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Title: Potential supply and actual use of cultural ecosystem services in mountain protected areas and their surroundings

- Emilie CROUZAT [a, b, c]
- Angel DE FRUTOS [a,b,r]
- Volker GRESCHO [a,b]
- Steve CARVER [e]
- Andrea BÜERMANN,[a,b]
- Claudia CARVALHO-SANTOS [n, o]
- Roland KRAEMER [a,b,f]
- Sarah MAYOR [h]
- Franziska PÖPPERL [p]
- Christian ROSSI [i,j,k]
- Matthias SCHRÖTER [g]
- Ana STRITIH [l,m,p]
- Ana Sofia VAZ [q,n]
- Jan WATZEMA [a,b]
- Aletta BONN [a,d,b]

	Affiliation	Address (full postal address including the country name)
a	Helmholtz Centre for Environmental Research –UFZ, Department Ecosystem Services	Permoserstrasse 15, 04318 Leipzig, Germany
b	German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig	Puschstr. 4, 04103 Leipzig, Germany
c	Univ. Grenoble Alpes, INRAE, LESSEM	2 rue de la Papeterie-BP 76, F-38402 St-Martin-d'Hères, France
d	Friedrich Schiller University, Institute of Biodiversity	Dornburger Str. 159. 07743 Jena, Germany
e	School of Geography, University of Leeds	Woodhouse Lane, Leeds, West Yorkshire, UK, LS2 9JT
f	Humboldt-Universität zu Berlin, Geography Department	Unter den Linden 6, 10099 Berlin, Germany
g	Helmholtz Centre for Environmental Research –UFZ, Department of Computational Landscape Ecology	Permoserstr. 15, 04318 Leipzig, Germany
h	Department of Evolutionary Biology and Environmental Studies, University of Zürich, Zürich, Switzerland	Winterthurerstrasse 190, 8057 Zürich
i	Remote Sensing Laboratories, Dept. of Geography, University of Zurich	Winterthurerstrasse 190, CH-8057, Zurich, Switzerland

j	Research Unit Community Ecology, Swiss Federal Institute for Forest, Snow and Landscape Research WSL	Zürcherstrasse 111, 8903, Birmensdorf, Switzerland
k	Swiss National Park	Chastè, Planta-Wildenberg, 7530, Zernez, Switzerland
l	ETH Zürich, Institute for Landscape and Spatial Development, Planning of Landscape and Urban Systems (PLUS)	Stefano-Franscini Pl. 5, 8093 Zürich, Switzerland
m	WSL Institute for Snow and Avalanche Research SLF	Flüelastrasse 11, 7260 Davos Dorf, Switzerland
n	Research Network in Biodiversity and Evolutionary Biology, Research Centre in Biodiversity and Genetic Resources (InBIO-CIBIO), University of Porto	Rua Padre Armando Quintas, Campus de Vairão, 4485-661, Vila do Conde, Portugal
o	Centre of Molecular and Environmental Biology (CBMA) & Institute for Bio-sustainability (IB-S), University of Minho	Campus de Gualtar 4710 – 057, Braga, Portugal
p	Ecosystem Dynamics and Forest Management Group, School of Life Sciences, Technical University of Munich	Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany
q	iEcolab, Andalusian Inter-University Institute for Earth System Research (IISTA-CEAMA), University of Granada	Avda. Del Mediterráneo, 18006 Granada, Spain
r	Universitat Jaume I	Campus Riu Sec, 12071, Castelló, Spain

Highlights

1. Locations for supply and use of cultural services are not always congruent.
2. Participatory mapping is a relevant tool to locate the use of cultural services.
3. Accessibility is a key predictor for actual use of cultural ecosystem services.
4. Attractive landscape features significantly relate to the use of cultural services.
5. Participatory mapping results from experts are valuable proxies for visitors' data.

Abstract

The potential supply of ecosystem services is often assessed using land cover data. Assessment of actual use of ecosystem services by beneficiaries remains less covered and often assumed to be congruent with potential supply. However, we believe that to contribute to the sustainable management of multifunctional landscapes, more insights are needed on the links between landscape characteristics and the various facets of ecosystem services. In this paper, we assessed cultural ecosystem services (CES) such as recreation, inspiration or scenic beauty in three European mountain protected areas and their surroundings. We study the alignment between the potential supply and actual use of CES. CES potential supply was modelled using six biophysical indicators derived from earth observation and open geospatial data. For CES actual use, we employed participatory mapping with protected area visitors and local experts. We modelled CES actual use as a function of landscape biophysical indicators, weighted by (i) stated and (ii) revealed visitor preferences, and accessibility in each protected area using generalized additive mixed-effects models. Accessibility alone could explain around 50% of the variability of CES actual use, and with the additional inclusion of the 'natural and cultural features' variable, the actual use models reached an explanatory power of around 80% for all three case-studies. Importantly, biophysical information alone cannot fully describe CES actual use, and there was little congruency between modelled potential supply and actual use. Additional socio-cultural features are required to explain the patterns of locations where protected area visitors enjoy CES. Our results can inform visitor management by addressing CES actual use and thereby provide evidence for landscape management and conservation planning and management, including offering a rewarding experience of nature for visitors.

Key words (6): cultural ecosystem service, potential supply, actual use, participatory mapping, protected area, expert knowledge elicitation

1 Introduction

Assessing the status and trends of ecosystem services usefully contributes to policy and management of sustainable social-ecological systems (IPBES 2019, Rieb et al. 2017). Ecosystem services (ES) mapping has seen great advances over the last decades (Burkhard & Maes 2017) while remaining a developing field of research (Pauna et al. 2018). Current challenges include the uneven assessment of ES categories (provisioning, regulating and cultural services) and of their facets (supply, demand and use) (Schägner et al. 2013, Boerema et al. 2017, Schröter et al. 2016, 2020). Moreover, most ES studies so far have assessed potential supply, while actual use or demand are less often evaluated, and few studies looked at both supply and demand (Lautenbach et al. 2019).

Despite their acknowledged contribution to human well-being, scientific assessments of cultural ES (CES) remain less developed compared to assessments of provisioning and regulating services (de Araujo Barbosa et al. 2015, Rendon et al. 2019). CES are rather intangible, which means that their value depends more on subjective individual and collective perceptions of their contribution to well-being than other ES categories (Palomo et al. 2016). CES are intrinsically dependent of human-nature interactions (Fish et al. 2016). This has been acknowledged both as a reason for the under-appraisal of CES so far as well as a motivation for future increased consideration in environmental assessments (Milcu et al. 2013, Bagstad et al. 2017).

While land cover and other remote sensing data are commonly employed to characterize provisioning or regulating ES based on the biophysical attributes of ecosystems, it is now commonly accepted that CES can be better captured through relational and place-based approaches. To explore how people interact with places, landscapes and species, CES assessments regularly mobilize participatory methods (e.g. Schirpke et al. 2016, van Riper et al. 2017), which often remain resource-consuming and produce non-spatially explicit outputs. Finding appropriate proxies and data sources to assess CES hence remains a key challenge (Hernández-Morcillo et al. 2013). Participatory mapping has been increasingly used to reveal place-based knowledge and local preferences or cultural benefits (Brown & Pullar 2012, Brown & Fagerholm 2015, Bagstad et al. 2016), possibly enabling a proactive management of conflicts and synergies across space (Bagstad et al. 2017).

