Satellite Imagery analysis for Land Use, Land Use Change and Forestry (LULUCF)

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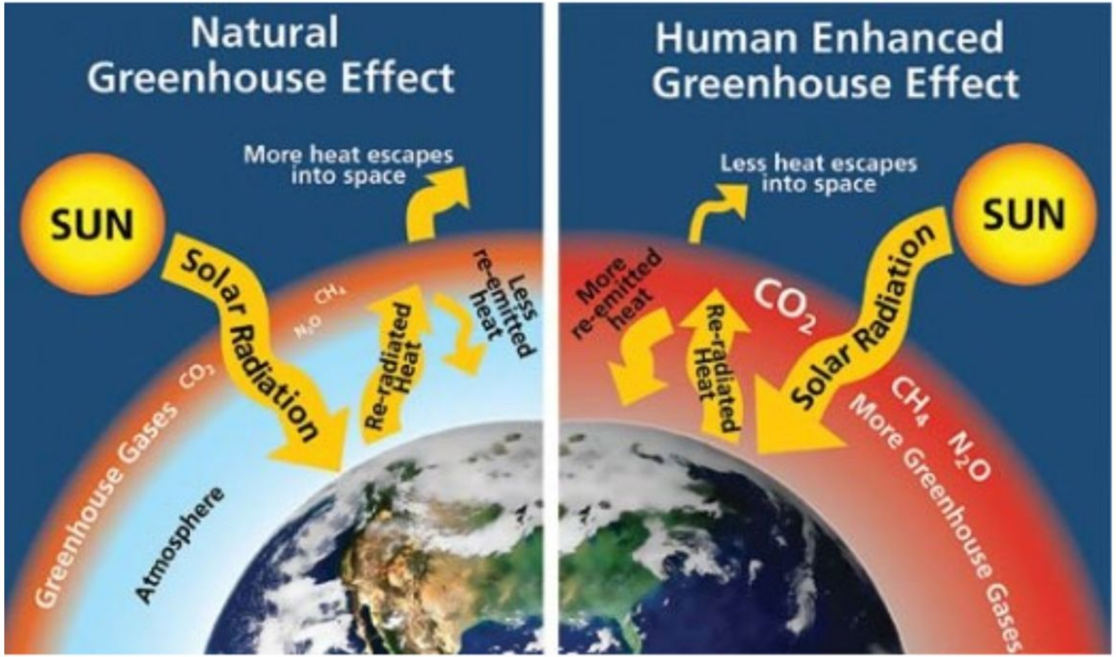
Introduction

Human enhanced Greenhouse effects prevents sun rays from escaping into the atmosphere, leading to;

- More re-emitted heat to the earth
- Global warming and its effects



The Problem

The main challenge facing many developing countries is the unavailability of activity data to be use in the calculation of greenhouse gas inventories; it is even more challenging in the Agriculture, Forestry and Other Land Use (AFOLU) sector since there are no proper documentation.

