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Application of multi-scale remote sensing imagery in monitoring of a mountain protected area

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Abstract

In highly human-dominated European regions traditional activities deeply shaped the landscape with strong consequences on biodiversity patterns. However, in the last few decades the rapid socio-economic change led to the abandonment of “marginal” land modifying the landscape structures.

In this context Alps are of great interest due to particular habitat disposition along the altitudinal gradient and to the presence of highly adapted species providing many ecosystem services.

In this scenario it is necessary to establish long-term monitoring programs to quantify the present and future landscape changes.

Remote sensed data are useful tools in understanding landscape processes through different scales of analysis. Assuming that landscape change at given scale is the result of many interacting process at smaller scales, in order to explore mechanisms shaping landscape structure there is the need to integrate information derived from different platforms to overtake gaps in spatial or temporal resolution.

We aim to understand the landscape dynamics and the effectiveness of different kind of remote sensed data at different scales of analysis in a mountain protected area context, Gran Paradiso National Park (North-Western Italian Alps). The broader landscape change occurred in the last few decades were reconstructed using satellite imagery. To understand the vegetation pattern change orthorectified aerial images were compared with recently acquired orthophotos; a preliminary study of image classification to derive land cover map was also carried out. UAV and field sampling were collected to link ground observation and remotely-sensed imagery.

In this study it was pointed out that the integration of different sensors and their peculiarities is a valuable tool to explore the ecological processes of complex Alpine environments. The proposed methods were set in perspective to sustain protected area management plans to protect the vanishing biodiversity patterns, strongly dependent the traditional land use.

Sommario

Gli ecosistemi europei sono stati profondamente modificati dalle attività tradizionali con forti conseguenze sugli assetti paesaggistici e sulla biodiversità.

Negli ultimi decenni i rapidi cambiamenti socio-economici hanno provocato l'abbandono delle "aree marginali" andando a modificare la struttura paesaggistica.

Le Alpi sono di particolare interesse a causa della particolare disposizione degli habitat lungo il gradiente altitudinale e per la presenza di specie fortemente adattate; inoltre le regioni montuose forniscono diversi servizi ecosistemici.

In questo scenario è necessario stabilire un monitoraggio a lungo termine per quantificare i cambiamenti paesaggistici.

I dati da remoto sono un valido strumento per comprendere i processi a diverse scale di analisi in quanto i cambiamenti paesaggistici sono determinati dall'interazione di diversi processi. Per comprendere i meccanismi che regolano queste strutture è necessario integrare le informazioni raccolte a diverse scale.

L'obiettivo di questo lavoro è quello di comprendere la dinamica del paesaggio e l'efficacia di differenti dati telerilevati a diverse scale di analisi, dai dati satellitari ai rilievi da drone, nell'area protetta del Parco Nazionale del Gran Paradiso.

La dinamica del paesaggio è stata ricostruita attraverso l'uso di immagini satellitari. Dalla comparazione di ortofoto sono stati ricostruiti i cambiamenti strutturali della vegetazione eseguendo uno studio preliminare sulla classificazione di immagini per ottenere mappe di copertura del suolo. Inoltre sono stati valutati l'uso di immagini rilevate da drone con rilievi in campo per incrementare la quantità di dati raccolti.

In questo studio sono state integrate le diverse informazioni raccolte da differenti sensori per esplorare i processi ecologici in ambiente alpino. I metodi proposti sono stati discussi per essere di supporto alle attività di gestione dell'area protetta per le attività di conservazione.

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1 | Introduction

1.1 | General introduction

In Mediterranean region ecosystems have been strongly shaped by a persistent and widespread human presence leading to the creation of many semi-natural habitats and creating a patchy landscape with a high biodiversity often defined as “cultural landscape” [Blondel et al., 2010].

In this context Alps are of great interest due to particular habitat disposition along the altitudinal gradient [Fischlin et al., 2007, Körner et al., 2011] and to the presence of highly adapted endemisms [Billings, 1974]. These regions are characterized by rare and fragile ecosystems [Diaz et al., 2003, Pauchard et al., 2009]. Among these, semi-natural grasslands located below the treeline are rapidly shrinking due to changes in socio-economic drivers leading to the abandonment of marginal lands [MacDonald et al., 2000, Silva et al., 2008, Galvánek and Lep, 2008, Parolo et al., 2011].

Habitat alteration is one of the most important factor in biodiversity loss [Wilson et al., 2016] and change in landscape composition and configuration lead to ecological consequences [Turner, 1989].

Landscape analysis and the multi-temporal analysis of landscape change are important tools in biodiversity conservation allowing to understand how patterns influenced the ecological process [Forman and Godron, 1986, Turner, 1989, Gutzwiller, 2002].

For these reasons it is necessary to assess past changes and to establish a long-term monitoring program to quantify the present and future landscape changes.

Remote sensing is a useful tool to study vegetation cover changes because data collection, especially over large areas, based on field-based method is often time-consuming and expensive [Xie et al., 2008, Kerr and Ostrovsky, 2003]; while remote-sensing platforms [Toth and Józ'kóv, 2016] produce averaged information over tens (or hundreds) of square meters per unit storing data as imagery representing area of square kilometers with a periodic revisit time [Turner et al., 2003].

The periodic remote sensed imagery are a valuable source of information to derive indices of landscape pattern [Groom et al., 2006] and a variety of remote sensing analysis have been proposed [Rogan et al., 2002, Morgan et al., 2010, Shahbazi et al., 2014].

Among the satellite imagery Landsat ones have been widely used to evaluate vegetation spatial pattern change [Cohen and Goward, 2004] because the joint NASA/USGS program achieved a globally consistent time series of continuous observations since 1972 making available multi-spectral information with a temporal

1. INTRODUCTION

resolution of ca. 16 days constituting the longest record of global-scale medium spatial resolution Earth observation data [Hansen and Loveland, 2012]. The strength of Landsat stays in its continuity and improvement of time series realizing a free for access image archive. Nowadays most of provided data are pre-processed to support land surface change studies furnishing terrain corrected surface radiance values generated by radiometrically calibrated sensor [Markham and Helder, 2012, Masek et al., 2006, Vermote et al., 2016].

Aerial photos were a fundamental mean providing the basis for map creation over large spatial scale constituting the first GIS databases [Paine and Kiser, 2003]. This imagery are the longest remote sensed data archive characterized by a spatial resolution very similar to field view that permits to detail the fine landscape features elements [Morgan et al., 2010]. Through manual interpretation [Rocchini et al., 2006] or semi-automatic techniques [Laliberte et al., 2004a] users can characterize landscape functionality delineating the spatial pattern and physiognomy of vegetation retrieving indices of landscape composition and structure.

In intermediate scale between “classic” remote sensed data and field sampling, Unmanned Aerial Vehicles (UAVs) have been widely used over the last decade for environmental purposes [Shahbazi et al., 2014, Colomina and Molina, 2014]. The UAV imagery resolution permits to explore small-scale [Gonçalves et al., 2016], complex [Getzin et al., 2012] habitats.

Assuming that landscape change at given scale is the resultant of many interacting process [Baker, 1989], to explore mechanisms shaping landscape structure, there is the need to integrate information derived from different platforms to overtake gaps in spatial or temporal resolution. Moving from these assumptions it is fundamental to integrate methods that allow to explore the complexity of mountain landscapes [Nagy and Grabherr, 2009].

According to Pauli et al. [2013] protected areas are fundamental to establish long term monitoring and to retrieve data and records about past and present events affecting ecosystem dynamics and furthermore protected areas are an efficient tool to address efforts against biodiversity loss and to preserve ecosystems services [Lopoukhine et al., 2012].

The integration of remote sensing in habitat monitoring is not new [Borre et al., 2011] and there were several application considering protected area context [Gross et al., 2009] and application of satellite imagery [Wang et al., 2009] and photogrammetric techniques [Welch et al., 2002], but at the best of our knowledge the potential and constraints of different remote sensed data were not evaluated in mountainous protected area management.

The purpose of this research is to provide a case study using existing and well-known remote sensing methods ranging from satellite to UAVs imagery to perform a mountain protected area monitoring considering the importance of cost and data availability.

As the intent of this study is the evaluation of different remote sensed data, the analyses and development of map products were carried out in an open source geographic information system (GIS) environment to promote the creation of databases to sustain conservation efforts.

1.2 | Objectives

The need to monitor habitat alterations at different scales of analysis in a protected area and challenging condition of Alpine regions, together with the importance of cost, data availability and reproducibility of methods provide a framework to develop this thesis in interdisciplinary context.

The scope of this work is to characterize a mountain protected area evaluating the vegetation pattern change occurred in the last few decades across different scale of analysis to explore the ecological process of complex Alpine environments. Furthermore the use of different remote sensed data to delineate landscape characteristics at different scale of analysis was set in perspective to integrate this tool in management efforts to preserve the vanishing biodiversity patterns.

According to these premises, the following objectives have been defined:

1. **To carry out a geomorphometry analysis** of study area. Since land-surface parameters and landforms are relevant factors in landscape processes [Hofierka et al., 2009]; therefore geomorphometry analysis could be a powerful tool to understand landscape patterns and their characteristics especially in a topographically complex Alpine regions. The aim of this analysis is to constitute a dataset of independent variables to quantify land surface characteristics providing a support for further analysis.

2. **To evaluate vegetation spatial pattern change using satellite imagery.** The purpose, at this scale of analysis, is to provide a general change analysis detecting the change occurred in an Alpine landscape. We are particularly interested in understanding of how the landscape change, to assess the change characteristics and how landscape composition changes in terms of fragmentation.

Following Lu et al. [2004] recommendations, we performed:

- a rapid qualitative change detection analysis through visual interpretation of multi-temporal image color composite and band ratios;
- a quantitative change detection analysis describing the four aspect of change; change/non-change area detection through a Principal Component Analysis (PCA) following [Neteler et al., 2012] method and describing the MacLeod and Congalton [1998] four aspects of change;
- a landscape composition evaluation in terms of fragmentation following a method based on Fourier transform [Rocchini et al., 2013b].

3. **To reconstruct habitat alteration using aerial images.** We aim to compare two different photogrammetric approaches to orthorectify aerial images evaluating which ones provide the most robust results in case of old aerial imagery and to retrieve qualitative and quantitative information from this dataset.

This topic is organized in:

- application of *Structure from motion* (SFM) and *orthorectification process* methods using test images and positional accuracy assessment. The

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scope of this test is to evaluate if the SFM can be a valid replacement of orthorectification process to create free-distortion image from old aerial photos where camera parameters are often unavailable;

- reconstruction of image historical archive in a long-term monitoring program;
- use of Fourier transform to derive change in vegetation pattern;
- image classification, as the process of assigning land cover classes to pixels, following an object-based image analysis approach.

4. **To link ground observations and remotely-sensed imagery** using a collection of High resolution UAV images and field data. We are interested in linking ground observations with remotely sensed imagery [Lobo et al., 1998] to increase the quantity and quality of retrieved information providing the basis for a small-scale monitoring.

The analysis is organized in:

- image collection of High resolution UAV images in different environmental conditions;
- Field sampling data collection;
- Visual interpretation to increase the quantity and quality of collected data.

2 | Materials and methods

2.1 | Study area

The study area chosen to carry out the geomorphometry analysis, change detection and fragmentation analysis is the Gran Paradiso National Park (GPNP; 45°31'N - 7°19'E WGS84) in northwestern Italian Alps, see fig. 2.1. The GPNP was established in 1922 in Piedmont and Aosta Valley regions to protect the only surviving population of Alpine ibex (*Capra ibex*). It extends on areas of 71.025 ha and the altitude ranges between 670 m a.s.l. and 4061 m a.s.l. with a mean elevation of 2405.59 ± 550.75 (standard deviation). It includes 5 valleys: Rhemes Valley, Valsavarenche and Cogne Valley in Aosta Valley region and Orco and Soana Valley on Piedmont side. The study area is characterized by a predominantly Alpine environment with vegetation ranging from mixed forest to rocky meadows and glaciers. Park is sparsely populated and generally human activities are limited and restricted to the lower altitude where the abandonment are leading habitat modifications.

The results of analysis carried out on entire park area are listed in 3.1 *Digital elevation model* and 3.2 *Satellite imagery* sections.

2.1.1 | Altitudinal transects

To detail the fine landscape elements through the use of historical aerial photos and UAV images with field sampling, we selected five altitudinal transects representative of Park area established in the "Alpine Biodiversity Monitoring program", a multi-taxa monitoring project started in 2006 [Viterbi et al., 2013]. Sampling units are 30 circular plots ($r=100$ m) separated, from each center, by an altitude difference of ca. 200 m, see table 2.1 and fig. 2.1. Each plot is representative of one of three altitudinal belts: Montane, below the timberline; Subalpine, between the timberline and the tree line, beyond which no upright tree occurs; Alpine, the zone above the tree line.

The results of analysis carried out along altitudinal transects are listed in 3.3 *Aerial images* and 3.4 *UAV images* sections.

2.1.2 | Gran Piano area

To test free-distortion image creation processes the Gran Piano area (Royal hunting House 45°28'20" N, 7°17'20" E WGS84) located in Orco Valley was chosen, see fig. 2.1. Gran Piano is located in altitudinal range comprised between 1084 and 3638 m a.s.l. encompassing different vegetation types along the altitudinal belts like broadleaf forest derived from wood re-establishment, low-altitude meadows/pastures,

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Valley	Transect	N. of plots	Altitudinal range (m)
Orco	gp	7	1240-2440
Soana	sb	6	1260-2180
Cogne	l	6	1680-2630
Valsavarenche	o	6	1636-2554
Rhemes	v	5	1887-2646

Table 2.1 | GPNP valleys and altitudinal transects. Table reports the number of plots for each transects and its altitudinal range computed in plot center.

shrublands and high-altitude grasslands. Several *malga* and *borgata* are scattered across the valley. The study area was chosen due: (i) to the topographical complexity that create particularly challenging conditions to achieve accurate data; (ii) to the presence of human settlements that are stable elements across the decades; (iii) to the location of *gp* altitudinal transect.

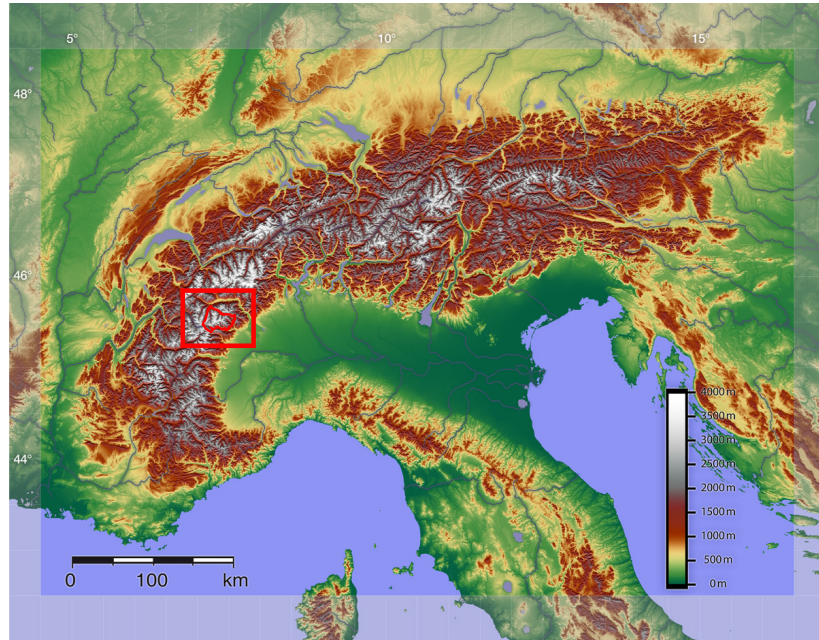
The results of test carried out in Gran Piano surveillance zone are reported in 3.3.1 *Process comparison* of 3.3 *Aerial images* section.

2.1.3 | Levionaz basin

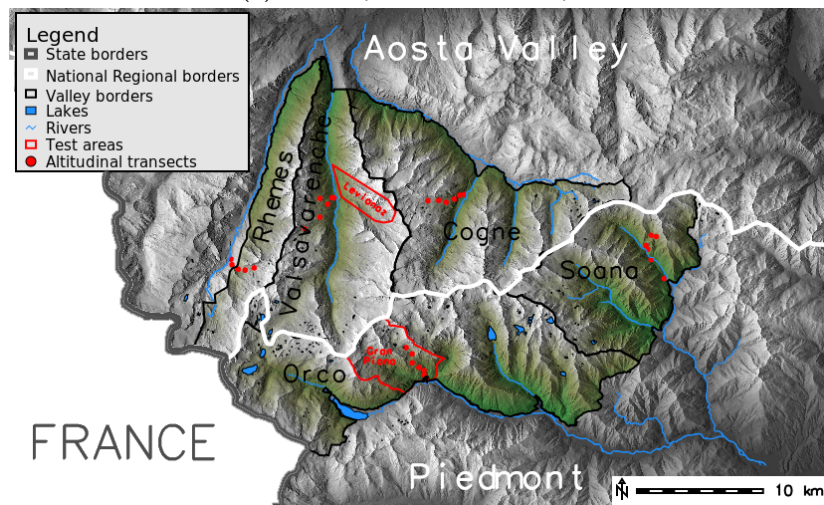
The study area chosen to test the object based image analysis (OBIA) method is the Alpine ibex study area located in Levionaz basin (45°35'25" N, 7°13'35" E WGS84), see in fig. 2.1. The glacial valley encompass an area between 1700 m a.s.l. near Degioz village and 2900 m a.s.l. Landscape pattern is more complex near village where coniferous forests (*Picea abies*, *Larix decidua* and *Pinus cembra*) come in succession with shrublands (*Rhododendron ferrugineum*, *Vaccinium myrtillus*, *Juniperus communis*) and pastures. Above the tree-line the (2100-2300 m a.s.l.) the land cover is characterized by cliffs, steep slopes and Alpine meadows dominated by *Carex curvula* and *Festuca spp.*

The results of analysis carried out in Levionaz basin are presented in 3.3.3 *Image classification* of 3.3 *Aerial images* section.

2.1. STUDY AREA



(a) *GNPN position within Alps.*



(b) *GNPN study areas*

Figure 2.1 | Image *a* shows the position of GNPN in NW Italian Alps. In image *b* are represented the altitudinal transects and test areas of Levionaz basin and Gran Piano surveillance zone. Image sources: image *a* background retrieved from Wikimedia Commons under Creative Commons Attribution CC BY 2.5; regional borders downloaded from ISTAT; image *b* background created in GRASS GIS using *r.relief* and *r.shade* modules and TINITALY/01 DEM [Tarquini et al., 2007].

2.2 | Digital elevation model

Geomorphometry following Pike definition is the science of quantitative land surface analysis [Pike et al., 2009].

Involving numerous mathematical, statistical and image processing techniques [MacMillan and Shary, 2008] geomorphometry aims to quantify land surface parameters (slope, aspect, curvatures and derivatives) and *landforms* that are scale-dependent delimited segments of land surface [Evans, 2012].

Geomorphometric data are needed across several disciplines and in particular to ecology and environmental field studies. Their application include: *a)* landscape ecology [Hengl and MacMillan, 2009, McGarigal et al., 2009]; *b)* predictive vegetation modelling [Franklin, 1995, Hörsch, 2003]; *c)* species distribution modeling [Sappington et al., 2007, Murphy et al., 2010, Danks and Klein, 2002]; *d)* quantitative geomorphometry [Mather, 1979, Walsh et al., 1998]; *e)* hydrology [Moore et al., 1991].

Using the TINITALY/01 DEM we carried out a geomorphometry analysis in the open-source GRASS GIS environment [GRASS Development Team, 2017]. The multi-purpose GIS [Neteler et al., 2012] provides different automated module and add-ons to parameterize geometrical properties of land surfaces [Hofierka et al., 2009].

We computed local land-surfaces parameters following [Lecours et al., 2017] suggestion providing a simple *variance inflation factor* (VIF) to assess the multi-collinearity of selected variables and we classified the study area landforms through different scales of analysis comparing results considering the study area characteristics. The scripts used for this analysis are listed in section *B.1 Digital elevation model* of Appendix B.

2.2.1 | Land-surfaces characterization

Elevation

Elevation is a fundamental parameter in environmental studies because it is one of the most important natural driver in shaping habitat distribution influencing land cover, temperature and precipitation.

Elevation values are often stored as a *digital elevation model* (DEM). It is a raster GIS layer in which each cell represents elevation and it can be acquired using photogrammetry, LiDAR, InSAR and land surveying techniques [Li et al., 2004]. Many dataset are globally available (see Shuttle Radar Topographic Mission (SRTM) and ASTER) but in this study we retrieved the free available TINITALY/01 DEM [Tarquini et al., 2007] that compared with the global-coverage DEMs allows to achieve higher resolution (10 m/px) and quality of data for Italian territories [Tarquini et al., 2012].

Slope

Slope is the steepness of surface defining the magnitude of gradient. It is very important environmental variable because land cover and possible land use are related to it influencing water flow and cost of movement.

2.2. DIGITAL ELEVATION MODEL

Slope was calculated following the Horn's formula implemented in *r.slope.aspect* module. This approach works well both for smoothed both for irregular areas [Lecours et al., 2017].

Aspect

Aspect is the slope orientation defining the direction of gradient. In our temperate zones it is a fundamental land surface parameter influencing the amount of solar radiation at ground. Temperature at ground, soil moisture and vegetation types are linked with this terrain characteristics.

To reduce bias of near-flat surface in aspect computation is required a minimum slope value that could change considering different contexts. To obtain more reliable values of aspect we defined a minimum slope value of 2% considering water flow that below two degrees of slope does not move (moves slowly).

We compute counterclockwise from east aspect (CCW; $n=90^\circ$, $w=180^\circ$, $s=270^\circ$, $e=360^\circ$) using *r.slope.aspect* module selecting the minimum slope value of 2°. Using the *r.northernness.easterness* add-on the circular land-surface parameter values (0° - 360°) were converted in a continuous gradient of northernness (north-south) and easternness (east-west) expressed, respectively, as cosine and sine of aspect.

Ruggedness

Terrain ruggedness is the topographic heterogeneity of surfaces. A quantitative measure of terrain unevenness is an important parameter to describe surface characteristics and many indices were developed across several disciplines. Indeed the definition of ruggedness depends on used calculation. Considering a biological perspective ruggedness is an important feature of structural niche [Riley et al., 1999] and it is a meaningful biological factor [Lecours et al., 2017] allowing to understand how animal perceive surrounding elements and how they use them [Sappington et al., 2007].

We used *r.vector.ruggedness* add-on to compute *vector ruggedness measure* (VRM) that express this terrain attribute as the magnitude of standardized form of vectors composing vector normal to DEM grid cell. In contrast to other roughness indices VRM is less correlated to slope [Sappington et al., 2007].

Solar radiation

Global solar radiation has a prominent importance across different research fields like environmental science, climatology, ecology, remote sensing and land management. Solar energy influences landscape processes especially in mountainous regions where terrain relief modify the amount of solar radiation on terrain surface creating local gradients [Hofierka and Suri, 2002].

To build a solar radiation model adapted to local variation in steepness of surfaces and orientation [Hofierka and Suri, 2002] we computed solar irradiation maps using *r.sun* module.

The solar irradiation computed is the global radiation that is the sum of the beam, diffuse and reflected radiation in clear-sky condition. For each month we created three daily maps of sun radiation expressed as solar energy falling on unit

2. MATERIALS AND METHODS

area over stated interval (expressed in MJ/m² x day) and isolation time maps. Using *r.mapcalc* module the created maps were averaged to annual mean.

2.2.2 | Landform identification

Traditional differential geometry based-methods to automatically group land elements in functional regions [Wood, 1996] could be computationally intensive and they depend by DEM characteristics and fixed-size moving window dimension.

To characterize the continuous surface we approached to the computer-vision approach based on *8-tuple pattern* of *geomorphon* algorithm to identify landforms dependent by local spatial pattern and magnitude of relief [Stepinski and Jasiewicz, 2011, Jasiewicz and Stepinski, 2013]. This approach implementig a ternary local operator assign an 8-tuple pattern to a focus pixel. Visually the 8-tuple pattern is represented by an octagon and it is a 3-valued pattern string constituted by 8 values: – =“lower”; 0 =“same” and + = “higher” to value of focus pixel, see fig. 2.2. The symbols are arranged in counterclockwise order starting from east neighbor and they are the representation of a ternary number (a number represented in the base 3) that can be converted into a decimal number representing the pattern label.

There are 3⁸=6561 possible ternary patterns but considering rotational and reflectional symmetries the initial number is reduced to a subset of 498 elements referred as geomorphons. Following a lookup table based on similarity between geomorphon ternary patterns, the geomorphon subset is reclassified to the most common landform: flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, and pit as represented in fig. 2.3. The results depend on the values of two parameters:

search radius (L): the adaptive line-of-sight that is the distance from a focus pixel with its 8 neighbors along the 8 principal directions;

flatness threshold (t): the difference between zenith and nadir line-of-sight expressed in degrees. The threshold indicates flat direction.

The method was implemented in *r.geomorphon* add-on used to classify DEM in 10 discrete classes.

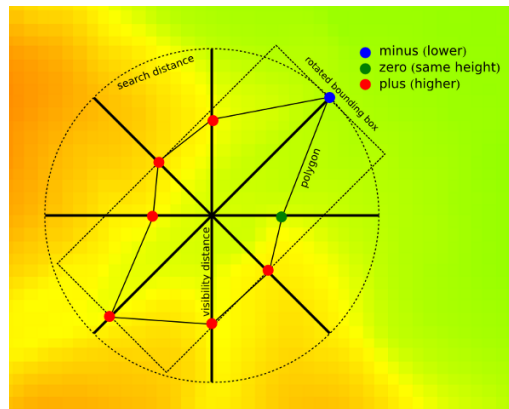


Figure 2.2 | Graphical representation of 8-tuple pattern. Source: GRASS GIS *r.geomorphon* manual page.

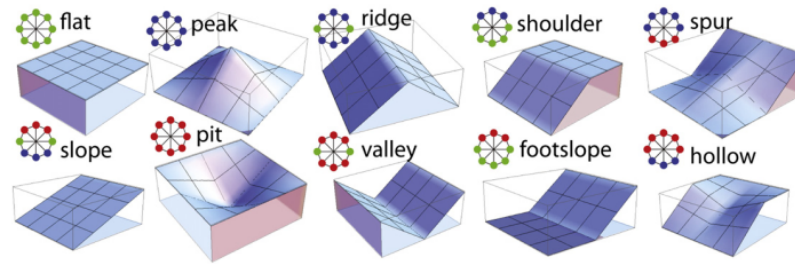


Figure 2.3 | Geomorphons ternary patterns representation for the 10 most common landform elements. Source: [Jasiewicz and Stepinski, 2013]

2.3 | Satellite imagery

To evaluate the structural change of GPNP landscape due to natural forest succession we approached to satellite imagery use providing quantitative and qualitative information. As general framework we followed the Lu et al. [2004] recommendations asserting that to produce reliable results it is fundamental: *a)* to select suitable image acquisition dates and sensor data; *b)* to establish the change categories and *c)* choose an appropriate algorithm. To provide quantitative information we implemented a change detection analysis [Singh, 1989] and to understand the change in terms of fragmentation we followed a method based on Fourier transform. The scripts used are reported in section *B.2 Satellite imagery* of Appendix B.

2.3.1 | Data selection

The study area is entirely covered by one Landsat scene path 195 row 28. For this study we retrieved from EarthExplorer two images acquired on 10th October 1986 (Landsat 5 TM) and 3rd October 2016 (Landsat 8 OLI/TIRS).

To highlight differences in vegetation pattern we selected early-autumn period image to highlight the forest distribution due to phenological mis-match between herbs, shrubs and trees. Considering the high topographical complexity and different sensor response we selected Landsat Surface Reflectance Higher-Level Data products that are already pre-processed images. No atmospheric or topographic correction was required and scene are already co-registered; furthermore the selected images were not affected by clouds cover. The application-ready to use images are well suited to land surface change studies [Young et al., 2017, Markham and Helder, 2012]. Data were only checked for quality and out-of-range values due to shadowed or snow-covered areas were cut-off using GRASS GIS module *r.mapcalc*.

A short description of selected band characteristics and their usage are given in tables 2.2 and 2.3.

2.3.2 | Change detection

As stated by [Singh, 1989] change detection is the process of identifying differences in the state of an object or phenomena observing it at different times. MacLeod and Congalton in 1998 defined four important aspects of change detection in natural resource monitoring: *a)* detecting if a change has occurred; *b)* identifying the nature

2. MATERIALS AND METHODS

Landsat 5 TM Bands	μm	Landsat 8 OLI and TIRS Bands	μm	Resolution (m)
Band 1 - Blue	0.45-0.52	Band 2 – Blue	0.452 – 0.512	30
Band 2 - Green	0.52-0.60	Band 3 - Green	0.533 - 0.590	30
Band 3 - Red	0.63-0.69	Band 4 - Red	0.636 - 0.673	30
Band 4 - Near Infrared (NIR)	0.76-0.90	Band 5 - Near Infrared (NIR)	0.851 - 0.879	30
Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	Band 6 - Shortwave Infrared (SWIR) 1	1.566 - 1.651	30
Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	Band 7 - Shortwave Infrared (SWIR) 2	2.107 - 2.294	30

Table 2.2 | Selected bands for GPNP landscape studies. Table adapted from <https://landsat.gsfc.nasa.gov/landsat-8/landsat-8-overview/>.

Bands	Useful for mapping
Blue	Bathymetric mapping, distinguishing soil from vegetation, and deciduous from coniferous vegetation
Green	Emphasizes peak vegetation, which is useful for assessing plant vigor
Red	Discriminates vegetation slopes
NIR	Emphasizes biomass content and shorelines
SWIR 1	Discriminates moisture content of soil and vegetation; penetrates thin clouds
SWIR 2	Landsat 5: hydrothermally altered rocks associated with mineral deposits. Landsat 8: improved moisture content of soil and vegetation and thin cloud penetration

Table 2.3 | Landsat bands application. Table adapted from <https://landsat.usgs.gov/what-are-best-spectral-bands-use-my-study>.

of the change; *c*) measuring the areal extent of the change and *d*) assessing the spatial pattern of the change.

Image comparison

To compare image captured in different periods band ratios were performed reducing the effects of different illumination condition and sensor response. Using the *r.mapcalc* module NIR and RED bands were ratioed to enhance vegetation distribution and NDVI was extracted for both periods.

Detection of change

To perform change/no-change area detection we chose Principal Component Analysis (PCA) [Lu et al., 2004] following the procedure proposed by Neteler et al. [2012]. Small modifications were necessary due to study area context.

The 3,4,5,7 Landsat 5 bands and 4,5,6,7 Landsat 8 bands – the most responsive to vegetation – were selected. To enhance the change-information *Optimal Index Factor* (OIF) analysis was performed to maximize the variance reducing data redundancy.

The best combination was used in PCA extracting the principal components of input maps.

After a visual inspection of principal components the change map was extracted from the third Principal Component selecting:

1. only values over the 90th percentile because of the similar landscape composition;
2. pixel located below 2800 m a.s.l. to avoid glacier and snow debris reflectance change.

These elements were converted in vector format removing areas smaller than a threshold of 0.81 ha (3x3 pixels where Landsat pixel=30 m) to remove random variation in pixel reflectance and vegetation phenology.

Identifying the nature of the change

The resultant map was used to assess the nature of change through a t-test for related samples with permutation test (R script created by P. Legendre and G. Blanchet retrieved from <http://adn.biol.umontreal.ca/~numeralecology/Rcode/>). Pixels classified as change were used as related samples while different NDVI values of 1986 and 2016 were used as paired variables.

Measuring the areal extent of the change

The areal extent was simply assessed through GRASS GIS *r.info* and *r.report* modules.

2. MATERIALS AND METHODS

Assessing the spatial pattern of the change

Using local land-surface parameters (elevation, slope, aspect, VRM, global solar radiation and insolation time) and landform classification (geomorphons) we extracted the main characteristics of changed area using *r.univariate* module.

Patterns were described using simple landscape ecology index implemented in Fragstats [McGarigal et al., 2012] such as:

patch number: the number of contiguous focal area, in this case changed area;

total edge: the total edge of patches expressed in m;

patch size: the dimension of focal area expressed in m², to sum up patch size distribution mean, standard deviation and coefficient of variation were used;

radius of gyration: is the mean distance (m) between patch centroid and each patch cell. It is a simple measure of patch extent affected by patch size and compaction.

2.3.3 | Fragmentation analysis

Fourier transform is a widely used function to find frequencies that made up a generic signal. Once the transform has been applied to a signal the result is a continuum of sinusoidal functions of frequencies that constitute the original signal.

Images are a simple raster matrix representing a spatial variable that can be assumed as two-dimensional function $f_{(x,y)}$. Applying the transform to the two-dimensional function the result can be conveniently represented as plot in an alternative coordinate space. Indeed the term of *Fourier transform* refers both to mathematical function both to new coordinate space known as *frequency domain representation*. Generally in Fourier domain representation the low-frequency components are plotted in the middle of the new coordinate space while the higher-ones toward the edges creating a simple representation of how much signals lie in the frequency range (refer to Rocchini et al. [2013] for in-depth explanation).

Using the GRASS GIS module *i.fft* the Fourier transform was applied on the first Principal Components (PC1s) of 1986 and 2016 Landsat bands –listed in table 2.2– accounting respectively for the 71.48% and 67.19% of variance.

To show the changes between the two selected periods a frequency plots based on kernel density functions and a linear models by hexagon binning was realized as proposed by Rocchini et al. [2013] following the code available in GRASS wiki.

2.4 | Aerial images

Despite the many advantages of aerial images, they have many limitations and the use of the older ones get complicated due to geometric distortions affecting images [Morgan et al., 2010]. To proceed with multi-temporal image analysis every distortion must be corrected placing each element in exact geographic position. The correct object placement avoids misleading between object change and spatial shift. Furthermore Rocchini [2004] showed that the landscape indices – mainly based on object area and shape – are very sensitive to geometric inaccuracies leading in estimation errors.

