**NASA DEVELOP National Program**



NASA Langley Research Center

*Spring 2016*

El Salvador Ecological Forecasting II

Utilizing NASA Earth Observations to Predict Deforestation and Degradation in El Salvador

 **Technical Report**

Rough Draft – March 31, 2016

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# I. Abstract

Tropical forests are vital ecosystems because of their rich biodiversity and carbon sequestration abilities. Unfortunately, due to a number of factors, these forests are threatened by deforestation and forest degradation and are in need of comprehensive management strategies. The conservation of forests is not only vital for biodiversity but also for the ecosystem services they provide. The micro-region of La Mancomunidad La Montañona in Chalatenango, El Salvador is a hilly area with a population dependent upon subsistence and livestock farming, often utilizing slash and burn agricultural techniques. Using NASA Earth observations in collaboration with El Salvador’s ministry of the environment, Ministerio de Medio Ambiente y Recursos Naturales (MARN), the Earth Institute at Columbia University, and 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 to predict significant changes in woody forest biomass. A baseline time series showing forest cover and land use land cover (LULC) from December 1986 to January 2016 was used to forecast forest cover change through the year 2030. These predictions will allow stakeholders to identify at-risk regions to focus forest conservation efforts and management strategies.

**Keywords**

Remote sensing, GIS, Google Earth Engine, TerrSet, Land Change Modeler, Chalatenango, REDD+

# II. Introduction

Tropical forests provide vital environmental and ecosystem services. As carbon sinks, forests remove 3.6 billion metric tons of carbon per year; however, tropical deforestation releases 2.7 billion metric tons annually (Reich, 2011). This destructive activity reduces the yearly net forest carbon sink to about 1 billion metric tons, one-seventh of annual fossil fuel emissions (Reich, 2011). Forests also play a crucial role in regulating the nutrient cycle and maintaining soil stability. Deforestation for agricultural purposes often leads to soil erosion and nutrient leaching. Trees maintain soil quality by providing organic matter from fallen leaves and branches. Their roots anchor the soil and prevent it, and the nutrients within it, from washing away, also helping to maintain watersheds (Vitousek & Sanford, 1986). Additionally, tropical forests are essential to global biodiversity as they contain over 50% of the world’s species, including 80% of all insects and 90% of primates (Houghton, Skole, & Lefkowitz, 1991).

Central America is home to 22,411 ha of tropical forest. From 1990 to 2005 Central American forest cover decreased by approximately 20% (Khatun, 2011). The primary causes of this deforestation were population growth and land use change (Redo et. al. 2012, Kahtun, 2011). The effects of deforestation in Central America are not just restricted to this region. Biologists have linked a decline in North American migratory bird species, such as the wood thrush, to the loss of forests in Central America given that three of the four major flyways connecting the Americas pass through Central America (Finch, 1991).

Like much of Central America, El Salvador has experienced extensive deforestation. High population density, coupled with poor enforcement of environmental regulations and unsustainable farming techniques, have been driving forces of deforestation (World Bank, 2014). Today, only 2% of El Salvador’s primary forest remains, the smallest amount in Latin America (Rainforest Alliance). The main contributors to this have been slash and burn techniques used by many farmers, known as Tavy farming, and urban expansion. Tavy farming is exceptionally harmful because it quickly depletes soils of their nutrients. This not only creates a need for plot expansion, but also makes it difficult for forest regrowth efforts to be successful (Hetch & Sattchi, 2007).

From 1980 to 1992, El Salvador experienced a civil war that led to a mass emigration of 25% of the population (Hetch & Sattchi, 2007; Gammage 2007). Carpet bombing and destructive land campaigns resulted in the desolation of crops and forests (Weinberg 1997). However, the reduction in agricultural and pastoral practices allowed for some successional forests to emerge in previously cultivated areas. The conclusion of the civil war led to rapid urbanization with the return of the war refugees (Hetch & Sattchi, 2007). In the post war era, environmental conservation started to become a priority. The government signed the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 and the Kyoto Protocol in 1998 (UNFCCC). In 1997, President Armando Calderon Sol issued a presidential decree creating a national ministry of the environment, Ministerio de Medio Ambiente y Recursos Naturales (MARN) (Foley & Hapipi, 2005). More recent initiatives include a push to implement sustainable farming techniques, such as agroforestry, preparations for REDD+ implementation, and development of a payment for ecosystem services (PES) plan. These programs are necessary to the preservation of what little primary forest remains and to expand environmental conservation efforts nationally.

The micro-region of La Mancomunidad La Montañona in Chalatenango, El Salvador is home to a pine oak forest with both ecological and cultural importance. The communities of La Montañona, the country’s capital of San Salvador, and other regions downstream, rely on the pine oak forests to maintain local stream and river quality (Balkan). The population of this hilly area is dependent upon subsistence and livestock farming, often utilizing slash and burn agricultural techniques which threaten the surrounding forest (Balkan).

