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Preliminary REDD+ Reporting in the Tonle Sap Region of Cambodia

Introduction:

In the past several years there has been an increasing amount of attention paid to the significant contribution of land use changes and in particular deforestation to global greenhouse gas emissions. Healthy forests have the potential to sequester far more carbon in their biomass, soils, and dead litter than can be stored in most other land covers. As a result of this, the conversion of forest to another land cover, or conversely from another land cover to forest represents net changes in carbon emissions to the atmosphere. In recognition of this, in 2005 at the Framework Convention on Climate Change (UNFCCC) the UN adopted the Reduced Emissions from Deforestation and Degradation (REDD+) program with the goal of incentivizing tropical low income countries to reduce emissions associated with forest loss. Until recently however, no specific guidelines or methodologies for REDD+ reporting were publicly available.

This study is an attempt to take advantage of the procedures described in the 2016 methods and guidance document for REDD+ reporting published by the Global Forests Resource Initiative to produce a preliminary report on REDD+ activities for an area near the Tonle Sap Lake in Cambodia (GFOI, 2016). It makes use of publicly available remotely sensed satellite data from the Landsat archive provided by the U.S. Geological Survey to estimate areas of both changing and stable land cover in the study area between the years 2006 and 2015. This information is then used to produce estimates of the change in carbon stocks present in the study area, and by implication, the change in carbon emissions associated with the study area.

Cambodia was chosen as region in which to implement this framework for two primary reasons. First, Cambodia is a tropical country (where REDD+ is intended to be implemented) which has experienced significant rates of deforestation in recent history. From 1973 to 2014 total forest cover fell from 72% to 48% of the country's area, and dense forest cover similarly dropped from 42% to 16% (Open Development Cambodia "Forest Cover", 2016). Figure 1 shows the trend forest cover over that time period, and in it we can see a significant increase in deforestation rates since roughly 2000. This indicates that the process of deforestation is currently 'speeding up' relative to the historical average rate, which in turn indicates that REDD+ reporting may be particularly pertinent for Cambodia. Second, I am currently involved in an extended research project involving predictive modeling of land use change and its biodiversity implications in the Tonle Sap region. I chose to focus my analysis on this region in particular in order to deepen my understanding of land cover change dynamics in the area.

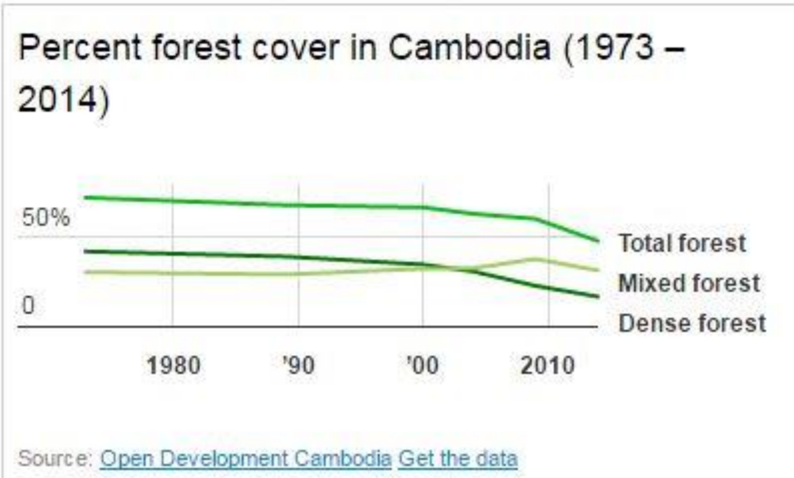

Figure 1: Time Series of Forest Cover in Cambodia, 1973-2014

Source: Open Development Cambodia, 2016

Methods:

The general workflow followed for this study can be described in the following steps:

1). Select images and time frame for analysis

2). Perform multi-date classification and change detection

3). Asses classification accuracy and produce unbiased estimates of activity data

4). Convert these estimates to the changes in carbon stocks associated with them

The change detection and area analysis portion of this study were conducted using multispectral images sourced from the USGS's Landsat Archive. Landsat images have been freely distributed through the internet since 2008, and the archive is one of the largest publicly available collection multispectral datasets suitable for use in REDD+ related analysis. Landsat data's 30m pixel size and reasonable spectral resolution allow for land cover classification on a spatial scale small enough to detect REDD+ activities at a local level yet large enough to avoid the limited spectral bands often associated with higher spatial resolution imagery.

The particular datasets used for change detection are two images produced using the Landsat 5 satellite as well as a single more recent image produced by Landsat 8. The images are from January 29th, 2006, May 31st, 2010, and February 7th, 2015, and are all from Landsat path 151 row 57. The images cover the eastern portion of the Tonle Sap lake and the surrounding forest and agricultural land. The particular spatial subset where change detection was performed includes the northeast corner of the Tonle Sap Lake as well as agricultural, forested, and small urban areas. Figure 2 shows the extent of both the scene and the subset in two different false color composites.