2.4.1 | Aerial image available collection

As public administration, GPNP in the last few decades realized a multi-temporal dataset of aerial photographs to qualitative monitor change in land cover. Table 2.4 reports all the collected flights; with the exception of the *Piemonte Alluvione 2000* flight all the images are analogic frames. Furthermore the GPNP owns different digital orthophotos provided in .ecw format (see table 2.5).

To improve dataset adding more images covering missing part of protected area from *Settore cartografico Regione Piemonte* we retrieved digital photo frames listed in 2.6 and digital orthophotos listed in 2.7.

Years	Flight	Channels	N. of photos	Approximate scale
1973	Alifoto Piemonte	RGB	64	1:16000
1974/75	CGR Valli RAVA	RGB	89	1:15000
1975	CGR RAVA	Panchromatic	154	1:17000
1976/80	R. Piemonte - Pian. Terr.	RGB	140	1:13000
1991	R. Valle d'Aosta '91	RGB	133	1:17000
1993	Valle d'Aosta Alluvione '93	RGB	125	1:15000
2000	Valle d'Aosta Alluvione 2000	RGB	46	1:15000
2000	Piemonte Alluvione 2000	RGB	204	1:15000

Table 2.4 | List of aerial images collected by GPNP. For every flight the main characteristics are listed.

Years	Flight	Channels	N. of photos	Resolution (m/pix)
1998/99	Volo Italia - "IT 2000"	RGB	33	1
2005	HABITALP IR	IRGB	353	0.15
2009/11	ICE RAVA	RGB	39	0.5
2009/11	ICE Piemonte	RGB	22	0.4

Table 2.5 | List of orthophotos collected by GPNP. For every flight the main characteristics are listed.

2. MATERIALS AND METHODS

Years	Flight	Channels	N. of photos	Approximate scale
1973	Alifoto Piemonte	RGB	144	1:16000
1975	RATI Piemonte	RGB	90	1:15000
1976/80	R. Piemonte - Pian. Terr.	RGB	187	1:13000
1980	CGR Fondovalle Piemonte	Panchromatic	57	1:13000
1991	CGR Rossi Piemonte	Panchromatic	47	1:13500
2000	Piemonte Alluvione 2000	RGB	222	1:15000

Table 2.6 | Aerial images retrieved from *Settore cartografico Regione Piemonte*. All data are freely distributed and images were provided through Geoportale Piemonte under Creative Commons Attribution CC BY 2.5

Years	Flight	Channels	N. of photos	Resolution (m/pix)
2006	Provincia Torino	RGB	81	0.25
2006	Provincia Torino	IRGB	63	0.25

Table 2.7 | Orthophotos retrieved from *Settore cartografico Regione Piemonte*. All data are freely distributed and images were provided through Geoportale Piemonte under Creative Commons Attribution CC BY 2.5

2.4.2 | Data preparation

Analogic aerial images were digitized using a flatbed A3 scanner to prepare data for further analysis preserving image quality to film degradation. Scanner allows to transform an analogic image in a digital image. The continuous analogic values are stored in a discrete numeric matrix made up of pixel elements. Each elements in scene should be composed by more than one pixel storing a radiometric information about represented object. Therefore scanning process resolution is a very important parameter influencing resolution on the ground. Usually a scanner has a resolution comprised between 300 (desktop publishing) to 4000 (photogrammetric application) *dots per inch* (dpi). To realize a low-cost image archive with ecological and management application we used a Plustek OpticPro A320 scanner. Following Neteler [2004] we take into account that on the ground resolution is established by:

$$M = \frac{h_g}{f} \quad (2.1)$$

$$m_b = \frac{1}{M} \quad (2.2)$$

where:

h_g is the difference between altitude value marked on aerial image and mean elevation of represented scene expressed in m referred to sea level;

f camera focal length in mm .

On ground resolution is defined by mean scale number and scanning resolution:

$$R_g[cm] = \frac{M}{R_s[lines/cm]} \quad (2.3)$$

where:

R_g is the resolution on the ground;

M is the scale number;

R_s is the scanning resolution.

So to define scanning resolution:

$$R_s[lines/cm] = \frac{M}{R_g[cm]} \quad (2.4)$$

Generally it is expressed in *dot per inch* (dpi) so equation 2.4 could be expressed as:

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$$R_s[dp\dot{i}] = \frac{M}{R_g[cm]} 2,54 \frac{cm}{inch} \quad (2.5)$$

Changing *dpi* densities modifies image pixel dimension (see table 2.8).

To preserve data integrity we selected a scanning resolution of 1200 *dpi* because to high *dpi* densities could lead in background noise and waste of disk memory. Panchromatic images were digitized using gray-scale mode in 8 bit color depth storing data in a range comprised between 0 and 255. The RGB ones were digitized using true-color mode in 24 bit (8 bit per each channel).

dpi	pixel (μm)
100	254
300	84.7
600	42.3
1200	21.2
2400	10.6
4000	6.35

Table 2.8 | Pixel size at different scanning resolution.

2.4.3 | Process comparison

To remove geometric distortion creating a free-distortion image we have two main approaches: *orthorectification process* and *structure from motion* (SFM). The former is the historical method based on camera geometric properties. The latter is a low-budget technique well-suited in the case of unknown geometric camera properties [Westoby et al., 2012]. A detailed explanation of two approaches are given in Appendix A *Theoretical backgrounds*.

To compare method the Gran Piano area was chosen and data used in method comparison were:

test images aerial photos N113 4721-4723-4725 and N114 4622 of *Ripresa aerea Alluvione Piemonte 2000* flight campaign. Images was taken at a relative flight altitude of 2280 m in RGB bands with a nominal scale of 1/15000, see fig. 2.4;

reference maps of *Ripresa aerea ICE Piemonte 2009-11* distributed in RGB bands with a pixel resolution of 0.4 m/px were chosen as reference maps to take GCP coordinates and to carry out the accuracy assessment, see fig. 2.5;

TINITALY/01 DEM [Tarquini et al., 2007] provided the elevation values of coordinates.

2.4. AERIAL IMAGES

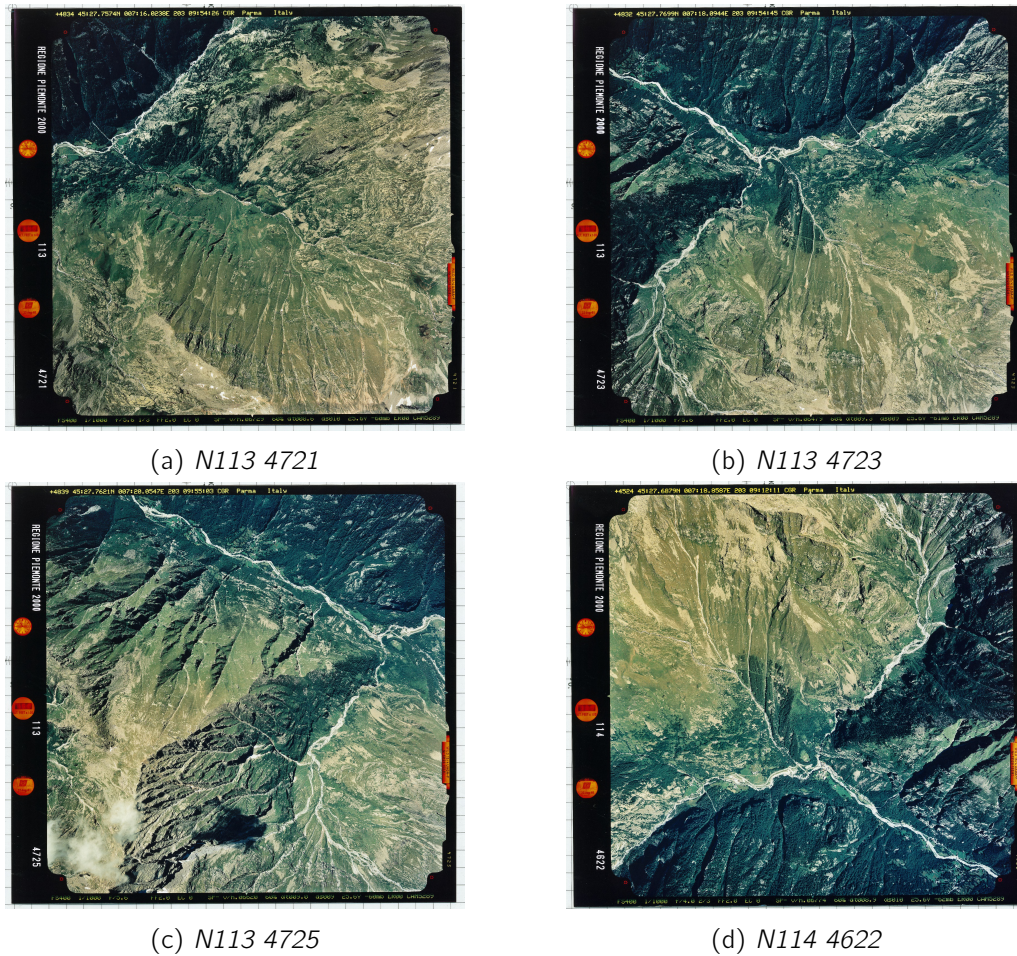


Figure 2.4 | Test images provided by Geoportale Piemonte.



Figure 2.5 | Gran Piano surveillance zone. Background are reference images of *ICE Piemonte 2009-11* flight provided by Geoportale Piemonte.

Orthorectification: the GRASS GIS approach

GRASS GIS was one of the earliest open-source GIS. It was created in 1982 by the U.S. Army Construction Engineering Research Laboratories and its development was abandoned in 1996. The project adopted the GNU General Public License (GPL,

2. MATERIALS AND METHODS

see <http://www.gnu.org>) in 1999 and in 2006 it became the founding member of the Open Source Geospatial Foundation. GRASS GIS is written in modular way implementing more than 450 modules to handle raster and vector data and their number is still growing thanks to the contribution of *add-ons* created by the community [Neteler et al., 2012].

To proceed with the orthorectification of image N114 4622 we choose the OSGEO-Live 7.9 operating system with GRASS GIS 6.4.4. The open-source operating system is required to run the module *i.ortho.photo* dependent by Vask library and XDRIVER monitors removed from newer version of GIS environment (see the repository on GitHub for more information). The camera metadata required in interior orientation step was retrieved by bibliography and image border.

Running the module user can generate an orthophoto following menu item:

Initialization options selection of imagery to be rectified in a generic XY coordinate system, DEM and reference maps in chosen geographic coordinate system and camera parameters specifications.

Transformation parameter computations between image-to-photo and photo-to-maps coordinate systems performing interior orientation and exterior orientation as illustrated in fig. 2.6.

Ortho-rectification option map name, resampling method and angle-camera map name.

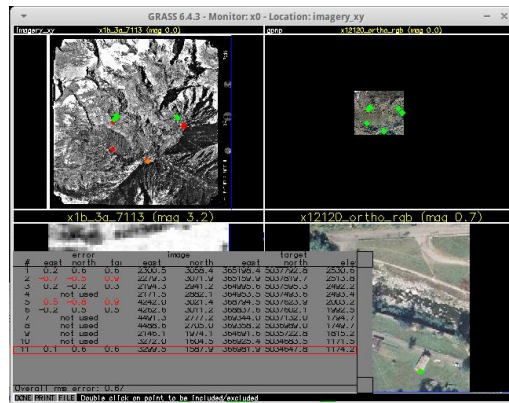


Figure 2.6 | GRASS GIS exterior orientation step.

Structure from motion: the Agisoft PhotoScan approach

Agisoft PhotoScan is a commercial computer vision application often used in structure from motion reconstruction [Turner et al., 2012, Verhoeven, 2011] allowing to accomplish all required task through a GUI. Software works well with a large number of image following a process similar to one described in *A.0.1 Structure from motion process* but it has some proprietary implementation and little is known about them [Remondino et al., 2014]. For this comparison the version 1.0 in Windows 8.0 environment was used.

2.4. AERIAL IMAGES

To reconstruct the scene we used all the selected images of *Ripresa aerea Alluvione Piemonte 2000* flight following the method proposed by Gomez et al. [2015]. All image was prepared cutting scene borders in IrfanView and to improve the entire workflow camera parameters was retrieved as in 2.4.3 *Orthorectification: the GRASS GIS approach* and on entire scene 60 GCP were previously selected.

Running the software GUI user can perform all the required steps:

Align photos detecting common points across input images software generates a first photo alignment and a sparse point clouds. During this step the image N114 4622 was discarded due to misalignment.

Place marker points on GCP of well-known coordinates to solve camera interior and exterior orientation using bundle-block adjustment.

Build dense point cloud reconstructing scene structure.

Build mesh surface of represented scene selecting surface type and source data.

Build texture on surface using image as source, see fig. 2.7.

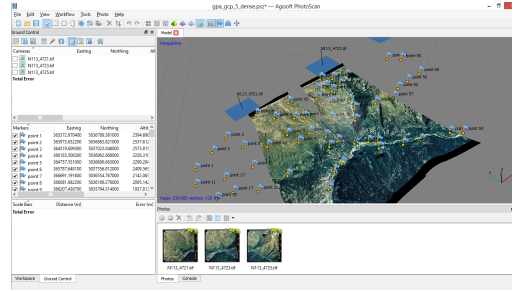


Figure 2.7 | Agisoft PhotoScan building texture step.

Accuracy assessment

To quantitatively assess the spatial accuracy of processed images we followed the American Society for Photogrammetry and Remote Sensing (ASPRS) guidelines [ASPRS, 2015]. Selecting the ortho-imagery and reference map coordinate values of a minimum recommended 20 checkpoints we compute the *Root Mean Square Error* (RMSE) in horizontal (x),

$$RMSE_x = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{i(reference)} - x_{i(orthorectified)})^2} \quad (2.6)$$

vertical (y)

$$RMSE_y = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_{i(reference)} - y_{i(orthorectified)})^2} \quad (2.7)$$

and radial (r) direction

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$$RMSE_r = \sqrt{RMSE_x^2 + RMSE_y^2} \quad (2.8)$$

providing also the accuracy level at 95% confidence level

$$RMSE_r(Acc95\%) = RMSE_r * 1.7308 \quad (2.9)$$

where:

$i_{(reference)}$ is the coordinate values in i^{th} checkpoint in reference map

$i_{(orthorectified)}$ is the coordinate values in i^{th} checkpoint in created map

n is the number of checkpoints

i in an integer ranging from 1 to n

The accuracy assessment was performed using QGIS 2.18 and R.

2.4.4 | Vegetation pattern change

To rapidly derive change in vegetation pattern change with no *a priori* assumptions we ran the Fourier transform through the *i.fft* module on orthorectified panchromatic images of 1975 RATI Piemonte flight and first principal component of RGB image of 2009/11 ICE Piemonte flight covering the entire Orco valley altitudinal transect.

Changes in signal spectrum between 1975 and 2009/11 images were evaluated using a frequency plots based on kernel density functions and a linear models by hexagon binning as proposed by Rocchini et al. [2013] following the code available in GRASS wiki. The modified script for our case study is included in subsection *B.3.1 Vegetation pattern change* of Appendix B.

2.4.5 | Image classification

To classify pixel values thresholding them in land cover classes we approached to object-classification [Blaschke, 2010a]. This method mainly differs from the traditional *pixel-based method* in a further step of image preparation – the segmentation – in which similar neighboring pixels are grouped together with an improvement of classification time and easily realising a linkage between image objects and habitat elements. The proposed workflow to classify Levionaz basin is available in subsection *B.3.2 Image classification* of Appendix B.

Image preparation

The study area chosen to test the method is the Levionaz basin and used images belongs to the 2009-2011 ICE flight. Images were distributed in *.ecw* proprietary format converted in *.tif* using QGIS 2.8.14 in Windows 10 OS. To reach the entire cover of study area 9 scenes were selected and merged in GRASS GIS 7.0.4 in OSgeo Live 10.0 OS using the function *nmax()* in module *r.mapcalc*.

Object creation

Segmentation was performed on first principal component of RGB channels to diminish data redundancy and image noise speeding up computational time. Running the module *i.pca* we obtained one image explaining almost the 98% of variance.

The process was carried out using *i.segment* module that implement the *region growing* segmentation method in which user have to define two main parameters:

- threshold: value comprised between 0 (only equal sided pixels are merged) and 1 (all pixels are merged);
- minimum object size: the minimum dimension of objects.

To objectively evaluate segmentation results using different parameter values we used *i.segment.uspo* add-on. The tool relying on unsupervised optimization methods [Espindola et al., 2006, Johnson et al., 2015] allows to assess the segmentation quality choosing a set of segmentation parameters [Grippa et al., 2017].

Using the *v.mkgrid* module the Levionaz basin was divided in 56 500X500 m grids used as computational regions to evaluate the segmentation threshold values comprised between 0.02 and 0.9 with a step of 0.02. The best 5 segmentation threshold results were used to evaluate the minimum object size in a range between 1 and 30 pixels selecting the best combination of threshold and minimum object size values.

Object characterization

Objects were characterized using:

spatial features: area, perimeter, compactness and fractal dimension;

geographic feature: DEM;

spectral features: the RGB bands were summed into brightness, used to calculate the bare ground index (BGI) and following the Manhattan's normalization the color chromaticity (R_c , G_c , B_c) were extracted to calculate normalized green red difference index (NGRDI) [Tucker, 1979], green excess index (GEI) [Richardson et al., 2009], green leaf algorithm (GLA) [Chianucci et al., 2016] and Woebbecke's index (WI) [Woebbecke et al., 1995] calculation;

texture: the brightness band were used to retrieve the grey level co-occurrence matrix (GLCM) as described by Haralick et al. [1973] selecting all the available second-order statistics (angular second moment, contrast, correlation, inverse difference moment) and adding two first-order ones (entropy and standard deviation) [Laliberte and Rango, 2009].

The module *r.covar* was ran on spectral and texture groups discarding the redundant features. To assess the collinearity between the features we used the stepwise variance inflation factor (VIF) implemented in *r.vif* add-on. The resultant dataset was increased with DEM and normalized using *r.mapcalc* module. Objects were characterized with range, average, standard deviation and variance statistics and normalized form of their shape features.

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Object labelling

In labelling process we randomly extract 200 objects to use as test set and 50 used as initial training set. Training set size was increased using a guided learning algorithm implemented in *r.object.activelearning* add-on that highlights the necessary objects to improve the classification score (see table 3.16).

The classification was performed connecting R and GRASS GIS through the *v.class.mlr* add-on that provides the access to *Caret* library [Kuhn, 2008]. The supervised classification algorithm used were Support Vector Machine with radial kernel (SVMradial), Random Forest (RF), Recursive partitioning (Rpart), C 5.0 and k-Nearest Neighbors (kNN). Furthermore the add-on allows to merge the individual classifier predictions through voting systems: Simple Majority Vote (SMV), Simple Weighted Vote (SWV), Best Worst Weighted Vote (BWWV), Quadratic Best Worst Weighted Vote (QBWWV) as described by Moreno-Seco et al. [2006].

Accuracy assessment

The accuracy assessment was carried out using Cohen's kappa statistics and overall accuracy implemented in *r.kappa* module.

2.5 | UAV images

Field sampling of plant species is a fundamental but complex and time-consuming activity, especially when carried out in mountain areas, that could lead in an incomplete overview of the area. The spread of UAV technology lead to cover very large area in short time rapidly acquiring high resolution images increasing the quality of collected data. These platforms are especially challenging in complex mountains landscape due to small scale features of altitudinal belts.

2.5.1 | Image collection

To avoid problems linked with complexity of mountain territories a fixed-wing UAV was chosen to provide image of altitudinal transects. Areas suitable to departure/landing of UAV were identified using images of Ripresa aerea ICE 2009-11, DEM and field survey.

The fixed-wing UAV used is a senseFly eBee of 960 mm with a weight of ca. 690 g equipped with Canon IXUS/ELPH, GPS unit, altimeter and wind speed sensor. Canon IXUS/ELPH have 1/2.3" back-illuminated CMOS sensor; images are captured in visible light in JPEG format with a 16 Mpix dimension and aspect ratio of 4:3. The declared maximum f/number and maximum shutter speed are 2.7 and 1/200s but camera was set in full-auto mode adjusting ISO, aperture and shutter speed.

Flight survey were carried out in full-auto mode except in particular conditions (complexity of territories and unexpected changes in weather) following the plant growing season. Flights took place in the 2nd half of June in Montane belt, in the 1st half of July for the Subalpine belt and the 2nd half of July for the Alpine belt. Collected images were created using the proprietary software Postflight Terra 3D Professional [Pix4D, 2012] obtaining 30 images with a resolution of 5.9 ± 1.5 cm (mean $\pm$ sd).

2.5.2 | Field sampling

Ground observation sites of altitudinal transects were randomly extracted in GRASS GIS using a random sampling on UAV images, 40 sampling units were extracted in each plot constituting the training set and test set.

During the vegetation growing season using 50X50 cm quadrat – subdivided in 25 10X10 cm squares suitable for both dense and poor vegetation areas – field sites were sampled collecting information about land cover; frequency of dominant species defined as the single species to a maximum of 3 species that cover more than 50% of quadrat; height and phenology stage.

2.5.3 | Visual interpretation

Visual interpretation was performed on *d* plot of Valsavarenche altitudinal transect due to the presence of four land cover classes. To retrieve information from UAV image the training set was used in the learning step and test set to evaluate user performance. After the trial and error learning image was visual inspected to increase the training set size.

3 | Results

3.1 | Digital elevation model

3.1.1 | Land-surfaces characterization

Table 3.1 shows the VIF values for the computed variables. For the sake of clarity in the analysis we did not include the *northernness* and *easterness* because they are simple conversion of circular values in continuous gradient and we did not include the insolation time map computed along solar global radiation maps due to their strong correlation, see fig. 3.1.

variable	vif	sqrtvif
DEM	1.030694	1.015231
Slope	1.074432	1.036548
Aspect	1.979122	1.406813
VRM	1.033946	1.016831
Solar radiation	1.986227	1.409336

Table 3.1 | VIF results show a low rate of collinearity between the selected features.

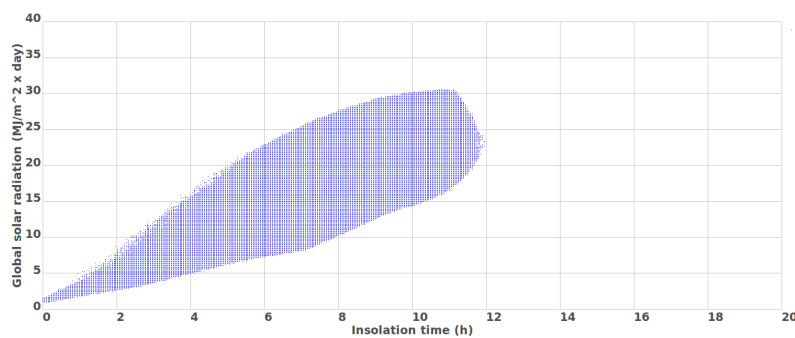


Figure 3.1 | Scatterplot of insolation time vs solar radiation annual means shows a strong correlation between parameters computed using *r.sun* ($R = 0.828105$).

In image 3.2 are reported the elevation, slope, aspect and VRM maps and in image 3.3 the annual mean maps of solar radiation and insolation time with value distribution referred to study area. In subsection *C.1.1 Land-surfaces characterization* of Appendix C for each maps descriptive statistics are tabbed referred to entire park area and for each valley.

3.1. DIGITAL ELEVATION MODEL

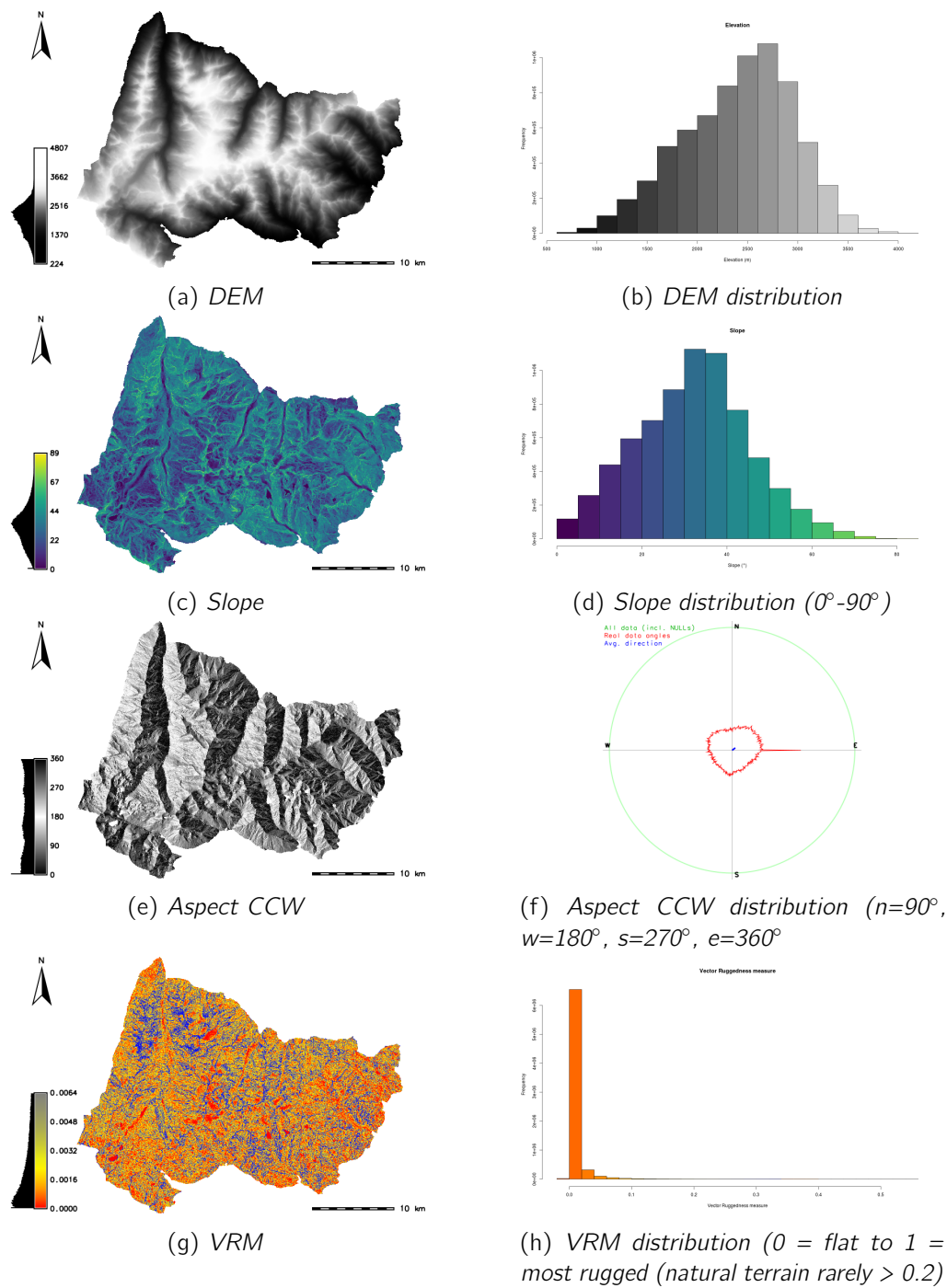


Figure 3.2 | Local land surface maps with value distributions.

3. RESULTS

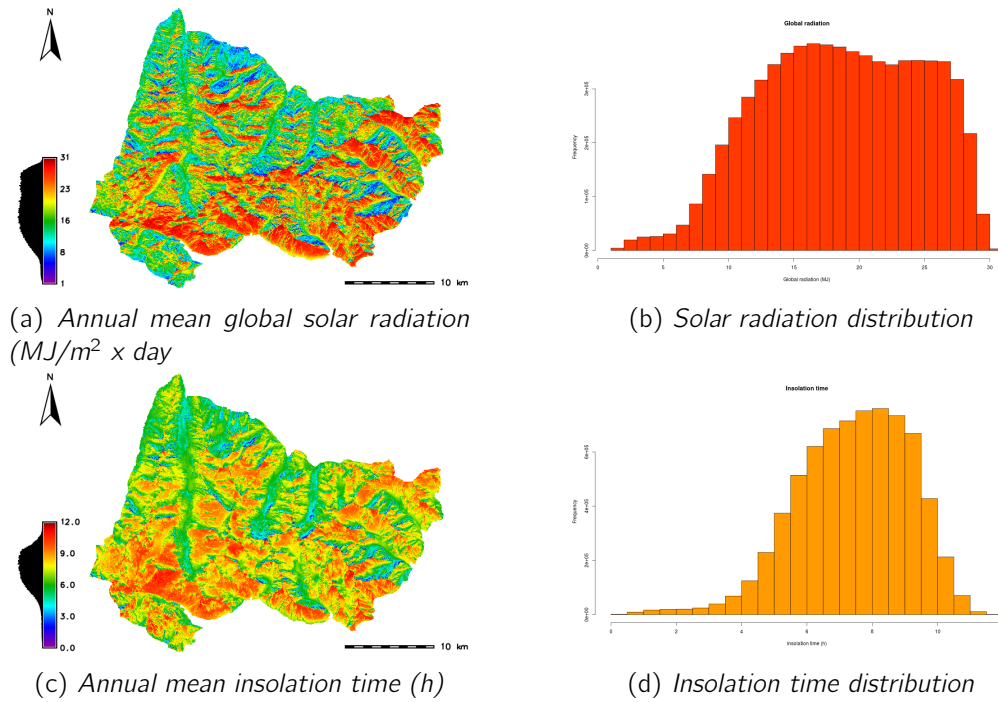


Figure 3.3 | Maps derived from *r.sun* module with frequency distribution.

3.1.2 | Landform identification

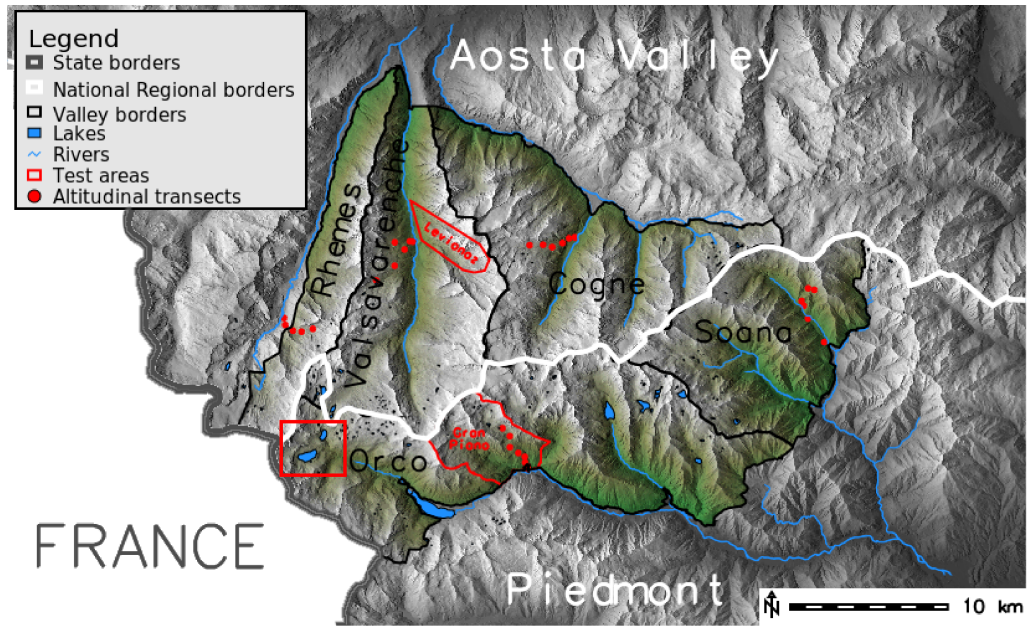
Study area landforms were classified using *r.geomorphon* add-on. The first map was created using the default parameters of $L=3$ cells and $t=1^\circ$ (image *a* in fig. 3.4). Then we created geomorphometric maps using values of L setted as multiple of 5 and the default flatness threshold (fig. 3.5).

Maps were firstly visual assessed finding a convergence for map with search radius of 15 cells. In image 3.4 are shown the Serru' and Agnel lakes (Orco valley $45^\circ 27' 56''$ N, $7^\circ 8' 7''$ E WGS84). Lakes are classified as flat surface and footslope but increasing the search radius we can observe as they are classified as valley. Looking at figure 3.5 we can see that $L=15$ cells is sufficient to map these landscape features with the DEM resolution of 10 m/px.

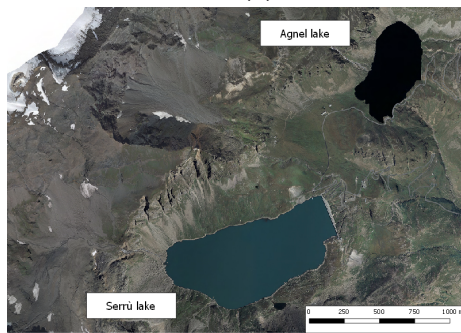
Results were statistically compared using the *r.object.spatialautocor* using as variable the DEM values and Moran's I index to assess the feature spatial autocorrelation. The index values range from -1 where values are dispersed (dissimilar next to each one) to 1 where values are clustered. The selected maps have a value of 0.0345481 indicating no spatial autocorrelation in DEM values (see table 3.2).

The figure 3.6 and table 3.3 show the landform distribution in GPNP and in table 3.4 are listed the results for valleys.