For a more comprehensive understanding, distinct facets of individual ES can be described along the ES cascade from ecological structures to human value attribution (Spangenberg et al. 2014). These facets distinguish i) the potential supply, i.e. the biophysical capacity of ecosystems to provide a service, ii) the demand, i.e. the amount of service desired by people, and iii) the actual use, i.e. the realized flow of ES actually benefiting to people (Schröter et al. 2014, Geijzendorffer et al. 2015, Crouzat et al. 2016). Indicators for potential supply tend to be more directly related to ecosystems functions than indicators for demand and use, and are therefore more easily derived from spatially explicit earth observation data (Cord et al. 2017). However, further research is needed to develop integrative approaches for CES assessments along all facets (Geijzendorffer et al 2015, Ala-Hulkko et al. 2016, Small et al. 2017).

Accessibility contributes to the spatial link between ES providing areas and ES benefiting areas (Fischer et al. 2009, Syrbe and Walz 2012). Many CES, such as recreation or wild plants picking, are enjoyed directly through in-situ experiential interactions with nature, which people need to actively reach through infrastructures such as trails and roads (Vigl et al. 2017). High access costs limit the probability of visit (long distances, road network of poor quality, etc.) and reduce the actual use of CES (Paracchini et al. 2014). Therefore, we posit accessibility to be a key driver of CES actual use, in accordance with recent literature (Ala-Hulkko et al. 2016, Mayer & Woltering 2018, Gestenberg et al. 2020).

CES assessments can be particularly useful when applied to protected areas (PAs), which strive to strike a balance between conserving areas in a desired environmental state and enabling the recreational experience (Suh & Harrisson 2005, Plieninger et al. 2015). Indeed, the International Union for Conservation of Nature (IUCN; Dudley 2008) states that national parks should: i) conserve species and genetic diversity, ii) maintain ES, and iii) provide opportunities for spiritual, scientific, educational and recreational activities “at a level which will not cause significant biological or ecological degradation to the natural resources” (Dudley 2008, p.16). Management objectives in biosphere reserves also seek to conserve biodiversity while contributing to a socio-culturally and environmentally sustainable development (UNESCO 1996).

In this paper, we assess the alignment between CES potential supply, CES accessibility and CES actual use in three European mountain PAs and their direct surroundings. Mountainous settings supply crucial ES, including CES, to their inhabitants and surrounding populations but they also undergo major anthropogenic pressures related e.g., to land-use and climate changes. A better understanding of the interlinkages between ES, societal demand and management alternatives remains topical if mountain social-ecological systems are to be driven towards sustainability (Schirpke et al. 2021). Here, we propose an integrated characterization of CES (Jacobs et al. 2018), considering biophysical characteristics, accessibility and actual use along the ES cascade. Throughout this study, we use an inclusive definition of what the values assigned to CES are, i.e. following Pascual et al. (2017), we posit that CES valuation can encompass both biophysical and sociocultural dimensions. To reach our objective, we derived indicators of CES potential supply and accessibility from earth observation and open geospatial data (OpenStreetMap). We also collected information on CES actual use through participatory mapping during fieldwork, both from PA visitors and PA experts. Our paper targets the three following research questions:

1. How congruent are locations of CES potential supply, modeled using landscape characteristics through earth observation data, with locations of CES actual use, informed through participatory mapping with PA visitors?
2. What is the contribution of biophysical landscape attributes and accessibility in explaining the locations of CES actual use?
3. How congruent are participatory mapping results of experts and visitors in locating areas of CES actual use in PAs and their direct surroundings?

2 Material and methods

To address our three research questions, we structured our CES assessment in three parts (Figure 1). First, we mapped six biophysical indicators, selected from the literature as proxies for the potential supply of CES. We then spatially combined all indicators to identify areas with high potential for CES supply. Additionally, we developed an indicator for accessibility, accounting for distance from a starting point, slope and terrain. Second, we assessed the actual use of CES i) during participatory workshops with local PA experts (PA managers, rangers and local stakeholders from e.g., forestry and tourism sectors), and ii) during field surveys with PA visitors. Third, we carried out spatially explicit analyses to detect significant relationships among our variables, based on generalized mixed models. Throughout the whole process, we focused on CES provided and used during the summer season, as seasonality in mountain systems is expected to exhibit considerable variations in CES patterns (Willemen 2020).

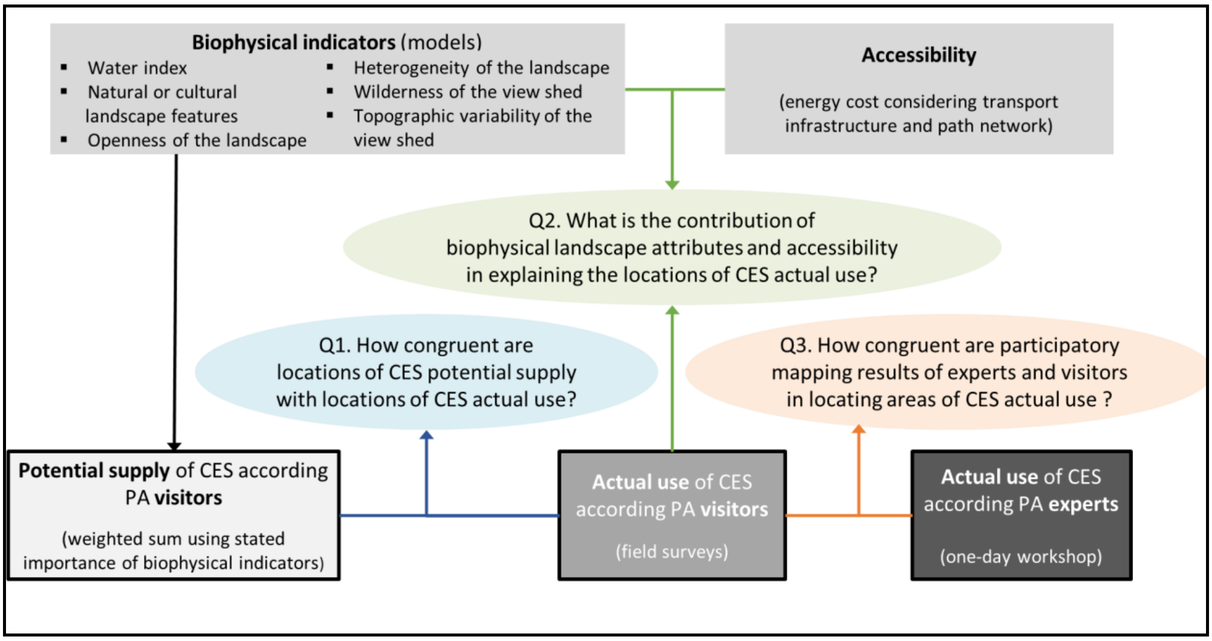

Figure 1: Conceptual representation of the study, which explores three research questions (Q1-Q3 – colored oval shapes) on the links among biophysical indicators, accessibility, CES potential supply and CES use (boxes of different shades of grey). Acronyms: CES - cultural ecosystem services; PA - protected area.

2.1 Study areas

Three mountain PAs were selected as case studies: i) Peneda-Geres national park, Portugal (PNP), ii) the UNESCO Biosphere Reserve Engiadina Val Müstair, Switzerland (UBREM), which includes the Swiss national park and iii) Kalkalpen national park, Austria (KA-NP) (Figure 2). In Switzerland, we decided to consider the UNESCO Biosphere Reserve (UBREM) and not solely the Swiss national park because this entity corresponds to the IUCN category II standards, as do PNP and KA-NP. Indeed, the Swiss national park constitutes the strictly protected zone of the Biosphere Reserve. Our three case studies supply a variety of ES and share characteristics of mountain areas, such as complex topography, remoteness, presence of wilderness areas and of cultural landscapes (Kozak et al. 2017). At the same time, the protected areas differ in level of protection and management, from the strictly protected core zone of the UBREM to a combination of different protection levels in PNP.

