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Using remote sensing products to classify landscape. A multi-spatial resolution approach

Q1 Paula García-Llamas[a,*], Leonor Calvo[a], José Manuel Álvarez-Martínez[b], Susana Suárez-Seoane[a]

Q2 [a] Biodiversity and Environmental Management Dpt., Faculty of Biological and Environmental Sciences, University of León, 24071 León, Spain
[b] Environmental Hydraulics Institute "IH Cantabria", C/Isabel Torres 15, Parque Científico y Tecnológico de Cantabria, 39011 Santander, Spain

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ABSTRACT

The European Landscape Convention encourages the inventory and characterization of landscapes for environmental management and planning actions. Among the range of data sources available for landscape classification, remote sensing has substantial applicability, although difficulties might arise when available data are not at the spatial resolution of operational interest. We evaluated the applicability of two remote sensing products informing on land cover (the categorical CORINE map at 30 m resolution and the continuous NDVI spectral index at 1 km resolution) in landscape classification across a range of spatial resolutions (30 m, 90 m, 180 m, 1 km), using the Cantabrian Mountains (NW Spain) as study case. Separate landscape classifications (using topography, urban influence and land cover as inputs) were accomplished, one per each land cover dataset and spatial resolution. Classification accuracy was estimated through confusion matrixes and uncertainty in terms of both membership probability and confusion indices. Regarding landscape classifications based on CORINE, both typology and number of landscape classes varied across spatial resolutions. Classification accuracy increased from 30 m (the original resolution of CORINE) to 90m, decreasing towards coarser resolutions. Uncertainty followed the opposite pattern. In the case of landscape classifications based on NDVI, the identified landscape patterns were geographically structured and showed little sensitivity to changes across spatial resolutions. Only the change from 1 km (the original resolution of NDVI) to 180 m improved classification accuracy. The value of confusion indices increased with resolution. We highlight the need for greater effort in selecting data sources at the suitable spatial resolution, matching regional peculiarities and minimizing error and uncertainty.

1. Introduction

Different policies have been developed in Europe aiming to regulate landscape conservation, such as the Pan-European Biological and Landscape Diversity Strategy (Council of Europe, 1996), the Action Plan for European Landscapes (ECNC, 1997) and the European Landscape Convention (Council of Europe, 2000). Specifically, the European Landscape Convention encourages Contracting Parties to identify and classify their landscapes for protection, management and planning. In this way, a wide range of initiatives has been implemented at continental, national and regional scales in Europe, attempting to accomplish this recommendation. Examples are the European Landscape Map (LANMAP2) (Mücher et al., 2010), the Spanish Landscape Atlas (Mata Olmo and Sanz Herráiz, 2003) and the German Typology of Landscapes (Gharadjedaghi et al., 2004). However, despite efforts, the European Landscape Character Initiative (ELCAI) (Wascher, 2005) highlighted discrepancies in these landscape classifications in terms of methodology, data sources, spatial resolution and nomenclature (Mücher et al., 2010), which make them incompatible and largely incomparable (Van Eetvelde and Antrop, 2008). Thus, the development of consistent methodologies for landscape classification, able to identify with realism, basic spatial units for use in environmental applications at a large scale, is necessary to fulfil policy and operational requirements (Blasi et al., 2000). Q3

Numerical landscape classifications allocate patches of territory with similar characteristics (e.g., geology, topography, hydrology, land cover, socio-economy) into homogeneous landscape units. Among all landscape components, land cover is probably the most relevant, as it represents the interface between natural conditions and human influences, both across space and time. There is a wide range of data sources that can be used to describe land cover in environmental applications (Tomaselli et al., 2013), mainly consisting

* Corresponding author.
E-mail addresses: pgarcl@unileon.es, paula.gllmas@gmail.com (P. García-Llamas).

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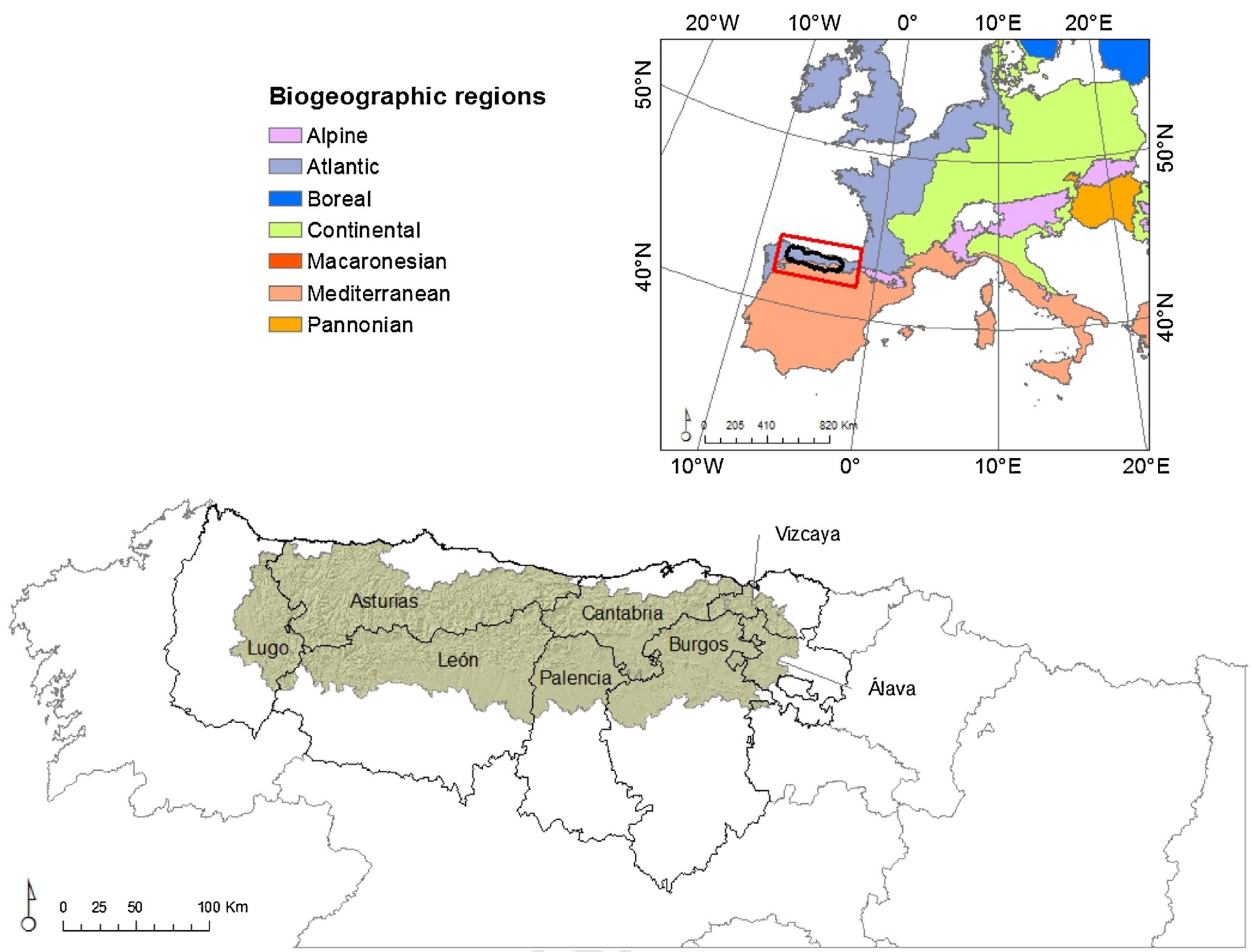

