SURFACE CHANGES IN THE ATACAMA DESERT DUE TO ~~TWO~~ THREE EXTREME RAINFALL EVENTS: INSIGHTS FROM IRMAD PROCESSING OF LANDSAT IMAGERY AND UNSUPERVISED CLASSIFICATION

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INTRODUCTION

The Atacama Desert is the one of the driest places in the world, achieving < 4 mm/year of rain in some areas (Figure 1). Even in this dryness, there are some extreme rain events that caused extensive damage to some locations such as the ones in June 1991, March 2015 and more recently February 2019 (Figure 2 and 3). Our remote sensing analysis focuses on two areas shown in figure 1b.

These extreme rain events provoked observable changes in the landscape. Nevertheless, the full spatial extent of surface changes remains challenging to determine. There have been other attempts to achieve this task, such as InSAR (Scott et al., 2017) and field observations (Wilcox et al., 2016). Here, we introduce a new method to delimit the areas of important change in physical characteristics of the surface using LANDSAT imagery and unsupervised classification with potential to even identify different kinds of change.

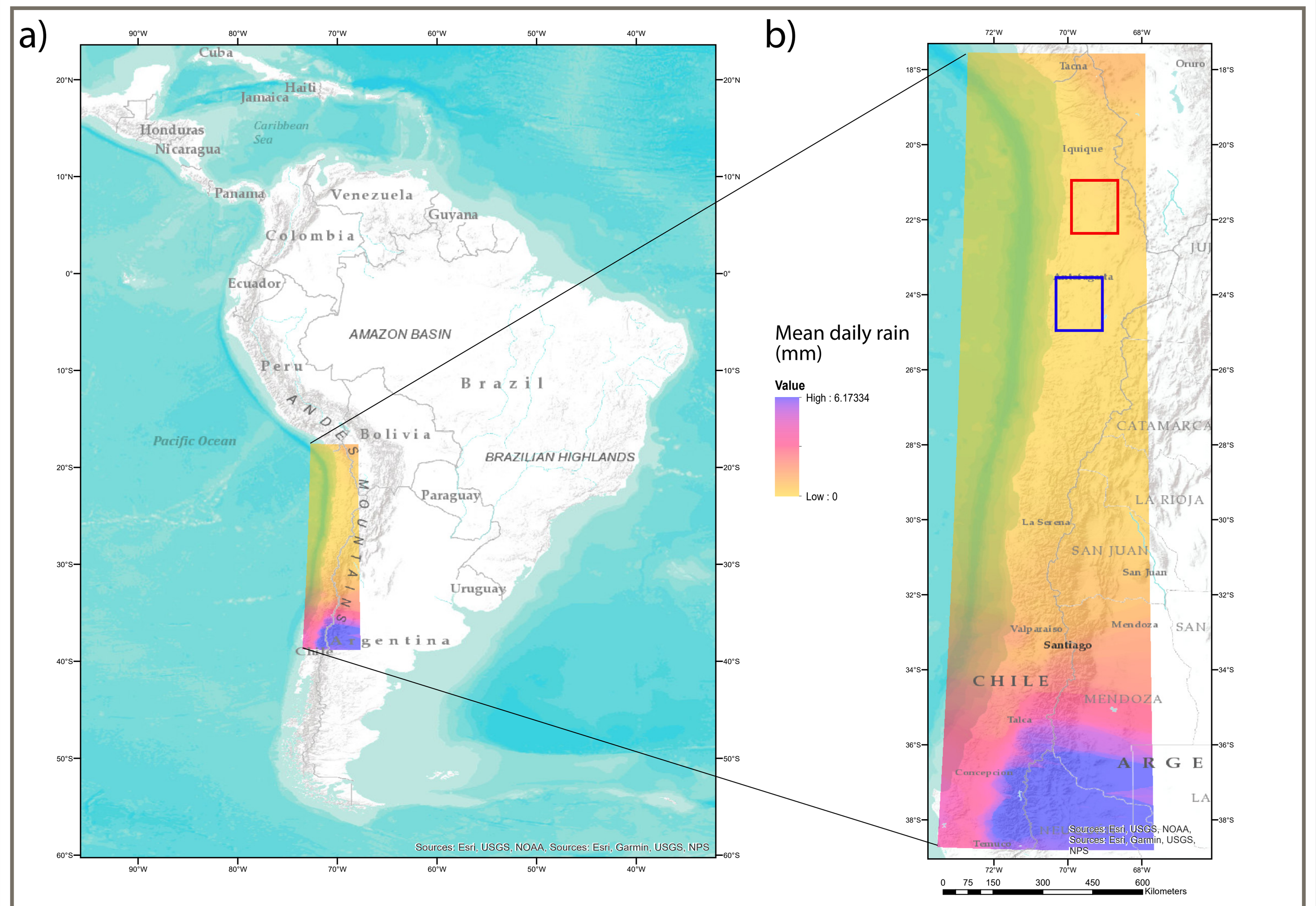

Figure 1: (a) Location map (b) mean daily precipitation rate in millimeters from 1940 to the present. Note the climate gradient from north to south, the red square shows the area analyzed for 2019 event, the blue square shows the area analyzed for 1991 and 2015 events. Source of the precipitation data: explorador.cr2.cl.

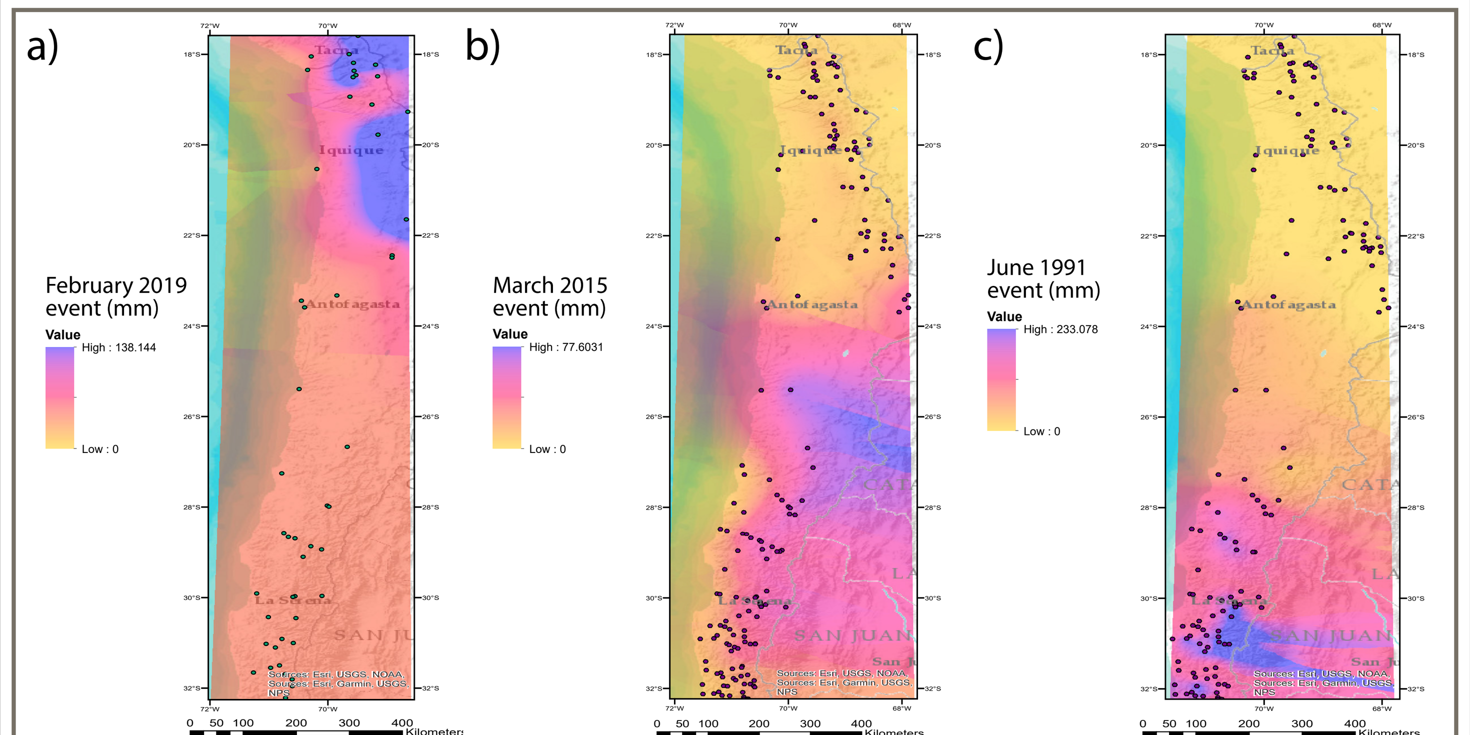

Figure 2: Precipitation data in millimeters for each extreme rain event. The measurement stations are marked as points. This interpolation was made using kriging method.