This project addresses the National Application Areas of Ecological Forecasting. It contributes to this application area by utilizing historical land classifications and providing the partner with forecasted land classifications which provides essential data used to develop a REDD+ strategie, a United Nations program focused on reducing emissions from deforestation and forest degradation in developing countries. The overall objective of the project is to develop a methodology for monitoring and forecasting ecological change in the La Mancomunidad La Montañona region in El Salvador by analyzing data from December 1986 - January 2016. MARN and other end-users will use this methodology to anticipate potential locations at risk of deforestation, allowing them to determine where to focus land use management and future REDD+ strategies at a national level.

# III. Methodology

**Data Acquisition**

Atmospherically corrected images from the Landsat 5 TM and Landsat 8 OLI satellites were extracted from the United States Geological Survey (USGS) for path 19, row 50 for the six focus years during the study period. These images were representative of the dry seasons for the study area which occurs from November to April. For consistency with the Fall 2015 term, additional images chosen were those with minimal cloud cover over the area of interest and as close to the month of December for each new year selected, 2009 and 2015. ABES provided RapidEye imagery for the 2015 season in addition to plot data in vector format which contained ground reference information at each point.

**Table 1. Earth Observing Systems and High Resolution Satellite Imagery**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Satellite** | **Source** | **Resolution** | **Research Use** | **Year Acquired** |
| **Landsat 4/5 TM** | USGS GLOVIS | 30 m | Land Use/Land Cover | December 1986, January 1997, February 2001, January 2010 |
| **Landsat 8 OLI** | USGS GLOVIS | 30 m | Land Use/Land Cover | January 2014, January 2016 |
| **RapidEye** | Project Collaborators (ABES) | 5 m | Ground Truth for Land Use Land Cover | December 2015 |

Data used for the forecasting model were collected from various open-sources. The digital elevation model and municipalities and country outlines were provided by the Fall 2015 from the Shuttle Radar Topography Mission (SRTM-1 Arc-Second Global, 2000) and the Global Administrative Areas Database respectively. The shapefile containing information of the roads system within the study area was collected from Open Street Map.

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

Preprocessing and projection of the images was unnecessary for this project since Google Earth Engine (GEE) provides a simplistic platform in which top of the atmosphere (TOA) images are extracted from USGS and automatically projected onto the base map. Images were cropped to the extent of the classified 2015 RapidEye imagery using a Google Fusion Table. Images were filtered to remove any ‘null’ value pixels.

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

The GEE platform, using maximum entropy and random forest classification methods, produce land use and land cover (LULC) maps for the six NASA Landsat images and the 2015 RapidEye image. While GEE is a user-friendly software, some knowledge of JavaScript or Python language is necessary to utilize the platform to its full potential. Provided scripts from GEE’s API guide were modified for use to produce the LULC maps. Review and refinement of the fusion tables created during the Fall 2015 term for class categories was performed. Training site quantity was increased from the Fall 2015 term from 20 sites per category to a minimum of 30 sites per category within ArcGIS. The increase to 30 training sites for each category was chosen in order for the results of each classification to be statistically significant and to improve overall classification accuracy. Additionally, the class categories were reduced from five to four due to complications of differentiating between pasture and croplands caused by the similarities of spectral reflectances. Pasture and croplands were combined into one class, rural/non-forest, leaving all others the same. The classifications used were: water, rural/non-forest (RNF), forest, and urban. Classes were identified by referencing a combination of high-resolution imagery, ABES plot classes ground reference data, and Google Earth. Various band composites enabled the visual distinction between closely related classes (Table A-2). After the best training sites were drawn, a supervised classification was performed through a modified script in GEE for each method. GEE could access the dataset through Google Fusion Tables created using data from the ArcGIS training sites. Bands used in the classification process are shown in Table A-3. Since for-loops are discouraged within GEE, each year was assigned an individual code for classification purposes.

**Accuracy Assessment – Land Cover Validation**

Confusion matrices, kappa coefficients, producers and consumers accuracies for the seasonal years of 2014 and 2015 were created in GEE by incorporating the appropriate scripts to compare the accuracy of the training sites to the ground truth data supplied by the classified 2015 RapidEye imagery. The RapidEye imagery was resampled to a pixel size of 30 meters during this process for consistent resolution and comparison. Results of the overall accuracy, confusion matrix tables, and kappa coefficients were extracted from the console within GEE.

**Quantifying Land Use Changes**

GEE supplied the ability to quantify the land use classifications by calculating the area of each pixel located within a vector shapefile outlining the area of interest. Each class area within the individual year of interest was quantified this way in order to produce a line graph to visualize the changes in land use over the historical time-line. The line graph was created through Excel using the areas generated in GEE, which housed each class areas in km2.

Rate of change for rural/non-forest, forest, and urban was calculated using the equation Rate of Change=[(Area Latter-Area Former)(Area Former)]100. The rate of change for each class was used to produce a line graph in Excel.

**Land Change Forecast – Data Processing**

Preprocessing of the data used in the forecasting model were conducted within ArcGIS. Classified images were exported from GEE into a .tif file, uploaded into ArcGIS, and reclassified as follows: 1 - Water, 2 - RNF, 3 - Forest, 4 - Urban, 0 - NoData. These images were then exported as an ‘Imagine Image’ for use in TerrSet. The digital elevation model was corrected for the sinks identified within the image. This allowed for the delineation of the watershed and drainage areas using spatial analyst and hydrology tools.

