

RAMI Module 3

Radar Mining Monitoring Tool (RAMI) Workflow and Practical

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Prepared for “Forest Monitoring and Carbon Stock Estimation with Multi-Source Remote
Sensing in the Context of Climate Change” at ITC
Quartile 4 2022-2023



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Prerequisites and Requirements

Requirements

For this module, you will need a...

- Computer
- Google Earth Engine Account
- Membership of the “rami-for-ITC” Google Cloud Project

Prerequisites

Before taking this module, it is required that you take [RAMI Module 1](#) and [RAMI Module 2](#). Module 1 will show you how to register a Google Earth Engine Account and join the “rami-for-itc” Google Cloud Project.

Before taking this module, it is recommended that you have some experience with Javascript and/or the Google Earth Engine Code Editor.

Learning Objectives

By the end of this module, you will...

- Understand the benefits and limitations of the Radar Mining Monitoring Tool
- Understand how RAMI’s change detection algorithm works
- Understand the limitations of RAMI’s change detection algorithm
- Be able to run RAMI for a customized time period of interest over the Madre De Dios Study area

Chapter 1: The Omnibus Q-test Change Detection Algorithm

1.1 The Covariance Matrix

Conradsen et al 2003 represented the backscatter signal for fully polarimetric SAR data (where all four polarization modes [VV, VH, HV, HH] are represented) with the following covariance matrix.

$$\langle \mathbf{C} \rangle = \begin{bmatrix} \langle S_{hh} S_{hh}^* \rangle & \langle S_{hh} S_{hv}^* \rangle & \langle S_{hh} S_{vv}^* \rangle \\ \langle S_{hv} S_{hh}^* \rangle & \langle S_{hv} S_{hv}^* \rangle & \langle S_{hv} S_{vv}^* \rangle \\ \langle S_{vv} S_{hh}^* \rangle & \langle S_{vv} S_{hv}^* \rangle & \langle S_{vv} S_{vv}^* \rangle \end{bmatrix}$$

Where

- * represents complex conjugation
- $\langle \rangle$ represents ensemble averaging, and
- S represents the complex scattering amplitude of the return signal

For a more in depth overview of Conradsen's 2003 paper, [click here](#).

Mention observed change manually in module 2.

1.2 Change Detection Algorithms

In Module 2, we were able to manually observe the difference between two SAR images. A Change Detection Algorithm automates this process for a certain set of dates by applying a mathematical algorithm to the covariance matrix for a number of SAR images. For more information on change detection algorithms as they relate to SAR, see [Section 3.5 in](#)

[SERVIR's SAR Handbook](#). RAMI uses a specific kind of change detection algorithm known as the Omnibus Q-test, which we will learn more about later in this module.

Chapter 2: RAMI Workflow

2.1 Generate a time series of SAR Images

Just as we did in Module 2, RAMI will acquire Sentinel-1 Synthetic Aperture Radar Images over a time period of interest. RAMI also undergoes some pre-processing steps before generating deforestation alerts.

SAR images are acquired at an oblique angle with respect to the Earth's surface. RAMI will mask SAR images that are acquired at an incidence angle less than 31 degrees or greater than 45 degrees.

Next, the images are filtered to a specific orbit pass. Sentinel-1 operates in either ascending or descending mode. "Ascending" refers to when the satellite moves from North to South, while "descending" refers to when the satellite moves from North to South.

Our final pre-processing step is to filter out duplicate dates. These are dates where we have more than one image in our image collection.

2.2 Apply Omnibus Q-test Algorithm

RAMI uses the Omnibus Q-test change detection algorithm to generate deforestation alerts. This equation is represented by the following equation.

$$\ln Q = n(pk \ln k + \sum_{i=1}^k \ln |X_i| - k \ln \left| \sum_{i=1}^k X_i \right|)$$

Before applying the SAR change detection algorithm, we need to define the input parameters such as the significance and the reducer to be applied. A reducer refers to a method of taking the value for each pixel in a time series of images and applying some mathematical function to it. This allows us to reduce the time series of pixel values to a

single pixel value. The reducer will then be applied to every pixel in the image. For more information on reducers, [click here](#) and scroll down to page 4 to read a chapter from the book “Cloud-Based Remote Sensing with Google Earth Engine”.

The application of this algorithm in RAMI is done in Google Earth Engine through the use of the “support scripts” (also referred to as modules or packages in the programming world), which we call into the “main script” with a single line of code. This support script will apply the algorithm to our customized time series of SAR images, and output an Earth Engine Dictionary (see Section 2.4).

