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Assessing the impact of post-fire restoration interventions using spectral vegetation indices: A case study in El Bruc, Spain

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Master thesis, 30 credits, in Geographical Information Sciences

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Abstract

Ecological restoration has become an increasingly used practice to revert degraded land and mitigate the effects of extreme events in vulnerable biomes such as drylands. Methods to improve the assessment of these restoration interventions are essential to ensure their success, optimize resources and identify improvement aspects for future interventions. This study develops a method to assess the performance of post-fire restoration interventions on a pixel level when access to pre- and post- fire field data is limited, therefore depending on remote sensing data. The approach takes into account restoration intervention objectives, the state of the area before the intervention efforts began and key terrain variables.

This method was applied to a restoration intervention made in a burnt forest in north-east Spain, where an agro-silvopastoral mosaic has been conceived under the frame of a Life 2020 program. To assess the restoration performance, different spectral vegetation indices (SVIs) linked to the objectives were used. By using the Before-After-Control-Impact (BACI) statistical method, the study isolates the impact of the interventions from temporal variability and natural regrowth. The study explored the effects of the interventions by comparing restoration types (active or passive), terrain variables and the post-fire recovery levels before the intervention efforts began. The study also showed that the sole use of one SVI to assess the impact of restoration interventions may lead to limited conclusions as the three selected indices were outputting different levels of performance for the comparisons undertaken. The pixel level analysis also allowed to map the detailed variation in performance across areas. The core of this method can be applied to other restoration intervention scenarios other than post-fire and its affordability could allow for its integration in monitoring protocols in large-scale endeavors such as the current UN Decade on Ecological Restoration program.

Acknowledgements

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1. Introduction

1.1 Background and justification

As climate shifts seem to be more evident, forest fires events are increasing both in number and magnitude (Mouillot et al., 2002). This is particularly prominent in the Mediterranean region, where vast areas are classified as types of drylands, especially semiarid and dry subhumid (Cherlet, Hutchinson, 2018). Fire events are amongst the main drivers of erosion and can accelerate the risk of desertification (López-Vicente et al., 2013).

Restoration interventions on degraded dryland can help mitigate the risk of desertification, increase ecosystem resilience to natural disturbances as well as improve socio-economic development (Bautista, Aronson, et al., 2010). Restoration can be defined as any intentional activity that initiates or accelerates the recovery of an ecosystem from a degraded state (Willemen, Nangendo, Belnap, 2018). Different kinds of restoration activities can be applied, depending on the given ecosystem, objectives and available resources (IUCN, 2021). In woodlands, shrublands and mixed-use areas some of the most common restoration activities include planting endemic or high-value tree and grass species, invasive species control measures, rainwater and runoff harvesting, grazing pressure management or the creation of integrated crop, livestock and forestry systems (FAO, 2020).

After a wildfire event, the implementation of a restoration intervention can help the ecosystem to recover. In these circumstances, key intervention measures are actions that encourage revegetation (MEA, 2005). Vegetation is a major soil erosion regulator as it prevents surface runoff and loss of soil organisms. Vegetative cover mitigate erosion caused by precipitation and biophysical conditions of a given area (Guerra et al., 2016). Another relevant measure that mitigates the risk of future fires is the inclusion of adaptation mechanisms in the intervention project. Examples of this include the introduction of more climate-adapted provenances of existing species to increase resilience to stressors or the design of multifunctional landscapes (Stanturf et al., 2015). Revegetation intervention actions can be active or passive. Active intervention involves management techniques such as planting seeds or seedlings and passive intervention is when no action is taken except to cease environmental stressors such as agriculture or grazing (Morrison & Lindell, 2011).

Restoration projects are often costly and require the consensus of numerous stakeholders such as governmental institutions, policy makers and land managers; therefore it is important to carry out an evaluation that considers ecological, technical and socio-economic issues (Bautista, Aronson, et al., 2010). The development of methodologies to evaluate restoration performance can help us improve future actions and allocate resources more efficiently, ensuring the achievement of the goals and the success of the projects (Bautista, Aronson, et al., 2010; del Río-Mena et al., 2021). One way to evaluate the effectiveness of a post-fire restoration intervention is by determining how much the provision of vegetative cover and soil moisture has increased. The use of spectral vegetation indices (SVI) can be used as proxies to assess this provision. This should be done in a way that includes the temporal aspect, that is, by assessing the state of vegetation and soil moisture ex-ante and ex-post the intervention. In this regard, the Before-After-Control-Impact (BACI), a spatio-temporal comparative method that avoids changes attributable to temporal variability of vegetation status, has proven to be a useful method to assess restoration interventions that involve an increase of vegetation cover (Meroni et al., 2017). BACI is considered optimal to help isolate the effect of the intervention if the timing and location of the impact are known and adequate pre-data are collected (Smokorowski & Randall, 2017) and is especially useful for monitoring heterogeneous landscapes where diverse topography of restoration sites can affect the intervention impact (del Río-Mena et al., 2021). The main output, called the BACI contrast, indicates the temporal difference (after - before) for the given variable in the impact area compared to the control area. Recently, BACI was applied for the first time to evaluate the biophysical impact of an intervention project (Meroni et al., 2017), using the Normalized Difference Vegetation Index (NDVI) as a proxy to evaluate restoration success.

1.2. Research problem

Evaluating the success of a restoration intervention over time can be cumbersome due to various constraints such as difficult-to-access areas, lack of long-term records or standardized methodologies (Meroni et al., 2017). Other major challenges include the high economic costs and capacity constraints of field monitoring and the intra- and inter-annual climate variability when making a direct comparison of the observed attributes (del Río-Mena et al., 2021). In the context of intervention after fire, the lack of pre-burn field data is often the case and there may be no immediately adjacent unburned sites to serve as reference conditions (Bautista, Aronson, et al., 2010). Therefore, the use of other types of data such as remote sensing can be key in post-fire evaluation studies. Another aspect to take into account while evaluating the success of a restoration intervention is the recovery state of the area at the start of the intervention efforts. On one hand, fires may not necessarily affect the whole area uniformly, hence measuring vegetation burn severity can help capture differences between areas. Vegetation burn severity is described as the aboveground organic matter consumption from fire (Keeley, 2009). On the other hand, post-fire restoration interventions do not always take place immediately after fire and the temporal gap in between could result in unequal natural recovery developments, depending on burn severity, heterogeneity of the landscape or vegetation types. This can lead to needing several separate evaluations for areas with different baselines to ensure that the performance of the intervention is properly assessed.

While the use of remotely sensed (RS) data can help cope with these constraints, few examples of its use to assess restoration interventions are available (Meroni et al., 2017). Del Río-Mena (2020) uses RS data to quantify the effect of the restoration interventions on ecosystem services. In this study, however, field data were available and was used to create a linear model to explain the analyzed ecosystem service by selecting the most appropriate SVI as the explanatory variable. In cases where no field data are available the evaluation becomes more challenging and the choice of a single SVI might lead to an incomplete view of the performance of the intervention. When only NDVI is used, as in Meroni et al. (2017), the applicability of the proposed method is limited to the biophysical impact in terms of vegetation cover. Hence, the use of additional indices and other remote-sensing-derived variables (e.g. soil moisture, topographic features) may be further expanded to explore the applicability of the BACI method in other post-fire restoration goals (Meroni et al., 2017) such as erosion prevention and mitigation of desertification risk. However, studies often lack indicators to address all intervention objectives. This is further compounded by the fact that studies frequently focus on sample plots, unable to capture the heterogeneity of the whole terrain, which may provide less conclusive results. In this sense, the application of a pixel-based methodology can help identify potential spatial patterns that affect the impact of the intervention.

1.3 Research objectives and questions

This study aims to evaluate the impact of a post-fire restoration intervention, passive and active with the use of remote sensing data. The evaluation uses three SVIs instead of the sole use of the main proxy indicator for vegetation cover, NDVI, on a pixel-based analysis using remote sensing data. The degree of divergence of the outcomes will ascertain the relevance of the choices of indices when evaluating interventions and will determine how much the conclusion of the assessment can be affected by the different SVIs analyzed. The BACI contrast will serve as the basis to evaluate the impact and will be calculated using the value of the selected SVIs before and after the intervention on each intervened pixel and comparing the resulting value with that of the non-intervened areas. The selected indices represent biophysical variables used as indicators related to the main intervention goals: regrowth, erosion prevention and mitigation of desertification risk. As such, the following research objectives and research questions (Q) were defined:

Objective 1. Assess the performance of the post-fire restoration interventions, passive and active, through SVIs using the BACI method.

Q1.1 What is the BACI contrast of the different levels of post-fire recovery?
Q1.2 What is the BACI contrast of the different types of intervention?
Q1.3 What is the BACI contrast of the different terrain variables?

Objective 2. Assess the sensitivity of the SVIs when evaluating the intervention using the BACI method.

Q2.1 How much does the choice of SVI impact the outcome when evaluating the effectiveness of the intervention?

2. Methodology

2.1 Study area

The study area chosen for this study is in El Bruc municipality, located 40km north-west from Barcelona, Spain and has an extent of approximately 600 ha. It is adjacent to Montserrat Natural Park, a unique geological formation and emblematic point in Catalonia. It has suffered several forest fires in the last decades, therefore making it a heavily degraded zone in risk of desertification.

The land cover currently consists in a mosaic of shrubland (most abundant species being *Salvia rosmarinus*, *Erica multiflora* and *Genista scorpius*) and fields cultivated for pastures, with scattered rural houses and some agricultural and animal husbandry activities; crops include olives and almonds and domestic livestock, mainly cattle, goats and poultry. This landscape is surrounded mostly by a uniform extension of Aleppo pine forest (*Pinus halepensis)* and residential areas. The area has a Mediterranean climate - Csa group in the Köppen climate classification - with hot-dry summers and mild-wet winters although being located inlands and having an altitude of around 500 meters a.s.l. makes winters be a bit colder than in areas closer to the coast. Annual precipitation is around 600 mm[1]. The soil type of the area has a high clay content - providing the landscape with its characteristic red color - as well as sand. The soil textural class ranges from clay loam or sandy clay loam at the surface to sandy loam 20-30 cm underneath while the stoniness presents moderate to very high values[2].

The area has been part of different European Commission's Life 2020 funding programs[3]. In July 2014, it was included in a program called Life Montserrat[4], co-financed by the regional government and the European Commission which covered an area of 32 000 ha, 64% being forest and included the whole Montserrat Natural Park. Its main objectives were the prevention of wildfires, the conservation of biodiversity and the creation of a mosaic of scrub, natural grasslands and forest connecting two Natura 2000 sites within the area[5]. The program contributed to the settlement of some husbandry and farming projects, with the aim of using cattle as a tool for forest management. According to the program, which finished in 2019, 1200 ha of forest were restored, 150 ha of open fields were recovered and husbandry projects of cows, goats and donkeys were established, to graze 1400 ha[6].

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[1] https://www.idescat.cat/

[2] https://thegreenlink.eu/wp-content/uploads/2021/02/CONCLUSIONS-AND-RECOMMENDATIONS-REPORT_feb2021.pdf

[3] https://cinea.ec.europa.eu/programmes/life_en

[4] https://lifemontserrat.eu/en/

[5] https://lifemontserrat.eu/en/objectives/

[6] https://lifemontserrat.eu/es/evolucion/final-del-proyecto/

However, soon after the start of the project, on July 26th 2015, the area suffered a fire that affected about 1300 ha, 80% of which was forest and the rest being fields. Subsequently a second Life 2020 program, "The Green Link" (July 2016), took place on the burnt area, whose goal was to restore desertified areas with an innovative tree growing method - Cocoon - across degraded locations in different Mediterranean locations, to increase resilience[7]. In El Bruc, this involved both passive and active restoration interventions aiming at reducing the vulnerability of the area against fire (mostly a former pine forest poorly maintained and therefore a fuel hazard) through a landscape transformation project and measures for climate resilience. Actions to achieve this were the reforestation of part of the damaged area (4150 trees in 24,1 ha), the creation of an agro-silvopastoral mosaic using adaptative and economically interesting species[8], the enhancement of ecosystem services, particularly in relation to soil quality improvement and biodiversity[9] and halting desertification processes[10]. Another objective was to evaluate the performance of the Cocoon ecotechnology tree growing method, which showed an increase in the survival and growth of the seedling planted (Carabassa et al., 2021). The restoration was led by the Ecological and Forestry Application Research Center (CREAF) team, based in the Autonomous University of Barcelona. In addition to the efforts done under "The Green Link", 10 ha were reforested in December 2017 within the frame of a partnership between a bank and Sylvestris, a natural engineering company. The project planted around 4000 trees with the goal of carbon offsetting[11].

Since 2021 the study area is involved in a new Life 2020 project, the "New Life 4 Drylands" [12], aiming to apply nature-based solutions to desertified lands. As its objective is to develop a protocol for the identification of dryland characteristics and for a mid and long-term monitoring of restoration interventions of desertified lands through the use of remote sensing techniques (Mazzetti, 2022), the conclusions extracted from this case study may be a useful contribution to the project. Figure 1 shows a map of the study with respect to the aspects and initiatives explained in this section.