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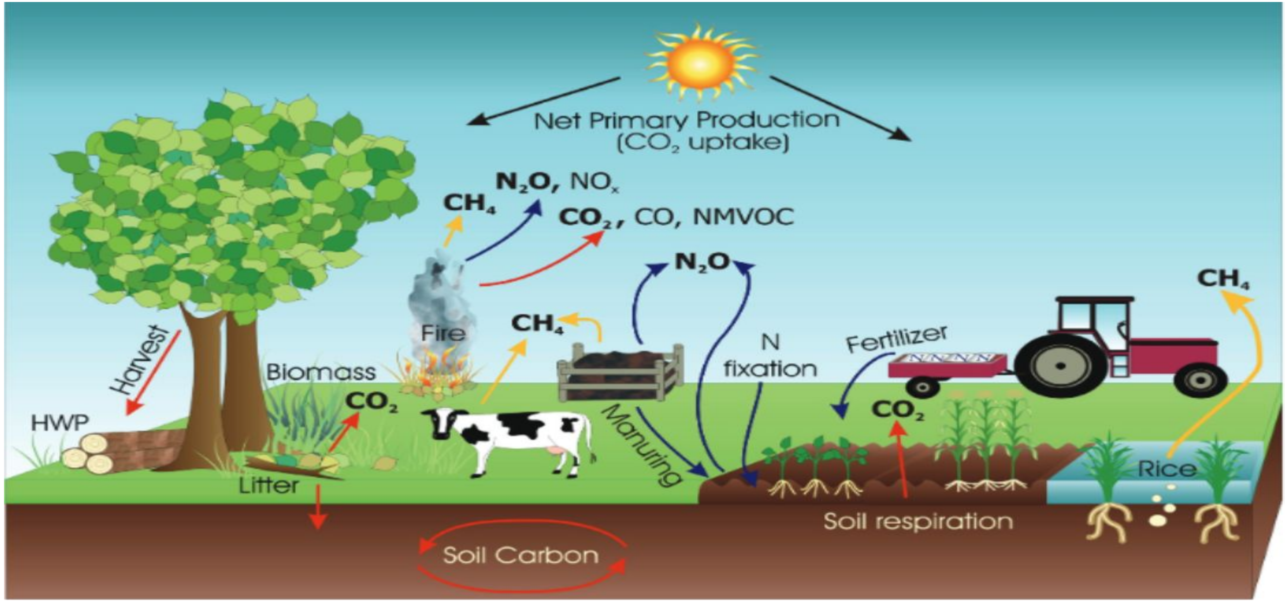
GHGs from the AFOLU sector

The Agriculture, Forestry and Other Land Use (AFOLU) is the only sector that involves the release and(or) the uptake of Greenhouse gases;

- Forestry is the main sink
- Other activities on the land are the sources



The Goal

The goal is to provide activity data on Land Use and Land Use Change towards the calculation of greenhouse gas emission from the AFOLU sector.

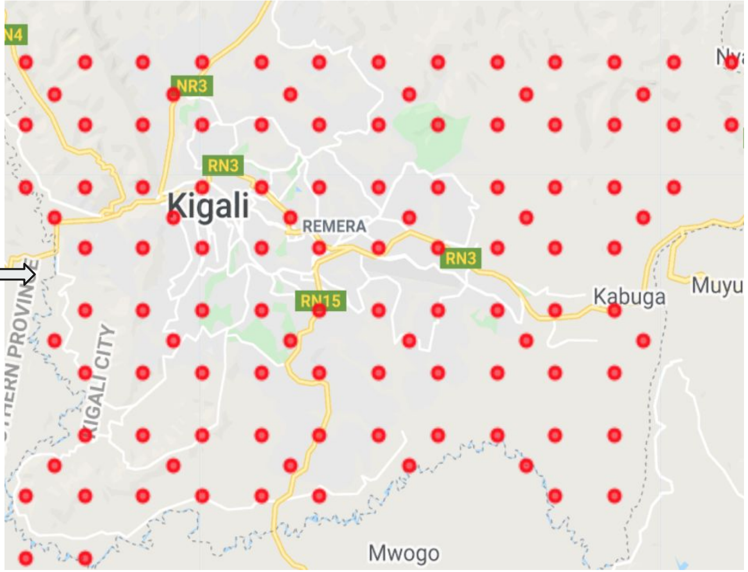
Emission = Activity data X Emission factor.