Figure 3: Images showing the devasting effects of the rain in different northern Chile cities. From left to right: a) Antofagasta, June 1991 rain event (source: www.timeline.cl). b) Chanaral, March 2015 rain event (source: www.biobio.cl). c) Calama, February 2019 rain event (source: lanacion.cl).

ABSTRACT

The Atacama Desert in northern Chile is the driest place in the world. Nevertheless, it has experienced some rare, extreme rainfall events that have caused landscape changes. Rain events of February 2019, March 2015 and July 1991 caused extensive damage in some locations. This study attempts spatially comprehensive detection of areas that change due to rainfall. In this work, we employ a new method to delimit the areas of important change in the physical characteristics of the surface using LANDSAT imagery. The process is an easy, semiautomatic, and reproducible methodology that has the potential to identify the types of surface change. The method is based on a succession of filters that constrain the area of change due to extreme rain, while deleting areas of human activities and of shadow change. Using the area of true change as a mask of the MAD (multivariate alteration determination) rasters, which corresponds to the variance in every spot in different wavelength of six spectral bands, we performed an unsupervised classification in ArcGIS software, selecting 10 classes. The unsupervised classification shows great potential for delimiting categories of change – erosion, deposition or moisture content - in the playa-lakes and channels. One class correlates strongly to alluvial fans and colluvium covered hillslopes. However, it is ambiguous whether the hillslope changes result from non-filtered shadow changes or real soil surface changes. Additionally, there are some classes that mainly show cloud change and LANDSAT misdetection areas.

METHODOLOGY

To detect areas that suffered changes due to an extreme rain event we used the Ir-MAD algorithm on LANDSAT images. Ir-MAD is based in a multivariate statistical technique called Canonical Correlation Analysis attempting to find correlation, in other words, similarities between two scenes (Nielsen and Canty, 2011). This analysis constructs new orthogonal variables (blue rasters in figure 4) from the original bands (red and yellow rasters in figure 4) with the largest correlation. The difference of each pair is called MAD (green rasters in figure 4) and they are ordered according to the decreasing variance. The amount of MAD rasters is the same as the number of bands used. The sum of squared MAD variates ideally will follow a chi squared distribution raster (bluish green raster in figure 4). In this one, higher values indicate, in a relative way, more change than lower values. In our study, we used LANDSAT 5 bands 1,2,3,4,5,6 to study the rain event of June 1991. To study the rain events of 2015 and 2019, we used LANDSAT 8 OLI bands 2,3,4,5,6,7 (Figure 5). For this last set we intentionally excluded band 1 (coastal aerosol) because it introduced considerable noise that was not related to actual surface changes.

