



USING RADAR IMAGERY TO ESTABLISH THE ACCOUNTABILITY OF GOLD MINING ASSETS IN STRATEGIC LANDSCAPES FOR CONSERVATION

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INTRODUCTION

Over the past few years WWF has been active in highlighting the threat mining operations pose to strategic landscapes for conservation in South America. As a result, various assessments utilizing the overlap between WWF's global dataset of commercial mining assets [1] and environmental sensitive areas as the Intact Forest Landscapes and the Amazon Biome, have been developed and used to engage with the industry and the financial sector to help address this issue.

Although different studies using visible and infrared satellite imagery have made progress to understand the extent of land use changes associated to specific mining sites in South America [2], there are still challenges to regional monitoring. This is mainly due to the atmospheric conditions, with some of the highest cloud coverage in the region, but also due to the lack of complementary information of the mining permissions in these areas. In this regard, the capabilities of new radar satellite free products such as Sentinel-1, combined with WWF commercial data [1] offer an opportunity to help delineate mining environmental footprints.

OBJECTIVE

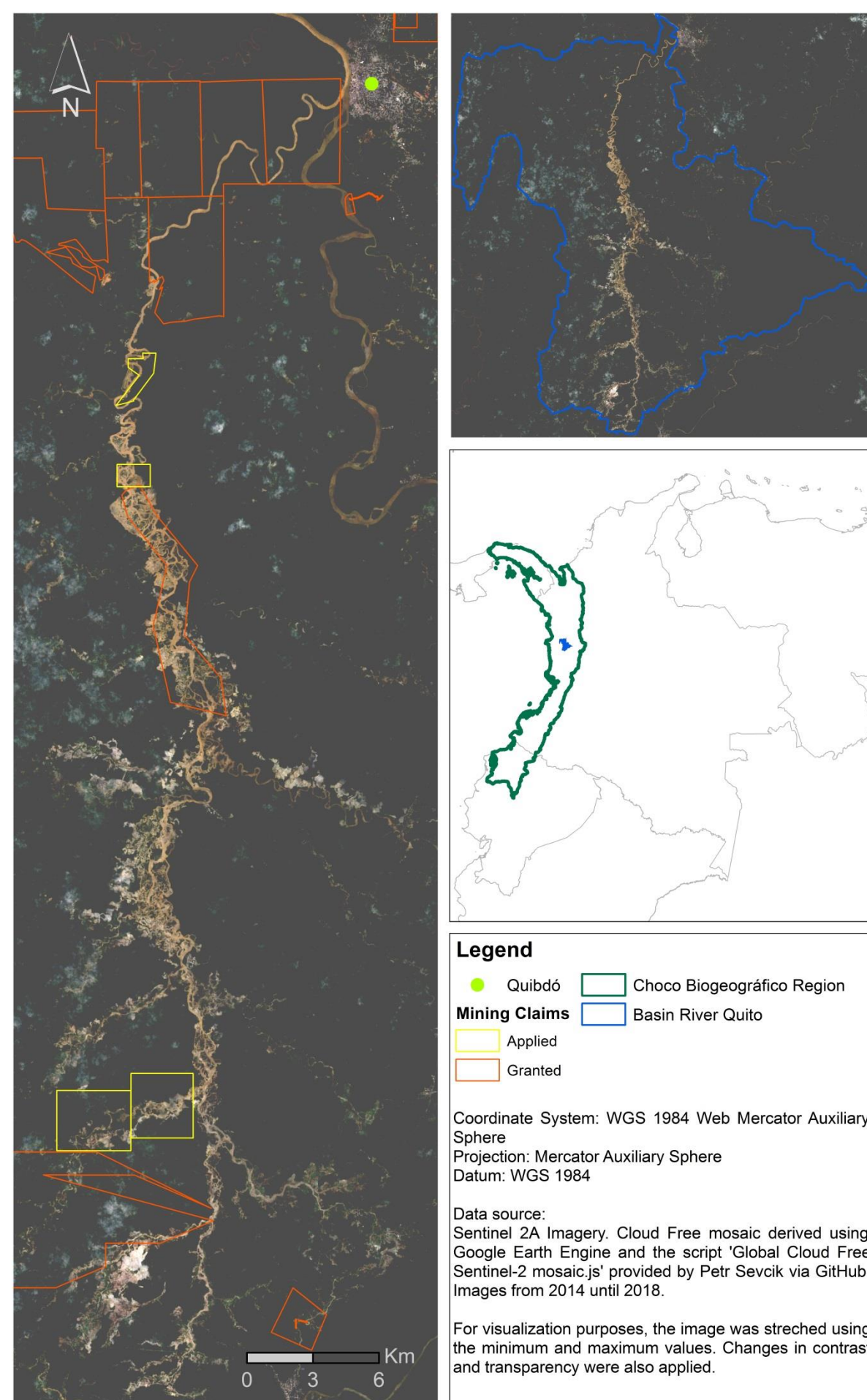
A case study is presented to explore how to extract footprints of open-pit gold mining river bed projects in the Rio Quito Basin located in the Choco Biogeographic (Colombia), using Sentinel-1. Further recommendations are indicated in relation of how to integrate WWF-s global dataset of commercial mining assets [1] to establish accountability, but also to understand the dimension of operations which are not associated to any authorized figure by law.

