**NASA DEVELOP National Program**



NASA Langley Research Center

*Fall 2015*

El Salvador Ecological Forecasting

Utilizing NASA Earth Observations to Develop a Historically Based

Trajectory of Deforestation and Degradation in El Salvador

 **Technical Report**

Final Draft – November 12, 2015

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# I. Abstract

Tropical rainforests have been recognized as a major contributor to maintaining the global carbon budget and contain a significant portion of the world's biodiversity. However, these ecosystems are threatened by deforestation and forest degradation and require careful management to retain their ecosystem services. La Mancomunidad La Montañona in Chalatenango, El Salvador is home to the critical Rio Lempa watershed where small scale farmers and pastoralists commonly practice slash and burn agriculture. Using NASA Earth observations in collaboration with Ministerio de Medio Ambiente y Recursos Naturales (MARN) and the Earth Institute of Columbia University, Agroforestry for Biodiversity and Ecosystem Services (ABES) Project, a methodology was developed for stakeholders and policy makers to monitor long-term changes in forest cover and identify indicators of forest degradation. A baseline time series showing forest cover and land-use, land-cover from December 1986 to January 2015 was used to forecast forest cover change. These predictions and tools will help assess priority areas for conservation and development of sustainable agricultural practices.

**Keywords**

Remote Sensing, Land Use/Land Cover, Classification, Earth Observing Systems, Landsat, Forecast

# II. Introduction

Forests of Mesoamerica are critical to global ecological stability. These forests support some of the most biodiverse ecosystems on Earth, remove carbon dioxide (CO2) from the atmosphere, and act as a carbon sink in the form of biomass accumulation (Houghton et al. 1991). In addition, in mountainous regions they purify the small streams and rivers which are critical sources of water for isolated rural communities (Rosa et al. 2003). These important forest ecosystems currently face many threats (Herold, et. al 2011). They are frequently exploited for timber, agriculture, and pastoralism, which lead to deforestation and forest degradation. Subsistence farmers in throughout Mesoamerica commonly practice “slash-and-burn” agriculture. In lightly populated regions, this method can be a sustainable practice, but intense agricultural activity make slash-and-burn methods unsustainable. Of the seven countries in Central America, El Salvador has the least forest cover (121,000 hectares) and the highest population density (295 people/km2) (World Bank, 2014; Billings et al. 2004/2).

In La Mancomunidad La Montañona, a mountainous region in Northern El Salvador the forests are being threatened by traditional slash-and-burn agricultural practices. Deforestation and forest degradation has a regional and global impact. The increasing runoff upstream of major rivers within the watershed, severely effects water quality (Paula et al. 2015). In addition, deforestation releases stored carbon into the atmosphere in the form of CO2 simultaneously decreasing the amount being removed through forest growth (Houghton et al. 1991).

The primary objectives of this project are to create a nationally applicable land use and land cover (LULC) classification and a forecast model based on historical imagery. The LULC classification for the years 1986, 1996, 2000, and 2014 uses regionally specific classes; lakes or rivers, forested areas, agricultural or crop land, pastoral plots or pasture, and urban development or roads. The forecast model predicts the extent of future land cover change based on the data derived from the classifications. The project period was based on the longest time series available, 1986-2015. Landsat imagery from the dry season (November to April) was selected to coincide with ancillary data sets provided by project collaborators and end-users.

In collaboration with the NASA DEVELOP El Salvador Ecological Forecasting team, the Agroforestry for Biodiversity and Ecosystem Services (ABES) Project through the Earth Institute (EI) at Columbia University provided field surveys and additional satellite imagery to use as ground truth and satellite calibration data. End-users of the project include La Mancomunidad La Montañona, Chalatenango, El Salvador and the Ministerio de Medio Ambiente y Recursos Naturales (MARN). The ABES project is working as an intermediary to incorporate the end products of this research into tangible results that address the concerns of the local community. The classification of the images from the Landsat archives will create a more complete understanding of past land use and land cover practices as well as an overview of regional trends. The model extrapolates on these trends and highlights high risk areas to inform La Mancomunidad La Montañona decisions in addressing water quality, forest degradation, and deforestation. In addition to helping at the regional scale, the project serves to develop an extensible methodology for national forest monitoring. MARN is in the process of developing strategic policies specially focused on reducing deforestation and degradation at the national scale by implementing Reducing Emission from Deforestation and Degradation (REDD+) guidelines set forth by the United Nations at the United Nations Framework Convention on Climate Change (UNFCCC). Therefore, there is a need to understand historic forest extent and continue to monitor forests with a replicable methodology throughout the country.

