**NASA DEVELOP National Program**



NASA Langley Research Center

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El Salvador Ecological Forecasting II

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

 **Technical Report**

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# I. Abstract

[Placeholder - do not put anything here until the final draft submission. The abstract in the project summary is where the working draft of the abstract should “live”]

**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 4 billion tons of carbon per year; however, tropical deforestation releases 3 billion tons annually. This destructive activity reduces the yearly net forest carbon sink to about 1.1 billion 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. 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. Without trees to regulate the soil, deforestation for agricultural purposes often leads to soil erosion and nutrient leaching, 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 (source).

Central America is home to 22,411 hectares of tropical forest. From 1990 to 2005 Central American forest cover decreased by almost 20% (Khatun 2011). The main causes of deforestation are population growth and land use change (Redo et. al. 2012, Kahtun 2011). The effects of this deforestation are not contained to Central America, but are felt in other regions as well. Biologists have linked a decline in North American bird species, such as the wood thrush, to the loss of forests in Central America due to the fact 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 deforestation on a catastrophic level. Its high population density, coupled with its poor enforcement of environmental regulations and unsustainable farming techniques, have been driving forces of deforestation (World Bank, 2014). El Salvador has only 2% of its primary forests remaining, 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 throughout the country. Tavy farming is exceptionally harmful because it quickly depletes soils of their nutrients, making 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). Environmental initiative became a priority in this post-war era. 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 the Ministry of the Environment and Natural Resources (MARN) (Foley & Hapipi, 2005). More recent initiatives include a push to implement sustainable farming techniques, such as agroforestry, preparing for REDD+ implementation, and developing 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 forests of La Montañona are critical to maintaining local stream and river quality, relied upon by many communities, such as San Salvador, as their main source of water (Balkan). This hilly area has a population dependent upon subsistence and livestock farming, often utilizing slash and burn agricultural techniques which threaten the surrounding forest.

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 REDD+ strategies. 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 4/5 and Landsat 8 OLI satellites were extracted from the United States Geological Survey (USGS) for path 19, row 50 for the years 2010 and 2016. The dry season for La Mancomunidad La Montañona runs from November to April, therefore these images were representative of the 2009 and 2015 dry seasons. For consistency with the Fall 2015 term, images chosen were those with minimal cloud cover over the area of interest and as close to the month of December for each selected year.

**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 2012 (Region)January 2016 |
| **QuickBird** | Project Collaborators (ABES) | 2.4 m | Global Forest Cover (GFC) validation, | December, 2012 |

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

Preprocessing and projection of the images was unnecessary for this project since Google Earth Engine 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 RapidEye imagery and cell size resampled to 30 meters. Additionally, images were filtered to remove any ‘null’ value pixels.

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

The Google Earth Engine (GEE) platform, using maximum entropy and random forest classification methods, was utilized to produce land use and land cover (LULC) maps. 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 guide were modified for use to produce the LULC maps. Review and refinement of the vector data created during the fall 2015 term for the water, urban or bare land, forest, crop, and pasture categories was performed and training sites increased from 20 per category to 30 sites per category. GEE could then access the dataset through Google Fusion Table. For the years 2010 and 2016, a total of 30 training sites for each category were drawn using the GEE platform directly. 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. Classes were identified by referencing a combination of high-resolution imagery and ABES plot classes ground truth data. Various band composites enabled the visual distinction between closely related classes. LULC maps were also created for the 2016 RapidEye 5 meter resolution imagery to use in the accuracy assessment. After the best training sites were drawn, a supervised classification was performed through a modified script for each method.

**Accuracy Assessment – Percent Similar**

In order to compare the accuracy between the two different classification methods, classes were reclassified into Boolean data types. The reclassification for the Boolean data type was such that “Class” = “1” and “Non-Class” = “0” for both RapidEye and Landsat images. Comparison included the combination of RapidEye 2012 with Landsat 2014 and RapidEye 2016 with Landsat 2016. These images were then added to each other using the Basic Image Calculation to determine the percentage of pixels that agree and disagree with the RapidEye images. Pixels with a resulting value of “2” and “0” were in agreement and those with a value of “1” were in disagreement.

Percent similar statistics were then extrapolated from pixels with values of “0” and “2”. These pixels were then added and divided by the total number of image pixels using (GEE code).

**Accuracy Assessment – Percent Accurate**

Confusion matrices and kappa coefficients were created easily through GEE by incorporating the appropriate scripts to compare the accuracy of the training sites. Results of the overall accuracy, confusion matrix tables, and kappa coefficients were extracted from the console within GEE.

**Land Use Time-lapse**

# IV. Results & Discussion

Insert images, graphs, maps, charts, etc. here. Choose the most important results to highlight here. No word cap, but two to six pages is a good range.

Things to discuss:

* Analysis of Results: What can you tell from your graphs, images, etc? What does this mean for your project?
* Errors & Uncertainty: What factors could you not account for, what things didn’t work out like you expected they would, etc.
* Future Work: If this project was to be selected for another term, what would be the focus? What other areas would be of interest?

# V. Conclusions

Final conclusions. Word count: 200-600 (~a page).

# VI. Acknowledgments

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

# VII. References

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# IV. Appendices

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