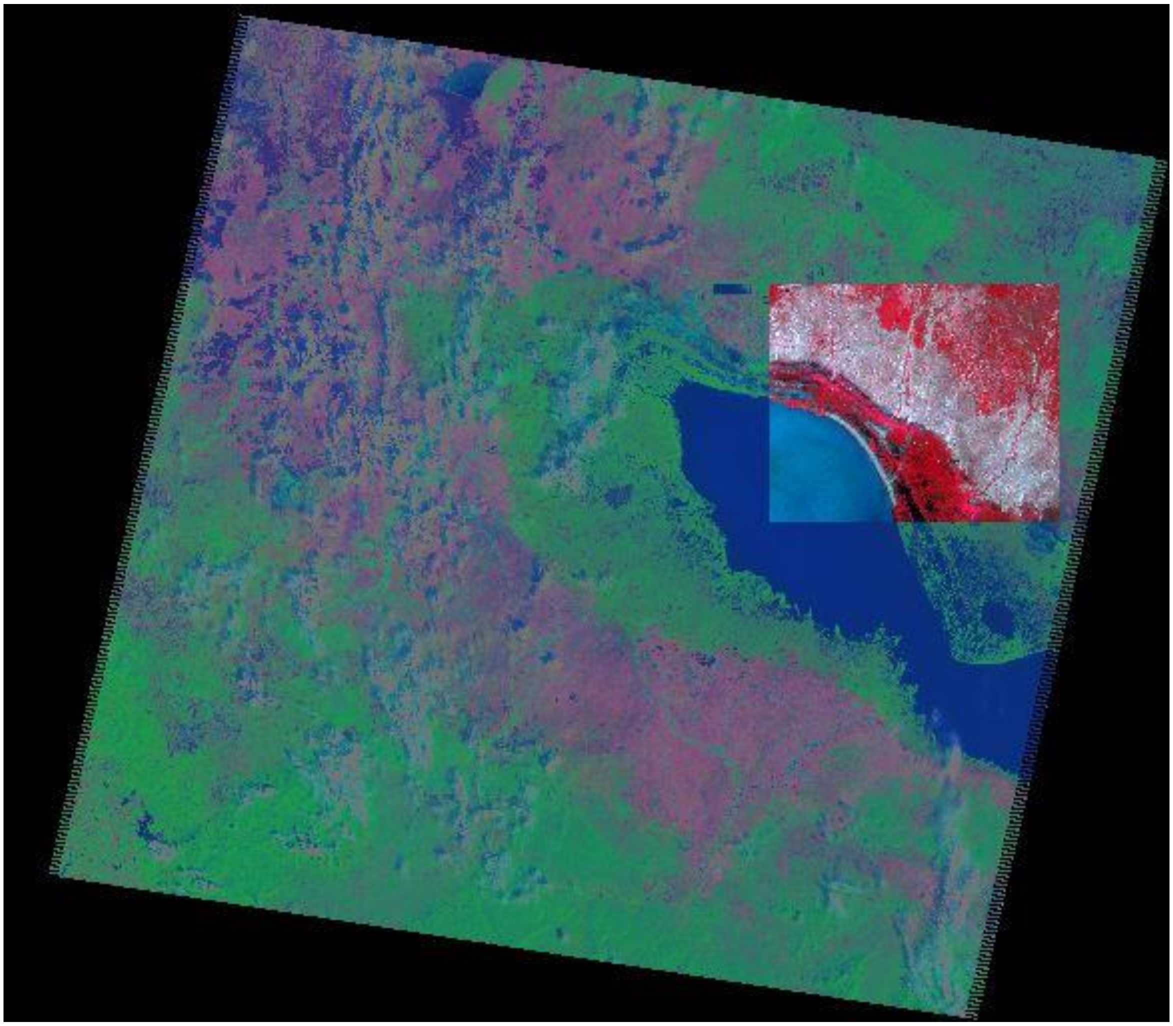

Figure 2: Full Landsat Scene and the Spatial Subset Used for this Study from January 29th, 2006

The images are displayed using false color composites

Cambodia, like much of southeast Asia, is a relatively cloudy country and the image selection process for this study was largely driven by a desire to find a cloud free (or very nearly) subset across every image while maintaining a reasonable time frame for REDD+ analysis. All three images were selected from others available around the same time based on a common cloud free area. In order to measure meaningful change in the REDD+ context with a limited amount of time for analysis (and thus time to perform classification), it was important to select images covering a relatively specific time frame. The images needed to be spread out enough to be significantly different from one another while still being close enough together to provide information on a relatively fine temporal scale. To this end images from close to the present day (Feb. 2015) as well as around the common REDD+ baseline year of 2005 (Jan. 2006) were chosen as the endpoints for the change detection. The image from May 2010 was selected as a rough midpoint between other two images.

A unique and important aspect of the study area is the Tonle Sap Lakes remarkable seasonal flood pattern. Every year, during the wet season, flow in the Tonle Sap River reverses direction and the lake floods the surrounding low lying forest nearly doubling in size (Altman, 2014). This is important in a REDD+ context because we are interested in reporting on meaningful changes which release or sequester carbon, not changes which only appear due to temporal variations in flood extent. In order to minimize this concern, all images were sourced from the dry season (~Feb-June) when the lake is at its lowest.