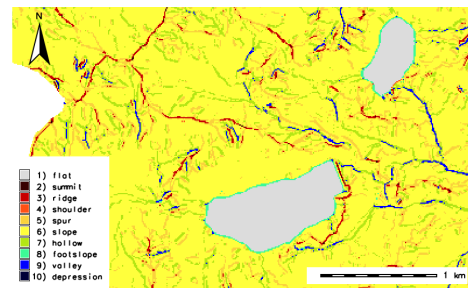
3.1. DIGITAL ELEVATION MODEL



(a) Serru' and Agnel lakes position within GPNP



(b) Serru and Agnel lakes represented in ICE Piemonte 2009/11 flight



(c) Landforms classified using the default $L=3$ and $t=1^\circ$

Figure 3.4 | Classification of Serru and Agnel lake using the the default add-on value.

Search radius	Moran's I index
3	-0.0611243
5	-0.0442582
10	-0.0232648
15	0.0345481
20	0.0590047
25	0.0379135
30	0.0961516
35	0.0834450
40	0.0918162
45	0.1004355
50	0.0950861

Table 3.2 | Moran's I index results for different search radius.

3. RESULTS

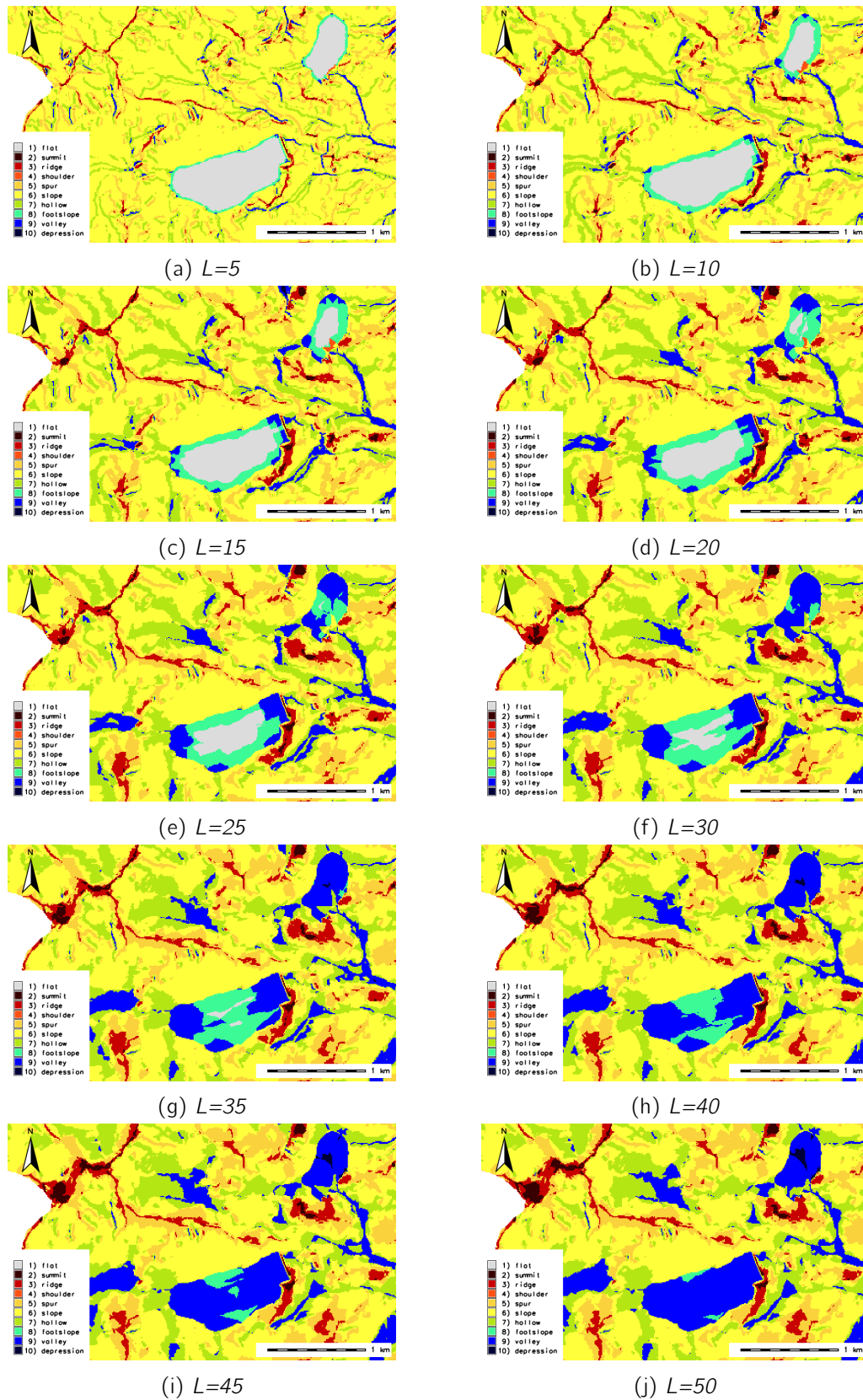


Figure 3.5 | Landform classification at different search radius size.

3.1. DIGITAL ELEVATION MODEL

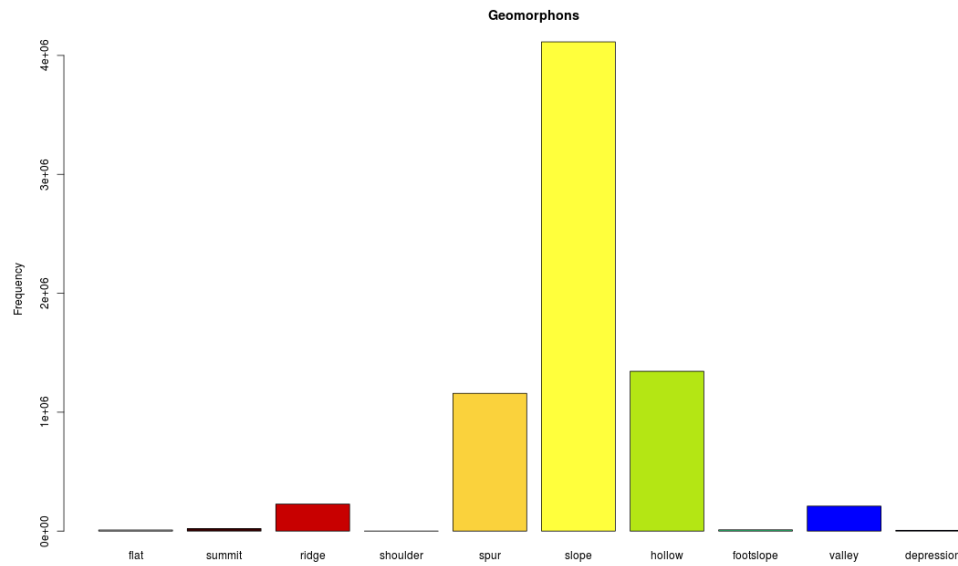


Figure 3.6 | Geomorphons ($L=15$) distribution in GPNP.

Landform	Hectares	Cell count	% cover
flat	95.52	9552	0.13
summit	211.28	21128	0.30
ridge	2271.26	227126	3.20
shoulder	5.10	510	0.01
spur	11,582.29	1158229	16.31
slope	41,140.23	4114023	57.93
hollow	13,438.57	1343857	18.92
fotslope	107.01	10701	0.15
valley	2101.93	210193	2.96
depression	69.35	6935	0.10

Table 3.3 | GPNP landform cover.

Landform	Rhemes	Valsara	Cogne	Soana	Orco
flat	0	8.57	0	0.33	86.62
summit	19.23	45.56	41.00	31.32	74.17
ridge	197.53	483.28	512.34	385.51	692.60
shoulder	0	1.20	0	0.09	3.81
spur	1042.42	2468.77	2664.84	1871.13	3535.15
slope	3806.60	8518.26	9282.98	6707.35	12,825.05
hollow	1192.51	2734.45	3195.50	2268.51	4047.61
fotslope	0	25.78	0.95	3.61	76.67
valley	150.58	489.47	463.41	342.39	656.09
depression	5.17	23.92	16.30	5.88	18.08

Table 3.4 | Landforms cover in hectares per valley.

3. RESULTS

3.2 | Satellite imagery

3.2.1 | Change detection

Image comparison

Using the *r.mapcalc* module the Landsat NIR and red bands were ratioed to create a map of vegetation distribution because vegetation has higher reflectance in NIR region and absorption in red region. The NIR/RED ratio defines vegetation distribution – in particular forest – because the higher values in image corresponds to higher amount of vegetation. The NDVI maps and value distribution confirm the change in vegetation derived from band ratios showing two different landscape configurations (see fig. 3.7 and 3.8).

Detection of change

The OIF analysis results indicate that the best band combination for vegetation assessment is given by the RED, NIR and SWIR channels (see table 3.5 and fig. 3.9).

The band combinations were used in PCA extracting the principal components of input maps, the results are listed in table 3.6.

The change/no-change map was extracted from the third Principal Component selecting only values over the 90th percentile and located below 2800 m a.s.l. removing smaller areas to avoid random variation in pixel reflectance, see image *a* in figure 3.10. To highlight areas where major change occurred a simple hexagon grid heat map (images *b* fig. 3.10) was created accounting for the number of changed cell. Map in image *a* and barplot in image *b* fig. 3.11 show that the major changes occurred in Orco and Soana valleys.

Landsat 5	Score	Landsat 8	Score
3-4-5	1625.3684	4-5-6	2603.9697
3-5-7	1556.7742	4-5-7	2354.0169
3-4-7	1489.5243	4-6-7	2264.1381
4-5-7	1415.5305	5-6-7	1695.6167

(a) Landsat 5 band score

(b) Landsat 8 band score

Table 3.5 | Tables report the three-band combination that maximize the information stored in multi-spectral image. The combination with highest scores was used in PCA.

Identifying the nature of the change

The change/no-change map was used to assess the nature of change through a t-test for related samples with permutation test. Pixels classified as change were used as related samples while different NDVI values of 1986 and 2016 were used as paired variables. Running the R script the means of two related samples are compared. Table 3.7 reports the results of t-test the higher value of t statistics shows difference between NDVI in selected periods with higher values in 2016 as shown in fig. 3.12.

3.2. SATELLITE IMAGERY

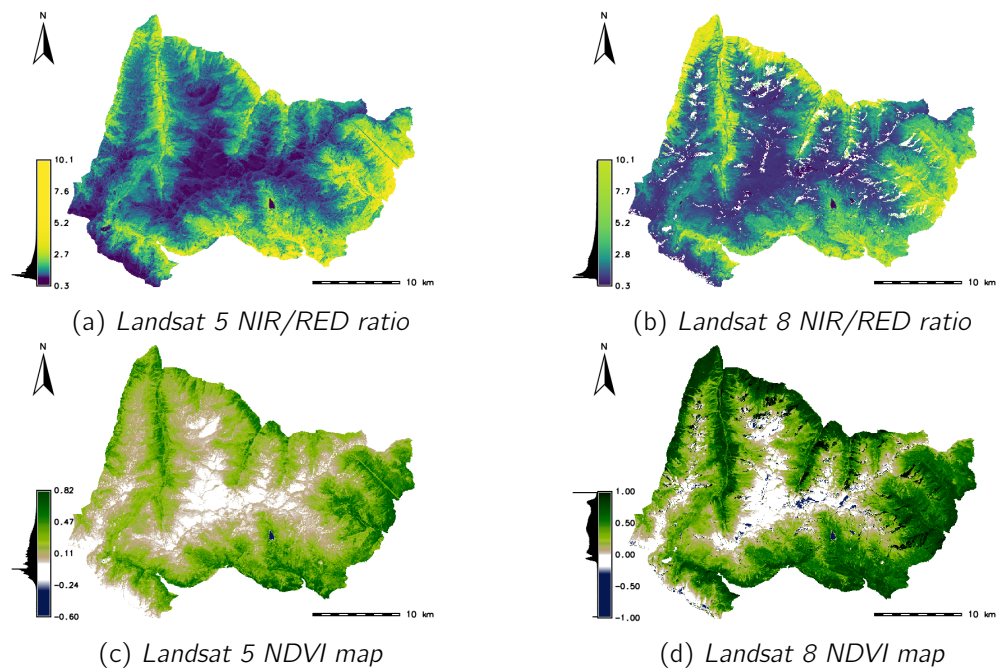


Figure 3.7 | The band ratio shows different vegetation distribution in park area The NDVI maps show change in vegetated areas within park area.

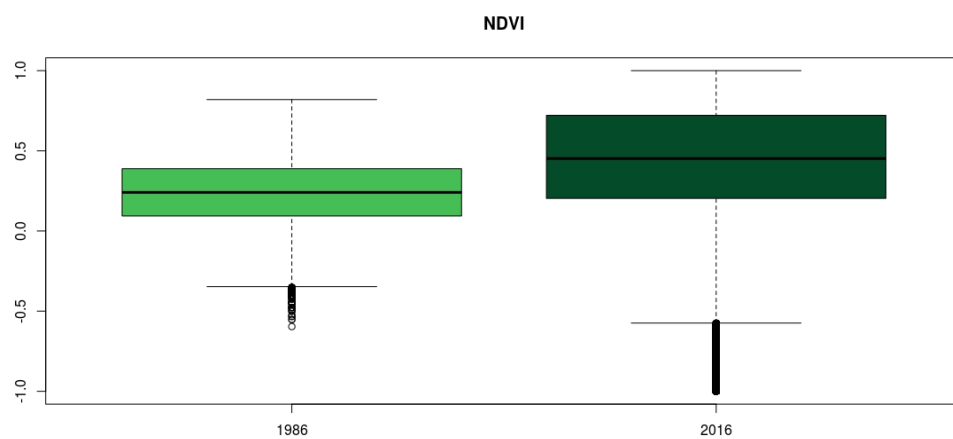


Figure 3.8 | NDVI value distributions for 1986 and 2016 periods.

3. RESULTS

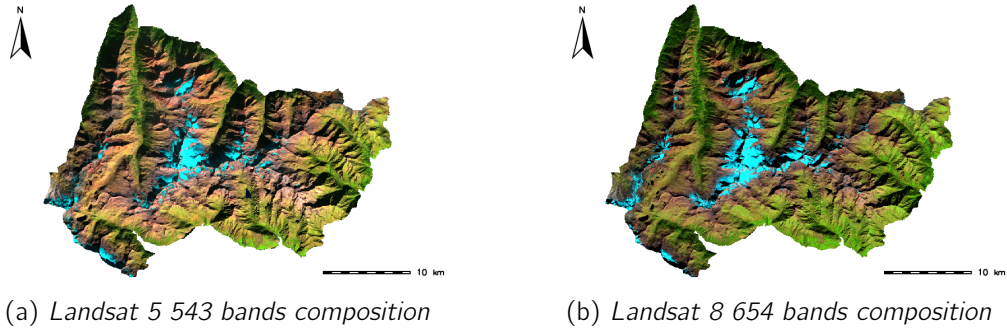


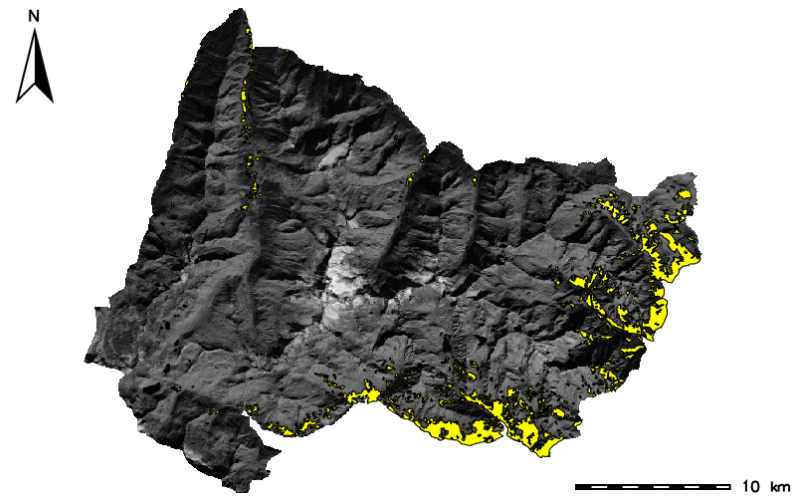
Figure 3.9 | The OIF analysis results optimize the variance of selected bands enhancing the vegetation distribution in park area.

Eigen values	Vectors	Percent importance
PC1 5509755.57	0.2813, 0.4274, 0.4525, 0.3406, 0.5103, 0.3963	67.20
PC2 1835911.45	0.2237,-0.0227,-0.5018, 0.6571, 0.2515,-0.4500	22.39
PC3 483766.99	-0.4280, 0.3164,-0.2311,-0.4312, 0.6486,-0.2380	5.90
PC4 261271.08	0.5190, 0.6458,-0.0445,- 0.3035,-0.3169,-0.3451	3.19
PC5 90568.22	-0.2639,-0.0298, 0.6820, 0.1754,-0.0411,-0.6571	1.10
PC6 17300.96	0.5904,-0.5466, 0.1511,-0.3787, 0.3919,-0.1812	0.21

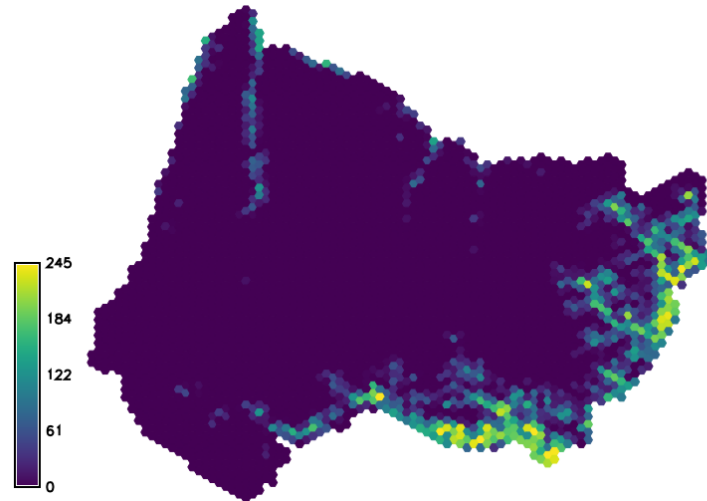
Table 3.6 | PCA analysis for OIF results.

t-test results	
Number of objects	46700
Mean of the differences	-0.1953118
t statistic (paired observations)	-563.1731
95% confidence interval of t	-0.1959916 -0.1946321
Degrees of freedom	46699
Alternative hypothesis	two sided
Prob (parametric)	0
Prob (999 permutations)	0.00100

Table 3.7 | t-test for related samples with permutation test results.



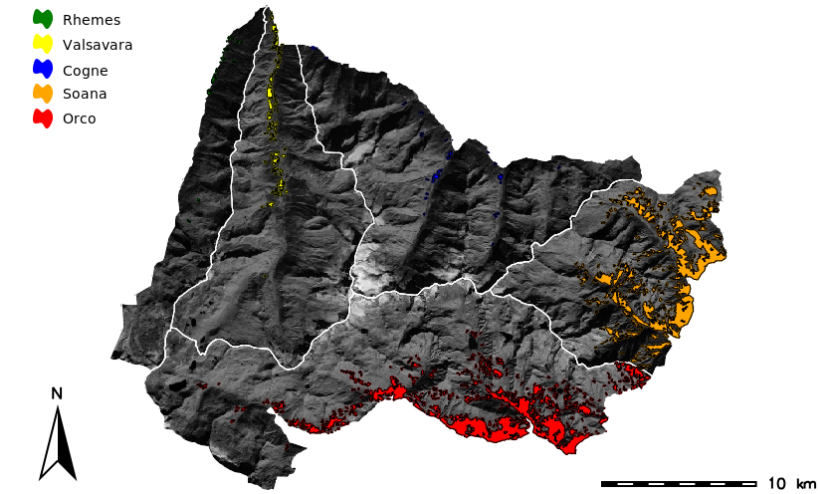
(a) *Major vegetation change*



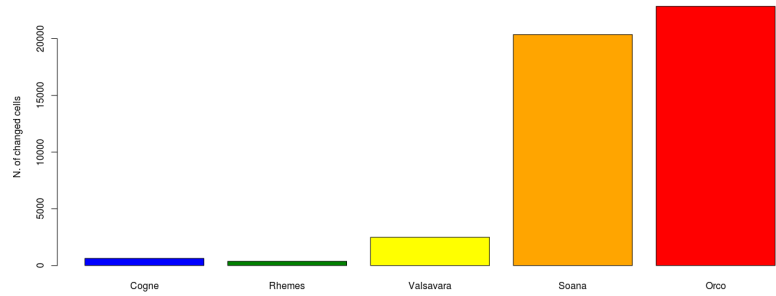
(b) *Heat map of major vegetation change*

Figure 3.10 | Image *a* show the vegetation change extracted from PC3 overlayed on the PC1 and image *b* is a hexagon heat map (grid 500 m) reporting the number of cells classified as change.

3. RESULTS



(a) Vegetation change in GPNP valleys



(b) Number of changed cells per valley

Figure 3.11 | The figure *a* show the distribution of vegetation change in GPNP valleys. The barplot in figure *b* accounts for the number of cell classified as change per valley.

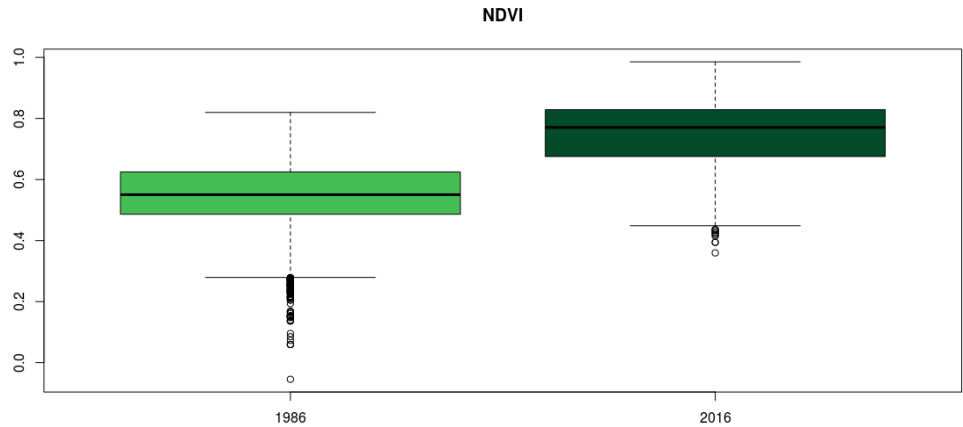


Figure 3.12 | NDVI value distributions in change area for 1986 and 2016 periods.

Measuring the areal extent of the change

In table 3.8 are listed the results of GRASS GIS module *r.report* referred to entire study area. Almost 6% of study area (4203 hectares) was classified as change. In table 3.9 are listed the results of *r.report* referred to each valley. Orco valley account for 48.93% of total change while Soana for 43.60% that has major surface interested by vegetation change with 15.78% of valley surface.

Assessing the spatial pattern of the change

Local land-surface parameters and landform classification were used to extract the main characteristics of change running *r.univariate* module. Results for each parameters are provided in section *C.2 Satellite imagery* of Appendix C. Fig. 3.13 shows the local land surface characteristics of changed area within study area. The major change occurred in Montane belt (1200-1800 m a.s.l.) on south-facing aspect (270° CCW) slopes comprised between ca. 35°-40°. VRM of changed surface did not show a clear pattern while global solar radiation and insolation time values are high with respectively ca. 24 MJ/m² and more than 8 hours per day as annual means. Observing the spatial distribution of vegetation pattern change the landform that encountered the major change is slope followed by spur and hollow.

Looking at local land-surface parameters distribution per valley (fig. 3.14) we can see a marked difference between Aosta Valley-side and Piedmont-side valleys. In general terms the surface interested by change on Aosta Valley-side have a more irregular distribution than Piedmont-side that have distribution values characterized by negative skewness. Considering the slope, global solar radiation and insolation time Orco and Soana valleys have the highest median values while Cogne has the highest elevation median value and Valsavara of VRM. Aspect values reflect the geographic position of valleys. Orco and Soana are mainly south-facing territories, Rhemes is west oriented while Valsavara is north-to-south oriented; only Cogne valley change has a non-uniform distribution encompassing almost all aspects. Change distribution on landforms confirming that the major change occurred on slopes.

Spatial patterns were assessed using patch number, total edge, mean patch size and radius of gyration. Results are listed in table 3.10. As the local land-surface parameters there are marked differences between valleys of two park sides. The major number of patches are located in Orco and Soana valley. Patch dimensions in Aosta Valley side are more regular than Piedmont side as we can see from descriptive statistics. Radius of gyration show how patches in Soana valley are slightly bigger and irregular than Orco valley.

	Hectares	Cell count	% cover
GPNP	71024.130	789157	100
Change	4203.00	46700	5.92

Table 3.8 | Table list major changes occurred in study area indicating the hectares, the cell count and the percentage over the total area.

3. RESULTS

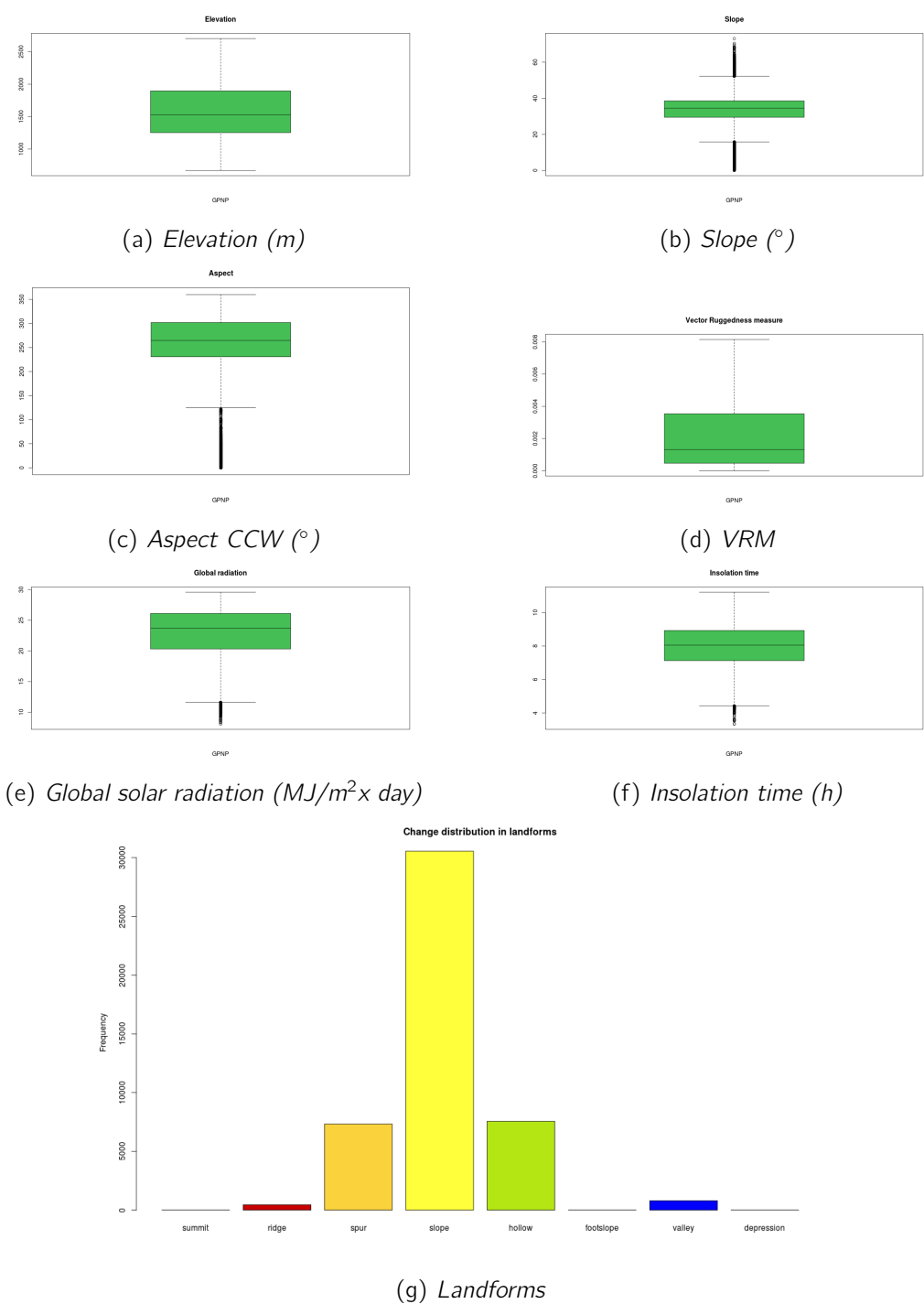
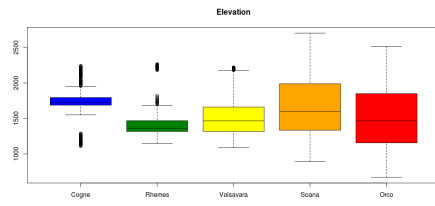
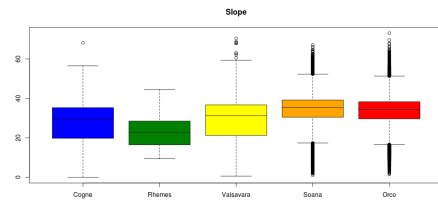


Figure 3.13 | Land surface characteristics and spatial distribution of change areas in GPNP. The boxplots show the land surface characteristics of changed area and barplot represent distribution in landforms.

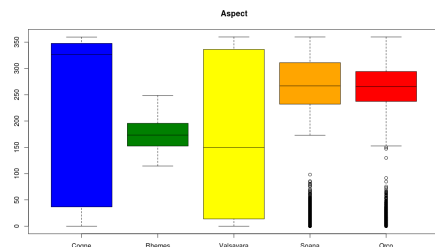
3.2. SATELLITE IMAGERY



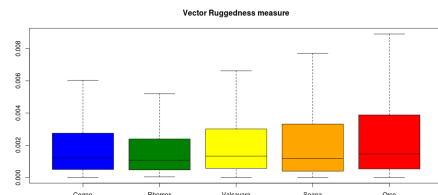
(a) Elevation (m)



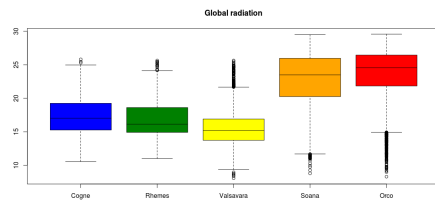
(b) Slope (°)



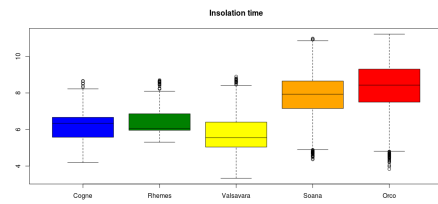
(c) Aspect CCW (°)



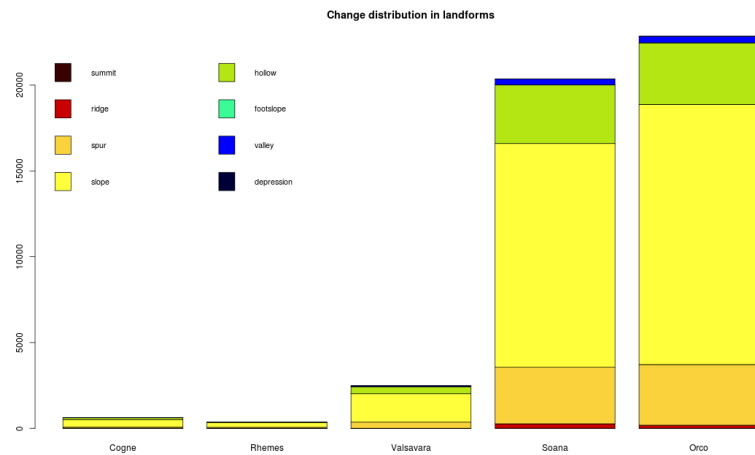
(d) VRM



(e) Global solar radiation (MJ/m² x day)



(f) Insolation time (h)



(g) Landforms

Figure 3.14 | Land surface characteristics and spatial distribution of change areas in GPNP valleys. The boxplots show the land surface characteristics of changed area and barplot represent distribution in landforms.

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Valley	Hectares	Cell count	% of total change	% valley cover
Rhemes	33.57	373	0.80	0.52
Cogne	56.52	628	1.34	0.35
Valsavara	223.83	2487	5.33	1.5
Soana	1832.49	20361	43.60	15.78
Orco	2056.59	22851	48.93	9.34

Table 3.9 | Table list major changes detected in each valley indicating the hectares, the cell count and the percentage over the total change and valley cover.

Valley	NP	TE	Patch size			Radius of gyration		
			Mean	SD	CV	Mean	SD	CV
Rhemes	19	14040	1.76	1.55	87.84	55.97	26.41	47.19
Valsavara	23	21420	2.45	2.71	110.33	66.66	36.18	54.28
Cogne	47	73080	4.76	4.87	102.44	97.57	52.17	53.47
Soana	154	374880	11.89	51.9	436.17	115.95	161.18	139.01
Orco	209	435240	9.84	47.08	478.45	103.68	150.96	145.59

Table 3.10 | Spatial patterns of changed area. For each valley are listed the number of patches (NP), total edge (TE), patch size and radius of gyration with descriptive statistics as mean, standard deviation (SD) and coefficient of variation (CV).

3.2.2 | Fragmentation analysis

In fig. 3.15 the Principal Components (PCs) of Landsat images of 1986 and 2016 and frequency domain representation are shown.

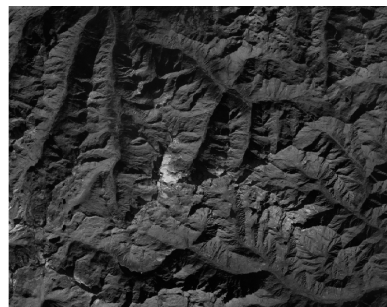
The transform results show two slightly different landscape configuration and looking at data distribution (fig. 3.16) is visible an increase of high and medium frequency part represented, respectively, in red and green.

The frequency distribution (fig. 3.17) derived from kernel density function [Bowman and Azzalini, 2013] applied to the Fourier transform values show two slightly different frequency distributions.