2.3 Post-Processing

The Omnibus Q-test algorithm is capable of telling us when and where a statistically significant change in the return signal of the Sentinel-1 dataset is occurring, **but tells us nothing about the nature of this change**. This means that just because RAMI creates a change detection alert, does not necessarily mean that this change is due to deforestation caused by illegal alluvial gold mining.

Thus, the use of change detection algorithms such as the one used by RAMI require *a priori* knowledge of your study area in order to discern true alerts from “false positives” (i.e. areas where RAMI has alerted there is a change but there is none or the change is not due to illegal gold mining). This *a priori* knowledge contributes to the application of vital post-processing steps that can mitigate the frequency of false positives.

The mitigation of false positives is a crucial step when designing geospatial services, as you want to save your end users time and resources when they are deciding which alerts to investigate on the ground.

Question 1

In Module 2, we learned that RAMI works by identifying areas where there is a **decrease** in the backscatter values from one date to another. Can you think of a situation in which the backscatter value for a pixel would decrease other than deforestation due to gold mining?

Solution to Question 1

The morphology of a river is not constant, and changes throughout time. This change in the shape of a river can lead to deforestation, and can cause false positives in our system.

In order to mitigate the potential for our change detection to return false positives, RAMI includes post-processing steps that are specific to the Madre de Dios region.

RAMI includes four post-processing steps:

1. Elevation and Slope
2. Pre-Existing Land Cover dataset
3. Pre-Existing Surface Water dataset
4. Isolated Pixels

2.3.1 Elevation and Slope

First, we filter out any positive alerts that occur at an altitude over 1000 meters above sea level and a slope over 15 degrees. This step is taken because mining activity in the Madre de Dios Region is located in lowlands. Furthermore, the SAR Sentinel-1 data provided in GEE are not radiometrically terrain corrected (RTC), which is a highly recommended pre-processing step when working with SAR data. Due to the lack of this correction, steep slopes generate geometric distortions in SAR images and increase the likelihood of generating a false positive. However, there are currently no operationally produced RTC products, so we are proceeding with the geometrically terrain corrected SAR product available in GEE.

2.3.2 Pre-Existing Land Cover datasets

We will also mask out pixels that are classified as forest until 2020 by the Hansen Global Forest Change dataset.

2.3.3. Pre-Existing Surface Water Dataset

Finally, we will mask out areas that are not classified as water bodies according to the Joint Research Centre's Yearly Water Classification History dataset.

2.3.4 Isolated pixels

Our final post-processing step includes the application of a function that eliminates small pixel patches and isolated patches that have generated deforestation alerts.

2.4 Interpreting RAMI Results

The result of the application of the Omnibus Q-test change detection algorithm is an Earth Engine Dictionary that contains several images: the “cmap”, “smap”, “fmap”, and “bmap” images.

The “cmap” image shows the occurrence of the most recent significant change.

The “smap” image shows the first significant change.

The “fmap” image shows the frequency of significant changes.

The “bmap” image shows the interval in which each significant change occurred.

The values for “cmap”, “smap”, and “bmap” are numbers that correspond to dates.

Chapter 3: RAMI Practical

RAMI runs via Google Earth Engine scripts. In this chapter, we will run the script for ourselves and see how RAMI’s outputs look before they are added to the user interface ([click here](#) to see RAMI’s user interface). RAMI will give us the potential deforested area for a certain time period (I say potential because some of the alerts may be false positives). We will then see how we can use Earth Engine to estimate the carbon emissions associated with this area.

3.1 Using RAMI to estimate carbon emissions

A publication released by Asner et al 2010 used Lidar remote sensing to estimate carbon stock in the Madre de Dios region of Peru. Looking at Figure 1 below (which is from Asner’s paper) look at the region in the blue box pointed at by the blue arrow. Does this area look familiar?