Variables used in the forecasting model were: distance to water, distance to roads, elevation, slope, and aspect. Distance to water and distance to roads were calculated using the roads and water files with the Euclidean Distance tool. Slope and aspect were derived from the corrected digital elevation model utilizing the slope and aspect tools. The roads and the waterbodies shapefiles were converted to a raster file. All raster images were then exported as an ‘Imagine Image’, imported into TerrSet, and converted to a .rst file.

**Land Change Forecast – Data Analysis**

TerrSet Land Change Modeler was used to forecast land change in the study area to the year 2030. Due to uncorrectable errors in the 1986 land classification, 1996 was used as the base year for the prediction. A forecasted LULC map was created for year 2030 as well as a video which shows the land change transition from 2015 to 2030 in five year intervals.

# IV. Results & Discussion

The random forest supervised classification was determined to have the best representation of the land use categories for the Landsat 5 TM images. Maximum entropy method performed best for the 2015 RapidEye image and Landsat 8 OLI images. Land cover errors in both classification methods were seen through all images. A likely source for these inconsistencies could be the result of a large amount of green biomass in the large body of water in the south west of the study area, the Embalse Cerron Grande water basin, which produced misclassification of water as forest (Figure 1). Some agricultural areas were uncultivated, exposing the soil and therefore were a probable cause to the confusion of urban classifications. Additionally, since these landsat images were acquired during the dry season, low river level exposed much of the river bank, causing them to be misclassified as urban (Figure 1). Lastly, the training sites themselves are possible sources to the class variations.

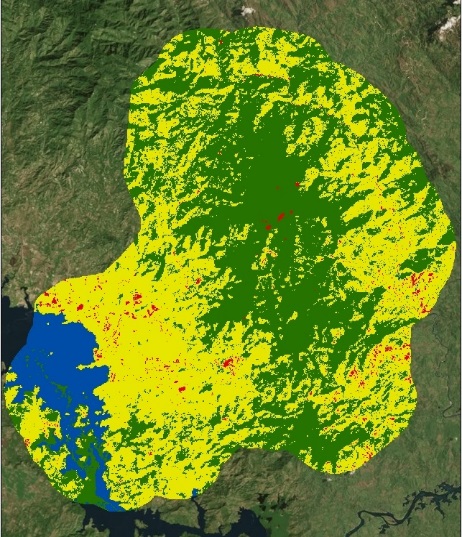
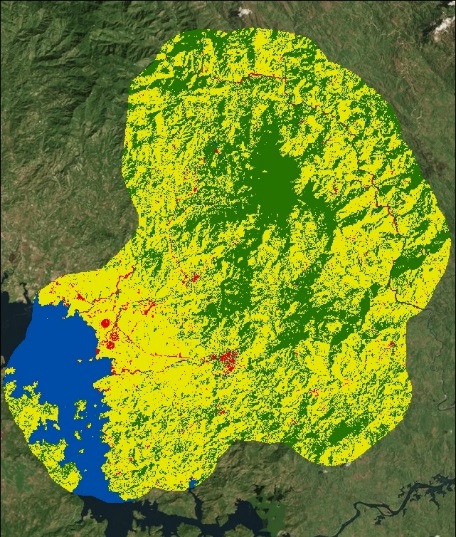
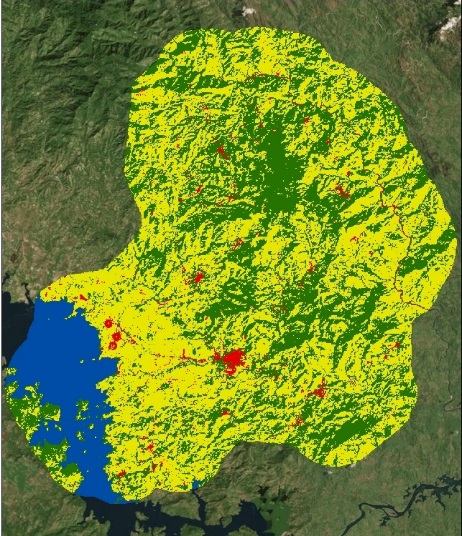
  

Figure 1. Classified images of the four predominant categories: water, rural/non-forest, forest, and urban. From left to right: 1986, 2000, 2015. Color representations: Blue = water, yellow = rural/non-forest, green = forest, and red = urban.

During the study period, deforestation appeared to be concentrated in the centrally located mountain range of the study area. The largest visible reforestation appeared in the eastern region of the study area, as well as the south western banks of the Embalse Cerron Grande water basin. Forest gain is speckled throughout the region rather than concentrating in one area (Figure B-2). Urban expansion was seen around already established communities but appeared minor overall. RNF areas displayed the most prevalent growth in the study area during the study period. It is possible that the reforestation observed on the south west side of the Embalse Cerron Grande water basin is influenced by the presence of a national park in the region. The main city in the study area of Chalatenango experienced sizeable growth which was expected due to the post-civil war return of El Salvadoran refugees and rising population density.

