.6%	**88.5%**	12910.7	26928.2 ± 3434.3
Producer's Accuracy	**97.7%**	**42.5%**		**Kappa Statistic**	**0.473**
Overall Accuracy			**81.4%**		

Table 10: The accuracy assessment of the 2000 Landsat VCF FNF map generated for the DRC study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

DRC 2000 Conventional Supervised Classification Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	212	6	**97.2%**	67726.5	74.4%
Non-Forest	81	201	**71.3%**	23356.7	25.6%
Producer's Accuracy	**72.4%**	**97.1%**		**Kappa Statistic**	**0.659**
Overall Accuracy			**82.6%**		

DRC 2000 Conventional Supervised Classification Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	72.3%	2.1%	**97.2%**	67726.5	72571.3 ± 1962.9
Non-Forest	7.4%	18.3%	**71.3%**	23356.7	18511.9 ± 1962.9
Producer's Accuracy	**90.8%**	**89.9%**		**Kappa Statistic**	**0.735**
Overall Accuracy			**90.6%**		

Table 11: The accuracy assessment of the 2000 Conventional Supervised Classification FNF map generated for the DRC study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

DRC 2000 FNF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	262	38	**87.3%**	75403.5	82.8%
Non-Forest	31	169	**84.5%**	15679.7	17.2%
Producer's Accuracy	**89.4%**	**81.6%**		**Kappa Statistic**	**0.714**
Overall Accuracy			**86.2%**		
DRC 2000 FNF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	72.3%	10.5%	**87.3%**	75403.5	68282.8 ± 3010.2
Non-Forest	2.7%	14.6%	**84.5%**	15679.7	22800.5 ± 3010.2
Producer's Accuracy	**96.4%**	**58.1%**		**Kappa Statistic**	**0.609**
Overall Accuracy			**86.9%**		

Table 12: The accuracy assessment of the 2000 FNF Masking FNF map generated for the DRC study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Producer's accuracies also varied for all maps. Based upon pixel counts, Landsat VCF had the highest forest producer's accuracy (93.9%), followed by FNF Masking (89.4%) and then the Conventional Classification (72.4%). Non-forest showed an opposite pattern with the Conventional Classification ranking the best for pixel counts at 97.1%, followed by FNF Masking (81.6%) and Landsat VCF (67.2%). When evaluating the area proportion data, Landsat VCF had the highest producer's accuracy for the forest class at 97.7% and was followed by FNF Masking at 96.4%. Conventional Supervised Classification had the lowest forest class producer's accuracy of 90.8%. Non-forest area proportion producer's accuracy results were once again the opposite of the forest class results with Conventional Classification possessing the best accuracy at 89.9%. This was followed by the FNF Masking at 58.1% and Landsat VCF at 42.5%. An evaluation of these data reveals that all classes generally had few errors of omission in the forest class. However, when evaluating the non-forest class, both FNF Masking and Landsat VCF FNF maps underestimate non-forest and omission errors are quite high.

Kappa statistics varied only a small amount and none indicate an exceptional classification. Based upon pixel counts, FNF Masking had the highest Kappa statistic (0.714), followed by Conventional Classification (0.659) and then Landsat VCF (0.632). When evaluating the area proportion data, the Conventional Classification map had the highest Kappa statistic of 0.735 followed by FNF Masking at 0.609. Landsat VCF map had a much lower Kappa statistic of 0.473.

Error adjusted area for each of these maps was fairly similar as well, however large non-forest omission errors that were present for the Landsat VCF and FNF Masking skew the original area estimates toward a more non-forest heavy map. Forest weights ranged from 74.4% (Conventional Classification) to 85.8% (Landsat VCF). Each method places error adjusted forest area between 64,155 ha and 72,571 ha. Non-Forest is estimated to be between 18,511 ha and 26,928 ha. Standard Error varies for each class with the Landsat VCF map possessing the greatest standard error of ~3,434 ha and the Conventional classification map had the smallest amount at ~1,962 ha. This indicates that the Landsat VCF map had the greatest uncertainty in its area estimates, followed by FNF Masking, and then Conventional Classification. Overall, when evaluating the full spectrum of the accuracy assessment, the Conventional classification produced the best classification, although it does overestimate non-forested LULC. FNF Masking also performed quite well, however it underestimates non-forest LULC. Landsat VCF performed the worst based upon Kappa score, and its obvious overestimations of forested LULC.

Indonesia

The next study site under evaluation was located in Indonesia. The same methodology used for DRC was also applied to the Indonesian site.

Approach 1: Conventional Supervised Classification

Following signature extraction a maximum-likelihood classifier was once again applied to the 2000 and 2009 Landsat imagery. FNF maps were generated and a change map was subsequently created using post-classification image differencing (Figure 11). An initial visual assessment reveals that this map appears to be quite accurate. As in the DRC site, some speckling once again occurs in areas of consistent forest. A large amount of both growth and loss is present in this scene. Two major growth areas are present in the western and southeastern portions of this scene. The majority of the growth results after human clearing of natural forest. Based upon Google Earth visual interpretations of these areas, this growth appears to be well planned and human induced. Although this is reforestation, it certainly is not natural reforestation. It appears to be agroforest that likely could be removed again sometime in the future. The large amounts of loss occurring in this scene may also be making way for more agroforestry in this region. Finally, this map indicates that some loss may be occurring in the protected Kerinci Seblat National Park; however this could still be a result of some misclassification.

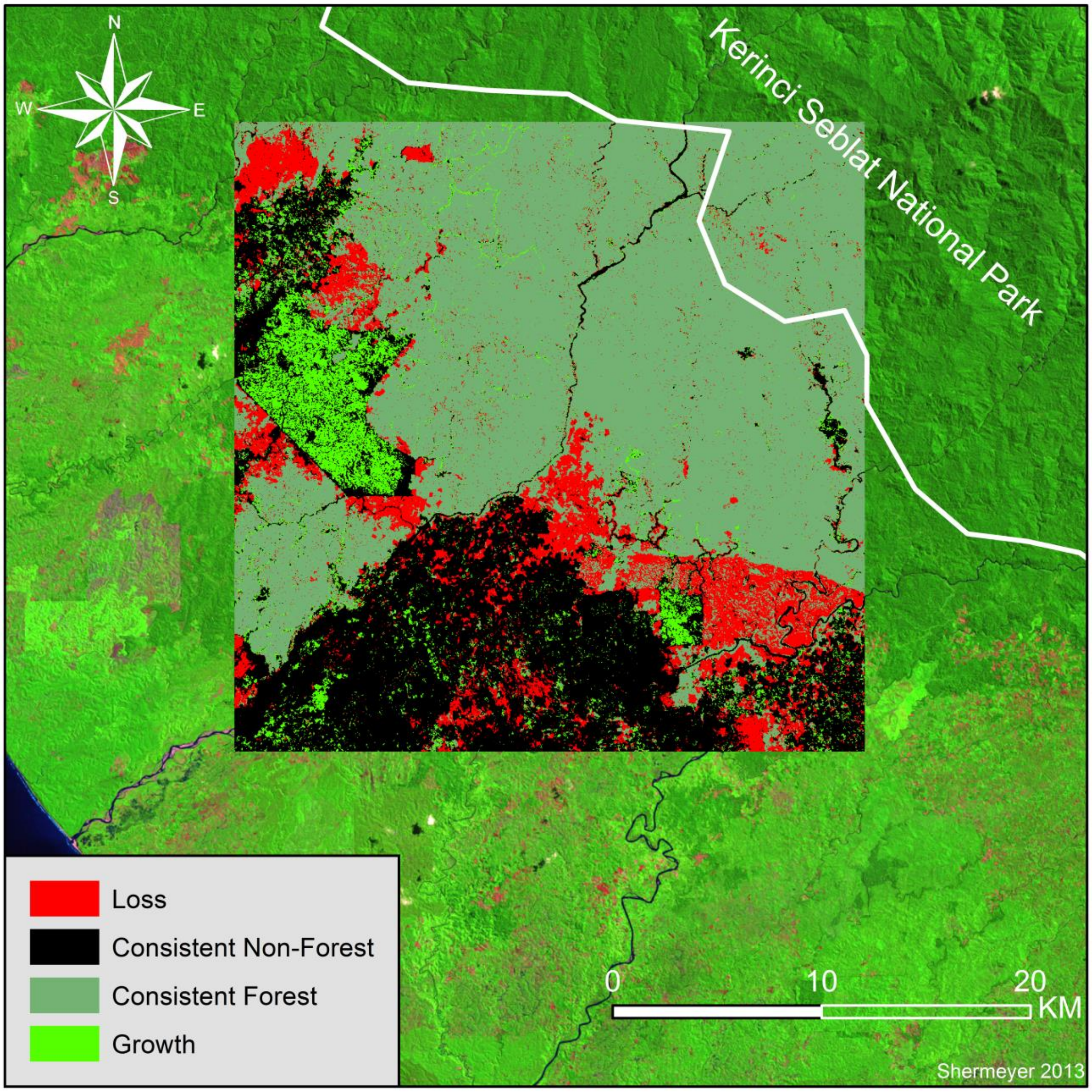

Figure 11: The 2000-2009 Conventional Supervised Classification change map generated for the Indonesian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

An accuracy assessment was generated for this site based upon 500 reference pixels (Table 13). The overall accuracy of this map based solely upon pixel counts is 84%. User accuracies for this classification are quite good. Accuracies range from

74.1% to 91.5% for each class. As in the DRC site, the CF class had the highest overall user accuracy. The loss and growth classes' user accuracies were much better than the DRC site at 81.9% and 83.3%. The CNF class had the lowest user accuracy at 74.1%. Producer's accuracy was also fairly good for this classification ranging between 92.4% and 68.8%. The CF (92.4%) and CNF (87.3%) classes had the best producer's accuracies. Loss and Growth classes producer's accuracies were slightly lower than the user accuracies at 73.9% and 68.8. The Kappa statistic of 0.773 is fairly strong and indicates satisfactory agreement and a good map classification. Based upon an assessment of the pixel count data, this map is of good quality, particularly for user's accuracies with few commission errors.

The accuracy of the Conventional Classification Indonesian map based upon area proportions is located in the second portion of Table 13. Due to this weighing change overall accuracy shifts slightly from 84% to 85.3%. User's accuracy once again remains consistent and producer's accuracy improves slightly for the CF (95.9%) and CNF (90%) classes while reducing for the Loss (62.3%) and Growth (54.7%) classes. This indicates that omission errors are fairly prevalent in the Loss and Growth classes. This means that these classes are likely being underestimated throughout the map. As the CF class covered the greatest area it had a large effect on changing producer's accuracies. Additionally, the lesser weighting of the Loss and Growth classes also maximizes omission errors present in the data, thus lowering producer's accuracy for both classes. The Kappa statistic generally remains consistent; however it does decline slightly to 0.765.

Error adjusted area data suggests that the map likely has overestimated CNF while underestimating Loss and Growth. The CF class was quite accurate based upon Error Adjusted Area and Standard Error estimates. Standard Error for all classes is roughly ±2000 hectares and indicates a fairly broad range of the actual possible area for each class.