Prior to analysis, both images were atmospherically corrected using the algorithm LEDAPS and cloud detection was performed using the algorithm Fmask (Masek et al., 2006; Zhu et al., 2015). Atmospheric correction removes the influence of atmospherically scattered radiation from our images, and cloud detection allows us to exclude data from cloudy pixels which might otherwise be misclassified. LEDAPS and Fmask are considered among the better techniques available for these preprocessing steps, and Landsat images are available to download from the USGS having been put through the algorithms already.

After identifying the study images, multi-date image stacks were prepared by combining the 2006 and 2010 images as well as the 2010 and 2015 images. The purpose of this was to create two unified datasets which could be used for multi-date classification and change detection. Multi-date classification is a method of change detection which compares the spectral signatures of pixels across two dates and attempts to classify them. The classification will include both stable (forest, agriculture, water) and change (forest->grassland, agriculture->urban) classes and through that estimates can be produced on land use change between the two dates.

Multi-date classification was performed using the Random Forests algorithim (Breiman, 2001). It is am “ensemble learning” algorithim which builds a series of decision tree classifiers and aggregates their results. Decision tree classifiers are a method of supervised classification which use a ‘tree’ of decision points (nodes) which separate data based on common values in a certain attribute. Individual decision trees are prone to overfitting data, which has led to the development of ensemble methods which produce many classifiers of bootstrapped versions of the data and attempt to aggregate them. Random Forests is just such a method, and represents an improvement over similar methods of ‘bagging’ decision trees by choosing to split its training data at each node based on the greatest information gain from a random subset of attributes rather than the full set. This further reduces the issues of overfitting, and Random Forests has proven to be an effective algorithm for image classification in remote sensing.

The training data used to fit the Random Forests model was collected from each scene using QGIS. The OpenLayers plugin was used to provide high quality reference imagery from Google Satellite, and individual polygons were drawn using the Add Feature tool. Training data were collected for the following classes: Water, Barren/Urban, Forest, Agriculture, and Forest->Agriculture. No other classes occurred with enough frequency on the map to collect meaningful training data.

The actual Random Forests classifier was fit using R and the randomForest package (Liaw and Wiener, 2002). The classifier was then applied to the stacked raster images using the predict() function in order to produce estimates of land use and land use change in the study area.

In spite the intent in the image selection process to minimize the effect of the seasonal flooding of the Tonle Sap Lake on change detection there was still significant inter-image variability in the pixels immediately bordering the lake. Because there is significant temporal variability in the magnitude and timing of the lake pulse which causes the flood even two images from the same time of year are not guaranteed to capture the lake at the same level. As previously discussed, this variability has the potential to result in erroneous change detection due to differences in the water content of a pixel rather than the fundamental nature of the land cover. Satellite reference data indicated that the area was intact flooded forest in 2015, and as such it was manually classified as stable forest for all images. This likely erroneously classified a few pixels, but the improvements in accuracy which resulted from ignoring the flood pattern were more than worth it.

In order to provide unbiased estimates of the areas associated with REDD+ activities an accuracy assessment was performed on a reference sample and a confusion matrix was produced. Since our classification results indicated a significantly unbalanced distribution of image pixels amongst the classes, a stratified random sample was chosen to ensure that all classes had enough representation in the reference sample to produce unbiased error estimates. More specifically, a stratified random sample of n=250 was taken from each classified image with 50 samples allocated to each land cover class.

This reference sample was then classified in QGIS using high resolution imagery from the OpenLayers plugin. A confusion matrix was calculated by comparing the values in the classification map for each pixel with the ‘ground truth’ reference class. From this matrix, unbiased estimates of area for REDD+ activities can be calculated by multiplying proportion of each reference class identified in each map class by that class’s proportion of the classified image and summing those values across each reference class. Standard errors of those estimates can be estimated using the following formula:

$$S(\hat{p}_{\cdot j}) = \sqrt{\sum_i \frac{W_i \hat{p}_{ij} - \hat{p}_{ij}^2}{n_{i\cdot} - 1}}$$

Where W_i is equal to the stratum weight (proportion of image pixels) of class i, $\hat{p}_{ij}$ is the proportion of the image represented by pixels in class i of reference class j, and n_i is the size of the stratum of reference pixels for class i. From those standard errors, 95% confidence intervals can be derived by multiplying the error by 1.96.

Once unbiased estimates of area have been produced, they can be used to estimate the changes in carbon stocks associated with the areas which are identified as REDD+ relevant land uses. This study asses changes in the following stocks: changes in living biomass from forests which remain forests and changes in living biomass from forests which are converted to agriculture at the Tier 1 level as defined by the REDD+ program.