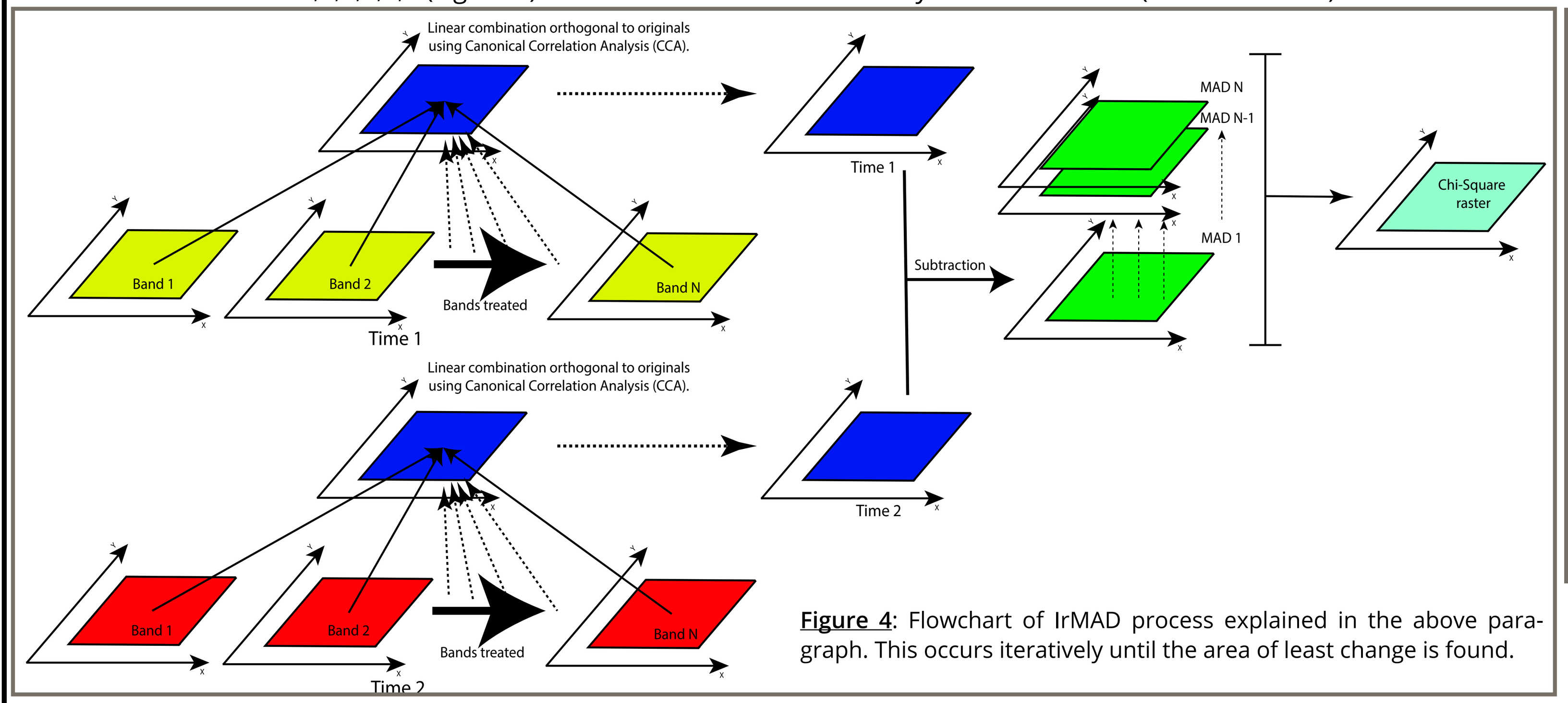

Figure 4: Flowchart of IrMAD process explained in the above paragraph. This occurs iteratively until the area of least change is found.

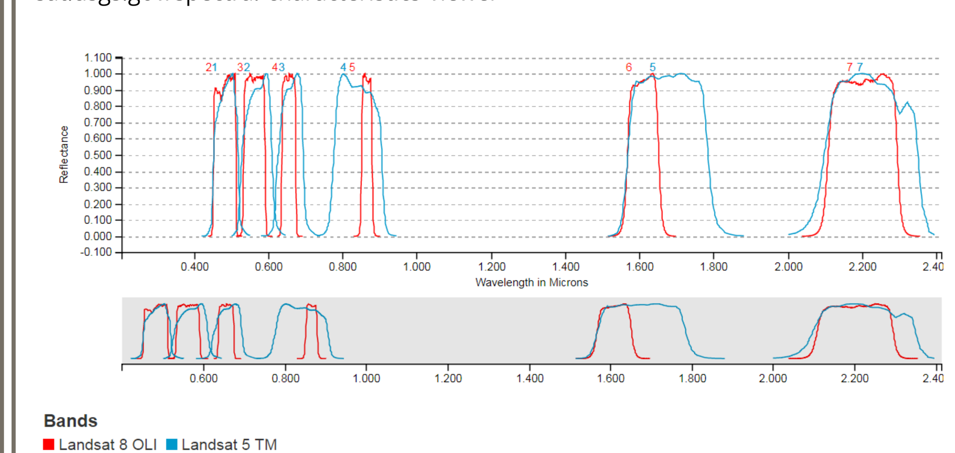

Figure 5: Differences between the wavelength detected by LANDSAT 5 and LANDSAT 8 OLI. Shown are only the bands used in this study. Image from https://landsat.usgs.gov/spectral-characteristics-viewer

Many things can change between two images, such as clouds, snow, shadows and human generated changes (Figure 6). We omit vegetation because the study area is unvegetated. To delete these areas, it is necessary to generate a series of filters in order to work with areas where changes were provoked by the rain effect (Figure 7).