Fig. 1. Study area: The Cantabrian Mountains (NW Spain). Information on biogeographic regions was obtained from the Spanish Ministry of Agriculture Food and Environment (http://www.magrama.gob.es/).

of categorical land cover maps derived from remote sensing data, as the International Geosphere-Biosphere Programme (Belward, 1996), the FAO land cover classification system (Di Gregorio and Jansen, 1998, 2004) or the CORINE Land Cover Programme (Bossard et al., 2000). Currently, most of these data can be found freely available, which can be useful for landscape managers, mainly when founding is limited (Nagendra et al., 2013). However, the matching between the spatial resolution of these products, with that at which landscape is intended to be characterized it is not always achievable (Garrigues et al., 2006; Shao and Wu, 2008). A lack of appropriate information can result in a gap between both, desired and hard-headed spatial resolution at which patterns and process can be represented (McCabe and Wood, 2006), generating spatial discrepancies between reality and analysis resolution.

Within the European context, CORINE is probably the data source most used to generate integrative landscape classifications in combination with other thematic data (Mücher et al., 2003, 2006, 2010; Van Eetvelde and Antrop, 2008; Cullotta and Barbera, 2011). However, despite its wide application, CORINE is a classification product derived from Landsat TM imagery that shows important problems of uncertainty (Regan et al., 2002), which can be propagated in subsequent analyses (Shao and Wu, 2008). Therefore, it should be carefully evaluated prior use to guaranty its applicability in management (Foody and Atkinson, 2002; Rae et al., 2007; Kennedy et al., 2009; Hou et al., 2013). This issue become especially relevant in mountain systems, where topographic and microclimatic patterns (Oke and Thompson, 2015) make ecological conditions to change substantially over relatively short distances, providing a wide range of environments and hence, a great diversity of habitats and species (Becker and Bugmann, 2001). Because of this environmental heterogeneity, classifying land cover in mountain areas is especially challenging due to the existence of mixed pixels that can mislead the final classifications (Álvarez-Martínez et al., 2010). Considering these constraints inherent to categorical maps, a good alternative could be the use of continuous variables as the spectral indices derived from remote sensing imagery (Suárez-Seoane et al., 2002; Morán-Ordóñez et al., 2012; Álvarez-Martínez et al., 2015; Roces-Díaz et al., 2015). The spectral index most commonly used in environmental research is the Normalized Vegetation Index (NDVI) (Rouse et al., 1973; Tucker, 1979). This index has been related to functional attributes of ecosystems like aboveground net primary production (Paruelo et al., 2001), vegetation functional characteristics such as phenology or primary productivity (Gamon et al., 2013) and vegetation structure such as aboveground biomass (Zhu and Liu, 2014). Many authors have applied this index to produce categorical land cover maps which are then used in subsequent analysis (Muniaty and Ratshibvumo, 2010; Tchuenté et al., 2011; Pervez et al., 2014). Nevertheless, we found no studies using this product as a direct input in integrative landscape classifications. The reason could be that NDVI provides an indication of the "greenness" of vegetation but does not inform directly on land cover, which may hamper the interpretation of final maps (Wang and Tenhunen, 2004).

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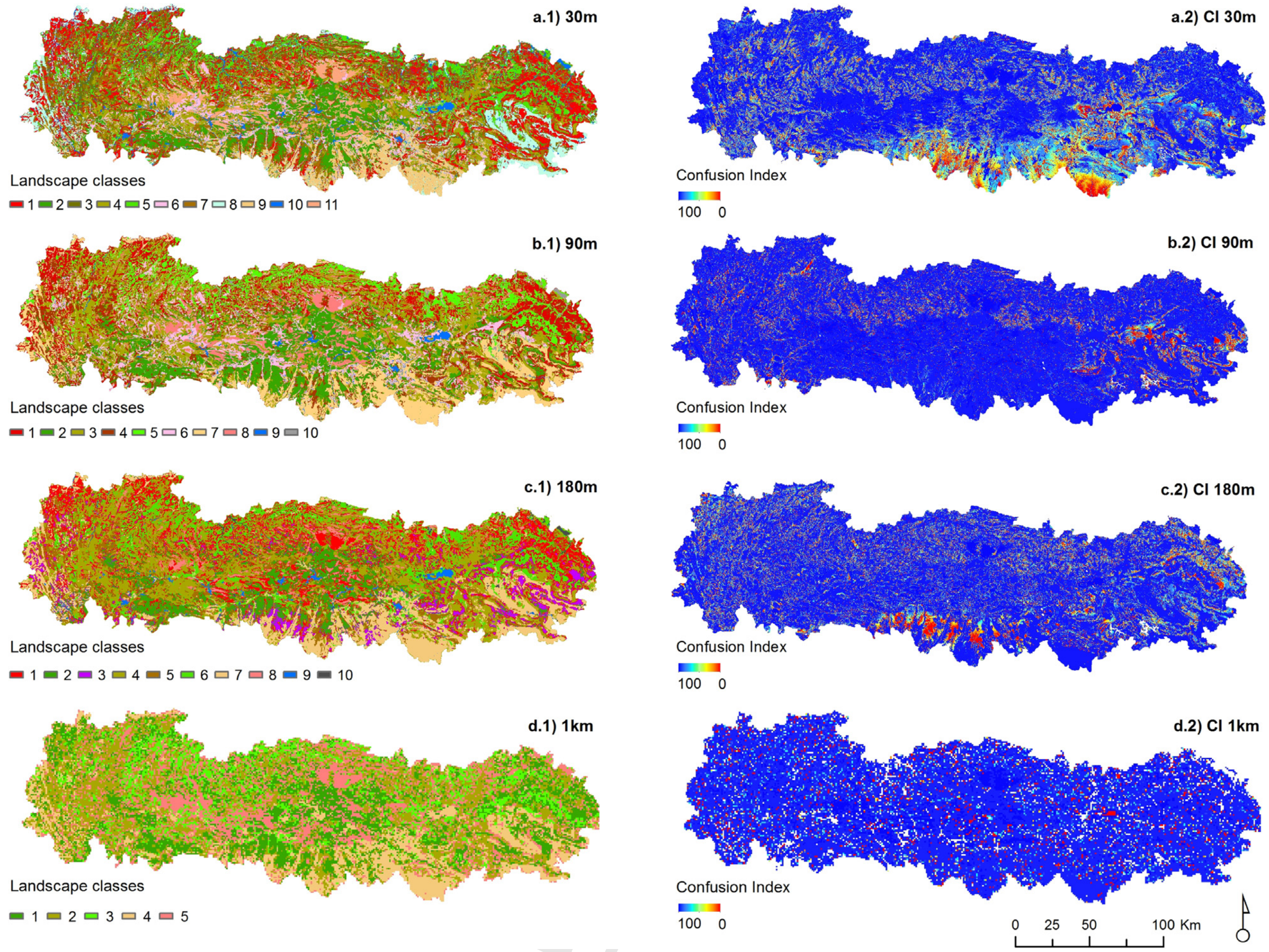