There are multiple tiers of REDD+ reporting, of which Tier 1 is the most simple. It uses global or biome specific values for its emissions factors in the calculations changes in carbon stocks, rather than the country, regional, or spatially explicit factors needed for Tiers 2 and 3. Tier 1 reporting is appropriate for this report as the data needed for Tiers 2 and 3 are not easily publicly available for Cambodia. In fact, even some data required for Tier 1 reporting emissions calculations such as soil maps (for stratification between organic and mineral soils) are not available for the country.

For forests remaining forests, annual change in carbon held in living biomass can be estimated using Equation 3.2.2 from the *Good Practice Guidance for Land Use, Land-Use Change and Forestry* (GPG) (IPCC, 2003).

EQUATION 3.2.2
ANNUAL CHANGE IN CARBON STOCKS IN LIVING BIOMASS IN FOREST LAND REMAINING FOREST LAND (DEFAULT METHOD)

$$\Delta C_{FF_{LB}} = (\Delta C_{FF_G} - \Delta C_{FF_L})$$

Where:

$\Delta C_{FF_{LB}}$ = annual change in carbon stocks in living biomass (includes above- and belowground biomass) in forest land remaining forest land, tonnes C yr^{-1}

ΔC_{FF_G} = annual increase in carbon stocks due to biomass growth, tonnes C yr^{-1}

ΔC_{FF_L} = annual decrease in carbon stocks due to biomass loss, tonnes C yr^{-1}

Annual increase in carbon stocks due to biomass growth can be estimated using equation 3.2.4 from the same document.

EQUATION 3.2.4
ANNUAL INCREASE IN CARBON STOCKS DUE TO BIOMASS INCREMENT IN FOREST LAND REMAINING FOREST LAND

$$\Delta C_{FF_G} = \Sigma_{ij} (A_{ij} \bullet G_{TOTAL_{ij}}) \bullet CF$$

Where:

ΔC_{FF_G} = annual increase in carbon stocks due to biomass increment in forest land remaining forest land by forest type and climatic zone, tonnes C yr^{-1}

A_{ij} = area of forest land remaining forest land, by forest type (i = 1 to n) and climatic zone (j = 1 to m), ha

$G_{TOTAL_{ij}}$ = average annual increment rate in total biomass in units of dry matter, by forest type (i = 1 to n) and climatic zone (j = 1 to m), tonnes d.m. ha^{-1} yr^{-1}

CF = carbon fraction of dry matter (default = 0.5), tonnes C $(\text{tonne d.m.})^{-1}$

For this study, area of forest remaining forest was not stratified by forest type or climatic zone and thus the summation in Equation 3.2.4 is not needed. Annual average increment rate can be calculated using Equation 3.2.5 from the GPG.

EQUATION 3.2.5
AVERAGE ANNUAL INCREMENT IN BIOMASS

$G_{TOTAL} = G_W \bullet (1 + R)$ **(A)** In case aboveground biomass increment (dry matter) data are used directly. Otherwise G_W is estimated using equation B or its equivalent

$G_W = I_V \bullet D \bullet BEF_1$ **(B)** In case net volume increment data are used to estimate G_W.

Where:

G_{TOTAL} = average annual biomass increment above and belowground, tonnes d.m. ha^{-1} yr^{-1}

G_W = average annual aboveground biomass increment, tonnes d.m. ha^{-1} yr^{-1}; Tables 3A.1.5 and 3A.1.6

R = root-to-shoot ratio appropriate to increments, dimensionless; Table 3A.1.8

I_V =average annual net increment in volume suitable for industrial processing, m^3 ha^{-1} yr^{-1}; Table 3A.1.7

D = basic wood density, tonnes d.m. m^{-3}; Table 3A.1.9

BEF_1 = biomass expansion factor for conversion of annual net increment (including bark) to aboveground tree biomass increment, dimensionless; Table 3A.1.10

Here the average aboveground biomass increment, root-shoot-ratio, and biomass expansion factor were identified using the aggregate values presented in the GPG. Annual changes in carbon stock due to biomass loss in forests remaining forests can be estimated using Equation 3.2.6 in the GPG.

EQUATION 3.2.6
ANNUAL DECREASE IN CARBON STOCKS DUE TO BIOMASS LOSS IN FOREST LAND REMAINING FOREST LAND

$$\Delta C_{FF_L} = L_{fellings} + L_{fuelwood} + L_{other\ losses}$$

Where:

ΔC_{FF_L} = annual decrease in carbon stocks due to biomass loss in forest land remaining forest land, tonnes C yr^{-1}

$L_{fellings}$ = annual carbon loss due to commercial fellings, tonnes C yr^{-1} (See Equation 3.2.7)

$L_{fuelwood}$ = annual carbon loss due to fuelwood gathering, tonnes C yr^{-1} (See Equation 3.2.8)

$L_{other\ losses}$ = annual other losses of carbon, tonnes C yr^{-1} (See Equation 3.2.9)

Unfortunately, estimating changes in carbon stocks associated with other losses involves detailed data on forest disturbances which was not available to me. For that reason, in this study $L_{other\ losses}$ is assumed to be 0. Annual carbon loss due to commercial fellings is estimated using Equation 3.2.7 from the GPG.