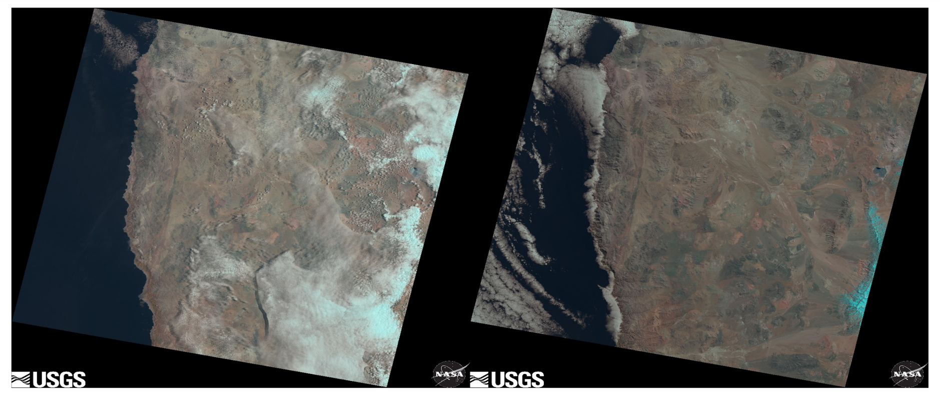

Figure 6: LANDSAT images showing the same area at different time, note the changes related to snow, cloudiness and shadow changes