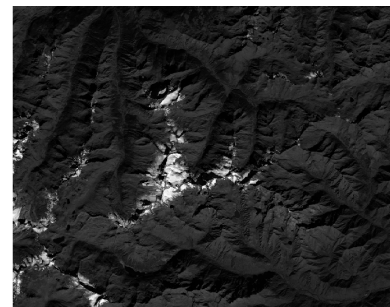
In 1986 we have a more skewed distribution while in 2016 we can observe a lower skewness and high peak of values indicating a more complex Fourier frequency domain space due to an increase of signals lying in the frequency range.

Plotting the frequency domain values by hexagon binning [Carr et al., 2013] the 2016 image shows higher values than 1986 (fig. 3.18). The major number of values are distributed toward the left part of scatterplot above the 1:1 line.

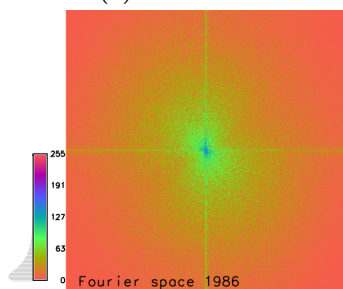
3.2. SATELLITE IMAGERY



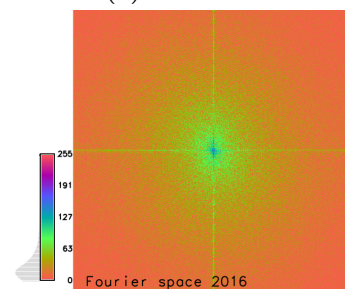
(a) Landsat 5 PC1



(b) Landsat 8 PC1

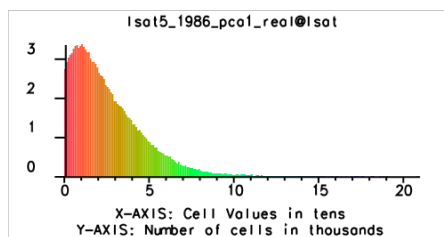


(c) Landsat 5 Fourier space 1986

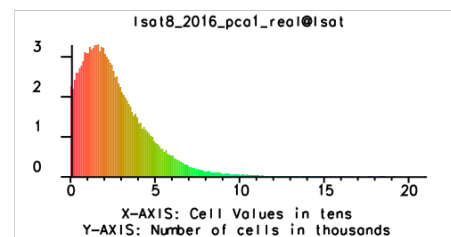


(d) Landsat 8 Fourier space 2016

Figure 3.15 | The Fourier spaces derived from first PCs of 1986 and 2016 Landsat images. The value distributions are very similar but in 2016 we have an increase of high (red) and medium (green) frequency part plotted around the low frequency part (blue).



(a) Landsat 5 Fourier space distribution 1986



(b) Landsat 8 Fourier space distribution 2016

Figure 3.16 | Histograms show Fourier frequency domain value distribution in 1986 and 2016. In 2016 is visible an increase in high and medium frequency part with a decrease of skewness.

3. RESULTS

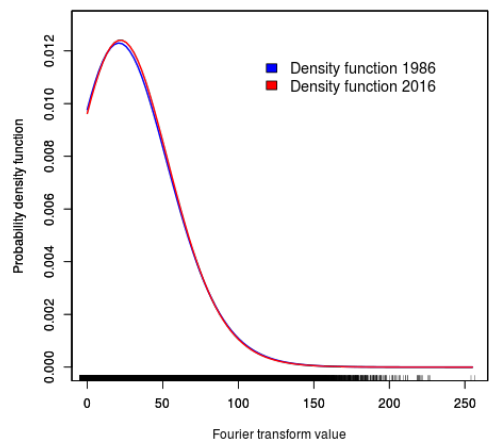


Figure 3.17 | Density function applied to Fourier space. The frequency distribution of transformed values is slightly skewed indicating a slightly different landscape configuration in 1986. In 2016 image is visible an increase of signals.

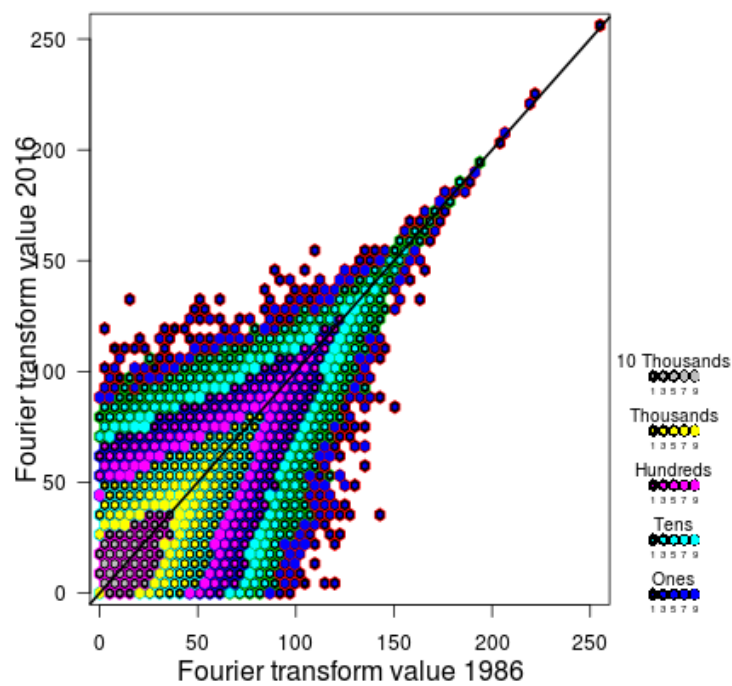


Figure 3.18 | Frequency domain plotted by hexagon binning. The higher values are distributed toward the left part of scatterplot above the 1:1 line.

3.3 | Aerial images

3.3.1 | Process comparison

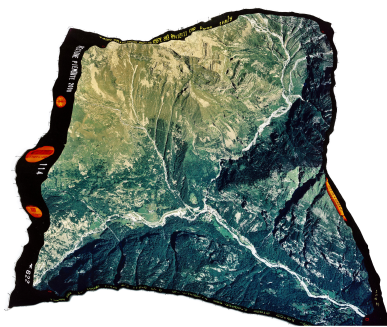
We performed a comparison of two different methods to remove geometric distortion affecting aerial images. The image 3.19 shows a comparison of orthophotos and both followed methods seem to be able to reconstruct topographical complex mountain environment.

A visual inspection of created image reveals that GRASS GIS orthorectification procedure is more robust in placing objects especially consider ones located at higher altitude as tracks, see figure 3.20.

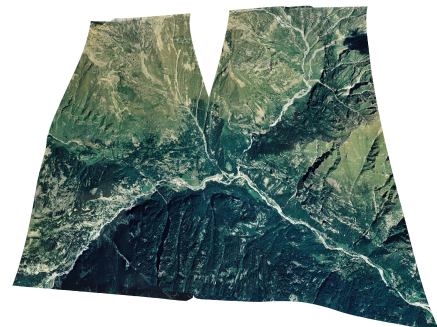
Table 3.11 summarize the statistics and RMSEs obtained using 20 randomly distributed checkpoints in each image to assess spatial displacement. The orthorectification process achieved lower RMSE values in (x) , (y) and (r) directions and figure 3.21 shows scatterplots with residual distribution along x and y axes.

Considering the results listed in 3.11 we orthorectified 14 aerial photo frames in open-source environment but it was possible to orthorectify only 8 images covering the altitudinal transects of Orco, Cogne and Valsavarenche valleys for both selected periods. We were unable to perform all tasks for other two valley due to a probable *bug* in interior orientation step. Image 3.22 shows spatial coverage of processed images. Table 3.12 summarizes the spatial distribution error statistics and the accuracy achieved.

The image 3.23 shows the distribution of residuals of 20 randomly distributed checkpoints extracted in each image. From table 3.12 and image 3.23 we can see that RMSEs in r direction are lower than 4 m and considering the confidence level they do not exceed 6 m .



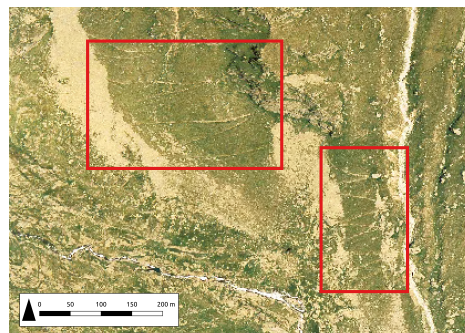
(a) GRASS GIS orthorectification result



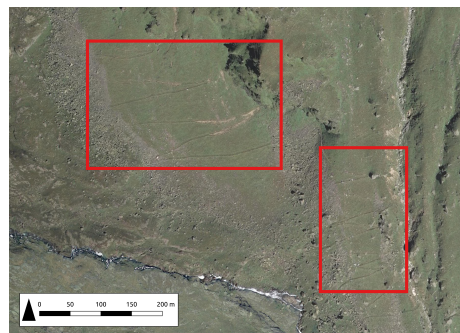
(b) PhotoScan SfM result

Figure 3.19 | Results of selected procedures to create free-distortion images.

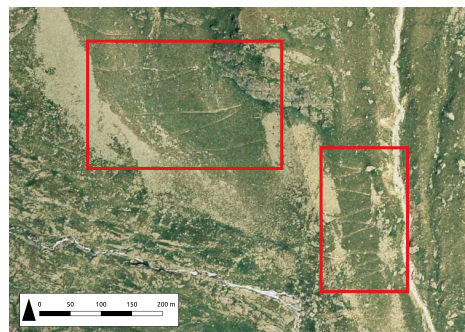
3. RESULTS



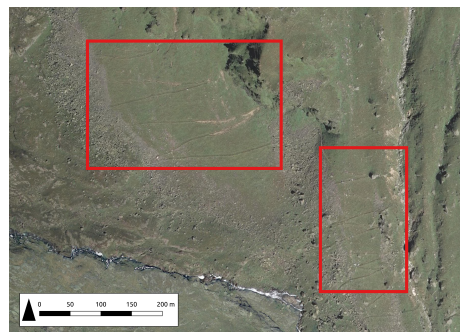
(a) GRASS GIS orthorectification result



(b) Reference image from Ripresa aerea ICE 2009-11



(c) PhotoScan SFM result

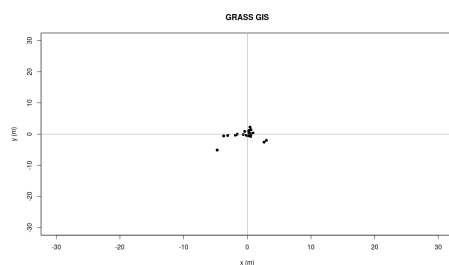


(d) Reference image from Ripresa aerea ICE 2009-11

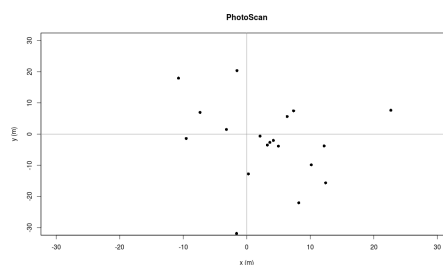
Figure 3.20 | The image shows the displacement affecting the position of objects in orthorectification and SFM results compared with reference image. The example shows track to Royal hunting House of Gran Piano in Orco Valley.

Software	RMSE _x	RMSE _y	RMSE _r	RMSE _r (Acc 95%)
GRASS GIS	1.88	1.55	2.43	4.21
Agisoft PhotoScan	8.84	15.81	18.11	31.34

Table 3.11 | Table reports the quantitative assessment of error. The RMSE values are expressed in meters *m*.



(a) Orthorectification



(b) SFM

Figure 3.21 | The scatterplots shows the distribution of checkpoint coordinates residuals along the x and y axes. The residuals are expressed in meters.

3.3. AERIAL IMAGES

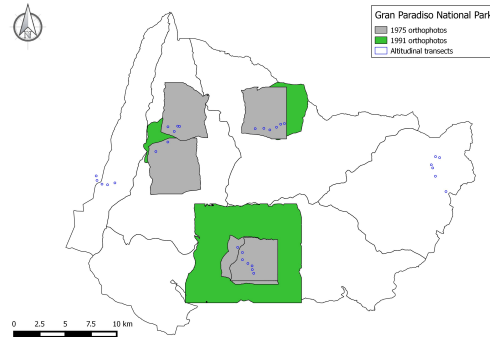
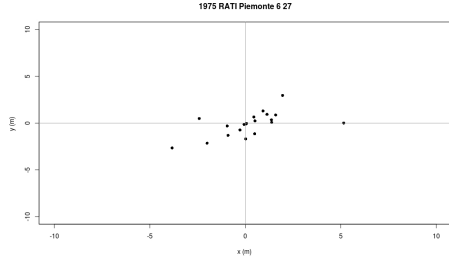


Figure 3.22 | Spatial coverage of orthorectified images of 1975 and 1991.

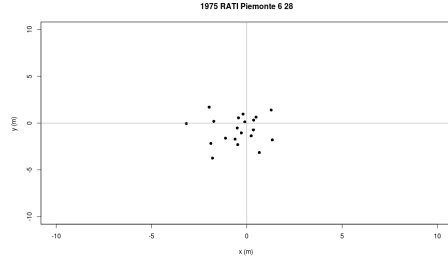
Year	Valley	Image	Res. (m/px)	RMSE _x	RMSE _y	RMSE _r	RMSE _r (Acc 95%)
1975	Orco	6 27	0.4	1.81	1.25	2.2	3.81
		6 28	0.85	1.24	1.63	2.04	3.54
	Cogne	AO-59 1345	0.44	1.37	1.49	2.02	3.5
		AO-59 1338	0.5	1.98	2.47	3.17	5.49
		AO-59 1348	0.43	1.14	1.92	2.23	3.86
1991	Orco	3A 7113	1.8	1.63	2.92	3.34	5.79
	Cogne	A23-1 1199	0.51	1.62	2.39	2.88	3.2
	Valsavar.	A24-1 1254	0.46	1.84	1.55	2.41	3.12

Table 3.12 | Spatial accuracies of orthorectified images

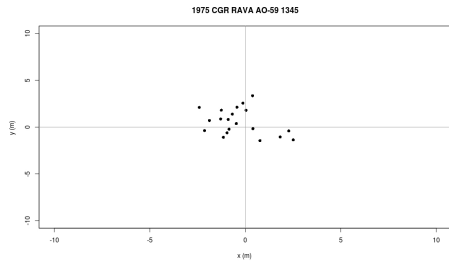
3. RESULTS



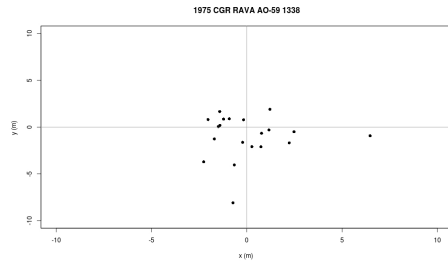
(a) Residual distribution for image 6 27 (gp transect in 1975)



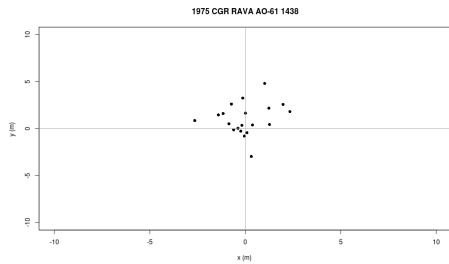
(b) Residual distribution for image 6 28 (gp transect in 1975)



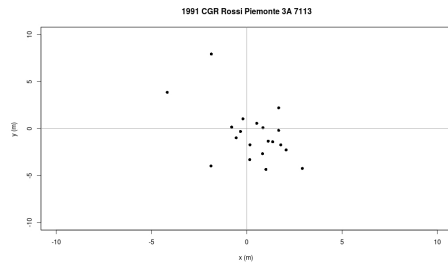
(c) Residual distribution for image AO-59 1345 (l transect in 1975)



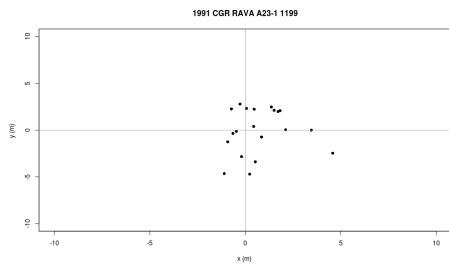
(d) Residual distribution for image AO-59 1338 (o transect in 1975)



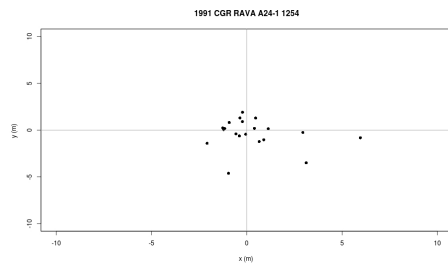
(e) Residual distribution for image AO-61 1438 (o transect in 1975)



(f) Residual distribution for image 3A 7113 (gp transect in 1991)



(g) Residual distribution for image A23-1 1199 (l transect in 1991)



(h) Residual distribution for image 324-1 1254 (o transect in 1991)

Figure 3.23 | Scatterplots of residuals along x and y axes for the 20 checkpoints selected in each orthorectified image.

3.3.2 | Vegetation pattern change

The Fourier transform was used on orthorectified panchromatic images of 1975 RATI Piemonte flight and first principal component of RGB image of 2009/11 ICE Piemonte flight covering the entire Orco valley altitudinal transect to rapidly evaluate change in vegetation patterns with no *a priori* assumptions.

In fig. 3.24 and 3.25 are shown the Orco transect representations in 1975 and 2010 with their frequency domain.

The transform results show two different vegetation pattern configuration of altitudinal transect. Furthermore two different trends are recognizable along the altitudinal gradient. The major change occur in the Montane belt with an increase in tree cover (see fig. 3.26) that lead into a change in Fourier space heterogeneity and in signal frequencies.

The change in Subalpine and Alpine plots are not in data distribution but in increase in medium frequency part, represented in green, due to less visibility of rocks in favour of grass cover as shown in fig. 3.27.

The frequency distribution derived from kernel density function [Bowman and Azzalini, 2013] applied to the Fourier transform values show the change in Fourier space heterogeneity in two selected periods and along the altitudinal gradient. The frequency domain values plotted by hexagon binning show changes in Fourier space and the relationship between values in two different periods.

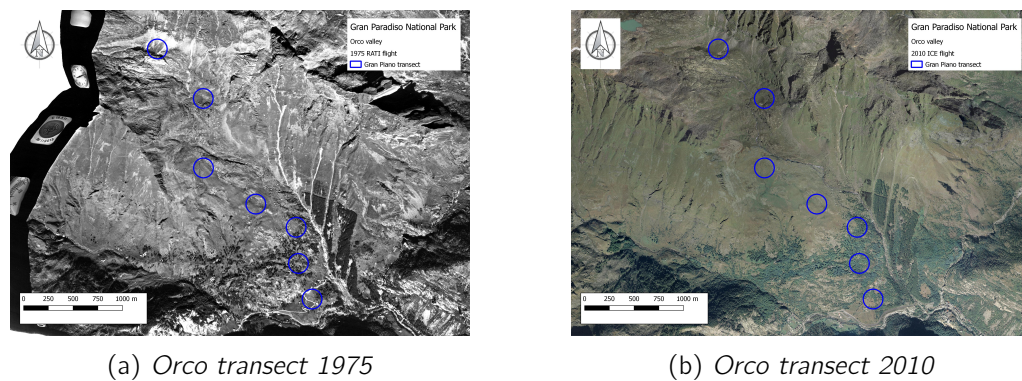


Figure 3.24 | The Orco transect in 1975 and 2010.

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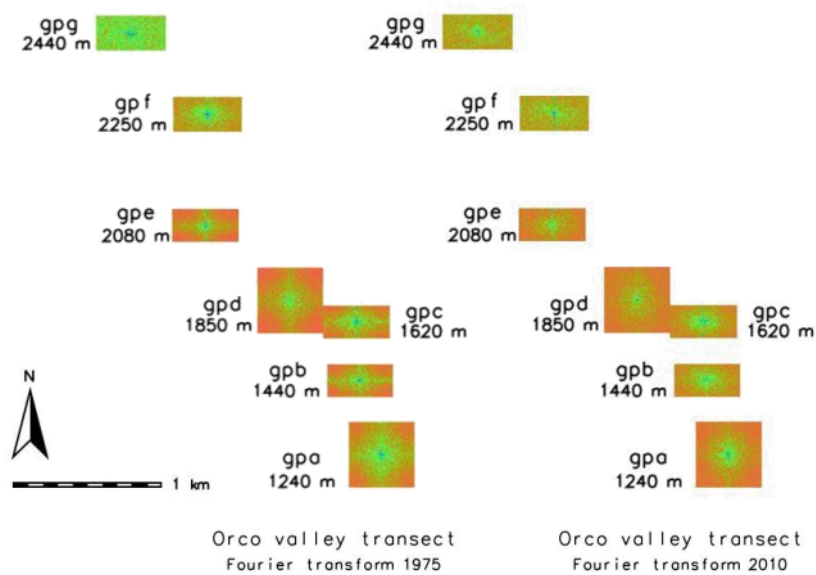
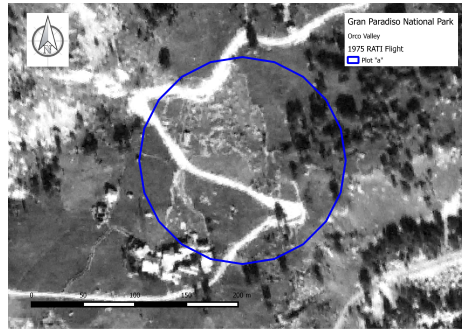
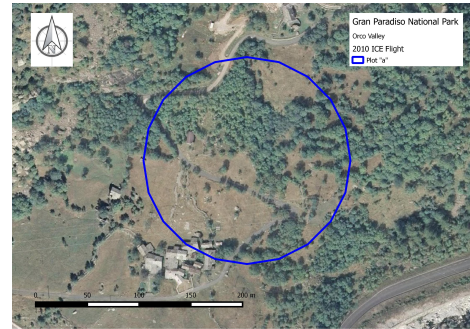


Figure 3.25 | The Fourier spaces derived from 1975 and 2010 aerial images. The high (red) and medium (green) frequency part are plotted around the low frequency part (blue).

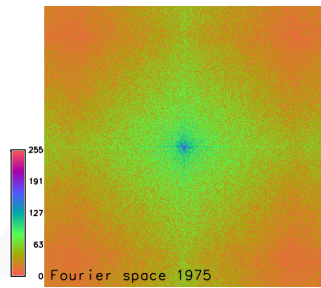
3.3. AERIAL IMAGES



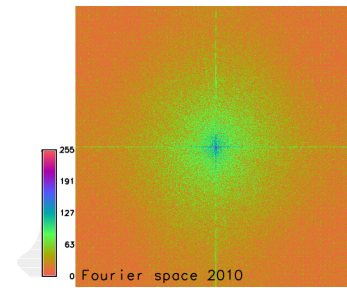
(a) Plot a Orco transect 1975



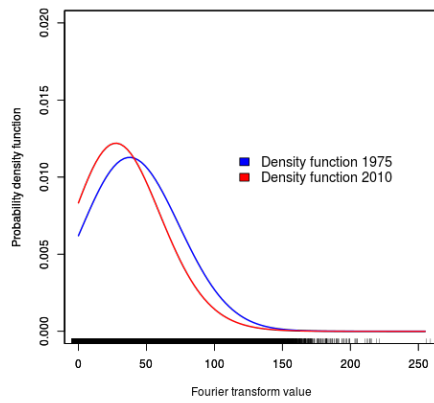
(b) Plot a Orco transect 2010



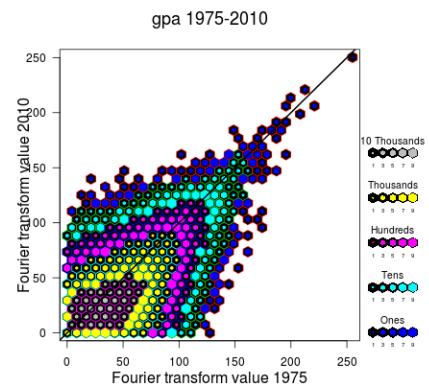
(c) Plot a Fourier space 1975



(d) Plot a Fourier space 2010



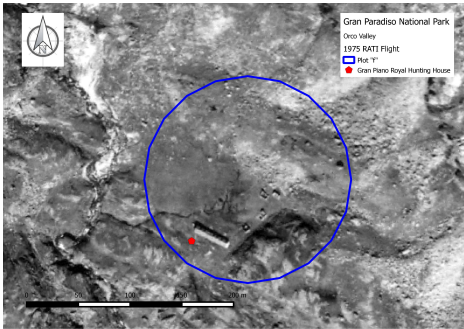
(e) Density function applied to Fourier spaces



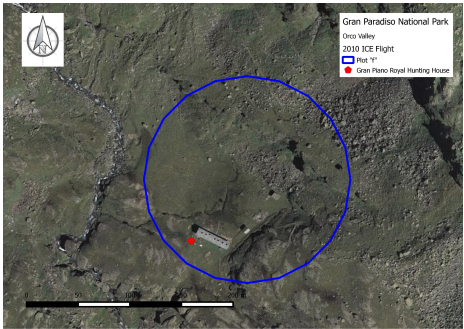
(f) Frequency domains plotted by hexagon binning

Figure 3.26 | Images show vegetation pattern change of plot a of Orco altitudinal transect.

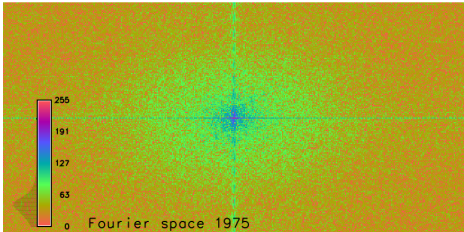
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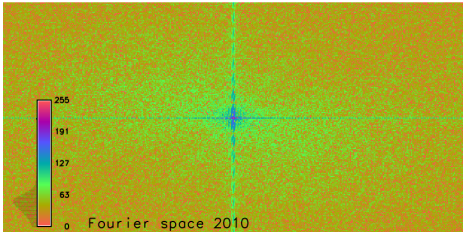
(a) Plot f Orco transect 1975



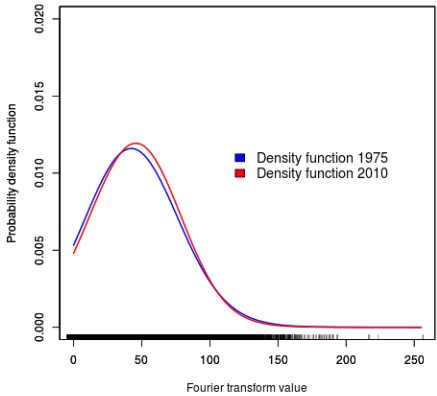
(b) Plot f Orco transect 2010



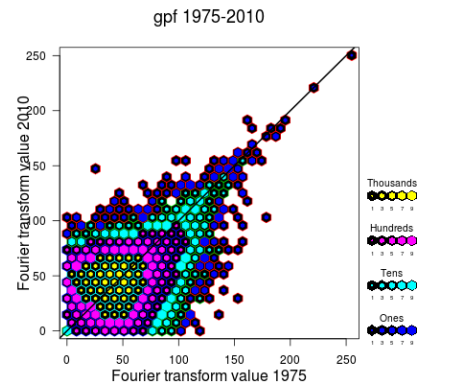
(c) Plot f Fourier space 1975



(d) Plot f Fourier space 2010



(e) Density function applied to Fourier spaces



(f) Frequency domains plotted by hexagon binning

Figure 3.27 | Images show vegetation pattern change of plot f of Orco altitudinal transect.

3.3.3 | Image classification

Object creation

The *i.segment.uspo* add-on was used to perform the unsupervised segmentation parameter optimization on first principal component of RGB channels. The add-on was firstly used to analyze a set of threshold comprised between 0.02 and 0.9 with a step of 0.02. After a visual inspection a threshold value of 0.32 was chosen and used to evaluate the object minimum size.

The segmentation step was achieved with *i.segment* module using 0.32 as threshold and 9 pixels as minimum object size as shown in fig. 3.28.

Object characterization

For the object characterization we evaluated spectral and textural features discarding the redundant ones; table 3.13 and 3.14 show the correlation among them. The remaining set was further assessed using the variance inflation analysis (see table 3.15) showing a low collinearity. The dataset was used to characterize objects was composed by object shape characteristics (area, perimeter, compactness, fractal dimension) and range, average, standard deviation and variance of spectral (brightness, NGRDI, GLA, WI) and textural (contrast, correlation, entropy and standard deviation) features.

Object labelling

Training set size was increased to 210 elements using a guided learning algorithm implemented in *r.object.activelearning* add-on that highlights the necessary objects to improve the classification score (see table 3.16). In image 3.29 is represented C5.0 algorithm classification performed through the *v.class.mlr*.

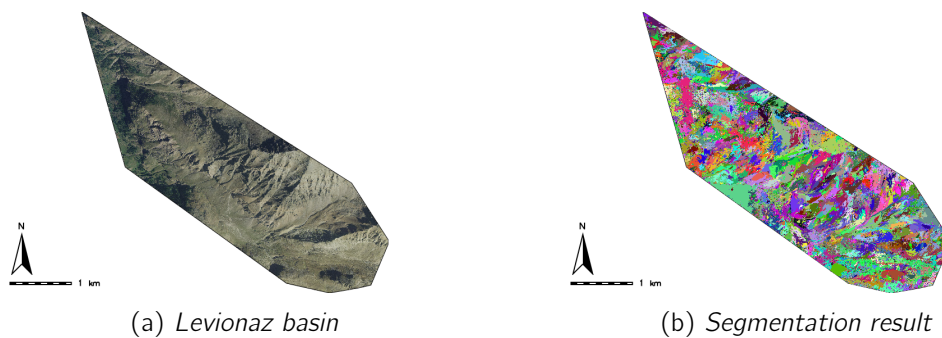


Figure 3.28 | Images show the segmentation result for Levionaz basin.

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	brightness	ngrdi	gei	gla	bgi	wi
brightness	1	-0.726717	0.248251	0.257916	0.990637	0.171796
ngrdi	-0.726717	1	0.012613	0.001272	-0.664974	-0.122552
gei	0.248251	0.012613	1	0.999593	0.359596	-0.106646
gla	0.257916	0.001272	0.999593	1	0.368129	-0.105042
bgi	0.990637	-0.664974	0.359596	0.368129	1	0.145283
wi	0.171796	-0.122552	-0.106646	-0.105042	0.145283	1

Table 3.13 | Covariance matrix for brightness channel and band ratios. ngrdi = *Normalized green red index*, gei = *Green excess index*, gla = *Green leaf algorithm*, bgi = *Bare ground index*, wi = *Woebbecke's index*.

	asm	contr	corr	entr	idm	sd
asm	1	-0.584268	-0.502863	-0.988469	0.738408	-0.584634
contr	-0.584268	1	-0.035125	0.616449	-0.792806	0.529354
corr	-0.502863	-0.035125	1	0.525276	-0.147536	0.536978
entr	-0.988469	0.616449	0.525276	1	-0.754408	0.622620
idm	0.738408	-0.792806	-0.147536	-0.754408	1	-0.533132
sd	-0.584634	0.529354	0.536978	0.622620	-0.533132	1

Table 3.14 | Covariance matrix for selected texture features. asm = *Angular second moment*, contr = *Contrast*, corr = *Correlation*, entr = *Entropy*, idm = *Inverse difference moment*, sd = *Standard deviation*.

variable	vif	sqrtvif
brightness	2.57	1.60
ngrdi	2.49	1.58
gla	1.29	1.14
wi	1.07	1.04
contr	3.83	1.96
corr	2.92	1.71
entr	4.35	2.08
idm	4.02	2.01
sd	2.54	1.59

Table 3.15 | VIF results show a low rate of collinearity between the selected features. ngrdi = *Normalized green red index*, gei = *Green excess index*, gla = *Green leaf algorithm*, wi = *Woebbecke's index*, contr = *Contrast*, corr = *Correlation*, entr = *Entropy*, idm = *Inverse difference moment*, sd = *Standard deviation*

Land cover	Training set	Test set
coniferous forest	7	11
subalpine grassland	39	59
pasture and meadows	6	6
scree	59	34
cliffs	44	61
shadow	55	29

Table 3.16 | Land cover legend and training set and test set objects.

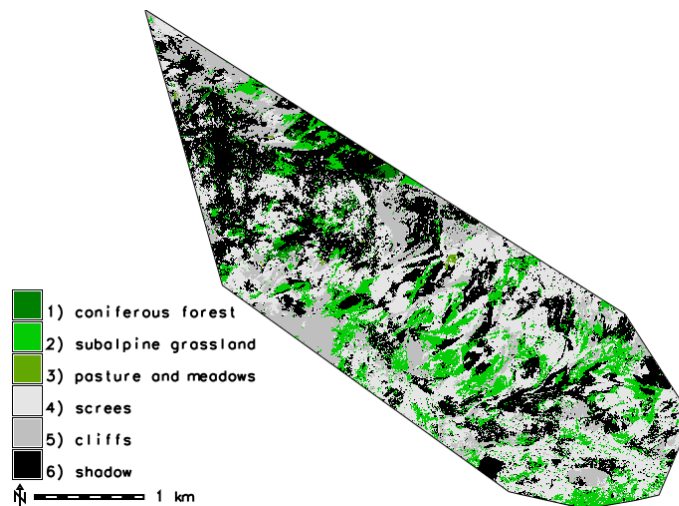


Figure 3.29 | Classification results of C5.0 classifier.

3. RESULTS

Accuracy assessment

The obtained classification accuracies were very low, see table 3.17. The C5.0 performed best followed by knn with, respectively, 27.7% and 24.81% of overall accuracy. The use of voting systems didn't improve the classification results. The bwwv and qbwwv performed better than other voting systems with an overall accuracy of 22.47%. To assess the accuracy for each land cover we used the F-score that is the harmonic mean of producer's and user's accuracy [Grippa et al., 2017]. The F-score of each class is listed in table 3.18 while the producer's and user's accuracy in subsection *C.3.1 Accuracy assessment* of Appendix C.