$$\textbf{EQUATION 3.2.7}$$
$$\textbf{ANNUAL CARBON LOSS DUE TO COMMERCIAL FELLINGS}$$
$$L_{fellings} = H \bullet D \bullet BEF_2 \bullet (1 - f_{BL}) \bullet CF$$

Where:

$L_{fellings}$ = annual carbon loss due to commercial fellings, tonnes C yr^{-1}

H = annually extracted volume, roundwood, $m^3\ yr^{-1}$

D = basic wood density, tonnes d.m. m^{-3}; Table 3A.1.9

BEF_2 = biomass expansion factor for converting volumes of extracted roundwood to total aboveground biomass (including bark), dimensionless; Table 3A.1.10

f_{BL} = fraction of biomass left to decay in forest (transferred to dead organic matter)

CF = carbon fraction of dry matter (default = 0.5), tonnes C (tonne d.m.)$^{-1}$

Data on annual roundwood production is available from the Food and Agriculture Organization of the UN. For this study, average values from 2006-2010 and 2010-2015 were used for the estimation of carbon stock changes. Basic wood density and the second biomass expansion factor were also provided at an aggregate level by the GPG. For a Tier 1 approach, the GPG suggests assuming that any removal of biomass due to commercial fellings is a total removal. In other words, F_{bl} is assumed to be zero. Annual carbon loss due to fuelwood gathering can be estimated using Equation 3.2.8 from the GPG.

$$\textbf{EQUATION 3.2.8}$$
$$\textbf{ANNUAL CARBON LOSS DUE TO FUELWOOD GATHERING}$$
$$L_{fuelwood} = FG \bullet D \bullet BEF_2 \bullet CF$$

Where:

$L_{fuelwood}$ = annual carbon loss due to fuelwood gathering, tonnes C. yr^{-1}

FG = annual volume of fuelwood gathering, $m^3\ yr^{-1}$

D = basic wood density, tonnes d.m. m^{-3}; Table 3A.1.9

BEF_2 = biomass expansion factor for converting volumes of extracted roundwood to total aboveground biomass (including bark), dimensionless; Table 3A.1.10

CF = carbon fraction of dry matter (default = 0.5), tonnes C (tonne d.m.)$^{-1}$

As before, data on the annual volume of fuelwood gathering is available from the FAO and average values from 2006-2010 and 2010-2015 were used to estimate carbon stock changes.

For agricultural land remaining agricultural land, changes in biomass can be estimated using Equation 3.3.1 in the GPG.

EQUATION 3.3.1

ANNUAL CHANGE IN CARBON STOCKS IN CROPLAND REMAINING CROPLAND

$$\Delta C_{CC} = \Delta C_{CC_{LB}} + \Delta C_{CC_{Soils}}$$

Where:

ΔC_{CC} = annual change in carbon stocks in cropland remaining cropland, tonnes C yr^{-1}

$\Delta C_{CC_{LB}}$ = annual change in carbon stocks in living biomass, tonnes C yr^{-1}

$\Delta C_{CC_{Soils}}$ = annual change in carbon stocks in soils, tonnes C yr^{-1}

Unfortunately, estimating annual change in carbon stocks in soils requires the ability to stratify data by soil type. In the absence of a soil map or similar data set, that change in stock was not estimated in this study. Annual change in carbon stocks in living biomass can be estimated using Equation 3.2.2 from the GPG, the same equation used to estimate that change in forests which remain forest, excluding considerations of belowground biomass. However, when that calculation is broken down it assumes that there is a total removal of biomass in an agricultural area after a certain number of years (termed a harvest cycle). For tropical wet climates like Cambodia, the Tier 1 aggregate value for the length of that cycle is 5 years. Since the course of this study essentially takes place over two five year increments, net change in agricultural areas would have essentially summed to zero. Because of that, no estimates were produced of changes in carbon stocks in lands remaining agriculture.

Just as with cropland remaining cropland annual changes in carbon related to conversion to agriculture are the sum of changes associated with both living biomass and soil carbon. Since estimating changes in soil carbon require soil type stratified data they were not produced in this study. Annual change in biomass from lands converted to agriculture can be estimated using

Equation 3.3.8 from the GPG

EQUATION 3.3.8
ANNUAL CHANGE IN CARBON STOCKS IN LIVING BIOMASS IN LAND CONVERTED TO CROPLAND

$$\Delta C_{LC_{LB}} = A_{Conversion} \bullet (L_{Conversion} + \Delta C_{Growth})$$

$$L_{Conversion} = C_{After} - C_{Before}$$

Where:

$\Delta C_{LC_{LB}}$ = annual change in carbon stocks in living biomass in land converted to cropland, tonnes C yr^{-1}

$A_{Conversion}$ = annual area of land converted to cropland, ha yr^{-1}

$L_{Conversion}$ = carbon stock change per area for that type of conversion when land is converted to cropland, tonnes C ha^{-1}

ΔC_{Growth} = changes in carbon stocks from one year of cropland growth, tonnes C ha^{-1}

C_{After}= carbon stocks in biomass immediately after conversion to cropland, tonnes C ha^{-1}

C_{Before}= carbon stocks in biomass immediately before conversion to cropland, tonnes C ha^{-1}

For a Tier 1 approach carbon remaining in biomass immediately after conversion is assumed to be zero, and changes in carbon from a year of crop growth along with initial biomass carbon stocks before conversion are provide by the GPG.