Fig. 2. On the left (a.1–d.1), landscape patterns achieved from classifications based on topography, urban influence and land cover (CORINE) and on the right (a.2–d.2) the associated Confusion Index maps (*CI*) at various spatial resolutions: (a) 30 m, (b) 90 m, (c) 180 m and (d) 1 km. See Table 2 and Supplementary material S4–S8 for explanation and statistical characterization of landscape classes.

This study aims to explore the applicability of two of the most readily available open remote sensing products accounting for land cover (the CORINE land cover classification from Landsat at 30 m resolution and the spectral index NDVI from NOAA-AVHRR at a 1 km) for integrative landscape classification across spatial resolutions. In particular, we explore: (i) how classification typology and landscape pattern change across spatial resolution; (ii) how the error and uncertainty associated with data source, spatial resolution and landscape classification process could influence results in a complex mountain system.

2. Material and methods

2.1. Study area

The study area lies in the Cantabrian Mountains (northwest Spain) located at the transition between Eurosiberian and Mediterranean biogeographical regions (Rivas-Martínez, 1987) (Fig. 1). This is an area of 31,494 km^2 with altitudes ranging from sea level to 2650 m.a.s.l. Average annual rainfall varies from 700 to 2400 mm and mean annual temperature from 4 °C to 22 °C. Landscape pattern is heterogeneous and is driven by climatic and topographic conditions, as well as human activities. Land cover types vary from crop fields (in lowlands) to natural vegetation (in mid-highlands), including heathlands scrublands and deciduous forests dominated by *Fagus sylvatica*, *Betula pubescens*, *Quercus petraea* and *Quercus robur* on northern slopes and *Quercus pyrenaica* and *Quercus rotundifolia* on southern slopes. In addition, plantations of *Pinus pinaster*, *Pinus radiata* and *Eucalyptus globulus* can be found in the study area, covering medium-to-low slopes previously occupied by shrubs and heathers. The Cantabrian Mountains have been widely recognized as a hot spot of biodiversity hosting a wide variety of ecosystems habitats and endemic species (Worboys et al., 2010; Álvarez-Martínez et al., 2011; Morán-Ordóñez et al., 2011).

2.2. Input environmental variables: topography, urban influence and land cover

We derived a set of environmental variables informing on topography, urban influence and land cover at four spatial resolutions (30 m, 90 m, 180 m and 1 km) (Table 1). Pixel sizes of 30 m and 1 km correspond to the original resolution of the remote sensing data accounting for land cover, while 90 m and 180 m are intermediate resolutions chosen according to data availability on topography and urban influence.

Topographic variables consisted on elevation solar radiation and slope. They were calculated separately from four Digital Elevation Models (DEM) proximal to the above-mentioned spatial resolutions and obtained from the Spanish Geographic Institute (www.ign.es), and the U.S. Geological Survey (www.usgs.gov). Urban influence was estimated as the Euclidian distance to urban settlements, independently for the target spatial resolutions, using data from

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Table 1
Variables used for landscape classification. Variables accounting for topography and urban influence were calculated independently at 30 m, 90 m, 180 m and 1 km of spatial resolution from different data sources, while those accounting for land cover (CORINE and NDVI) were derived at each target spatial resolution by pixel aggregation or pixel resampling from the original data source.

Family	Code	Description	Original data set
Topography	DEM SLO SOLR	Elevation (in meters) Slope (in percentage) Solar radiation ($\times 10^6$ W/h)	Digital Elevation Models (DEM) at 25 m, 90 m,200 m and 1 km of spatial resolution
Urban influence	AC	Urban influence across the territory measured as Euclidian distance to settlements (in meters)	Vector layers at 1:25,000, 1:100,000, 1:200,000 and 1:500,000.
Land cover (CORINE)	INFRA MIN HERC WOOC PAS FOR TWOOD SCRUB SPAR BARE WET WAT	Human infrastructures (%) Mineral extraction sites (%) Herbaceous crop lands (%) Woody crop land coverage (%) Pasturelands (%) Forest coverage (%) Transitional woodland-shrublands (%) Mosaic of sclerophyllous-herbaceous vegetation (%) Sparsely vegetated areas (%) Bare areas (%) Wetlands (%) Water (%)	CORINE Land Cover 2006 at 30 m spatial resolution
Land cover (NDVI)	NDVI	Annual average NDVI index (no units ranging from −1 to +1)	NDVI from NOAA-AVHRR at 1 km of spatial resolution for years 1983, 1985, 1990, 1993 and 1996

