Using Planet Data and Google Earth Engine to Automate Mapping of Informal Roads in the Amazon Borderlands

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Introduction

The Amazon provides a multitude of ecosystem services, acting as a carbon sink and biodiversity hotspot, regulating global precipitation, and providing a way of life for millions of people[1-4]. However, informal road development and associated deforestation threatens these and other ecosystem services[5,6]. High-resolution satellite imagery and machine learning techniques have been used to classify and detect land-cover changes[7,8], but using these resources to automate road network mapping remains difficult. A common method for road detection in the Amazon involves the manual interpretation and hand-digitization of high-resolution satellite data[9]. While this method is accurate and precise, it also time consuming and requires regional expertise, and thus not ideal in monitoring the annual expansion of informal roads. Here, I show progress toward a method of merging high-resolution data with traditional multi-spectral techniques and object-based image classification to map informal road networks across the Southwestern Amazon (Figure 1).

Figure 1. Area of interest (AOI, grey box) across Ucayali, Peru and Acre, Brazil

Methodology

I initially tried to use only Google Earth Engine (GEE) to map informal roads because it is an open source platform that allows for code to be easily shared, but this proved unsuccessful. As highlighted below, I did much of the Planet data pre-processing in GEE then moved to an object based image analysis software E-Cognition which I have access to under a student license. See Figure 2 and below:

1. Use GEE to select monthly mosaic of 3-5 m resolution Planet data from dry season
2. Filter the data based on AOI, date and cloud cover, then mosaic to create a cloud-free dry-season scene
3. Add elevation dataset, and compute NDVI, NDWI, TGI, SAVI, VARI and export band stack
4. Import data stack into eCogniton, reproject data and assign class labels
5. Develop rule set to define roads and exclude deforested areas (See eCognition box, right column)
6. Export roads layer