Indonesia Conventional Supervised Classification Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	194	3	14	1	**91.5%**	50378.0	55.3%
CNF	2	103	10	24	**74.1%**	24115.1	26.5%
Loss	11	4	68	0	**81.9%**	10216.1	11.2%
Growth	3	8	0	55	**83.3%**	6374.0	7.0%
Producer's Accuracy	**92.4%**	**87.3%**	**73.9%**	**68.8%**		**Kappa Statistic**	**0.773**
Overall Accuracy					**84.0%**		
Indonesia Conventional Supervised Classification Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	50.6%	0.8%	3.7%	0.3%	**91.5%**	50378.0	48091.3 ± 2161.3
CNF	0.4%	19.6%	1.9%	4.6%	**74.1%**	24115.1	19847.3 ± 2099.1
Loss	1.5%	0.5%	9.2%	0.0%	**81.9%**	10216.1	13431.6 ± 2201.5
Growth	0.3%	0.9%	0.0%	5.8%	**83.3%**	6374.0	9713 ± 1726.6
Producer's Accuracy	**95.9%**	**90.0%**	**62.3%**	**54.7%**		**Kappa Statistic**	**0.765**
Overall Accuracy					**85.3%**		

Table 13: The accuracy assessment of the 2000-2009 Conventional Supervised Classification change map generated for the Indonesian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Approach 2: FNF Masking

Two FNF maps were generated via a k-nn classification of 2000 and 2009 Landsat imagery. A change map was subsequently generated using post-classification image differencing (Figure 12). An initial visual assessment reveals that this map is of good quality. Growth and loss classifications are quite accurate and located appropriately. Some speckling is once again present in the consistent forest regions. Rivers are not as distinctive due to misclassifications in this map which is caused by the lack of water pixels in the MODIS VCF data.

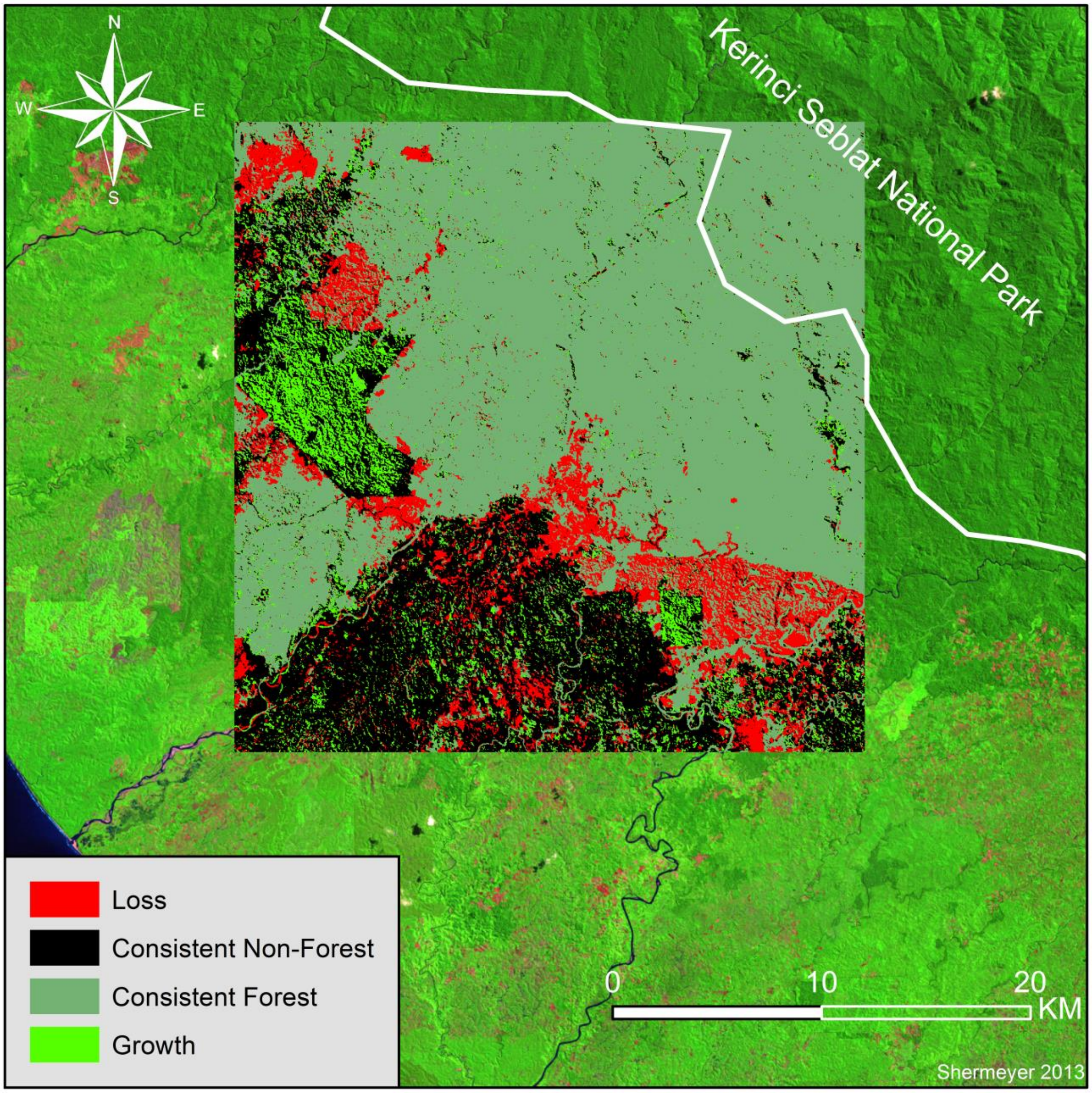

Figure 12: The 2000-2009 FNF Masking change map generated for the DRC study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

An accuracy assessment was generated for this site based upon the same 500 reference pixels utilized in Approach 1 (Table 14). The overall accuracy of this map based solely upon pixel counts is excellent at 89.6%. User accuracies for both CF and CNF classes were high at 96.5% and 93% respectively. Both the CF and CNF classes had 7 commission errors each. User's accuracies for the Loss and Growth classes were only slightly lower at 88.0% and 74.0%. Producer's accuracies were excellent for all classes. Accuracies for the CF, Loss, and Growth classes were all over 90%. The CNF class had the lowest producer's accuracy at 78.8%. The Kappa statistic of 0.855 is high indicating excellent map accuracy. Based upon an assessment of the pixel count data, this map is of excellent all around quality with only limited room for improvement.

The second portion of Table 14 displays the accuracy of the map based upon area proportions. Overall accuracy shifts to 93.3% and producer's accuracies remain consistently high for each class. The CF and CNF classes producer's accuracies both improve to 96.9% and 90.3% respectively. The CF accuracies improve because of the 59% weighting of the CF class. The CNF class accuracy also improves due to the lesser weighting of the Loss and Growth classes. The Loss (90.4%) and Growth (76.4%) classes producer's accuracies decline as the majority of the error is associated with the misclassification to the CF and CNF classes. The Kappa statistic improves to 0.884 which indicates excellent map accuracy. Overall this change map is highly accurate and generally is an excellent classification of forest change for the study site. There is little commission or omission error present in any of the classes indicating a properly proportioned classification.

The lower portion of Table 14 also includes error adjusted area and standard error. Overall these data suggest that the map was nearly perfect for all classes. Loss and Growth were both slightly overestimated, and the CF and CNF classes were both slightly underestimated. Standard error numbers indicate a 95% confidence interval of the Error

Adjusted Area estimates. The Loss class had the smallest standard error value and the CF class had the largest. Standard Error for all classes is under ±1000 ha indicating a fairly precise classification of map area.

Indonesia FNF Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	193	2	3	2	**96.5%**	53761.3	59.0%
CNF	3	93	0	4	**93.0%**	21845.6	24.0%
Loss	5	7	88	0	**88.0%**	9300.3	10.2%
Growth	9	16	1	74	**74.0%**	6176.0	6.8%
Producer's Accuracy	**91.9%**	**78.8%**	**95.7%**	**92.5%**		**Kappa Statistic**	**0.855**
Overall Accuracy					**89.6%**		
Indonesia FNF Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	57.0%	0.6%	0.9%	0.6%	**96.5%**	53761.3	53555.9 ± 986.6
CNF	0.7%	22.3%	0.0%	1.0%	**93.0%**	21845.6	22493.2 ± 371.7
Loss	0.5%	0.7%	9.0%	0.0%	**88.0%**	9300.3	9052.5 ± 110.8
Growth	0.6%	1.1%	0.1%	5.0%	**74.0%**	6176.0	5981.7 ± 83.4
Producer's Accuracy	**96.9%**	**90.3%**	**90.4%**	**76.4%**		**Kappa Statistic**	**0.884**
Overall Accuracy					**93.3%**		

Table 14: The accuracy assessment of the 2000-2009 FNF Masking change map generated for the Indonesian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Comparison of Approaches 1 and 2

A comparison of Approaches 1 and 2 indicates that in the Indonesian study site the FNF Masking approach once again outperformed Conventional Supervised Classification. Overall accuracy was again higher for the FNF Masking change map in terms of both pixel counts and area proportions. Additionally the Kappa statistics were once again larger for the FNF Masking change map. FNF Masking change map user accuracies were higher for the CF, CNF, and Loss classes. Conventional Supervised Classification user accuracy was only higher for the Growth class. This indicates that the FNF Masking map had fewer errors of commission indicating a lower amount of false-positive classifications of LULC with the exception of growth.

Producer's accuracies varied across all classes and methods. Both methods had high producer accuracies for the CF and CNF classes; however the FNF Masking methodology provided higher producer accuracies for the Growth and Loss classes. This indicates the FNF Masking change map displayed fewer omission errors for two of the four classes signifying fewer misclassifications in areas of change. Error adjusted area estimates are quite different between these methods. The Approach 2 change map estimates that consistent forest was likely more prevalent in this study area than estimates derived from the Approach 1 change map. Consistent non-forest is more prevalent in the Approach 2 change map. Loss and Growth estimates are substantially higher for the Approach 1 change map versus the Approach 2 change map. Standard error is much lower for the FNF Masking change map indicating a more precise estimate of error adjusted area.

When evaluating these maps in terms of change assessment in the study site; Approach 2: FNF Masking once again outperforms Approach 1: Conventional Supervised Classification. Approach 2 has a higher overall accuracy and has fewer errors of commission and omission. Additionally areas of actual change are more accurate in this map as areas of loss and growth are more accurately and precisely classified. Error adjusted area estimates are likely more accurate for the FNF Masking map due to fewer omission errors and a higher overall accuracy. Finally standard error indicates that the Approach 2 change map is more precise in LULC area estimates.

Comparison to Landsat VCF

The 2000 Landsat VCF data layer for the Indonesian study site was converted via a simple reclassification to a basic FNF map (Figure 13). Any value under 60 was reclassified to Non-Forest and any value greater than or equal to 60 was classified as forest. Water was naturally classified as non-forest. Some clouds were also present in the Landsat VCF data layer that were masked as “No-data”. Comparisons were drawn to the 2000 Conventional Classification FNF map (Figure 14) and the 2000 FNF Masking FNF map (Figure 15) once again via an accuracy assessment.

Comparatively these maps are all fairly visually similar and only have subtle differences. The largest differences can be seen in the southern areas of non-forest. Patchy areas of forest in this area change slightly for each map. Another difference is the definition of rivers in each map. The Conventional Supervised Classification appears to have the best definition of rivers followed by Landsat VCF and the FNF Masking approach. Additionally, the FNF Masking map appears to have the greatest amount of speckling present in the northeastern forested area.