[7] https://thegreenlink.eu/description/

[8] https://thegreenlink.eu/project-areas/cataluna/

[9] https://thegreenlink.eu/wp-content/uploads/2016/11/Summary-and-participants_LIFE-The-Green-LInk_V2ENG.pdf

[10] https://thegreenlink.eu/objectives/

[11] https://gruposylvestris.com/proyectos/reforestacion-montserrat-barcelona/

[12] https://www.newlife4drylands.eu/language/en/

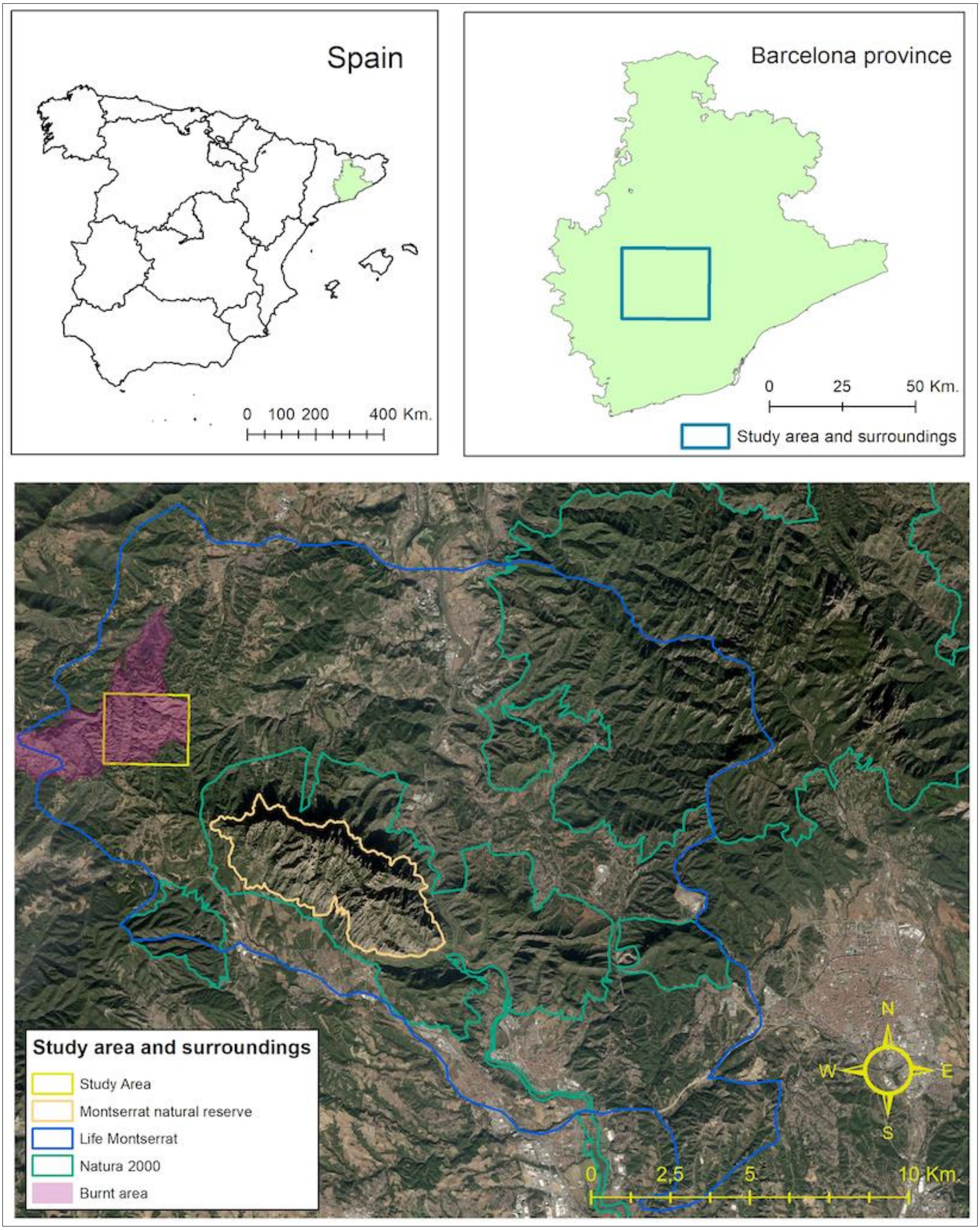

Figure 1 Study area location in Spain (A), Barcelona province (B) and surrounding area with respect to the 2015 fire, Life Montserrat project, Montserrat mountain natural partial reserve and Natura 2000 sites (C).
Source: National Center of Geographical Information of Spain. Background image: Satellite view of the area taken from Sentinel-2 Level 2A, RGB, 10m resolution.

2.2 Workflow overview and dataset

The workflow is summarized in Figures 2 and 3. The first stage was to set up the areas that would be compared on the impact assessment according to the intervention implemented: active intervention area, passive intervention area and non-intervention area. A second stage consisted of the retrieval of the values of the SVIs that were selected in consistency with the intervention objectives of the restoration. I selected one Sentinel-2 image from 2016 - before the interventions took place - and another one from 2021. To do a coherent comparison between impact and control areas, the pixels of each of the three intervention areas were classified in clusters. Each cluster grouped the pixels according to the recovery level before the interventions took place (partly recovered or non-recovered), the slope (steep or gentle) and the aspect (north or south) leading to eight clusters, that is, all the possible combinations. Twenty control pixels were randomly selected from each cluster of the non-intervention area, from which we obtained an average value that was used against each intervened pixel of the same cluster to obtain the BACI contrast. With the BACI contrast value for each pixel I was able to do the appropriate comparisons to answer the research questions by grouping the pixel BACI contrast values according to the objectives as well as by specific intervention locations to assess different performance between them.

To assess the performance of the post-fire interventions I compared the BACI contrast values obtained on each intervened pixel in three different ways, corresponding to the three questions:
Firstly, grouping the pixels in the two different recovery levels, to evaluate whether different post-fire regrowth affected the success of the intervention efforts differently.
Secondly, grouping them according to the type of restoration intervention (i.e. active or passive), to assess the performance of the two different types of intervention. Additional comparisons were done using the before-after difference of the SVIs values instead of BACI contrast (i.e. excluding the control-impact effect). This allowed me to include non-intervention areas to the comparison.
Thirdly, grouping them according to the terrain variables. Two comparisons were made, one for its slope type and another for its aspect. An additional multiple comparison was done between the eight land type clusters in which the pixels were originally grouped.
In every case, all the calculations were done for each of the three SVIs chosen for the study.

To assess the sensitivity of the SVIs when evaluating the intervention I compared the BACI contrast values of each SVI in all the intervened pixels. This allowed me to calculate their degree of correlation and therefore compare whether the choice of the SVI was relevant to assess the performance of the restoration intervention. I also ranked the SVI's according to the hectares of land in absolute terms of performance (i.e. positive, negative or no effect). Additionally, I identified the pixels where the absolute BACI effect differed between the three SVIs.

Lastly, I did the necessary hypothesis tests to verify the statistical significance of the results.

The datasets used for the study are shown in Table1. In regard to software programs, ArcGIS Desktop version 10.5.1 (ESRI) was used for the creation of intermediary products (Intervention area map, post-fire recovery map, cluster map), final maps and calculations like control-pixel selection, slope or aspect. Google Earth Engine was used for the retrieval of SVI values. Microsoft Excel was used for the calculation of the BACI analysis and SPSS for the statistical significance evaluation. Also, phone device app Field Maps (v. 21.4.0) from ESRI was used to record the boundaries of the non-intervention and the passive intervention areas in the field and ArcGIS Online to export the layers created in Field Maps into shapefiles for its use in ArcMap.

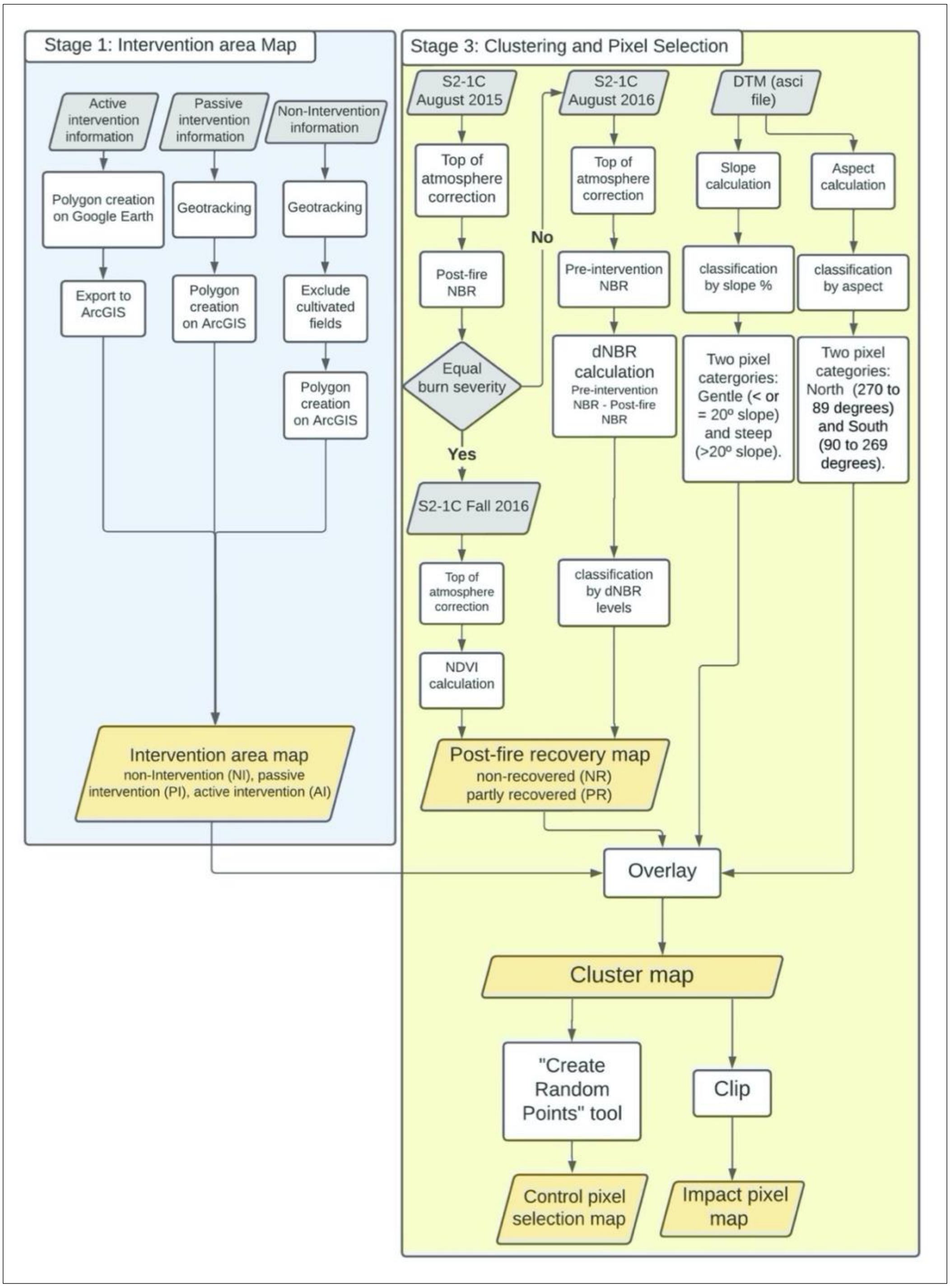

Figure 2 Workflow of stage 1 (Intervention area map) and part of stage 3 (Pixel selection).

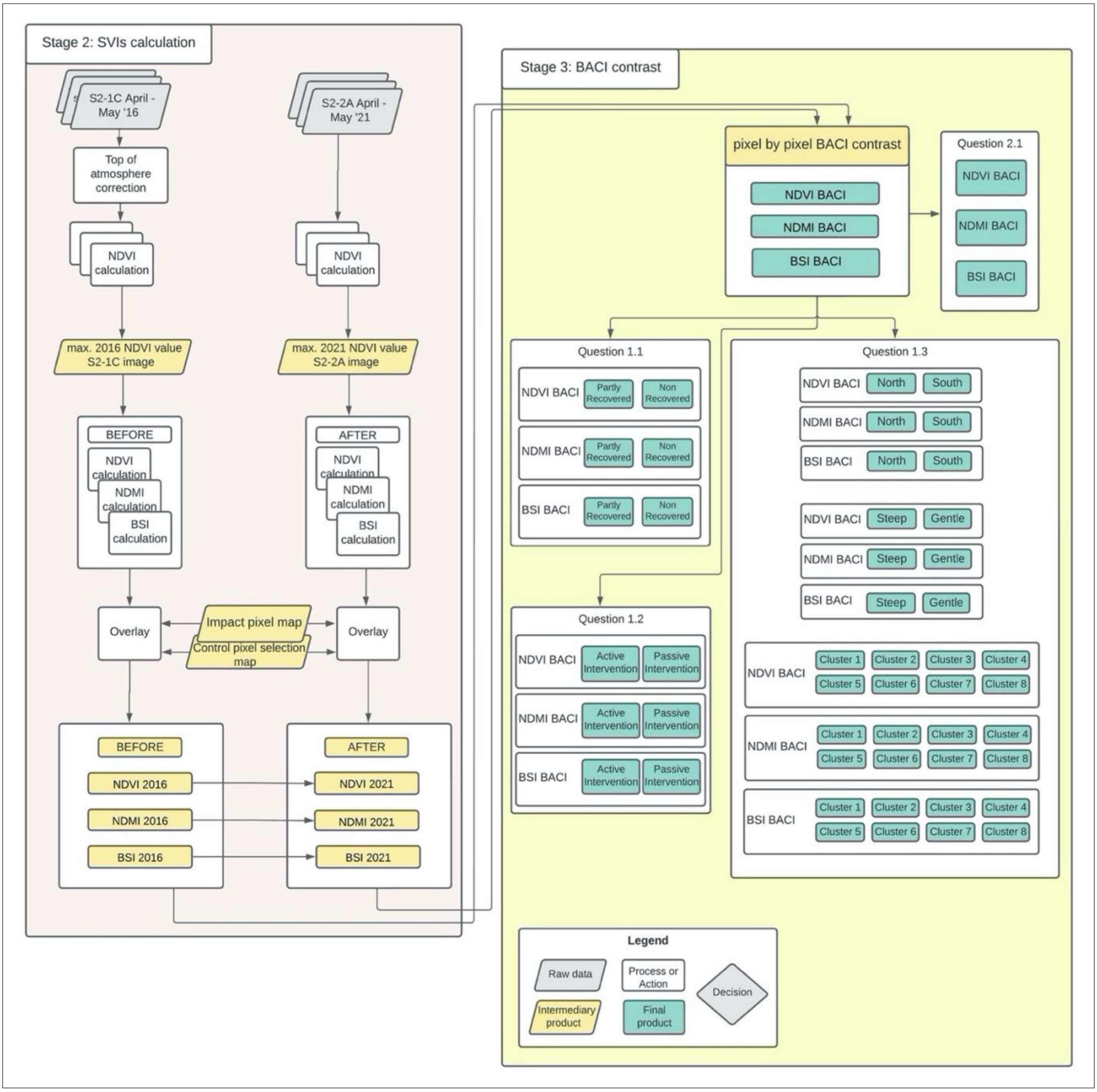

Figure 3 Workflow of stage 2 (SVIs calculation) and part of stage 3 (BACI calculation).

Table 1 Datasets used for the study.

Data	Source	Type	Year
Sentinel-2 Level 1C (before 2017) and Level 2A (after 2017) satellite imagery	*Google Earth Engine*	tif	August 2015, August 2016, April - May 2016, April - May 2021
Digital Terrain Model, 2 meter grid spacing, ETRS89	*National Center of Geographical Information of Spain*	asc	2016
Active intervention location areas	*CREAF, Autonomous University of Barcelona*	kml	2019
Passive intervention and pasture areas	*Area recording field trip with Field Maps app.*	shp	2022

2.3 Stage 1: Mapping restoration interventions areas

The first stage, summarized in Figure 2, defined the areas that were used for the study. I considered three areas under the following criteria: The first area was active intervention, consisting of the plantation of different endemic trees as well as clearing burned wood. A total of five different locations were included in this study, four of them corresponding to the Green Link program in which the Cocoon ecotechnology was used - featuring different species and densities - and the other one being the carbon offsetting planting project, Sylvestris. The second area was passive intervention, where only protection against grazing occurred and two locations were selected. The third area was non-intervention, where cattle grazing occurred and no protection or revegetation enhancement measures were undertaken. This was chosen to illustrate the most representative grazing intensity of the area, with a herd of 25 to 30 cows on a rotational, low-intensity basis with two to three uses a year per plot, depending on the need. With the selection of the three areas and their respective locations, I obtained an intervention area map (Figure 4) with two types of impact areas - active intervention and passive intervention - and one control area – non-intervention.

The identification and creation of the active intervention polygons was undertaken with the help of a kml file provided by CREAF that includes locations of the trees being planted on the Green Link study. The passive intervention and non-intervention areas were delineated using ArcMap after geotracking the locations on the field with the ESRI Field Maps mobile application. I identified the locations on two different field trips carried out on the 29th January and 28th February of 2022 with the help of a local herdsman. Within non-intervention areas, some fields have been cultivated with alfalfa as fodder for the cattle. These fields were omitted to include only areas disturbed by cows. Table 2 describes the characteristics of each area that are relevant for the study.