AREA OF STUDY

In 2014, the river basin Quito in the Choco Biogeographic, was identified to contain 15% of the stream bed mining gold sites in Colombia (6125.85 ha) [2]. The figure on the right displays a cloud-free Sentinel-2A mosaic of the area generated in Google Earth Engine using images from 2014 until 2018. The mining assets are display across the river and the correspondent mining licences in orange (granted: active) and yellow (application: further developments).

METHODS

This research looks to define mining footprints within the Quito river basin for 2015 and 2018.



For this purpose, two Sentinel-1 GRDH IW images, taken on January 7th 2015 and July 20th 2018 were selected and downloaded from the Copernicus Platform. The image from 2015 only contained information for the VV polarization, while the image from 2018 brought both VV and VH polarizations.

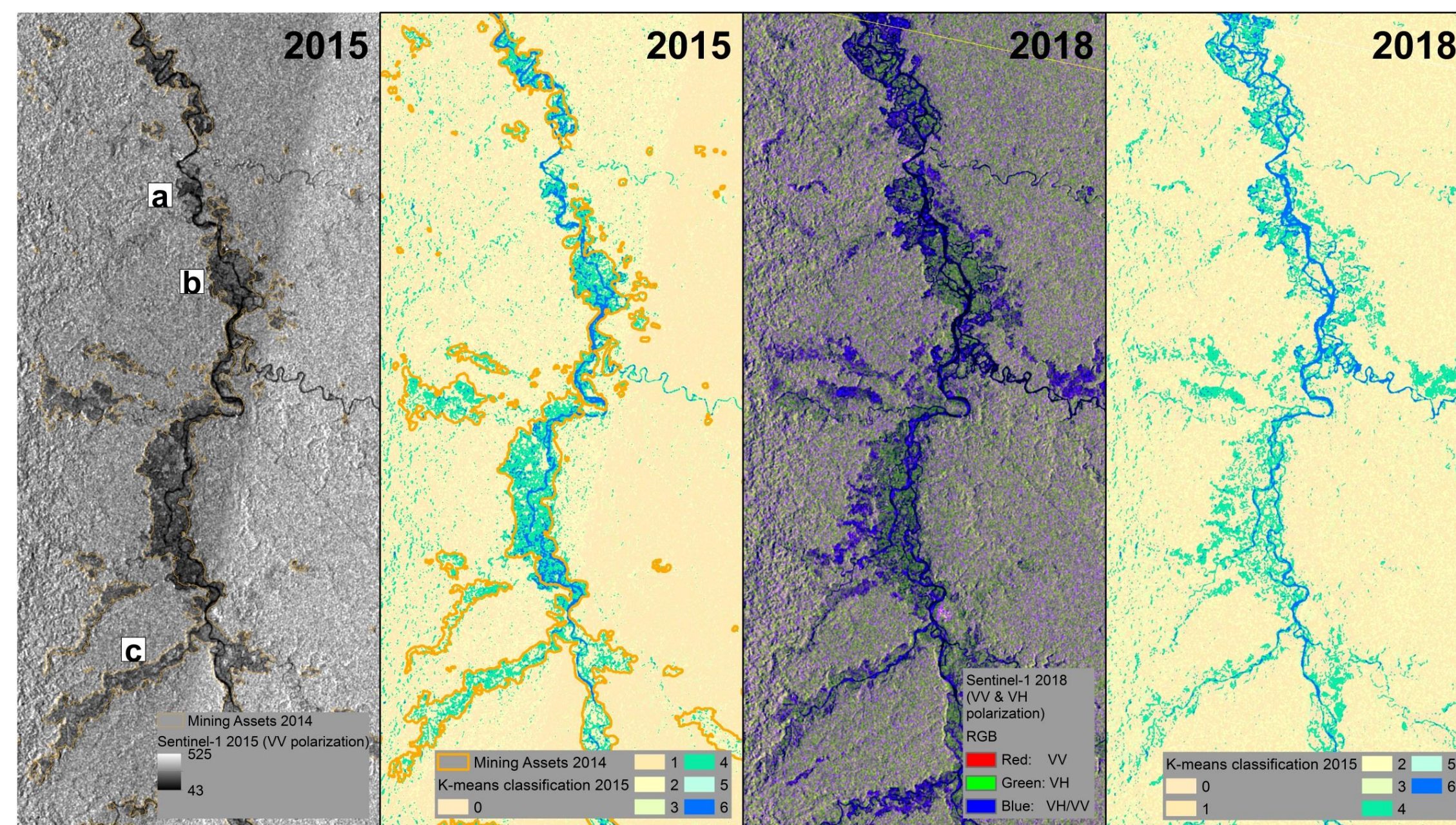
The images from 2018 were pre-processed using the SNAP software and applying the steps as followed in [3]: i) calibration, ii) correction of speckle using the filter Lee with a moving window of 5*5 and iii) geometric correction using the associated UTM projected system.