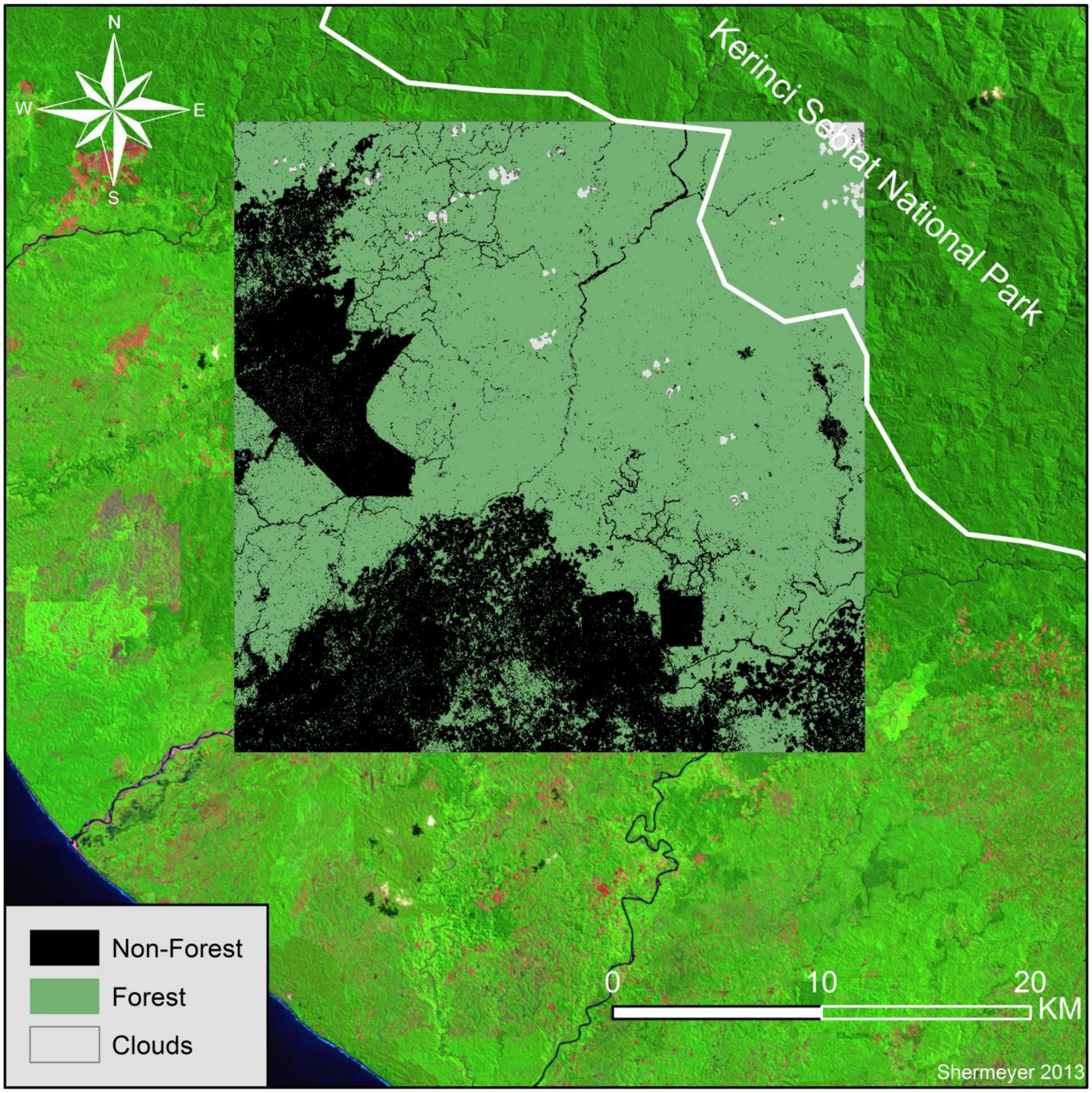

Figure 13: The 2000 Landsat VCF FNF map generated for the Indonesian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

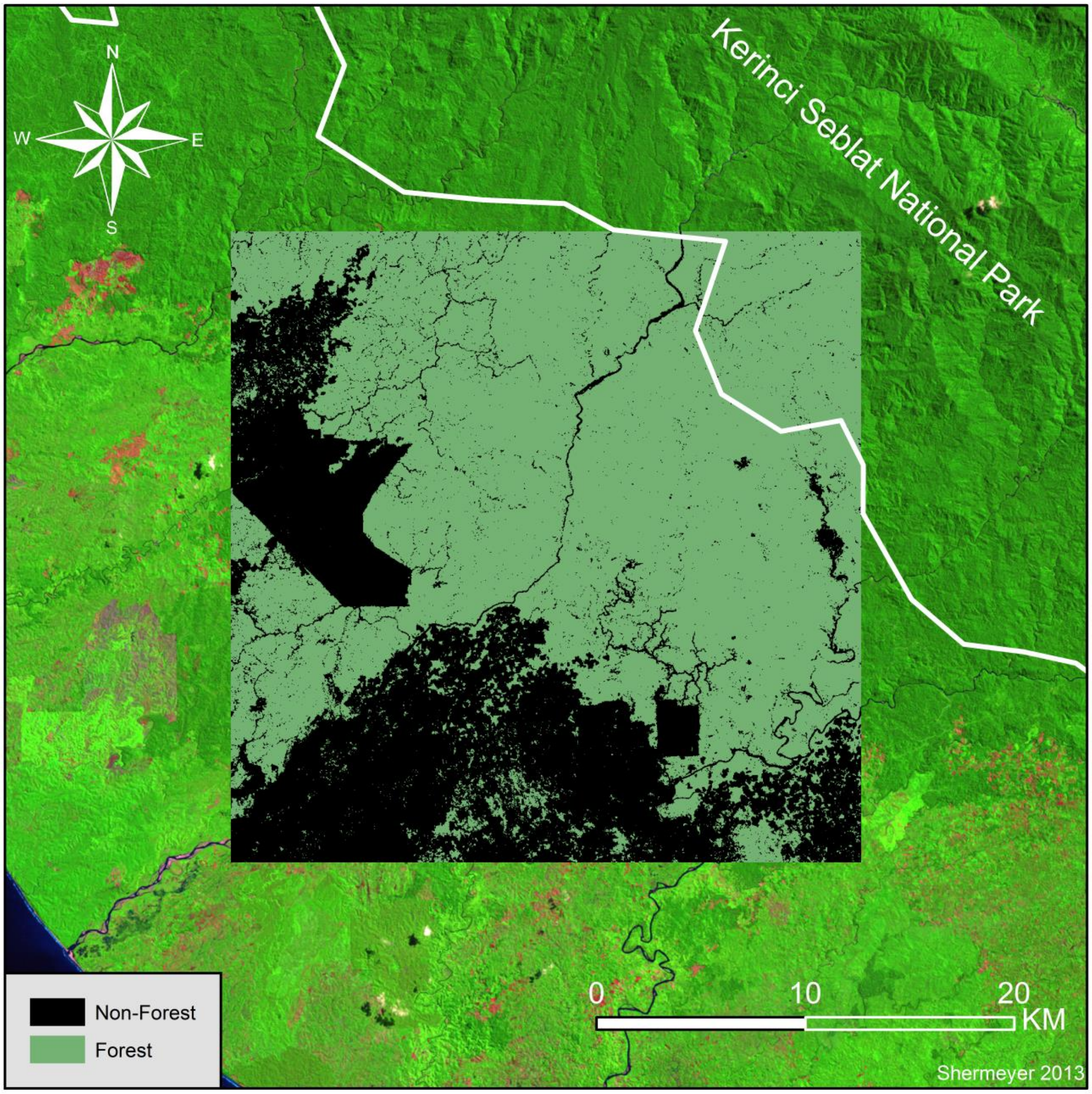

Figure 14: The 2000 Conventional Supervised Classification FNF map generated for the Indonesian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

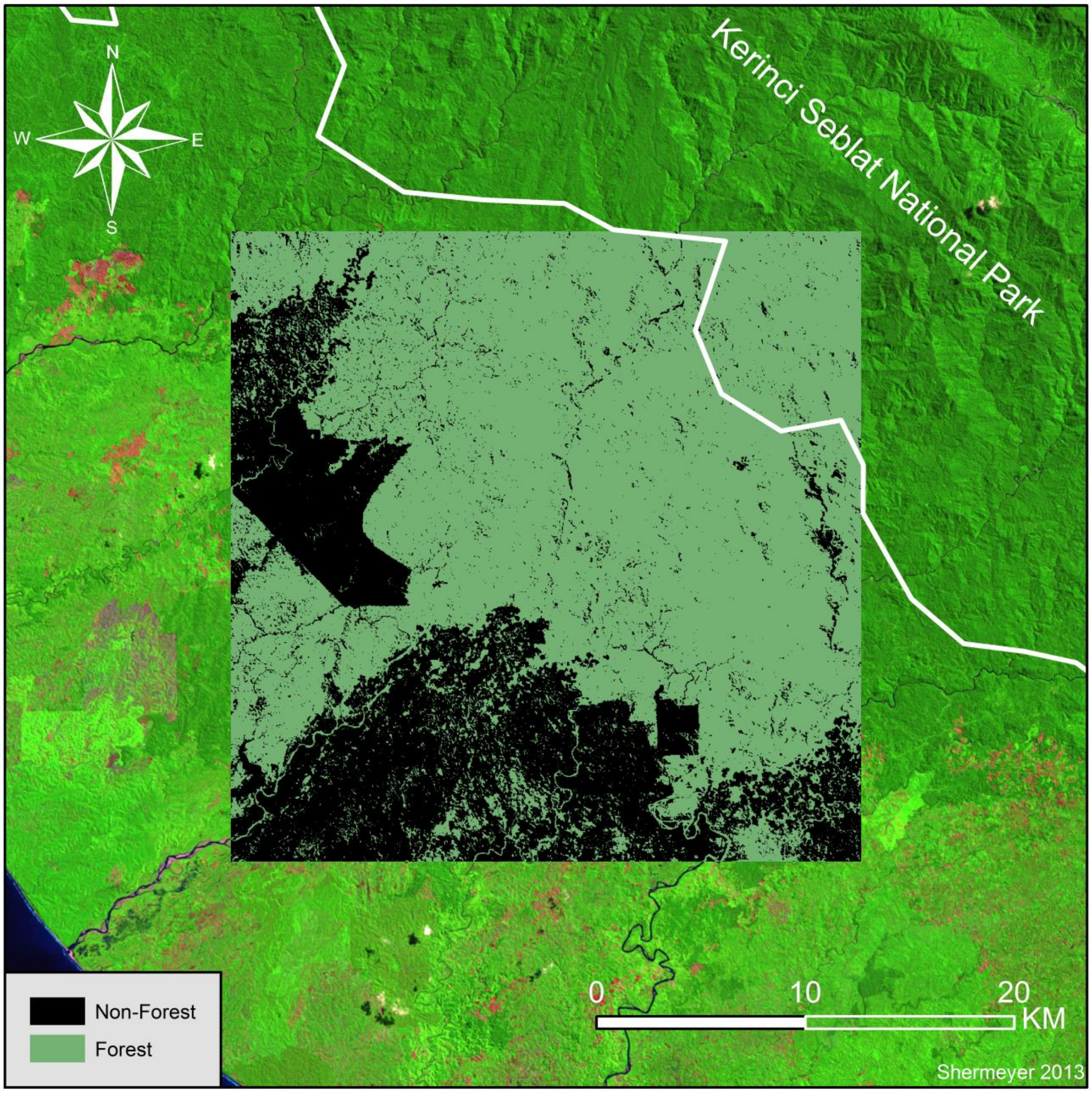

Figure 15: The 2000 FNF Masking FNF map generated for the Indonesian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The accuracy assessment was generated for each FNF map based upon the same 500 reference pixels utilized in Approach 1 and Approach 2 (Tables 15-17). Overall accuracies based upon both pixel counts and area proportions were high and changed only a small amount for the area proportion part of the assessment. The Conventional

Supervised Classification map had the highest overall accuracy (95.8%) and the Landsat VCF had the lowest (90.8%). User accuracies were high for all classes and all FNF maps. Forest classifications were all above 92% for each map and CNF classes were all above 88.3% for each map. The Landsat VCF map had the lowest combined user accuracies while the Conventional Supervised Classification map and the FNF Masking map were nearly identical. This indicates few errors of commission present in each map. None of the maps are generally overestimating forest and non-forest LULC. Producer's accuracies were also quite high for all maps. The Conventional Supervised Classification and the FNF Masking maps once again performed quite similarly in terms of producer's accuracies. Both classifications were excellent. Conventional classification had a pixel count producer's accuracy of 95% for forest and 96% for non-forest. Accuracies shift to 96.4% and 95.4% respectively for forest and non-forest when evaluating area proportion data. FNF Masking had a pixel count producer's accuracy of 95.7% for forest and 94.4% for non-forest. Accuracies shift to 97.1% and 91.9% respectively for forest and non-forest when evaluating area proportion data. The Landsat VCF map performed well for the forest classification; however producer accuracies are slightly lower for Non-Forest classifications. This indicates some errors of omission in the non-forest LULC portion of the map. As in the DRC map, this indicates that Landsat VCF is underestimating non-forested LULC. Landsat VCF has pixel count producer's accuracies of 92.3% for forest and 87.8% for non-forest. Accuracies shift to 94.3% and 83.9% respectively for forest and non-forest when evaluating area proportion data. Kappa statistics were only affected slightly by the area proportion analysis. The Conventional Classification map had the highest Kappa statistic of 0.904 and the Landsat VCF map had the smallest Kappa statistic of 0.792. These scores are generally excellent and indicate strong agreement and an excellent classification.