Around each PA, a buffer zone of 10 km was accounted for to better incorporate visitors' experiences, as we do not expect visitors to be familiar with the exact location of the PA perimeter. Instead, the 10 km buffer zone applied around the PAs accounts for the wider perspectives and perceptions of visitors, which were one core focus in this CES assessment. Despite differences in management regulations between the inner protected perimeter and their immediate surroundings, we contend that these areas relate to the same accommodation offer, they attract the same guests and they can thus be considered as the same travel destination. In addition, strictly defined geographical boundaries of PAs are being challenged by the current context of global changes, as PAs "are no islands" but are rather "entangled with their immediate and far-off surroundings in manifold ways" (Egner & Jungmeier 2016, p.124). These arguments altogether open the way to a wider conceptualization around PA perimeters as illustrated in this paper, with the consideration of a buffer zone around the inner protected perimeter. In the whole paper, the acronyms PNP, UBREM and KA-NP refer jointly to the PAs and the buffer zone around them. We include additional information specifically focused on the inner PA perimeters (without the surrounding 10 km buffer) for in-depth understanding of our results in sections specifically identified. Our whole study areas (inner protected zone and surrounding buffer) cover respectively 2846 km^2 (PNP), 1887 km^2 (UBREM) and 1375 km^2 (KA-NP). While both PNP and KA-NP are predominantly located between 500 and 1000 m of elevation, UBREM extends towards a higher altitudinal range, with almost 40% of its territory between 2000 and 2500 m (Supplementary Material SM1). Regarding land cover distributions (CLC 2012, Supplementary Material SM1), all three case studies present little artificial cover such as roads and urban fabric (<3% of total area). In UBREM and KA-NP, agricultural lands are mostly pastures (respectively, 6% and 11 % of total area) dedicated to livestock farming, while PNP also includes crop uses. Forests cover a large area, respectively 18% in PNP, 25% in UBREM and 76% in KA-NP. A diversity of open or semi-open habitats is also present, with for instance 27% of PNP covered by moors and heathlands, and 18% of UBREM covered by natural grasslands.

Figure 2: Location of the three case studies in Europe. Photos and logos are properties of each protected area and are extracted from their official websites. Further details on each study site are available as Supplementary Material SM1.

2.2 Biophysical indicators

To map CES potential supply, we targeted indicators expected to impact human perception and enjoyment of landscapes, based upon a comprehensive literature review of existing indicators by Boerema et al. (2017) which we completed and updated. We excluded indicators for which data was unavailable in our case studies or which were nearly invariant at PA scale, such as the presence of attractive species (invariance might be due to the lack of detailed data). Six indicators were mapped using exclusively freely available earth observation and geospatial data, thereby ensuring the repeatability of such CES assessment (Table 1, Supplementary Material SM6). These indicators are: i) water index, i.e. presence of water bodies (*water* - e.g. Schirpke et al. 2018), ii) presence of distinctive natural or cultural landscape features such as historical trees or mountain crosses (*featu* - e.g. van Berkel & Verburg 2014, Vlami et al. 2017), iii) openness of the landscape (*openn* – e.g., Schirpke et al. 2016), iv) heterogeneity of landscape (*heter* - e.g. Kienast et al. 2012), v) wilderness of the viewshed (*wilde* - e.g. Carver et al. 2012, Swetnam et al. 2017), and vi) topographic variability of the viewshed (*topog* - e.g. Schirpke et al. 2016).

Continuous pixel values for each indicator were standardized between 0 and 1 over each area following Eq.1 (Paracchini et al. 2011).

Equation 1. $\mathrm{Xstand} = (\mathrm{X} - \mathrm{Xmin})/(\mathrm{Xmax} - \mathrm{Xmin})$

With:

- X_{stand}: final standardized pixel value,
- X: initial pixel value before standardization,
- X_{max}: maximum value for the indicator in the considered case study
- X_{min}: minimum value for the indicator in the considered case study.

Ultimately, high values represent a high contribution to CES potential supply. For natural and cultural features (*featu*), we computed a binary indicator of presence/absence of features as the distribution of features was highly skewed towards low values.

For final maps of CES potential supply, we weighted parameters using visitors' stated preferences (see section 2.5).

Table 1: Biophysical indicators of CES potential supply. Individual maps of indicators for each case study are proposed as Supplementary Material SM3 (PNP), SM4 (UBREM) and SM5 (KA-NP). Workflows for individual indicators are provided as Supplementary Material SM6.

	Definition	Metric	Data sources
Water index Acronym: ***water***	Inverse Euclidean distance to water bodies, weighted by importance of water body types using a Strahler index for rivers and area for lakes, and affected by slope	Index between 0 (*no large water bodies accessible*) to 1 (*large water bodies accessible*)	- DEM (Copernicus product) - EU-Hydro River Network (Copernicus product) - Strahler Index (Tarboton et al. 1991)
Presence of natural and cultural features Acronym: ***featu***	Presence of natural and cultural attractive landscape elements such as hilltop crosses, cave entrances or waterfalls	Binary index: 0 (*no attractive feature*) - 1 (*presence of at least one attractive feature*)	- OSM data, whole list of selected features in SM6
Openness of the landscape Acronym: ***open***	Density of open space per pixel (based on tree cover), to inform the local feeling of space and openness	Index between 0 (*100% tree cover in the pixel*) to 1 (*0% tree cover in the pixel*)	- Tree Cover Density (Copernicus product)
Landscape heterogeneity Acronym: ***heter***	Variety of land cover types in the surrounding 1*1km window of each pixel, not considering actual visibility or accessibility within the 1km² window	Index between 0 (*homogeneous land cover types in the surrounding window*) to 1 (*high diversity of land cover types in the surrounding window*)	- Corine Land Cover 2012 at level 3 (Copernicus product)
Wilderness of the view shed Acronym: ***wilde***	Natural character of the view shed, unaffected by human visual disturbances such as artificial areas and roads, for each stand point (tree cover < 90%)	Index between 0 (*view shed is highly artificial, or no view point*) to 1 (*view shed is highly natural*)	- OSM data, whole list of selected artificial features in SM6 - Tree Cover Density (Copernicus product) - DEM (Copernicus product) - Viewshed Explorer software (Carver and Washtell, 2012)
Topographic variability of the view shed Acronym: ***topog***	Variability of the altitudinal profile of the view shed for each stand point (tree cover < 90%)	Index between 0 (*view shed is completely flat, or no view point*) to 1 (*topography in the view shed has highest heterogeneity*)	- DEM (Copernicus product) to compute terrain roughness index after Riley et al. 1999 - Tree Cover Density (Copernicus product) - Viewshed Explorer software (Carver and Washtell, 2012)

2.3 Accessibility

Accessibility is a key determinant of CES use, based on the presence and characteristics of infrastructures that facilitate the visit of areas of interest (Ala-Hulkko et al. 2016, Vigl et al. 2017). Data on accessibility comprises line features representing transport infrastructure and pathways (e.g., roads, cable cars, pedestrian trails), and point features representing starting locations, such as parking spaces and settlements (e.g., Schröter et al 2014). To acquire the best possible data while testing an easily reproducible methodology, we used geospatial information from OpenStreetMap (OSM).

We computed the minimum travel cost along existing pathways over the whole case study areas, starting from each possible source point using the ArcGIS Path distance tool. The cost includes the effect of linear distance, slope and quality of trails or roads: it increases with distance, cumulative steepness and decreasing walkability. Results were inverted and standardized over each study area as a continuous 0 to 1 index (*acces*) following Eq.1; thereby high values indicate high accessibility.