The NASA National Science Application area addressed in this project is Ecological Forecasting. The project uses time series images from the study area to examine historic forest change over four epochs. This information will be used to determine regional forest dynamics, including which areas face the greatest risk of deforestation and forest degradation, through a forecast model.

# III. Methodology

The team used the Landsat archive to examine the Pine-Oak forests of Chalatenango. The end users and collaborators have decided the community would benefit the most from historic LULC classification and a forecast model predicting vulnerable areas and extrapolating trends in forest change. For a selection of years between 1986 and 2015, LULC classifications were created identifying forest, pasture, crops, water, and urban land classes in order to gain a better understanding of regional forest dynamics. Scenes from the LULC classifications and addition data sets were inputs to a forecasting model. The methodology is designed to be easily replicable at similar regions of concern. The team is searching for ways to incorporate the Hansen Global Forest Cover data set as a “ground truth” source for regions that lack additional resources, like those provided in this project.

**Data Acquisition**

Landsat 4, 5, 7, and 8 imagery for path 19, row 50, were downloaded from United States Geological Survey (USGS) for the years of 1986-2015 during the dry season, which runs from November to April. An image was downloaded for each season as close to the month of December as possible based on availability, while maintaining minimal cloud cover. This was determined by manually choosing each scene from the USGS Global Visualization (GLOVIS) for the yearly season between the months of November and February.

The ABES Project and MARN provided survey data and additional satellite imagery. The end products and accuracy assessments will use the ABES Field Surveys from the 2012, ground observations that were performed on forest sites ranging from 0.01 hectares to 1 hectare. This data were shared by ABES, who also provided both RapidEye imagery from 2012, 2014, and 2015 of the La Mancomunidad region, a 2010/2011 RapidEye of the whole country, QuickBird imagery of the area from December 2012, and a LULC classification created from the QuickBird imagery.

Additional data were acquired from various open sources. The terrain and elevation layers used as inputs for the forecasting model were acquired from SRTM-1 (SRTM, 2000). The municipalities and country outlines were downloaded from the Global Administrative Areas Database. A global forest cover (GFC) data set for 2014 was obtained from a study conducted by Matt Hansen working in the Department of Geographical Sciences at the University of Maryland (GFC, 2013). This data set comes as raster data with resolution similar to Landsat satellites, both being 30 meters (Hansen et al. 2013).

**Land Use/Land Cover Classification ­– Data Processing**

The data was processed to streamline the production of the two end products through a three-step standardization method. First, all the imagery and additional data was cropped to the extent of the RapidEye imagery, a slightly larger scope than the study area to ensure that influential regions were not excluded. Second, the geospatial data was projected to UTM-16N. Finally, a duplicate of all images were filtered and resampled to match the Landsat 30 m resolution, creating more statistically valid comparisons when assessing accuracy.

**Land Use/Land Cover Classification ­– Data Analysis**

The most accurate LULC was created based on the available ground truth data and its concurrent Landsat imagery by testing several classification methods and software platforms. In order to build the base for the forecast model, four epochs (1986, 1996, 2000, 2014) were selected based on the availability of quality imagery and evenly spaced dates. In ArcGIS a minimum of 20 training sites were drawn in each epoch for water, urban or bare land, forest, crop, and pasture. These classes were identified on the Landsat images using a combination of high resolution imagery, ABES plot classes, band composites, and knowledge of the region.