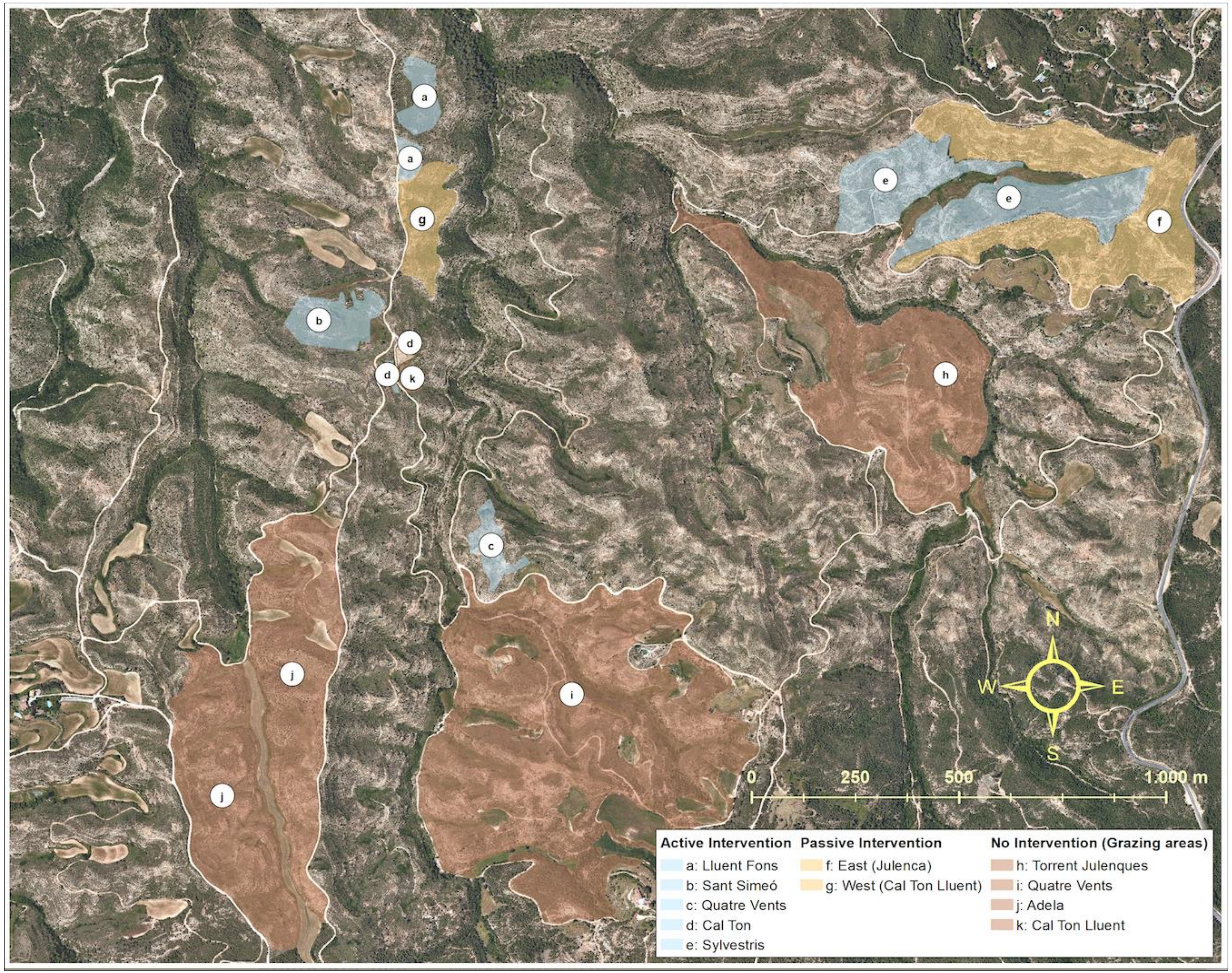

Figure 4 Intervention area map, indicating the active, passive and non-intervention areas as well as the location names used for the study. Background image: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

Table 2 Characteristics of the locations included on the study.

Location name	**Beginning of use / intervention**	**Surface & planting denisity**	**Planted Species & Approx. number**	**Fencing**	**Burned wood removal**	**Textural Class**	**Stoniness**	**Other observations**
Active Intervention Lluent Fons	May 2017	1,71 Ha. 190 trees / Ha.	Olive (*Olea europaea cv cornicabra)* & Portuguese Oak *(Quercus faginea)* // 300-350 approx.	no	yes	Sandy clay loam on 0-10 cm and Sandy loam on 20-30cm	Very high (63,5%) on 0-10 cm and moderate (33,3%) on 20-30cm	Very thin soil (<30cm depth), therefore high hydric stress.
Active Intervention Sant Simeó	Fall 2016	2,33 Ha. 193 trees / Ha.	Olive (Olea europaea cv cornicabra), Evergreen Oak (Quercus Ilex) & Fig *(Ficus carica)* // 450 approx.	yes	yes	Sandy clay loam on 0-10 cm and Sandy loam on 20-30cm	Moderate (27,23%) on 0-10 cm and high (54,89%) on 20-30cm	Failed attempt due to bad state of seedlings.
Active Intervention Quatre Vents	May 2017	1,09 Ha. 360 trees / Ha.	Evergree*n Oak (Quercus ilex subsp, ball* ota) i Portuguese Oak *(Quercus faginea)* // 400 approx.	yes	yes	no data	no data	Very thin soil (<30cm depth), therefore high hydric stress.
Active Intervention Cal Ton	May 2017	0,18 Ha. 388 trees / Ha.	Carob *(Ceratonia siliqua)* // 70 approx.	no	yes	Clay loam on 0-10 cm and Sandy loam on 20-30cm	Moderate (31,25% on 0-10 cm and 23,02% on 20-30cm)	Very thin soil (<30cm depth), therefore high hydric stress.
Active Intervention Sylvestris	Dec. 2017	10,2 Ha. 405 trees / Ha.	Evergreen Oak *(Quercus Ilex)* Almond *(Prunus dulcis) Common hawthorn (Crataegus monogyna)* Strawberry tree *(Arbutus unedo)* Aleppo pine *(Pinus halepensis)* // 4K approx.	no	no data	no data	no data	
Passive Intervention East (Julenca)	Fall 2016	14,36 Ha.	n/a	no	no	no data	no data	
Passive Intervention West (Cal Ton Lluent)	Fall 2016	2,74 Ha.	n/a	no	no	no data	no data	
Non-Intervention Torrent julenques	Fall 2016	17,66 Ha.	n/a	No	no	no data	no data	
Non-Intervention Quatre vents	Fall 2016	39,45 Ha.	n/a	Yes	partly	no data	no data	Use of vehicles for preparing the land
Non-Intervention Adela 1&2	Fall 2016	25,48 Ha.	n/a	No	Grinded spread over the field	no data	no data	Use of vehicles for preparing the land
Non-Intervention Cal Ton Lluent	Fall 2016	0,26 Ha.	n/a	No	partly	no data	no data	

2.4 Stage 2: Calculating spectral vegetation indices

With the second stage, summarized in Figure 3, I obtained the values of the selected SVIs across the whole area from which the BACI contrast was carried out.

2.4.1 SVIs selection

The SVIs were calculated from the multispectral instrument on-board of Sentinel 2A and 2B satellites (S2) that are part of European Space Agency's Copernicus program. Their images provide data of 13 bands in the visible, near infrared and short wave infrared part of the spectrum, covering all of the Mediterranean region. The S2 constellation has a revisiting time of 5 days (10 days per each of its two satellites) and the images have a spatial resolution - pixel size - of 10, 20 and 60 meters, depending on the band.

One key criterion for the selection of the indices is their capacity to predict biophysical variables that can be used as proxies to assess restoration intervention objectives. As seen in the study area section, the objectives involve regrowth of vegetative cover, the improvement of soil quality and the mitigation of desertification by preventing erosion. Secondly, I used indices of which its spectral composition differed in at least one band, to avoid correlation of the results. Indices formed with the same bands would enhance similar surface features, therefore evaluating the state of the intervention in the same way. Lastly, one of the chosen indices is the Normalized Difference Vegetation Index (NDVI) as it is one of the most commonly used and therefore will be key in proving its status as a reference index by comparing its outcome with the others. Table 3 shows the three selected indices along with their features. Due to the fact that the NDMI bands have a 20 meters spatial resolution I resampled their raster files to 10 x 10 meters for consistency with NDVI and BSI outputs.

Table 3 Spectral indices with corresponding equations and related biophysical variables with intervention objectives. NIR = Near infrared; SWIR = Short wave infrared.

Name	**Index Equation**	**Bands in Sentinel-2**	**Biophysical Variable**	**Intervention Objective**
Normalized Difference Vegetation Index *(Eq.1)*	(NIR - Red) / (NIR + Red)	(8 - 4) / (8 + 4)	Vegetative cover	Regrowth
Normalized Difference Moisture Index *(Eq. 2)*	(NIR - SWIR) / (NIR + SWIR)	(8A-11) / (8A+11)	Moisture	Soil quality improvement
Bare Soil Index *(Eq. 3)*	((Red+SWIR) – (NIR+Blue)) / ((Red+SWIR) + (NIR+Blue))	((4+11) – (8+2)) / ((4+11) + (8+2))	Bare Soil	Erosion Prevention

a Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) (Tucker, 1979) is an effective index for quantifying green vegetation and measures vegetative health based on how plants reflect near-infrared light in comparison with the absorption of the red light which is needed for photosynthesis. The value range of the NDVI is -1 to 1. Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Low, positive values represent scarce vegetation (approximately 0.2 to 0.4), while high values indicate dense vegetation (values approaching 1). NDVI has gained particular recognition in the scientific community as a good proxy indicator of vegetation cover. This is a relevant indicator given the importance of the vegetation canopy in preventing land degradation in drylands (Jucker Riva et al., 2017) and has been used in post-fire vegetation regrowth detection in Mediterranean regions (Solans Vila & Barbosa, 2010).

b Normalized Difference Moisture Index

The Normalized Difference Moisture Index (NDMI) is an indicator of moisture and plant humidity that has been used in restoration effectiveness assessments of desertified areas (Qi et al., 2013). Soil moisture is a critical element in drylands and the improvement of its provision can help mitigate desertification. It is used as an indicator of the water regulation services (del Río-Mena et al., 2020) and determines the allocation of rainfall for enrichment of soil moisture (Safriel et al., 2005). The NDMI uses NIR and SWIR bands. In this case I used the narrow NIR band (8A) as provided by the repository of custom scripts of the Sentinel-Hub services[13].

c Bare Soil Index

The Bare Soil Index (BSI) accounts for the exposed soil and is reliable in situations where the vegetation covers small areas (Rikimaru et al., 2002), detecting recent deforestation or monitoring droughts. It can also be used to detect landslides or determine the extent of erosion in non-vegetated areas[14]. In the Mediterranean dryland it has been used for assessing reforestation projects (del Campo et al., 2021) as well as desertification risk in semi-arid highlands (Becerril-Piña et al., 2015). It is also included in restoration assessment studies as for quantifying the erosion prevention ecosystem service (del Río-Mena et al., 2021).

[13] https://custom-scripts.sentinel-hub.com/sentinel-2/ndmi/#

[14] https://custom-scripts.sentinel-hub.com/sentinel-2/barren_soil/

2.4.2 Annual image selection

The annual images for both 2016 - before any intervention took place - and 2021 - last available year - to retrieve the SVIs data were selected by calculating the NDVI at the vegetation's peak development - April and May. From the available images I selected the one having the highest average value of the study area. Images having a cloud cover pixel percentage higher than 20 were filtered out. Figure 5 shows the average NDVI values of the image retrieval. 16 images were available for 2021 and 7 images were available for 2016. In accordance with the criteria described, the selected image for 2016 was that of the 21st of May while for 2021 it was 17th of April.

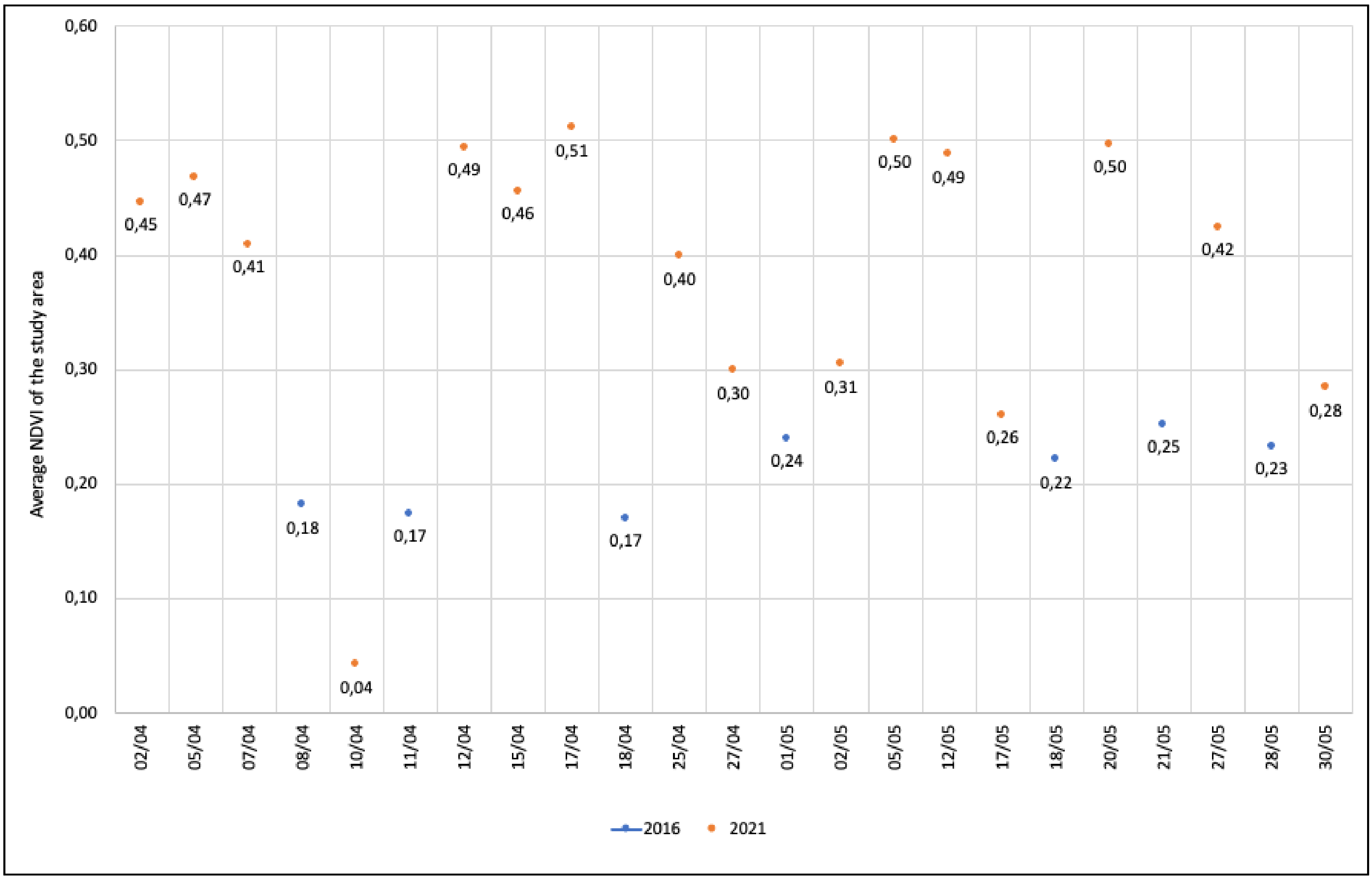

Figure 5 Average NDVI value of the area in April - May of 2016 and 2021.