2.4 Actual use of CES

To assess the actual use of CES, we applied participatory methods aimed at identifying locations frequently used for CES and in particular participatory mapping (Brown and Pullar 2012, van Riper et al. 2017).

First, we organized a one-day focus group workshop at each PA in spring 2018, gathering respectively 9, 11 and 13 local experts in PNP, UBREM and KA-NP. Experts represented diverse sectors, e.g., tourism, forestry or protected area management. To ensure a common understanding of CES, participants were provided with a list of eight CES potentially relevant for the selected PAs with a short description and picture (Supplementary Material SM2). In the following analyses, for the sake of publication's clarity and length, the eight distinct services have been considered as one single broad category referred to as CES. Expert participants were individually asked to identify important locations for CES actual use by placing a maximum number of 20 dots on an A3 map of the study area. Maps included basic topographic and land cover information as well as main location names. Dots consisted in one cm round markers that respondents stuck to the map. We digitized all markers using their center as points and overlaid all results per case study.

Second, during summer 2018, we conducted short individual field interviews. We asked visitors of the PAs, both locals and non-locals, to map their CES use individually. Providing them with the same detailed list of CES as presented to the experts, visitors were asked to place up to 10 dots on maps of the study area (same dots as for experts) (Supplementary Material SM2). Following local experts' advice, we reached visitors during day-time in known local points of tourist attraction within the PAs such as visitor centers or view points, and at starting points for outdoor activities (e.g., parking lots). In each PA, a continuous set of ten days has been dedicated to carrying out the survey during the summer time. Visitors were asked to identify locations that they consider of particular importance regarding CES use. We ensured visitors identified locations not only in the direct surroundings of the survey place but in the whole case study area they knew. Importantly, to obtain results on actual CES use, dots identify places that respondents actually visited, and not only heard about or thought it would be interesting to visit. All contributions were addressed to adults older than 18, who freely and without compensation accepted to dedicate approximately 10 minutes of their time to our survey. Additionally, respondents could provide us with basic demographics (local inhabitant or not, age, gender). All results were digitized and overlaid following the same methodology described for experts' results.

The number of dots assigned to experts and PAs' visitors (20 versus 10) differed for pragmatic reasons. Experts were expected to hold more knowledge of the place than many of the visitors, and their contributions were considered as incorporating the experiences of several individual visitors. Importantly, experts could dedicate more time to answering the mapping exercise (full-day workshop versus 10 minutes contribution). To account for these differences between experts and visitors, as well as between individual participants, the number of dots per person was accounted for in the models (section 2.6).

2.5 Potential supply of CES

PA visitors were additionally asked to state their landscape preferences in order to inform models on locations of expected CES supply, assuming that people would benefit more from CES in places holding the landscape characteristics they state to prefer. Specifically, we wanted to know how important each of the biophysical indicators described in section 2.2 was to them regarding their experience of CES in the study area. Importance was rated along a 7-point Likert scale, from 0 to 6 (not at all to very important to CES enjoyment, Krosnick and Presser 2010).

We used these stated preferences to assign each biophysical indicator a weight, following Eq. 2. Then, the six biophysical indicators were aggregated through a weighted sum using these weights. Ultimately, the weighted sum was standardized following Eq. 1 resulting in a continuous 0 to 1 index of CES potential supply for each study area.

Equation 2.

$$W = \left(\sum_{0}^{6} Ri * i\right) / (R * 6)$$

Where:

- *W* is the weight of a landscape indicator in a given case study,
- *Ri* is the respective number of respondents who rated the indicator as a score of *i*, varying from 0 to 6, in each case study (R_1 is the number of respondents who stated the indicator had an importance of 1, etc.),
- *R* is the total number of respondents (i.e., the sum of respondents R_1 to R_6)

2.6 Statistical analyses

For all subsequent analyses, values attributed to the locations mapped by visitors and experts corresponded to the mean value of each of the biophysical indicators on a buffer of 500 m radius around the center of the dot placed on the printed map (i.e. not only the pixel value where the dot center stood but the mean value of all pixels in the 500 m buffer around). The only exception was for the *featu* indicator, for which the maximum value instead of the mean was computed due to the presence of many null values for this indicator. In line with a previous study (Ridding et al. 2018), the buffer's diameter was chosen considering the size of the dot used to locate CES use, map scale, and visitors estimated ability to identify locations on the map. Similarly, to compare locations of CES use to random locations, we created a number of random points (namely, in the ratio 1:1) to calculate the value of each indicator excluding any pixel values of CES use.

To assess the congruency between potential CES supply and actual use (research question 1), we compared locations of modelled CES supply based on visitor's stated preferences for landscape attributes with locations mapped for actual CES use by visitors. We consider these models as 'constrained' by visitors' stated preferences. We modelled CES actual use as a function of CES potential supply in each case study using generalized additive mixed-effects models (GAMM; Zuur et al. 2009) for locations of CES use versus random locations, with a logistic link function, a binomial error distribution and a random effect of visitors (i.e., number of dots placed on the map per visitor). We included a smoother with the spatial coordinates (i.e. X and Y of the dot locations) in the GAMM model, as recommended by Zuur et al. (2009) to deal with high spatial autocorrelation in residuals.

To identify the main predictors of CES actual use (research question 2), we assessed the contribution of six landscape biophysical indicators and the accessibility variable towards determining the realized patterns of CES actual use. Instead of using visitors' stated preferences for biophysical indicators, here we identified their revealed preferences based on the locations mapped in the field for CES actual use. We consider these models 'unconstrained' as they do not depend on visitors' stated preferences. We modelled CES actual use as a function of the explanatory variables (landscape biophysical indicators and accessibility) using GAMM for locations of CES actual use versus random locations, with a logistic link function, a binomial error distribution and a random effect of visitors. To remove collinear explanatory variables that affect the independency among them before running the models, we selected for each case study the indicators with variance inflation factors (VIF) below three according to Zuur et al (2009). In other words, we chose a more conservative VIF threshold of three than the suggested cut-off value of five to remove potential collinearity in all GAMMs (Zuur et al 2009). For KA-NP, we also used a smoother of spatial coordinates because the starting model did not converge. Regression coefficients are sensitive to the scale of the input data. In order to directly compare the importance of independent variables after modelling (i.e. the regression coefficients) and interpret them like those of binary predictors, we followed Gelman (2008) and standardized the continuous variables by centering and dividing by two standard deviations. Coefficient values were then used to compare variables' importance regarding actual use as in Ridding et al. (2018). We also checked the assumption of independent errors of all GAMMs by plotting residuals versus fitted values (Zuur et al 2009).

To assess the accuracy of relying on local expert knowledge in comparison to collecting data by visitor surveys (research question 3), we compared whether local experts and visitors provide congruent information on patterns of CES distribution in PAs and their surroundings. First, we measured the distances in meters between each location of CES use identified by visitors with the nearest location of CES use identified by experts in each case study. The median of these expert-visitor distances was compared with the median of the distances from visitors to random points using 1000 simulations. The number of random points was the same as the number of expert points in each case study. We estimated the pseudo p-value using a

Monte Carlo simulation. Second, we assessed whether experts' data on CES actual use was related to landscape indicators in the same way as visitors' data by computing GAMMs with expert data following the same workflow as described for visitor data.