There are no current methods for assessing the carbon implications of land remaining urban or water, so no estimates of stocks for those areas were made in this study.

Results:

Two classification maps were produced of the study area, one for each time period (2006-2010 and 2010-2015) examined in the study. Figures 2 and 3 show the results of that classification.

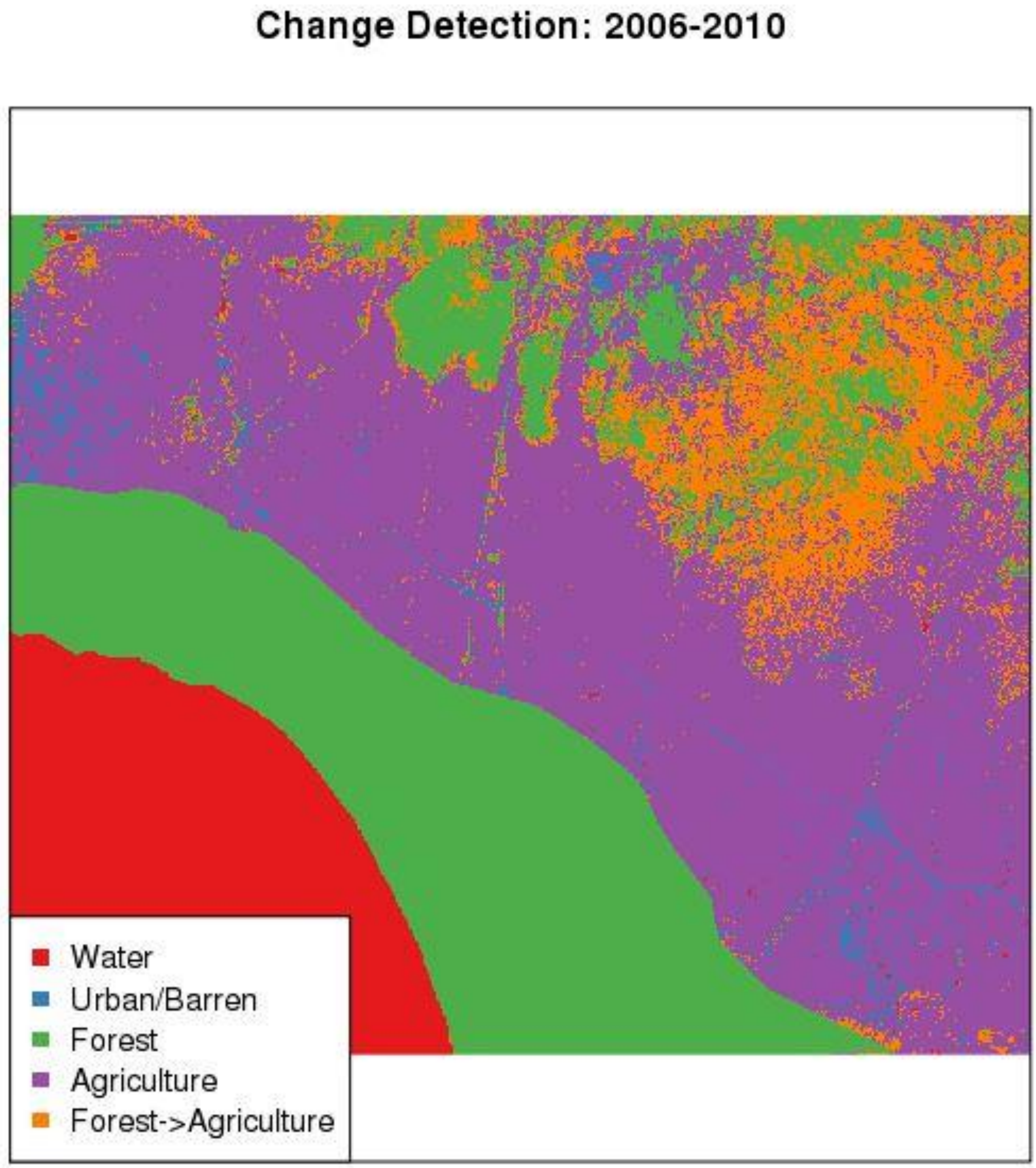

Figure 3: Multi-date Classification of the Study Area: 2006-2010

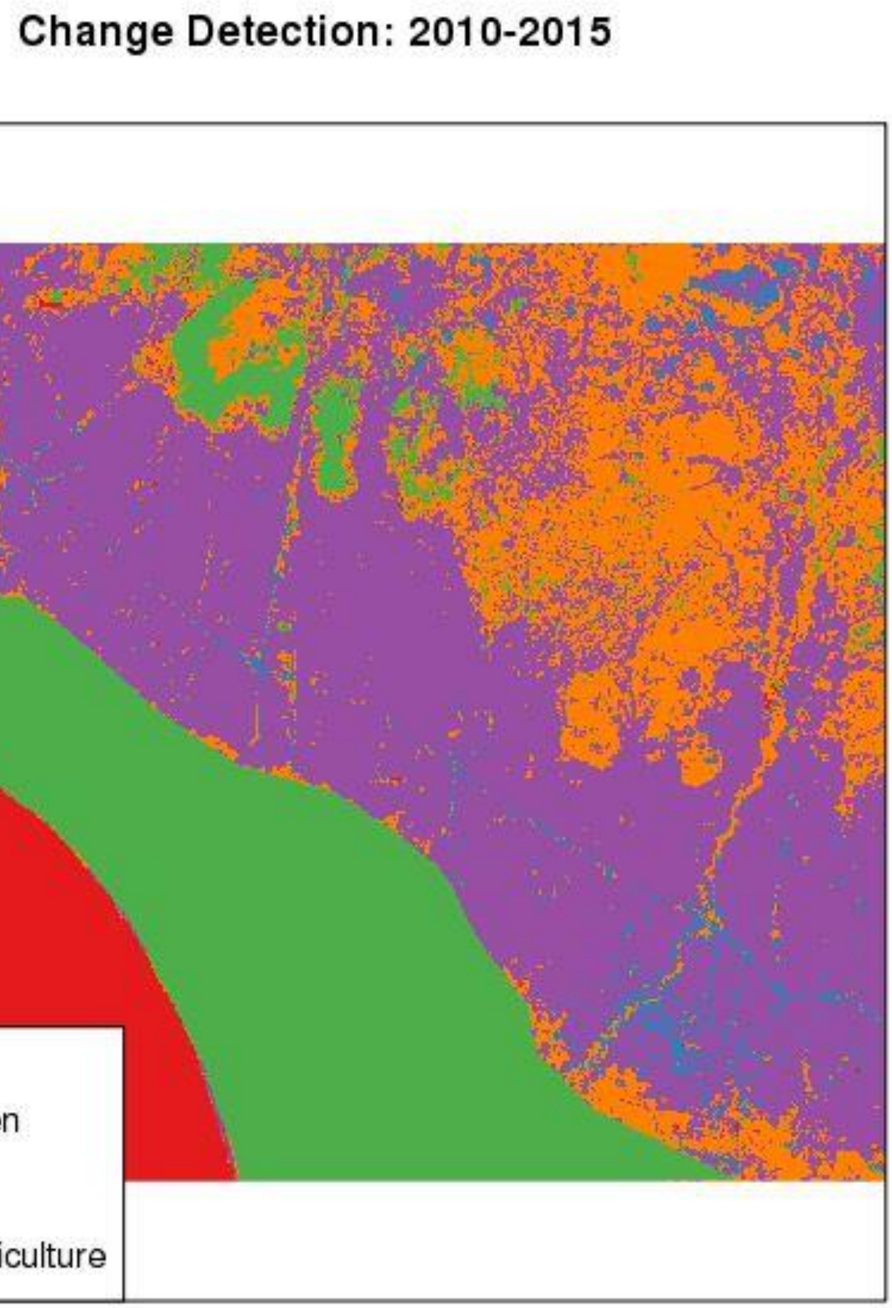

Figure 3: Multi-date Classification of the Study Area: 2010-2015

We can see from these maps, that there is a relatively high rate of conversion of forest to agricultural land, particularly in the northeast portion of the image. Indeed, according to our classification there is hardly any forest remaining in what was once one of the more forested areas of the entire map (outside of the flooded forest surrounding the Tonle Sap).