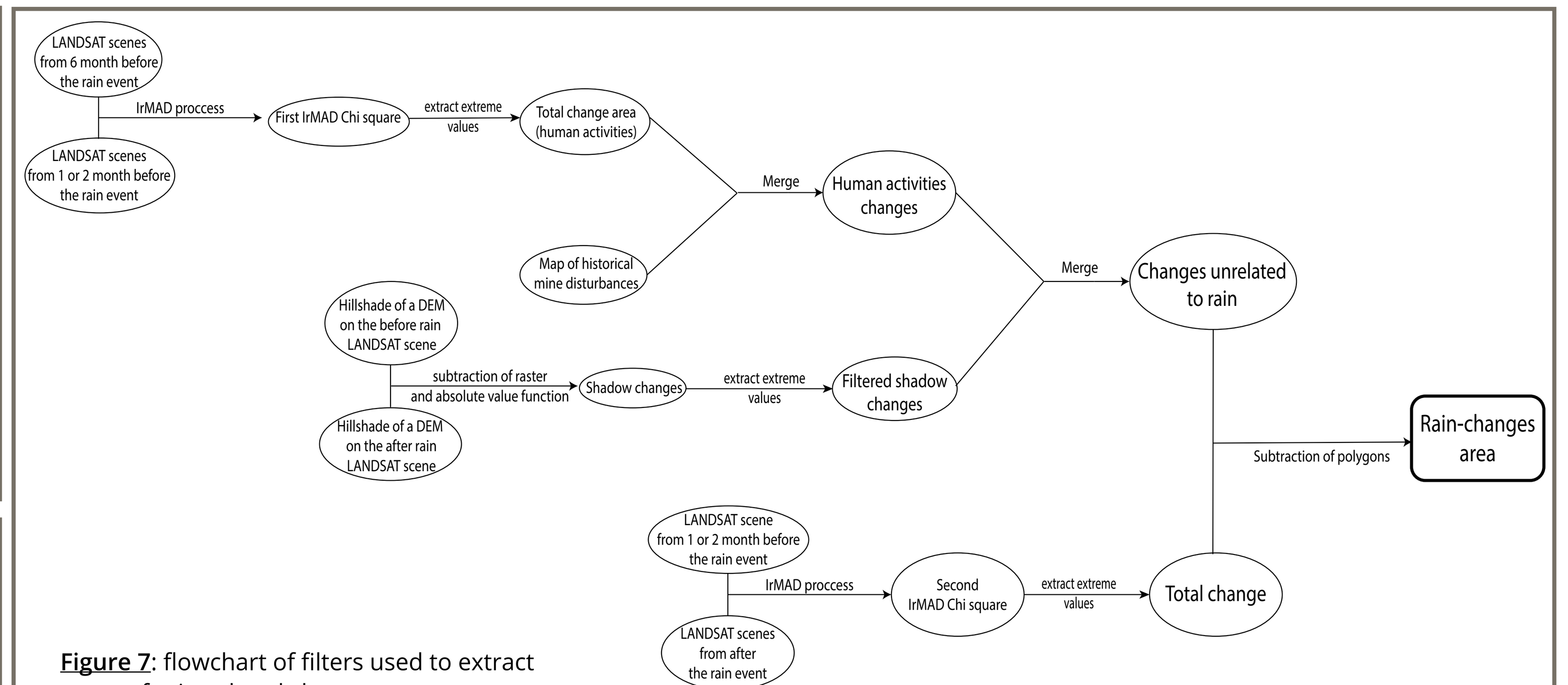

Figure 7: flowchart of filters used to extract areas of rain-related change.

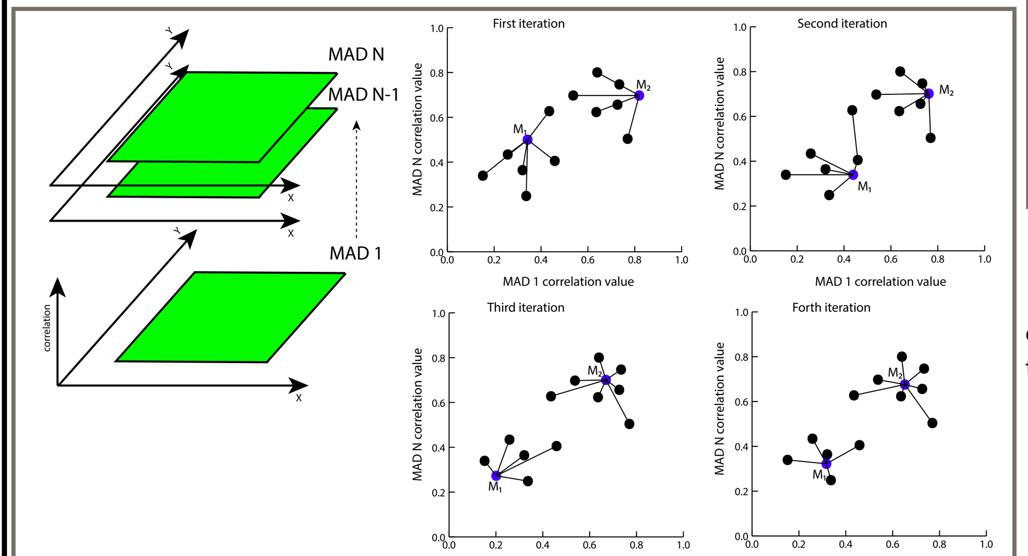

Figure 8: Scheme of unsupervised classification. Note the movement of the cluster cores (M_1 and M_2). This reflects an unsupervised classification in two dimension. However, we perfomed this in six dimension. Image modified from Richards and Jia 2013.

After delimiting the areas of changes related to rainfall (Figure 7), we used this polygon to mask each MAD created (variance of change at each point) and we applied unsupervised classification algorithm to that area (Figure 8), generating 10 classes of different kind of changes in the surface.

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RESULTS

This method shows great potential to identify and separate different kinds of changes, at the scale of a LANDSAT scene. It clearly identifies areas related to deposition in playa-lakes, alluvial fans and erosion in channels (Figure 9, 10 and 11). However, the changes in hillslope are somewhat doubtful given the fact that shadow changes between scenes might not be entirely deleted.