Methodology

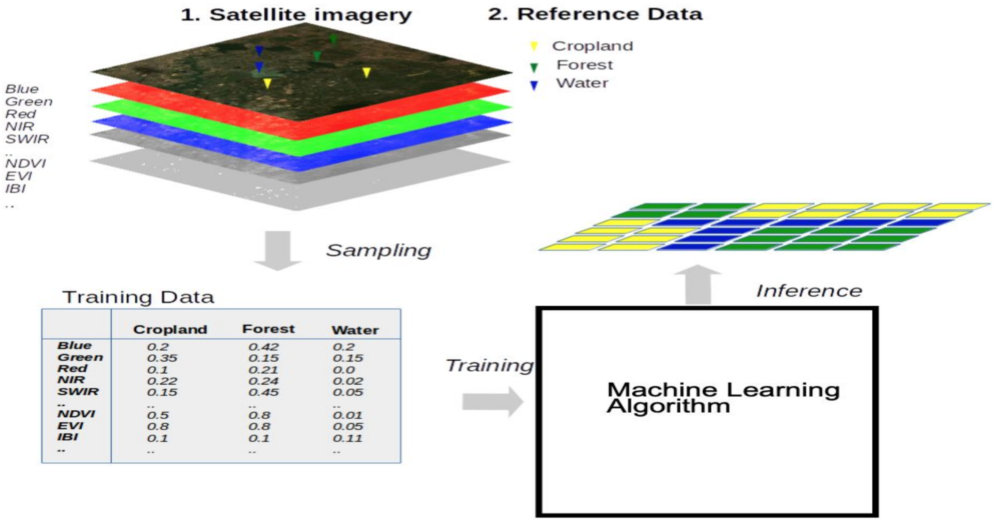
- Collect and analyse satellite imagery on various land use forms
- Using ground data (with labels) as reference , we pass them through Machine Learning algorithm to;
    a) Calculate the areas associated with each land type
    b) Calculate the land use change matrix
    c) Draw a land cover map for the country

Imagery collection period: 2006-2019

Area of study



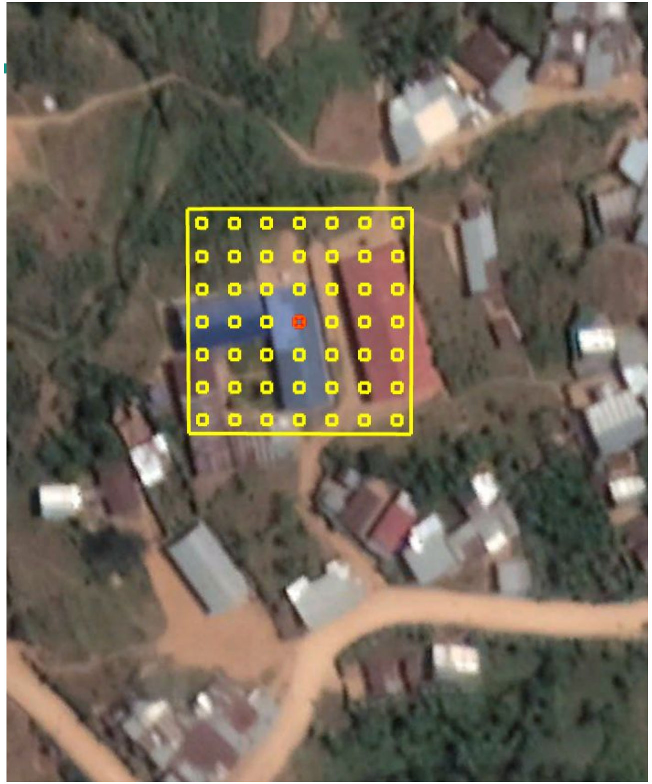
Machine Learning(ML) workflow in imagery