the Spanish Geographic Institute (www.ign.es). Land cover variables were generated from two datasets: (i) the CORINE categorical map for the year 2006 at 30 m of spatial resolution; and (ii) a mean annual NDVI spectral index at 1 km, derived from a temporal monthly series for years 1983, 1985, 1990, 1993, 1996 and 1999. The CORINE Land Cover classification (http://www.eea.europa.eu/publications/COR0-landcover) comprises 44 land cover classes at the most detailed of the three available levels (Bossard et al., 2000). But, in the study area, only 38 out of the 44 classes were present. These classes were reclassified into 12 main categories with the purpose of simplifying the original dataset (see S1). With the aim of improving map reliability, the resulting product was merged with an extra dataset of rivers and infrastructures (roads, railways and settlements) downloaded from the Spanish Geographic Institute site (www.ign.es), at 1:200,000 spatial resolution. To account for the accuracy of this new CORINE map, we carried out a visual validation based on coetaneous orthophotographs (years 2006–2009, at 1:5000–1:10,000 spatial resolution) and field surveys (Bossard et al., 2000; Vogiatzakis et al., 2006; Kienast et al., 2009) on a dataset of 320 sampling points. We followed a stratified random sampling design by municipality and land cover class, being, therefore, the sampling size proportional to the extent of the municipalities and land cover classes. Accumulative adjustment curves were created to identify a representative number of points. The overall accuracy of the new CORINE was 82.5%, ranging across land cover classes from 66.67 to 100% (S1). The map was resampled at the four target spatial resolutions by using the majority rule, which is one of the most common approaches to aggregate categorical data (Wu, 2004). The 12 classes of the new CORINE were subsequently turned into independent continuous variables by calculating the proportion covered by class at each pixel of 30 m, 90 m, 180 m and 1 km. NDVI original data were captured by an Advanced Very High Resolution Radiometer (AVHRR) on board the NOAA satellite, received by the Natural Environment Research Council Satellite Receiving Station at Dundee (UK) and processed by the Remote Sensing Group at the Plymouth Marine Laboratory (UK). See Suárez-Seoane et al. (2002) and Osborne et al. (2007) for technical details on these data. The original NDVI dataset had a pixel size of 1 km and was resampled to the above-mentioned spatial resolutions using a nearest algorithm.

Prior to landscape classification analysis we standardized all continuous environmental variables (Table 1) to set them to the same range, by applying the Eq. (1)

$$Z = \frac{(X - oldmin) \times (newmax - newmin)}{(oldmax - oldmin)} + newmin \quad (1)$$

where Z is the output raster with new data ranges, X is the input raster, *oldmin* is the minimum value of the input raster, *oldmax* is the maximum value of the input raster, *newmin* is the desired minimum value for the output raster and *newmax* is the desired maximum value for the output raster.

2.3. Landscape classification across spatial resolutions: accuracy and uncertainty

We accomplished eight landscape classification analyses for the Cantabrian Mountains based on topography, urban influence and land cover (Table 1). We carried out an independent analysis for each land cover dataset (CORINE and NDVI) and spatial resolution (30 m, 90 m, 180 m and 1 km). First, we ran a Principal Components Analysis (PCA) over the standardized variables. We then clustered similar pixels into comprehensive landscape classes, by applying an unsupervised classification with the maximum likelihood algorithm on the PCA components (Schowengerdt, 1983; Conese and Maselli, 1992). A similar methodological approach to classify landscape has been used by other authors such as Owen et al. (2006), Morán-Ordóñez et al. (2011) and Gan et al. (2012).

The error of each landscape classification was measured in terms of accuracy, which was quantified by using thematic information related to topography, urban influence and land cover and *ortho*-photographs (years 2006–2009, scale 1:5000–1:10,000), (Bossard et al., 2000; Vogiatzakis et al., 2006; Kienast et al., 2009). Each landscape map was evaluated using independent datasets of 300 points each, that were collected across the study area by applying a random sampling design stratified by class. This sampling size guaranteed an adequate representativeness of all landscape classes and was defined according to accumulative adjustment curves (S2), which allowed for identifying the appropriated number of valida-

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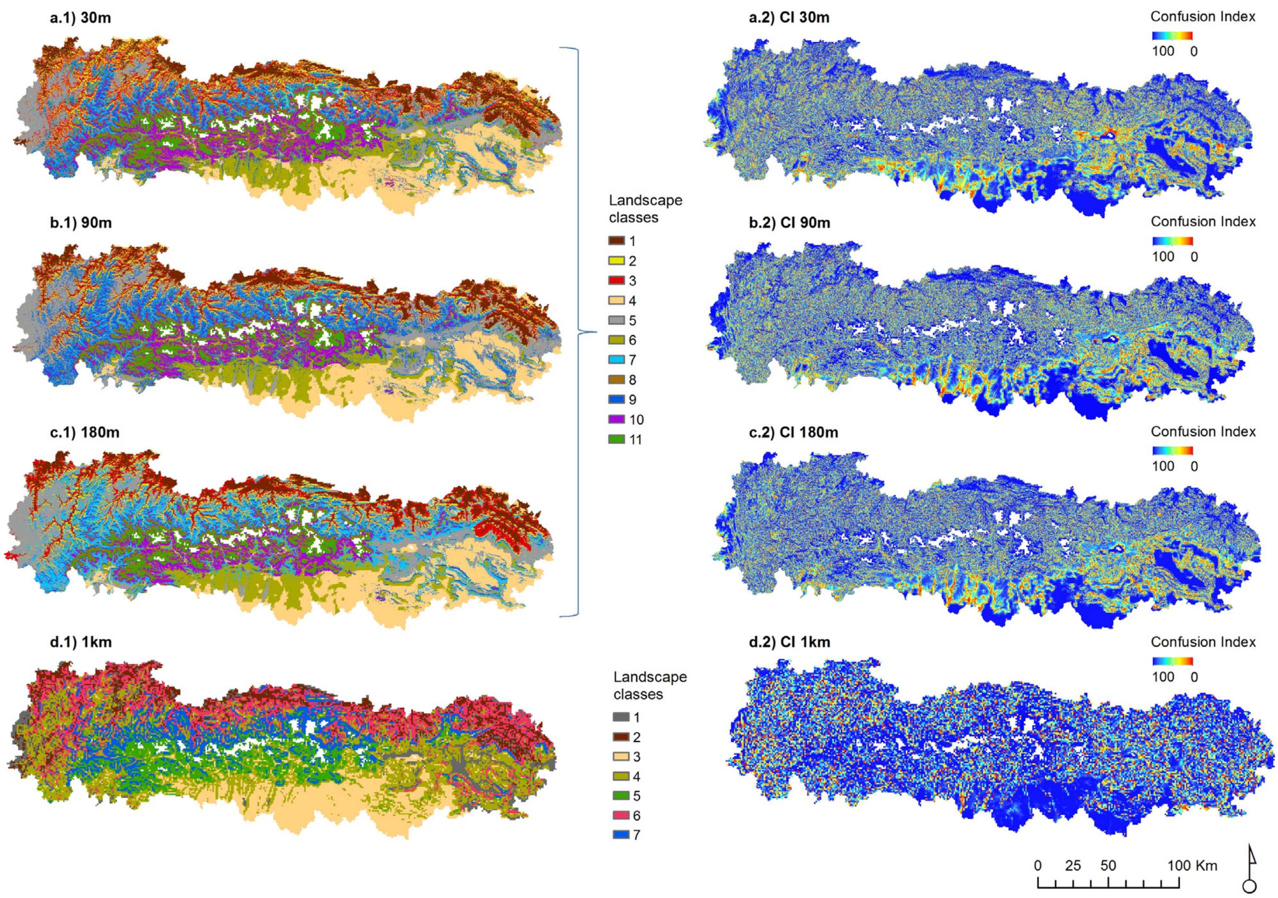