We computed all spatial indicators at a regular grid resolution of 100*100m. The spatial data was processed in ArcGIS version 10.6 (Environmental Systems Research Institute, Redlands, CA) and QGIS version 2.18 (QGIS Geographic Information System. Open Source Geospatial Foundation Project). Open geospatial data was extracted from Open Street Map (OSM 2018), through the API and QuickOSM. All viewshed calculations were performed using Viewshed Explorer (Carver and Washtell, 2012). All statistical analyses were performed using R version 3.5.1 (R Core Team, 2018) with the packages mgcv (Wood, 2017), raster (Hijmans, 2020), sf (Pebesmba, 2018), and ggplot2 (Wickham, 2016).

All these analyses were performed over the complete study areas (i.e. inner zones and their 10 km surrounding buffer). To detect possible discrepancies between results for the inner PAs and for their buffers, we also ran all models only for the inner zones (detailed results in Supplementary Materials).

3 Results

3.1 Participatory outputs

Regarding the participatory mapping, we asked experts to map up to 20 points and visitors to map up to 10 points for CES actual use. Response rates differed among participants, thus we included the number of points per respondent as a random effect in our models. In PNP, 158 points were mapped by 9 experts, and 574 points by 98 visitors. In UBREM, 213 points were mapped by 9 experts, and 1219 points by 182 visitors. In KA-NP, 124 points were mapped by 10 experts, and 944 points by 142 visitors. Of these, a percentage of points was placed in the inner zones (not in the surrounding buffer): of the total number of points they represent in PNP 77% (experts) and 68% (visitors), in UBREM 71% (experts) and 45% (visitors), and in KA-NP 76% (experts) and 48% (visitors). While our field efforts and methodologies remained consistent over the three case studies, we hypothesize that the numbers of visitors that we could reach in each case varied in relation to the weather conditions during the surveys, to the overall frequentation rate in the study area and to the degree of individual agreement for contributing to the study. These differences in point numbers do not affect our conclusions, which are made independently for each case study.

Visitors' characteristics who answered the surveys varied among case studies. First, the rate of local respondents (inhabitants who considered themselves as living in the study area or its direct surroundings) represented 2% in PNP, 7% in UBREM and 37% in KA-NP. More familiarity with the local settings might therefore be expected in KA-NP compared to the other PAs. Second, more than 70% of the respondents ranged between 26 and 65 years old, with respectively 47%, 34% and 25% of respondents in the age class 26-45 years in PNP, UBREM and KA-NP, and 26%, 43% and 48% of respondents in the age class 46-65 years in PNP, UBREM and KA-NP. Thus, we assume that an active exploration of the study area through e.g., walking can be expected from the respondents beyond the very edges of starting points such as parking lots. Third, in the three case studies, gender balance was found to be almost even among respondents.

Overall, all biophysical landscape attributes scored high in visitors' answers. The lowest weights were attributed to the presence of attractive landscape features (*featu*), particularly in UBREM, while topographic variability in the view shed (*topog*), local landscape heterogeneity (*heter*) and the water index (*water*) obtained the highest weights (Table 2).

Table 2: Calculated weights per landscape biophysical indicator (detailed in Table 1) and case study in Peneda-Geres National Park (PNP), UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM) and Kalkalpen National Park (KA-NP).

Weights	**Water index** *water*	**Presence of natural and cultural features** *featu*	**Openness of the landscape** *open*	**Landscape heterogeneity** *heter*	**Wilderness of the view shed** *wilde*	**Topographic variability of the view shed** *topog*
PNP	0.84	0.79	0.83	0.84	0.81	0.86
UBREM	0.86	0.68	0.79	0.86	0.83	0.89
KA-NP	0.86	0.77	0.76	0.84	0.77	0.84
Average weight for the three case studies	0.85	0.75	0.79	0.85	0.80	0.87

3.2 Modelled CES potential supply versus mapped actual use

Modelled CES potential supply was positively associated with mapped actual CES use in two of the case studies, PNP and KA-NP (Figure 3, research question 1). Models using the single index of potential supply based on visitors' stated preferences weighting explained only 30% and 28.7% respectively of independent variability in CES actual use for PNP and KA-NP (ANOVA tests in PNP: F=5.53, P=0.02, KA-NP: F=11.53, P=0.001). In UBREM, modelled potential CES supply did not significantly explain actual CES use (ANOVA test, F=0.02, P=0.898) (detailed models in Supplementary Material SM7). Our results show that locations of actual CES use are generally poorly congruent with locations of modelled CES supply (overall low spatial match). When models were run exclusively for points situated in the inner zones, they were significant only for KA-NP, where the modelled potential CES supply explained 47% of independent variability in CES actual use (Supplementary Material SM10).

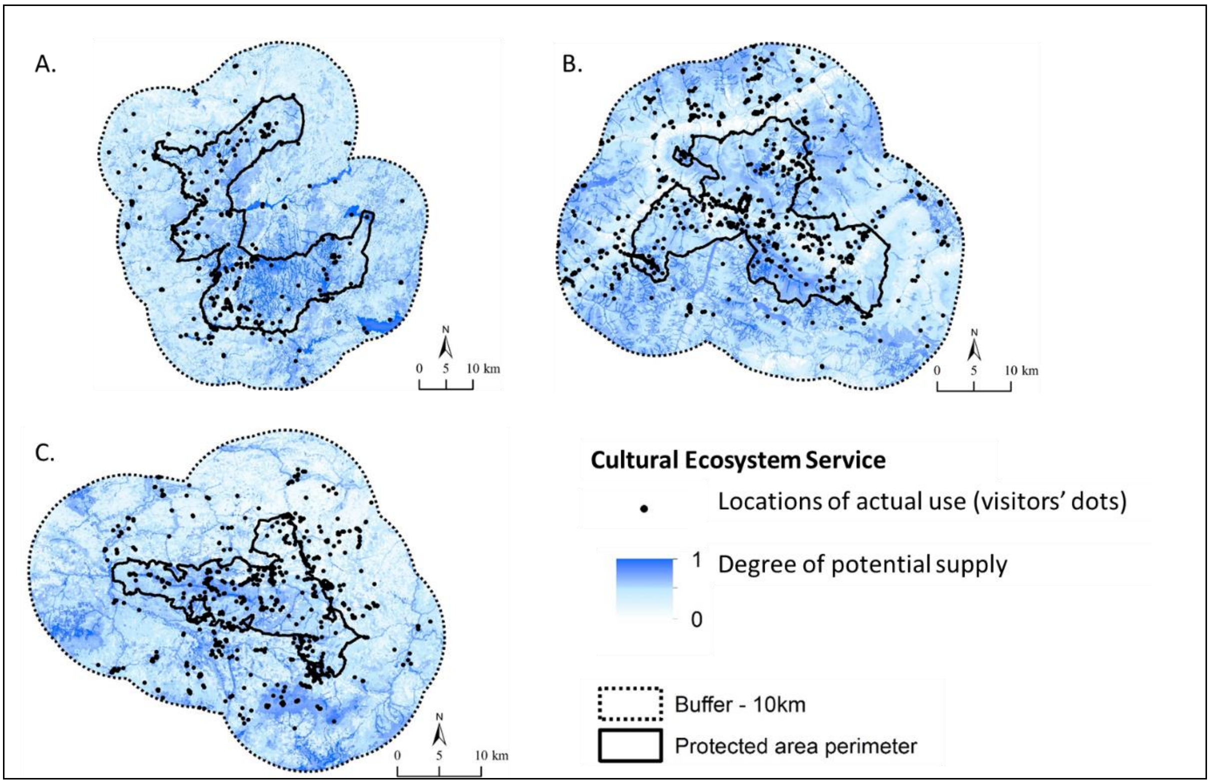

Figure 3: Overlap of modelled CES potential supply, as the weighted sum of biophysical indicators derived from visitor stated preferences (blue shades), and CES actual use identified by visitors' participatory mapping (black dots) in the protected areas and their surrounding 10 km buffer: A. Peneda-Geres National Park (PNP), B. UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM) and C. Kalkalpen National Park (KA-NP).