2.5 Stage 3: Assessing restoration impact

In the third stage, two main steps were carried out. Firstly, the pixel selection (Figure 2), where I developed a criterion to classify pixels in clusters, using the restoration intervention map obtained in stage 1 and adding relevant variables. Secondly, the SVI's calculation undertaken in stage 2 was used to calculate BACI contrast (Figure 3) over the pixel selection. After that, I validated the results and answered the research questions accordingly.

2.5.1 Pixel Selection

A sampling strategy was required to ensure consistency when comparing sites to assess restoration impact. For that, instead of merely selecting pixels from the areas identified in the restoration intervention map, two other aspects were taken into account to refine the selection: Post-fire recovery levels and topographic variables.

a. Post-fire recovery levels

To set the reference values to determine the degree of post-fire recovery I classified the area by levels of natural regrowth before the intervention activities started in the fall of 2016. The objective of this classification was to ensure that the comparison of control and impact pixels was undertaken only between areas that have evolved similarly, to avoid attributing the natural regeneration of the area to the intervention effort. A first step for that was to verify the effect that the fire had on the area using the Normalized Burn Ratio (NRB) index (Eq. 4) from a range of images directly after the fire took place (1st to 20th of August 2015). This index showed that the burn severity was not homogeneous, as I encountered severely and moderately burned areas. If the NBR would have shown similar values it could be assumed that the baseline from which the whole area begins its recovery process is the same and therefore the calculation of the NDVI at the beginning of the intervention (i.e. fall 2016) would suffice to classify the area by recovery levels. The disparity on the NBR values led me to classify the study area based on the delta Normalized Burn Ratio (dNBR) (Eq. 5), calculated between just after the fire (1st to 20th of August 2015) and before the interventions (1st to 20th of August 2016, to avoid seasonality). This showed the gap in vegetation one year after the fire took place, providing a reliable source to evaluate the regrowth of the study area which I split in two categories, Non-recovery (high and moderately-high severity values) and Partly recovered (moderate-low and low severity values). I applied the dNBR thresholds in a similar way that is used to obtain the difference between the pre-fire and post-fire NBR and that are proposed by the United States Geological Survey (USGS) and the United Nations Platform for Space-based Information and Disaster Management and Emergency Response (UN-SPIDER)[15]. Therefore, values above 0.44 indicated that the fire effects were still severe and the areas have not been able to self-recover (i.e. non-recovered). A value between 0.1 and 0.44 indicated that there was some regrowth (i.e. partly recovered). Values under 0.1 were interpreted

[15] https://un-spider.org/advisory-support/recommended-practices/recommended-practice-burn-severity/in-detail/normalized-burn-ratio

as unburned or totally recovered areas and therefore were left out to avoid ambiguity. The study area classified according to its recovery level is shown in Figure 12 of the Appendix.

The Normalized Burned Ratio uses near-infrared (NIR) and shortwave-infrared (SWIR) wavelengths. Healthy vegetation before the fire has very high NIR reflectance and a low SWIR response. In contrast, burned areas have a low reflectance in the NIR and high reflectance in the SWIR band.

$$\mathrm{NBR} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}} \quad (Eq. 4)$$

$$\delta\mathrm{NBR} = \mathrm{Pre\_intervention\ NBR} - \mathrm{Post\_fire\ NBR} \quad (Eq. 5)$$

b. Topographic variables

Slope and aspect were considered for the selection to avoid comparing pixels having significant differences that might affect relevant aspects like regrowth of the vegetative cover or water runoff. These variables are key for the development of vegetation and moisture content due to the hilly and steep relief and the amount of sunshine hours characteristic of the Mediterranean region. For slope, I split the selection in two categories according to the level of steepness (i.e. gentle or steep), being 20 degrees the chosen cutoff point. This value is the midpoint of what is considered a median slope range (Carabassa et al., 2012). For slope extraction, a digital terrain model made from lidar cloud points and 2 meters resolution was used for it[16]. In regard to aspect, I classified pixels in two categories: North facing, that is, ranging from 270 degrees to 89 degrees and south facing, that is, ranging from 90 degrees to 269 degrees.

c. Clustering and control pixel selection

I classified the pixels by taking into account the results of the restoration intervention map, the post-fire recovery levels and the topographic variables obtaining eight clusters for each type of intervention area type as shown in Table 4. A map of spatial distribution of pixel clusters can be seen in Figure 13 of the Appendix.

For the control pixels (i.e. non-intervention) twenty pixels were randomly selected for each cluster as in del-Río-Mena (2021). By selecting twenty control pixels for each category, I minimized the chance of selecting a specific point that has experienced an undetected occurrence that might distort the comparison (e.g. intensively grazed, not grazed, heavily modified by wild fauna). The control pixels were selected with a minimum allowed distance of 20 meters between them to avoid pseudoreplication, that is, the use of replicates that may not be statistically

[16] https://centrodedescargas.cnig.es/CentroDescargas/locale?request_locale=en

independent (Hurlbert & Monographs, 2010). A map showing the location of the control pixels can be seen in Figure 14 of the Appendix.

Table 4 Clusters for each intervention area type after overlaying the recovery level map and the topographic variables.

	Post-fire recovery class	**Cluster**	Cluster number
NORTH · GENTLE SLOPE	Non-Recovered	**north-gentle-non**	1
	Partly recovered	**north-gentle-partly**	2
NORTH · STEEP SLOPE	Non-Recovered	**north-steep-non**	3
	Partly recovered	**north-steep-partly**	4
SOUTH · GENTLE SLOPE	Non-Recovered	**south-gentle-non**	5
	Partly recovered	**south-gentle-partly**	6
SOUTH · STEEP SLOPE	Non-Recovered	**south-steep-non**	7
	Partly recovered	**south-steep-partly**	8

2.5.2 BACI calculation

To compare the intervention pixels against the non-intervention ones before and after the intervention I used the Before-After-Control-Impact (BACI) approach. The impact of the intervention was estimated for each pixel using the BACI contrast (Eq. 6), expressed in natural numbers in the same units as the variable of interest.

$$\text{BACI contrast} = (\mu_{CA} - \mu_{CB}) - (\mu_{IA} - \mu_{IB}) \quad \textit{(Eq. 6)}$$

Where,

μ is the SVI value of the pixel at the date of the NDVI maximum annual value date (if impact) or the mean of the twenty pixels of the corresponding cluster (if control)

C is control (i.e. non-intervention)

I is impact (i.e. active intervention or passive intervention)

A is after (i.e. 2021)

B is before (i.e. 2016)

Therefore, a negative result indicated that the intervention pixel had a higher SVI temporal variation with respect to non-intervention pixels, therefore showing a positive intervention effect. This is the opposite in the case of BSI, as this index measures bare soil. In this case, a negative result showed a negative intervention effect. To facilitate the understanding of the outcomes I multiplied the BSI results by -1 and referred to negative BACI contrast values as positive performance. The calculation of the BACI contrast for each pixel and SVI was later combined accordingly to answer the questions of the two objectives.

2.5.3 Comparing performances across sites and indices

To determine if the differences of the BACI contrast results between groups were significant I did statistical hypothesis tests and the outcome allowed me to answer the research questions. The tests and null hypothesis summarized in Table 5 were in accordance to the questions as well as groups being compared and normality was always examined first. For that, I applied the Shapiro-Wilk and the Kolmogorov-Smirnov tests setting a p-value of 0.05. Skewness and kurtosis were also taken into account, considering acceptable values those ranging between -2 and 2 (George & Mallery, 2010). In all cases data were found to not be normally distributed for at least one of the groups being compared and therefore I used non-parametric tests.

I used the Mann-Whitney U when comparing the performance of two groups whose samples were independent (i.e. non-paired). This was the case for post-fire recovery (Question 1.1) and for slope and aspect terrain variables (Question 1.3). As part of Question 1.3 I also considered it relevant to compare the different land clusters since the BACI contrast was performed taking into account the land cluster in which each pixel belonged. For this, I used the Kruskal-Wallis test, indicated when having more than two sample groups. I also did extra Mann-Whitney U test between the land clusters whose pairwise comparison turned out similar when doing the Kruskal-Wallis test.

In regards of the types of intervention (Question 1.2) I did two different comparisons. The first one based on the BACI contrast to know if active and passive intervention groups performed differently. As the comparison is done between two groups I used the Mann-Whitney U test. The other comparison was undertaken based on the difference of the SVIs values of 2021 and 2016, that is, excluding the impact-control difference and hence not using the BACI contrast. This allowed me to include the non-intervention area into the comparison, which does not have BACI contrast. The control group does not have BACI contrast as it is required to calculate the BACI contrast of the impact groups (i.e. active and passive intervention). In this case, as we are comparing three groups, I used a Kruskal-Wallis test. I also used the difference of the SVIs values of 2021 and 2016 to do three additional Mann-Whitney U tests, pairing all three intervention types against each other (active and passive, active and non-intervention and passive and non-intervention).

To evaluate if there are significant differences on the SVIs performances based on the BACI contrast I used a Friedman's test, which is indicated to compare repeated measures in more than two groups. To determine the effect of the restoration interventions in absolute terms of performance I classified, for each SVI, pixels having a BACI contrast of -0.01 or less as positive effect category. Pixels having 0.01 or more were grouped on the negative effect category whereas pixels having a BACI contrast under 0.01 and above -0.01 were considered areas were no effect took place. Lastly, to identify areas where the absolute BACI effect differed between the three SVIs I classified their output between positive effect (<0.00) and negative effect (>0.00) and compared the values in each pixel.

In all hypothesis testing I applied a two-sided test with a 5% significance level for null hypothesis rejection. For each question I did tests for the three SVIs used in the study.

Table 5 Statistical hypothesis of each research question along with the test used.

Code	Research question	Null hypothesis	Data used	Normality	Method
Q1.1	What is the BACI contrast of the two different levels of post-fire recovery?)	The recovery level does not affect the impact of the interventions significantly	BACI contrast. Partly recovered against non-recovered	No	Mann-Whitney U Test
Q1.2	What is the BACI contrast of the different types of intervention?	The restoration intervention type does not affect the impact of the interventions significantly	BACI contrast. Active intervention area against passive intervention area	No	Mann-Whitney U Test
		The intervention types do not show significant differences compared to the non-intervention area	SVI difference (After - Before). Active intervention area against passive intervention area against non-intervention area	No, except the non-intervention data	Kruskal-Wallis Test
		Passive intervention do not show significant difference compared to the non-intervention area	SVI difference (After - Before). Passive intervention area against non-intervention area	No, except the non-intervention data	Mann-Whitney U Test
		Active intervention do not show significant difference compared to the non-intervention area	SVI difference (After - Before). Active intervention area against non-intervention area	No, except the non-intervention data	Mann-Whitney U Test
		The restoration intervention type does not affect the impact of the interventions significantly	SVI difference (After - Before). Active intervention area against passive intervention area	No	Mann-Whitney U Test
Q1.3	What is the BACI contrast of the different terrain variables?	The aspect does not affect the impact of the interventions significantly	BACI contrast. North against south	No	Mann-Whitney U Test
		The slope does not affect the impact of the interventions significantly	BACI contrast. Steep against gentle	No	Mann-Whitney U Test
		The clusters do not show significant diifference on the impact of the interventions.	BACI contrast. 8 clusters.	No	Kruskal-Wallis Test
					Mann-Whitney U Test between the clusters whose pairwise comparison is similar
Q2.1	How much does the choice of the SVIs impacts the outcome when evaluating the effectiveness of the intervention?	The choice of SVI does not impact the outcome when evaluating the effectiveness of the intervention significantly	BACI contrast of the three SVIs.	No	Friedman's test

3 Results

3.1 BACI contrast of post-fire recovery levels

Interventions in non-recovered areas performed better than in partly-recovered ones, as it can be seen in Table 6. The results were found to be significant as the null hypothesis was rejected on the three SVIs (p-values for NDVI, NDMI and BSI being 0.00, 0.02 and 0.00 respectively) confirming that the recovery level of the vegetation before the interventions took place had an impact on the intervention. The maps showing the BACI contrast for the two post-fire recovery levels and three SVIs are presented in Figure 6. Figure 7 shows data ranges in boxplots, providing information about the locality and spread of the data. It is noticeable the large number of potential outliers, especially in the partly-recovered data.

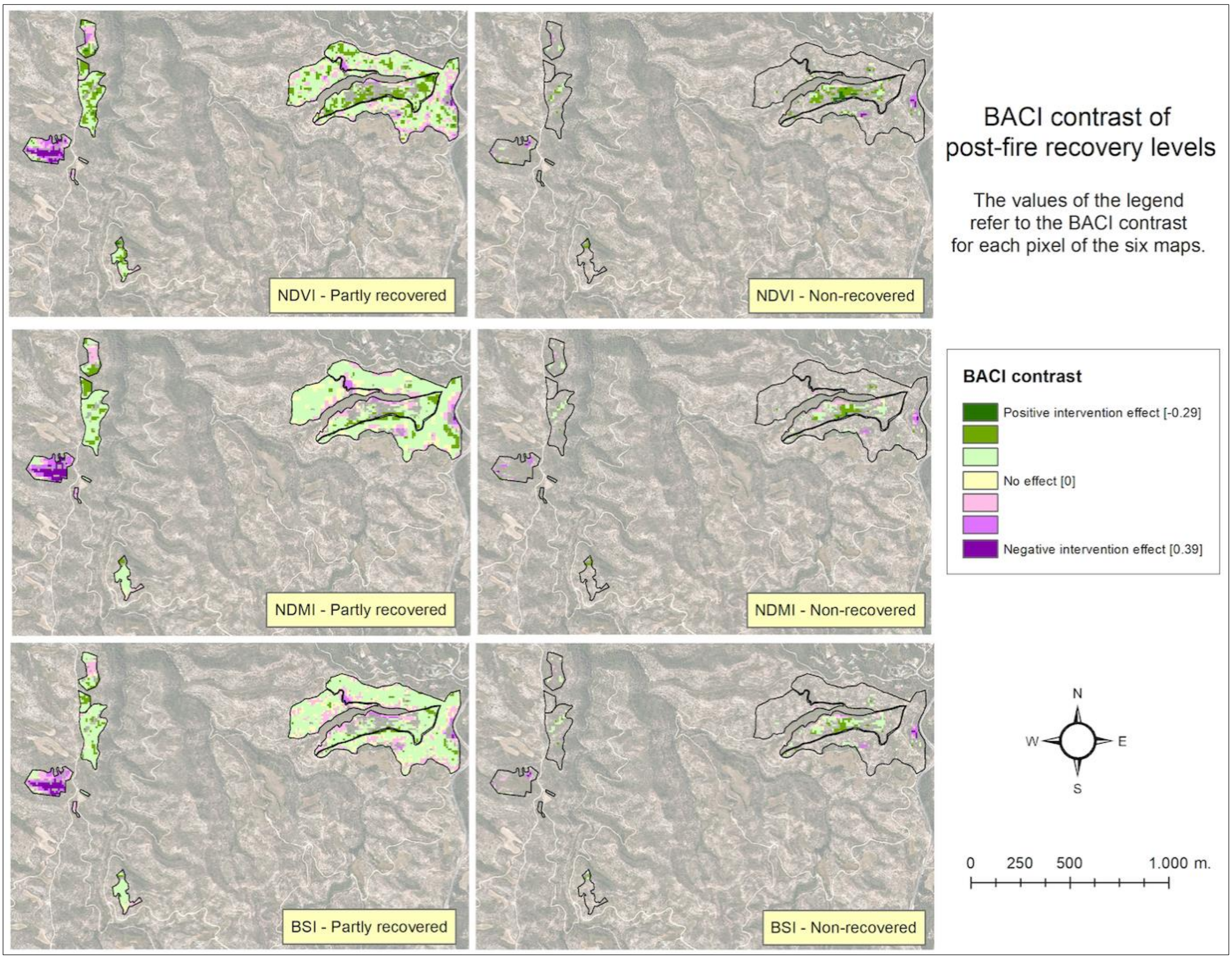

Figure 6 Maps showing the BACI contrast for both classes of post-fire recovery levels on each SVI. Background images: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

Table 6 Average BACI contrast of both classes of post-fire recovery level. The % diff. column refers to the percentage difference of the non-recovered values compared to that of the partly-recovered ones.