Fig. 3. On the left (a.1–d.1), landscape patterns achieved from classifications based on topography, urban influence and land cover (NDVI) and on the right (a.2–d.2) the associated Confusion Index maps (*CI*) at various spatial resolutions: (a) 30 m, (b) 90 m, (c) 180 m and (d) 1 km. See Table 3 and Supplementary material S4, S9 and S10 for explanation and statistical characterization of landscape classes.

tion points for each landscape classification. We avoided the use of a unique testing dataset for validating all landscape classifications because any selection of points would be biased towards a particular spatial resolution and/or original data source. We created a confusion matrix for each classification obtaining the overall percentage of points correctly allocated to landscape classes and the user's and producer's accuracy per class.

The maximum likelihood rule allocates pixels to classes according to their maximum membership probability. However, a pixel may have a certain degree of similarity to more than one class and therefore, almost equal probability of membership to all of them. In these cases, pixel allocation can be erroneous (Lewis et al., 2000). This problem is considered a main source of uncertainty in classification processes (Foody, 2000; Owen et al., 2006). To assess the uncertainty derived from erroneous allocations for each pixel in each class, we applied the methodology of Álvarez-Martínez et al. (2010), which is based on fuzzy membership to all landscape classifications. We distinguished between two aspects of classification uncertainty: (i) the uncertainty of pixel allocation to a particular class (probability of membership); and (ii) the confusion associated with the classification of a pixel among classes accepting that one pixel can belong to more than one class (expressed by the Confusion Index). Membership is a measure of the similarity between the characteristics of a particular pixel and the representative vector of a class (Bollinger and Mladenoff, 2005). It was estimated by calculating the Euclidian distance between each pixel value and the characteristic vector of the class. A large Euclidian distance indicates large differences between the pixel attributes and the typical case of the target class. In this case, membership probability will be low and uncertainty high. Membership values were then used to create a Confusion Index (*CI*) map. We calculated the difference between the highest membership probability to a class and the second-largest membership probability for the same pixel to another class. When a class dominates, differences between the highest and the second highest class membership probability is large. In this situation, *CI* tends towards "1" and there is little confusion in class allocation. Otherwise, when membership is similar to more than one class, confusion among classes is high and *CI* tends towards "0".

All analyses were done in ArcGIS 10.2 (Esri. 2014).

3. Results

3.1. Landscape patterns and classification typologies

Landscape patterns derived from landscape classifications based on CORINE, as a proxy of land cover, showed a weak geographic structure (Fig. 2, cases a.1–d.1). The number of landscape classes decreased when pixel size became coarser: eleven classes at 30 m, ten at 90 m and 180 m and five at a 1 km spatial resolution. The typology of the classes also varied among these spatial resolutions.

When using NDVI as land cover data source in landscape classification, the resulting landscape mosaic was strongly structured across a gradient North to South, being this geographic pattern consistent across spatial resolutions (Fig. 3, cases a.1–d.1, S3). Classifications led to the identification of 11 classes at 30 m, 90 m and 180 m and 7 at 1 km pixel size. Thus, classification typology showed little sensitivity to changes across spatial resolutions.

Table 2
Description of landscape classes obtained from a set of variables accounting for topography, urban influence and land cover (CORINE). See Supplementary material S4–S8 for further explanations.

Class	Description
30 m resolution	
1	Forests covering coastal and middle-mountain areas under 1000 m.a.s.l.
2	Forests covering central mountains and piedmont areas at altitudes above 1000 m.a.s.l.
3	Transitional to woodlands with relatively low urban influence covering mainly Atlantic and Sub-Atlantic mountains, in areas with mid-low altitudes (600 m.a.s.l.)
4	Transitional woodlands from central and southern areas of the Cantabrian Mountains, with altitudes from1500 to 900 m.a.s.l.
5	Pastures in mid-low (under 800 m.a.s.l.) Atlantic mountains and coastal areas
6	Pastures covering bottom valleys and hillsides of central Cantabrian Mountains, with altitudes ranging from 1500 to 1000 m.a.s.l.
7	Shrub-herbaceous associations lying at altitudes between 1200–500 m.a.s.l.
8	Croplands from depressions and coastal areas at low altitude close to settlements
9	Croplands (non-irrigated arable lands) from paramos and countrysides under 1000 m.a.s.l., being the closest class to settlements
10	Water surfaces and artificial surfaces in areas of wide altitudinal ranges
11	Rocks and areas with little or no vegetation covering wide altitudinal ranges
90 m resolution	
1	Forests covering coastal and middle-mountain areas mainly from Atlantic and Sub-Atlantic mountains, under 850 m.a.s.l. and relatively close to settlements
2	Forests covering central mountains and piedmont areas with low urban influence at altitudes above 900 m.a.s.l., with low urban influence
3	Transitional to woodland areas across a wide altitudinal range
4	Shrub-herbaceous associations lying at altitudes between 1200–500 m.a.s.l.
5	Pastures in mid-low Atlantic mountains and coastal areas under 600 m.a.s.l.
6	Pastures covering bottom valleys and hillsides of central Cantabrian Mountains with altitudes ranging from 1400 to 700 m.a.s.l.
7	Croplands from coastal areas depressions paramos and country sides under 1000 m.a.s.l.
8	Rocks and areas with little or no vegetation covering a wide altitudinal range
9	Water surfaces covering a wide altitudinal range
10	Settlements roads railways or mines at very low altitude
180 m resolution	
1	Areas with little vegetation and forests, covering coastal and middle-mountain areas mainly from Atlantic and Sub-Atlantic mountains, situated at a wide altitude range
2	Forests covering high central mountains and piedmont areas with relative urban influence, at altitudes above 1000 m.a.s.l.
3	Forests covering depressions paramos and countrysides in altitudes under 1000 m.a.s.l.
4	Transitional to woodland areas at wide altitudinal ranges and relative high urban influence
5	Shrub-herbaceous associations lying at altitudes between 1200–500 m.a.s.l.
6	Pastures covering areas with wide altitudinal and solar radiation range at middle to slight slope
7	Croplands from coastal areas depressions paramos and country sides under 1000 m.a.s.l.
8	Rocks and areas with no vegetation covering a wide altitudinal range
9	Water surfaces covering a wide altitudinal range
10	Settlements roads railways or mines at very low altitude
1 km resolution	
1	Forests lying at wide altitude range
2	Transitional woodland and shrub areas with fairly urban influence at wide altitudinal ranges
3	Pastures covering areas with relative urban influence and wide altitudinal
4	Croplands from coastal areas depressions paramos and countryside along with water surfaces under 1000 m.a.s.l.
5	Rocks areas with no vegetation and artificial surfaces covering a wide altitudinal range

See Tables 2 and 3 and Supplementary material S4–S10 for a detailed characterization of landscape classes.