The classification exercise was only somewhat successful, with both maps achieving an overall accuracy between 60 and 65%. Despite that, we are still able to use the confusion matrix to calculate the (relatively wide) 95% confidence interval for each area estimate. Tables 1 and 2 show the confusion matrix for each classification while Tables 3 and 4 show area estimates and 95% confidence intervals for each classification.

Table 1: Confusion Matrix for 2006-2010 Classification

	Map-Water	Map-Barren/Urban	Map-Forest	Map-Agriculture	Map-Forest->Agriculture	Total
Ref-Water	48	0	0	1	0	49
Ref-Barren/Urban	0	11	0	2	0	13
Ref-Forest	1	6	45	3	15	70
Ref-Agriculture	1	33	2	43	20	99
Ref-Forest->Agriculture	0	0	3	1	15	19
Total	50	50	50	50	50	250

Table 2: Confusion Matrix for 2010-2015 Classification

	Map-Water	Map-Barren/Urban	Map-Forest	Map-Agriculture	Map-Forest->Agriculture	Total
Ref-Water	50	0	0	0	0	50
Ref-Barren/Urban	0	9	0	1	0	10
Ref-Forest	0	11	47	4	18	80
Ref-Agriculture	0	27	1	41	11	80
Ref-	0	3	2	4	21	30