	Partly-recovered	**Non-recovered**	**% Diff.**
NDVI	-0,032	-0,069	116,7
NDMI	-0,021	-0,028	29,8
BSI	-0,016	-0,027	69,0

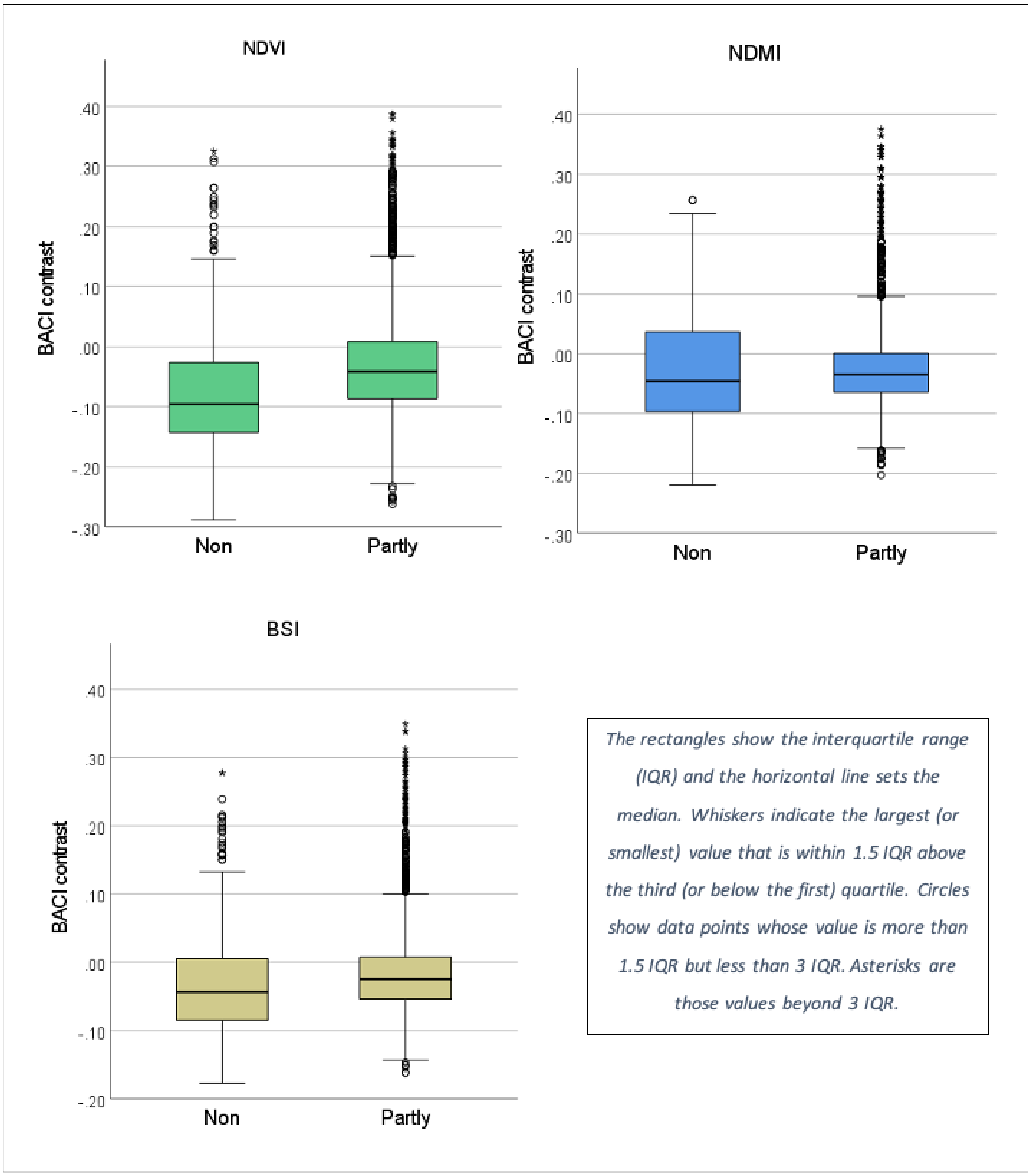

Figure 7 Boxplots showing the data of the two types of recovery levels for the three SVIs.

3.2 BACI contrast of intervention types

Passive intervention areas performed better than active intervention ones in regard to NDMI and BSI but NDVI showed a slightly stronger improvement in active areas. Table 7 summarizes the average BACI contrast values and Figure 9 provides visual information through boxplots. The tests done over the BACI contrast values rejected the null hypothesis on the three SVIs (p-values for the three SVIs being < 0.001) showing that the type of restoration intervention, active or passive, had a significant effect on its performance. Figure 8 shows the performance of the three SVIs throughout the locations and it can be observed that the outputs varied significantly depending on specific areas, as it can be confirmed with the numbers presented in Table 8. All of them except Cal Ton and Sant Simeó showed positive results. Passive area "West" was the area where interventions had the stronger positive effect in all three SVIs.

The hypothesis testing done for active, passive and non-intervention areas using the before-after difference of the SVI values also showed significant differences among the three populations, with a p-value of < 0.001 for NDVI and 0 for NDMI and BSI. The three Mann-Whitney U test combining the three land intervention areas (i.e. active vs. non, passive vs. non and active vs. passive) also showed significant differences among the three populations except the NDVI between active and passive intervention areas where the null hypothesis is not rejected (p-value = 0.435). This is a relevant outcome as the statistical test done with BACI contrast showed significant differences between the two areas, also for NDVI.

Table 7 Average BACI contrast of both restoration intervention types. The % diff. column refers to the percentage difference of the passive group values compared to that of the active ones.

	Active	Passive	% Diff.
NDVI	-0,038	-0,033	-14,6
NDMI	-0,009	-0,034	261,3
BSI	-0,008	-0,025	207,4

Table 8 Average BACI contrast of both types of restoration intervention, broken down per restoration location. Negative effect is indicated in red.

	Active intervention					Passive intervention	
	Quatre Vents	Cal Ton	Lluent Fons	Sant Simeó	Sylvestris	West (Cal Ton)	East (Julenca)
NDVI	-0,07	0,02	-0,04	0,12	-0,07	-0,08	-0,02
NDMI	-0,05	0,02	-0,05	0,16	-0,03	-0,07	-0,03
BSI	-0,05	0,00	-0,04	0,12	-0,03	-0,05	-0,02

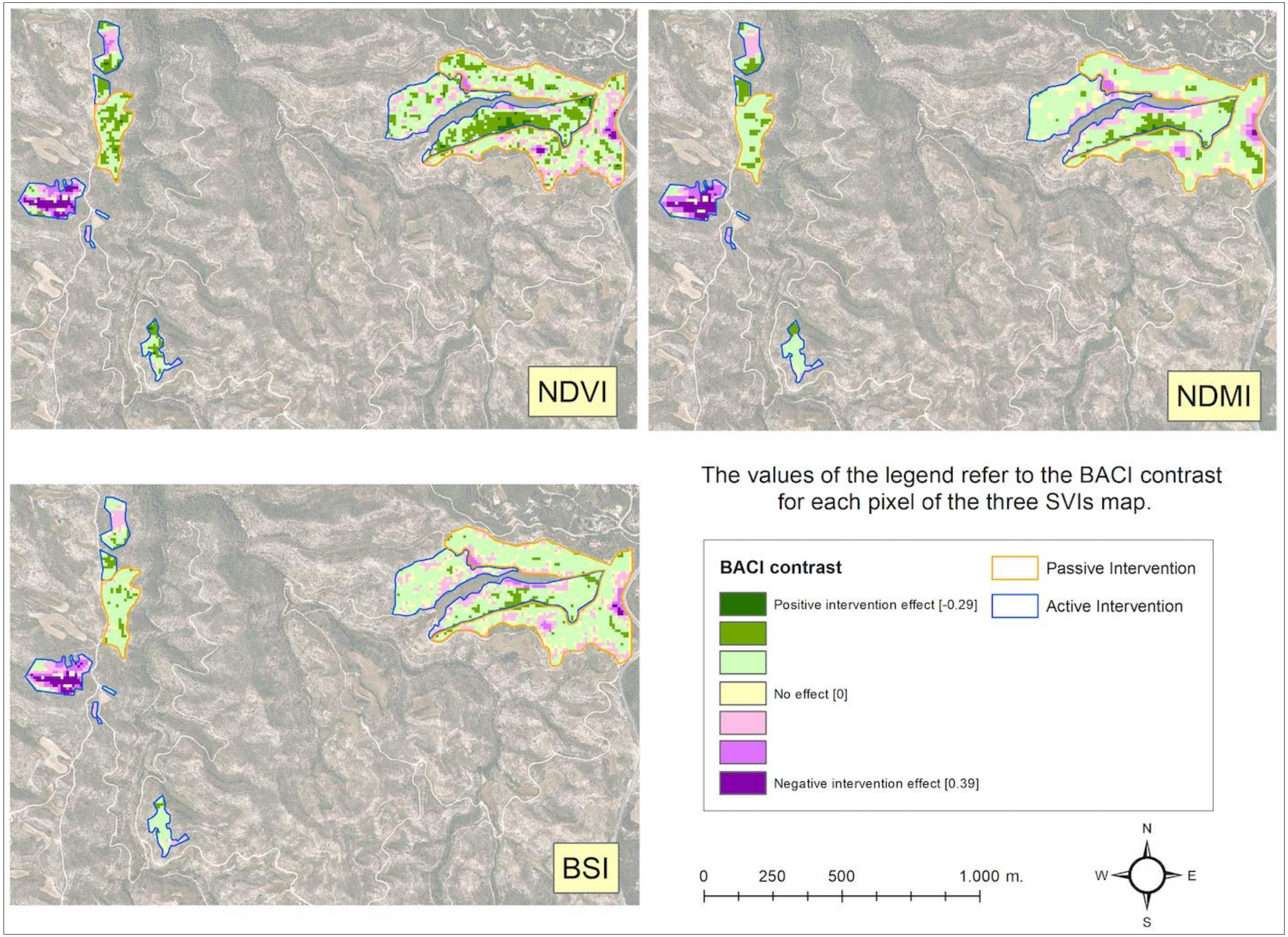

Figure 8 Maps showing the BACI contrast for both restoration intervention types on each SVI. Background images: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

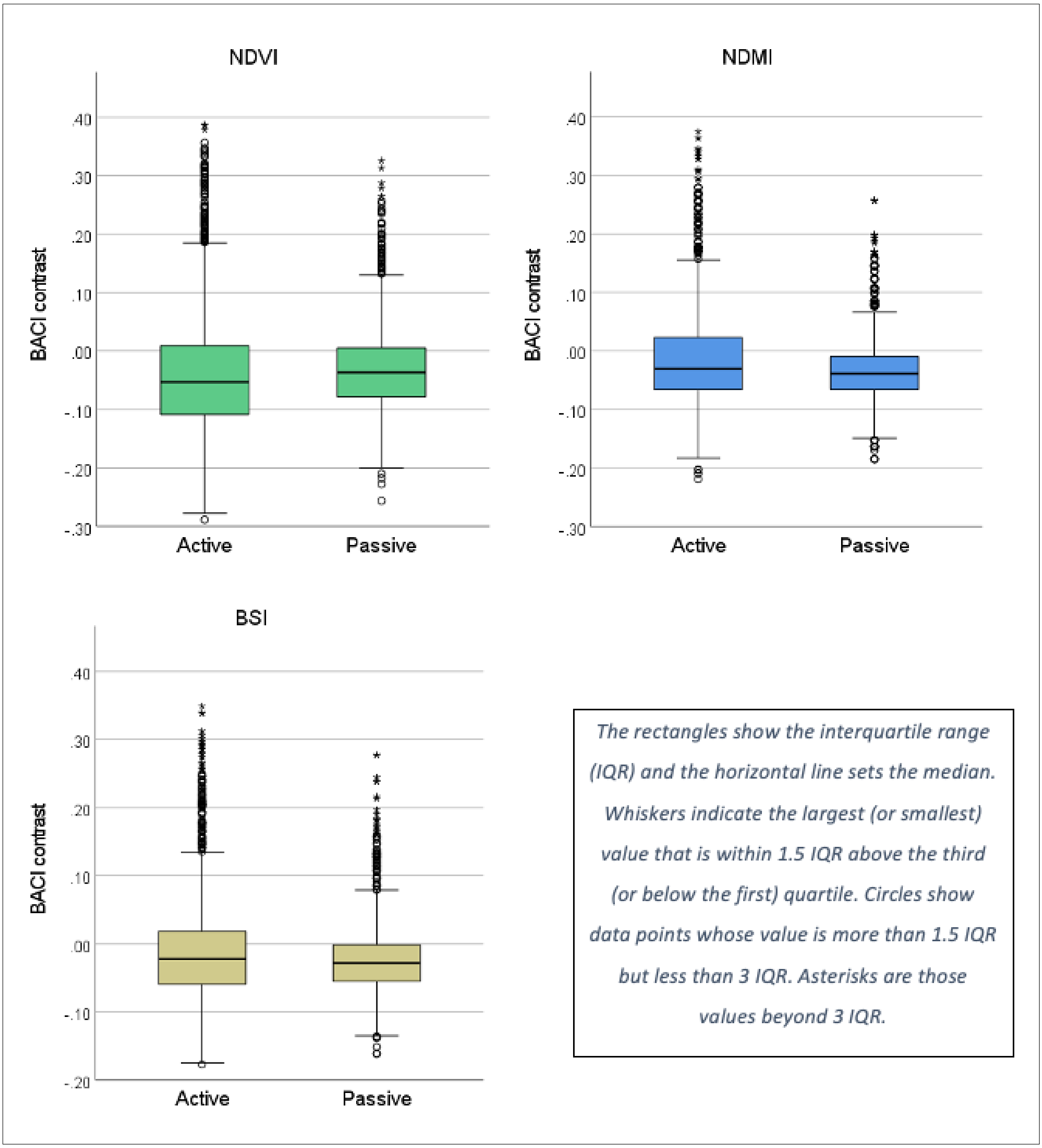

Figure 9 Boxplots showing the data of the two types of restoration intervention for the three SVIs.