Indonesia 2000 Landsat VCF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	277	24	**92.0%**	61372.7	68.0%
Non-Forest	23	173	**88.3%**	28860.1	32.0%
Producer's Accuracy	**92.3%**	**87.8%**		**Kappa Statistic**	**0.802**
Overall Accuracy			**90.5%**		
Indonesia 2000 Landsat VCF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	62.6%	5.4%	**92.0%**	61372.7	59865.9 ± 2335.5
Non-Forest	3.8%	28.2%	**88.3%**	28860.1	30366.9 ± 2335.5
Producer's Accuracy	**94.3%**	**83.9%**		**Kappa Statistic**	**0.792**
Overall Accuracy			**90.8%**		

Table 15: The accuracy assessment of the 2000 Landsat VCF FNF map generated for the Indonesian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Indonesia 2000 Conventional Supervised Classification Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	287	8	**97.3%**	60594.1	66.5%
Non-Forest	15	190	**92.7%**	30489.1	33.5%
Producer's Accuracy	**95.0%**	**96.0%**		**Kappa Statistic**	**0.904**
Overall Accuracy			**95.4%**		
Indonesia 2000 Conventional Supervised Classification Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	64.7%	1.8%	**97.3%**	60594.1	61181.8 ± 1598.1
Non-Forest	2.5%	31.0%	**92.7%**	30489.1	29901.4 ± 1598.1
Producer's Accuracy	**96.4%**	**94.5%**		**Kappa Statistic**	**0.904**
Overall Accuracy			**95.8%**		

Table 16: The accuracy assessment of the 2000 Conventional Supervised Classification FNF map generated for the Indonesian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Indonesia 2000 FNF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	289	11	**96.3%**	63061.7	69.2%
Non-Forest	13	187	**93.5%**	28021.6	30.8%
Producer's Accuracy	**95.7%**	**94.4%**		**Kappa Statistic**	**0.900**
Overall Accuracy			**95.2%**		
Indonesia 2000 FNF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	66.7%	2.5%	**96.3%**	63061.7	62570.8 ± 1684.8
Non-Forest	2.0%	28.8%	**93.5%**	28021.6	28512.4 ± 1684.8
Producer's Accuracy	**97.1%**	**91.9%**		**Kappa Statistic**	**0.894**
Overall Accuracy			**95.5%**		

Table 17: The accuracy assessment of the 2000 FNF Masking FNF map generated for the Indonesian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Peru

The final study site under evaluation was located in Peru. The same methodology used for DRC and Indonesia was also applied to the Peruvian site.

Approach 1: Conventional Supervised Classification

The maximum-likelihood classifier following signature extraction was once again applied to the 2000 and 2010 Landsat imagery. FNF maps were generated and a change map was subsequently created using post-classification image differencing (Figure 16). The Conventional Classification generated a favorable classification. Generally the classification appears fairly accurate; however there does seem to be an excessive amount of growth in areas of obvious consistent forest. This misclassification is probably due to the swampy landscape present in the study site. There is a large amount of loss in this scene that is unsurprisingly near the river system, agricultural areas, and other previous non-forest areas. Additionally a fairly substantial amount of loss can be seen in the Proyecto Infierno protected area. This loss occurs primarily along the river system. The loss is certainly human induced deforestation as the river shifts only a small amount in this area.

An accuracy assessment was generated for this site and was once again based upon 500 reference pixels (Table 18). The overall accuracy of this map based solely upon pixel counts is 82.2%. User accuracies for this classification are fairly good. The Peruvian site, as in DRC and Indonesia, once again had the highest user accuracies for the CF class (90.9%). The CNF and Loss class user accuracies were 76.8% and 75.0%.

The Growth class had the lowest user accuracy at 58.3%. Producer accuracies were also quite good for three of the four classes including the CF (86.1%), CNF (92.5%) and Loss (87.2%) classes. The Growth class had a poor producer's accuracy of just 38.2% indicating a large amount of omission error. The Kappa statistic of 0.725 is fairly high and indicates a satisfactory classification. Based upon an assessment of the pixel count data, this map is of good quality, however the growth class is mostly inaccurate.

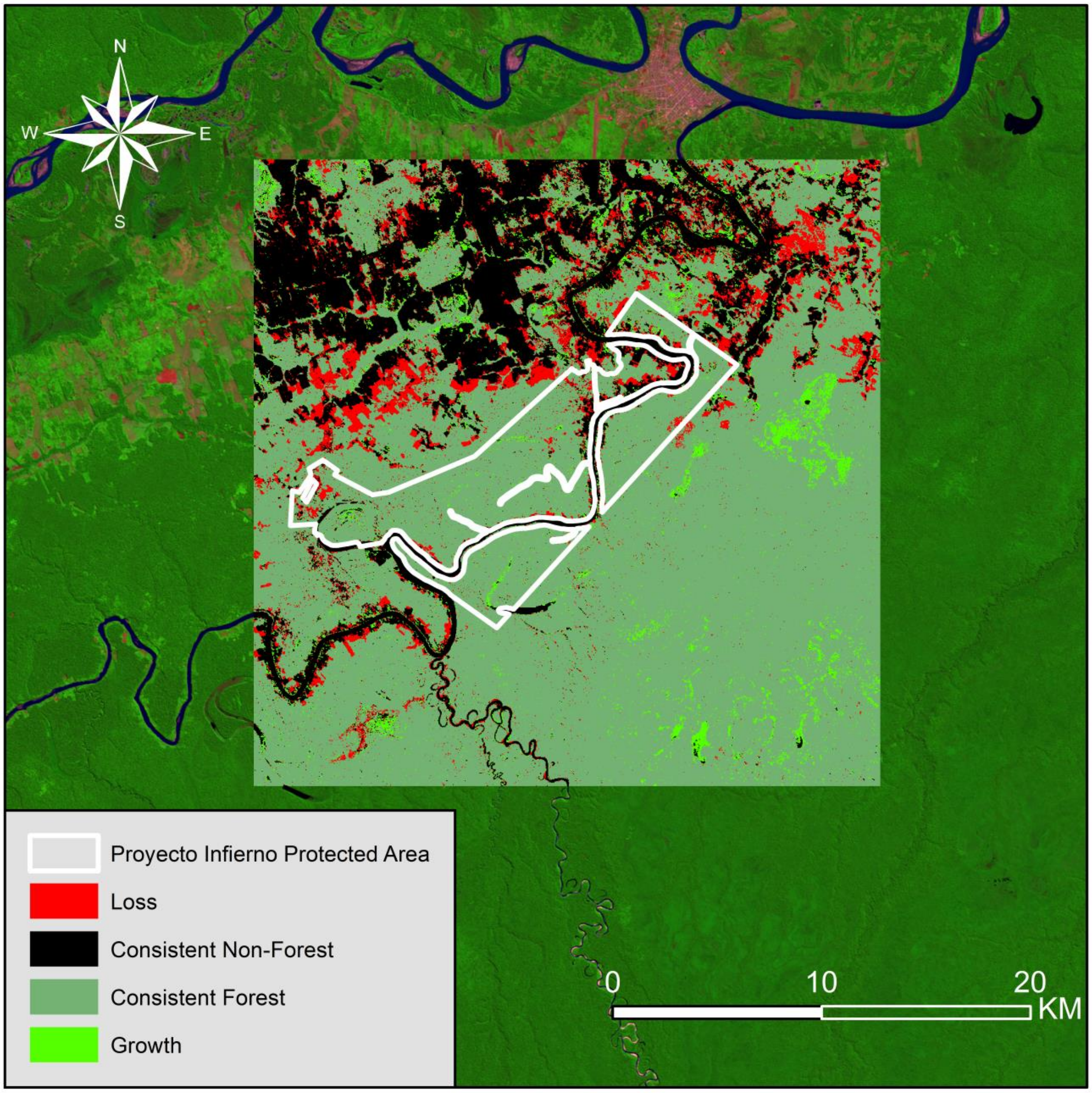

Figure 16: The 2000-2010 Conventional Supervised Classification change map generated for the Peruvian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The accuracy of the Peruvian map based upon area proportions is located in the second portion of Table 18. Overall accuracy shifts slightly from 82.2% to 85.34%. Much like the Indonesian Conventional Classification change map, accuracy improves slightly for the CF (93.6%) and CNF (96.3%) classes while dipping for the Loss (70.2%)

and Growth (26.8%) classes. As the CF class covered 67.8% of the area it had a sizeable effect on changing producer's accuracies. Additionally, the lesser weighting of the Loss and Growth classes also maximizes omission errors present in the data, thus lowering producer accuracies for both classes. This indicates an underestimation of both Loss and Growth. The Kappa statistic generally remains consistent; however it does decline slightly to 0.713.

Peru Conventional Supervised Classification Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	229	0	6	17	**90.9%**	60980.5	67.8%
CNF	7	86	4	15	**76.8%**	17921.7	19.9%
Loss	17	6	75	2	**75.0%**	6925.0	7.7%
Growth	13	1	1	21	**58.3%**	4172.9	4.6%
Producer's Accuracy	**86.1%**	**92.5%**	**87.2%**	**38.2%**		**Kappa Statistic**	**0.725**
Overall Accuracy					**82.2%**		
Peru Conventional Supervised Classification Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	61.6%	0.0%	1.6%	4.6%	**90.9%**	60980.5	59219 ± 2515.1
CNF	1.2%	15.3%	0.7%	2.7%	**76.8%**	17921.7	14292.7 ± 1492
Loss	1.3%	0.5%	5.8%	0.2%	**75.0%**	6925.0	7401.6 ± 1480.9
Growth	1.7%	0.1%	0.1%	2.7%	**58.3%**	4172.9	9086.7 ± 2364.8
Producer's Accuracy	**93.6%**	**96.3%**	**70.2%**	**26.8%**		**Kappa Statistic**	**0.713**
Overall Accuracy					**85.3%**		

Table 18: The accuracy assessment of the 2000-2010 Conventional Supervised Classification change map generated for the Peruvian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Error adjusted area data also suggests that the map likely has overestimated CNF while underestimating Loss and Growth. The CF class was quite accurate based upon Error Adjusted Area and Standard Error estimates. Standard Error for all classes ranges from ±1480 to 2515 ha which indicates a fairly broad range of the actual possible area for each class.