The first round of training sites were used for the 1986, 1996, and 2000 classifications, but an additional analysis was performed to refine the 2014 classes. The classes were refined based on both logical and statistical methods. The training sites that seemed to be introducing error through placement in ambiguous land cover areas were removed and were placed in less ambiguous spaces. A statistical analysis was then conducted by compiling average and individual training site reflectance values for the entire scene and by class. This helped identify the differences between the spectral responses in all bands, maximizing the use of all available information. Training sites that fell outside of a standard deviation from the average were reevaluated and removed if there was an indication that the land class was not correct. This method also allowed us to identify a critical difference between the two most closely related classes, pasture and crop. The difference between bands 5 and 6 is larger on average for pasture than it is for crop, therefore a new band ratio was created subtracting band 6 from band 5 to help identify this difference. Once all the training sites were refined the classification were run on the same Landsat scene and compared on the basis of their percent similar and accuracy statistics.

**Accuracy Assessment**

An accuracy assessment on the Landsat LULC classifications was performed using ABES field surveys, which consists of ground observations conducted on forest sites ranging from 0.1 hectares to 1 hectare. The first step in calculating accuracy was to convert the ABES field surveys from polygon vector data into point vector data, this allows the use of a tool in ArcGIS called “*Extract Values to Points*”. This tool will pull the pixel value of a raster (in this case the Landsat LULC is the raster) and associate it with the point data (ABES field surveys) within the attribute table. It is very important to run a definition query on the newly formed attribute table that picks out the cases where the raster has a NoData pixel value for the associated survey plot; these can be deleted from the table. Next, the “*Frequency*” tool in ArcGIS creates a summary table detailing which pixels from the raster layer were correctly classified and which were incorrectly classified. An example of where the pixel is correctly classified would be: the field survey value is “Pasture” and the pixel underneath is classified as “Pasture”. An example of an incorrectly classified pixel would be: the field survey value is “Pasture” and the pixel underneath is classified as “Urban” (or anything that isn’t pasture). The summary table is then put into an ArcGIS tool called “*Pivot Table*”. This tool simply rearranges the information in the summary table into a confusion matrix, which is where the numbers used in calculating the accuracy are organized (Table 1.)

Table 1. Confusion matrix used for calculating accuracy of the Landsat LULC classification. The numbers represented in this table are from the ArcGIS maximum likelihood method of classification.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Truth (Field Survey)** | | **Tree** | **Crop** | **Pasture** | **Urban** | **Water** | **Total** |
| ***Predicted***  ***(Raster)*** | **Tree** | 65 | 11 | 11 | 0 | 0 | 87 |
| **Crop** | 20 | 21 | 11 | 0 | 0 | 52 |
| **Pasture** | 25 | 24 | 45 | 0 | 0 | 94 |
| **Urban** | 2 | 4 | 6 | 16 | 2 | 30 |
| **Water** | 1 | 0 | 0 | 0 | 29 | 30 |
| *Total* | | 113 | 60 | 73 | 16 | 31 | **293** |

The overall accuracy is calculated by summing the correctly predicted pixels (values in the light orange cells), dividing the summed value by the total number of predictions (value in the dark orange cell), and then converting the resulting decimal into a percent by multiplying by one hundred. The equation for this calculation is seen below in Figure 1.

**Percent Similarity to Existing LULC Classifications**

Percent Similarity between four methods of Landsat LULC classifications and a LULC classification created from RapidEye 5 meter resolution imagery. Calculating percent similar statistics on pre-existing LULC classifications reinforces claims made by resulting LULC classifications. Four different classification methods were compared to the RapidEye classification: maximum likelihood and unsupervised in ArcGIS, and maximum entropy and random forests in Google Earth Engine. The statistics were calculated for

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Method** | **Forest** | **Water** | **Urban** | **Crop** | **Pasture** |
| **Earth Engine** | *Maximum Entropy* | 81.7 | 98.5 | 95.7 | 73.6 | 73.1 |
| *Random Forest* | 81.7 | 98.5 | 95.7 | 73.6 | 73.1 |
| **ArcGIS** | *Maximum Likelihood* | 82.0 | 99.5 | 96.0 | 68.2 | 69.7 |
| *Unsupervised* | 69.4 | 99.5 | 86.8 | 70.4 | 66.9 |

individual classes forest, water, urban, crop, and pasture; the results from the calculation are shown in Table 2.

Table 2. Percent similar statistics of four LULC classification methods. Statistics are for individual classes within the LULC forest, water, urban, crop, and pasture.