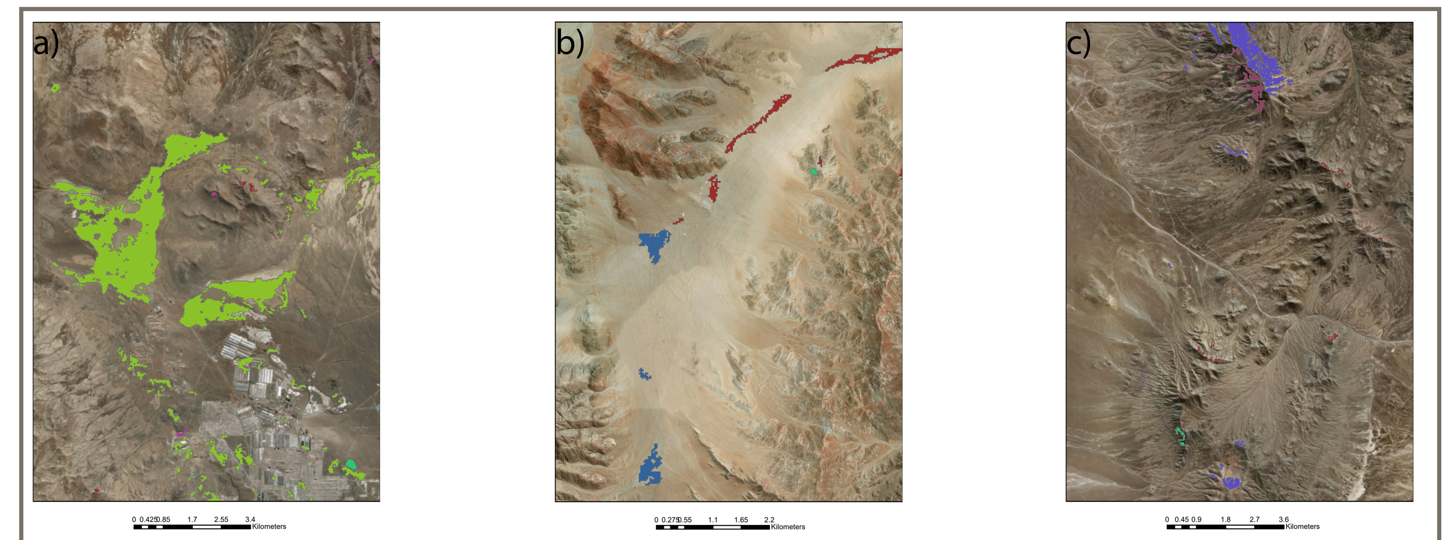

Figure 9: Surface changes due to the 1991 June rain event. (a) the green reveals playa-lake deposition, (b) the light-blue reveals alluvial fans and the red class reveals changes in channels. (c) Furthermore, there are some changes in hillslopes.