3.3 BACI contrast of terrain variables

The BACI contrast shows that the intervention in north aspect pixels had a stronger impact than in the south and the difference was proven to be significant for all three SVIs when doing the hypothesis testing (p-value = 0 regarding NDVI and NDMI and <0.001 for BSI). Similar to the "partly - non recovered" comparison, the improvement on NDVI was more than double in the north (Table 9). The differences were smaller for NDMI and BSI but yet, higher contrast was observed in the north side areas.

Table 9 Average BACI contrast of the two aspect categories. The % diff. column refers to the percentage difference of the south group values compared to that of the north ones.

	North	South	% Diff.
NDVI	-0,056	-0,025	-54,4
NDMI	-0,027	-0,020	-28,0
BSI	-0,020	-0,015	-22,6

The results were more ambiguous when grouping pixels by slope type. No significant differences between gentle and steep were found on NDVI and NDMI (p-values being 0.056 and 0.375 respectively) although the average BACI contrast was higher on the steep population (Table 10). In the case of BSI the test showed significant differences (p-value < 0.001) and gentle slope areas had a stronger positive intervention effect.

Table 10 Average BACI contrast of the two slope categories. The % diff. column refers to the percentage difference of the steep group values compared to that of the gentle ones.

	Soft	Steep	% Diff.
NDVI	-0,033	-0,040	22,0
NDMI	-0,017	-0,031	85,2
BSI	-0,017	-0,016	-5,2

In regard to the analysis done on the land type clusters, south-gentle-non was the only cluster that presented negative intervention performance (Table 11). A Kruskal-Wallis test revealed that there were significant differences among clusters for all three SVIs. However, when doing pairwise comparisons some of them showed similarities and a Mann-Whitney U test was done between them. The analysis concluded that intervention effects were stronger in the north-steep-non cluster than in any other cluster for the three SVIs and also confirmed that south-gentle-non was the cluster with the lowest performance in NDMI and BSI. In NDVI however, two other clusters showed no significant differences compared to it (i.e. south-steep-partly and south-steep-non). Figure 10 shows data ranges in boxplots, providing numerical information of the differences.

Table 11 Average BACI contrast of the eight cluster categories, showing absolute values. Negative effect is indicated in red.

	north-soft-non	north-soft-partly	north-steep-non	north-steep-partly	south-soft-non	south-soft-partly	south-steep-non	south-steep-partly
NDVI	-0,08	-0,04	-0,12	-0,07	0,03	-0,03	-0,04	-0,02
NDMI	-0,02	-0,02	-0,07	-0,03	0,03	-0,02	-0,04	-0,03
BSI	-0,03	-0,01	-0,06	-0,01	0,04	-0,02	-0,03	-0,01

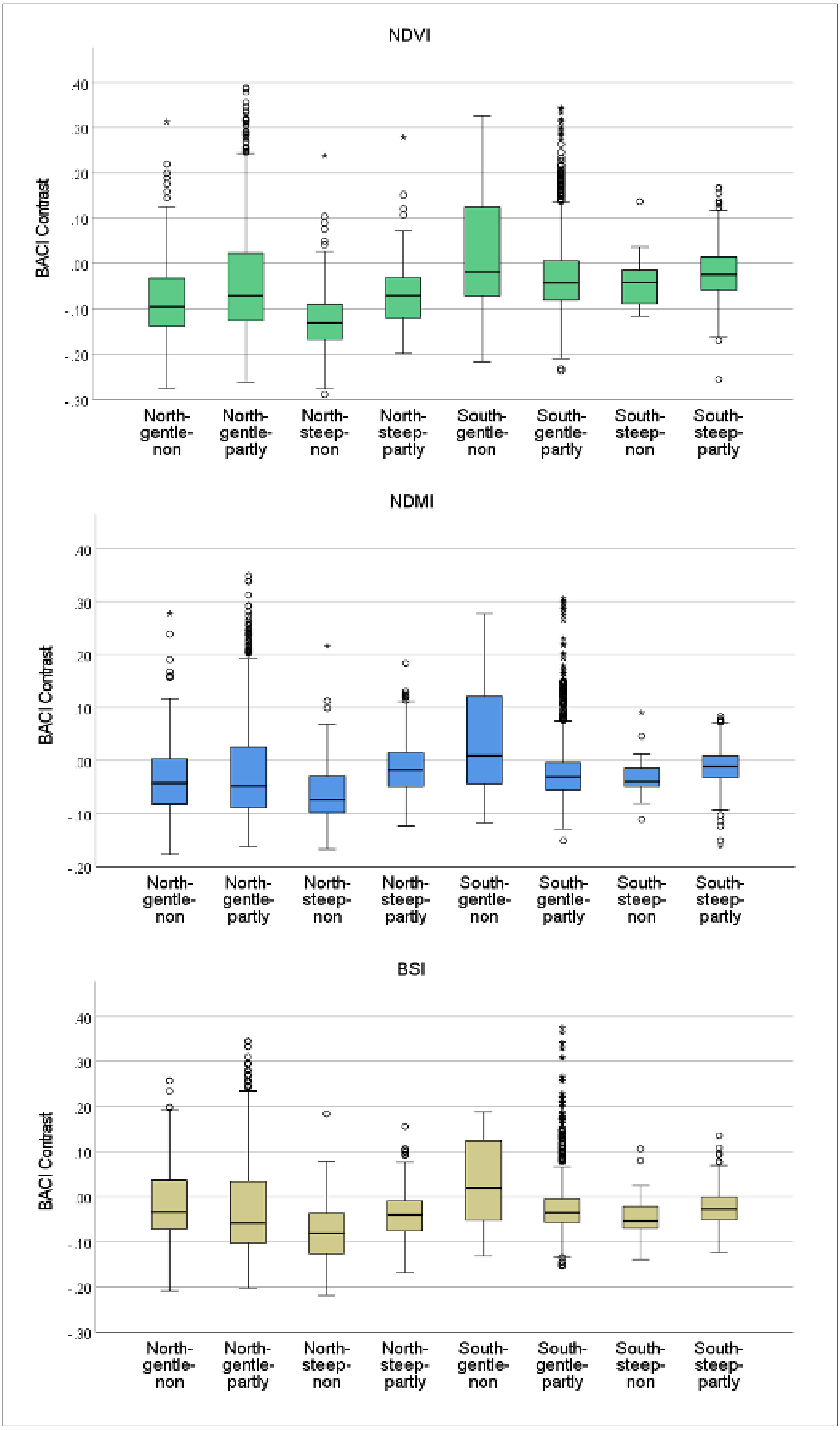

Figure 10 Boxplots showing the data points of the eight clusters for the three SVIs. The rectangles show the interquartile range (IQR) and the horizontal line sets the median. Whiskers indicate the largest (or smallest) value that is within 1.5 IQR above the third (or below the first) quartile. Circles show data points whose value is more than 1.5 IQR but less than 3 IQR. Asterisks are those values beyond 3 IQR.

3.4 SVI sensitivity analysis

The null hypothesis was rejected and showed that the choice of SVI does affect the outcome (p-value being < 0.001). NDVI showed stronger increase after restoration than NDMI and BSI in most of the plots and groups analyzed. Table 12 shows how overall, BSI increased about the half and NDMI a third less than NDVI. However, this difference varied between types of intervention. In passive intervention areas NDVI increase was a 30% higher than BSI (lowest SVI) whereas in active intervention it showed an increase that is almost five times larger than BSI.

The comparison in absolute terms of performance (i.e. positive effect, no effect, negative effect) ranked the SVIs differently (Table 13). NDMI is the vegetation index that showed a larger area of positive effect as well as a smaller area of negative effect. BSI showed the smallest positive area and NDVI the largest negative area.

Another comparison aimed at identifying areas where not all three SVIs showed the same result (positive or negative) which occurred on 26% of the pixels (59% of the pixels had a positive effect in all three SVIs while 15% had a negative effect). This is captured in Figure 11. The results showed that when only one of the three SVIs was positive on a certain pixel, 61% of the times it corresponded to NDVI while very rarely was BSI the positive index (11%). When two out of the three SVIs showed positive on a pixel BSI and NDMI became the most frequent combination (54% of the times) whereas it was not often to have NDVI and BSI both be positive at the same time (17%). As it can be seen in the map, a significant number of the pixels performing positive only in NDVI were located in Sylvestris active intervention area (65% of the times) whereas the combination of BSI and NDMI being positive while NDVI being negative happened mostly in passive restoration areas (70% of the times).

A correlation between SVIs was done (Figure 15 and 16 in the Appendix) with BSI and NDMI showing the strongest correlation (0.93) while NDVI and NDMI showing the lowest (0.79). This is remarkable as BSI and NDMI only share one band, whereas NDVI and BSI share two bands. NDVI and NDMI do not share any band.

Table 12 BACI contrast of the three SVIs, showing average values of active and passive intervention areas as well as the aggregate value of all the restoration intervention points. The % diff. column refers to the percentage difference of the total NDMI and BSI values compared to that of the NDVI.

	Active	Passive	Total	% Diff from NDVI
NDVI	-0,04	-0,033	-0,035	
NDMI	-0,01	-0,034	-0,022	-37,67
BSI	-0,01	-0,025	-0,017	-52,25

Table 13 Area (hectares) per category of BACI contrast for the different SVI's.

SVI	Positive	Non	Negative
NDVI	22.19	2.86	7.8
NDMI	22.23	3.81	6.81
BSI	20.52	4.67	7.66

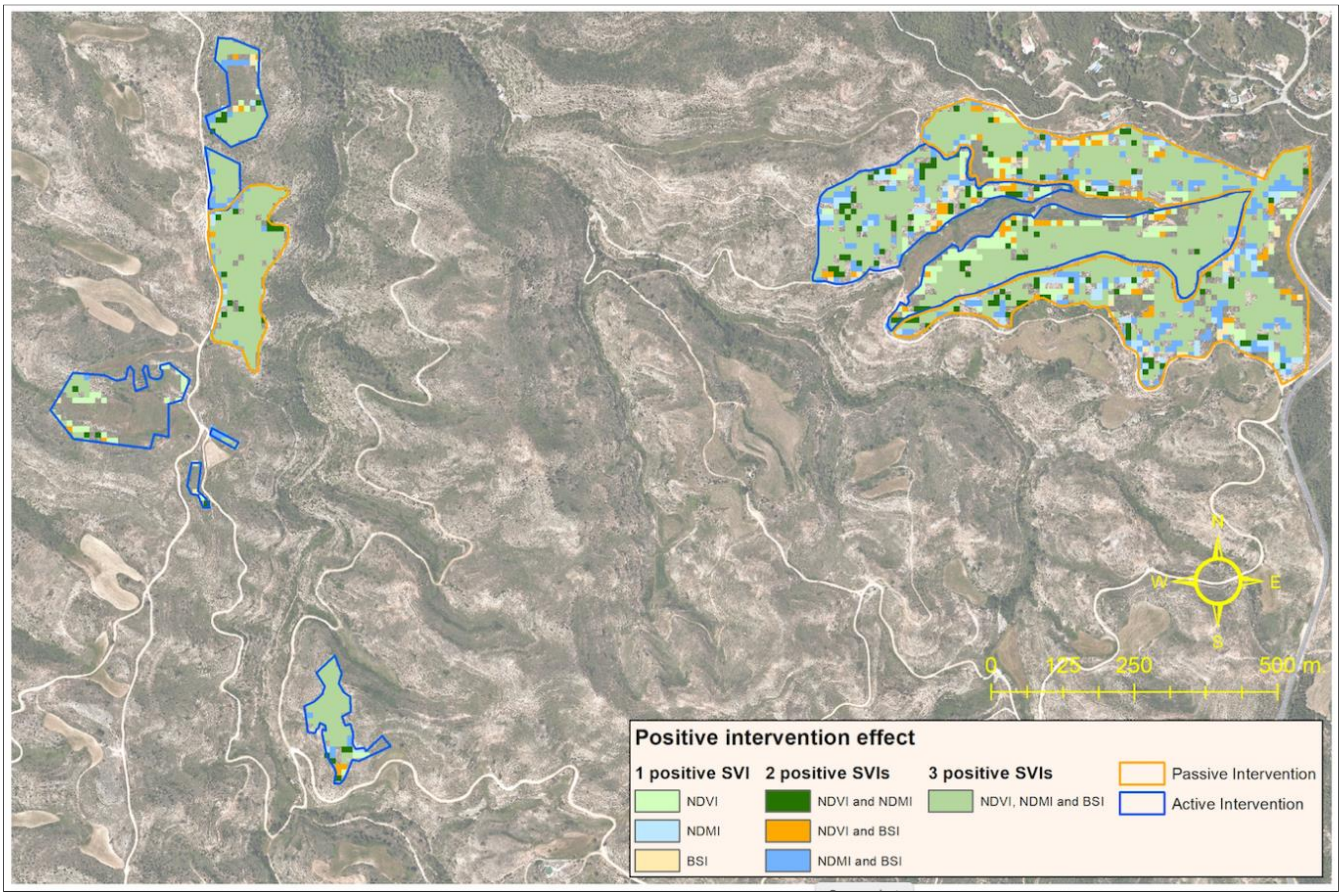

Figure 11 Map showing pixels where a positive intervention effect is found. Background image: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

4. Discussion

4.1 Choices and limitations of the study

The study initially aimed at assessing the restoration interventions including additional types of data such as field data. The impossibility to access sufficient information was a limiting factor and determined the final choice of solely using remote sensing data for the objective. This, however, provided me with the opportunity to deeply investigate statistical methods of properly analyzing restoration efforts excluding factors that are external to the performance such as temporal variability. This also led to study the implications of using particular SVIs to evaluate results.

The broad definition of the intervention goals -growth, erosion prevention and mitigation of desertification risk- hinders the evaluation of their success in absolute terms. Moreover, goal achievement and general structural and functional quality should be evaluated using long-term assessment data (Bautista, Aronson, et al., 2010) and in this study the period since the interventions were carried out is still quite short. However, narrowing the findings to the starting and end point of the study, the three indicators that relate to each of the goals showed improvement.

Regarding the spectral vegetation indices used in the study, NDMI was chosen as a proxy for moisture which served to interpret soil quality improvement - through water infiltration - although it is normally used as an indicator of moisture and plant humidity rather than soil. Therefore, even if there is a relationship between plant and soil moisture this has to be taken into account. The Sentinel-1 C-band Synthetic Aperture Radar (SAR) is a tool specifically designed to monitor surface soil moisture[17], yet I discarded the option due to its spatial resolution - excessively coarse for the study area - and therefore focusing on Sentinel-2 derived products. Other indices like the temperature-vegetation wetness index, an indirect way of estimating soil water content (Hassan et al. 2007) had similar resolution issues.