A non-supervised classification using the “K-means cluster analysis” method was carried over the 2015 image and setting the parameters to 7 classes and 30 iterations. The results of the area identified as mining footprints were visually compared using ArcGIS with the delineation of mining assets established by the Government in Colombia during 2014 [2].

The same classification was applied for the year 2018. In addition, the polarimetric unsupervised classification “Halpfa Wishart Dual Pol” was applied for the year 2018 as explained in [4]: i) calibration, ii) deburst, iii) polarimetric speckle filter using the Refined Lee Filter with a moving window of 5*5, iv) terrain correction, and v) classification setting the parameters set to 5*5 window size and 3 iterations. For this purpose, it was required to download the SLC IW image taken on the same day of the analysis (July 20th 2018). The 2015 and 2018 outputs were then compared visually for change detection using ArcGIS.

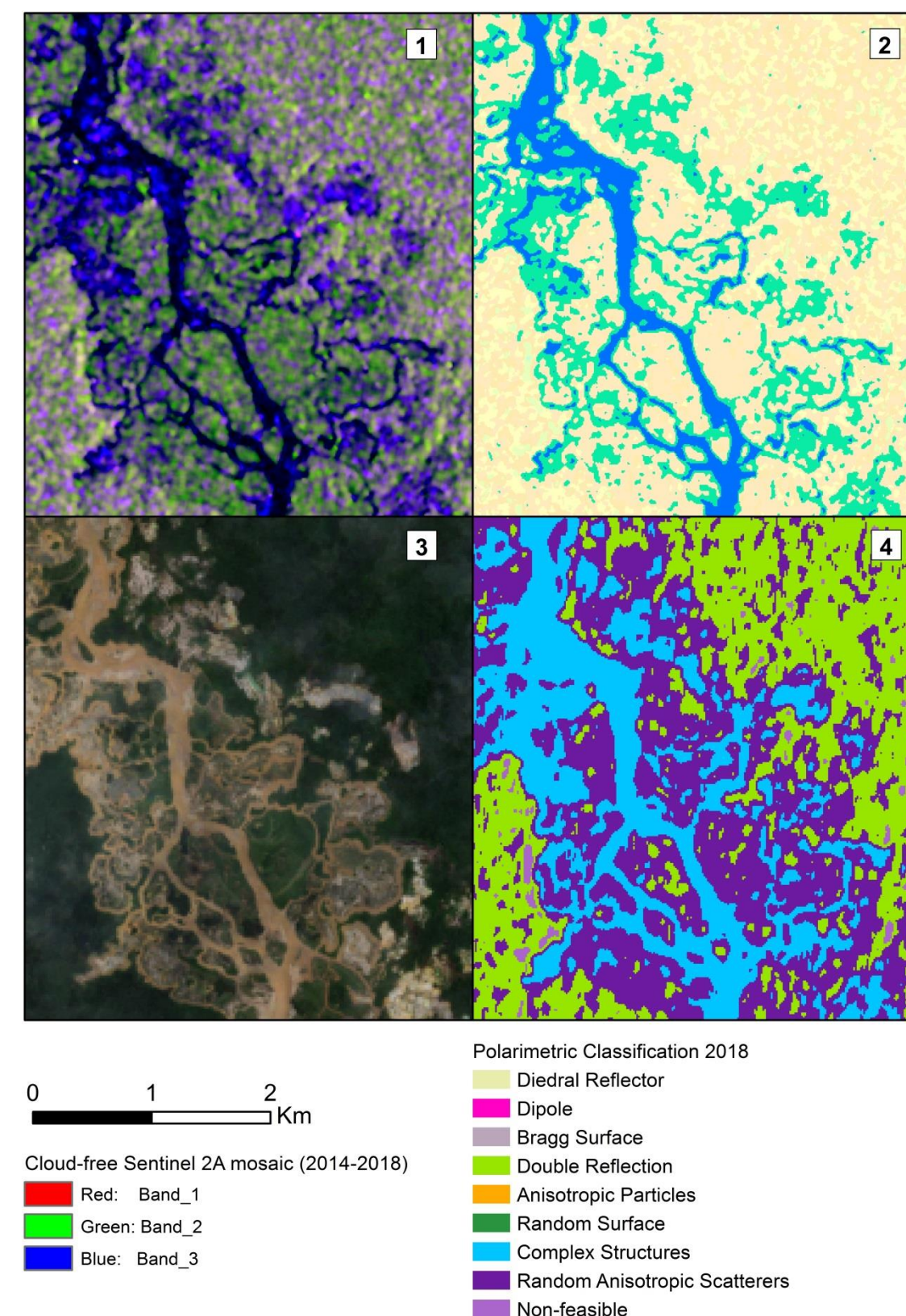
RESULTS

The figure below depicts the radar images and the K-mean classifications obtained for the years 2015 and 2018. From the classes generated, the classes 4 and 6 were identified to match visually with the Quito River and the delineation of mining assets realized by the Government of Colombia during the year 2014 [2] (orange polygons). For the year 2015 and using the Magna Sirgas Projection, these areas were identified to sum 14427.15 and 2896.23 ha respectively for class 4 and 6. The differences of this value and the reported in [2] can be explained due to misclassified pixels in each of the classes 4 and 6, as the observed blue and green pixels in the border of the 2015 classification below (second image from left to right). For the year 2018, classes 4 and 6 correspond respectively to 14521.15 and 2743.48 sqkm.



Another reason of the observed changes can be due to an expansion or new development of a mining activity. For instance, the region marked as ‘a’ in the images above, although not contained within the orange polygons, presents similar patters to the observed for the mining assets delineated in 2014 [2]. When observed the evolution of this region in 2015 and 2018, it is inferred that this is a new area of mining development.

The expansion of the zone ‘b’ can be visualized in the RGB composition for the year 2018 (third image from left to right above). The water and flat bare soil areas can be visualized in blue tones, while green areas correspond to areas with vegetation or continuous terrain changes that interact with the radar wavelength (Sentinel-1 , C band: 7.5 to 3.75 cm). A zoom of this area and the correspondent K-means classification can be observed with detail on the right figure (1 & 2). The image 4 corresponds to the obtained classification applying the algorithm “Halpfa Wishart Dual Pol”. When compared this image with the visual image in 3, it stands out the more detailed and homogeneous delineation than the obtained with K-means algorithm (2). The areas within the classes 4 and 6 appears in the image 2, appear differentiated from the surroundings in the image 4.