On average our results showed a decrease in forested areas by 2.2% from the 1986 to 2015 dry seasons while rural-non forest land area increased by an average rate of 1.6% and urban areas increased by 15.6% during the study period (Table A-4). The accuracies of the 2014 and 2015 dry season classifications Landsat images using maximum entropy were 71.4% and 81.5% respectively, indicating the percentages of correctly identified pixels in each category (Tables A-5 and A-7). The Kappa Coefficients for both years indicate a moderate agreement (0.8 > KHAT > 0.4) between the classification results and the 2015 RapidEye imagery ground reference image. Random forest classification method produced results with lower accuracies (Tables A-6 and A-8). Producer accuracy and user accuracy were the highest for the water category with urban showing the lowest in both accuracies for 2014. The 2015 classification image displayed both urban and water as having the highest producer and user accuracies. The lowest producer and user accuracies were RNF and forest correspondingly. Water likely produced the highest producer and user accuracies due to the large focus on training sites in the water areas in an attempt to correct for obvious misclassifications caused by the excessive biomass present in water bodies. Still, while the producer and user accuracies are very high for water, it is evident that there are few misclassifications with the water class as slight variations were observed. RNF and forest classes had areas of similar reflectances which was a likely reason for the lower producer and user accuracies.

Using the classified images, calculated areas, and graphs produced by TerrSet, RNF was determined to be the main contributor to the decrease in forest cover over the historical timeline (Figures B-2, 3, 4). This deforestation occurred primarily along the edges of the forests where RNF areas were already established (Figure 1). Due to the problems surrounding the water and urban classifications, the water and urban categories were shown to increase the net change in forest (Figure 3). This resulted in an inaccurate representation of the contribution of these classes of their effect on forest change.

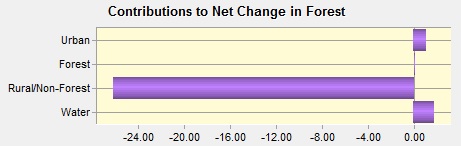


Figure 3. Contributors to the net change in forest cover area in km2 from 1996 to 2015. Rural/Non-Forest contributes the largest amount of reduction in forest change.

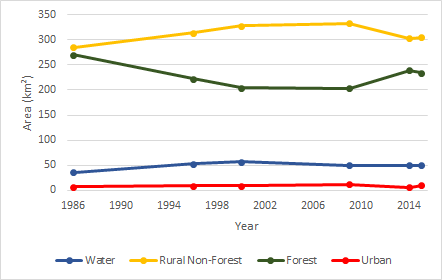


Figure 4. The area of land use classes estimated for each year of interest (km2).

Limitations were identified that affected the historical baseline and prediction results. One of the limitations faced was the lack of imagery before the year 1986 which restricted the historical starting point. In addition, difficulties arose in collecting imagery through the time series during the dry season that was void of clouds over the study area. Uncorrectable errors in the water class for the 1986 image caused visible errors in the final prediction image and estimated area result. This affected the rate of change from 1986 to 1996 and inadvertently the average rate of change for the forested class. With similarities in forest and RNF reflectances, minor misclassifications were unavoidable but the overall LULC trend was as expected. Finally, a lack of ground reference plot data or high resolution imagery earlier than 2012 prevented any accuracy assessment of the earlier classified images.

The variables used to predict changes in LULC were run in TerrSet Land Change Modeler to display how the study area may appear in 2030 with variables remaining constant. Incorporating reforestation into the forecasting model resulted in an overestimation of the amount of forest and urban expansion based on the historical baseline created (Figure 6). Therefore, a forecasting model excluding reforestation was also used to estimate the predicted forest cover. The exclusion of reforestation over-estimated the deforestation that will likely occur (Figure 7). The predictions displayed a consistent pattern that many areas of forest would continue to see deforestation and forest degradation at a rapid rate with the main contributor being rRNF and, to a lesser extent, urban expansion (Figures B-8 and B-9). In addition to the predicted map for 2030, A transition potential based on each class identified for the study of areas that would be at the highest risk for change on a scale of 0-100% (Figures 5 and 6). The edges of forests adjacent to RNF areas were identified as having the highest risk of deforestation.