Before each calculation the rasters are reclassified into boolean “Forest” and “Non-Forest” classes with pixels values of “1” and “0”, respectively. Raster addition was then performed on the newly reclassified rasters, producing a new raster with values “0”, “1”, and “2”. Resulting pixels with a value of “0” and “2” mean the pixel values from the two rasters agree (an example, the pixel value for the Landsat LULC is equal to “1”, and the other LULC also has a pixel value equal to “1”, giving the pixel a value of “2” in the resulting raster). Resulting pixels with a value of “1” mean the pixel values do not agree. For each class the total number of correct pixels divided by the total number of pixels in the study area will give the percent similarity in decimal form, to convert this to an actual percent simply multiply by one hundred.

**Forecast Model**

Finally, the data were processed to become four separate driver variables for the forecast model. The influence of urban areas and water on all classes were determined to be the strongest so the classifications were used to create nearness rasters in ArcGIS for urban and water land cover classes. In order to account for the slope in predicting changes in land use the SRTM data was converted to percent slope. Finally, a layer of roads downloaded from open source map was converted to a raster with primary, secondary, and tertiary roads.

The forecast model was produced using Clark Labs Terrset Land Change Modeler, which also is available as an ArcGIS extension. The program was setup to model the land use land cover changes between the earliest image from 1986 and the latest image from 2014. The overall change in land use and land cover was examined for each classification. The ArcGIS Maximum likelihood classification was used in the forecast model because, the changes observed over this time period aligned most closely with the changes that would have been predicted. Forest area was lost, urban area increased, water remained nearly the same, and crop and pasture showed less predictable fluctuations. Each potential land use land cover transition was then modeled using the aforementioned variables determined to be drivers of change. Following this, the model was set to forecast change to the year 2030.

**Global Forest Cover Validation – Data Processing**

Two rasters were used in this method, the GFC and the QuickBird LULC classification rasters. The extent of the QuickBird image is much smaller than the GFC extent and the study area defined by RapidEye. Therefore, the GFC was clipped to the extent of the QuickBird LULC classification to remove as many NoData values as possible. Since the QuickBird imagery has much higher resolution (2.4 meters) the raster was resampled to match the resolution of Landsat at 30 meters. These two steps ensured the pixels lined up to create a smooth analysis. Finally the QuickBird image was resampled into “Forest” and “Non-Forest” classes.

**Global Forest Cover Validation – Data Analysis**

Using a Python script in ArcGIS, the 2014 GFC raster was replicated and reclassified ninety-nine times. For each iteration a threshold pixel value ranging from 1 to 100 was set, all values above the threshold are considered Forest and assigned a value of “1”. The threshold value and all those below are considered Non-Forest and assigned a value of “0”. Percent similarity was then calculated to determine which percent threshold forest cover from the GFC associates best with the “Forest” class from the Quickbird LULC classification. The percent similarity was calculated by performing raster math. The first step overlays the Quickbird raster with the different GFC rasters ensuring the pixel cells aline properly. It then adds individual pixel values from the GFC data to the corresponding pixel value from the Quickbird raster. Resulting in a raster containing three different pixel values: “0”, “1”, and “2”. A value of “0” following the addition implies that both the GFC and the QuickBird rasters classified their pixel as Non-Forest. A pixel value of “1” after addition means the rasters did not agree. A value of “2” implies both rasters classified their pixels as Forest. Table 3. details the possible combinations of raster addition and their resulting values.

|  |  |  |  |
| --- | --- | --- | --- |
| GFC Pixel Value | QuickBird  Pixel Value | Result  Pixel Value |  |
| 0 | 0 | 0 | Match - “Correct” |
| 1 | 1 | 2 |
| 1 | 0 | 1 | No Match - “Incorrect” |
| 0 | 1 | 1 |

The number of pixels whose values are either “0” or “2” in the result raster were added together and divided by the total number of pixels in the image. The percent similarities values produced from the script were exported to an excel document and then graphed. It was determined that a threshold at 28% tree cover was closest to the QuickBird image being 72.475% similar. Although the Fall 2015 team did not analyze the GFC data beyond determining the best percent threshold, future work is discussed later within the conclusions section of this paper.