Approach 2: FNF Masking

Two FNF maps were generated via a k-nn classification of 2000 and 2010 Landsat imagery. A change map was subsequently created using post-classification image differencing (Figure 17). An initial visual assessment reveals that this map is of good quality. Growth and loss classifications are quite accurate and localized appropriately around areas of consistent non-forest. The exception to this is the cluster of growth pixels in the southwestern portion of this scene. There is a large amount of loss in this scene that is unsurprisingly near the river system, agricultural areas, and other non-forest areas. Loss can once again be seen in the Proyecto Infierno protected area along the riparian zone of the river. Furthermore, this map has a limited amount of speckling misclassifications in the southeastern consistent forest area that is favorable.

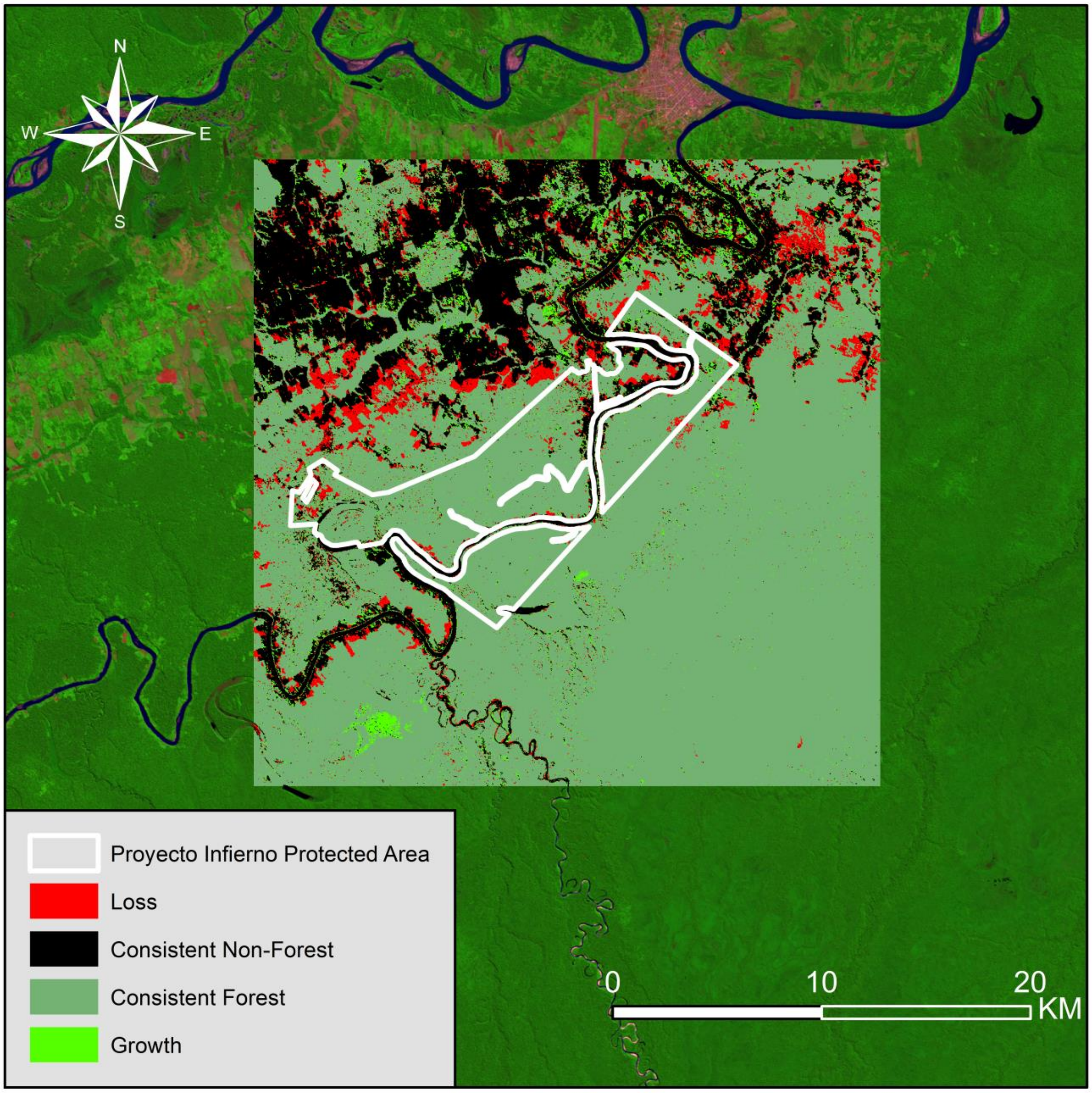

Figure 17: The 2000-2010 FNF Masking change map generated for the Peruvian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

An accuracy assessment was generated for this site based upon the same 500 reference pixels utilized in Approach 1 (Table 19). The overall accuracy of this map based solely upon pixel counts is quite good at 82%. User accuracies for both CF and CNF classes were high at 98% and 86% respectively. The CF class had 4 commission errors and the CNF class had 14 commission errors. User's accuracy for the Loss class was slightly lower at 78%. The Growth class performed the worst in terms of user's accuracy at 50%. Producer accuracies were quite high for all classes. Accuracies for the CNF, Loss, and Growth classes were all above 90%. The CF class had the lowest producer's accuracy at 73.7%. The Kappa statistic of 0.74 is relatively high. This once again indicates satisfactory agreement and good map accuracy. Based upon an assessment of the pixel count data, this map is of good quality with only limited room for improvement.

Peru FNF Pixel Counts							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	196	0	2	2	**98.0%**	62043.5	68.9%
CNF	6	86	5	3	**86.0%**	18829.4	20.9%
Loss	20	2	78	0	**78.0%**	5621.4	6.3%
Growth	44	5	1	50	**50.0%**	3505.7	3.9%
Producer's Accuracy	**73.7%**	**92.5%**	**90.7%**	**90.9%**		**Kappa Statistic**	**0.740**
Overall Accuracy					**82.0%**		
Peru FNF Area Proportions							
Land Cover/Use	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	67.6%	0.0%	0.7%	0.7%	**98.0%**	62043.5	64599.2 ± 1628.2
CNF	1.3%	18.0%	1.1%	0.6%	**86.0%**	18829.4	16481 ± 1331.7
Loss	1.3%	0.1%	4.9%	0.0%	**78.0%**	5621.4	5981.7 ± 1292.5
Growth	1.7%	0.2%	0.0%	2.0%	**50.0%**	3505.7	2938.2 ± 1143.2
Producer's Accuracy	**94.1%**	**98.3%**	**73.3%**	**59.7%**		**Kappa Statistic**	**0.835**
Overall Accuracy					**92.4%**		

Table 19: The accuracy assessment of the 2000-2010 FNF Masking change map generated for the Peruvian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

The second portion of Table 19 displays the accuracy of the map based upon area proportions. Overall accuracy shifts to 92.4% and producer's accuracies improve for the CF and CNF class while declining for the Loss and Growth classes. Both the CF and CNF classes producer's accuracies remain above 90%. The Loss class producer's accuracy drops to 73.3% and the Growth class declines to 59.7%. CF and CNF accuracies improve as errors of omission are mostly grouped in the lesser weighted Loss and Growth categories. Conversely the Loss and Growth classes producer's accuracies decline as the majority of the error is associated with the misclassification to the CF and CNF classes. The Kappa statistic improves to 0.835 which indicates an excellent classification and strong agreement. Overall this change map is accurate and generally is effective at evaluating forest change.

The lower portion of Table 19 also includes error adjusted area and standard error. Overall these data indicate minimal adjustments to map area. CNF and Growth were both slightly overestimated, and the CF and Loss classes were both slightly underestimated. Standard error area values were also fairly consistent ranging from ±1143.2 to 1628.2 indicating a moderately large confidence interval for these data.

Comparison of Approaches 1 and 2

A comparison of Approaches 1 and 2 indicates that in the Peruvian study site the FNF Masking approach slightly outperformed Conventional Supervised Classification. Overall accuracy was again higher for the FNF Masking change map in terms of area proportions. When considering pixel counts overall accuracies were nearly identical at 82%. Kappa statistics were once again higher for the FNF Masking change map. User accuracies were fairly similar for both methods. The FNF Masking change map user accuracies were higher for the CF and CNF classes. The Loss class had slightly higher user accuracy for Approach 2 while Growth had slightly higher user accuracy for Approach 1. Overall the FNF Masking map had fewer errors of commission indicating a lower amount of false-positive classifications of LULC.

Producer accuracies were higher for all FNF Masking classes in terms of area proportion. However, these accuracies were only slightly higher for the CF, CNF, and Loss classes. FNF Masking producer accuracies were substantially higher than the Conventional Classification for the growth class. FNF Masking once again displayed fewer omission errors signifying fewer misclassifications and less underestimation in all classes. Error adjusted area estimates are once again varied between these methods. The Approach 2 change map estimates that consistent forest was likely more prevalent in this study area than estimates derived from the Approach 1 change map. Consistent non-forest is slightly more prevalent in the Approach 2 change map. Loss and Growth estimates are once again substantially higher for the Approach 1 change map versus the Approach 2 change map. Standard error is lower for the FNF Masking change map indicating a more precise estimate of error adjusted area. However, both maps show a fairly similar amount of estimated standard error.

As in the DRC and Indonesian study sites; Approach 2: FNF Masking once again outperforms Approach 1: Conventional Supervised Classification for the Peruvian study site. Approach 2 has a higher overall accuracy in terms of area proportion and has fewer errors of commission and omission. Additionally areas of actual change are not particularly accurate for either map. Both are reasonable in mapping loss; however growth estimates are generally poor for both maps, however the FNF Masking is slightly better. Error adjusted area estimates are likely more accurate for the FNF Masking map due to fewer omission errors and a higher overall accuracy. Finally standard error indicates that the Approach 2 change map is more precise in LULC area estimates.

Comparison to Landsat VCF

The 2000 Landsat VCF data layer for the Peruvian study site was converted via a simple reclassification to a basic FNF map (Figure 18). Any value under 60 was once again reclassified to Non-Forest and any value greater than or equal to 60 was classified as Forest. Water was naturally classified as non-forest. Comparisons were made to the 2000 Conventional Classification FNF map (Figure 19) and the 2000 FNF Masking FNF map (Figure 20) via accuracy assessments.

Comparatively these maps have some noticeable differences. The Landsat VCF map has a limited amount of non-forest area. This is particularly noticeable in the southern forested portion of this map and around northern developed areas. As in the previous two study sites, the Landsat VCF map appears to be overestimating Forest LULC while underestimating Non-Forest LULC. Contrastingly the Conventional Classification map appears to be overestimating Non-Forest LULC while underestimating Forest LULC. A large amount of non-forest speckling is present in the Conventional Classification map in the southern forested areas. However this map seems to have an appropriate amount of non-forested area. The FNF Masking map seems to have the best balance of Forest and Non-Forest with a lesser amount of non-forest speckling in the southern forests and a similar interpretation as the Conventional Classification of the northern developed and agricultural areas.