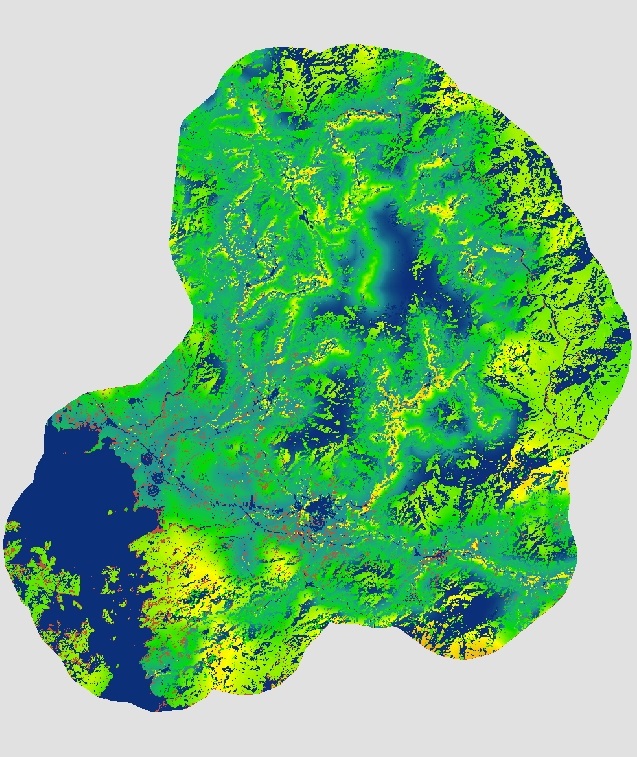
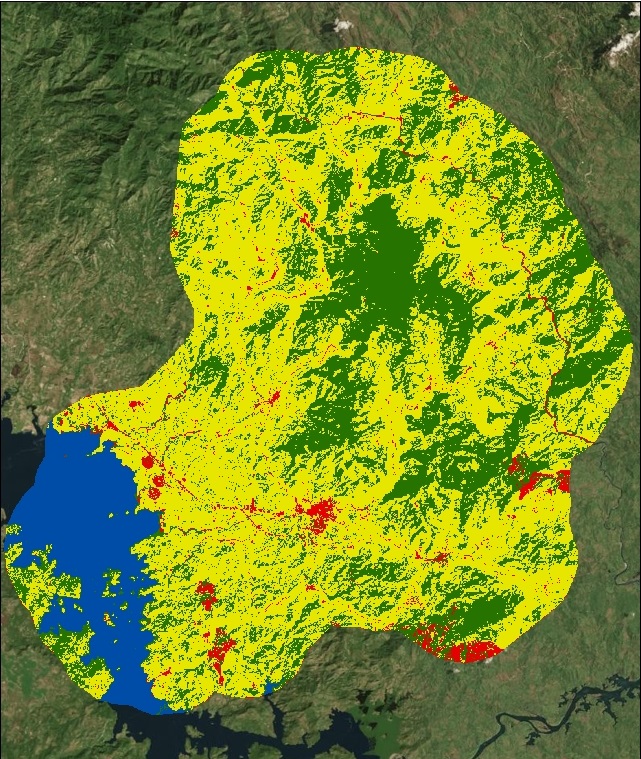


Figure 6. Land change predicted to 2030 with reforestation. Left: projected land cover. Color representations: Blue = water, yellow = rural/non-forest, green = forest, and red = urban. Right: projected transition potential for each land category to transition to another category from 0 to 100%. Color representations: Blue = ~0%, Yellow = ~50%, Red = ~100%.

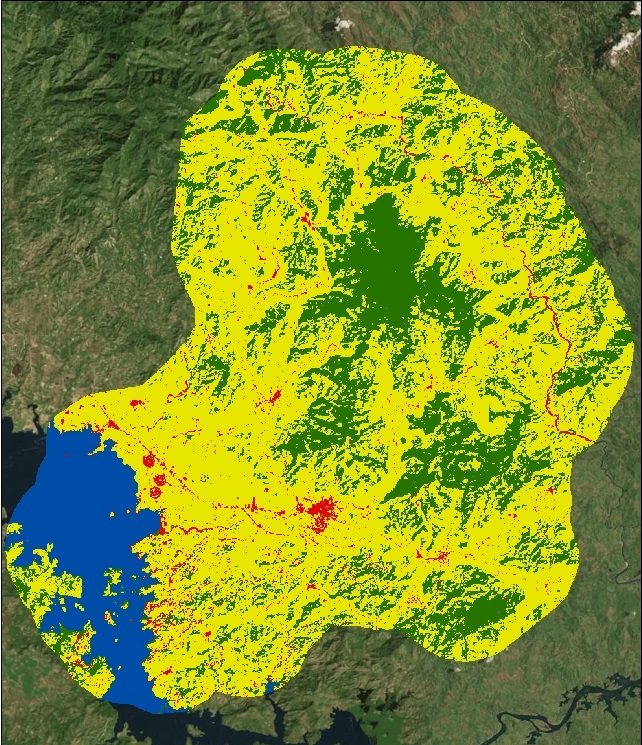
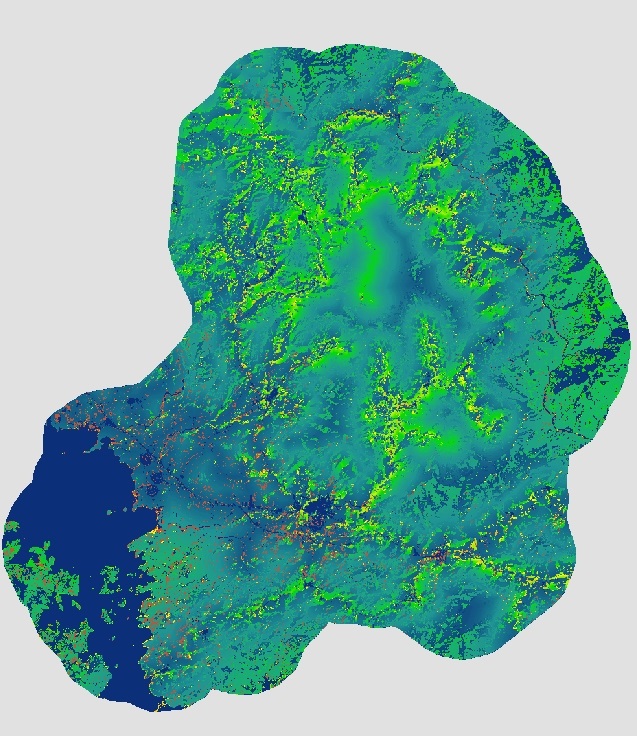
 