Table 3.

# IV. Results & Discussion

The map produced by each LULC classification method had slightly different results (See appendix A1), which initially appear to be more or less correct at a qualitative level. The unsupervised classification was the least correct and clearly over identified forest extent and failed to clearly outline any urban areas. The max entropy and the random forests classifications were similar and appear to identify more forest cover and more variance in land use than the maximum likelihood classification.

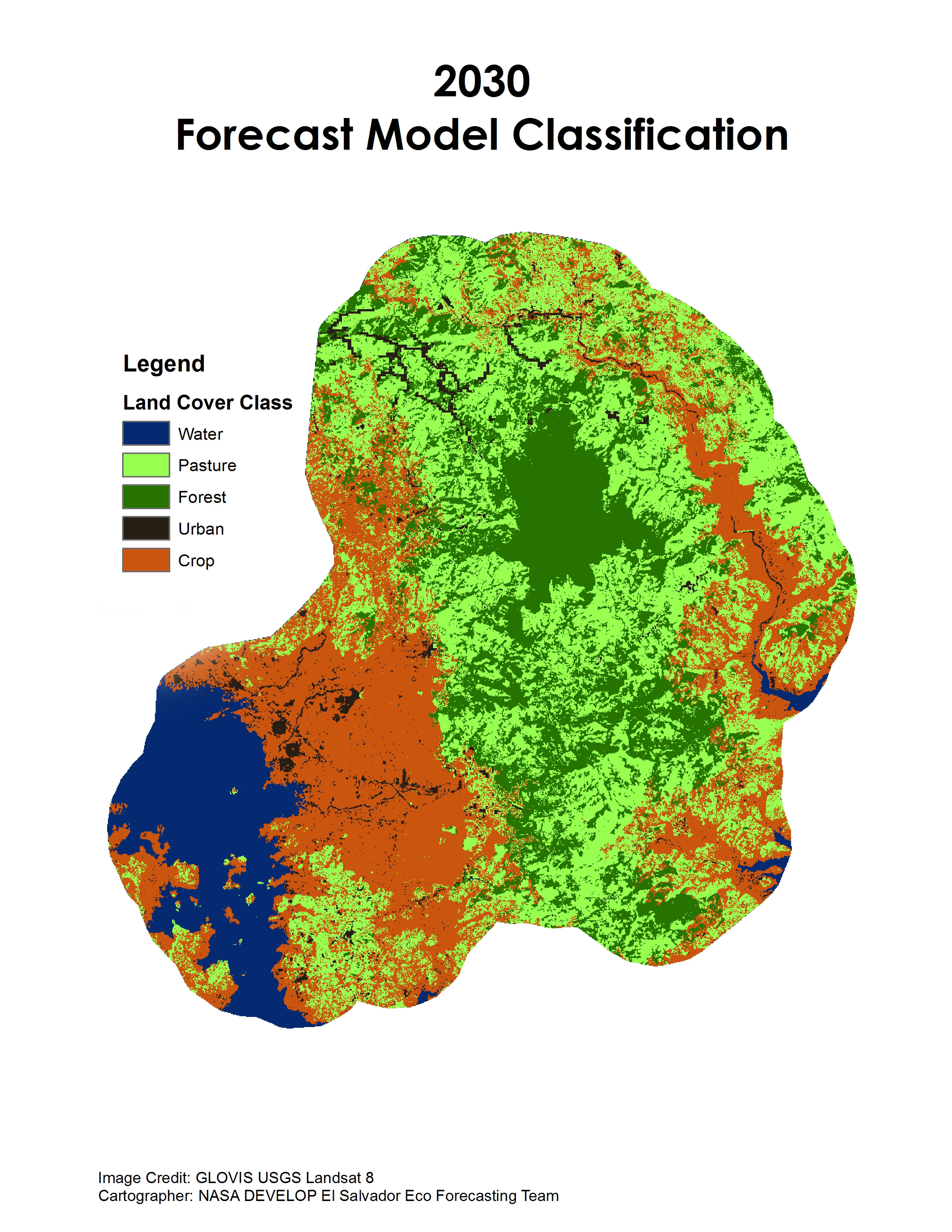
In order to assess the ideal classification method, an assessment was required at the quantitative level. The validity was checked by measuring percent similarity statistics and accuracy assessment calculations, respectively. Percent similar statistics were calculated on an individual class basis and the results can be seen in Table 4.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ***Truth (Field Survey)*** | | **Tree** | **Crop** | **Pasture** | **Urban** | **Water** | *Total* |
| ***Predicted***  ***(Raster)*** | **Tree** | 65 | 11 | 11 | 0 | 0 | 87 |
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| **Urban** | 2 | 4 | 6 | 16 | 2 | 30 |
| **Water** | 1 | 0 | 0 | 0 | 29 | 30 |
| *Total* | | 113 | 60 | 73 | 16 | 31 | **293** |