	Individual classifiers					Votes			
	svmRadial	rf	rpart	C5.0	knn	smv	swv	bwwv	qbwwv
kappa	0.04	0.02	0	0.06	0.06	0.01	0	0.03	0.03
OA	24.18	21.17	16.93	27.7	24.81	21.05	20.47	22.47	22.47

Table 3.17 | Kappa and overall accuracy for individual classifiers and votes. svmRadial = Support vector machine with radial kernel, rf = Random forest, rpart = Recursive partitioning, C5.0, knn = k-nearest neighbors, smv = Simple majority vote, swv = Simple weighted vote, bwwv = Best worst weighted vote, qbwwv = Quadratic best worst weighted vote.

Category	Individual classifiers					Votes			
	svmRadial	rf	rpart	C5.0	knn	smv	swv	bwwv	qbwwv
1	0.03	0.03	NA	0	20.88	20.92	0.03	0.03	0.03
2	30.2	30.6	2.65	44.62	12.5	29.76	29.76	36.7	36.7
3	NA	NA	NA	NA	NA	NA	NA	NA	NA
4	17.14	14.1	14.51	6.29	25.89	12.59	12.85	12.9	12.9
5	14.52	15.47	6.31	12.48	19.56	13.52	15.09	15.09	15.09
6	39.52	29.01	36.82	40.87	37.8	27.6	27.45	28.76	28.76

Table 3.18 | F-score for each class. Category: 1 = Coniferous forest, 2 = Subalpine grassland, 3 = Pasture and meadows, 4 = Scree, 5 = Cliffs, 6 = Shadow. Individual classifiers and voting scheme: svmRadial = Support vector machine with radial kernel, rf = Random forest, rpart = Recursive partitioning, C5.0, knn = k-nearest neighbors, smv = Simple majority vote, swv = Simple weighted vote, bwwv = Best worst weighted vote, qbwwv = Quadratic best worst weighted vote.

3.4 | UAV images

3.4.1 | Image collection

A sequence of images was collected in each flight mission to cover the entire plot. Images were processed with the proprietary software Postflight Terra 3D Professional [Pix4D, 2012] furnished with fixed-wing senseFly UAV.

3.4.2 | Field sampling

Ground observation sites were sampled collecting information about LC; frequency of dominant species defined as the single species to a maximum of 3 species that cover more than 50% of quadrat; height and phenology stage. Currently all plots were sampled but data are ready to use for the d plot of Valsavarenche transect as shown in fig. 3.30 and table 3.19.

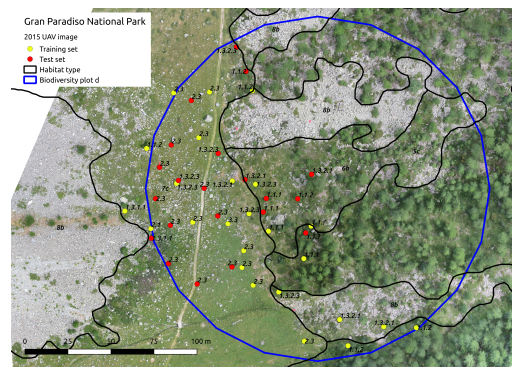


Figure 3.30 | Field sampling result.

3.4.3 | Visual interpretation

Visual interpretation was performed on d plot of Valsavarenche altitudinal transect due to the presence of four land cover classes. To retrieve information from UAV image the training set was used in the learning step and test set to evaluate user performance, see fig. 3.31. After the trial and error learning image was visual inspected to increase the training set size of 200 points as shown in fig. 3.32.

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Transect	Plot	Data	Dominant species	Freq %	Height (m)
Orvieilles	d	Training set	<i>Juniperus communis</i>	100	0.3
Orvieilles	d	Training set	Rocks	100	
Orvieilles	d	Training set	<i>Nardus stricta</i>	76	0.15
Orvieilles	d	Training set	<i>Epilobium angustifolia</i>	100	1.35
Orvieilles	d	Training set	<i>Sambucus racemosa</i>	100	2
Orvieilles	d	Training set	<i>Juniperus communis</i>	100	0.5
Orvieilles	d	Training set	<i>Nardus stricta</i>	92	0.2
Orvieilles	d	Training set	<i>Nardus stricta</i>	100	0.15
Orvieilles	d	Training set	<i>Larix decidua</i>	100	12
Orvieilles	d	Training set	<i>Rhododendron ferrugineum</i>	100	0.4
Orvieilles	d	Training set	<i>Juniperus communis</i>	100	0.4
Orvieilles	d	Training set	<i>Pinus cembra</i>	100	7
Orvieilles	d	Training set	<i>Deschampsia caespitosa</i>	100	1
Orvieilles	d	Training set	<i>Larix decidua</i>	100	0.1
Orvieilles	d	Training set	<i>Deschampsia caespitosa</i>	100	0.85
Orvieilles	d	Training set	<i>Deschampsia caespitosa</i>	100	1
Orvieilles	d	Training set	<i>Picea abies</i>	100	10
Orvieilles	d	Training set	<i>Picea abies</i>	100	8
Orvieilles	d	Training set	<i>Rhododendron ferrugineum</i>	100	0.3
Orvieilles	d	Training set	<i>Rhododendron ferrugineum</i>	100	0.3
Orvieilles	d	Training set	<i>Larix decidua</i>	100	6
Orvieilles	d	Training set	<i>Juniperus communis</i>	100	0.6
Orvieilles	d	Training set	<i>Deschampsia caespitosa</i>	100	1.2
Orvieilles	d	Training set	<i>Nardus stricta</i>	76	0.25
Orvieilles	d	Training set	<i>Picea abies</i>	100	0.2
Orvieilles	d	Test set	<i>Juniperus communis</i>	100	0.3
Orvieilles	d	Test set	<i>Larix decidua</i>	100	8
Orvieilles	d	Test set	<i>Nardus stricta</i>	84	0.2
Orvieilles	d	Test set	<i>Juniperus communis</i>	100	0.4
Orvieilles	d	Test set	<i>Nardus stricta</i>	84	0.2
Orvieilles	d	Test set	<i>Festuca nigrescens</i>	20	0.1
Orvieilles	d	Test set	<i>Juniperus communis</i>	100	0.15
Orvieilles	d	Test set	<i>Rhododendron ferrugineum</i>	100	0.3
Orvieilles	d	Test set	<i>Picea abies</i>	100	4
Orvieilles	d	Test set	<i>Picea abies</i>	100	6
Orvieilles	d	Test set	<i>Deschampsia caespitosa</i>	100	0.7
Orvieilles	d	Test set	<i>Deschampsia caespitosa</i>	80	0.8
Orvieilles	d	Test set	<i>Festuca nigrescens</i>	92	0.15
Orvieilles	d	Test set	<i>Epilobium angustifolia</i>	100	1.1
Orvieilles	d	Test set	<i>Sambucus racemosa</i>	100	2
Orvieilles	d	Test set	<i>Epilobium angustifolia</i>	100	1.1
Orvieilles	d	Test set	<i>Deschampsia caespitosa</i>	100	1
Orvieilles	d	Test set	<i>Deschampsia caespitosa</i>	100	0.8
Orvieilles	d	Test set	<i>Larix decidua</i>	100	8
Orvieilles	d	Test set	<i>Rhododendron ferrugineum</i>	100	0.4
Orvieilles	d	Test set	<i>Pinus cembra</i>	100	12

Table 3.19 | Result of field sampling. In table are listed dominant species and percentage of cover in each quadrat sampling unit.

3.4. UAV IMAGES



(a) *Larix decidua*



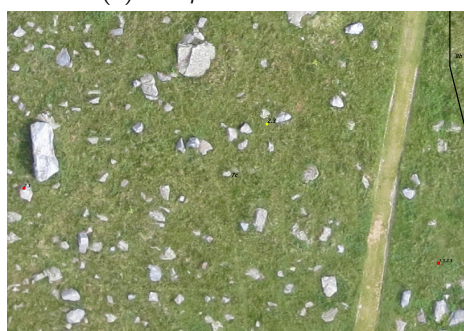
(b) *Pinus cembra*



(c) *Juniperus communis*



(d) *Rhododendron ferrugineum*



(e) *Nardus stricta*



(f) *Deschampsia caespitosa*

Figure 3.31 | Species observed in learning step.

3. RESULTS

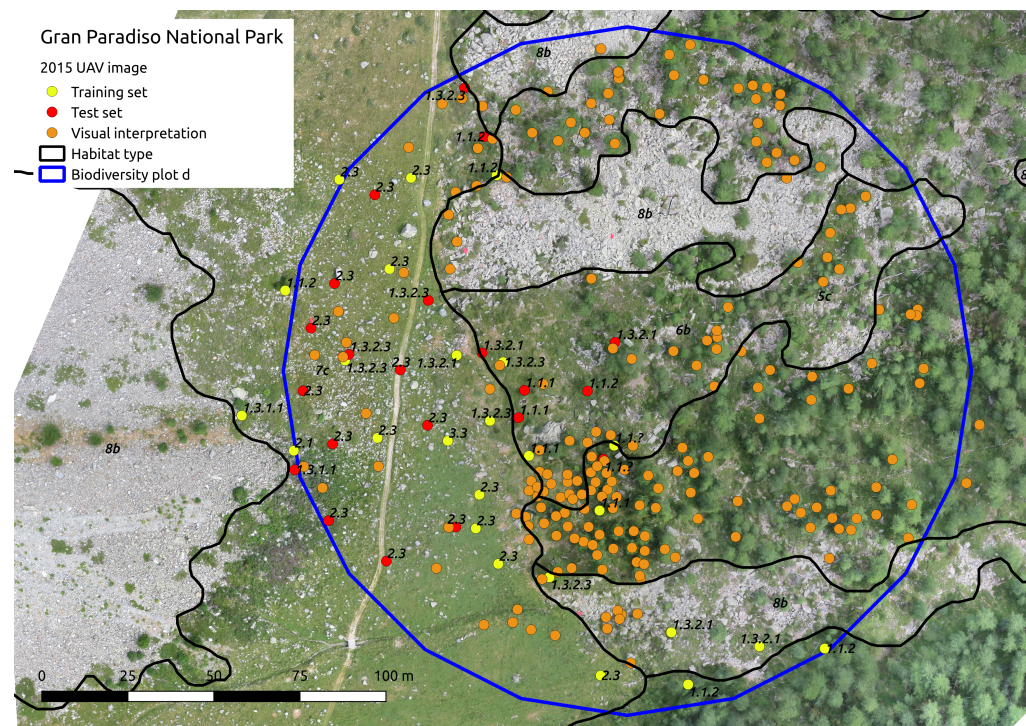


Figure 3.32 | Results of visual interpretation. Yellow and red points are the training set and test set used in trial phase. The orange point are the visual retrieved data.

4 | Discussions

4.1 | Digital elevation model

Exploring the complexity of a given landscape structure is essential in understanding landscape processes. The quantitative information of geomorphometry are strictly necessary in habitat mapping and to relate species environmental parameters. These are the most important information to address efforts in conservation and management actions.

The geomorphometry analysis was carried out in a multi-purpose open source GIS environment [Neteler et al., 2012] that provided robust and peer-reviewed algorithms to quantitatively measure the continuous land-surface parameters and to identify the discrete landforms [Hofierka et al., 2009, Jasiewicz and Stepinski, 2013].

To identify a group of local land-surface parameters to represent the continuous and complex geographic variation we followed the results of Lecours et al. [2017] selecting the most common and routinely used ones. To improve our dataset we further calculate solar radiation [Hofierka and Suri, 2002] and the topographic index (*r.topidx* module) could be added [Leempoel et al., 2015].

To extract discrete surfaces from 10 m TINITALY DEM [Tarquini et al., 2007, Tarquini et al., 2012] we addressed to computer vision approach implemented in *r.geomorphon* add-on. The module was very simple to understand allowing to rapidly define the main study area landforms. Despite this approach is well suited to multi-scale analysis we used the Moran's I index to define a trade-off considering DEM resolution and study area spatial variability to avoid increase in computational efforts [Jasiewicz and Stepinski, 2013]. This qualitative analysis should be complemented by a quantitative assessment of error (e.g. using lake surface to validate classification result finds out omission and commission errors and assesses overall accuracy).

As stated by Pike [Pike et al., 2009] geomorphometry is an essential tool to model and map natural landscapes and the results of this section were used to evaluate the GPNP changed area parameters (see *Satellite imagery results 3.2.1* and *discussions 4.2.2*).

4.2 | Satellite imagery

4.2.1 | Data selection

In change detection [Singh, 1989] a proper choice of dataset is essential to extract change information. Landsat imagery were chosen due to the longest time series of

4. DISCUSSIONS

multi spectral medium spatial resolution Earth observation. Our primary intention was to collect satellite images near aerial photograph flights to perform a data integration (e.g. using aerial images as ground truth and test set in supervised classification of satellite images). In data retrieving we were able to obtain only two free-cloud images collected in early autumn to highlights vegetation cover phenological mis-match.

The preliminary challenge to face is the precise (sub-pixel) image geometric co-registration and the maximization of signal-to-noise ratio with a radiometric calibration [Coppin et al., 2004, Lu and Weng, 2007]. A proper image pre-processing is essential to avoid detection of unreal changes and to increase change detection algorithm capabilities [Young et al., 2017].

The Landsat Surface Reflectance Higher-Level Data products chosen for this work are ready to use image for change detection application. Images are already co-registered and calibrated [Young et al., 2017, Markham and Helder, 2012] allowing us to avoid the complex pre-process step that could lead in data degradation considering the topographical complexity of Alpine regions. Data were only checked for quality but looking at NIR/RED ratio and NDVI data distribution in two different periods a marked difference is apparent since these two missions have a payload of slightly different sensors, with different wavelenght windows, especially in the NIR. Li et al. [2014] showed high linear correlation coefficient between vegetation indices based on Landsat-7 (ETM+) and Landsat-8 (OLI) sensors. Further analysis should be addressed to understand if the marked change is due to the two different algorithm used to pre-process Landsat-5 and Landsat-8 images or there was a systematic change of early/late response from the broad-leaf vegetation component due to seasonal variability. To overcome this bias a normalization method should be provided [Teillet et al., 2006] or an alternative approach could rely upon the use of tasselled cap transformation to investigate the different data distribution causes by comparing images [Kauth and Thomas, 1976].

4.2.2 | Change detection

In this section we extracted the area of GPNP were major change – in terms of vegetation pattern – occurred by enhancing and extracting information trough PCA.

Almost 6% of park area was changed (see table 3.9) and changed area are localized in Montane belt (1200-1800 m a.s.l.) on south-facing aspect (270° CCW) slopes comprised between ca. 35°-40°.

Once a pre-process step or the chosen of ready-to-use data is performed and image comparison reveals changes in observed phenomena that lead in reflectance changes user have to face the selection of a suitable method for extract change information that is important but not easy task (see for a review [Hayes and Sader, 2001, Jianya et al., 2008, Coppin et al., 2004, Lu et al., 2004, Singh, 1989]).

To keep simple our task of change/no change map creation we chose a PCA (see [Lu et al., 2004] for potentials and drawbacks and [Deng et al., 2008] for a case study and good description of algorithm) following code provided in Neteler and Mitasova [2013]. The adjustments were due considering the natural context determining the threshold of 90th percentile and removing pixels above the 2800 m a.s.l.. To avoid the random variation of sensors and phenology stage a spatial

4.2. SATELLITE IMAGERY

threshold of 3X3 pixels was applied following the proposed method evaluating the results with orthophotos created in *3.3.1 Process comparison*.

The nature of change was investigated with a t-test revealing a strong increase in NDVI values in changed area. The map was further analyzed with topographical variables showing a marked difference between Aosta Valley and Piedmont side trends with a specific topographical patterns for each valleys. The main changes are localized in Montane belt with an elevation ranging from 1200-1800 m a.s.l. suggesting that the semi-natural grassland located below the treeline shrunk in favour of woody plant species. Surface interested by change has slope range of 20-40° indicating that probably the steeper and difficult to reach surface were abandoned on a greater extent than flat surfaces. Aspect suffers from main valley orientation the major changes occurred in Orco and Soana valleys that are south exposed areas. VRM did not show a clear pattern ranging between very low values. Global radiation and insolation time values are higher in Piedmont side and also these values could be biased by aspect. The change pattern was described with landscape ecology index showing the main characteristics.

Our preliminary analysis seems to confirm how the abandonment of traditional primary activities as a strong effect on our "cultural landscape" [Blondel et al., 2010]. Orco and especially Soana valley suffer from depopulation furthermore in Orco valley there was the establishment of IREN hydroelectric plants that caused change to primary production to other remunerative productions.

The achieved results revealed a structural change of protected areas. The new emerging landscape is connected with an increase of wood vegetation cover as revealed by the results of t-test for related sample. The change in traditional land use is one of the cause that could contribute to pattern of change [Falcucci et al., 2006, Rocchini et al., 2006, Amici et al., 2017, Pelorosso et al., 2009, Geri et al., 2010, Pornaro et al., 2013, Gehrig-Fasel et al., 2007] as often reported for Mediterranean basin [Serra et al., 2008, Tasser et al., 2007, Lasanta-Martínez et al., 2005, Peco et al., 2006, MacDonald et al., 2000]; where the herbaceous formations are of great interest due to threatened species, high rate of biodiversity and their aesthetic value [Silva et al., 2008].

The structural changes in vegetation cover has strong consequences on biodiversity pattern affecting soil properties [Pornaro, 2012, Zeller et al., 2001, Cousins, 2009]; plant species composition [Pornaro et al., 2013, Dullinger et al., 2003, Parolo et al., 2011, Tasser and Tappeiner, 2002, Barbaro et al., 2001] and animal species distribution [Tocco et al., 2013, Rolando et al., 2014, Anthelme et al., 2001, Scozzafava and De Sanctis, 2006, Acevedo et al., 2011].

This is the first attempt to outline the changed area in GPNP protected areas and further analysis should be carried out. Our scope was to highlight the major change occurred in our study area at landscape level.

PCA is a powerful tool in change detection because working on continuous data it assures that there was no data loss due to thresholding in discrete classes. Another PCA-based method to test is the image subtraction of first PC1s of two selected periods. To understand the magnitude and direction of change we suggest to work on altitudinal belts following a method like one proposed by Mancino et al. [2014] or implementing a Change Vector Analysis (CVA).

In change detection analysis the accuracy assessment is a prominent phase to

4. DISCUSSIONS

understand the reliability of the achieved results. In this specific case of ground truth data lack the ancient aerial images play a relevant role providing small scale feature information. In this section the orthorectified images of *CGR Rossi Piemonte 1991* flight (see 3.3 *Aerial images*) were used to fine tune the change detection parameters and visually evaluate the obtained results. A comprehensive quantitative assessment of error is necessary and it could be achieved using a reference dataset as images of *Volo Italia '88-'89* flight (retrieved from other public administration) or orthorectified images of *R. Valle d'Aosta '91* and *CGR Rossi Piemonte 1991* flights (see 2.4.1 *Aerial image available collection* and 3.3 *Aerial images*) because of the coarseness of CORINE Land Cover project minimum mapping unit (25 ha) [Büttner et al., 2004].

After the individuation of change it is necessary to perform a classification in discrete classes which should be integrated with botanical investigation in order to understand and quantify change for management purposes. A further step is the link of the obtained data with other sources of information like cadastral map and census data to delineate the change in land use and land cover. Such information can be finally linked to quali-quantitative faunal data to create a comprehensive management plan taking into account biodiversity conservation, landscape protection and continuity of traditional human activities.

4.2.3 | Fragmentation analysis

To explore the complexity of an Alpine landscape in 1986 and 2016 we used a method relying on Fourier transform application [Rocchini et al., 2013b] to objectively detect the change without any *a priori* assumptions.

Landscape change are the resultant of many continuous small scale interacting process [Turner, 1989] and reclassification of continuous data in more manageable discrete categories could lead a loss of information [Rocchini et al., 2013a].

Observing the complexity of Fourier space, trend of kernel density functions and plot of Fourier space values by hexagon binning we can observe that no marked change in landscape composition occurred in GPNP in 1986-2016 period. There was only an increase in heterogeneity of Fourier space as shown by data distribution.

The structure of kernel density functions probably indicates a relative long-term stable area above the Montane belt. The slightly increase in Fourier transform values could be explained by the slight increase of vegetation cover in Montane belt. Indeed the major change in Alpine region are located in Montane belt [Tasser et al., 2007] and are less evident compared with a landscape fragmentation process with spread of urban areas in homogeneous environment (see Rocchini et al. [2013] for the case study).

4.3 | Aerial images

4.3.1 | Process comparison

In this section we compared two different approach in two different software environments to generate robust orthoimagery to overlay onto each other in order to achieve a historical aerial image archive. Using test image representing topographically

complex mountainous environments we compared: the historical orthorectification process strongly based on reconstruction of interior and exterior camera parameters and the SFM a new approach spreaded with UAV technology well suited in the case of unknown camera parameters. The orthoimages were created removing camera distortion and relief displacements. Errors in element spatial placement was quantitatively assessed using RMSE statistics. Using the comparison results we applied the more robust method to constitute an archive of orthophoto.

Aerial photos constitute the longest remote-sensed data time series providing a valid support to detail the fine scale landscape elements and as stressed by [Morgan et al., 2010] in ecological research they are a challenging datasets among the remote sensed data archive allowing to reconstruct landscape structure over-broad scale of analysis in decades when satellite or UAV imagery were still not available.

Despite their advantages the user must take into account many limiting factors as the need to remove geometric distortion affecting image to retrieve quantitative information [Rocchini and Di Rita, 2005, Rocchini, 2004] and image classification approach strongly based on time-consuming and subjective manual interpretation and irregularities in time series archive [Morgan et al., 2010].

We focused on free-distortion image creation and in our opinion the SFM approach seems an attractive technique in order to obtain ortho-imagery from scanned historical aerial image solving the often unknown camera interior and exterior orientation. Indeed camera calibration certificate providing camera parameters are often unavailable allowing the user to retrieve only qualitative information. In this test despite the numerous implementation in several research field [Westoby et al., 2012, Fonstad et al., 2013, Green et al., 2014] and following the same method proposed by Gomez in 2015 SFM approach furnished weak results. Further analysis should be performed to understand if the entire workflow is not well suited in the case of our study area due to strong camera distortion combined with terrain relief or we had some limitation in software use. On the other side the orthorectification approach provided robust results but the research of camera certificate calibration is time consuming and often inconclusive and the use of uncalibrated focal length and standard parameters could led in unusable results.

Using the comparison results we could assess that orthorectification provides more robust results and we tested the method reliability to constitute an orthophoto archive. To solve the problem of irregularities in time series and spatial extent we retrieved materials from different public administrations as *Regione Piemonte* that adopted the (Cc-by-2.5 license) in photo frame distribution. Another possible solution could be the adoption of framework similar to one proposed by Petit and Lambin, 2001. The open-source image orthorectification implemented in GRASS GIS allowed to create accurate maps ($RMSE_r$ at 95% < 6 m) but we couldn't accomplish the entire archive reconstruction due to a probable bug affecting the process.

The obtained results will be fundamental to reconstruct habitat change occurred along the altitudinal gradients in the last few decades. To overcome the limitations of manual photo-interpretation that could be too subjective and time-consuming. We are addressed in image object-based classification [Blaschke, 2010a] to retrieve data on landscape change through multi-temporal analysis [Hussain et al., 2013a]. The supervised classification approach seems to be particularly suited in our case.

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As showed in [Laliberte et al., 2004a] extending information of training areas on whole area of interesting we could reduce the computational time, achieve more reliable results and increase accuracy removing *salt and pepper* effect. Furthermore to avoid error due to the classification performed on image with different quality an approach similar to one proposed by Rocchini in [2006] could be implemented with *a priori* defined *minimum mapping unit* taking in account also pixel resolution and RMSE values in order to reduce spatial displacement errors.

Aerial photos are a valuable source of information about disappearing landscape that has strong ecological consequences [Falcucci et al., 2006, Gehrig-Fasel et al., 2007, Pelorosso et al., 2009, Geri et al., 2010, Amici et al., 2017] taking in account our results to assess this dynamics we suggest to use an open source solution to provide more robust results, to reduce cost and to be supported by motivated community.

4.3.2 | Vegetation pattern change

To evaluate the change in structural heterogeneity along the altitudinal gradient due to natural forest succession we used the Fourier transform. The method is particularly useful to investigate images without loss of information by thresholding them in discrete classes.

The transform results showed two different vegetation pattern configurations of altitudinal transect and two different trends are recognizable along the altitudinal belts. The major change occurred in Montane belt where woodland tend to replace herbaceous communities with a consequent decrease in Fourier space heterogeneity, see fig. 4.1.

The data distributions of plot located in Montane belt showed a decrease in skewness and kurtosis. The Fourier space of Subalpine and Alpine plots showed an increase in medium frequency part, represented in green, but data distribution did not change although a slight change could be observed in the uppermost quadrat of *gp* transect, which could be interpreted as a probable effect of climatic warming rather than of land use change.

The general trend is the same observed in Alpine regions [Gehrig-Fasel et al., 2007, Müllerová, 2005] but further analysis should be addressed in the understanding

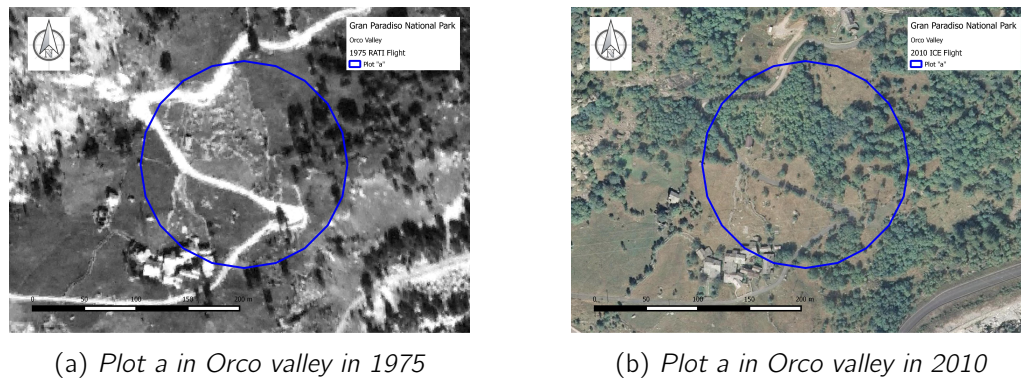


Figure 4.1 | Image show change in land cover occurred in the first plot of Orco valley transect (gp).

of change at higher plots. In the 1975 image rocks are clearly visible while in 2010 they are partially covered by grass. The phenomena could be relate to a major sensibility of older panchromatic camera to stone reflectivity, to major erosion of grassland or to an increase of grass cover due to climate change [Parolo and Rossi, 2008, Dirnböck et al., 2011, Thuiller et al., 2005].

To avoid data degradation we did not perform any pre-processing to enhance image quality. The Fourier transform results may be affected by light conditions and image noise. Therefore it is fundamental to apply a pre-process with radiometric normalization. A proper pre-process should rely as presented in Neteler et al. [2011]: on robust orthorectification [Rocchini et al., 2012], a radiometric calibration with a terrain flattening, an histogram matching, use of camera angle to select the proper portion of image if area fall in more than two images and smoothing with Mumford-Shah [Vitti, 2012].

4.3.3 | Image classification

In this section we classify an image of Levionaz basin following a supervised OBIA approach using five individual classifiers and four voting schemes. The best classification in terms of overall accuracy was given by C5.0 with 27.7%.

The entire workflow was adapted on one proposed by Grippa et al. [2017] available at https://github.com/tgrippa/Opensource_OBIA_processing_chain and shared under the CC-BY 4.0 Creative Common License. This reproducible research relying on free and open-source solutions allows us to assess limitations affecting object-based image classification in Alpine environment. Here are discussed the main critical aspects.

The used support are matched images belonging to ICE 2009-11 flight. Aerial images are distributed already orthorectified and radiometrically corrected but considering the high resolution (0.5 m/px) and the format conversion (.ecw to .tif) a pre-processing step is strongly recommended to remove image noise. A solution proposed is the piece-wise smooth approximation with the Mumford-Shah variational model implemented in *r.smooth.seg* module [Vitti, 2012]. The smoothing function could speed up the convergence of segmentation results.

The selected image colour space was the highly correlated RGB. We reduced the space dimensionality trough PCA removing part of image noise. Following the workflows proposed in literature HIS could be a good alternative space and Alsultanny [2010] highlighted that the segmentation results of RGB and I channels are comparable.

The most critical step is the unsupervised segmentation parameter optimization phase with the threshold and minimum object size fine-tuning. The biggest limitation affecting the entire process was the chosen of one threshold and minimum object size value over entire image because the Alpine environment is characterized by different type of habitats along the altitudinal gradient. The peculiarities of each habitat made difficult to establish single segmentation parameters. For example a single threshold value suitable for segmentation of Subalpine belt could lead in under-segmentation of wooded land (trees mixed with shadow) in mountain belt or over-segmentation of rock and screes (stone in sun-light or slightly shadowed) at higher altitude. To overcome limitations of this scale of analysis is necessary to search the best segmentation parameters for each altitudinal belts in order to

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delineate the habitat characteristics and speed up computational time. In the unsupervised parameter optimization is required a proper threshold range selection (preliminary analysis on smaller representative area) and a better assessment of intra and inter-segment homogeneity using optimization functions implemented in *i.segment.uspo* add-on.

To characterize objects we selected spectral, textural [Laliberte and Rango, 2008], geometric and topographic features [Yu et al., 2006]. Considering the topographical complexity of Alps we used brightness, NGRDI, GLA and WI as spectral features to eliminate possible effects of noise and to derive un-correlated characteristics. We suppose that this kind of band ratios are well suited for un-calibrated sensors of high resolution UAV images and we suggest a deeper analysis of RGB and HIS spectral information. Another feature that could improve the object characterization is NIR band due to RGB spectral similarity of dry Alpine grassland with stone. As textural features we used contrast, correlation, entropy, homogeneity and standard deviation but considering literature as Laliberte et al. [2004] for the discrimination of shrubs and Savio [Savio, 2011][2011] for forest characterization we can reduce the number of textures and increase the moving window size evaluating the responsiveness through the use of coefficient of variation [Niphadkar et al., 2017] or PCA [Rico and Maseda, 2012]. TINITALY DEM [Tarquini et al., 2007, Tarquini et al., 2012] is too coarse to characterize objects retrieved from 0.5 m/px resolution image and probably a simple contextualization of workflow for altitudinal belts could improve the results avoiding DEM use. We tried to use normalized features due to strong differences in their scales; *r.mapcalc* module and R [R Core Team, 2017] were valuable tools to prepare a normalized dataset. Data normalization are not required but often it can boost the classification performance increasing optimization convergence of some machine learning algorithms (eg. support vector machine perform well with normalized data while random forest do not require normalization).

The object labelling step suffered from error committed in unsupervised parameter optimization stage.

The choice of training set not independent by object to classify was done considering environmental research where often the ground truth data cannot be independent to image to classify (extension, accessibility, limited resources, ecc.). To perform this task we used the *r.object.activelearning* add-on that require the labelling of the most meaningful objects to improve classification score, often the add-on required to highlight objects of ambiguous meaning as shade in screes or small trees interspersed in shadow. To overcome these limitations, in addition to the improvement of unsupervised parameter optimization phase, user must take in account to enrich legend with shadow classes for each land cover class [Zohmann et al., 2013].

To classify objects we used the *v.class.mlR* add-on that interface GRASS GIS to R allowing to classify image selecting different individual classifiers and voting schemes. The best results were performed by C5.0 and k-Nearest Neighbors followed by Support Vector Machine and Random Forest. The obtained results confirm that Random Forest, Support Vector Machine and C5.0 are among the best individual classifiers [Fernández-Delgado et al., 2014].

The accuracy assessment is a fundamental step to accomplish an image classification. It was performed with *r.kappa* module that provides well known and

established accuracy statistics [Congalton, 1991]. To overcome problems linked with kappa statistics we suggest the use of method described in [Pontius Jr and Millones, 2011] and its packages available for R.

As stated by Zohman et al. [2013] the OBIA approach is well suited for many context and purposes [Blaschke, 2002, Burnett and Blaschke, 2003, Blaschke, 2010b, Hussain et al., 2013b] but its application in Montane habitats are scarce. OBIA could be a valuable mean to represent in a meaningful ecological way land covers especially where field survey can be difficult or expensive. Furthermore the supervised techniques are attractive because they allow to extend our knowledge over larger areas [Lobo et al., 1998]. Our results showed that there are many limitations in applying these techniques over a topographically and ecological complex environment as Alpine regions. The need to map this threatened environment is high and we tried to highlight the main limitations suggesting overcoming methods. At this scale of analysis we remark to treat each altitudinal belt as different environment defining different segmentation parameters and we suggest to perform a separate classification for each vegetation type (a hierarchical classification could improve the results). Furthermore we have to consider also the purposes of this classification. In fact, if we consider a research context the improvement of each proposed step is mandatory, but considering the need of protected area management is necessary to take into account also time and process ease. A suggested workflow could be the proper unsupervised segmentation parameter optimization and segmentation steps manually labelling objects [Marignani et al., 2008, Geri et al., 2010, Amici et al., 2017] to assure spatial coherence and repeatability of methods.

4.4 | UAV images

4.4.1 | Image collection

Mountain areas aerial survey could be a complex activity and UAV are proven to be a valuable tool in acquiring data over complex area in short time [Piras et al., 2017] and inexpensive compared with typical airborne surveys [Matese et al., 2015].