Figure 7. Land change predicted to 2030 with no reforestation. Left: projected land cover. Color representations: Blue = water, yellow = rural/non-forest, green = forest, and red = urban. Right: projected potential for each land category to transition to another category from 0 to 100%. Color representations: Blue = ~0%, Yellow = ~50%, Red = ~100%.

# V. Conclusions

NASA Landsat imagery coupled with Google Earth Engine have proven to be inexpensive and useful tools for identifying changes in land cover. Using remotely sensed imagery reduces the time spent on data collection and allows for analysis where there is a lack of ground reference data. The software created through Google Earth Engine provides the ability to run multiple analyses and calculations in an easy to use form. This software can be modified to extend the size of the study area; an invaluable tool for research where there is limited or no ground reference data.

Improvements to the classified images can be acquired by reducing the number of predominant land classes. Decreasing the number of classes has the potential to increase the accuracy of the images since it produces a simplified image with broader categories which presents less room for error. Modification and refinement of the training sites is another option for enhancement. While the ground reference plot data was beneficial in classifying the 2015 RapidEye image, obtaining more current data would have improved the validity of the classifications and accuracy assessment.

The results of this project may be used to better understand how the landscape of the study area is changing which will help in the development of environmental initiatives, such as REDD+ and PES. In order to implement a REDD+ program, certain preparations must be made, including the creation of a forest index, to which this project contributes. PES provides economic incentive for forest conservation. This project allows for the identification of where PES efforts could be effective. More recent initiatives include a push to implement sustainable farming techniques, such as agroforestry, at a community level. These programs are necessary to the preservation of what little primary forest remains and to expand environmental conservation efforts.

# VI. Acknowledgments

Dr. Kenton Ross - National Science Advisor, NASA DEVELOP National Program

Dr. Sean Smukler & Sean Kearney - The Earth Institute, Columbia University (ABES Project)

Arnulfo Alberto - La Mancomunidad La Montanona, Chalatenango

Giovanni Molina - Ministerio de Medio Ambiente y Recursos Naturales (MARN)

Rolando Barillas, ABES Project Manager

Mary Rodriguez, Environment Officer, USAID/El Salvador

Dr. Jason Paul Landrum, Regional Science and Technology Advisor, USAID/El Salvador

This material is based upon work supported by NASA through contract NNL11AA00B and cooperative agreement NNX14AB60A.

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# IV. Appendix A

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GEE Chart

**Table A-2. Band Combinations Used to Identify Land Cover Classes**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Land Use/Land Cover Class | | | | |
| **Composite/Ratio** | **Water** | **Pasture** | **Forest** | **Urban** | **Crop** |
| TM 3/2/1 (‘True Color’) | x | x | x | x | x |
| TM 4/3/2 (‘False Color’) |  |  | x | x |  |
| TM 5/4/3 | x | x | x |  | x |
| TM 5/4/1 |  | x |  |  | x |
| OLI 4/3/2 (‘True Color’) | x | x | x | x | x |
| OLI 5/4/3 (‘Color Infrared’) |  | x | x |  | x |
| OLI 7/6/4 |  |  |  | x |  |
| OLI 6/5/2 |  | x |  |  | x |

**Table A-3. Spectral Bands for Satellites Used in Classifications**

|  |  |  |  |
| --- | --- | --- | --- |
| **Satellite** | **Bands** | **Wavelength (micrometers)** | **Resolution (meters)** |
| **Landsat 5 TM (Thematic Mapper)** | Band 1 - Blue | 0.45-0.52 | 30 |
| Band 2 - Green | 0.52-0.60 | 30 |
| Band 3 - Red | 0.63-0.69 | 30 |
| Band 4 - NIR | 0.76-0.90 | 30 |
| Band 5 - mid-IR | 1.55-1.75 | 30 |
| Band 6 - Thermal | 10.40-12.50 | 120\* (30) |
| Band 7 - SWIR | 2.08-2.35 | 30 |
| **Landsat 8 Operational Land Imager (OLI)** | Band 2 - Blue | 0.45 - 0.51 | 30 |
| Band 3 - Green | 0.53 - 0.59 | 30 |
| Band 4 - Red | 0.64 - 0.67 | 30 |
| Band 5 - NIR | 0.85 - 0.88 | 30 |
| Band 6 - SWIR 1 | 1.57 - 1.65 | 30 |
| Band 7 - SWIR 2 | 2.11 - 2.29 | 30 |
| Band 8 - Panchromatic | 0.50 - 0.68 | 15 |

\*Landsat 5 TM Band 6 was acquired at 120-meter resolution and then resampled to 30-meter resolution.