Table 4. Confusion matrix used for calculating accuracy of the Landsat LULC classification. The numbers represented in this table are from the ArcGIS maximum likelihood method of classification.

The information gained from Table 4 indicates the classification tools and methods in Google Earth Engine produce similar results to existing the LULC classifications produced from high resolution imagery. Water and Urban classes are the easiest to correctly classify, while Forests are moderately easy, leaving Crop and Pasture as the two most difficult classes to differentiate. The percent similar statistic is not the most robust measure of the LULC classification accuracy, because it relies entirely on the accuracy of another LULC map. Although, this statistic can give some indication of how well a classification method performs, especially in contrast to other methods, an accuracy assessment using ground truth is a more valid measure. Percent accuracy statistics were calculated based on plot surveys and the results can be seen in Table A-1.

The overall accuracy was measured at 60.1% for the 2014 maximum likelihood classification.  This is much lower than the percent similar statistic, but is also an indicator of how varied the land use patterns are in the region. The confusion matrix indicates where the misclassifications are arising. It seems that the most common error was an over identification of trees as crops and trees as pasture. There was also some under identification with the opposite errors. This indicates that not only was it difficult to distinguish between crop and pasture as the percent similar statistic showed, but also that it was difficult to differentiate between forest, crop, and pasture. There were a few errors distributed in the urban statistic and the water proved to fairly accurate. Further refinement of the training sites for forest, pasture, and crop might improve the accuracy of the classification. One approach might look at, or even use in classification, images across multiple seasons through 2014 to identify crops more accurately. The smallholder agriculture is always likely to result in some misclassification given that the land use changes so frequently, but there is undoubtedly room for improvement in the identification of forest cover and the errors between the three most inaccurate classes.

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The forecast model predicting land use and land cover change to the year 2030 shows a positive, but unlikely future for La Mancomunidad La Montañona. The forests in the region seem to have increased around the core primary forest while crop land around the urban areas and along the river banks appears to have consolidated. Additionally some urban areas have grown, but others are predicted to return to forest and pasture land (see image). These predicted trends, especially the last transition from urban to forest, seem unlikely to take place given current practices and observations. Therefore our results indicate that the forecast model is unlikely to be very accurate. This inaccuracy could be due either to the inputs or the definition of the model.

A likely source of error was introduced to the model through its inputs. The fact that the original LULC map for 2014 was only 60.1% accuracy introduces inherent error to the forecast. As the LULC classifications undergo the aforementioned refinement, it is possible that the forecast model would begin to show a more accurate prediction.

There are also at least two possible errors which arise from the way that the model was defined or in other words specification errors. The first is the choice of transition driver variables. As shown in Appendix A1 each transition was modeled from the same set of 5 different variables, which were included based on their theoretical influence. Additional variables could be unaccounted for or the existing variables could be refined to only include those that had a statistically significant effect. The second is the end of the civil war in 1992, which falls in between the model’s base years. This could be a major confounding event, because it had significant implications for land use trends. If the earlier year in the model was changed to years following the end of the civil war it might gain accuracy.