3.3 Characteristics of locations for CES use

Links between the six biophysical indicators and CES actual use were identified through the unconstrained GAMMs, thereby elucidating revealed preferences of visitors (research question 2). These models explained 75.7%, 59.9% and 75.1% of the variation of CES actual use in PNP, UBREM and KA-NP, respectively (R^2 in Table 3.A., detailed models in Supplementary Material SM8). Presence of attractive landscape features (*featu*) was the best indicator to explain actual CES use in all three models, as attractive landscape features were significantly more present in areas identified for actual CES use by visitors (ANOVA tests in PNP: $F = 191.55$, $P<0.001$; UBREM: $F = 302.12$, $P<0.001$; KA-NP: $F = 277.54$, $P<0.001$). Interestingly, this parameter *featu* had the lowest stated preference values chosen by visitors (Table 2). Additionally, wilderness of the viewshed (*wilde*) had a significant negative association with actual use locations for PNP and UBREM. The water index (*water*) was included with varying influence, positive for UBREM and negative for KA-NP, while topographic variability of the viewshed (*topog*) was positively associated with actual use of CES in PNP.

Including accessibility (*access*) as an additional variable to the six biophysical indicators into the unconstrained models improved GAMMs considerably for all three PAs, with R^2 up to 87.6% (PNP), 75.7% (UBREM) and 80.5% (KA-NP), respectively. Accessibility (*acces*) and presence of attractive landscape features (*featu*) were significant in all the final models, with a similar high importance of both factors to explain CES use. In KA-NP, the water index (*water*) exerted a significant negative influence (ANOVA test, $F = 22.84$, $P<0.001$). Additionally, openness of the landscape (*open*) had a significant positive effect in KA-NP, and heterogeneity of the landscape (*heter*) was negatively significant for UBREM in explaining CES actual use.

When using accessibility (*access*) only as a single explanatory variable, GAMMs reached an explanatory power of around 50% of the CES actual use variation (R^2 of 53.8%, 55.4% and 49.4% in PNP, UBREM and KA-NP, respectively).

In addition, we ran GAMMs exclusively for the inner protected perimeters and these results converge with those obtained over the whole study areas. They highlight the predominant influence of accessibility (*acces*) and presence of attractive landscape features (*featu*), as well as the increased R^2 in models accounting for accessibility in addition to the six biophysical indicators (Supplementary Material 11).

Table 3: Variation of CES actual use explained by GAMMs accounting for biophysical indicators and / or accessibility, and model coefficients for the variables in each model in the protected areas and their surrounding 10 km buffer: Peneda-Geres National Park (PNP), UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM) and Kalkalpen National Park (KA-NP). A. Models using mapped visitors' data (detailed models in Supplementary Material SM8), B. Models using mapped experts' data (detailed models in Supplementary Material SM9). See Table 1 for variables' acronym. n.s. – no significant effect ($p \geq 0.05$). R^2 (adj) means R^2 adjusted.

A. Visitors		Models without *acces*			Models with *acces*			Models only *acces*		
		PNP	UBREM	KA-NP	PNP	UBREM	KA-NP	PNP	UBREM	KA-NP
Biophysical indicator	*featu*	5.1	3.9	4.6	5.9	3.7	4.2			
	heter	n.s.	n.s.	n.s.	n.s.	-0.4	n.s.			
	openn	n.s.	n.s.	n.s.	n.s.	n.s.	0.7			
	topog	1.2	n.s.	n.s.	n.s.	n.s.	n.s.			
	water	n.s.	0.6	-0.9	n.s.	n.s.	-3.4			
	wilde	-1.8	-0.6	n.s.	n.s.	n.s.	n.s.			
Accessibility	*acces*				6.0	3.6	4.0	4.8	3.9	3.2
	R^2 (adj)	75.7%	59.9%	75.1%	87.6%	75.7%	80.5%	53.8%	55.4%	49.4%

B. Local experts		Models without *acces*			Models with *acces*			Models only *acces*		
		PNP	UBREM	KA-NP	PNP	UBREM	KA-NP	PNP	UBREM	KA-NP
Biophysical indicator	*featu*	2.9	2.8	2.7	3.7	2.4	2.7			
	heter	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.			
	openn	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.			
	topog	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.			
	water	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.			
	wilde	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.			
Accessibility	*acces*				2.6	1.8		1.7	2.3	1.5
	R^2 (adj)	37.7%	33.2%	40.8%	55.1%	49.5%	40.8%	11.6%	23.7%	8.3%

3.4 Congruency between expert and visitor data

Two main results are presented here to assess the congruency between experts and visitors' data (research question 3). First, the median distance between the locations of actual CES use mapped by experts and visitors was 605m, 831m and 1071m for UBREM, PNP and KA-NP, respectively (Figure 4). These median distances between visitors' versus experts' points were significantly lower than the median distances between visitors' versus random points for CES use in the three case studies (Monte Carlo simulation pseudo p-value < 0.001). The median of the 1000 simulated medians for the distances between visitors versus random points was 1405 m, 1572 m and 1990 m for UBREM, KA-NP and PNP, respectively (Figure 4). The same analysis run exclusively with data of the inner zones provided similar results for PNP and UBREM: median distances were significantly lower for visitors-experts data compared to visitors-random data, while for KA-NP; the difference between median distances was not significant (Supplementary Material 13).

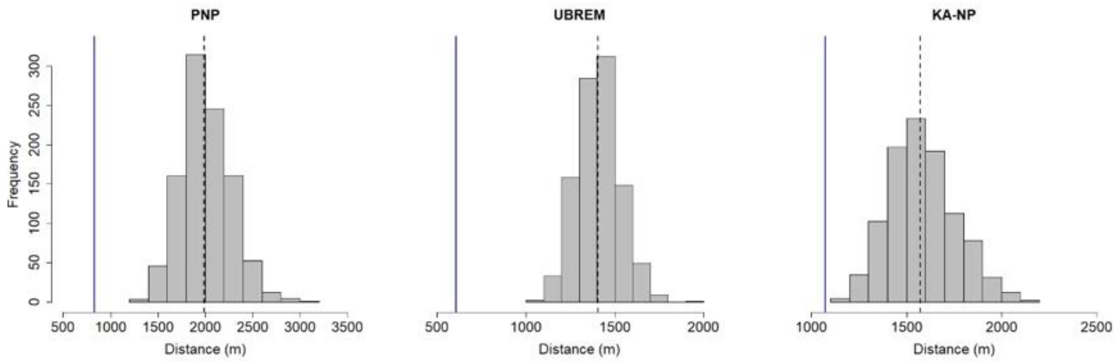

Figure 4: Median distance between visitor and expert points (blue solid line), compared to median distances between visitor and random points (diagram, with black dashed line showing the median of the 1000 runs) in the protected areas and their surroundings (10 km buffer): Peneda-Geres National Park (PNP, A.), UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM, B.) and Kalkalpen National Park (KA-NP, C.).