**Table A-4. Rate of Change (%) Rural Non-Forest, Forest, and Urban**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **1986** | **1996** | **2000** | **2009** | **2014** | **2015** | **Average** |
| **RNF** | N/A | 10.44 | 4.39 | 1.35 | -8.93 | 0.79 | 1.61 |
| **Forest** | N/A | -18.01 | -7.67 | -0.38 | 17.65 | -2.26 | -2.19 |
| **Urban** | N/A | 38.43 | -0.37 | 34.67 | -51.38 | 60 | 15.62 |

**Table A-5. Confusion Matrix for 2014 Using Maximum Entropy Classification**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Prediction** | **Ground Reference** | | | | | |
| ***Class*** | **Water** | **Rural/Non-Forest** | **Forest** | **Urban** | **Total** |
| **Water** | 6 | 0 | 0 | 0 | 6 |
| **Rural/Non-Forest** | 1 | 31 | 15 | 1 | 48 |
| **Forest** | 0 | 3 | 15 | 0 | 18 |
| **Urban** | 1 | 2 | 0 | 0 | 3 |
| **Total** | 8 | 36 | 30 | 1 | 75 |
|  |  | | | | | |
|  | ***Class*** | Commission (%) | Omission (%) | Prod. Acc. (%) | User Acc. (%) |  |
| **Water** | 0 | 25 | 75 | 100 |
| **Rural/Non-Forest** | 35 | 14 | 86 | 65 |
| **Forest** | 17 | 50 | 50 | 83 |
| **Urban** | 100 | 100 | 0 | 0 |

Table \_\_ shows the confusion matrix with commission and omission for 2014 using maximum entropy classification. The overall accuracy: (52/75)\*100 = 69.3% and the Kappa Coefficient (KHAT): 0.478.

**Table A-6. Confusion Matrix for 2014 Using Random Forest Classification**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Prediction** | **Ground Reference** | | | | | |
| ***Class*** | **Water** | **Rural/Non-Forest** | **Forest** | **Urban** | **Total** |
| **Water** | 6 | 0 | 0 | 0 | 6 |
| **Rural/Non-Forest** | 1 | 33 | 13 | 1 | 48 |
| **Forest** | 0 | 5 | 13 | 0 | 18 |
| **Urban** | 1 | 2 | 0 | 0 | 3 |
| **Total** | 8 | 40 | 26 | 1 | 75 |
|  |  | | | | | |
|  | ***Class*** | Commission (%) | Omission (%) | Prod. Acc. (%) | User Acc. (%) |  |
| **Water** | 0 | 25 | 75 | 100 |
| **Rural/Non-Forest** | 31 | 18 | 83 | 69 |
| **Forest** | 27 | 50 | 50 | 72 |
| **Urban** | 100 | 100 | 0 | 0 |

Table \_\_ shows the confusion matrix with commission and omission for 2014 using random forest classification. The overall accuracy: (52/75)\*100 = 69.3% and the Kappa Coefficient (KHAT): 0.459.

**Table A-7. Confusion Matrix for 2015 Using Maximum Entropy Classification**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Prediction** | **Ground Reference** | | | | | |
| ***Class*** | **Water** | **Rural/Non-Forest** | **Forest** | **Urban** | **Total** |
| **Water** | 4 | 0 | 0 | 0 | 4 |
| **Rural/Non-Forest** | 0 | 26 | 11 | 1 | 38 |
| **Forest** | 0 | 11 | 23 | 0 | 34 |
| **Urban** | 0 | 5 | 0 | 0 | 5 |
| **Total** | 4 | 42 | 34 | 1 | 81 |
|  |  | | | | | |
|  | ***Class*** | Commission (%) | Omission (%) | Prod. Acc. (%) | User Acc. (%) |  |
| **Water** | 0 | 0 | 100 | 100 |
| **Rural/Non-Forest** | 32 | 38 | 62 | 68 |
| **Forest** | 32 | 32 | 67 | 67 |
| **Urban** | 100 | 100 | 0 | 0 |

Table \_\_ shows the confusion matrix with commission and omission for 2014 using maximum entropy classification. The overall accuracy: (53/81 )\*100 = 65.4% and the Kappa Coefficient (KHAT): 0.401.

**Table A-8. Confusion Matrix for 2015 Using Random Forest Classification**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Prediction** | **Ground Reference** | | | | | |
| ***Class*** | **Water** | **Rural/Non-Forest** | **Forest** | **Urban** | **Total** |
| **Water** | 4 | 0 | 0 | 0 | 4 |
| **Rural/Non-Forest** | 0 | 28 | 9 | 1 | 38 |
| **Forest** | 0 | 11 | 23 | 0 | 34 |
| **Urban** | 0 | 4 | 0 | 1 | 5 |
| **Total** | 4 | 43 | 32 | 2 | 81 |
|  | | | | | | |
|  | ***Class*** | Commission (%) | Omission (%) | Prod. Acc. (%) | User Acc. (%) |  |
| **Water** | 0 | 0 | 100 | 100 |
| **Rural/Non-Forest** | 26 | 35 | 65 | 74 |
| **Forest** | 32 | 28 | 72 | 68 |
| **Urban** | 80 | 50 | 50 | 20 |

Table \_\_ shows the confusion matrix with commission and omission for 2015 using random forest classification. The overall accuracy: (56/81 )\*100 = 69.1% and the Kappa Coefficient (KHAT): 0.469.