# V. Conclusions

The results presented in this paper have sources of error that can be reduced or corrected with more time. Following the conclusion of the Fall 2015 term this project will be continued by the Spring 2016 El Salvador Ecological Forecasting team. Much of the work conducted during this term was geared toward being a precursor for the research to be done in the Spring 2016 term. Further refinement of training sites used in the LULC classification will help increase the overall accuracy of the classification. More accurate inputs for the forecasting model, including LULC classifications and other ancillary variables listed previously, will also increase the predicting capabilities of this software. Incorporating the Hansen GFC dataset is meant to broaden the scope of applicability for this methodology. Validating the accuracy of the global dataset at a regional scale allows for regional end-user such as MARN to apply the methods used in this paper to other regions that may lack the ground truth data necessary for a proper accuracy assessment of the resulting LULC classification.

# VI. Acknowledgments

# VII. References

Billings R.F., S.R. Clarke, V. Espino Mendoza, P. Cordón Cabrera, B. Meléndez Figueroa,

J. Ramón Campos and G. Baeza. 2004/2. Bark beetle outbreaks and fire: a devastating combination for Central America’s pine forests. *An international journal of forestry and forest industries, 55: 16-21.*

Garcia and Gonzalez. 2004. Change in oak to pine dominance in secondary forests may reduce shifting agriculture yields: experimental evidence from Chiapas, Mexico. *Agriculture, Ecosystems and Environment*, 102:389-401.

Global Forest Change (GFC) 2000-2014 Data Download Version 1.2 Hansen M., et al.

Hansen M., et. al, 2013 "High-Resolution Global Maps of 21st Century Forest Cover Change." Science.

Herold M., R.M. Roman-Cuesta, D. Mollicone, Y. Hirata, P. Van Laake, G.P. Asner, C. Souza, M. Skutsch, V. Avitabile, and K. MacDicken. 2011. Options for monitoring and estimating historical carbon emissions from forest degradation in the context of REDD+. *Carbon Balance and Management*, 6:13.

Houghton R.A., D.L. Skole, and D.S. Lefkowitz. 1991. Changes in the landscape of Latin America between 1850 and 1985: II a net release of CO2 into the atmosphere. *Journal of Forest Ecology and Management*, 38:133-199.

Paula M.D., J. Groeneveld, and A. Huth. 2015. Tropical forest degradation and recovery in fragmented landscapes -- Simulating changes in tree community, forest hydrology and carbon balance. *Global Ecology and Conservation*, 3: 664-677.

Rosa H., I. Gomez, S. Kandel. 2003. Gestión territorial rural: Enfoque, experiencias y lecciones de Centroamérica. PRISMA.

SRTM Digital Elevation Data 30m, 2000 USGS Data Pool accessed via Google Earth Engine

# VIII. Content Innovation

* Virtual Poster Session
* Interactive Map Viewer
* Interactive Glossary

# IV. Appendices

**Table A1 - Landsat 4/5 TM Band Composites and Ratios Used to Identify Land Cover and Land Use Class**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Land Use/Land Cover Class | | | | |
| Composite/Ratio | Water | Pasture | Forest | Urban | Crop |
| TM 3/4 |  |  |  | x |  |
| TM 4/3 |  |  | x |  |  |
| TM 3/2 |  |  | x |  | x |
| TM 7/2 |  |  | x |  | x |
| TM 5 - 4 |  | x |  |  | x |
| 7,4,2 |  | x | x |  | x |
| 5,4,3 |  |  | x |  |  |
| ‘True Color’ 3,2,1 | x | x | x | x | x |
| ‘False Color’ 4,3,2 |  |  |  | x | x |
| NDVI |  |  | x |  | x |

**Table A2 - Landsat 8 OLI Band Composites and Ratios Used to Identify Land Cover and Land Use Class**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Land Use/Land Cover Class | | | | |
| Composite/Ratio | Water | Pasture | Forest | Urban | Crop |
| TM 4/5 |  |  |  | x |  |
| TM 5/4 |  |  | x |  |  |
| TM 4/3 |  |  | x |  | x |
| TM 8/3 |  |  | x |  | x |
| TM 6 - 5 |  | x |  |  | x |
| 7,5,2 |  | x | x |  | x |
| 6,5,3 |  |  | x |  |  |
| ‘True Color’ 4,3,2 | x | x | x | x | x |
| ‘False Color’ 7,6,4 |  |  |  | x | x |
| NDVI |  |  | x |  | x |