A sequence of images was collected in each flight mission covering the entire plots of 5 altitudinal transects. The flight surveys generally are planned to occur close to solar noon to avoid the shadow effects; nonetheless the weather conditions and gusts presence had a considerable effect in flight planning. Consider time efforts is important for repeatability studies using UAV images acquired for the same areas at different times. To carry out a complete plot survey UAV requires almost 5-10 minutes; the main time limitations were due to physical plot distance, presence of suitable areas for departure/landing of UAV, set GPS receiver, image download with their preliminary check and weather instability. Another important limitant factor in this context is the sun illumination due to topographically heterogeneity. These difficulties are increased in Montane belt due to major vegetation cover and increase of slopes.

The proprietary software Postflight Terra 3D Professional [Pix4D, 2012] furnished with senseFly UAV allowed to automatically align, orthorectify and match images retrieving the geographical position and principal axes (roll, pitch and yaw) of the vehicle in *Exif* of each acquired image. Montane belt plots were the most problematic

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due to closed vegetation cover and steep surfaces that lead in difficulties in UAV departure/landings and image creation. During this step a manual marking of image common elements (tree crowns) was required due to particular dense and homogeneous tree cover.

4.4.2 | Field sampling

Ground observation sites were sampled collecting information about land cover; frequency of dominant species defined as the single species to a maximum of 3 species that cover more than 50% of quadrat; height and phenology stage. The ground observations were extracted with a simple random sampling but a stratified random sampling is suggested in this phase to better distribute the ground data increasing the number of field sampling sites in grassland. Gonçalves et al. [2016] proposed 60X60 m regularly spaced grids for field sampling. Such dimensions do not fit with our study area but we have to take into account that using this type of field sampling reduce the required time to move while with a random sampling the required time to locate and reach selected field sites strongly affects the overall required time. The accessibility of selected areas must be taken in account. To increase the potentiality of proposed method is necessary to adopt a stratified random sampling after image visual inspection, increase the number of field sites in grassland and generally increase the field sites number on easy accessible area to reduce time in reach location and increase visited locations number to constitute major number of training set and test to use in visual interpretation and try to extending information with manual visual interpretation or semi-automatic technique [Gonçalves et al., 2016, Gini et al., 2014].

4.4.3 | Visual interpretation

In visual interpretation we performed different trials to recognize dominant species. The shrub and tree species are generally clearly recognizable while in herbaceous formations some difficulties could be related to the identification of grasses (family Graminaceae). This task could also be affected by the season and the subsequent phenological status of the species. The accurate interpretation of species is strongly related to training site and test site dimensions indeed it is suggested to increase the field sampling sites. Furthermore the blind test methodology could be a valuable tool to ensure the reliability of method.

5 | Conclusions

The remote sensing approach used to characterize a mountain protected area appeared to be a reliable tool to evaluate the vegetation pattern change occurred in the last few decades. The processing of free-distributed data in (mainly) open-source software allowed to produce robust and reliable results and furthermore it is scarcely affected by the often scarce resources addressed into environmental research.

We carried out the research in a mountain protected area management context. This choice was made considering that mountain ecosystems are one of most critical and vulnerable biodiversity hotspot providing fundamental ecosystem services [Beniston, 2003, Fischlin et al., 2007, Zimmermann et al., 2010]; the protected areas are still the basis for the biodiversity conservation efforts [Lopoukhine et al., 2012, Pauli et al., 2013]; to explore one of the most complex relation between human land use and natural process [MacDonald et al., 2000, Galvánek and Lep, 2008].

In this study it was pointed out that the integration of different sensors and their peculiarities is a valuable tool to explore the ecological process of complex Alpine environments.

Satellite imagery and particularly Landsat program with the availability of already pre-processed *High-Level Products* allowed to compare different images taken with different sensors and to extract the vegetation pattern change in study area underlying the link between pattern of change and *marginal land* abandonment.

A proper image orthorectification process is an essential task to create robust map to reconstruct habitat change. Aerial images constituting the longest remote sensed data archive characterized by a spatial resolution similar to field-view have a prominent ecological meaning [Morgan et al., 2010] allowing to characterize habitat structure change along an altitudinal gradient.

UAVs are flexible and low-cost solution that can overcome the issues linked to spatial or temporal resolution with several applications [Shahbazi et al., 2014, Colomina and Molina, 2014]. The flexibility of UAVs was highlighted in ground observation and remotely-sensed imagery linking [Lobo et al., 1998] and in characterization of fine-scale feature elements of a intensively monitored plot.

Many drawbacks and limitations were also highlighted in the use of remote sensed data.

Landsat imagery are widely affected by clouds and the small scale process could be not recognized due to resolution of 30 m/px and particular complexity of Alpine area. A solution could be the integration with the ESA Copernicus constellation (Sentinel 2A and Sentinel 2B) data which allows 5 days revisiting frequency to complement Landsat acquisitions.

Aerial images are often characterized by irregular time series, inadequate spatial coverage and different type of sensor response and the oldest ones require the

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accomplishment of orthorectification process that is a complex process often affected by lack of camera metadata.

UAVs may have some difficulties in flight and images could be affected by environmental conditions. Often camera parameters (position of camera and sensor response) are unknown and there are difficulties in sensor calibration.

Future research should be addressed to overcome these limitations considering the strong potentials of this support in biodiversity conservation [Nagendra, 2001] and management purposes (see Gross et al. [2009] for a discussion and Pelorosso et al. [2009], Geri et al.[2010], Amici et al. [2017], Marignani et al. [2008], Rocchini et al. [2006] for method using different data) through a landscape ecology approach [Blondel et al., 2010, Groom et al., 2006]. With particular reference to animal species management, it is possible to outline some general statements.

Satellite imagery could be used to delineate landscape composition at coarser scale of analysis assessing if ecological process affects the major ungulate species population and distribution [Dunning et al., 1992].

Orthophotos are a valuable source of information allowing to define in the last century vegetation type and spatial pattern [Sanz-Elorza et al., 2003, Müllerová, 2005]. This kind of information could be used to reconstruct habitat change evaluating vertebrate habitat suitability [Zohmann et al., 2013].

UAV and field sampling monitoring could be used to detail the small scale habitat features creating high spatially detailed map. This kind of monitoring is potentially adapted to invertebrates or small vertebrates research delineating spatially explicit variables [Linchant et al., 2015].

To protect the vanishing biodiversity patterns strongly dependent by the traditional land use, many efforts should be addressed in understanding the process of landscape structure change in space and time and to depict the driving forces involved in these processes. To preserve or reintroduce traditional activities that shaped our landscape and biodiversity pattern, protected areas play a fundamental role for their ability to implement management actions as the difficult restoration practices [Galvánek and Lep, 2008]. This would not only lead to perceive protected areas as a set of constraints but as a place where a system of traditional activities based on proper management of natural resources may become profitable because often in the Mediterranean areas radically modified by human presence the biodiversity preserving can be pursued through traditional practices.

Annex

A | Theoretical backgrounds

A.0.1 | Theoretical backgrounds

Elements of Photogrammetry

Photogrammetry is the art, science, and technology of obtaining reliable information about physical objects and the environment, through processes of recording, measuring, and interpreting images and patterns of electromagnetic radiant energy and other phenomena. [Manual of Photogrammetry. 5th edition, 1980]

In aerial photogrammetry, to retrieve object position we can use *direct* or *indirect* techniques. The former use camera parameters and its position. This method is well suited with modern aerial camera and the widespread of GPS technology. The latter were implemented in the past decades using analogic aerial camera and they require camera parameters and coordinates of represented objects in scene, the so-called *Ground Control Points* (GCP).

In this work, using scanned digital data we will focus on indirect techniques.

Photogrammetric camera and aerial photos

Images taken by a camera have a proper coordinate system. This system is established by camera internal geometric properties called *interior orientation*. The metric camera are characterized by a constant and well known interior orientation while in consumer grade camera the interior orientation is unknown and variable in time.

Analogic aerial photos are taken by metric camera mounted on aerial platform and generally they have an overlap of 60% and a sidelap of 20-30% in order to perform stereoscopic analysis. They were produced in a standard format of 23x23 *cm*. The image coordinate system is reconstructed using the *fiducial marks* impressed on scene border. The fiducial marks are fundamental to reconstruct the *XY* image coordinate system expressed in *mm*. The metadata image as un-calibrated focal length, altitude, timestamp, date and image counter are printed on left side of north-oriented image.

The aerial images should be accomplished by *camera calibration certificate* that describe the interior orientation parameters:

Fiducial marks sequential order and coordinates expressed in *mm*.

Principal Point and Principal Point of Autocollimation positions expressed in *mm*.

Calibrated focal length focal length measured in camera calibration.

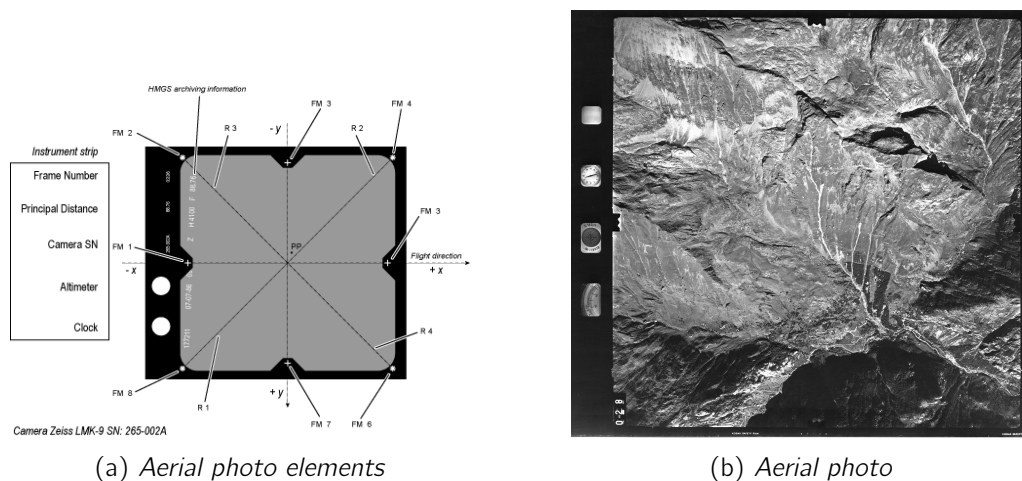


Figure A.1 | Aerial photo and its elements. Image (a) available at GRASS GIS *i.ortho.camera* manual page. Image (b) available at Geoportale Piemonte under Cc-by-2.5 license.

Radial distortion graphic representing radial distortion of camera.

Date timestamp of calibration process.

The calibration certificate should be no more old than two years of flight date. If it is not available parameters in bibliography or reported on each frame should be used.

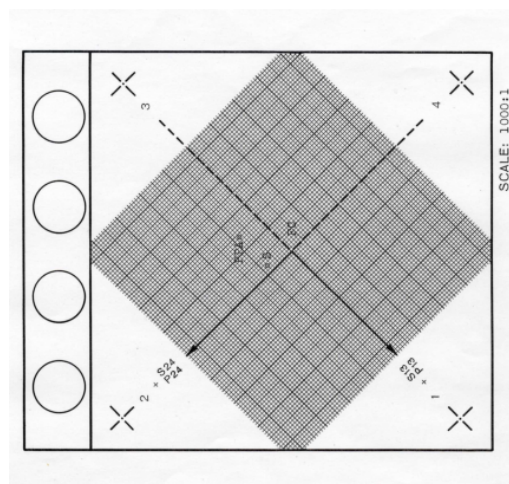


Figure A.2 | Example of camera calibration certificate with position of *fiducial marks*, FC, PPA and PP.

Central projection

As a theoretical assumption the *central projection* of photo is realized when image plane is perfectly parallel to object plane.

Considering the aerial photo case the central projection is realized when aircraft bringing camera flights following a line perfectly parallel to ground surface creating a *true vertical image*. In this case a trajectory line starting from camera lenses –

A. THEORETICAL BACKGROUNDS

called *optical axis* – is perpendicular to horizontal plane. In image plane optical axis through the intersection of fiducial marks called *Principal Point* (PP) and in object plane it through *nadir*. If camera is tilted the optical axis and perpendicular line create an angle called *nadir distance* ν . If ν is smaller than 3° photos are called *tilted vertical images* preserving the central projection condition while if it is greater than 3° it is called *oblique photos* that are not in central projection [Neteler and Mitasova, 2004].

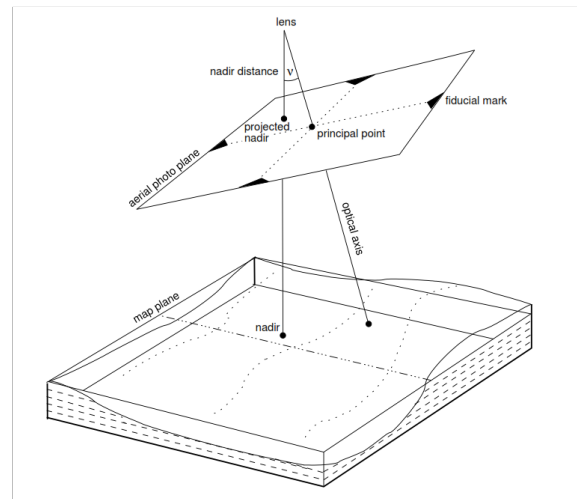


Figure A.3 | Theoretical simplification of aerial photo plane and horizontal plane. Source [Neteler and Mitasova, 2004].

The cases above described are theoretical simplifications of central projection. To reconstruct image central projection we have to know the characteristics of image coordinate system, see Fig. A.2. After the assembly of all parts of camera there are a small amount of errors and optical axis through the *fiducial centre* in image plane. The fiducial marks are fundamental to reconstruct the the *XY* image coordinate system expressed in *mm* indeed connecting the opposite marks we can find fiducial centre that is the (0, 0) point of image coordinate system. During camera calibration a new reference axis called *principal axis of autocollimation* perpendicular to lenses is measured. In image plane this axis through the *principal point of autocollimation* (PPA). Furthermore we have to consider that there are other residual errors (eg.: tilted photo film) and image plane is not perfectly perpendicular to principal axis of autocollimation. This type of residual error are called *residual distortion*. This type of error is measured along the 4 semi-diagonals of image and it allows to mathematically find a new reference axis called *principal axis of symmetry* that intersect the image plane in the perspective centre that is the PP also known as *principal point of symmetry* (PPS) or *point of best symmetry* (PBS) [Schenk, 2005].

Orthorectification process

The orthorectification process is the transformation of image central projection in map orthogonal projection. The process aims to create a free-distortion image [Rocchini

et al., 2012].

Generally the proposed method to geometrically correct remotely sensed data are based on *polynomial function* or *differential function* [Novak, 1992]. Rocchini [2005] showed the robustness of differential functions over polynomial ones. In brief in the orthorectification process – based on differential functions – the coordinates of some well known points, their elevation and camera parameters are used to compute the *collinearity equations*. These equations allow to transform the image coordinate system in a geographic coordinate system [Neteler and Mitasova, 2004].

Often older aerial image are distributed as scanned digital image allowing to carry out orthorectification process in a digital environment. Generally a photogrammetric software uses three different coordinate systems:

Image coordinate system is the scanned aerial image coordinate system expressed in pixel units.

Photo coordinate system is the aerial image coordinate system expressed in *mm*. The centre of this coordinate system is the fiducial centre (0, 0) and the important parameters as fiducial marks and PP position is reported in calibration certificate.

Target coordinate system is the chosen coordinate system defined by datum and projection.

The entire process is composed by 4 main steps:

Parameters definition main parameters definition as geographic coordinate system, *digital elevation model* (DEM) and camera parameters (focal length, fiducial marks and PP position).

Interior orientation the purpose is to define the position of perspective centre. In scanned image defining the position of fiducial marks and knowing the position of PP software can perform the transformation of photo coordinate system in image coordinate system.

Exterior orientation the position of image in the real world is reconstructed using the coordinates and the elevation of well distributed GCP represented in the image. The exterior orientation could be performed using *spatial resection* method working on one image at time and using at least 4 GCP or using the *bundle block adjustment* working on more than two photos refining the position of images using common GCP coordinates. In this step the image coordinate system is transformed in target coordinate system.

Rectification normalization of spatial displacement due to terrain relief using interior and exterior orientation parameters. The image is resampled obtaining a constant scale across the map.

Structure from motion process

The structure from motion framework permits to reconstruct scene derived from overlapping photos with unknown camera parameters and position. Many studies [Westoby et al., 2012, Fonstad et al., 2013, Green et al., 2014] showed the

A. THEORETICAL BACKGROUNDS

robustness of method in map creation in different research context. The workflow may vary (see Remondino et al. [2014] for method and software implementation) but in general software recognize common elements in images to reconstruct camera exterior orientation and internal parameters through an implementation of bundle block adjustment. A common workflow is composed by the following steps:

Pre-processing during this step overlapping-images are selected and if information about used camera, exterior orientation parameters and GCP are known they are entered to improve process results.

Feature detection using a region detector algorithms as *Scale Invariant Feature Transform* (SIFT) or *Speeded up robust features* (SURF) the image key points are recognized.

Feature matching using the position of key points images are aligned.

Sparse reconstruction of image elements. The scene is reconstructed triangulating image elements and if available the GCP.

Bundle adjustment algorithm using image elements compute the coordinates of each recognized elements. If provided the less accurated exterior orientation parameters can improve the reconstruction of absolute image position while the entire model is refined by GCP. The entire scene configuration is adjusted using bundle adjustment providing accurate information of internal camera parameters and its position.

Dense reconstruction of scene using algorithms as *Clustering Views for Multi-view Stereo* (CMVS) and *Patch-based Multi-view Stereo vers.2* (PMVS2) [Furukawa and Ponce, 2010]. The former create different manageable cluster of input images to process in parallel and latter compute the object structures.

Surface reconstruction using method as *Delauney triangulation* or *Poisson surface reconstruction*.

Texture creation the surfaces are reconstructed using input images.

B | Scripts

In this appendix are listed or explained all the implemented scripts during this PhD project. Scripts retrieved from other sources are specified and the authors cited.

```
1 #Script implemented in bash language
```

```
1 #Script implemented in R language
```

```
1 #Script implemented in Python language
```

B.1 | Digital elevation model

B.1.1 | Land-surfaces characterization

```
1 #Compute slope and aspect
2 r.slope.aspect elevation=DEM slope=slope aspect=aspect min_slope=2
3
4 #Convert slope in northerness and easternness values
5 r.northerness.easterness elevation=DEM
6
7 #Compute vector ruggedness measure
8 r.vector.ruggedness elevation=DEM output=VRM
9
10 #Compute solar irradiation maps every 10 days starting from 8th
    day of month (the script is incomplete due to the huge number of
    lines we suggest to implement in a more efficient way the command
    in a python script).
11 r.sun --overwrite elevation=DEM aspect=aspect aspect_value=270
    slope=slope slope_value=0.0 linke_value=1.5 albedo_value=0.2
    glob_rad=gr_8 insol_time=it_8 day=8 step=0.5 distance_step=1.0
    npartitions=1
12 r.sun --overwrite elevation=DEM aspect=aspect aspect_value=270
    slope=slope slope_value=0.0 linke_value=1.5 albedo_value=0.2
    glob_rad=gr_18 insol_time=it_18 day=18 step=0.5 distance_step=1.0
    npartitions=1
13 r.sun --overwrite elevation=DEM aspect=aspect aspect_value=270
    slope=slope slope_value=0.0 linke_value=1.5 albedo_value=0.2
```

B. SCRIPTS

```
glob_rad=gr_28 insol_time=it_28 day=28 step=0.5 distance_step=1.0
npartitions=1
14
15 #Calculate the global radiation mean for the month
16 r.mapcalc expression=gr_jan = ( gr_8 + gr_18 +gr_28)/3
17
18 #Convert in MJ/m2$ x day
19 r.mapcalc expression=gr_jan_MJ= gr_jan*0.0036
20
21 #Calculate the insolation time mean for the month
22 r.mapcalc expression=it_jan = ( it_8 + it_18 +it_28)/3
23
24 #Using r.mapcalc calculate the global radiation and insolation
    time annual mean
```

```
1 #Export univariate raster statistics
2 #MASK on GPNP is turned on
3 geomorphometry=['DEM', 'slope', 'aspect', 'gr_year_MJ', 'it_year',
    'vrn']
4
5 for raster in geomorphometry:
6     input="" + raster
7     output="/home/user/Desktop/raster_statistics/" + input + ".csv"
8     grass.run_command('r.univar', flags='e', map=input, output=
        output)
9
10 for raster in geomorphometry:
11     input="" + raster
12     output="/home/user/Desktop/raster_statistics/" + input + "_valley.
        csv"
13     grass.run_command('r.univar', flags='e', map=input, zones='
        Valli', output=output)
```

```
1 #Histograms in PERMANENT location
2 #Switch in R trough GRASS shell with R command
3 #Load rgrass7 library
4 library(rgrass7)
5 gnp_data <- readRAST(c("DEM", "slope", "aspect", "vrn", "gr_year_
    MJ", "it_year"), cat=c(FALSE, FALSE, FALSE, FALSE, FALSE, FALSE))
6
7 #GRASS GIS has very useful histogram function but in R it's better,
    furthermore GRASS has some small bugs in export PNG files
8
9 #Create DEM histogram
10 colDEM <- colorRampPalette(c("black", "white"))
11 hist(gnp_data$DEM,
12     main="Elevation",
```

```

13     xlab="Elevation (m)",
14     col=colDEM(18))
15
16 #Copy plot
17 dev.copy(png,'/media/sf_osgeo10.5/lsat/hist_dem.png', width=1120,
18 height=674)
19 dev.off()
20
21 #Create slope histogram
22 colSLOPE <- colorRampPalette(c("#440154FF", "#481567FF", "#482677
23 FF", "#453781FF", "#404788FF", "#39568CFF", "#33638DFF", "#2D708EFF",
24 "#287D8EFF", "#238A8DFF", "#1F968BFF", "#20A387FF", "#29AF7FFF", "#3
25 CBB75FF", "#55C667FF", "#73D055FF", "#95D840FF", "#B8DE29FF", "#
26 DCE319FF", "#FDE725FF"))
27 hist(gpnp_data$slope,
28     main="Slope",
29     xlab="Slope",
30     col=colSLOPE(18))
31
32 dev.copy(png,'/media/sf_osgeo10.5/lsat/hist_slope.png', width=1120,
33 height=674)
34 dev.off()
35
36 #Create aspect histogram
37 colASPECT <- colorRampPalette(c("black", "white", "black"))
38 hist(gpnp_data$aspect,
39     main="Aspect",
40     xlab="Aspect",
41     col=colASPECT(18))
42
43 dev.copy(png,'/media/sf_osgeo10.5/lsat/hist_aspect.png', width
44 =1120,height=674)
45 dev.off()
46
47 #Create vrm histogram
48 #create ryb palette
49 colVRM <- colorRampPalette(c("#FF5600", "#FDF202", "#0101FE"))
50 hist(gpnp_data$vrms,
51     main="Vector Ruggedness measure",
52     xlab="Vector Ruggedness measure",
53     col=colVRM(18))
54
55 dev.copy(png,'/media/sf_osgeo10.5/lsat/hist_vrm.png', width=1120,
56 height=674)
57 dev.off()
58
59 #Create gr_year_MJ histogram

```


B. SCRIPTS

```
52 hist(gpnp_data$gr_year_MJ,  
53      main="Global radiation",  
54      xlab="Global radiation (MJ)",  
55      col="#FF3900")  
56  
57 dev.copy(png, '/media/sf_osgeo10.5/lsat/hist_gr.png', width=1120,  
58          height=674)  
59 dev.off()  
60 #Create it_year histogram  
61 hist(gpnp_data$it_year,  
62      main="Insolation time",  
63      xlab = "Insolation time (h)",  
64      col="#FF9A00")  
65  
66 dev.copy(png, '/media/sf_osgeo10.5/lsat/hist_it.png', width=1120,  
67          height=674)  
68 dev.off()
```

B.1.2 | Landform identification

```
1 #Classify DEM using different search radius  
2 r.geomorphon elevation=DEM search=3 flat=1 forms=geomorph_dem_10_3  
3 r.geomorphon elevation=DEM search=3 flat=1 forms=geomorph_dem_10_5  
4 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_10  
5 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_15  
6 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_20  
7 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_25  
8 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_30  
9 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_35  
10 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_40  
11 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_45  
12 r.geomorphon elevation=DEM search=3 flat=1 forms=  
geomorph_dem_10_50  
13  
14 #Assessing the convenient L radius with r.object.spatialautocorr  
15 r.object.spatialautocor object_map=geomorph_dem_10_3 variable_map=  
DEM method=moran
```

B.1. DIGITAL ELEVATION MODEL

```
16 r.object.spatialautocor object_map=geomorph_dem_10_5 variable_map=
DEM method=moran
17 r.object.spatialautocor object_map=geomorph_dem_10_10 variable_map
=DEM method=moran
18 r.object.spatialautocor object_map=geomorph_dem_10_15 variable_map
=DEM method=moran
19 r.object.spatialautocor object_map=geomorph_dem_10_20 variable_map
=DEM method=moran
20 r.object.spatialautocor object_map=geomorph_dem_10_25 variable_map
=DEM method=moran
21 r.object.spatialautocor object_map=geomorph_dem_10_30 variable_map
=DEM method=moran
22 r.object.spatialautocor object_map=geomorph_dem_10_35 variable_map
=DEM method=moran
23 r.object.spatialautocor object_map=geomorph_dem_10_40 variable_map
=DEM method=moran
24 r.object.spatialautocor object_map=geomorph_dem_10_45 variable_map
=DEM method=moran
25 r.object.spatialautocor object_map=geomorph_dem_10_50 variable_map
=DEM method=moran
26
27 #MASK on GPNP is turned on
28 r.report map=geomorph_dem_10_15 units=h,c,p output=/home/user/
Desktop/raster_statistics/geomorph_dem_10_15.txt
29
30 #Iterate the r.report command using 'valli' raster values as mask
```

```
1 #Create barplot in R
2 #Set working directory
3 setwd('/home/user/Desktop/raster_statistics')
4 getwd()
5 geomorph_values<-read.table('/home/user/Desktop/raster_statistics/
geomorph_dem_10_15.csv', header=TRUE, sep=",")
6
7 #Use table command to count elements
8 geomorphons<-geomorph_values$geomorph
9 counts<-table(geomorphons)
10
11 #Create the barplot
12 barplot(counts,
13         ylab = "Frequency",
14         main = "Geomorphons",
15         col = c("#DCDCDC", "#380000", "#C80000", "#E15014", "#FAD23C",
16               "#FFFF3C", "#B4E614", "#3CFA96", "#0000FF", "#000038"),
17         names.arg = c("flat", "summit", "ridge", "shoulder", "spur",
18                       "slope", "hollow", "footslope", "valley", "depression")
19     )
```

B. SCRIPTS

```
18
19 dev.copy(png, '/media/sf_osgeo10.5/lsat/barplot_geomorph.png',
20          width=1120,height=674)
21 dev.off()
```

B.2 | Satellite imagery

B.2.1 | Change detection

Data preparation

```
1 #Import data and rename with r.in.gdal as unchecked data
2
3 #Adjusting default computational region
4 g.region -d -p n=n+300 s=s-300 e=e+300 w=w-300 align=
   lsat8_2016_50_un
5
6 #Look at data and quality assessment image
7
8 #Adjust color legend
9 r.colors -e map=lsat5_1986_10_un,lsat5_1986_20_un,lsat5_1986_30_un,
   lsat5_1986_40_un,lsat5_1986_50_un,lsat5_1986_70_un,
   lsat8_2016_10_un,lsat8_2016_20_un,lsat8_2016_30_un,
   lsat8_2016_40_un,lsat8_2016_50_un,lsat8_2016_60_un,
   lsat8_2016_70_un color=grey
10
11 #Simple data visualization only adjusting brightness
12 i.colors.enhance -p red=lsat8_2016_40_un green=lsat8_2016_30_un
   blue=lsat8_2016_20_un
13 d.rgb red=lsat8_2016_40_un green=lsat8_2016_30_un blue=
   lsat8_2016_20_un
14 i.colors.enhance -p red=lsat5_1986_30_un green=lsat5_1986_20_un
   blue=lsat5_1986_10_un
15 d.rgb red=lsat8_2016_40_un green=lsat8_2016_30_un blue=
   lsat8_2016_20_un
16
17 #Combine expression to create maps of surface reflectance error
18 #0s are in range values, 1s are the shadowed ones and 2 the
   saturated ones
19 r.mapcalc "expression=lsat5_1986_10_sr_err =if(lsat5_1986_10_un
   <0,1,0) + if(lsat5_1986_10_un>10000,2,0)"
20 r.mapcalc "expression=lsat5_1986_20_sr_err =if(lsat5_1986_20_un
   <0,1,0) + if(lsat5_1986_20_un>10000,2,0)"
21 r.mapcalc "expression=lsat5_1986_30_sr_err =if(lsat5_1986_30_un
   <0,1,0) + if(lsat5_1986_30_un>10000,2,0)"
```

```

22 r.mapcalc "expression=lsat5_1986_40_sr_err =if(lsat5_1986_40_un
    <0,1,0) + if(lsat5_1986_40_un>10000,2,0)"
23 r.mapcalc "expression=lsat5_1986_50_sr_err =if(lsat5_1986_50_un
    <0,1,0) + if(lsat5_1986_50_un>10000,2,0)"
24 r.mapcalc "expression=lsat5_1986_70_sr_err =if(lsat5_1986_70_un
    <0,1,0) + if(lsat5_1986_70_un>10000,2,0)"
25 r.mapcalc "expression=lsat8_2016_10_sr_err =if(lsat8_2016_10_un
    <0,1,0) + if(lsat8_2016_10_un>10000,2,0)"
26 r.mapcalc "expression=lsat8_2016_20_sr_err =if(lsat8_2016_20_un
    <0,1,0) + if(lsat8_2016_20_un>10000,2,0)"
27 r.mapcalc "expression=lsat8_2016_30_sr_err =if(lsat8_2016_30_un
    <0,1,0) + if(lsat8_2016_30_un>10000,2,0)"
28 r.mapcalc "expression=lsat8_2016_40_sr_err =if(lsat8_2016_40_un
    <0,1,0) + if(lsat8_2016_40_un>10000,2,0)"
29 r.mapcalc "expression=lsat8_2016_50_sr_err =if(lsat8_2016_50_un
    <0,1,0) + if(lsat8_2016_50_un>10000,2,0)"
30 r.mapcalc "expression=lsat8_2016_60_sr_err =if(lsat8_2016_60_un
    <0,1,0) + if(lsat8_2016_60_un>10000,2,0)"
31 r.mapcalc "expression=lsat8_2016_70_sr_err =if(lsat8_2016_70_un
    <0,1,0) + if(lsat8_2016_70_un>10000,2,0)"
32
33 #Create corrected landsat bands
34 #Another possible solution is to replace the out-of-range values
    with null values and fill them with r.fillnulls performing a
    statistical assessment with r.mapcalc and r.univar.
35 r.mapcalc "expression=lsat5_1986_10=if(lsat5_1986_10_un < 0, 0, 0)
    + if((lsat5_1986_10_un > 0 && lsat5_1986_10_un < 10000),
    lsat5_1986_10_un, 0) + if(lsat5_1986_10_un > 10000, 10000, 0)"
36 r.mapcalc "expression=lsat5_1986_20=if(lsat5_1986_20_un < 0, 0, 0)
    + if((lsat5_1986_20_un > 0 && lsat5_1986_20_un < 10000),
    lsat5_1986_20_un, 0) + if(lsat5_1986_20_un > 10000, 10000, 0)"
37 r.mapcalc "expression=lsat5_1986_30=if(lsat5_1986_30_un < 0, 0, 0)
    + if((lsat5_1986_30_un > 0 && lsat5_1986_30_un < 10000),
    lsat5_1986_30_un, 0) + if(lsat5_1986_30_un > 10000, 10000, 0)"
38 r.mapcalc "expression=lsat5_1986_40=if(lsat5_1986_40_un < 0, 0, 0)
    + if((lsat5_1986_40_un > 0 && lsat5_1986_40_un < 10000),
    lsat5_1986_40_un, 0) + if(lsat5_1986_40_un > 10000, 10000, 0)"
39 r.mapcalc "expression=lsat5_1986_50=if(lsat5_1986_50_un < 0, 0, 0)
    + if((lsat5_1986_50_un > 0 && lsat5_1986_50_un < 10000),
    lsat5_1986_50_un, 0) + if(lsat5_1986_50_un > 10000, 10000, 0)"
40 r.mapcalc "expression=lsat5_1986_70=if(lsat5_1986_70_un < 0, 0, 0)
    + if((lsat5_1986_70_un > 0 && lsat5_1986_70_un < 10000),
    lsat5_1986_70_un, 0) + if(lsat5_1986_70_un > 10000, 10000, 0)"
41 r.mapcalc "expression=lsat8_2016_10=if(lsat8_2016_10_un < 0, 0, 0)
    + if((lsat8_2016_10_un > 0 && lsat8_2016_10_un < 10000),
    lsat8_2016_10_un, 0) + if(lsat8_2016_10_un > 10000, 10000, 0)"