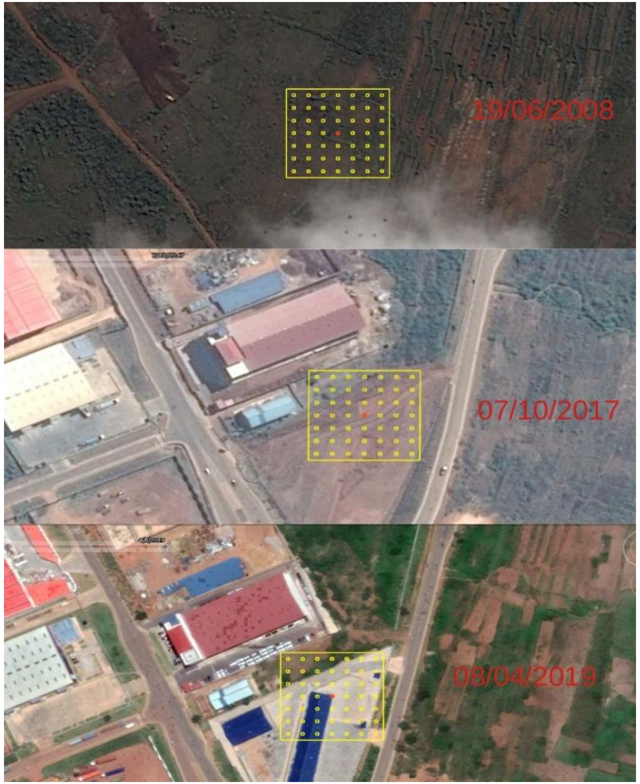
1. Operational Land Imager(OLI) and Thermal Infrared Sensors(TIS) for Earth (land) images

2. Label data on each of the six land types with their coordinate systems

Sample imagery



Land cover with control points



Land use change with control points

Imagery band selection

Sensors on earth observing satellites measures the amount of electromagnetic radiation (EMR) that is reflected or emitted from the Earth's surface

- These multispectral sensors, measures data in multiple regions of the electromagnetic spectrum
- The range of the electromagnetic wavelengths measured by sensors is known as the band

Imagery bands

- The band selection and (or) the various combinations is dependent on the kind of application or use case

Landsat 8 Operational Land Image (OLI) and Thermal Infrared Sensor (TIRS)

Band	Wavelength	Useful for mapping
Band 1 - coastal aerosol	0.43-0.45	Coastal and aerosol studies
Band 2 - blue	0.45-0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 - green	0.53-0.59	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 - red	0.64-0.67	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.85-0.88	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.57-1.65	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11-2.29	Improved moisture content of soil and vegetation; penetrates thin clouds
Band 8 - Panchromatic	0.50-0.68	15 meter resolution, sharper image definition
Band 9 - Cirrus	1.36-1.38	Improved detection of cirrus cloud contamination
Band 10 - TIRS 1	10.60-11.19	100 meter resolution, thermal mapping and estimated soil moisture
Band 11 - TIRS 2	11.50-12.51	100 meter resolution, improved thermal mapping and estimated soil moisture

Machine Learning

Classification techniques:

In land use applications, the purpose of classification is commonly to reveal the spatial distribution of various land use forms.

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Machine Learning

There are two types of ML classification techniques used with satellite imageries

- Pixel based classification

Individual pixel images are analysed based on the spectral information they contain

- Object based image analysis

A combination of spectral, textural and contextual information to identify thematic classes in images.

ML implementation with satellite imagery

These steps lead to the machine learning implementation of our land use classification and quantification;

- Load cloud free imageries
- Define the bands (combination) to be used
- Overlay the points (with labels) on the imagery
- Split data
- Train a classifier
- Quantify each land type using their pixel counts

Result of the pilot study(Kigali)

The results showed much improvement using the Classification and Regression Trees(CART) and RandomForest(RF) ML algorithms. Our model accuracies were 97% for CART and 95% for RF .

Land classification error & Land Use matrix_Kigali

Overall validity of our classification together with the classification errors (in red) are on the right. Land use and their conversion are on the left; quantified in hectares .