3.2. Landscape classification accuracy

Landscape classifications based in CORINE land cover data reached an overall accuracy higher than 80% at all spatial resolutions, with user's and producer's accuracy per class higher than 50% and 68%, respectively (Table 4). When the spatial resolution of analysis decreased from 30 m (the original pixel size of CORINE) to 90 m, classification accuracy improved. However, when the spatial resolution was coarser than 90m, classification accuracy diminished.

Landscape classifications based on NDVI grasped an overall accuracy higher than 79% at all spatial resolutions, with user's and producer's accuracy per class higher than 57% and 65% respectively (Table 5). When the spatial resolution of analysis increased from 1 km (the original pixel size of NDVI) to 180m, classification accuracy improved. Nevertheless, when the spatial resolution was higher than this, classification accuracy decreased.

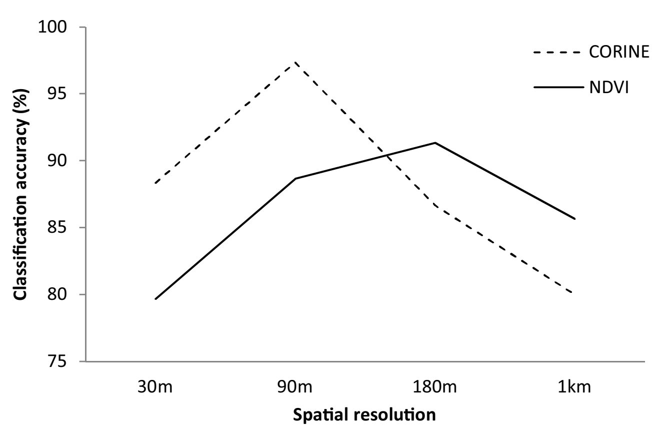

Fig. 4. Landscape classification accuracy across spatial resolutions.

In none of the cases, classification accuracy was maximal at the original spatial resolution of NDVI and CORINE land cover datasets (i.e., 30 m and 1 km pixel size respectively) (Fig. 4).

Table 3
Description of landscape classes obtained from a set of variables accounting for topography, urban influence and land cover (NDVI). See supplementary material S4, S9 and S10 for further explanations.

Class	Description
30 m 90 m and 180 m resolution	
1	Sea inlets, coastal plains and sub-coastal valleys, located at the lowest altitude dominated by a mosaic of crops and pastures with a high presence of natural vegetation
2	Hillsides under a.s.l. with a northern exposure and mid-high slope from Atlantic and Sub-Atlantic mountains, covered by a mosaic of scrubs and forests mixed with pastures in coastal areas
3	Hillsides under 650 m.a.s.l., with a southern exposure and mid-high slope from Atlantic and Sub-Atlantic mountains, covering by a mosaic of scrubs and forests mixed with pastures in coastal areas
4	Complex cultivation patterns (crops and pasture mosaic) with high presence of natural vegetation in areas, with moderate slope at low altitude
5	Woody and scrub vegetation with rock formations covering northern faces of the upper part of Atlantic mountains
6	Woody and scrub vegetation with rock formations covering southern faces of the upper part of Atlantic mountains
7	Hillsides in the central area of the Cantabrian Mountains above 1400 m.a.s.l., with northern exposure and dominated by rock formations with moors and high mountain forests
8	Hillsides and mid-hillsides under 1400 m.a.s.l. and valleys above 1300 m.a.s.l. in the central area of the Cantabrian Mountains, with sun-facing exposure and dominated by broadleaf forest mixed with pastures and heathlands
9	Peaks and mountainsides above 1400 m.a.s.l. with southern western and eastern exposures in the central areas of the Cantabrian Mountains and dominated by rock formations pastures moors heathlands and forests
10	Valley bottoms from high central areas of the Cantabrian Mountains extending to piedmont areas, dominated by pastures in the valley bottoms and mosaics of forests scrubs and crops in piedmont areas
11	Paramos, countryside and depressions at low altitude, with moderate to high solar radiation rates and dominated by intensive crops
1 km resolution	
1	Sea inlets, coastal plains and sub-coastal valleys, located at the lowest altitude and dominated by a mosaic of crops and pastures with a high presence of natural vegetation.
2	Coastal hills under 800m, with moderate solar radiation and slope dominated by pastures with natural vegetation areas
3	Depressions mainly covered by complex cultivation patterns in areas with an average altitude of 600 m. 600 m.a.s.l., slight slope and moderate to high solar radiation rates
4	Middle mountain areas under 1400 m.a.s.l. with moderate solar radiation and slope rates, dominated by forests scrub and transitional woodland formations
5	High central mountains with an average altitude around 1400 m.a.s.l. with moderate slope, high solar radiation rates and dominated by forests, scrubs and bare and semi-bared areas
6	Valley bottoms from high central areas of the Cantabrian Mountains extending to piedmont areas and Sub-Atlantic mountains, with gentle slope and dominated by pastures in valley bottoms and forest formations accompanied by scrubs and mosaic of crops fields in piedmont areas
7	Paramos, countryside and depressions with moderate to high solar radiation rates and dominated by crops

3.3. Landscape classification uncertainty

Regarding CORINE-based landscape classifications, membership probability was dependent on the spatial resolution, as Euclidean distances between pixel attributes and the characteristic vector of the class decreased when pixel size increased from 30 m to 90m. However, they consistently increased when pixel size became coarser than 90 m (Table 4). The higher differences in Euclidean distances among classes were detected at 30 m resolution. Additionally, the confusion associated with the classification of a pixel among classes was also dependent on the spatial resolution of analysis (Fig. 2; cases a.2–d.2). Classes were represented with lower confusion at 1 km and 90 m pixel size. In contrast, the highest confusion was found at the original (30 m) and intermediate (180 m) spatial resolutions.

Considering NDVI-based classifications, membership probability almost did not vary across spatial resolutions (Table 5). There were no clear differences in Euclidean distances among classes at any spatial resolution. The use of NDVI in landscape classification produced high confusion among classes (*CI* values closer to 0) (Fig. 3; cases a.2–d.2). We did not find consistent differences in *CI* values among 30 m, 90 m and 180 m spatial resolutions, with *CI* increasing only at 1 km grain size.