**Table A-9. Area for Land Use and Land Cover Classifications (km2)**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **1986** | **1996** | **2000** | **2009** | **2014** | **2015** |
| **Water** | 36.39 | 52.72 | 56.9 | 50.1 | 50.2 | 49.6 |
| **Rural/ Non-Forest** | 284.62 | 314.34 | 328.15 | 332.6 | 302.9 | 305.3 |
| **Forest** | 270.52 | 221.81 | 204.17 | 203.4 | 239.3 | 233.9 |
| **Urban** | 6.87 | 9.52 | 9.17 | 12.34 | 6 | 9.6 |

# V. Appendix B

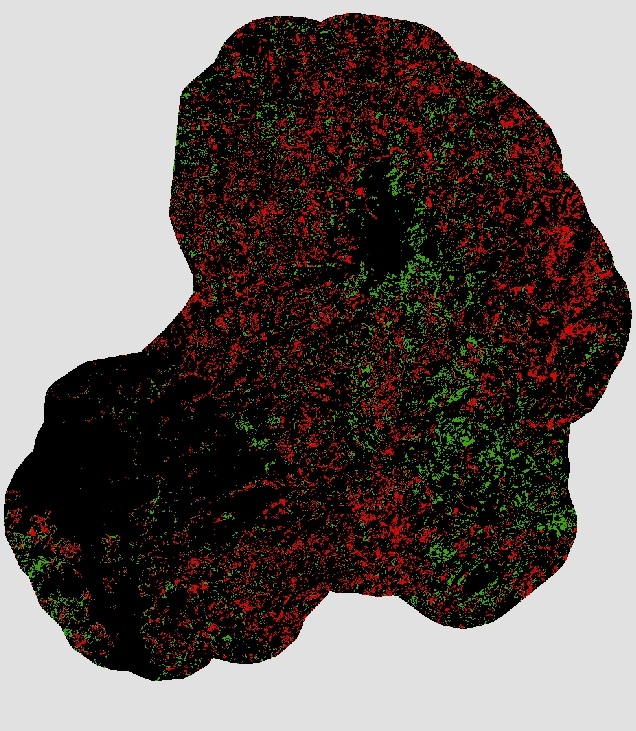
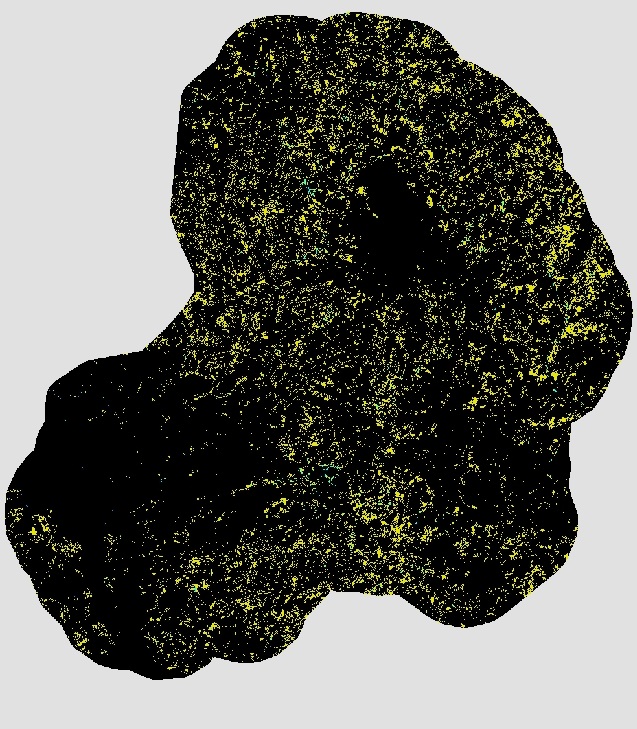
 

Figure B-2. Forest changes from 1986 - 2015. Left: Forest gains (green) and losses (red). Right: Forest losses to rural/non-forest (yellow) and urban(red).

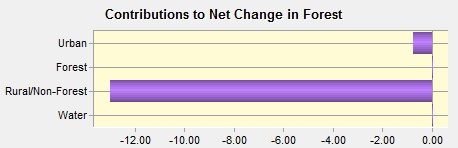


Figure B-8. Predicted contributors to the net change in forest cover area in km2 with reforestation included.

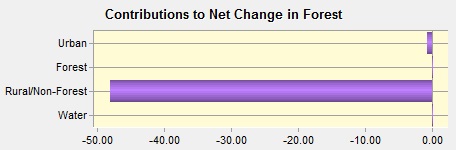


Figure B-9. Predicted contributors to the net change in forest cover area in km2 with reforestation excluded.