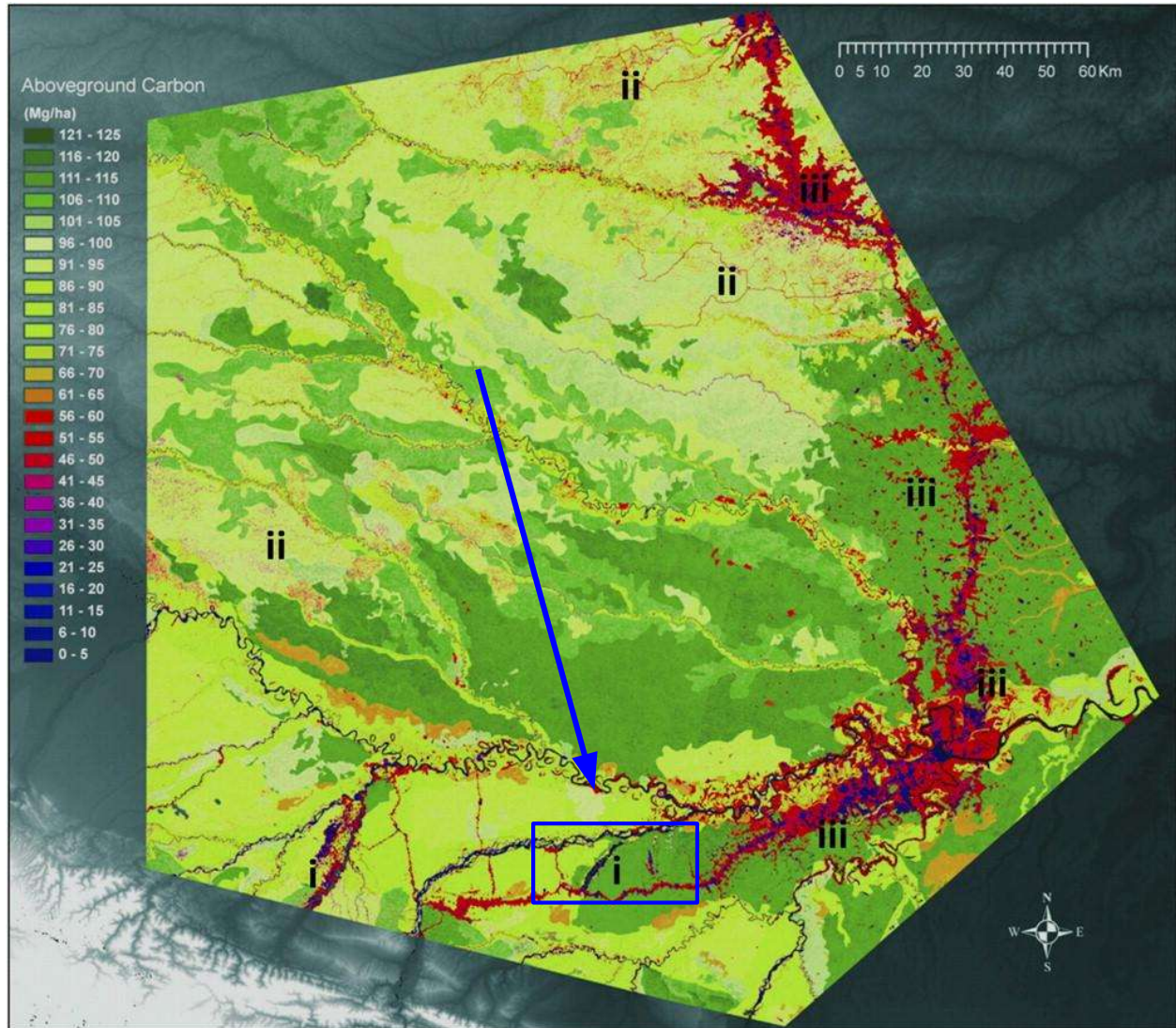


Figure 1: Carbon Stock Map over the Madre de Dios region of Peru per Asner et al 2010

It is the same mining corridor we have been investigating in Module 2! Based on the legend, it appears that the majority of this region has an aboveground carbon between 111-115 Mg/ha.

Multiplying this carbon stock (measured in mass/area) times the deforested area we observe in RAMI, we can then get the total carbon stock of the deforested area. Then, we can multiply this by the molecular mass ratio of carbon dioxide to carbon (which is 44/12) based on [McPherson et al 2016](#) in order to estimate the carbon emissions in the area. Thus, we can use Equation 1 below to calculate E , the amount of carbon dioxide emitted from deforestation in our study area.

$$E = S * A * C \quad (I)$$

Where $E = CO_{2\text{ emitted}}$ (mass)

$S = \text{Carbon Stock (mass/area)}$

$A = \text{Area that is Deforested}$

$C = \text{Constant for Molecular Mass Ratio of } CO_2/C = 44/12 \approx 3.67$

3.2 Adding RAMI Scripts to your GEE Repository

[Click here](#) to add RAMI's code repository to your specific Google Earth Engine Code. RAMI's scripts will then be available in the script manager panel of GEE to view, run, or modify. If you have trouble finding the repository, [click here](#) for help.

3.3 Try RAMI Yourself!

[Click here](#) to view the supplementary material for this module, which is a GEE script that will show you how to run RAMI for yourself.

After clicking on the link, scroll through the code and read the comments before clicking the "Run" button in the upper right corner.

Chapters 1 and 2 of this module walked you through how this script works!

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