```

B. SCRIPTS

```
42 r.mapcalc "expression=lsat8_2016_20=if(lsat8_2016_20_un < 0, 0, 0)
+ if((lsat8_2016_20_un > 0 && lsat8_2016_20_un < 10000),
lsat8_2016_20_un, 0) + if(lsat8_2016_20_un > 10000, 10000, 0)"
43 r.mapcalc "expression=lsat8_2016_30=if(lsat8_2016_30_un < 0, 0, 0)
+ if((lsat8_2016_30_un > 0 && lsat8_2016_30_un < 10000),
lsat8_2016_30_un, 0) + if(lsat8_2016_30_un > 10000, 10000, 0)"
44 r.mapcalc "expression=lsat8_2016_40=if(lsat8_2016_40_un < 0, 0, 0)
+ if((lsat8_2016_40_un > 0 && lsat8_2016_40_un < 10000),
lsat8_2016_40_un, 0) + if(lsat8_2016_40_un > 10000, 10000, 0)"
45 r.mapcalc "expression=lsat8_2016_50=if(lsat8_2016_50_un < 0, 0, 0)
+ if((lsat8_2016_50_un > 0 && lsat8_2016_50_un < 10000),
lsat8_2016_50_un, 0) + if(lsat8_2016_50_un > 10000, 10000, 0)"
46 r.mapcalc "expression=lsat8_2016_60=if(lsat8_2016_60_un < 0, 0, 0)
+ if((lsat8_2016_60_un > 0 && lsat8_2016_60_un < 10000),
lsat8_2016_60_un, 0) + if(lsat8_2016_60_un > 10000, 10000, 0)"
47 r.mapcalc "expression=lsat8_2016_70=if(lsat8_2016_70_un < 0, 0, 0)
+ if((lsat8_2016_70_un > 0 && lsat8_2016_70_un < 10000),
lsat8_2016_70_un, 0) + if(lsat8_2016_70_un > 10000, 10000, 0)"
48
49 #Simple data visualization only adjusting brightness
50 i.colors.enhance -p red=lsat5_1986_30 green=lsat5_1986_20 blue=
lsat5_1986_10
51 d.rgb red=lsat8_2016_40 green=lsat8_2016_30 blue=lsat8_2016_20
52 i.colors.enhance -p red=lsat8_2016_40 green=lsat8_2016_30 blue=
lsat8_2016_20
53 d.rgb red=lsat8_2016_40 green=lsat8_2016_30 blue=lsat8_2016_20
```

Image comparison

```
1 #Compute band NIR/RED ratios
2 r.mapcalc "expression=lsat5_1986_ratio_40_30 = float(lsat5_1986_40)
/lsat5_1986_30"
3 r.mapcalc "expression=lsat8_2016_ratio_50_40 = float(lsat8_2016_50)
/lsat8_2016_40"
4
5 #Compute NDVI maps
6 r.mapcalc "expression=lsat5_1986_ndvi = float(lsat5_1986_40-
lsat5_1986_30)/(lsat5_1986_40 + lsat5_1986_30)"
7 r.mapcalc "expression=lsat8_2016_ndvi = float(lsat8_2016_50-
lsat8_2016_40)/(lsat8_2016_50 + lsat8_2016_40)"
8
9 #Switch in R through GRASS shell
10 R

1 #Create boxplot of NDVI
2 #Require rgrass7 library
3 library(rgrass7)
```

```

4 ndvi<-readRAST(c("lsat5_1986_ndvi", "lsat8_2016_ndvi"))
5 summary(ndvi)
6 boxplot(ndvi$lsat5_1986_ndvi,
7         ndvi$lsat8_2016_ndvi,
8         na.action=NULL,
9         col = c("#45BF55", "#044C29"),
10        main="NDVI",
11        names=(c("1986", "2016")))
12 )

```

Detection of change

```

1 #Code adapted from Neteler and Mitsova 2013
2 #Select more responsive bands to vegetation
3 lsat5= ['lsat5_1986_30', 'lsat5_1986_40', 'lsat5_1986_50', '
lsat5_1986_70']
4 lsat8= ['lsat8_2016_40', 'lsat8_2016_50', 'lsat8_2016_60', '
lsat8_2016_70']
5
6 #Choose between spectral bands that maximize variance
7 grass.read_command('i.oif', input=lsat5)
8 grass.read_command('i.oif', input=lsat8)
9
10 #Perform PCA with OIF results
11 lsat_bands=['lsat5_1986_30', 'lsat5_1986_40', 'lsat5_1986_50', '
lsat8_2016_40', 'lsat8_2016_50', 'lsat8_2016_60']
12 grass.run_command('i.pca', input=lsat_bands, output="lsat_pca")
13
14 #Perform a simple change detection analysis
15 #look at data with i.color.enhance, d.rgb and r.univar
16 grass.read_command('r.univar', flags="e", map="lsat_pca.3")
17
18 #Consider as change in vegetation values over the 90th percentile
19 formula="changes=if(lsat_pca.3 > 163,1,null())"
20 grass.mapcalc(formula)
21
22 #Consider only change in vegetation reflectance
23 formula="changes_veg_noise=if((changes==1 && DEM<2800), 1, null())"
24 grass.mapcalc(formula)
25
26 #Vectorize results
27 grass.run_command('r.to.vect', flags="s", type='area', input="
changes_veg_noise", output="changes_veg_noise")
28
29 #Remove small changes due to possible variation in pixel
reflectance or vegetation phenology

```

B. SCRIPTS

```
30 #(3*30)^2 = 8100 m^2
31 grass.run_command('v.clean', input="changes_veg_noise", output="
   changes_veg", tool='rmarea', threshold="8100")
32
33 #Select only changes in park boundary
34 grass.run_command('v.overlay', ainput="changes_veg", binput="
   Confine", operator='and', output="changes_veg_pngp")
35
36 #Change occurred in each valley
37 grass.run_command('v.to.rast', input="changes_veg_pngp", output="
   changes_veg_pngp", use='val')
38 grass.run_command('v.to.rast', input="Valli", output="valli", use='
   cat')
39 formula="change_veg_pngp_valley = if(changes_veg_pngp,valli,null())
   "
40 grass.mapcalc(formula)
41
42 #Heat map
43 grass.run_command('g.region', flags='ad', res='500')
44 grass.run_command('v.mkgrid', flags='h', map="hex_grid_500")
45 grass.run_command('g.region', flags='d', n="n+300", s="s-300", e="
   e+300", w="w-300", align="lsat8_2016_50" )
46 grass.run_command('v.select', ainput="hex_grid_500", binput="
   Confine", output="hex_grid_500_pngp", operator='overlap')
47 grass.run_command('v.rast.stats', map="hex_grid_500_pngp", raster=
   "changes_veg", column_prefix="count", method='number')
48 grass.run_command('v.colors', map="hex_grid_500_pngp", use="attr",
   column="count_number", color='viridis')
```

```
1 #Export categorical values of change_veg_pngp_valley map using r.
   out.xyz giving "comma" as field separator.
2 #Give the header to the table with a simple text editor
3 #Import dataset in R
4 change<-read.table('/home/user/Desktop/change_pngp/change_valley.
   csv', header=TRUE, sep=",")
5
6 #Use table command to count elements
7 change<-change$valley
8 counts<-table(change)
9
10 #Create the barplot
11 barplot(counts,
12         ylab="N. of changed cells",
13         ylim=c(0,2500),
14         names.arg=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"
15         ),
16         col =c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000
```

```

16         ")
        )

```

Identifying the nature of the change

```

1 #Set change as mask
2 #Report descriptive statistics
3 ndvi=grass.list_grouped(type='raster', pattern="*ndvi")['lsat']
4 print ndvi
5 for raster in ndvi:
6     input="" + raster
7     output="/home/user/Desktop/change_ndvi/stats_"+raster+".csv"
8     grass.run_command('r.univar', flags='te', map=raster, output=
9         output, separator='comma')
10 #Create group and export values including null data
11 for raster in ndvi:
12     input="" + raster
13     output="/home/user/Desktop/change_ndvi/"+raster+".csv"
14     grass.run_command('r.out.xyz', flags='i', input=raster, output=
15         output, separator='comma')

```

```

1 #Create dataset in a spreadsheet and check for null (faster for
2 small datasets)
3 #Import dataset in R
4 setwd('/home/user/Desktop/change_ndvi')
5 getwd()
6 ndvi_values<-read.table('ndvi_1986_2016.csv', header = TRUE, dec =
7     '.', sep = ',')
8 ndvi_1986<-ndvi_values$ndvi_1986
9 ndvi_2016<-ndvi_values$ndvi_2016
10 #Create boxplot for change values
11 summary(ndvi_1986)
12 summary(ndvi_2016)
13 boxplot(ndvi_1986,
14     ndvi_2016,
15     col = c("#45BF55", "#044C29"),
16     main="NDVI",
17     names=(c("1986", "2016")))
18 )
19
20 dev.copy(png, "change_ndvi_1986_2016.png", width=1162, height=567)
21 dev.off
22

```


B. SCRIPTS

```
23 #Check for significant difference with t-test for related samples
    with permutation test
24 #code was adapted from the code created by P. Legendre and G.
    Blanchet retrieved from
25 #http://adn.biol.umontreal.ca/~numericaledcology/Rcode/
26 t.paired.perm <- function(vec1, vec2, nperm=999, alternative="two.
    sided", silent=FALSE)
27
28 {
29   n1 <- length(vec1)
30   n2 <- length(vec2)
31   if(n1 != n2) stop("The two vectors have different lengths. They
    cannot be paired.")
32
33   tail <- match.arg(alternative, c("two.sided", "less", "greater"))
34
35   res = t.test(vec1, vec2, paired=TRUE, alternative=tail)
36   t.ref = res$statistic
37
38   # Print these first results
39   if(!silent) cat('\nt-test comparing the means of two related
    samples','\n','\n')
40   if(!silent) cat('Number of objects:',n1,'\n')
41   if(!silent) cat('Mean of the differences:',res$estimate,'\n')
42   if(!silent) cat('t statistic (paired observations):',t.ref,'\n')
43   if(!silent) cat('95 percent confidence interval of t:',res$conf.
    int,'\n')
44   if(!silent) cat('Degrees of freedom:',res$parameter,'\n')
45   if(!silent) cat('Alternative hypothesis:',tail,'\n')
46   if(!silent) cat('Prob (parametric):',res$p.value,'\n')
47
48   # Perform the permutation test
49   # Permutations are restricted to the two related observations for
    each object.
50   nPGE <- 1
51
52   for(i in 1:nperm)
53   {
54     ## New permutation code, GB
55     mat <- cbind(vec1,vec2)
56     topermute <- rbinom(n1,1,0.5)
57     mat[topermute==1,] <- mat[topermute==1,2:1]
58     ## End new code, GB
59
60     res.perm = t.test(mat[,1], mat[,2], paired=TRUE, alternative=
    tail)
61     t.perm = res.perm$statistic
```

```

62
63     if(tail == "two.sided") if( abs(t.perm) >= abs(t.ref) ) nPGE <-
        nPGE+1
64     if(tail == "less") if(t.perm <= t.ref) nPGE <- nPGE+1
65     if(tail == "greater") if(t.perm >= t.ref) nPGE <- nPGE+1
66 }
67
68 # Compute and print the permutational p-value
69 P <- nPGE/(nperm+1)
70 if(!silent) cat('Prob (',nperm,'permutations):',formatC(P,digits
    =5,width=7,format="f"),'\n')
71 #
72 return(list(t.ref=t.ref, p.param=res$p.value, p.perm=P, nperm=
    nperm))
73 }
74
75 res_tpair = t.paired.perm(ndvi_1986, ndvi_2016)
76
77 #Comparison with t test
78 res_ttest = t.test(ndvi_1986, ndvi_2016, paired=TRUE)

```

Measuring the areal extent of the change

```

1 r.report map=changes_veg_pngp units=h,c,p
2 r.report map=change_veg_pngp_valley units=h,c,p

```

Assessing the spatial pattern of the change

```

1 #Export univariate raster statistics
2 geomorphometry=['DEM', 'slope', 'aspect', 'gr_year_MJ', 'it_year',
    'vrn']
3
4 for raster in geomorphometry:
5     input="" + raster
6     output="/home/user/Desktop/raster_statistics/change_stats/
    valley_"+input+".csv"
7     grass.run_command('r.univar', flags='te', map=input, output=
    output, separator='comma', zones="change_veg_pngp_valley")
8
9 for raster in geomorphometry:
10     input="" + raster
11     output="/home/user/Desktop/raster_statistics/change_stats/gpnp_
    "+input+".csv"
12     grass.run_command('r.univar', flags='te', map=input, output=
    output, separator='comma', zones="changes_veg_pngp")

```

B. SCRIPTS

```
1 #Export geomorphons
2 r.mapcalc "expression=change_geomorphons=if(changes_veg_pngp,
   geomorph_dem_10_15, null())"
3 r.report map=change_geomorphons units=h,c,p output=/home/user/
   Desktop/raster_statistics/change_stats/change_geomorph_dem_10_15.
   txt
4
5 #Running the above r.report command for each valley setted as mask
6
7 #Switch in R
8 R

1 #Change spatial pattern representations
2 #Load rgrass7 library
3 library(rgrass7)
4 gnp_data <- readRAST(c("changes_veg_pngp", "change_veg_pngp_
   valley", "DEM", "slope", "aspect", "vrm", "gr_year_MJ", "it_year"),
   cat=c(TRUE, TRUE, FALSE, FALSE, FALSE, FALSE, FALSE, FALSE))
5
6 #DEM GPNP
7 boxplot(gnp_data$DEM ~ gnp_data$changes_veg_pngp,
8         medlwd = 1,
9         main="Elevation",
10        col = "#45BF55",
11        xlab = "GPNP"
12        )
13
14 #DEM valleys
15 boxplot(gnp_data$DEM ~ gnp_data$change_veg_pngp_valley,
16        medlwd = 1,
17        main="Elevation",
18        names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
19        col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000")
20        )
21
22 #Slope GPNP
23 boxplot(gnp_data$slope ~ gnp_data$changes_veg_pngp,
24        medlwd = 1,
25        main="Slope",
26        col = "#45BF55",
27        xlab = "GPNP"
28        )
29
30 #Slope valleys
31 boxplot(gnp_data$slope ~ gnp_data$change_veg_pngp_valley,
32        medlwd = 1,
```

```

33     main="Slope",
34     names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
35     col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000"
36         )
37 )
38 #Aspect GPNP
39 boxplot(gnpn_data$aspect ~ gnpn_data$changes_veg_pngp,
40     medlwd = 1,
41     main="Aspect",
42     col = "#45BF55",
43     xlab = "GPNP"
44 )
45
46 #Aspect valleys
47 boxplot(gnpn_data$aspect ~ gnpn_data$change_veg_pngp_valley,
48     medlwd = 1,
49     main="Aspect",
50     names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
51     col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000"
52         )
53 )
54 #vrm GPNP
55 boxplot(gnpn_data$vrm ~ gnpn_data$changes_veg_pngp,
56     medlwd = 1,
57     outline=FALSE,
58     main="Vector Ruggedness measure",
59     col = "#45BF55",
60     xlab = "GPNP"
61 )
62
63 #vrm valleys
64 boxplot(gnpn_data$vrm ~ gnpn_data$change_veg_pngp_valley,
65     medlwd = 1,
66     outline=FALSE,
67     main="Vector Ruggedness measure",
68     names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
69     col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000"
70         )
71 )
72 #Global radiation GPNP
73 boxplot(gnpn_data$gr_year_MJ ~ gnpn_data$changes_veg_pngp,
74     medlwd = 1,
75     main="Global radiation",
76     col = "#45BF55",

```

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```
77     xlab = "GPNP"
78   )
79
80 #Global radiation valleys
81 boxplot(gnp_data$gr_year_MJ ~ gnp_data$change_veg_pngp_valley,
82         medlwd = 1,
83         main="Global radiation",
84         names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
85         col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000"
86         )
87   )
88
89 #Insolation time GPNP
90 boxplot(gnp_data$it_year ~ gnp_data$changes_veg_pngp,
91         medlwd = 1,
92         main="Insolation time",
93         col = "#45BF55",
94         xlab = "GPNP"
95   )
96
97 #Insolation time valleys
98 boxplot(gnp_data$it_year ~ gnp_data$change_veg_pngp_valley,
99         medlwd = 1,
100        main="Insolation time",
101        names=c("Cogne", "Rhemes", "Valsavara", "Soana", "Orco"),
102        col=c("#0000FF", "#008000", "#FFFF00", "#FFA500", "#FF0000"
103        )
104  )
```

```
1 #Using r.out.xyz and a spreadsheet to create geomorphon value and
  change per valley tables
2 #Set working directory
3 setwd('/home/user/Desktop/raster_statistics/change_stats/')
4 getwd()
5 geomorph_values<-read.table('/home/user/Desktop/raster_statistics/
  change_stats/change_geomorph_dem_10_15.csv', header=TRUE, sep=",")
6 valley<-read.table('/home/user/Desktop/raster_statistics/change_
  stats/change_valley.csv', header=TRUE, sep=",")
7
8 #GPNP change distribution in landforms
9 #Use table command to count elements
10 geomorphons<-geomorph_values$value
11 counts<-table(geomorphons)
12
13 #Create the barplot
14 barplot(counts,
15         ylab = "Frequency",
```

```

16     main = "Change distribution in landforms",
17     col = c("#380000", "#C80000", "#FAD23C", "#FFFF3C", "#
      B4E614", "#3CFA96", "#0000FF", "#000038"),
18     names.arg = c("summit", "ridge", "spur", "slope", "hollow",
      "footslope", "valley", "depression")
19   )
20
21 dev.copy(png, '/media/sf_osgeo10.5/lsat/barplot_change_geomorph.png',
      , width=1120, height=674)
22 dev.off()
23
24 #GPNP valley change distribution in landforms
25 #Use table command to count elements
26 geomorphons<-geomorph_values$value
27 valley<-valley$valley
28 counts<-table(geomorphons, valley)
29
30 barplot(counts,
31         main="Change distribution in landforms",
32         names.arg = c("Cogne", "Rhemes", "Valsavara", "Soana", "
      Orco"),
33         col = c("#380000", "#C80000", "#FAD23C", "#FFFF3C", "#
      B4E614", "#3CFA96", "#0000FF", "#000038")
34       )
35 legend("topleft",
36       c("summit", "ridge", "spur", "slope", "hollow", "footslope",
      "valley", "depression"),
37       cex=0.9,
38       bty="n",
39       fill=c("#380000", "#C80000", "#FAD23C", "#FFFF3C", "#B4E614",
      "#3CFA96", "#0000FF", "#000038"),
40       ncol=2)
41
42 dev.copy(png, '/media/sf_osgeo10.5/lsat/barplot_change_valley_
      geomorph.png', width=1120, height=674)
43 dev.off()

```

B.2.2 | Fragmentation analysis

```

1 #Fourier transform analysis following Rocchini et al. 2013 code
  retrieved from:
2 #https://grasswiki.osgeo.org/wiki/
  Fourier_transforms_for_multitemporal_analysis
3
4 #Compute principal component analysis
5 i.pca input=lsat5_1986_10,lsat5_1986_20,lsat5_1986_30,
  lsat5_1986_40,lsat5_1986_50,lsat5_1986_70 output=lsat5_1986_pca

```

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```
6 i.pca input=lsat8_2016_20,lsat8_2016_30,lsat8_2016_40,  
lsat8_2016_50,lsat8_2016_60,lsat8_2016_70 output=lsat8_2016_pca  
7  
8 #Import and esport data from a virtual machine hosting OSGEO Live  
7.9 with r.pack and r.unpack. The module i.fft gives different  
results between GRASS GIS 6.4.3 and GRASS GIS 7.2  
9  
10 #Switch in R  
11 R
```

```
1 #Require the rgrass7 library  
2 library(rgrass7)  
3  
4 #Import data as object  
5 fft.images<-readRAST(c('lsat5_1986_pca1_real','lsat8_2016_pca1_  
real'), cat=c(F,F), ignore.stderr=TRUE, plugin=NULL)  
6  
7 #Import the library sm  
8 library(sm)  
9  
10 #Apply kernel density function and create kernel density plot  
11 sm.density(fft.images$lsat5_1986_pca1_real, lty=1,lwd=2, ann=T,  
xlim=c(0,255), ylim=c(0,0.013), xlab='Fourier transform value',  
col='blue', cex.label=4)  
12 par(new=T)  
13 sm.density(fft.images$lsat8_2016_pca1_real, lty=1, lwd=2, ann=F,  
xlim=c(0,255), ylim=c(0,0.013), xlab=' ', col='red', cex.label=4)  
14 legend(110, 0.012, c('Density function 1986', 'Density function  
2016'), fill = c('blue', 'red'), cex=1.2, box.lty=0)  
15  
16 #Require hexbin package  
17 library(hexbin)  
18  
19 #Plot the Fourier-transformed values by hexagon binning  
20 library(hexbin)  
21 hbin <- hexbin(fft.images$lsat5_1986_pca1_real, fft.images$lsat8_  
2016_pca1_real, xbins = 50)  
22 plot.bin<-plot(hbin, legend = 1.2, lcex = 0.5, minarea = 0.04,  
maxarea = 0.8, style = 'nested.lattice', xlab='Fourier transform  
value 1987', ylab='Fourier transform value 2002')  
23 hexVP.abline(plot.bin$plot.vp, 0, 1)
```

B.3 | Aerial images

B.3.1 | Vegetation pattern change

```

1 #In GRASS GIS 6
2 #Import the image through GUI and r.in.gdal
3 #Choose the computational regions from display extent and
  adjusting them
4 regions=['gpa', 'gpb', 'gpc', 'gpd', 'gpe', 'gpf', 'gpg']
5
6 for region in regions:
7     region="" + region
8     grass.run_command('g.region', flags='a', overwrite='TRUE',
9         region=region, res="1", save=region)
10
11 #Compute fft for each plot for the two images of 1975 RATI flight
12 #Select plots in 75R_6 27 image
13 plot_image_6_27=['gpa', 'gpb', 'gpc', 'gpd', 'gpe']
14
15 for plot_04 in plot_image_6_27:
16     plot_04="" + plot_04
17     real="fft_1975_" + plot_04 + "_real"
18     imag="fft_1975_" + plot_04 + "_imag"
19     grass.run_command('g.region', flags='a', region=plot_04, align=
20         "x5R_6_27_ortho")
21     grass.run_command('i.fft', input_image="x5R_6_27_ortho",
22         real_image=real, imaginary_image=imag)
23
24 #Select plots in 75R_6 28 image
25 plot_image_6_28=['gpf', 'gpg']
26
27 for plot_085 in plot_image_6_28:
28     plot_085="" + plot_085
29     real="fft_1975_" + plot_085 + "_real"
30     imag="fft_1975_" + plot_085 + "_imag"
31     grass.run_command('g.region', flags='a', region=plot_085, align=
32         "x5R_6_28_ortho_nearest")
33     grass.run_command('i.fft', input_image="x5R_6_28_ortho_nearest",
34         real_image=real, imaginary_image=imag)
35
36 #Compute ffts for 112120 image of 2010 ICE Piemonte flight
37 #To compare results we have to set different computational regions
38 #Select computational regions and perform pca
39 grass.run_command('g.region', rast="x5R_6_27_ortho")
40 grass.run_command('i.pca', input="Orco_ICE_2010.red,Orco_ICE_2010.
41     green,Orco_ICE_2010.blue", output_prefix="pca_04_orco_2010")
42 grass.run_command('g.region', rast="x5R_6_28_ortho_nearest")

```


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```
37 grass.run_command('i.pca', input="Orco_ICE_2010.red,Orco_ICE_2010.  
green,Orco_ICE_2010.blue", output_prefix="pca_085_orco_2010")  
38  
39 #Select plots in 75R_6 27 image and compute ffts  
40 for plot_04 in plot_image_6_27:  
41     plot_04="" + plot_04  
42     real="fft_04_2010_" + plot_04 + "_real"  
43     imag="fft_04_2010_" + plot_04 + "_imag"  
44     grass.run_command('g.region', flags='a', region=plot_04, align=  
"pca_04_orco_2010.1")  
45     grass.run_command('i.fft', input_image="pca_04_orco_2010.1",  
real_image=real, imaginary_image=imag)  
46  
47 #Select plots in 75R_6 28 image and compute ffts  
48 for plot_085 in plot_image_6_28:  
49     plot="" + plot_085  
50     real="fft_085_2010_" + plot_085 + "_real"  
51     imag="fft_085_2010_" + plot_085 + "_imag"  
52     grass.run_command('g.region', flags='a', region=plot_085, align=  
"pca_085_orco_2010.1")  
53     grass.run_command('i.fft', input_image="pca_085_orco_2010.1",  
real_image=real, imaginary_image=imag)  
54  
55 Export using r.pack to compute R analysis  
56  
57 fft=grass.mlist_grouped('rast', pattern='fft*')['lsat']  
58  
59 for raster in fft:  
60     raster="" + raster  
61     pack="/home/user/Desktop/fft_pack/" + raster + ".pack"  
62     grass.run_command('r.pack', input=raster, output=pack)
```

```
1 #To import in GRASS GIS 7 use shell and navigate to folder  
2 cd ~/fft_pack  
3 #create group with ls  
4 pack='ls -a *pack'  
5 #import data  
6 for raster in $pack  
7 do  
8     r.unpack input=$raster  
9 done  
10  
11 #Switch in R  
12 R
```

```
1 #Import libraries  
2 library(rgrass7)
```

```

3 library(sm)
4 library(hexbin)
5
6 #1975-2010
7 #gpa
8 #Import data
9 execGRASS("g.region", raster = "fft_04_2010_gpa_real,fft_04_2010_
  gpb_real,fft_04_2010_gpc_real,fft_04_2010_gpd_real,fft_04_2010_gpe
  _real", flags = "p")
10 fft.images<-readRAST(c('fft_1975_gpa_real','fft_04_2010_gpa_real'),
  cat=c(F,F),ignore.stderr=TRUE,plugin=NULL)
11
12 #Kernel density plot
13 sm.density(fft.images$fft_1975_gpa_real,lty=1,lwd=2,ann=T,xlim=c
  (0,255),ylim=c(0,0.02),xlab='Fourier transform value',col='blue',
  cex.label=4)
14 par(new=T)
15 sm.density(fft.images$fft_04_2010_gpa_real,lty=1,lwd=2,ann=F,xlim=
  c(0,255),ylim=c(0,0.02),xlab='',col='red',cex.label=4)
16 legend(110,0.012,c('Density function 1975','Density function 2010')
  ,fill=c('blue','red'),cex=1.2,box.lty=0)
17
18 #Export image
19 dev.copy(png,'fourier_fd_1975_2010_gpa.png')
20 dev.off()
21
22 #Hexagon binning
23 hbin<-hexbin(fft.images$fft_1975_gpa_real,fft.images$fft_04_2010_
  gpa_real)
24 plot.bin<-plot(hbin, style='nested.lattice', legend=1.2, lcex=0.5,
  minarea=0.04, maxarea=0.8, xlab='Fourier transform value 1975',
  ylab='Fourier transform value 2010', main='gpa 1975-2010')
25 hexVP.abline(plot.bin$plot.vp,0,1)
26
27 #Export image
28 dev.copy(png,'hexbin_1975_2010_gpa.png')
29 dev.off()
30
31 #gpf
32 #Import data
33 execGRASS("g.region", raster = "fft_085_2010_gpf_real,fft_085_2010_
  _gpg_real", flags = "p")
34 fft.images<-readRAST(c('fft_1975_gpf_real','fft_085_2010_gpf_real')
  ,cat=c(F,F),ignore.stderr=TRUE,plugin=NULL)
35
36 #Kernel density plot
37 sm.density(fft.images$fft_1975_gpf_real,lty=1,lwd=2,ann=T,xlim=c

```

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```
(0,255),ylim=c(0,0.02),xlab='Fourier transform value',col='blue',
cex.label=4)
38 par(new=T)
39 sm.density(fft.images$fft_085_2010_gpf_real,lty=1,lwd=2,ann=F,xlim
=c(0,255),ylim=c(0,0.02),xlab='',col='red',cex.label=4)
40 legend(110,0.012,c('Density function 1975','Density function 2010')
,fill=c('blue','red'),cex=1.2,box.lty=0)
41
42 #Export image
43 dev.copy(png,'fourier_fd_1975_2010_gpf.png')
44 dev.off()
45
46 #Hexagon binning
47 hbin<-hexbin(fft.images$fft_1975_gpf_real,fft.images$fft_085_2010_
gpf_real)
48 plot.bin<-plot(hbin, style='nested.lattice', legend=1.2, lcex=0.5,
minarea=0.04, maxarea=0.8, xlab='Fourier transform value 1975',
ylab='Fourier transform value 2010', main='gpf 1975-2010')
49 hexVP.abline(plot.bin$plot.vp,0,1)
50
51 #Export image
52 dev.copy(png,'hexbin_1975_2010_gpf.png')
53 dev.off()
```

B.3.2 | Image classification

Image preparation

```
1 #Set the PERMANENT location
2 #Import data using the module r.in.gdal through the GUI
3 #Rename the imported data assign to band number the band color
4 g.rename raster=c_2011_ice_x_6646.1,c_2011_ice_x_6646.red,
c_2011_ice_x_6650.1,c_2011_ice_x_6650.red,c_2011_ice_x_6654.1,
c_2011_ice_x_6654.red,v_2011_ice_x_5846.1,v_2011_ice_x_5846.red,
v_2011_ice_x_5850.1,v_2011_ice_x_5850.red,v_2011_ice_x_5854.1,
v_2011_ice_x_5854.red,v_2011_ice_x_6246.1,v_2011_ice_x_6246.red,
v_2011_ice_x_6250.1,v_2011_ice_x_6250.red,v_2011_ice_x_6254.1,
v_2011_ice_x_6254.red
5 g.rename raster=c_2011_ice_x_6646.2,c_2011_ice_x_6646.green,
c_2011_ice_x_6650.2,c_2011_ice_x_6650.green,c_2011_ice_x_6654.2,
c_2011_ice_x_6654.green,v_2011_ice_x_5846.2,v_2011_ice_x_5846.
green,v_2011_ice_x_5850.2,v_2011_ice_x_5850.green,
v_2011_ice_x_5854.2,v_2011_ice_x_5854.green,v_2011_ice_x_6246.2,
v_2011_ice_x_6246.green,v_2011_ice_x_6250.2,v_2011_ice_x_6250.
green,v_2011_ice_x_6254.2,v_2011_ice_x_6254.green
6 g.rename raster=c_2011_ice_x_6646.3,c_2011_ice_x_6646.blue,
c_2011_ice_x_6650.3,c_2011_ice_x_6650.blue,c_2011_ice_x_6654.3,
```

```

c_2011_ice_x_6654.blue,v_2011_ice_x_5846.3,v_2011_ice_x_5846.blue,
v_2011_ice_x_5850.3,v_2011_ice_x_5850.blue,v_2011_ice_x_5854.3,
v_2011_ice_x_5854.blue,v_2011_ice_x_6246.3,v_2011_ice_x_6246.blue,
v_2011_ice_x_6250.3,v_2011_ice_x_6250.blue,v_2011_ice_x_6254.3,
v_2011_ice_x_6254.blue
7
8 #In GRASS shell set region and resolution saving as levionaz
9 MAPS=$(g.list -m type=raster pattern=*.red mapset=PERMANENT
separator=comma)
10 g.region -p -a -d res=0.5 save=levionaz raster=$MAPS
11
12 #Set the user location in this case 'levionaz'
13 #match maps avoiding tile line
14 r.mapcalc expression="levionaz.red = nmax(c_2011_ice_x_6646.
red@PERMANENT,c_2011_ice_x_6650.red@PERMANENT,c_2011_ice_x_6654.
red@PERMANENT,v_2011_ice_x_5846.red@PERMANENT,v_2011_ice_x_5850.
red@PERMANENT,v_2011_ice_x_5854.red@PERMANENT,v_2011_ice_x_6246.
red@PERMANENT,v_2011_ice_x_6250.red@PERMANENT,v_2011_ice_x_6254.
red@PERMANENT)"
15 r.mapcalc expression="levionaz.green = nmax(c_2011_ice_x_6646.
green@PERMANENT,c_2011_ice_x_6650.green@PERMANENT,
c_2011_ice_x_6654.green@PERMANENT,v_2011_ice_x_5846.
green@PERMANENT,v_2011_ice_x_5850.green@PERMANENT,
v_2011_ice_x_5854.green@PERMANENT,v_2011_ice_x_6246.
green@PERMANENT,v_2011_ice_x_6250.green@PERMANENT,
v_2011_ice_x_6254.green@PERMANENT)"
16 r.mapcalc expression="levionaz.blue = nmax(c_2011_ice_x_6646.
blue@PERMANENT,c_2011_ice_x_6650.blue@PERMANENT,c_2011_ice_x_6654.
blue@PERMANENT,v_2011_ice_x_5846.blue@PERMANENT,v_2011_ice_x_5850.
blue@PERMANENT,v_2011_ice_x_5854.blue@PERMANENT,v_2011_ice_x_6246.
blue@PERMANENT,v_2011_ice_x_6250.blue@PERMANENT,v_2011_ice_x_6254.
blue@PERMANENT)"
17
18 #Calculate the Principal Component Analysis on visible bands to
reduce data redundancy in segmentation process
19 i.pca input=levionaz.red,levionaz.green,levionaz.blue output=
levionaz_pca

```

Object creation

```

1 #The following Python script is adapted by the code uploaded (
https://github.com/tgrippa/Opensource_OBIA_processing_chain).
2
3 #Create subregion in which analyze variance
4 grass.run_command('g.region', region="levionaz")
5 grass.run_command('v.mkgrid', map="grid", box="500,500")

```

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```
6 grass.run_command('v.select', ainput="grid", binput="MPC100",
  output="region_uspo", operator="overlap")
7
8 #Create a computational region for each polygon
9 for cat in grass.parse_command('v.db.select', map='region_uspo',
  columns='cat', flags='c'):
10     condition="cat="+cat
11     outputname="region_uspo_"+cat
12     regionname="subset_uspo_"+cat
13     grass.run_command('v.extract', input="region_uspo", type="area"
  , where=condition, output=outputname)
14     grass.run_command('g.region', vector=outputname, save=
  regionname, align="levionaz_pca.1", flags="u")
15     grass.run_command('g.remove', type="vector", name=outputname,
  flags="f")
16
17 #Define i.segment.uspo parameters
18 grass.run_command('i.group', group="levionaz_pca", input="
  levionaz_pca.1")
19 group="levionaz_pca"
20 start="0.02"
21 stop="0.91"
22 step="0.02"
23
24 #Define region
25 regions=grass.list_strings(type='region', pattern="subset", mapset
  ="levionaz", flag='r')
26
27 #Run i.segment.uspo
28 for region in regions:
29     regions_uspo="" + region
30     outputcsv="/home/user/Desktop/Levionaz/thres_" + region + ".csv"
31     grass.run_command('i.segment.uspo', flags='k', group=group,
  output=outputcsv, segment_map="best", regions=regions_uspo,
  threshold_start=start, threshold_stop=stop, threshold_step=step
  , minsizes="1", number_best="5", memory="30720", processes="5")
32
33 #Define parameters derived from previous step
34 start="0.26"
35 stop="0.35"
36 step="0.02"
37
38 for region in regions:
39     regions_uspo="" + region
40     outputcsv="/home/user/Desktop/Levionaz/best_thresholds/
  best_thres_" + region + ".csv"
```