4. Discussion

We have demonstrated the value of two of the most readily available remote sensing products accounting for land cover (the CORINE land cover map from Landsat TM at a 30 m pixel size and the spectral index NDVI from NOAA-AVHRR at a 1 km) in landscape classification at different spatial resolutions. The consistency of classifications across spatial resolutions is a key concern for landscape managers, because information achieved at a particular level should be reproducible ideally at other decision-making levels (Rocchini and Ricotta, 2007). Nevertheless, although this consistency might be desirable, caution is urged, as landscape is hierarchically structured and most ecological processes and patterns are scale-dependent (Schröder and Seppelt, 2006). Thus, ecological patterns and processes should be evaluated only when the spatial resolution of available data matches the target phenomenon; otherwise, we could miss it (Jelinski and Wu, 1996). Information that can be relevant at low hierarchical levels might become irrelevant over a given threshold of aggregation or vice versa (Karl and Maurer, 2010). In this sense, our multi-spatial resolution approach showed how the perception of landscape patterns can be affected by using input data collected at a spatial resolution different to that of the landscape classification analyses.

When using CORINE 30 m as an input in landscape classification analysis, the number and typology of classes differed across spatial resolutions. From a practical perspective, this fact is relevant as it could limit the implementation of this approach for management purposes (Rocchini and Ricotta, 2007). It is well known that thematic resolution (number and typology of classes) of landscape maps may constrain results of further landscape analyses (Suárez-Seoane and Baudry, 2002; Gimona et al., 2009), leading to different ecological findings. Nevertheless, the use of CORINE in landscape classification was advantageous, since landscape classes were easily characterized and interpreted, as CORINE account directly for land cover. Regarding the error and uncertainty of CORINE-based classifications, we found the original data to be a main source of error for further classification process, being the generaliza-

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Table 4
User's, producer's and overall accuracy of landscape classification based on topography, urban influence and CORINE (as a proxy of land cover) at different spatial resolutions. The table also shows the probability of membership (i.e., the Euclidian distance from pixel values to the characteristic vector of each class; mean ± SD).

	Code		User's accuracy (%)	Producer's accuracy (%)	Euclidean distance
30 m	1		93.33	88.89	3.46 ± 3.28
	2		85.29	78.38	5.93 ± 5.63
	3		83.33	68.97	2.93 ± 3.01
	4		86.49	96.97	2.82 ± 4.23
	5		100.00	91.18	2.95 ± 3.09
	6		94.12	94.12	2.82 ± 2.52
	7		96.15	100.00	2.66 ± 2.52
	8		89.47	85.00	2.62 ± 2.04
	9		85.00	89.47	2.69 ± 4.08
	10		50.00	100.00	3.87 ± 1.71
	11		93.33	100.00	3.46 ± 3.28
	Overall	88.33			3.21 ± 0.98
90 m	1		93.33	93.33	2.90 ± 2.37
	2		96.08	92.45	2.86 ± 2.41
	3		95.23	100.00	3.01 ± 2.22
	4		86.67	89.66	3.06 ± 2.16
	5		100.00	100.00	2.86 ± 2.21
	6		100.00	100.00	3.14 ± 2.27
	7		100.00	100.00	2.74 ± 1.87
	8		100.00	100.00	3.20 ± 1.95
	9		100.00	75.00	3.15 ± 2.01
	10		100.00	100.00	3.32 ± 1.73
	Overall	97.33			3.02 ± 0.18
180 m	1		83.64	82.14	3.15 ± 1.75
	2		93.75	90.91	2.98 ± 2.84
	3		53.33	72.73	2.38 ± 1.84
	4		88.89	98.46	3.23 ± 2.23
	5		100.00	93.75	3.32 ± 2.08
	6		92.31	83.72	3.04 ± 2.09
	7		100.00	100.00	2.94 ± 1.89
	8		100.00	83.33	3.26 ± 1.88
	9		75.00	75.00	3.43 ± 1.42
	10		100.00	80.00	3.68 ± 1.69
	Overall	86.66			3.14 ± 0.35
1 km	1		95.52	75.29	3.47 ± 2.21
	2		75.32	74.36	3.30 ± 2.07
	3		92.86	78.00	3.56 ± 2.58
	4		84.44	88.37	3.42 ± 2.63
	5		59.42	93.18	3.56 ± 2.18
	Overall	80.00			3.46 ± 0.11

tion and simplification of reality into a limited set of classes (Hou et al., 2013), as well as the existence of spectral interferences, mixed pixels, system errors or conceptual mistakes (Bossard et al., 2000) the possible causes behind this error. Addressing specifically landscape classification process, transferring information from one resolution to other generally involves generalization and loss of accuracy and reliability (Hou et al., 2013). Nevertheless, according to some authors (Ju et al., 2005; Dronova et al., 2012), this transfer of information not always imply a loss of accuracy. In heterogeneous landscapes, such as mountain systems, high local variability might lead to high landscape complexity on the ground and noise in the remote sensing, making class allocation processes difficult and partially erroneous (Kennedy et al., 2009; Rocchini et al., 2013; Nagendra et al., 2013). Therefore, coarsening the spatial resolution of data (from 30 m to 90 m) could help to reduce the perception of this local variability, improving then the accuracy of classification (Ju et al., 2005). Nevertheless, with further coarsening (beyond 90m), boundaries between patches could be poorly represented due to a loss of resolution and distortion in land cover information (Shao and Wu, 2008), causing a new error. The loss of the capacity to detect local variability could be also suggested as an explanation of the overall increase of membership probability (and consequent decrease of uncertainty) associated to data coarsening. In this sense, beyond 90 m spatial resolution, the existence of some classes constituted by rather disparate landscape features resulted in large differences between some pixels and the characteristic vector of the class, increasing uncertainty. Additionally, our study suggested that the use of discrete maps, such as CORINE, in landscape classification might reduce partially confusion, allowing to depict landscape classes with high certainty. It is reasonable to expect that a reduction of mutually-exclusive classes would decrease confusion among classes (i.e., CI values close to 1) (Strand, 2011). Consistent with this statement, the reduction of classes shearing very similar landscape attributes (classes 8 and 9 were reduced to class 7) when spatial resolution changed from 30 m to 90 m could explain the decrease in confusion. On the contrary, at 180 m resolution, the definition of rather similar classes (like classes 2 and 3) implied an increase in confusion. The reduction in the number of classes at 1 km resolution was probably related to the decrease in CI, due to the lower probability of definition of classes with some degree of overlap. The dependence of CI on spatial resolution could be related to the modifiable areal unit problem (MAUP), since changes in spatial resolution provided different landscape spatial configuration (Wong, 2009).