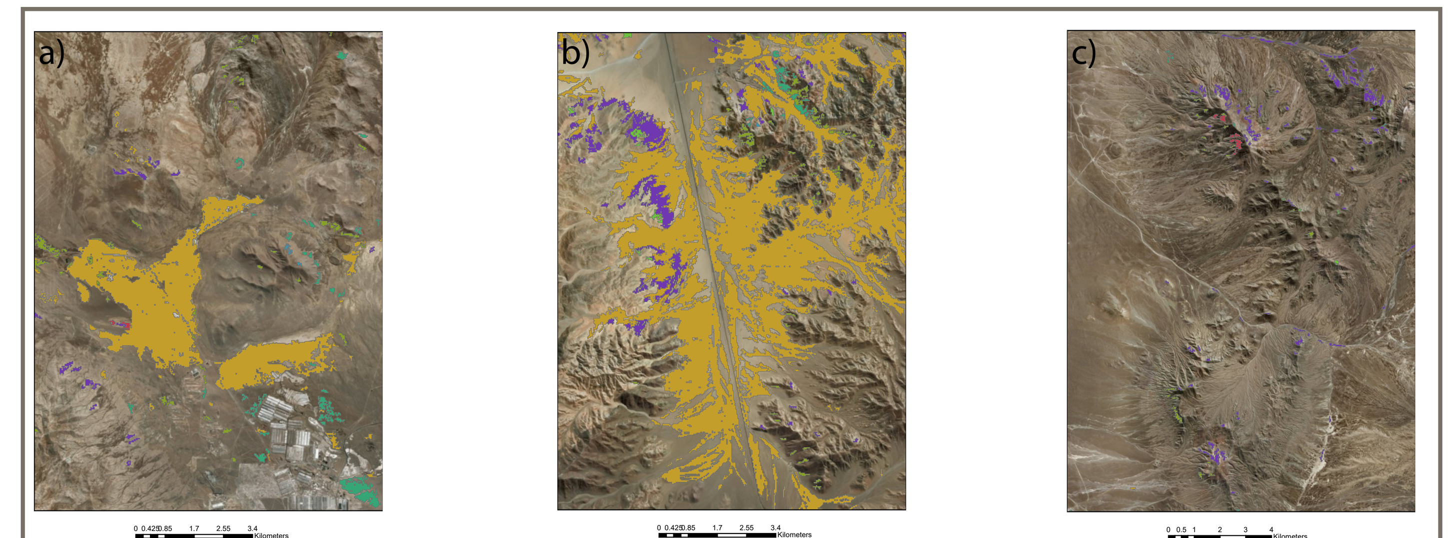

Figure 10: Surface changes due to the 2015 March rain event. (a) the light-brown is coincident with the green class in Figure 9a. (b) the light-brown is extended to other areas, such as alluvial fans and channels. This might be an error or due to the enhanced intensity of the 2015 rain event in comparison with the 1991 event. (c) It reveals changes in hillslopes.

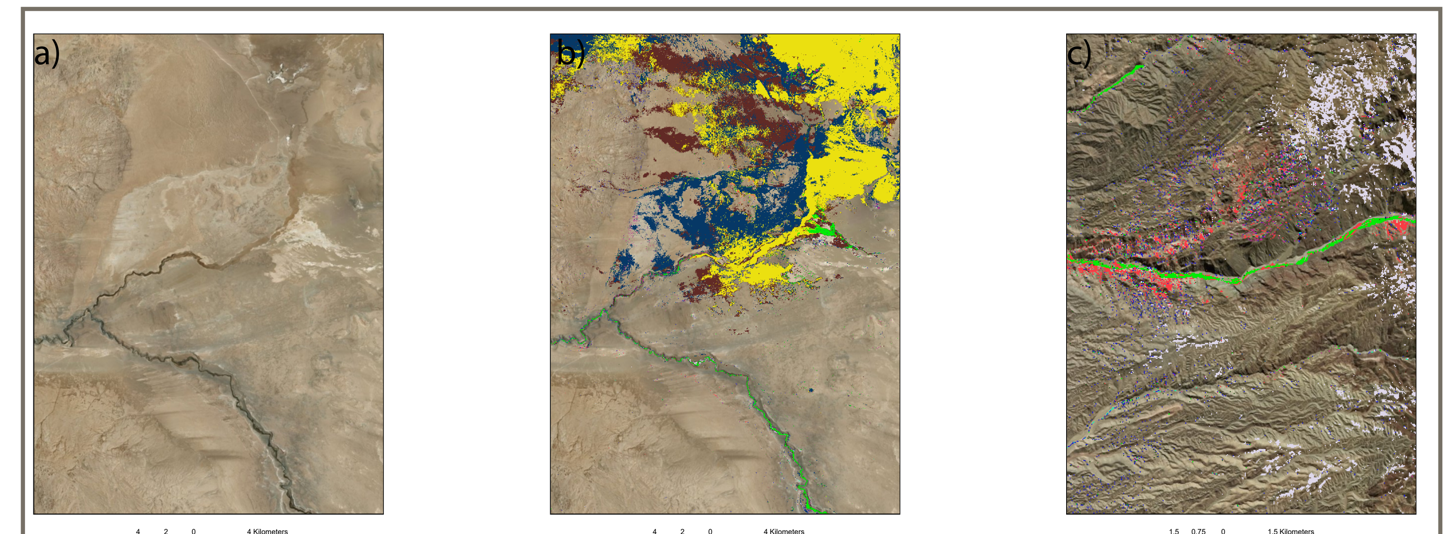

Figure 11: Surface changes due to the 2019 February rain event. (a) and (b) show the same area. (b) shows the results of unsupervised classification results. Note the good differentiation of the deposits in (a) and (b). (c) shows two different kinds of hillslope changes detected (white and red classes).

Taking into account that the hillslope changes are not well constrained by the filter process used (shadow changes), we are already working in some improvements of this technique in order to create a more reliable procedure.

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