Another aspect that would be worth exploring is the impact that the image selection had on the results. In this case I used the day with higher NDVI as the reference image, therefore the findings are based on the state that the biophysical variables were on that particular day. In a similar way, the image selection could have been based on other factors such as the day outputting the highest NDMI or the lowest BSI. An assessment of potential differences in the outcomes based on this choice could be further studied.

[17] https://eo4society.esa.int/projects/s1-for-surface-soil-moisture/

4.2 Restoration assessment outcomes

The results revealed a positive impact of the interventions on the three SVIs, although with relatively small improvements, with average BACI contrast values often ranging 0.02 to 0.08 in the comparisons done. In relative figures, that is between a 1 to 4% increase of a given SVI - assuming the -1 to 1 range of the indices - compared to non-intervention areas. Therefore, the positive results must be read with prudence. Results in the study by Del-Río et al. (2021) showed higher improvements - and deterioration - with values in some pixels reaching 0.98 for some SVIs. In this case restoration types and periods were larger, with 30 years old passive interventions and 5 to 20 year old active ones. Meroni et al. (2017), however, showed similar numbers and the age of the restoration projects - reforestation and improved fodder production - was between 5 and 9 years. As every restoration intervention has its particularities, results are hardly comparable between them. One of the driving factors of success is the age of the interventions. The short period between intervention and evaluation, which in this study was between four and a half and three and a half years may explain the low improvement rates. Also, post-fire restoration intervention is particularly challenging, especially in dryland ecosystems where recovery tends to be slower than in other climates (Bautista, Orr, et al., 2010). Another key factor is the plantation density and the approach in which a restoration activity has been carried out. The fact that most of the reforested locations studied were planted on the frame of a study aiming to evaluate the performance of a seedling system - Cocoon - and had a rather low density (dehesa style - agroforestry ecosystem) might also have influenced the results. In addition to that, it is important to note that non-intervention zones were chosen to represent the most common grazing intensity of the area and its density - around 0.3 cow/ha – is considered low (Hadjigeorgiou et al., 2005). A different intensity could have yielded other results.

The better performance of the non-recovered areas in comparison with the partly recovered ones is remarkable as most studies show a different trend (Romo Leon et al., 2012; Viana-Soto et al., 2017). One reason for that could be the smaller margin of improvement that partly-recovered areas can have in an dry area with risk of desertification where recovery could be limited or at least complex. It could also be due to location, as most of the non-recovered pixels were located in Sylvestris, the active intervention area that shows the strongest positive impact, as it was seen on Figure 6.

The differences in the results of each location invites to look at their particularities and to keep in mind that the aggregate values hide significant differences. In a way, Sant Simeó could be considered an outlier due to the characteristics of its intervention and therefore, its inclusion has consequences on the total results that should not be overlooked. Like stated in Table 2, Sant Simeó was the first to be restored, obtaining ineffective results as it is suspected that olive seedlings – the main tree species planted - were in bad state. After that, most of the plot was tilled. If Sant Simeó is excluded from the total values, the results of the three SVIs would show a better performance in active intervention areas with respect to passive intervention, with an average difference of near 50%. In the case of Sylvestris, where the intervention objective was to offset carbon and had the highest density plantation, it was significant that its results were similar to other intervention areas like Quatre Vents or

West. Also relevant is the fact that a passive intervention area - West - achieves the highest performance in the three SVIs.

Regarding terrain variables, while the aspect comparison seemed to show the expected trend - north being decisive in hilly areas in this kind of ecosystems and latitudes - (Vallejo et al., 2012; Van Andel & Aronson, 2014; Viana-Soto et al., 2017) slope did not seem to have a consistent effect on the performance, contrary to some results found in literature (Bautista, Aronson, et al., 2010; Van Andel & Aronson, 2014). BSI seemed to perform better in gentle slopes while NDVI and NDMI seemed to yield better results in steep zones, although statistical analysis showed significance only regarding BSI. This could perhaps be due to the fact that for vegetation it is more challenging to grow in steep areas whereas for attributes related to NDVI and NDMI (i.e. greenness and moisture) the role of the slope is not as relevant. Also, it is important to consider the effect of steep slopes in RS data, as they generally produce shadow that may affect satellite images (del Río-Mena et al., 2020), therefore risking distortion on the retrieved values. Regarding the clusters performance, results seemed to confirm that aspect was a more decisive attribute than slope but also post-fire recovery level, as a northern aspect is the distinguishing feature of the majority of the most succeeding groups.

The higher correlation found between NDMI and BSI is in line to results found in other studies (Pazmiño et al., 2021). The decrease of bare soil could be expected to be comparable to the increase of vegetative cover (Kumar et al., 2016), however this is often not directly proportional - as seen in the correlation results -, hence the interest of measuring both indices. In this study, the highest NDVI BACI contrast of a single pixel in the study is -0.29, whereas for NDMI is -0.22 and for BSI is 0.18. The fact that the improvement is stronger in NDVI may indicate that the biophysical variable related to it (i.e. vegetative cover) has improved more than those related to BSI and NDMI (bare soil and moisture). However, it could also indicate that the indices response to the variations of their corresponding biophysical variables is not equally sensitive in between them. An example could be that a small change in vegetative cover could produce a stronger reaction in NDVI than an equivalent change in bare soil can affect BSI. Some studies mention that BSI does not indicate whether an area is extremely low in vegetation (Alqasemi et al., 2021), unlike NDVI, which may already capture greenness. A similar result can be seen in Del Río study (2021) where BSI BACI contrast improvement is also significantly lower than in other SVIs analyzed. Therefore, it could be worth analyzing if a similar BACI contrast value in the three SVIs could relate to a more significant change on the biophysical variables of which NDMI and BSI are related to. The fact that NDVI has the largest area with negative BACI contrast effect (Table 13) yet having the highest BACI contrast value may reinforce the interest to look into this topic.

4.3 Management implications

As mentioned in the Introduction section, restoration interventions require the consensus of numerous stakeholders who often have different views on how to plan them. Studies that monitor the projects and that provide results can help distinguish choices that had the expected results from those that did not. This could be used to redirect initial strategies beyond personal beliefs. In regards to this case study I am aware that there has been inclusive discussions between affected actors on how to manage the restoration and that, as usual, opinions have not always been unanimous. Further than contributing to the progress of the state of the art subject this study could also have an impact on the individuals whose life's are directly affected by the decision-makers. In this sense, planners such as the competent public entities, landowners and private investors could make use of this study to discuss new steps to be taken in the area. It could also be useful for farmers and herdsmen when discussing land use options, to prioritize activities that benefit the sustainability of the land. The fact that passive restoration areas had positive results showed that grazing may not be contributing to the recovery from the fire. Also, areas that show less moisture increase could be destined to less water intensive crops. Ideally, regular effectiveness monitoring should be done to assess the effect of the restoration actions on target attributes previously selected (Bautista, Aronson, et al., 2010) and long-term monitoring should be promoted. In this sense it is crucial that restoration plans include and endorse funding to support it (Nunes et al., 2016). This way, decision-making can evolve in line with the evolution of the outcomes.

In a more general context of post-fire interventions, the significant difference in performance found in this study between aspects like north and south or the level of recovery could encourage the specialization of the restoration tasks based on them, to optimize resources in other restoration interventions and improve results. Also, the outputs showing a higher improvement of passive intervention areas in two of the three SVIs analyzed reveal the potential of a type of intervention that is generally more affordable. In this sense, this result is in line with other post-restoration studies - (Birch et al., 2010; Su et al., 2021) - whereas others findings conclude otherwise - (Kiely et al., 2021; Mirzabaev et al., 2022). Different restoration needs, ecosystems and baselines can determine the economic effectiveness of the intervention strategies, therefore making a cost-benefit analysis a key aspect in decision-making.

Some findings of this study could also be applicable in contexts other than post-fire restoration assessments, like the sensitivity analysis of the three selected SVIs, which showed that the choice of one sole index to evaluate an intervention could lead to an incomplete conclusion as their outputs were significantly different between them. Other research areas, like precision agriculture where SVIs from multispectral images are used for crop management decision making or quantification of ecosystem services studies can find this result relevant.

Lastly, this study can be useful in the frame of national and international initiatives aiming at combating desertification. Land restoration and combating desertification is one of the goals set on the 2030 agenda of

United Nations[18]. FAO's action against desertification has land restoration as one of its key points and highlights monitoring as one of the five steps in model restoration approach[19]. Moreover, both UN environment program and FAO are driving the Decade on Ecological Restoration, a program coordinating projects around the globe aiming to halt the degradation of the ecosystems and restore them to achieve global goals[20]. Similarly, the National action program against desertification[21] in Spain, set within the framework of the United Nations convention to combat desertification[22], needs to complement the restoration tasks with an effective assessment to monitor the performance of the proposed actions. In this context, this study can be an affordable approach to help improve the assessments.

[18] https://sdgs.un.org/2030agenda

[19] https://www.fao.org/in-action/action-against-desertification/activities/land-restoration/en/

[20] https://www.decadeonrestoration.org/about-un-decade

[21] https://www.miteco.gob.es/es/biodiversidad/temas/desertificacion-restauracion/lucha-contra-la-desertificacion/lch_pand.aspx

[22] https://www.unccd.int/

5 Conclusions

This study developed a method to assess the performance of post-fire restoration interventions on a pixel-based level when access to pre- and post-fire field data is limited, therefore depending on remote sensing data. The method takes into account restoration intervention objectives, the state of the area before the intervention efforts began and different spectral vegetation indices, preferably linked to the objectives.

The evaluation of the intervention performances, both passive and active, showed to be positive overall with respect to areas that have been open for grazing, with average BACI contrast results often ranging 0.02 to 0.08 difference on the SVIs calculated. On the contrary, two of the seven analyzed locations – both part of the active intervention area - showed negative performance. Therefore, the importance to take into account the heterogeneity of the results of each specific location.

Active intervention areas - reforested areas - had the strongest impact on the index measuring vegetative cover (NDVI), although the improvement was not always complemented by the other biophysical variables - moisture and reduction of bare soil - or at least the general performance of their indices was weaker. Passive intervention areas - cattle exclusion only - might have helped reduce bare soil and increase moisture in a greater extent, leading to better results in the other two intervention objectives - erosion prevention and soil quality improvement - compared to active intervention areas. Regarding terrain variables, north orientation of the terrain had a positive effect on the performance of the interventions while slope only seemed to have a significant impact on BSI, having the success of the restoration been benefited by gentle slopes. A clear result was obtained when comparing areas with different pre-intervention recovery levels after the fire, where those with the lowest recovery also showed stronger improvement.

The sensitivity analysis undertaken with the three selected SVIs showed that the choice of one sole index to evaluate an intervention could lead to an incomplete conclusion as the outputs varied significantly between them. Aggregating the results of both active and passive intervention areas, NDVI had a significantly higher performance than NDMI (which is a 38% lower) and BSI (52% lower). However, NDVI appeared to be the index with a larger negative BACI contrast area.

The difference in the outputs between most of the groups compared were subtle, therefore caution is recommended when making conclusions. Yet, they show the usefulness of this approach when it comes to the use of specific SVIs, especially when assessing different restoration objectives. The study evaluates many factors that can influence post-fire restoration interventions, showing that this research can be extended in line with the limitations and aspects included in the discussion. This can be especially relevant in a future scenario where fires are expected to be much larger and numerous due to shifts in climate. Good preventive measures will be even more necessary than today, as will decision-making to mitigate the fire effects in the most efficient way. In this sense, improving the evaluation methods of post-fire restoration will be key to gain knowledge and better allocate resources.

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7 Appendix

7.1 Post-fire recovery map (Delta Normalized Burn Ratio)

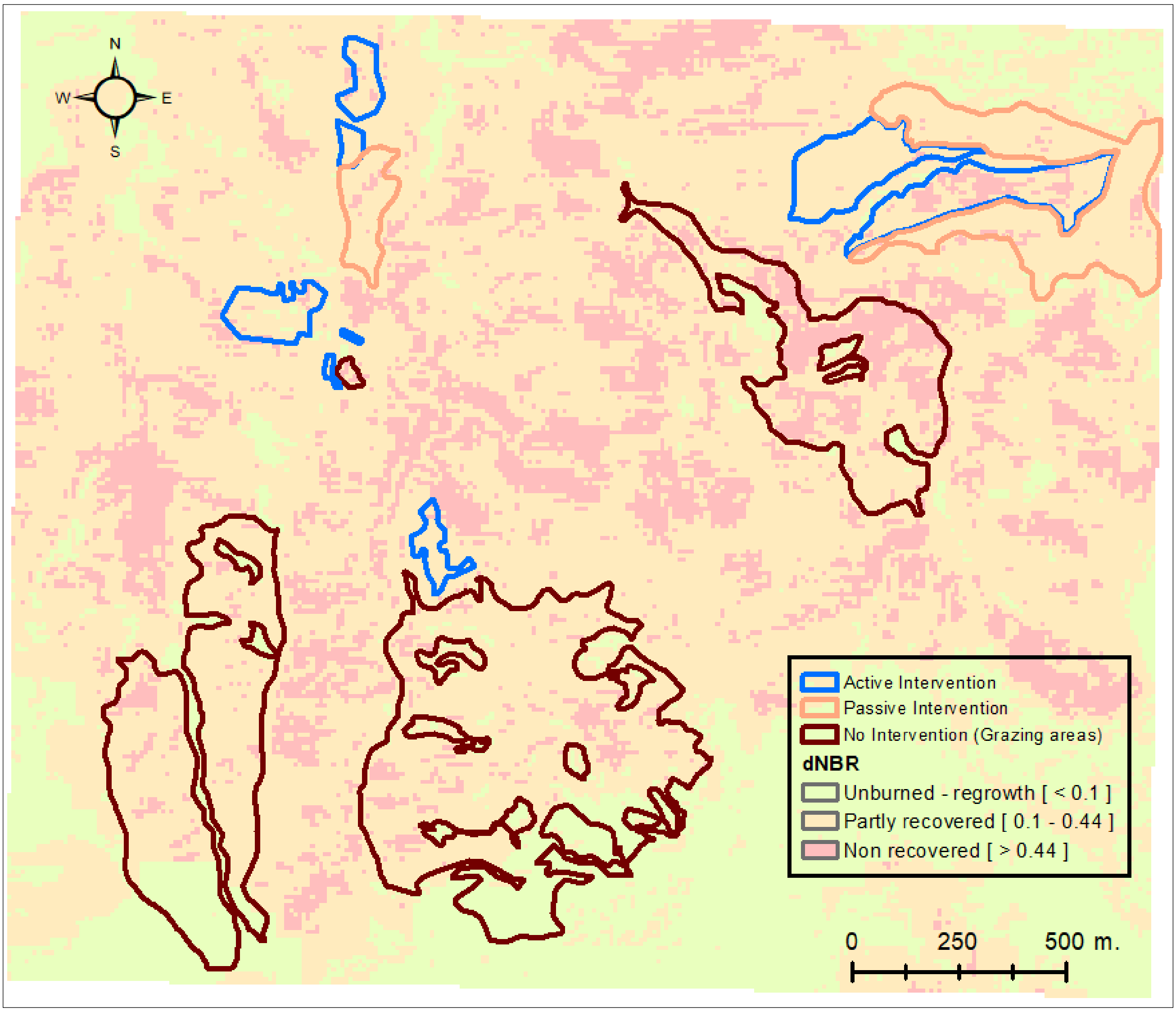


Figure 12 Map showing the difference of the normalized burn ratio one year after the fire. High and moderate-high severity values (above 0.44) were interpreted as Non-recovered while moderate-low and low severity values (0.1 to 0.44) were interpreted as Partly recovered. Values under 0.1 were interpreted as unburned or regrowth areas.