Accounting for NDVI-based landscape classifications, we found that the number and typology of landscape classes was only sensitive to change from coarse (1 km) to middle and high spatial resolution (180 m, 90 m and 30 m). This lack in classification consistency from 1 km to the more detailed resolutions could be explained by the role of input variables used in combination with NDVI, especially topography, which is of key relevance to describe landscape in mountain systems. The more detailed information on topography and urban influence included in landscape classifications at middle and high spatial resolution, as a consequence of the real change of resolution, let depict regional peculiarities that could not be addressed at 1 km (Hou et al., 2013). Consequently, the number of classes represented increased. The consistency of NDVI-based landscape classifications across middle and high spatial resolution suggested the adequacy of using spectral indexes, in combination with other variables, in landscape classification processes from a practical point of view. However, the use of NDVI could hamper the description and interpretation of landscape classes, since it informs on biophysical parameters related to vegetation activity, not accounting for land cover directly (Wang and Tenhunen, 2004). Furthermore, some additional considerations should be taken in account concerning the error and uncertainty associated to this data source (Hou et al., 2013). Atmospheric influences and aerosols tend to decrease NDVI values (Carlson and Ripley, 1997) and fluctuations in soil brightness might also lead to large variations in NDVI signal among images (Liu and Huete, 1995). NDVI signal is sensitive to canopy background and could be saturated at high leaf area index (LAI) values (Pettorelli et al., 2005). Looking at the error of NDVI-based landscape classifications, we found that landscape maps developed at 1 km (the original resolution of NDVI) showed less accuracy than those developed at intermediate resolutions. Maps at the coarsest pixel size might result overly non-specific to be useful (Ju et al., 2005) affecting, therefore, the correct characterization of spatial details of the landscape, due to the vagueness of information (Hou et al., 2013). The decrease in classification accuracy from 90 m to 30 m was suggested to be associated with local landscape complexity and variability, making class allocation processes difficult and partially erroneous (Kennedy et al., 2009; Rocchini et al., 2013; Nagendra et al., 2013). Addressing membership probability, the poor influence of spatial resolution change on results might suggest that NDVI index facilitates the definition of homogeneous classes providing accurate pixel allocation, with independence of spatial resolution. Additionally, the increase in confusion among classes at higher spatial resolution than the original one could be associated with both, the increase in the number of classes and the inherent properties of NDVI as a continuous variable. Assumptions for classification methods include that classes are crisp and mutually exclusive, setting boundaries in sites where classes slightly differ (Foody, 2002; Bollinger and Mladenoff, 2005). This might be a problem when working with continuous data in heterogeneous mountain systems, where classes can be inter-grade and co-exist spatially (Foody, 2002; Morán-Ordóñez et al., 2012), resulting in high confusion in regards to which class a pixel should belong (Álvarez-Martínez et al., 2010). This problem would be reduced in more homogeneous systems, where classes are very different and with clear dominance of one of them across space (Bollinger and Mladenoff, 2005).

5. Conclusions

Remote sensing products informing on land cover, such as the CORINE Land Cover map at 30 m or the NDVI spectral index from NOAA at 1 km, are valuable tools that, used in combination with other thematic information, allow for producing landscape classifications useful for practical applications. The multi-spatial resolution approach here developed provided a relevant framework for landscape managers, particularly when funding is limited and data source at an appropriated spatial resolution are not available. Efforts should be made to select data at suitable resolutions, matching regional peculiarities and minimizing error and uncertainty in results.

Table 5
User's, producer's and overall accuracy of landscape classifications based on topography, urban influence and NDVI (as a proxy of land cover) at different spatial resolutions. The table also shows the probability of membership (i.e., the Euclidian distance from pixel values to the characteristic vector of each class; mean ± SD).

	Code	User's accuracy (%)	Producer's accuracy (%)	Euclidean distance
30 m	1	96.43	65.85	2.02 ± 0.66
	2	57.14	100.00	2.14 ± 0.67
	3	64.00	88.89	2.19 ± 0.54
	4	87.50	63.64	2.10 ± 0.59
	5	81.25	86.67	2.13 ± 0.84
	6	64.29	90.00	2.14 ± 0.52
	7	88.89	100.00	2.11 ± 0.82
	8	88.00	88.00	2.05 ± 0.64
	9	100.00	94.74	2.38 ± 0.61
	10	83.78	65.96	2.01 ± 0.75
	11	74.51	90.48	2.02 ± 0.92
	Overall		79.67	2.12 ± 0.10
90 m	1	100.00	68.57	2.20 ± 0.58
	2	72.22	100.00	2.09 ± 0.78
	3	73.33	100.00	2.12 ± 0.69
	4	85.19	92.00	2.15 ± 0.61
	5	83.33	100.00	2.03 ± 0.90
	6	82.22	94.87	2.14 ± 0.63
	7	100.00	88.24	2.07 ± 0.96
	8	100.00	95.45	2.14 ± 0.66
	9	100.00	100.00	2.12 ± 0.73
	10	96.97	71.11	2.14 ± 0.64
	11	87.50	97.67	2.03 ± 0.94
	Overall		88.66	2.11 ± 0.05
180 m	1	100.00	84.00	2.08 ± 0.82
	2	83.33	90.91	2.13 ± 0.67
	3	77.78	82.35	2.06 ± 0.87
	4	92.16	87.04	2.15 ± 0.63
	5	100.00	93.75	2.09 ± 0.80
	6	93.75	97.83	2.11 ± 0.76
	7	91.67	100.00	2.07 ± 0.84
	8	100.00	95.45	2.13 ± 0.68
	9	100.00	100.00	2.07 ± 0.81
	10	100.00	83.33	2.14 ± 0.67
	11	77.78	97.22	2.03 ± 0.93
	Overall		91.33	2.10 ± 0.03
1 km	1	83.33	83.33	1.96 ± 1.21
	2	72.73	84.21	2.08 ± 0.86
	3	87.50	75.68	1.88 ± 1.13
	4	86.84	80.49	2.03 ± 0.78
	5	91.43	91.43	2.15 ± 0.76
	6	85.53	86.67	1.99 ± 1.00
	7	93.33	95.45	1.76 ± 1.28
	Overall		85.67	1.98 ± 0.13

Q6 Uncited references

Alves et al. (2014), Bradley and Mustard (2005), Burrough et al. (1997), EEA (2006), Körner (2007), Morán-Ordóñez et al. (2013) and Sepp et al. (1999).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jag.2016.03.010.

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