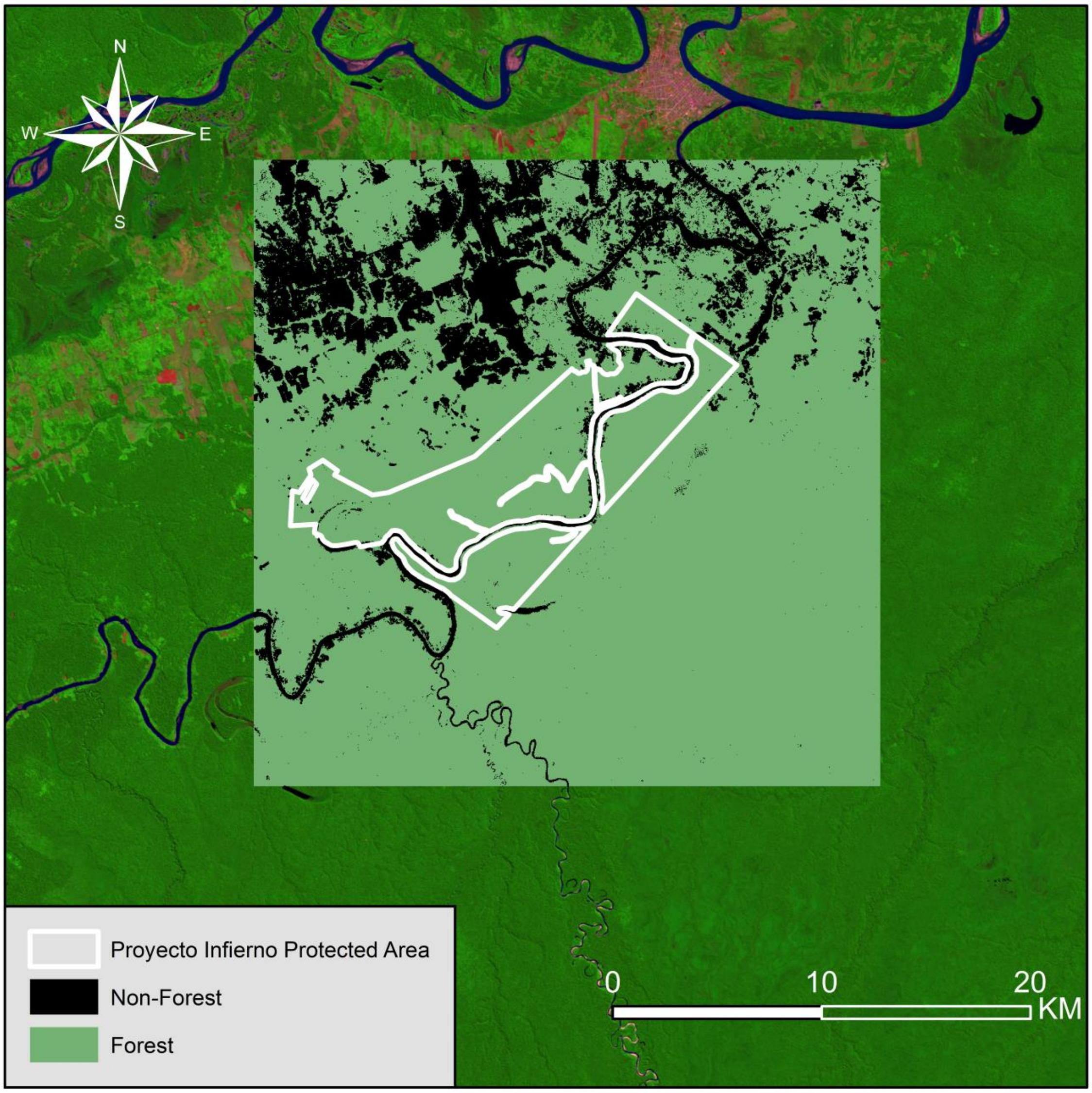

Figure 18: The 2000 Landsat VCF FNF map generated for the Peruvian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

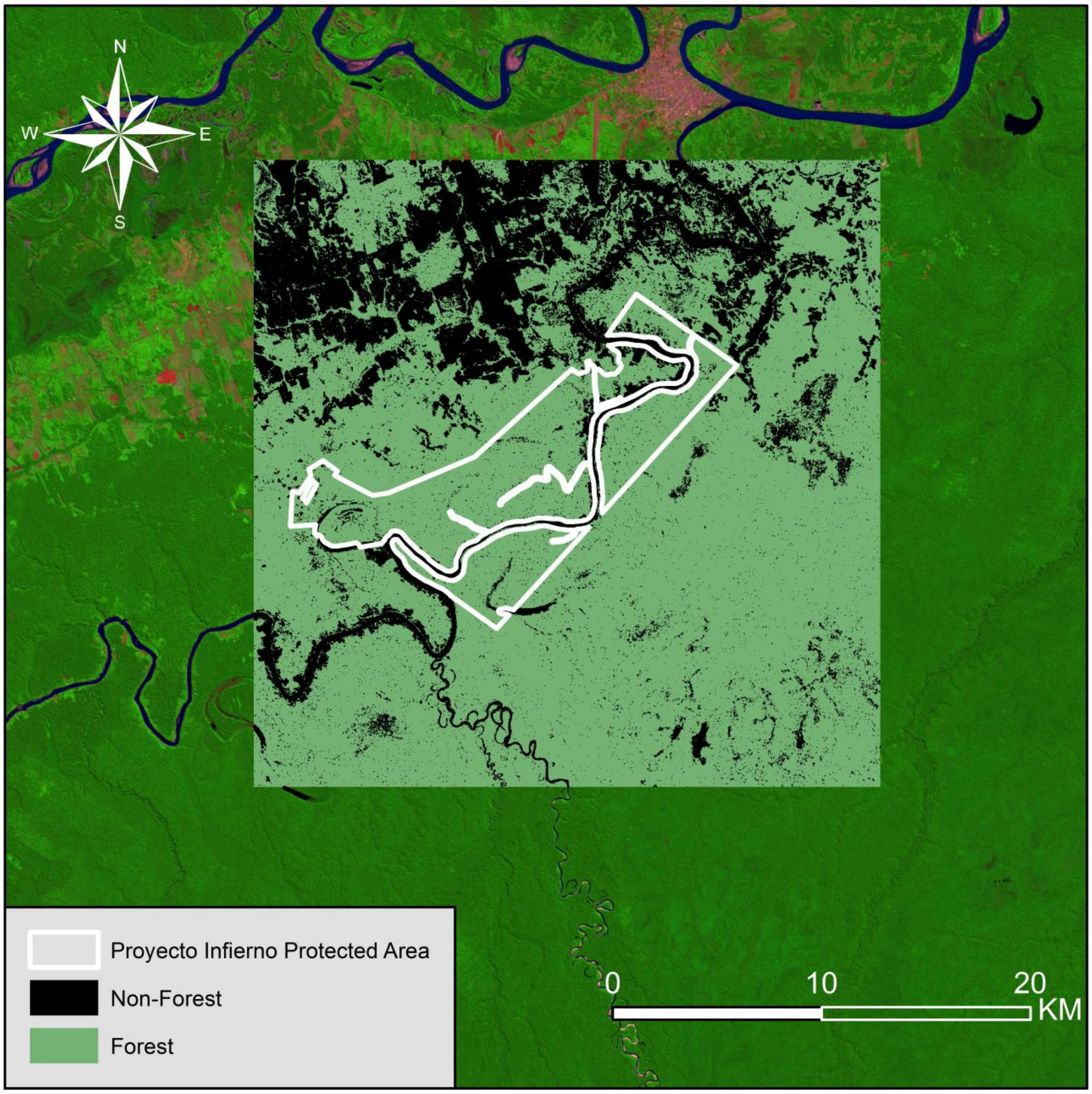

Figure 19: The 2000 Conventional Supervised Classification FNF map generated for the Peruvian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

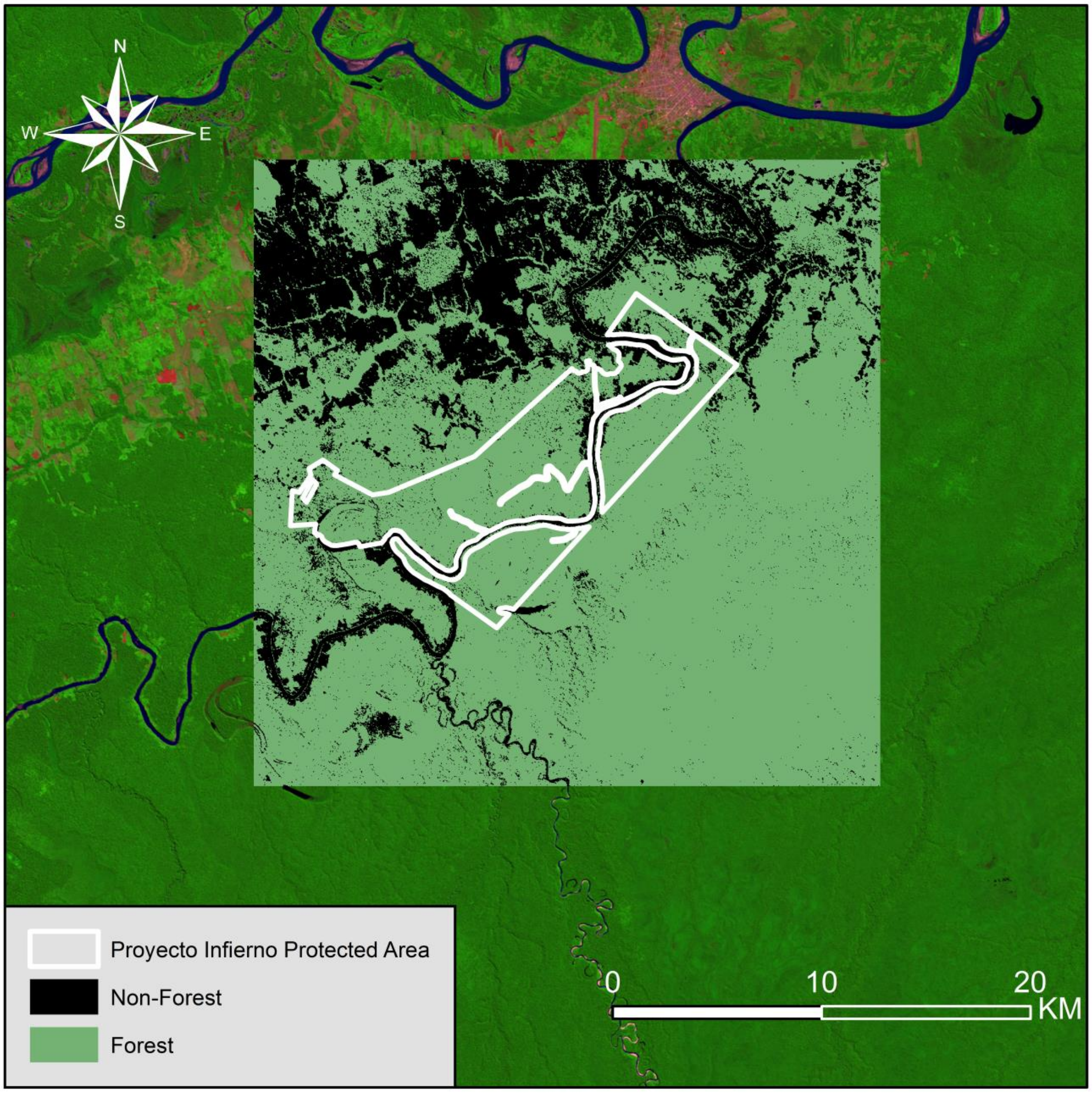

Figure 20: The 2000 FNF Masking FNF map generated for the Peruvian study site overlaid on 2000 Landsat TM imagery visualized in False Natural Color (Bands R:7, G:4, &B:3).

The accuracy assessment was generated for each FNF map based upon the same 500 reference pixels utilized in Approach 1 and Approach 2 (Tables 20-22). Overall accuracies based upon both pixel counts and area proportions were once again relatively high and changed only a small amount for the area proportion part of the assessment.