Second, all models computed with local experts data (representing their perceptions of CES actual use by visitors) showed a lower explanatory power than models accounting for mapped visitors data (realized CES actual use) (R^2 in Table 3.B., detailed models in Supplementary Material SM9). GAMMs computed using the six biophysical indicators without accessibility explained 37.7% (PNP), 33.2% (UBREM) and 40.8% (KA-NP) of the variation of CES actual use as located by local experts. Presence of attractive landscape features (*featu*) was the only variable included in these models, being significantly more present in areas identified for CES use by local experts (Table 3.B.; ANOVA tests in PNP: $F = 16.4$, $P<0.001$; UBREM: $F = 17.72$, $P<0.001$; KA-NP: $F = 14.14$, $P<0.001$). The explanatory power of the GAMMs improved with the integration of the accessibility (*acces*) variable in PNP (55.1%) and UBREM (49.5%), but not in KA-NP (40.8%). In PNP and UBREM, the models included accessibility (*access*) and presence of attractive landscape features (*featu*), the latter showing a higher importance than accessibility to explain CES use as allocated by local experts (Table 3.B.). Other biophysical indicators did not have a significant effect in any of the models. GAMMs performed only with the accessibility (*acces*) variable explained a lesser part of CES actual use compared to models including other variables in PNP, UBREM and KA-NP, reaching only a maximum R^2 of 24%. Models run exclusively with data for the inner zones provided convergent conclusions overall, i.e. i) lower explanatory powers in general than the ones obtained with visitor data, and ii) accessibility (*access*) and presence of attractive landscape features (*featu*) as the two main explaining variables of the GAMMs (Supplementary Material 12).

4 Discussion

Knowledge on the distribution of ES actual use and their relationships to potential supply is key to inform natural resource management, sustainable tourism planning and policy development (Villamagna et al. 2013, IPBES 2019). Our study contributes important insights by covering different CES facets and by combining biophysical modelling and stated preference for modelling potential CES supply and comparing this to CES actual use elicited through participatory mapping (Bagstad et al. 2016, 2017). In addition, our results show that most conclusions obtained for the broader area of PA and surrounding 10 km buffer also hold true when restricting analyses to the inner zones only. As a comparison on the inner versus surrounding characteristics of PAs was not our initial objective, our discussion should be understood as relating to the broader level of PA destinations, i.e. the locations commonly experienced by visitors during their stay over the three case studies, both within and in the vicinity of protected perimeters.

4.1 Using revealed preferences allows modelling CES niche for visitors

To identify areas of particular importance for CES use and their relationships with landscape biophysical indicators, we used GAMMs that compared values for locations identified by PA visitors with random locations. Such an approach is comparable to the use of pseudo-absence in species distribution models and has proved successful in other settings with survey data, including for CES assessment (e.g., Sherrouse et al. 2014, Schröter et al. 2014, Ridding et al. 2018). Our results could be considered as ‘habitat suitability’ maps for visitors regarding their landscape preferences, which are either based on stated preferences through weighting of landscape attributes by visitors (research question 1) or based on CES actual use elicited through participatory mapping (research questions 2 and 3) (Scholte et al. 2015). We show that revealed preferences may differ from preferences stated by visitors for landscape attributes associated with CES actual use.

There was a strong spatial mismatch between modelled CES potential supply, based on stated preferences, and mapped CES actual use, based on participatory mapping. When we incorporated stated preferences into models, the modelled distribution of potential CES supply only explained around one third of the variability of CES actual use for PNP and KA-NP, and was not significant for UBREM. Interestingly, when using visitor data on mapped CES actual use and not considering their stated preferences, the explanatory capacity of biophysical indicators remarkably increased to up to around 60% (UBREM) and 75% (PNP and KA-NP). Thus, understanding actual behaviors regarding CES use calls for more than using stated preferences on landscape attributes: attributes that people value in absolute terms as stated preferences (also called *de dicto* values) might not wholly reflect their actual uses and preferences, revealed through the characteristics of the specific places people visited and experienced (*de re* values) (James 2015). Or put differently, even if some locations may potentially provide desired CES, this potential CES supply may not be actually used, either due to accessibility issues (see below) or because stated and revealed preferences differ for CES.

On a methodological perspective, we modelled biophysical indicators at a fine grain (resolution of one ha) while the resolution at which visitors indicated important locations of CES use was coarser. However, the 500 m buffer used around each visitor's point to average biophysical indicators' values is intended to smooth this difference.

4.2 Towards a generic hierarchy of biophysical attributes for explaining CES use?

We built a local model for each case study (as done in Tenerelli et al. 2016) and found a comparable influence of most significant landscape indicators across our case studies. From the set of variables considered to explain the distribution of CES actual use, we found that the presence of cultural and natural features of special interest (*featu*), such as hilltop crosses or monumental trees, as well as accessibility (*acces*) were significantly and positively driving the models in all three cases. Accessibility positively explains CES actual use both as a standalone variable (explaining around 50% of the variability of CES actual use) or in addition to the biophysical indicators in the GAMMs (extra 5 to 15 percentage points, influence comparable to *featu*). While we contribute to closing the knowledge gap regarding the importance of biophysical attributes for explaining CES use, we also question whether a generic model of such importance of biophysical attributes could be elaborated and generalized across contexts (see also Schirpke et al. 2016, Van Berkel et al. 2018, Vaz et al. 2020, Gestenberg et al. 2020). Indeed, the other factors we tested, namely water index, openness and heterogeneity of the landscape, and wilderness and mountainous topography of the view shed, exerted varying influences over the case studies, in terms both of significance and direction (positive versus negative). The lack of consistency in contributions of biophysical attributes across PAs could be linked, among others, to distinct preferences of visitors in each location and to local characteristics of the environment, making landscape attributes more or less attractive depending on their relative rarity for instance. To improve the explanatory power of the models, additional factors not captured here might have been included in the models, such as the presence of iconic species. While a balance needs to be attained in terms of feasibility versus exhaustiveness of the modelling process, our results encourage a tailored selection of explanatory attributes with regards to the CES addressed. This has also been highlighted by Zoderer et al. (2019), who found lower model fits for CES than for provisioning and regulating ES when using a fixed set of biophysical indicators across the landscape to explain ES distribution.

4.3 Natural and cultural features and accessibility drive CES use

Features of natural and cultural interest (*featu*) included in the analysis match partly with the indicators of cultural heritage related to landscapes reviewed by Sowińska-Świerkosz (2017) (Supplementary Material SM6). Specifically, they correspond to cultural heritage and to landscape elements designed or maintained by humans (including monumental trees or hedgerow networks). Furthermore, the natural features included here, such as springs, waterfalls or mountain peaks, have also been considered in previous studies to map CES (Cortinovis & Geneletti 2018). Why do attractive landscape features (*featu*) perform so high in our GAMMs to explain CES actual use? Bieling (2014) showed that concrete landscape features, places or biophysical attributes are given a high importance in narratives about individual experiences of CES. Recreation facilities ease nature experience by providing e.g., shade, rest, tranquility or comfort. Besides these utilitarian assets, we hypothesize that such features act as points of significance that PA visitors and local experts can remember and use for orientation and to refer to their outdoor experience (Bieling & Plieninger 2013, van Berkel et al. 2018). As familiarity with the area is required for meaningful participatory mapping, places best known or easy to recall because of striking features are likely to be better located during surveys (Scholtes et al. 2015). In the process of translating immaterial benefits during the participatory mapping exercise, it might be convenient to rely on features people can physically describe and locate. Interestingly, such features remain tangible but might refer to immaterial, mental and experiential benefits, such as shared legends about places and associated creatures (Sowińska-Świerkosz 2017, Small et al. 2017).