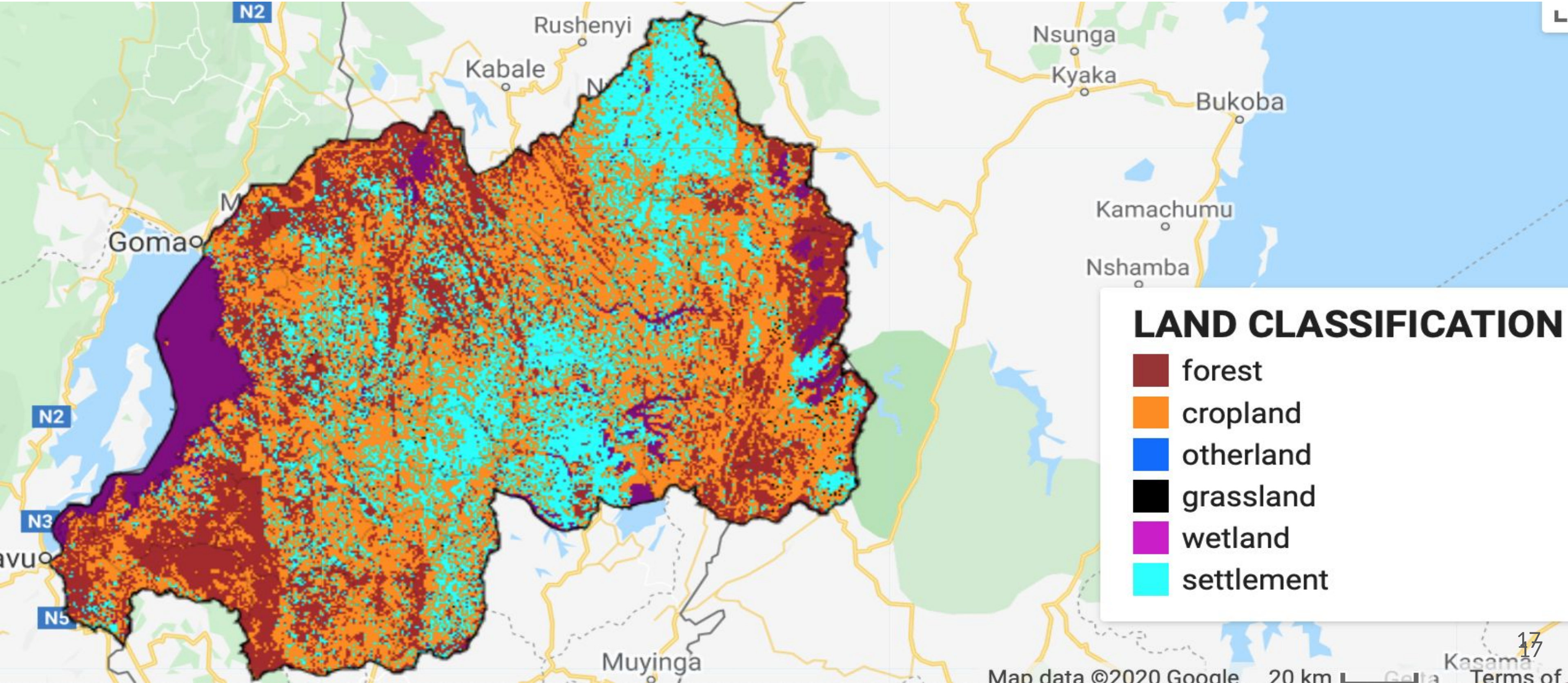
Overall validity: 97.44%

	# Points	Forest	Cropland	Grassland	Settlement	Wetland
Forest	9	100%	0%	0%	0%	0%
Cropland	47	0%	95.74%	0%	4.26%	0%
Grassland	1	0%	0%	100%	0%	0%
Settlement	56	0%	1.79%	0%	98.21%	0%
Wetland	4	0%	0%	0%	0%	100%

Lan use conversion

Conversion	Areas in Hectares
Forest to Forest	5005.13
Cropland to Forest	625.64
Cropland to Cropland	28779.49
Wetland to Cropland	625.64
Grassland to Grassland	625.64
Wetland to Wetland	1876.92
Cropland to Wetland	625.64
Settlement to Settlement	15641.03
Cropland to Settlement	18769.23
Grassland to Settlement	625.64

Land cover map classified



Impact

- Extraction of Activity data for the estimation of greenhouse gases from the AFOLU sector
- Improvement in the Tier levels (from Tier 1 to Tier 2) used for greenhouse estimations
- Contributing to sustainability of Land Use and Land Use Change monitoring systems in Rwanda

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Some references

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Link to paper: https://doi.org/10.1145/3378393.3402268

THANK YOU