Based upon pixel counts, the Conventional Supervised Classification map had the highest overall accuracy (90%) and the Landsat VCF had the lowest (86.2%). When evaluating area proportions, the FNF Masking map had the highest overall accuracy (92%) and Landsat VCF remained the lowest (86.2%). User accuracies were varied across all maps with each map holding its own strengths and weaknesses. The FNF Masking map had the highest user accuracy for Forest at 97.8 % followed by the Conventional Classification map at 92.9%. Landsat VCF had the lowest user accuracy for forest at 86.2%. Conversely Landsat VCF had the highest user accuracy for non-forest at 86.2% followed by Conventional Classification at 83.1%. User accuracy for the FNF Masking map drops substantially for non-forest classification to 72.0%. This indicates that commission error and overestimation of the forest class were highest for Landsat VCF. Non-Forest overestimations are the most prevalent in the FNF Masking map.

Producer accuracies also varied for all maps. Landsat VCF had the highest area proportion producer's accuracy for the forest class at 96.8% and was followed by the Conventional Classification at 94.4%. FNF Masking had the lowest area proportion forest LULC producer's accuracy of 91.4%. Non-forest area proportion producer's accuracy results were once again the opposite of the forest class results with FNF Masking have the best value at 94.7%. This was followed by the Conventional Classification at 79.2% and Landsat VCF at 56.2%. This indicates that forest omission errors were not that prevalent in any of the maps. Conversely, Landsat VCF had a large amount of non-forest omission indicating a substantial underestimation of non-forest LULC. Kappa statistics were once again only affected slightly by the area proportion analysis. The FNF Masking map had the highest Kappa statistic of 0.768 followed by Conventional Classification at 0.748. Landsat VCF map had a much lower Kappa statistic of 0.597.

Error adjusted area is fairly diverse for each of these maps. The Landsat VCF and Conventional Supervised classification maps place error adjusted area for forests at about 66,000 ha. The FNF Masking map estimates forest area markedly higher at 73,000 ha. Conversely Landsat VCF and the Conventional Classification map place error adjusted area for non-forests at 23,000 ha. FNF Masking estimates non-forest at 16,983 ha. As Landsat VCF and the Conventional Supervised Classification had the highest amount of omission error for the non-forest class, original area estimates were shifted toward a more prevalent non-forest LULC area estimate. As the FNF map had the most non-forest commission error, forest LULC area increases.

The standard error data were fairly consistent for each map. The Landsat VCF map had the greatest standard error of ~2,799.5 ha followed by the Conventional classification map with ~2309.1 ha. The FNF Masking map had the smallest standard error at ~1681.5 ha. Although the results of the accuracy assessment indicate once again that each of the methods were of about equal accuracy, the Landsat VCF data produced less accurate results than the Conventional Supervised Classification and the FNF Masking approaches. Overall FNF Masking was only slightly more accurate than the Conventional Classification approach in terms of overall accuracy and Kappa score.

Peru 2000 Landsat VCF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	337	54	**86.2%**	74643.7	82.8%
Non-Forest	15	94	**86.2%**	15343.1	17.2%
Producer's Accuracy	**95.7%**	**63.5%**		**Kappa Statistic**	**0.642**
Overall Accuracy			**86.2%**		
Peru 2000 Landsat VCF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	71.5%	11.5%	**86.2%**	74643.7	66446.3 ± 2799.5
Non-Forest	2.4%	14.7%	**86.2%**	15343.1	23540.5 ± 2799.5
Producer's Accuracy	**96.8%**	**56.2%**		**Kappa Statistic**	**0.597**
Overall Accuracy			**86.2%**		

Table 20: The accuracy assessment of the 2000 Landsat VCF FNF map generated for the Peruvian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Peru 2000 Conventional Supervised Classification Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	327	25	**92.9%**	67905.5	75.5%
Non-Forest	25	123	**83.1%**	22094.6	24.5%
Producer's Accuracy	**92.9%**	**83.1%**		**Kappa Statistic**	**0.760**
Overall Accuracy			**90.0%**		
Peru 2000 Conventional Supervised Classification Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	70.1%	5.4%	**92.9%**	67905.5	66814.8 ± 2309.1
Non-Forest	4.2%	20.4%	**83.1%**	22094.6	23185.2 ± 2309.1
Producer's Accuracy	**94.4%**	**79.2%**		**Kappa Statistic**	**0.748**
Overall Accuracy			**90.5%**		

Table 21: The accuracy assessment of the 2000 Conventional Supervised Classification FNF map generated for the Peruvian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Peru 2000 FNF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	296	4	**98.7%**	67664.9	75.2%
Non-Forest	56	144	**72.0%**	22335.1	24.8%
Producer's Accuracy	**84.1%**	**97.3%**		**Kappa Statistic**	**0.739**
Overall Accuracy			**88.0%**		
Peru 2000 FNF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	74.2%	1.0%	**98.7%**	67664.9	73016.5 ± 1681.5
Non-Forest	7.0%	17.9%	**72.0%**	22335.1	16983.5 ± 1681.5
Producer's Accuracy	**91.4%**	**94.7%**		**Kappa Statistic**	**0.768**
Overall Accuracy			**92.0%**		

Table 22: The accuracy assessment of the 2000 FNF Masking FNF map generated for the Peruvian study site. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Overall Comparison of Results

An overall comparison of results was conducted by adding all pixel count data from each accuracy assessment. This generated a combined dataset of 1500 reference pixels and two overall accuracy assessment tables (Tables 23 & 24) for Approaches 1 and 2. Additionally three combined accuracy assessment tables were generated to compare 2000 FNF maps for approaches 1 and 2 against the Landsat VCF dataset. These data can be seen in Tables 25, 26, and 27.

Total Conventional Supervised Classification Pixel Counts							
Land Cover/ Uses	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	607	4	20	20	**93.2%**	173940.0	63.9%
CNF	34	338	53	81	**66.8%**	61142.8	22.5%
Loss	38	13	161	2	**75.2%**	22286.1	8.2%
Growth	32	10	2	85	**65.9%**	14797.6	5.4%
Producer's Accuracy	**85.4%**	**92.6%**	**68.2%**	**45.2%**		**Kappa Statistic**	**0.697**
Overall Accuracy					**79.4%**		

Total Conventional Supervised Classification Area Proportions							
Land Cover/ Uses	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	59.6%	0.4%	2.0%	2.0%	**93.2%**	173940.0	173920.2 ± 4028.4
CNF	1.5%	15.0%	2.4%	3.6%	**66.8%**	61142.8	44412.1 ± 2953.9
Loss	1.5%	0.5%	6.2%	0.1%	**75.2%**	22286.1	28744.1 ± 3188
Growth	1.4%	0.4%	0.1%	3.6%	**65.9%**	14797.6	25090.1 ± 3339.1
Producer's Accuracy	**93.3%**	**92.0%**	**58.3%**	**38.9%**		**Kappa Statistic**	**0.711**
Overall Accuracy					**84.3%**		

Table 23: The combined accuracy assessment of the 2000-2010 Conventional Supervised Classification change map generated for all study sites. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Total FNF Pixel Counts							
Land Cover/ Uses	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
CF	586	3	5	6	**97.7%**	188307.5	69.2%
CNF	13	273	6	8	**91.0%**	51460.1	18.9%
Loss	33	42	223	2	**74.3%**	17822.6	6.6%
Growth	79	47	2	172	**57.3%**	14576.3	5.4%
Producer's Accuracy	**82.4%**	**74.8%**	**94.5%**	**91.5%**		**Kappa Statistic**	**0.767**
Overall Accuracy					**83.6%**		

Total FNF Area Proportions							
Land Cover/ Uses	CF	CNF	Loss	Growth	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
CF	67.6%	0.4%	0.6%	0.7%	**97.7%**	188307.5	191942.5 ± 2798.6
CNF	0.8%	17.2%	0.4%	0.5%	**91.0%**	51460.1	52549 ± 2228.6
Loss	0.7%	0.9%	4.9%	0.0%	**74.3%**	17822.6	15943.7 ± 1865.7
Growth	1.4%	0.8%	0.0%	3.1%	**57.3%**	14576.3	11731.2 ± 1996.8
Producer's Accuracy	**95.8%**	**89.1%**	**83.1%**	**71.2%**		**Kappa Statistic**	**0.845**
Overall Accuracy					**92.7%**		

Table 24: The combined accuracy assessment of the 2000-2010 FNF Masking change map generated for all study sites. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Based upon pixel count data overall accuracy was 79.4% for Approach 1 and 83.6% for Approach 2. User accuracies for the CF and CNF classes were higher for Approach 2, while user accuracies for the Loss and Growth classes were higher for Approach 1. Contrastingly, producer accuracies were higher for the CF and CNF classes for Approach 1 and Loss and Growth classes were higher for Approach 2. The Approach 1 Kappa statistic of 0.697 was slightly lower than the Approach 2 score of 0.767. Overall this analysis displays a balance of commission and omission errors. Conventional Classification accurately classifies CF, overestimates CNF, and generally poorly classifies areas of change. FNF Masking slightly underestimates CF and CNF and slightly overestimates Loss and Growth. When accounting for these errors, accuracy scores, and the Kappa statistics, Approach 2: FNF Masking slightly outperforms Approach 1: Conventional Supervised Classification in terms of pixel counts.

The area proportion accuracy assessment data provides a slightly more detailed analysis of these methods. The overall accuracy of the change maps shifts to 84.3% for Approach 1 and to 92.7% for Approach 2. User accuracies remain consistent for each change map. Producer’s accuracies change fairly dramatically for each method. When evaluating the Approach 1 producer accuracies, the CF class improves slightly while the Loss and Growth classes both decline. The CNF class producer accuracies remain consistent for both pixel counts and area proportions. Approach 2 perform fairly similarly. The CF and CNF class producer accuracies improve, while the Loss and Growth classes decline. Overall, Approach 2 had higher producer accuracies for the CF, Loss, and Growth classes while Approach 1 had slightly higher producer accuracy for the

CNF class. Based upon the shift to area proportion, Conventional Classification still accurately classifies CF, overestimates CNF, and poorly classifies areas of change. FNF Masking accurately classifies CF and CNF and slightly overestimates Loss. Growth classification is poor for FNF Masking. When evaluating each class individually in terms of both producer accuracy and user accuracy, Approach 2 outperforms Approach 1 for every class. The overall amount of error present for each class for each approach is lower for Approach 2. When analyzing Kappa statistics, Approach 2 remains higher than Approach 1 with Kappa statistics of 0.845 and 0.711 respectively. This indicates that Approach 2 outperformed Approach 1 in terms of statistical agreement and overall map accuracy. Error adjusted area estimates for the CF and CNF classes are much lower for Approach 1 versus Approach 2. Contrastingly Approach 2 has much lower error adjusted area estimates of the Loss and Growth classes versus Approach 1. The Approach 1 error adjusted area estimates indicate that it is correctly estimating CF, overestimating CNF, and underestimating Loss and Growth. Approach 2 estimates indicate that the map is correctly estimating CNF, slightly overestimating Loss and Growth, and slightly underestimating CF. Standard error estimates for Approach 1 vary between ~3000 and 4000 ha. Approach 2 standard error varies between ~1800 and ~2800 ha. This indicates a more precise classification for Approach 2.

The comparison of Landsat VCF and Approaches 1 and 2 can be seen in Tables 25, 26, and 27. Based upon pixel count data overall accuracy was quite similar for all methodologies. Landsat VCF had the lowest overall accuracy of 86.5%. This was followed by Approach 1 at 89.3% and 89.8% for Approach 2. User accuracies varied across each method. When analyzing the Forest class, Approach 1 (95.5%) had slightly higher user accuracy than Approach 2 (94.1%). Landsat VCF had the lowest user accuracy (85.9%) for the forest classification. Landsat VCF had the highest user accuracy for Non-Forest (87.9%). Approach 2 (83.3%) had slightly higher user accuracy for the Non-Forest class than Approach 1 (80.9%). Producer accuracy for the Forest class pixel count data was highest for Landsat VCF (94.1%), followed by Approach 2 (89.4%) and then Approach 1 (87.2%). Non-Forest pixel count producer accuracy was highest for Approach 1 (92.9%) followed by Approach 2 (90.4%). Landsat VCF had a substantially lower Non-Forest producer's accuracy of 73.6%. Kappa statistics were all quite similar with FNF Masking generating the largest score of 0.785. This was followed by Conventional Supervised Classification at 0.778 and Landsat VCF at 0.700.