7.2 Cluster map

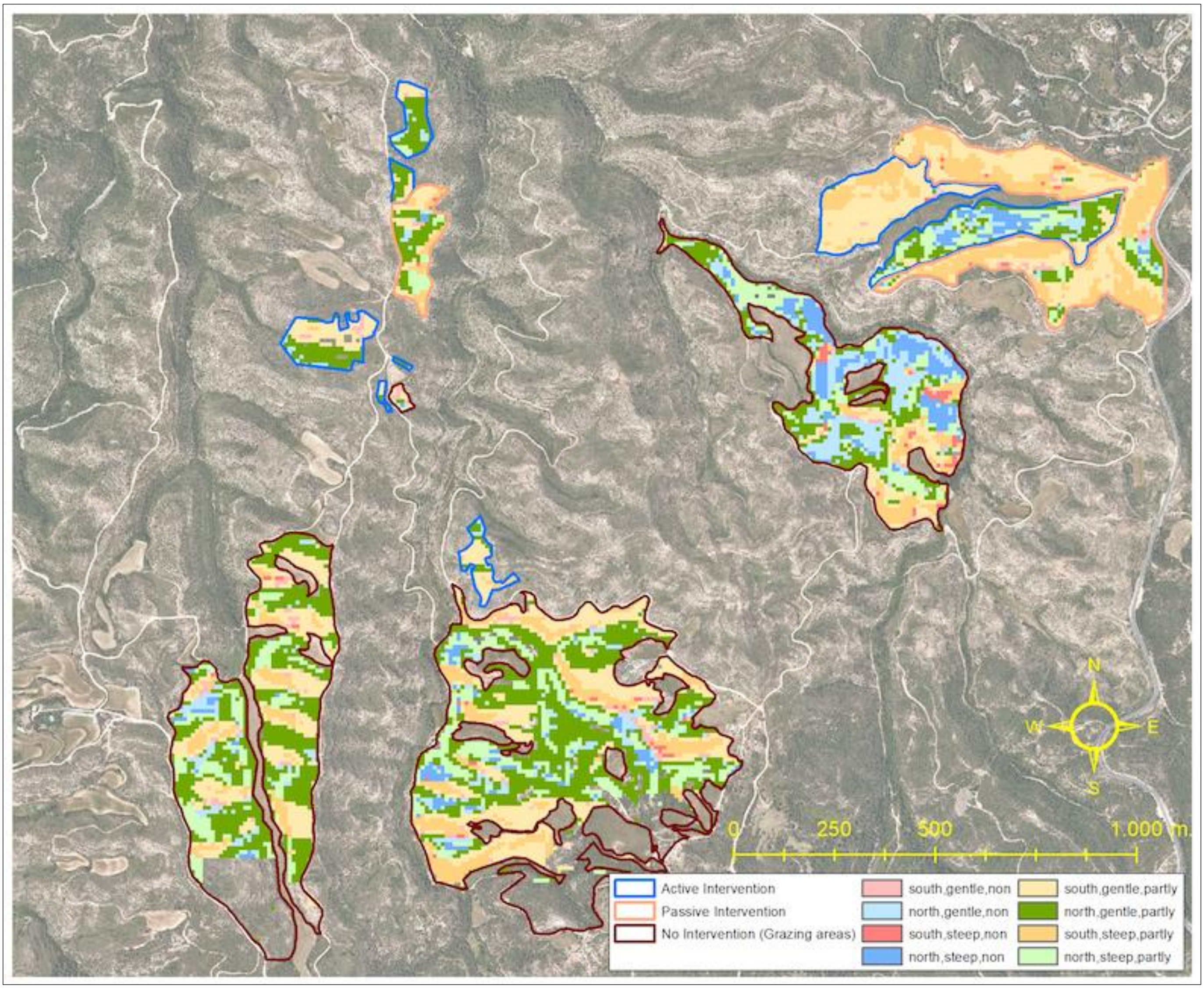


Figure 13 Map showing the eight clusters for each type of intervention area. The pixels were classified taking into account the results of the intervention area map, the post-fire recovery levels, the aspect and the slope. Background image: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

7.3 Control pixel map

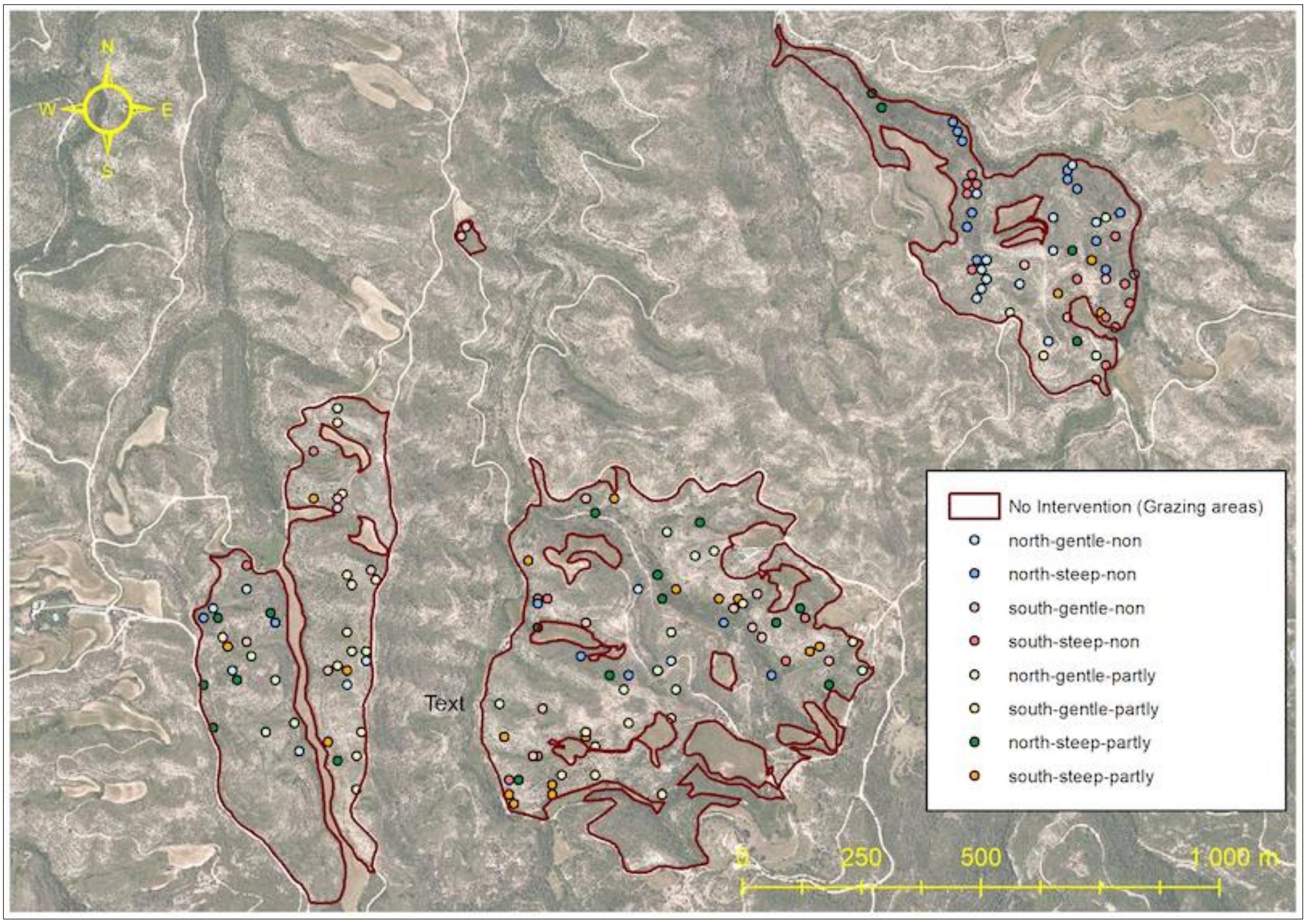
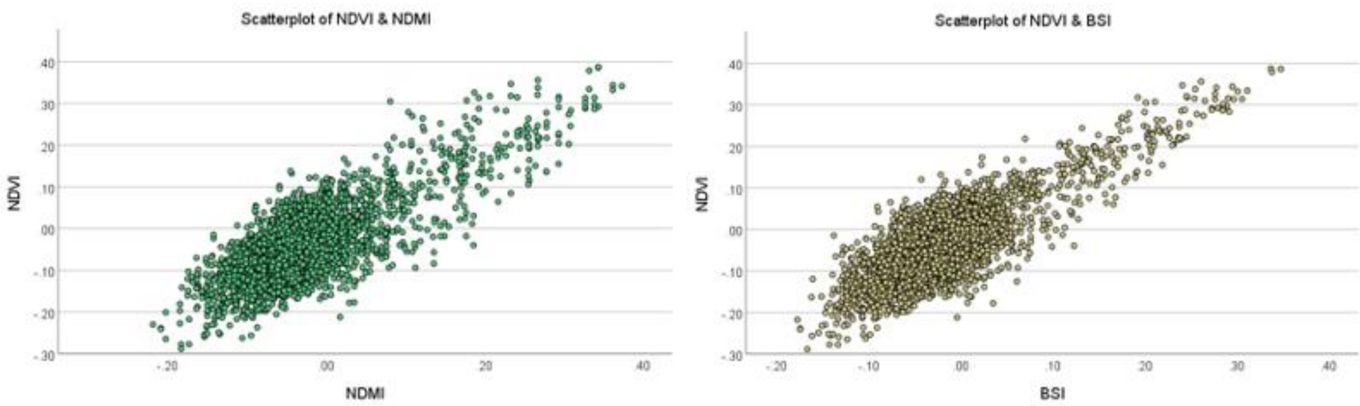
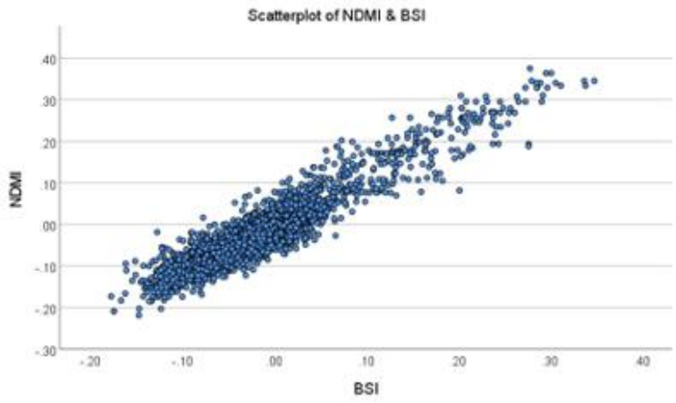


Figure 14 Map showing the location of the control pixels. 20 pixels were randomly selected for each of the 8 cluster classes. Background image: Orthophoto of the study area, 25cm resolution. Source: Cartographic and geological institute of Catalonia.

7.4 SVIs correlation figures





Correlations

		NDVI	NDMI	BSI
NDVI	Pearson Correlation	1	.786	.823
	Sig. (2-tailed)		.000	.000
	N	3244	3244	3244
NDMI	Pearson Correlation	.786	1	.931
	Sig. (2-tailed)	.000		.000
	N	3244	3244	3244
BSI	Pearson Correlation	.823	.931	1
	Sig. (2-tailed)	.000	.000	
	N	3244	3244	3244

Figure 15 Correlation between SVIs and corresponding scatterplots

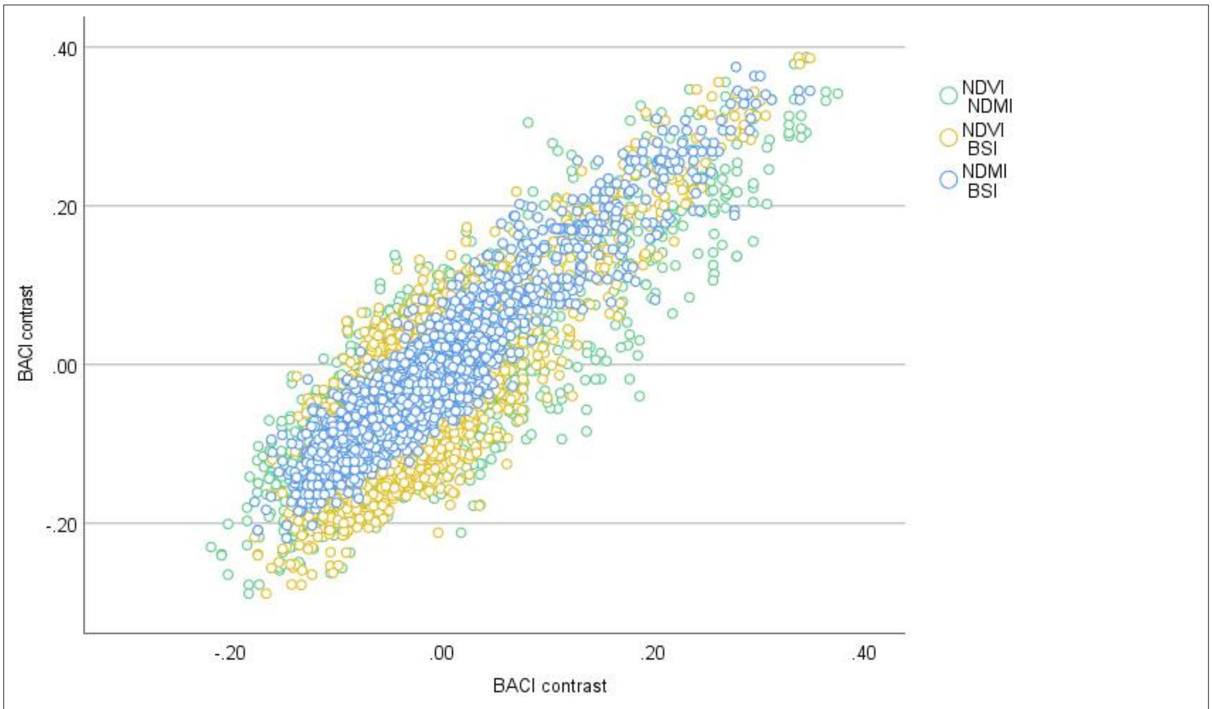


Figure 16 Overlay scatterplot

Series from Lund University

Department of Physical Geography and Ecosystem Science

Master Thesis in Geographical Information Science

1. *Anthony Lawther:* The application of GIS-based binary logistic regression for slope failure susceptibility mapping in the Western Grampian Mountains, Scotland (2008).
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