As the “Halpfa Wishart Dual Pol” classification is based on the entropy and alpha (α) classification plane, some of the areas within the mining footprints were classified as (i) ‘Random Anisotropic Scatterers’, while the external ones fall in the class (ii) ‘Double Reflection’. The first one presents a volume scatter with higher entropy, while the second one a double bouncing scattering with average probability [5]. The average entropy of (ii) can be associated to the double bouncing mechanisms on the high part of canopies, while the higher entropy of (i) due to elements that interact strongly with the C-band as the sediments associated to soil movement in mining areas.

To finalize, the zone ‘c’ in the image above, displays a recovery from 2015 to 2018. The reason for it can be associated to an abandoned mine, and denotes the complexities of the classification to realize in terms of the mining stage of the projects and the associated environmental impacts detected using Seninel-1.

DISCUSSION

Although the study presented an advance in terms of the delineation of stream bed mining footprints using Sentinel-1, still there are some challenges to overcome in the implementation of unsupervised methods. The polarimetric classification “Halpfa Wishart Dual Pol” in comparison to the “K-means cluster analysis” method improved the differentiation of spectral classes within and outside mining assets. The biggest challenge remains then in establishing the land cover delineations explaining the different stages of the mining projects present.

One alternative could be to utilize additional polarimetric parameters in the classifications (i.e. span or specific correlations) [5]. This accompanied of a statistical validation using the delineations in [2] and some of the attributes in [1] to establish the dates of the concessions and associated environmental impacts, but also the extent of operations that do not fall within these categories and need to be monitored.

REFERENCES
[1] SNL Metals & Mining, an offering of S&P Global Market Intelligence [06/ 2018]. Information for 1,132,589 mining concessions and 34,376 commercial mines globally.
[2] Colombian Government (UNODC & SIMCI), 2014. “Explotación de oro de aluvión. Evidencias a partir de percepción remota”.
[3] Wajs, J. (2018). First experience with Remote Sensing methods and selected sensors in the monitoring of mining areas – a case study of the Belchatow open cast mine. E3S Web of Conferences, 29, 23.
[4] European Spatial Agency. “Sentinel-1 Toolbox: Polarimetric Tutorial”.
http://step.esa.int/docs/tutorials/S1TBX%20SAR%20Basics%20Tutorial.pdf
[5] Pottier E, Lee J-S & Ferro-Famil L. “PolSARpro v- Lecture notes”
http://earth.esa.int/landtraining07/polsar_advanced_concepts.pdf