```

41 grass.run_command('i.segment.uspo', flags='k', group=group,
    output=outputcsv, segment_map="best_thres", regions=
    regions_uspo, threshold_start=start, threshold_stop=stop,
    threshold_step=step, minsizes="1", number_best="5", memory="
    30720", processes="5")
42
43 #Define parameters for minsize
44 best_thres="0.32"
45 min_start="1"
46 min_stop="30"
47 min_step="1"
48
49 for region in regions:
50     regions_uspo="" + region
51     outputcsv="/home/user/Desktop/Levionaz/min/min_" + region + ".csv"
52     grass.run_command('i.segment.uspo', flags='k', group=group,
        output=outputcsv, segment_map="min", regions=regions_uspo,
        thresholds=best_thres, minsize_start=min_start, minsize_stop=
        min_stop, minsize_step=min_step, number_best="5", memory="30720
        ", processes="5")
53
54
55 #Select the home range as mask
56 grass.run_command('r.mask', vector="MPC100")
57
58 #Run the segmentation
59 group="levionaz_pca"
60 seg="seg_levionaz_032_9"
61 best_thres="0.32"
62 best_min="9"
63 good="seg_goodness_levionaz_032_9"
64 grass.run_command('i.segment', group=group, output=seg, threshold=
    best_thres, minsize=best_min, memory="8192", goodness=good)

```

Object characterization

```

1 #Create the features for object classification
2 #Band ratio
3 #Color normalization using rgb chromaticity also known as rgb
    chromatic coordinates (Manhattan normalization). Sometimes the
    results of color normalization is multiplied to constant 255.
4 r.mapcalc expression="levionaz.rc=float(levionaz.red) / (levionaz.
    red + levionaz.green + levionaz.blue)"
5 r.mapcalc expression="levionaz.gc=float(levionaz.green) / (
    levionaz.red + levionaz.green + levionaz.blue)"
6 r.mapcalc expression="levionaz.bc=float(levionaz.blue) / (levionaz.
    red + levionaz.green + levionaz.blue)"

```

B. SCRIPTS

```
7
8 #Calculate the normalized green red difference index
9 r.mapcalc expression="levionaz_ngrdi=(levionaz.gc - levionaz.rc) /
  (levionaz.gc + levionaz.rc)"
10
11 #Calculate the green excess index
12 r.mapcalc expression="levionaz_gei=2*levionaz.gc - levionaz.rc -
  levionaz.bc"
13
14 #Calculate the green leaf algorithm
15 r.mapcalc expression="levionaz_gla=(2 * levionaz.gc - levionaz.rc -
  levionaz.bc) / (2 *levionaz.gc + levionaz.rc + levionaz.bc)"
16
17 #Calculate the bare ground index
18 r.mapcalc expression="levionaz_bgi=3*levionaz.green - levionaz.red
  - 100"
19
20 #Calculate the Woebbecke's index
21 r.mapcalc expression="levionaz_wi=(levionaz.gc - levionaz.bc) / (
  levionaz.rc - levionaz.gc)"
22
23 #Brightness
24 r.mapcalc expression="levionaz_brightness=levionaz.red+levionaz.
  green+levionaz.blue"
25
26 #Texture
27 #Choose a smaller region to reduce computational time
28 g.region -p n=5051940 s=5046710 e=365180 w=359780 res=0.5 align=
  levionaz.red save=home_range_text
29
30 #Calculate texture features for brightness channel selecting the
  most used in literature
31 r.texture input="levionaz_brightness" output="text_bright_5" size
  =5 distance=1 method="asm,contrast,corr,idm,entr"
32
33 #Compute the standard deviation
34 r.neighbors input="levionaz_brightness" output="text_bright_5_sd"
  method="stddev" size=5
35
36 #Check data and remove the redundant ones
37 #Adjust computational region and create a mask on home range
38 g.region -p zoom=text_red_5_ASM save=home_range
39 r.mask maskcats=* vector=MPC100 layer=1
40
41 #Check brightness and band ratio
42 r.covar -r map=levionaz_brightness,levionaz_ngrdi,levionaz_gei,
  levionaz_gla,levionaz_bgi,levionaz_wi
```

```

43
44 #Textures
45 r.covar -r map=text_bright_5_ASM,text_bright_5_Contr,
    text_bright_5_Corr,text_bright_5_Entr,text_bright_5_IDM,
    text_bright_5_sd
46
47 #Check for data collinearity
48 r.vif maps=levionaz.brightness,levionaz.ngrdi,levionaz.gla,
    levionaz.wi,text_bright_5_Contr,text_bright_5_Corr,
    text_bright_5_Entr,text_bright_5_IDM,text_bright_5_sd n=100% file=
    home/user/Desktop/Levionaz/vif_results.csv

```

```

1 #Normalize selected features. The normalization process chosen is
  the feature scaling also known as unity-based normalization.
2 #Create group
3 bands=['levionaz_brightness','levionaz_ngrdi','levionaz_gla','
  levionaz_wi']
4 textures=grass.list_grouped('raster', pattern='text_bright_5*')['
  levionaz']
5 features=bands+textures+['DEM']
6
7 #Normalize with r.mapcalc (float is for brightness).
8 for raster in features:
9     stats = grass.parse_command('r.univar', map=raster, flags='g')
10    output="res_"+raster
11    range=stats['range']
12    min=stats['min']
13    grass.mapcalc('{res_map}=float({map}-{min})/{range}'.format(
        res_map=output, map=raster, min=min, range=range))
14
15
16 #Calculate the segment stats
17 #Give unique id to segments
18 grass.run_command('r.clump', input="seg_levionaz_026_9", output="
  seg_home_range")
19
20 #Vectorize results
21 grass.run_command('r.to.vect', input="seg_home_range", output="
  seg_home_range_stats", type='area')
22
23 #Removing undesired column
24 grass.run_command('v.db.dropcolumn', map="seg_home_range_stats",
  columns="value,label")
25
26 #Fill the table attribute
27 #with shape features
28 shape_feature=['area','perimeter', 'compact', 'fd']

```


B. SCRIPTS

```
29 for shape in shape_feature:
30     shape="" + shape
31     column_type="" + shape + " double precision"
32     grass.run_command('v.db.addcolumn', map="seg_home_range_stats",
33                       columns=column_type)
34     grass.run_command('v.to.db', map="seg_home_range_stats", option=
35                       shape, columns=shape)
36 #with rescaled features
37 res_features=grass.list_grouped('raster', pattern='res_*')['
38 levionaz']
39 for raster in res_features:
40     raster="" + raster
41     grass.run_command('v.rast.stats', map="seg_home_range_stats",
42                       raster=raster, column_prefix=raster, method='range,average,stddev
43                       ,variance')
44 #Normalize shape statistics in R it's faster.
45 #Export table as csv
46 grass.run_command('db.out.ogr', input="seg_home_range_stats",
47                   output="/home/user/Desktop/Levionaz/classification/feature_stats.
48                   csv", format='CSV')
```

```
1 #switch in R
2 #Normalize vector table in R leaving cat column
3 #export table as csv and importing working directory
4 setwd('/home/user/Desktop/Levionaz/classification')
5 getwd()
6 segment_stats<-read.table('/home/user/Desktop/Levionaz/
7 classification/feature_stats.csv', header=TRUE, sep=',')
8
9 #check for null data
10 is.null(segment_stats)
11
12 #create normalization function
13 range01<-function(x){(x-min(x))/(max(x)-min(x))}
14
15 #create dataset leaving cat column and normalizing only shape
16 statistics
17 norm_seg_stats<-data.frame(segment_stats[1:1],lapply(segment_stats
18 [2:5], range01), segment_stats[6:49])
19
20 #check new table
21 lapply(norm_seg_stats,range)
22
23 #export as csv removing the word quotes and row names
24 write.table(norm_seg_stats, file = "unlabeled_res_feature_stats.
```

```
csv", dec=".", sep = ",", quote = FALSE, col.names = TRUE, row.
names = FALSE)
```

Object labelling

```
1 #Create or import the initial training set and test set
2 #We used v.random to create starting points. v.db.addcolumn, v.
  what.vect, v.db.update to select land cover from an already
  created layer (v.vect.stats to find objects with more than one
  random point). This phase was accomplished using QGIS as GUI.
3 #Start the guided learning algorithm
4 r.object.activelearning training_set=/home/user/Desktop/
  classification/training_set.csv test_set=/home/user/Desktop/
  classification/test_set.csv unlabeled_set=/home/user/Desktop/
  classification/unlabeled_set.csv
5
6 #Classify the results
7 v.class.mlR segments_file=segstats.csv training_file=training_set.
  csv train_class_column=class output_prob_column=prob
  raster_segments_map=seg_home_range classified_map=class
  classification_results=class_results.csv classifiers=svmRadial,rf,
  rpart,C5.0,knn folds=5 partitions=10 tunelength=10 weighting_modes
  =smv,swv,bwv,qbwv weighting_metric=accuracy
```

Accuracy assessment

```
1 #Compute accuracy assessment
2 legend="/home/user/Desktop/classification/legend.txt"
3 colors="/home/user/Desktop/classification/colors.txt"
4 output_path="/home/user/Desktop/classification/"
5
6 maps_to_rec=grass.list_grouped('raster', pattern="class_*")["
  levionaz"]+['test_set']
7
8 for map in maps_to_rec:
9     grass.run_command('r.reclass', overwrite='TRUE', input=map,
10      output="rec_"+map, rules=legend)
11     grass.run_command('r.colors', map="rec_"+map, rules=colors)
12 for classification in grass.list_grouped('raster', pattern="
  rec_class_*")["levionaz"]:
13     grass.run_command('r.kappa', flags="w", classification=
      classification, reference="rec_test_set", output=output_path+
      classification+".txt")
```

C | Results

C.1 | Digital elevation model

C.1.1 | Land-surfaces characterization

Elevation

DEM	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	7102254	641404	1479926	1617727	1161612	2201584
min	669.11	1102	1085.43	1050.23	895.26	669.11
max	4059.9	3444.19	4055.74	4059.9	3404.8	4021.68
range	3390.79	2342.19	2970.31	3009.66	2509.54	3352.57
mean	2405.59	2438.66	2558.36	2562.66	2130.19	2323.16
sd	550.755	490.197	519.501	516.186	512.477	558.397
variance	303331	240293	269881	266448	262633	311807
cv (%)	22.8948	20.1011	20.306	20.1425	24.0578	24.0361
1 st quart	2021.18	2131.55	2234.7	2215.1	1737.58	1939.99
median	2468.79	2532.79	2647.56	2599.66	2170	2371
3 rd quart	2803.65	2804.31	2919.02	2915.79	2528.16	2737.98
90 th perc	3071.81	2998.74	3163.8	3231.6	2782.94	3008.94

Table C.1 | Elevation (m) descriptive statistics.

Slope

Slope	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	7102058	641404	1479926	1617727	1161612	2201388
min	0	0	0	0	0	0
max	83.7766	79.4298	81.8849	83.7766	78.4804	78.5308
range	83.7766	79.4298	81.8849	83.7766	78.4804	78.5308
mean	32.0156	30.2215	31.0791	32.0119	33.8524	32.2015
sd	13.3467	12.258	14.2358	13.6152	11.9388	13.4123
variance	178.134	150.258	202.658	185.375	142.536	179.89
cv (%)	41.688	40.5605	45.805	42.5318	35.2674	41.6512
1 st quart	22.7079	21.6078	20.1746	22.4242	26.5083	23.2562
median	32.5479	30.2601	31.5038	32.0579	34.7143	32.8424
3 rd quart	40.5335	37.696	40.499	40.9397	41.374	40.5856
90 th perc	48.9875	45.2385	49.5015	49.8294	48.3386	49.2198

Table C.2 | Slope (°) descriptive statistics (196 null-values in Orco valley).

Aspect

Aspect	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	7102058	641404	1479926	1617727	1161612	2201388
min	0	0	0	0	0	0
max	360	359.999	360	360	360	360
range	360	359.999	360	360	360	360
mean	172.705	150.797	166.249	135.316	189.728	201.922
sd	107.33	56.3636	100.088	104.144	121.221	107.603
variance	11519.7	3176.86	10017.7	10845.9	14694.5	11578.3
cv (%)	62.1462	37.3772	60.2038	76.9633	63.8919	53.2892
1 st quart	75.3308	120.163	92.2881	53.9502	59.2986	97.2859
median	167.88	149.532	161.39	106.877	228.998	234.411
3 rd quart	266.141	179.743	228.573	184.418	297.293	286.103
90 th perc	325.446	216.865	324.447	325.318	337.356	326.375

Table C.3 | Aspect CCW (°) descriptive statistics (196 null-values in Orco valley).

C. RESULTS

Ruggedness

VRM	GPNP
n	7102254
min	-3.76278e-08
max	0.555244
range	0.555244
mean	0.00700932
sd	0.0159636
variance	0.000254838
cv (%)	227.749
1 st quart	0.000891861
median	0.00240836
3 rd quart	0.0063699
90 th perc	0.0156905

Table C.4 | VRM descriptive statistics referred to park area.

VRM	Rhemes	Valsavara	Cogne	Soana	Orco
n	641404	1479926	1617727	1161612	2201584
min	-1.61478e-08	-2.23715e-08	-1.56083e-08	-9.18908e-09	-3.76278e-08
max	0.401569	0.555244	0.543273	0.374952	0.466669
range	0.401569	0.555244	0.543273	0.374952	0.466669
mean	0.006884	0.00776217	0.00782497	0.00643748	0.00624214
sd	0.0158639	0.0172096	0.0173034	0.0150014	0.0144677
variance	0.000251662	0.000296171	0.000299408	0.000225043	0.000209313
cv (%)	230.445	221.712	221.131	233.033	231.774
1 st quart	0.0010093	0.00104402	0.00111236	0.000686069	0.000745421
median	0.00242319	0.00270464	0.00287439	0.00200068	0.00211852
3 rd quart	0.0061082	0.00713692	0.00728087	0.00557256	0.00569209
90 th perc	0.015003	0.017549	0.0173118	0.0145545	0.0139772

Table C.5 | VRM descriptive statistics referred to park valley.

Solar radiation

GR	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	7102058	641404	1479926	1617727	1161612	2201388
min	1.07296	1.12129	1.07296	1.10036	1.2253	1.22897
max	30.6811	30.1964	30.5772	30.5557	30.3157	30.6811
range	29.6081	29.0751	29.5042	29.4553	29.0904	29.4521
mean	18.6296	16.347	18.1613	15.7229	19.5621	21.2535
sd	6.0216	4.86105	5.34573	5.37257	6.50627	5.66718
variance	36.2597	23.6298	28.5768	28.8645	42.3316	32.117
cv (%)	32.3228	29.7367	29.4347	34.1703	33.2597	26.6647
1 st quart	14.0147	13.0111	14.2353	11.7916	14.7011	17.4661
median	18.7065	16.1132	18.0405	15.2877	20.694	22.4581
3 rd quart	23.6771	19.5674	22.1891	19.2629	25.0779	25.8935
90 th perc	26.6995	23.0529	25.481	23.4293	27.3055	27.6888

Table C.6 | Global solar radiation (MJ/m² × day) descriptive statistics (196 null-values in Orco valley).

IT	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	7102058	641404	1479926	1617727	1161612	2201388
min	0	0	0	0	0	0
max	12	11.9028	12	11.9028	11.8472	11.9583
range	12	11.9028	12	11.9028	11.8472	11.9583
mean	7.43474	6.99974	7.34872	6.6754	7.47727	8.15489
sd	1.70548	1.45427	1.61998	1.65899	1.77698	1.52028
variance	2.90867	2.1149	2.62434	2.75225	3.15767	2.31127
cv (%)	22.9394	20.776	22.0444	24.8523	23.7652	18.6426
1 st quart	6.29167	6.08333	6.19444	5.56944	6.375	7.25
median	7.56944	7.06944	7.41667	6.65278	7.75	8.29167
3 rd quart	8.73611	8.05556	8.66667	7.875	8.86111	9.27778
90 th perc	9.51389	8.79167	9.375	8.88889	9.5	9.97222

Table C.7 | Insolation time (h) descriptive statistics (196 null-values in Orco valley).

C.2 | Satellite imagery

C.2.1 | Change detection

Assessing the spatial pattern of the change

Elevation

DEM	GNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	46700	373	2487	628	20361	22851
min	671.22	1146.11	1087.16	1107.73	894.1	671.22
max	2702.77	2266.39	2222.33	2242.29	2702.77	2513.85
range	2031.54	1120.28	1135.16	1134.55	1808.66	1842.63
mean	1571.72	1468.22	1497.25	1745.48	1662.68	1495.7
sd	409.42	287.06	254.84	220.96	408.21	411.79
variance	167629.08	82403.8	64947.91	48824.88	166643.44	169579.02
cv (%)	26.04	19.55	17.02	12.65	24.55	27.53
1 st	1253.14	1315.94	1316.81	1686.68	1334.15	1155.69
median	1526.53	1360.3	1466.03	1726.12	1599.89	1465.65
3 rd	1896.23	1468.02	1660.02	1794.27	1988.45	1849.43
90 th	2147.93	2184.78	1823.37	2074.63	2254.5	2066.22

Table C.8 | Elevation (m) descriptive statistics for cells classified as change.

Slope

Slope	GNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	46700	373	2487	628	20361	22851
min	0.06	9.45	0.58	0.06	1.02	1.62
max	73.07	44.47	70.4	68.23	67.1	73.07
range	73.01	35.01	69.82	68.16	66.07	71.45
mean	33.31	23.16	28.57	27.37	34.04	33.5
sd	8.84	7.86	11.78	11.27	8.72	8.17
variance	78.16	61.88	138.78	127.2	76.06	66.76
cv (%)	26.53	33.95	41.22	41.19	25.61	24.38
1 st	29.47	16.33	21.25	19.63	30.46	29.64
median	34.5	22.89	31.17	29.7	35.26	34.27
3 rd	38.58	28.5	36.71	35.3	39.18	38.31
90 th	42.6	34.1	41.01	40.12	43	42.45

Table C.9 | Slope (°) descriptive statistics for cells classified as change.

Aspect

Aspect	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	46700	628	373	2487	20361	22851
min	0	0	114.53	0	0	0.01
max	360	359.77	248.59	359.99	360	359.98
range	360	359.77	134.06	359.99	360	359.97
mean	248.4	235.02	175.52	158.74	250.82	257.55
sd	87.76	146.97	27.9	146.25	91.64	65.32
variance	7702.11	21601.51	778.62	21390.03	8399.44	4266.7
cv (%)	35.33	62.53	15.89	92.12	36.53	25.36
1 st	230.63	34.41	152.3	13.7	232.11	237.33
median	264.67	326.21	173.25	147.12	266.91	265.15
3 rd	301.96	347.57	195.71	336.19	311.05	294.22
90 th	335.35	353.92	214.54	353.26	340.07	319.92

Table C.10 | Aspect CCW (°) descriptive statistics for cells classified as change.

Ruggedness

VRM	GPNP
n	46700
min	6.25443e-09
max	0.180298
range	0.180298
mean	0.00357372
sd	0.00732879
variance	5.37112e-05
cv (%)	205.074
1 st	0.000463695
median	0.00131602
3 rd	0.00353974
90 th	0.0084017

Table C.11 | VRM descriptive statistics for cells classified as change referred to study area.

C. RESULTS

VRM	Rhemes	Valsavara	Cogne	Soana	Orco
n	373	2487	628	20361	22851
min	3.52553e-05	6.25443e-09	1.6897e-07	1.08301e-07	1.63248e-07
max	0.0166711	0.0724753	0.0264191	0.16359	0.180298
range	0.0166358	0.0724753	0.0264189	0.16359	0.180298
mean	0.00195742	0.00261941	0.00246134	0.00344478	0.00384943
sd	0.00252595	0.0040212	0.00365334	0.0072748	0.00775337
variance	6.38044e-06	1.617e-05	1.33469e-05	5.29227e-05	6.01148e-05
cv (%)	129.045	153.516	148.429	211.183	201.416
1 st	0.000465773	0.000568069	0.000487267	0.000386335	0.00052646
median	0.00106752	0.00132077	0.0012072	0.00118111	0.00145669
3 rd	0.00238746	0.00300724	0.0027443	0.00331334	0.0038808
90 th	0.00493115	0.00620175	0.00576271	0.00821735	0.00902224

Table C.12 | VRM descriptive statistics for cells classified as change referred to GPNP valleys.

Solar radiation

GR	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	46700	373	2487	628	20361	22851
min	8.08	11.02	8.08	10.56	8.8	8.3
max	29.57	25.63	25.63	25.81	29.49	29.57
range	21.49	14.61	17.55	15.24	20.68	21.26
mean	22.87	16.95	15.56	17.23	22.92	23.87
sd	3.97	2.96	2.78	2.7	3.72	3.24
variance	15.8	8.78	7.78	7.33	13.86	10.5
cv (%)	17.38	17.47	17.92	15.71	16.23	13.57
1 st	20.31	14.9	13.73	15.26	20.25	21.84
median	23.7	16.13	15.2	17.02	23.48	24.54
3 rd	26.1	18.61	16.9	19.23	25.96	26.44
90 th	27.31	21.16	19.21	20.57	27.38	27.39

Table C.13 | Global solar radiation (MJ/m² x day) descriptive statistics for cells classified as change.

IT	GPNP	Rhemes	Valsavara	Cogne	Soana	Orco
n	46700	373	2487	628	20361	22851
min	3.33	5.3	3.33	4.19	4.36	3.83
max	11.22	8.7	8.9	8.66	10.98	11.22
range	7.88	3.4	5.56	4.47	6.62	7.38
mean	7.97	6.42	5.71	6.23	7.91	8.35
sd	1.25	0.72	0.87	0.82	1.05	1.13
variance	1.56	0.52	0.76	0.68	1.1	1.28
cv (%)	15.69	11.22	15.26	13.26	13.28	13.57
1 st	7.12	5.95	5.04	5.56	7.15	7.5
median	8.05	6.04	5.55	6.34	7.93	8.43
3 rd	8.93	6.86	6.4	6.66	8.65	9.3
90 th	9.58	7.38	6.79	7.38	9.26	9.76

Table C.14 | Insolation time (h) descriptive statistics for cells classified as change.

Landform

Landform	Hectares	Cell count	% cover
summit	0.36	4	0.01
ridge	71.82	798	1.71
spur	708.75	7875	16.86
slope	42567.07	28523	61.08
hollow	738.18	8202	17.56
footslope	0.99	11	0.02
valley	115.56	1284	2.75
depression	0.270	3	0.01

Table C.15 | Change occurrence in GPNP landform.

Landform	Rhemes	Valsara	Cogne	Soana	Orco
summit	0	0	0	0.09	0.27
ridge	0.09	0.36	0.18	42.84	28.35
spur	6.93	37.17	6.48	312.21	345.96
slope	22.23	140.49	38.43	1098.54	1267.38
hollow	4.14	38.88	10.26	326.79	358.11
footslope	0	0.99	0	0	0
valley	0.18	5.85	1.17	51.84	56.52
depression	0	0.09	0	0.18	0

Table C.16 | Change occurrence in valley landforms in hectares.

C.3 | Aerial images

C.3.1 | Image classification

Accuracy assessment

	Category description	Training set	Test set
1	coniferous forest	73236	1028823
2	subalpine grassland	1020647	4218734
3	pasture and meadows	341509	451224
4	scree	766774	1422997
5	cliffs	415381	2878087
6	shadow	1474487	2566513

Table C.17 | Classification legend and size of the training and test sets in pixel.

	Accuracy	Individual classifiers					Votes			
		svmRadial	rf	rpart	C5.0	knn	smv	swv	bwwv	qbwwv
1	PA	0.02	0.02	0	0	12.66	12.69	0.02	0.02	0.02
	UA	0.09	0.28	-nan	0	59.69	59.67	0.28	0.14	0.14
2	PA	23.81	20.75	1.39	37.28	7.91	20.39	20.39	26.43	26.43
	UA	41.3	58.31	28.86	55.58	29.88	55.1	55.1	60.06	60.06
3	PA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	UA	NA	NA	NA	NA	NA	NA	NA	NA	NA
4	PA	29.08	28.8	33.51	8.08	37.18	23.52	23.52	23.34	23.34
	UA	12.16	9.34	9.26	5.15	19.86	8.6	8.84	8.92	8.92
5	PA	14.82	14.74	5.31	12.79	19.52	12.82	14.83	14.83	14.83
	UA	14.25	16.29	7.79	12.2	19.61	14.32	15.37	15.37	15.37
6	PA	46.5	37.03	56.07	55.51	60.91	37.03	37.03	37.03	37.03
	UA	34.37	23.85	27.41	32.35	27.41	22.01	21.82	23.52	23.52

Table C.18 | Producer and user accuracy for each class. Refer to table C.17 for the category description.

Support Vector Machine with a radial kernel

	cat	Test set					
		1	2	3	4	5	6
svmRadial	1	0.02	1.9	0	0	6.47	0.01
	2	12.8	23.81	59.47	21.22	13.76	12.82
	3	0	0	0	0	0	0
	4	1.52	34.62	3.37	29.08	40.26	13.18
	5	80.48	13.61	20.48	25.72	14.82	27.47
	6	5.16	26.05	16.66	23.96	24.67	46.5

Table C.19 | Error matrix for the support vector machine with a radial kernel (svmRadial). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	99.9	99.97	-0.08
2	58.69	76.18	0.11
3	NA	NA	NA
4	87.83	70.91	0
5	85.74	85.17	-0.11
6	65.62	53.49	0.17

Table C.20 | Percentage of commission and omission errors and estimated kappa value of svmRadial for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
3038944	12566378	0.04	0	24.18

Table C.21 | Kappa, overall accuracy and percentage of correct observations of svmRadial.

C. RESULTS

Random Forest

	cat	Test set					
		1	2	3	4	5	6
rf	1	0.02	0	0	0	3.05	0.01
	2	0.13	20.75	10.25	8.09	15.37	0.79
	3	0	0	0	0	0	0
	4	21.27	44.01	3.37	28.8	34.22	35.15
	5	76.64	5.5	13.44	28.43	14.74	27.01
	6	1.92	29.72	72.92	34.66	32.58	37.03

Table C.22 | Error matrix for the Random Forest (rf). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	99.71	99.97	-0.08
2	41.68	79.24	0.37
3	NA	NA	NA
4	90.65	71.19	-0.02
5	83.7	85.25	-0.08
6	76.14	62.96	0.04

Table C.23 | Percentage of commission and omission errors and estimated kappa value of rf for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2660612	12566378	0.02	0	21.17

Table C.24 | Kappa, overall accuracy and percentage of correct observations of rf.

Recursive partitioning

	cat	Test set					
		1	2	3	4	5	6
rpart	1	0	0	0	0	0	0
	2	1.39	1.39	0	0	4.34	0.23
	3	0	0	0	0	0	0
	4	15.73	48.01	34.11	33.51	52.36	32.08
	5	68.24	11.2	13.44	19.52	5.31	11.61
	6	14.61	39.39	52.43	46.95	37.97	56.07

Table C.25 | Error matrix for the Recursive partitioning (rpart). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	-nan	100	-999
2	71.13	98.6	-0.07
3	NA	NA	NA
4	90.73	66.48	-0.02
5	92.2	94.68	-0.19
6	72.58	43.92	0.08

Table C.26 | Percentage of commission and omission errors and estimated kappa value of rpart for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2128155	12566378	0	0	16.93

Table C.27 | Kappa, overall accuracy and percentage of correct observations of rpart.

C. RESULTS

C5.0

	cat	Test set					
		1	2	3	4	5	6
C5.0	1	0	1.9	0	0	0.05	0.01
	2	0.13	37.28	10.25	33.35	22.33	3.57
	3	0	0	0	0	0	0
	4	0	21.48	3.37	8.08	29.43	13.64
	5	94.41	13.21	13.44	25.3	12.79	27.25
	6	5.44	26.11	72.92	33.25	35.38	55.51

Table C.28 | Error matrix for the C5.0. Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	100	100	-0.08
2	44.41	62.71	0.33
3	NA	NA	NA
4	94.84	91.91	-0.06
5	87.79	87.2	-0.13
6	67.64	44.48	0.14

Table C.29 | Percentage of commission and omission and estimated kappa value of C5.0 for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
3480996	12566378	0.06	0	27.7

Table C.30 | Kappa, overall accuracy and percentage of correct observations of C5.0.

k-Nearest Neighbors

	cat	Test set					
		1	2	3	4	5	6
knn	1	12.66	0	0	0	3.05	0
	2	0.13	7.91	16.81	19.57	11.68	3.54
	3	0	0	0	0	0	0
	4	0	29.8	0	37.18	22.42	9.05
	5	85.67	16.48	10.25	0.01	19.52	26.48
	6	1.52	45.8	72.92	43.22	43.31	60.91

Table C.31 | Error matrix for the k-Nearest Neighbors (knn). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	40.3	87.33	0.56
2	70.11	92.08	-0.05
3	NA	NA	NA
4	80.13	62.81	0.09
5	80.38	80.47	-0.04
6	72.58	39.08	0.08

Table C.32 | Percentage of commission and omission errors and estimated kappa value of knn for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
3118561	12566378	0.06	0	24.81

Table C.33 | Kappa, overall accuracy and percentage of correct observations of knn.

C. RESULTS

Simple Majority Vote

	cat	Test set					
		1	2	3	4	5	6
smv	1	12.69	0	0	0	3.05	0.01
	2	0.13	20.39	10.25	13.37	15.37	0.79
	3	0	0	0	0	0	0
	4	0.25	37.75	3.37	23.52	36.26	35.15
	5	84.99	4.14	13.44	28.43	12.82	27.01
	6	1.92	37.7	72.92	34.66	32.46	37.03

Table C.34 | Error matrix for the Simple Majority Vote (smv). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	40.32	87.3	0.56
2	44.89	79.6	0.32
3	NA	NA	NA
4	91.39	76.47	-0.03
5	85.67	87.17	-0.11
6	77.98	62.96	0.01

Table C.35 | Percentage of commission and omission errors and estimated kappa value of smv for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2645426	12566378	0.01	0	21.05

Table C.36 | Kappa, overall accuracy and percentage of correct observations of smv.

Simple Weighted Vote

	cat	Test set					
		1	2	3	4	5	6
swv	1	0.02	0	0	0	3.05	0.01
	2	0.13	20.39	10.25	13.37	15.37	0.79
	3	0	0	0	0	0	0
	4	0.25	36.71	3.37	23.52	34.14	35.15
	5	94.41	5.18	13.44	28.43	14.83	27.01
	6	5.16	37.7	72.92	34.66	32.58	37.03

Table C.37 | Error matrix for the Simple Weighted Vote (swv). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	99.71	99.97	-0.08
2	44.89	79.6	0.32
3	NA	NA	NA
4	91.15	76.47	-0.02
5	84.62	85.16	-0.09
6	78.17	62.96	0.01

Table C.38 | Percentage of commission and omission errors and estimated kappa value of swv for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2572690	12566378	0	0	20.47

Table C.39 | Kappa, overall accuracy and percentage of correct observations of swv.

C. RESULTS

Best Worst Weighted Vote

	cat	Test set					
		1	2	3	4	5	6
bwwv	1	0.02	1.9	0	0	3.11	0.01
	2	0.13	26.43	10.25	16.22	15.37	0.79
	3	0	0	0	0	0	0
	4	0.25	32.87	3.37	23.34	37.68	35.15
	5	94.41	5.18	13.44	28.43	14.83	27.01
	6	5.16	33.61	72.92	32	28.98	37.03

Table C.40 | Error matrix for the Best Worst Weighted Vote (bwwv). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	99.85	99.97	-0.08
2	39.93	73.56	0.39
3	NA	NA	NA
4	91.07	76.65	-0.02
5	84.62	85.16	-0.09
6	76.47	62.96	0.03

Table C.41 | Percentage of commission and omission errors and estimated kappa value of bwwv for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2824798	12566378	0.03	0	22.47

Table C.42 | Kappa, overall accuracy and percentage of correct observations of bwwv.

Quadratic Best Worst Weighted Vote

	cat	Test set					
		1	2	3	4	5	6
qbwwv	1	0.02	1.9	0	0	3.11	0.01
	2	0.13	26.43	10.25	16.22	15.37	0.79
	3	0	0	0	0	0	0
	4	0.25	32.87	3.37	23.34	37.68	35.15
	5	94.41	5.18	13.44	28.43	14.83	27.01
	6	5.16	33.61	72.92	32	28.98	37.03

Table C.43 | Error matrix for the Quadratic Best Worst Weighted Vote (qbwwv). Values are column-based normalized (percentage of the reference test set) and diagonal ones correspond to the producer accuracy. Refer to table C.17 for the category description.

Cats	% Commission	% Omission	Estimated Kappa
1	99.85	99.97	-0.08
2	39.93	73.56	0.39
3	NA	NA	NA
4	91.07	76.65	-0.02
5	84.62	85.16	-0.09
6	76.47	62.96	0.03

Table C.44 | Percentage of commission and omission errors and estimated kappa value of qbwwv for each class.

Obs Correct	Total Obs	Kappa	Kappa Variance	% Observed Correct
2824798	12566378	0.03	0	22.47

Table C.45 | Kappa, overall accuracy and percentage of correct observations of qbwwv.

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