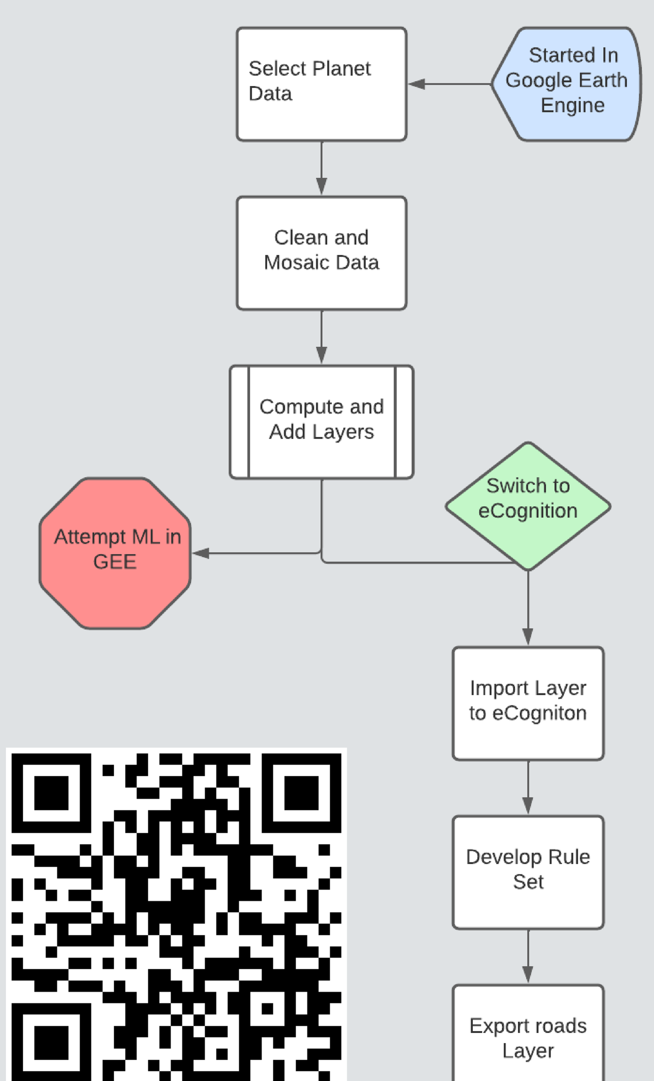

Figure 2. Informal road mapping workflow. Scan QR code for link to GEE code

Initial Results


Figure 3: Subset of AOI, with complex land-cover and network of informal roads

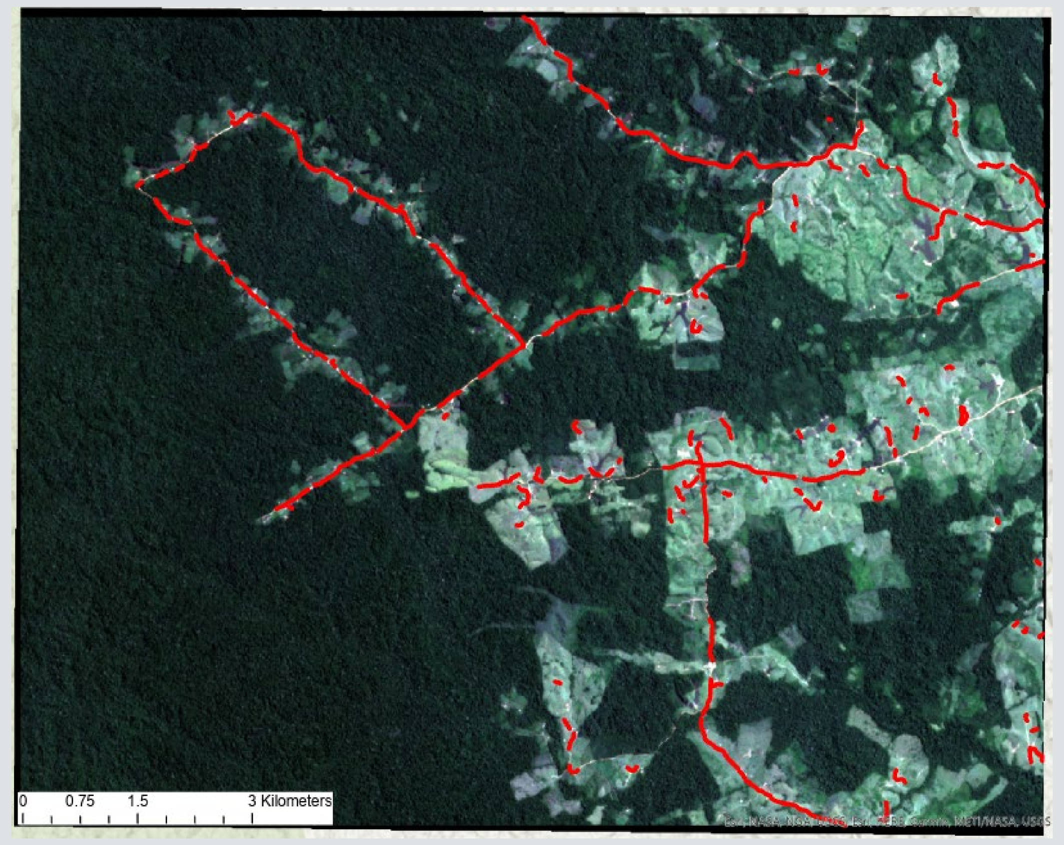
Figure 4: Resultant road network. Linear features extracted, but they are not continuous


Figure 5: Subset of AOI with complex land-cover and network of informal roads

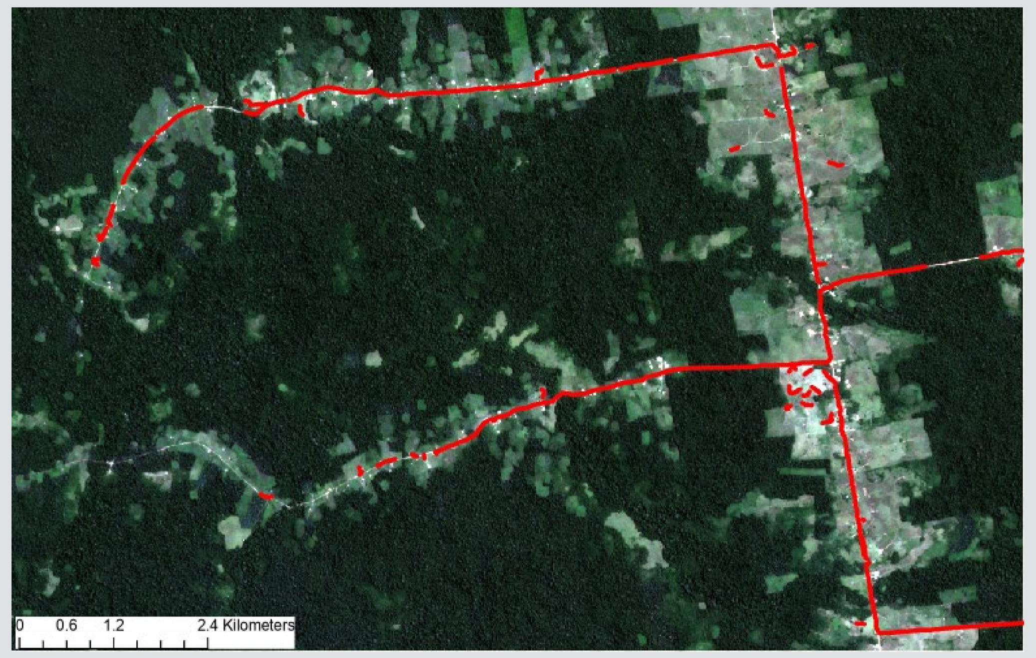
Figure 6: Resultant road network extraction

Successes

- GEE allows one to easily access high-resolution Planet data, and calculate indices on the cloud
- Roads were differentiated from fallow fields with similar spectral properties (Fig 4, 6)
- Long, linear features easily extracted (Fig 3-6)
- Due to high-resolution of Planet data, smaller roads highlighted than if one were to use 30 m resolution Landsat data[9]

Challenges

- Difficult to differentiate between informal roads and small, sediment-filled rivers
- Extracted roads often discontinuous and not connected (Fig 4)
- Small, bright patches within fallow fields sometimes confused for roads (Fig 6)
- Due to GEE limitations, relied on expensive, proprietary software to perform analysis

eCognition Methodology

Ruleset for eCognition was determined based on continuous trial and error:

- Double the weight NDVI and SAVI because differences in photosynthetic vegetation (NDVI) and soil brightness (SAVI) should allow for greatest differentiation between forest and road
- Filter merged resultant roads based on proximity to other roads and shape

Rule Set for Roads

Value 1	Operator	Value 2
Red + Blue	>	1000
Number of Pixels	<	150
Mean Blue	>	300
Mean NDVI	<	.8
Mean Difference to Brighter Neighbors (NDVI)	>	.03
Elliptic fit	<	.45
Roundness	>	1

Figure 7: eCognition ruleset

Future work

- Refine ruleset, specifically to remove sediment-filled river features
- Validate data using hand-digitalized map to test for accuracy
- Apply ruleset across entire AOI to evaluate efficacy of this more automated methodology vs hand-digitalization
- Determine how to connect discontinuous roads features

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