Forest->Agriculture						
	50	50	50	50	50	250

Table 3: Unbiased Area Estimates for 2006-2010 Classification

	Water	Barren/Urban	Forest	Agriculture	Forest->Agriculture
Total	0.1621	0.214075	0.175578	0.254097	0.19395
Total (ha)	7626.052	101.3698	13177.44	28587.01	2097.1
Std. Err	0	0.02638	0.017008	0.026445	0.023105
Std. Err (ha)	0	150.8253	1372.212	3364.648	681.3022
95% CI (ha)	0	295.6176	2689.536	6594.71	1335.352

Table 4: Unbiased Area Estimates for 2010-2015 Classification

	Water	Barren/Urban	Forest	Agriculture	Forest->Agriculture
Total	0.167192	0.186631	0.203613	0.214017	0.228348
Total (ha)	7470.418	95.30496	14419.09	24227.47	2365.151
Std. Err	0.006806	0.022974	0.019293	0.023907	0.024496
Std. Err (ha)	320.2053	131.3515	1556.619	3041.756	722.307
95% CI (ha)	627.6024	257.449	3050.974	5961.842	1415.722

As we can see from the confusion matrices, it was particularly difficult to correctly identify urban areas. This is due to two primary reasons. First, a very small portion of the study area is urban and it was relatively difficult to collect training data for the class. Only ~900 pixels of urban area were used to train the classifiers. Additionally, the highly disaggregated and rural nature of communities in the study area made it difficult to resolve ‘pure’ pixels of urban areas. Nearly every pixel which was classified as urban in the reference sample was muddled to a high degree with agricultural land or vegetation. This mixed pixel issue likely made it very difficult for the classifier to distinguish between urban and agricultural areas, which we can see from the confusion matrix were often misattributed.

Table 5 presents the changes in carbon stocks calculated using the unbiased area estimates for the various land covers. In it, we can see that deforestation and degradation activities in Cambodia are driving a significant decrease in the living biomass carbon stocks in forests. Those decreases are occurring at roughly the same pace in each time period we examined in the study, although the rate is lower for both stocks between 2010 and 2015 than 2006-2010.

Table 5: Total Changes in Carbon Stocks due to REDD+ Activities (tonnes C/year)

REDD+ Activity	Year	Estimate
Forest Biomass	2006-2010	-3.4E+07
	2010-2015	-3.4E+07
Forest->Agriculture Biomass	2006-2010	-1838434
	2010-2015	-1680124

Discussion:

Ultimately, this report has laid out a preliminary framework and methodology for REDD+ reporting in Cambodia. That said, the questionable accuracy and high degree of imprecision in both the estimation of REDD+ activities and the estimation of emissions factors do not inspire a lot of confidence in the specific estimates produced. The general trends of deforestation and degradation driving a decrease in living biomass carbon stocks is almost certainly true to reality, but the relative magnitudes and specific estimates of stock changes are much less trustworthy. The limits of publicly available data severely curtailed which particular stock changes were estimated in this report, and made necessary the use of a Tier 1 approach rather than a more specific (and therefore accurate) Tier 2 or 3 approach. This indicates that one of the biggest obstacles to REDD+ reporting is not necessarily the ability to analyze data, the current guidance documents are very thorough and helpful. Instead, the collecting and organizing huge amounts of supplementary data from a wide variety of sources needed for thorough reporting poses a significant obstacle.

The accuracy of this report, and particularly of the change detection portion, could be improved in several ways. First, in order to limit the effect of clouds and temporal variation in the size of the lake dry season composites could be used rather than single images. This would ensure that the most possible cloud free pixels are included in the images analyzed, and using a compositing algorithm such as minimum Blue could reduce the noise associated with changes in the seasonal flood pattern. Second, if possible, the use of higher spatial resolution imagery (10-20m pixels) than Landsats 30m may help with separating urban areas from the forest and agricultural areas in which they are ingrained. There are obviously costs associated with going to high resolution imagery, particularly literally if one is abandoning a free data source such a Landsat, and the added complexity and expense may not balance out the increase in accuracy.

The presence of such a ‘mixed pixel issue’ suggests that Spectral Mixture Analysis (SMA) is an appropriate tool to apply here. SMA is a regression model that calculates the reflectance as a function of various ‘pure’ endmember spectra in order to estimate their proportional contribution to that pixel. The challenge with applying it to this analysis is that due to the generally small spatial scale of urban activities it may be particularly difficult to identify an endmember for that class as there may be very few if any pure pixels in the dataset to begin with. If that problem can be resolved and appropriate endmembers identified than spectral mixture analysis could likely be applied with great affect to this problem.

The procedure laid out in this paper is relatively easy to follow and represents an implementable preliminary framework for REDD+ reporting in Cambodia. It demonstrates the relative ease of performing remote sensing analysis related to REDD+ activities and provides unbiased estimates for the changes in relevant carbon stocks associated with the study area. There is still a large degree of general and country specific supplementary data need to approach highly accurate estimates of the changes in those carbon stocks, but as the data becomes more available the methodologies with which to apply them will already exist and have been tested.

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