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Omnibus Q-Test

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Introduction → CEO → what CEO does → what they will use CEO for

Hello everyone ,

My name is Micky Maganini, and I work for SERVIR, a U.S. Government organization and partner of ITC. Today I am going to introduce you to a web-based tool called RAMI that was developed by SERVIR. RAMI is a change detection algorithm used by SERVIR to monitor deforestation in the Amazon due to illegal gold mining. You will be using RAMI in this class to …

Context

Before we learn more about RAMI, I want to provide some context about What SERVIR is.

Omnibus Q Test Background

- Fully Polarimetric SAR Data can be represented by the following covariance matrix (Conradsen 2003)

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

where

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

Omnibus Q Test Background (Continued)

- For a series (Σ) of k SAR images (represented by their respective covariance matrices X_i) with dimensionality p, the test statistic Q is represented by the following equation (Canty 2019)

$$lnQ = n\,(pk\,lnk + \sum_{i=1}^{k} ln|X_i| - k\,ln \sum_{i=1}^{k} ln|X_i|)$$

- Depending on the magnitude of the calculated Q the null hypothesis (no change) is tested
- The algorithm starts with the first two images. If the null hypothesis is not detected, it moves to the third image, and so on until a change (if any) is detected

Canty et al 2019

remote sensing

MDPI

Article

Statistical Analysis of Changes in Sentinel-1 Time Series on the Google Earth Engine

Morton J. Canty [1,*], Allan A. Nielsen [2], Knut Conradsen [2] and Henning Skriver [3]

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check for updates

Abstract: Time series analysis of Sentinel-1 SAR imagery made available by the Google Earth Engine (GEE) is described. Advantage is taken of a recent modification of a sequential complex Wishart-based algorithm which is applicable to the dual polarization intensity data archived on the GEE. Both the algorithm and a software interface to the GEE Python API for convenient data exploration and analysis are presented; the latter can be run from a platform independent Docker container and the source code is available on GitHub. Application examples are given involving the monitoring of anthropogenic activity (shipping, uranium mining, deforestation) and disaster assessment (flash floods). These highlight the advantages of the good temporal resolution resulting from cloud cover independence, short revisit times and near real time data availability.

Keywords: dual polarization SAR; change detection; flood monitoring; deforestation; port activity; uranium mining; Google Earth Engine; Python; Jupyter notebook

1. Introduction

The Sentinel-1a and -1b Synthetic Aperture Radar (SAR) satellite platforms, with spatial resolutions as low as 20 meters depending on acquisition mode, combined revisit times of the order of six days and complete independence from solar illumination and cloud cover, provide an attractive source of Earth observation data for change detection tasks. The Google Earth Engine (GEE) [1,2] includes, in its extensive and up-to-date archive, Sentinel-1 data in dual polarization (vertical transmission and vertical and horizontal reception over land surfaces) multi-look intensity format. The GEE makes available not only near real time data access but also a very powerful application programming interface (API) for processing and visualizing the data. The GEE API is presently written in JavaScript for direct interaction with the web-based GEE Code Editor and in Python for data analysis outside the GEE web environment. Relatively little work [3] has been published till now involving the use of the GEE's Sentinel-1 archive for change detection. Since single look complex (SLC) data are not included in the archive for technical reasons, commonly used iterferometric coherence methods are unavailable. Change detection with GEE Sentinel-1 imagery in forest land cover based on Otsu thresholding [4] and K -means clustering is investigated in [5]. The use of multitemporal SAR for automated monitoring of coastal structures with the COSMOS-SkyMed platform is described in [6], and in [7] long-term flood monitoring in Greece is investigated with time series involving a combination of COSMO-SkyMed, Sentinel-1 and Landsat 8 imagery.

In their original publication on polarimetric SAR data analysis, Conradsen et al. [8] introduced a change detection procedure for multi-look SAR data involving a test statistic for the equality of

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- Dr. Morton J. Canty authored code to apply the Omnibus Q-test change detection algorithm developed by Conradsen et al 2003 in Google Earth Engine
- Canty's code adapts the change detection procedure for multi-look SAR data
- Adaptation of the original code was necessary because the full covariance matrix is not available in GEE (only the diagonal 2x2 matrix is available, not the 3x3 full covariance matrix shown in Slide 3)

So what's the theory behind why we would be able to detect areas where alluvial gold mining is occurring using SAR signals? Well, the process of alluvial gold mining involves the removal of topsoil, excavation, and the use of water to extract the gold from the loose sediment. So while the backscattering signal from forested areas are volume scattering, the backscattering signal from areas where gold mining is occurring is specular scattering due to the water used. So RAMI uses a change detection algorithm known as the omnibus q test, developed by Dr. Morton Canty, in order to do this. So on the left side we can see the paper where he published the change detection on Sentinel-1 time series

RAMI Workflow

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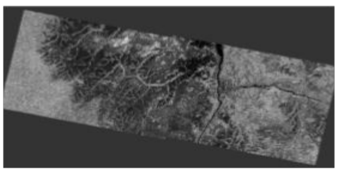
- Below you can see how SERVIR's Radar Mining Monitoring (RAMI) Tool implements the Omnibus Q-test Change Detection Algorithm

Step 1: Create a Time Series of SAR Images → Step 2: Apply Omnibus Q-test Algorithm → Step 3: Post-processing



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

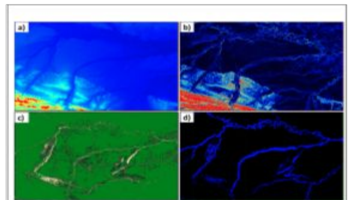


Fig. A1.8.9 Layers used to filter false positives alerts: a) SRTM elevation, red color shows areas over 1000 meters above sea level; b) SRTM slope, red color shows areas with slope over 15 degrees; c) Hansen Global Forest Change, green color shows forested areas updated to 2020; d) JRC Yearly Water Classification History, blue color shows the maximum extent of water surface detected from 1984 to 2020.

Here we can see the general workflow of RAMI. Our first Step is to pre-process the SAR data (specifically masking SAR images acquired at an incidence angle less than 31 or greater than 45 degrees), then creating a time series of mosaic of SAR images for a given time, region, and orbit pass. In Step 2, we apply the omnibus Q-test algorithm to our time series to generate change alerts. In Step 3 we will filter and eliminate potential false positive alerts coming from other activities with the same temporal pattern as the mining activity (e.g. natural forest loss by river expansion or water over bare soil during the rainy season). We do this by filtering out alerts that occur at an elevation above 1000 meters, in areas with a slope of 15 degrees, areas where there is not forest, and areas that were identified as water bodies. The elevation postprocessing step is taken due to the fact that in the Madre De Dios region, mining occurs in lowland areas. The slope step is taken because radiometric terrain correction is not applied to our SAR data, so sheep regions show distortions. The forest step is employed using the Hansebn Global Forest Change dataset, and the water step is taken via the JRC Global Surface Water Dataset. The water step is to remove false alerts that occur due to natural forest loss due to changes in river morphology.

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