Total Landsat VCF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	889	146	**85.9%**	214189	79%
Non-Forest	56	406	**87.9%**	57113.9	21%
Producer's Accuracy	**94.1%**	**73.6%**		**Kappa Statistic**	**0.700**
Overall Accuracy			**86.5%**		
Total Landsat VCF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	67.8%	11.1%	**85.9%**	214189	190897.7 ± 4951.6
Non-Forest	2.6%	18.5%	**87.9%**	57113.9	80405.1 ± 4951.6
Producer's Accuracy	**96.4%**	**62.4%**		**Kappa Statistic**	**0.642**
Overall Accuracy			**86.3%**		

Table 25: The combined accuracy assessment of the 2000 Landsat VCF FNF map generated for all study sites. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Total 2000 Conventional Classification FNF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	826	39	**95.5%**	196226	72.1%
Non-Forest	121	514	**80.9%**	75940.4	27.9%
Producer's Accuracy	**87.2%**	**92.9%**		**Kappa Statistic**	**0.778**
Overall Accuracy			**89.3%**		
Total 2000 Conventional Classification FNF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	68.9%	3.3%	**95.5%**	196226	201849.4 ± 3645.1
Non-Forest	5.3%	22.6%	**80.9%**	75940.4	70317 ± 3645.1
Producer's Accuracy	**92.8%**	**87.4%**		**Kappa Statistic**	**0.782**
Overall Accuracy			**91.4%**		

Table 26: The combined accuracy assessment of the 2000 Conventional Supervised Classification FNF map generated for all study sites. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Total 2000 FNF Masking FNF Map Pixel Counts					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Weight (Proportion of Study Area)**
Forest	847	53	**94.1%**	206130	75.7%
Non-Forest	100	500	**83.3%**	66036.4	24.3%
Producer's Accuracy	**89.4%**	**90.4%**		**Kappa Statistic**	**0.785**
Overall Accuracy			**89.8%**		

Total 2000 FNF Masking FNF Map Area Proportions					
Land Cover/Use	Forest	Non-Forest	**User's Accuracy**	**Map Area (ha)**	**Error Adjusted Area ± Standard Error (ha)**
Forest	71.3%	4.5%	**94.1%**	206130	204997.4 ± 3810.8
Non-Forest	4.0%	20.2%	**83.3%**	66036.4	67169.1 ± 3810.8
Producer's Accuracy	**94.6%**	**81.9%**		**Kappa Statistic**	**0.770**
Overall Accuracy			**91.5%**		

Table 27: The combined accuracy assessment of the 2000 FNF Masking FNF map generated for all study sites. The top table describes accuracy in pixel counts and the bottom table describes accuracy in area proportions.

Area proportion data provides greater insight into the accuracy assessment data. Overall accuracy increases for Conventional Classification and FNF Masking to 91.4% and 91.5% respectively. Overall accuracy remains consistent for the combined Landsat VCF area proportion accuracy assessment at 86.3%. User accuracies remain consistent once again and producer accuracies shift slightly. Producer accuracies for the Forest class increase for every method. Landsat VCF still has the highest producer accuracy for the Forest class at 96.4%. This is followed by FNF Masking (94.6%) and lastly the Conventional Classification (92.8%). This indicates that there are only minor discrepancies between each FNF map and minimal omission errors. Comparatively, non-forest LULC producer accuracy ranges broadly for each FNF map. Approach 1 has the best producer accuracy for Non-Forest at 87.4%. This is followed by Approach 2 at 81.9%. Finally Landsat VCF has the lowest producer accuracy for the Non-Forest class at just 62.4%. This indicates high errors of omission and misclassification in the Non-Forest class for the Landsat VCF product. When analyzing Kappa statistics, Approach 1 has the best values of 0.782, followed by Approach 2 (0.770) and finally Landsat VCF (0.642). Error adjusted area estimates indicate minimal discrepancies between Approaches 1 and 2. The Conventional Classification methodology estimates there are ~3000 more ha of Forest and ~3000 ha less of Non-Forest versus the FNF Masking methodology. Standard error estimates of ± 3645 ha and ± 3810 ha mean that these maps have nearly identical estimates of Forest and Non-Forest. Landsat VCF has a quite different estimation of Forest and Non-Forest area. It indicates that there are ~10,000 less ha of Forest and ~10,000 more ha of Non-Forest. Standard error estimates are also larger for Landsat VCF at ± 4951 ha. This indicates that Approaches 1 and 2 outperformed Landsat VCF in terms of classification precision as well.

When evaluating each FNF map and each class individually in terms of both producer accuracy and user accuracy, Approach 2 and Approach 1 perform similarly. There are only minor discrepancies between these maps and both generally generate an excellent classification. Landsat VCF classifies forest accurately; however there is a large amount of omission error present in the Non-Forest classification portion of this map that minimizes its overall value. Thus, both Approach 1 and 2 outperform Landsat VCF in a combined analysis of all study areas.

SUMMARY AND CONCLUSIONS

In this study two forestry change detection methodologies were developed, tested, and evaluated for tracking deforestation in threatened areas in three separate regions of the Earth. Although results are limited to these sites, the methods can be extended to other LULC studies. Evaluating these methodologies in different regions has helped to minimize discrepancies in the results. The results of this study are substantial and significant and should contribute to forestry change detection knowledge and research. Results of the methodologies are evaluated over three study areas are summarized in the following sections.

Approach 1: Conventional Supervised Classification

Generally, in each study area the Conventional Supervised Classification forest change detection methodology performed quite well. Overall accuracy was extremely consistent and ranged from 84.7% to 85.3%. This approach exhibited consistently high user accuracies for the CF class. Additionally producer accuracies were high for the CF and CNF classes. Thus CF was extremely accurately classified and CNF was not under-classified. Nevertheless, this method did have some key weaknesses. Altogether the method failed to classify both growth and loss accurately. The method had low user and producer accuracies for growth and loss in all study areas, with the exception of the Indonesian site. In the Indonesian study area loss and growth both had high user accuracy. These low user and producer accuracies indicate a general misclassification of both classes. This indicates that loss and growth were overestimated and underestimated at the same time, generating a poor classification of change in each map. Furthermore the CNF class had low user accuracy in the DRC study area and average user accuracy in the Indonesian and Peruvian study areas. This indicates a moderate over-classification of CNF in each map. This was evident throughout all of the study areas.

Overall this approach generated passable change maps; however the poor classification of growth and loss minimizes the results. As the focus of this study was to track forest change, the accuracy of the loss and growth classes is of the highest priority. Naturally tracking both CF and CNF is also important; however this method also overestimates the CNF class consistently. This could be due to the signature extraction process or the maximum likelihood classification. Generating a perfect set of signatures is highly challenging as it is difficult to determine how well each map will classify change.

Approach 2: FNF Masking

Overall, the MODIS VCF guided FNF Masking approach for tracking forest change performed admirably. Overall accuracies for this method were high and ranged from 92.4% to 93.9%. User accuracies for the CF and CNF classes were high for all study sites. Also user accuracies for the Loss class were high for two of the three study sites. Producer accuracies were high for the CF, CNF, and Loss classes in all study areas. This indicates a highly accurate classification of the CF, CNF, and Loss classes. In particular the CF and CNF classes were all of exceptional accuracy. However, the growth class was typically of lesser quality in all study areas. The Growth class had low user accuracies in the DRC and Peruvian study sites and average user accuracy in the Indonesian study site. Growth had average producer accuracies in the DRC and Indonesian study areas and low producer accuracy in the Peruvian site. This indicates that the Growth class was mostly over-classified in all study sites. Some under classification is also present, particularly in the Peruvian site.

The FNF Masking approach generated good change maps. The primary limitation of this method was the poorly classified growth class. Contrastingly loss class producer and user accuracies were mostly quite high. Combined, this method tracks forest change satisfactorily. In addition to tracking change this method exceeds at producing highly accurate CF and CNF LULC classifications. The causes for the differences in accuracy between the loss and growth classes is likely due to some imagery inconsistencies. In particular the 2000 Peruvian image has a large amount of swamp area that is darker than normal forest and easier to misclassify. Also the DRC study area has several locations in the 2000 and 2010 scenes that are quite difficult to differentiate between forest and agriculture. Naturally accuracy issues in the MODIS VCF data may also cause accuracy problems.

Comparison of Approaches 1 and 2

Overall, Approach 2: FNF Masking outperforms Approach 1: Conventional Supervised Classification. In terms of overall accuracy, Approach 2 has higher accuracies in all study areas. In terms of user accuracy, both methods classify CF excellently. FNF Masking has higher user accuracies than Conventional Classification when classifying the CNF and Loss classes. Both methods perform poorly and have high commission error when classifying growth. In terms of producer accuracy, both methods classify the CF and CNF superbly. However the FNF Masking methodology has higher producer accuracies than the Conventional Classification method for both loss and growth.

Comparison to Landsat VCF

FNF maps generated using Landsat VCF and Approaches 1 and 2 were compared. Altogether, Approaches 1 and 2 outperform Landsat VCF when generating FNF maps. These methods perform quite similarly for all study areas exhibiting only minor discrepancies. When evaluating overall accuracy, both FNF Masking and Conventional Supervised Classification have higher overall accuracies than Landsat VCF at every study area. User accuracies for the forest class are high for all classes; however Landsat VCF has slightly lower user accuracy for forest in the DRC study area. This indicates some over-classification of forest in this area. User accuracy for non-forest was quite similar for all methods, however in this case Landsat VCF performed the best when estimating non-forested LULC areas. On average, Conventional Classification and FNF Masking both had slightly lower user accuracies for non-forested regions indicating slight over-classification of non-forested areas. Producer accuracies for forest were high for all methods. The true difference between each of these methods were in producer accuracies for the non-forest classification. Conventional Classification and FNF Masking had some omission error present in this class, indicating both methods slightly under-classified non-forest. Conversely Landsat VCF had a large amount of omission error for the non-forest classification at all sites except the Indonesian study area. This indicates that Landsat VCF is significantly underestimating non-forest in all study areas. As there are only two LULC classifications in these maps, this suggests that Landsat VCF is likely overestimating forestation. Although these study areas represent only a small portion of the total Landsat VCF global product, this dataset may be substantially overestimating the amount of forest globally.

Future Research Suggestions

Further research utilizing variations of the FNF Masking or Conventional Classification techniques could be useful. When utilizing a supervised signature extraction schema, the use of image or NDVI differencing may assist an analyst in evaluating obvious areas of change. These areas could then be used as examples in the signature extraction process, theoretically generating a more accurate change map. Research expansions of the FNF Masking technique are broad and numerous. For example, utilizing radar imagery instead of Landsat imagery could be useful, particularly in cloud prone areas. Secondly, the evaluation of FNF Masking over a larger study area, such as a full Landsat scene could provide some compelling results. Next, the use of coarse spatial resolution value added products similar to MODIS VCF that estimate other types of LULC could be utilized in a similar way as presented in this study. These products could be used to analyze various issues such as urban or agricultural expansion. Finally the combination of FNF Masking and Conventional Classification may prove interesting. For example, Conventional classification may be able to more accurately identify agricultural areas than FNF Masking. Agricultural areas could first be masked as non-forest utilizing a Conventional Classification. Following this step FNF Masking could then be utilized to classify the remainder of the image, theoretically improving Forest and Agriculture seperabilitiy. As a result classification accuracy would improve.

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