In many CES assessments at regional, national or continental scales, accessibility is considered through travelling times, distances or costs following the road network between settlements and places with potential recreation status or high quality natural state (e.g., Ala-Hulkko et al. 2016). Areas providing services are then identified broadly, with e.g., PAs considered as homogeneous attractive entities. Such analyses can inform the environmental management of areas most likely to deliver benefits to a large number of people or to be submitted to anthropogenic pressures (overuse, congestion in the vicinity of urban areas, and others). Here, we proposed a complementary approach at local scale, focused on accessibility within PAs and their surroundings accounting for walking costs (using non-motorized ways) to local service provisioning areas. We found that CES are more likely to be used in easily accessible places, coherent with previous findings (e.g., Ridding et al. 2018, Gestenberg et al. 2020), which does not, however, imply causality among accessibility and use of CES as discussed in Schägner et al. (2016). Accessibility alone explained half of the variability in CES use in the three case studies, underlying the necessity to account for additional socio-economic and environmental determinants to better understand CES distribution. We limited our exploration of accessibility to areas along paths, considering that visitors would stick to PA legislations and not wander off-track to visit every potentially attractive location. It is also known that most visitors use paths, when available, even when open access across the adjacent areas is a possibility (Pearce-Higgins & Yalden 1997). However, in alternative settings, our model could include the varying impedance (i.e. resistance to crossing) of land covers around tracks as well (Doherty et al. 2014). Although what 'accessible' means remains subjective and related to individual characteristics, we did not account for varying physical capabilities and preferences of visitors (e.g., Schamel & Job 2017). Following Páez et al. (2012), we focused on *positive* accessibility, considering how far people actually could go, and not on *normative* accessibility, which would have induced making hypotheses on the expected distances or willingness to make efforts that visitors would exert to reach service providing areas.

4.4 Managing mismatches between CES supply and actual use

A key result of our study is the spatial mismatch of potential CES supply and CES actual use. Not every location potentially supplying CES based on landscape attributes is actually visited by PA visitors, and visitors do not enjoy solely locations with high potential supply of CES. This is coherent with previous results, e.g., in the European Alps (Schirpke et al. 2018), and suggests that the cultural dimension reaches beyond a pure biophysical approach. Indeed, CES are co-produced through interactions between people and ecosystems (Chan et al. 2012, Fish et al. 2016, Palomo et al. 2016). They depend on various capitals such as anthropogenic inputs (e.g., density and quality of trails), on individual perceptions related for instance to the popularity of some places or to individual preferences, and on tourism marketing effects as conveyed e.g., by guidebooks, tour offers or social medias. This was confirmed during the workshops by local experts, who mentioned many important drivers of CES use not related to biophysical properties of the landscapes but rather to socio-economic and governance factors. For instance, the communication strategy of the PA and of its surrounding region drives visitors' destination choices, as well as the structuring of local tourism industry and its offers (activities, target audience, prices, etc.). More generally, cultural factors such as local gastronomy and products (Vaz et al. 2018) support attractiveness for visitors at the level of the PA and its surroundings, while higher level governance decisions, e.g. at national and European scales, influence the dynamics of landscapes and of human activities therein (agricultural subsidies, fire regulation, measures for biodiversity conservation, etc.). Our results align with IUCN guidelines for tourism management in PAs: visitor's presence in PAs can be directed through intentional management, infrastructure design and frequentation channeling, while still allowing visitors to get an enjoyable experience of nature(Leung et al. 2018, see also Manning et al. 2017).

4.5 Recording social preferences to assess CES

While eliciting expert knowledge through focus groups usually proves to be more cost effective than an extensive visitor field survey (Brown & Fagerholm 2015), there is still little evidence of comparability between data collection methods addressed to experts and to non-experts. We show that expert knowledge can form a promising avenue to CES mapping. In each of our case studies, the median distance between important locations for CES use identified by visitors and experts was lower than 1100m and significantly lower from median distance between visitors and random points. Considering the size of the mapped dot, the scale and resolution of the map and the estimated ability of visitors to locate places of importance for CES use, we conclude on a good fit between results from experts and visitors. This appears interesting considering that the total number of experts consulted was around ten times lower than the total number of visitors reached. If these results could be confirmed by a larger set of studies, expert-based CES assessment could help to carry out assessments in resource-scarce contexts, and to increase robustness of results through cross-comparison with visitor field surveys. However, our results also demonstrate that models computed with experts' data reached a lower explanatory power that the ones based on visitors' data. We hypothesize that this lower fit could arise partly from the lower sample size of experts compared to visitors, and from the possibly understated importance of accessibility in experts' answers. Indeed, accessibility was attributed a comparatively lower importance in experts results compared to models built from visitor data, which highlights the opportunity for PA managers to further integrate accessibility as a key management feature for regulating recreation in protected areas.

Participatory approaches are promoted to reveal people's perspectives on their relationships to nature (Milcu et al. 2013, Tew et al. 2019). Considering beneficiaries in CES assessments could help to integrate direct local and experiential knowledge derived from people's interaction with their environment (Bieling et al. 2014, Zoderer et al. 2019). Our methodology builds upon recent academic progress and methodological advices for participatory mapping (Brown & Fagerholm 2015). By using a participatory approach and comparing visitors and experts' results, we confirm that direct mapping in the field by CES beneficiaries can be considered a valid methodology to describe actual use of CES, despite unexplored uncertainty on the positional accuracy and completeness of the areas identified (Brown & Fagerholm 2015). To facilitate the mapping of actual CES use, recent studies have used available data from social media platforms where people express their preferences to certain places at certain time, such as Twitter, Geocaching or photo sharing platforms like Flickr or Panoramio (e.g., Tenerelli et al. 2016, Schirpke et al. 2018, Richards & Tunçer 2018, Lee et al. 2019, Vaz et al. 2020, Chien et al. 2020). These studies consider that social media content like uploaded photos act as a proxy for recreational value and can be used to derive visitation rates and to capture visitors' profiles (Sinclair et al. 2020). Use of social media platforms to assess the actual use of CES has a great potential to reduce costs for on-site surveys and to provide empirical evidence of landscape appreciation in PAs or any other landscape of interest (van Berkel et al. 2018). However, the social media technique cannot substitute field surveys, as their results have been shown to be rather complementary than redundant (Moreno-Llorca et al. 2020). Further, relying on social media for CES assessment still suffers from limitations (Oteros-Rozas et al. 2018, Ghermandi & Sinclair 2019). More research is therefore needed before a more systematic and technically easy use of social media could be considered in CES assessment.

5 Conclusion

Integrative approaches for CES assessments - contrasting modelled potential supply and mapped actual use - are valuable in order to understand associations between CES and landscape attributes. Using stated preferences on landscape attributes was not sufficient to identify areas of CES actual use in our study. Rather, we highlight the differentiated potential of landscape indicators to relate to preferred locations for CES actual use by visitors through 'habitat suitability models'. In particular, across our case studies the presence of attractive landscape features was repeatedly and positively associated with CES actual use. Similarly, accessibility was revealed as a key determinant for CES use in our study, which might be of particular relevance in protected areas, which strive to find a balance between welcoming visitors and conserving sensitive habitats and species. Our results, which combine strict PA perimeters with 10 km buffers that are commonly used by visitors, align with international guidelines for PAs, stating that visitor distribution can be managed through facilitated accessibility, infrastructure design and frequentation channeling. We also show that results obtained by consulting experts from diverse backgrounds to identify the spatial distribution of CES use can approximate results obtained from visitors, although with a lesser explanatory power than in-situ mapping in our case studies. We conclude that experts' data may thereby serve as valuable proxies, in particular in resource-scarce projects. We believe our methodology can be of interest for resource managers and landscape planners to help identifying locations of high importance for CES use, and to identify synergies and trade-offs with hotspots for other management targets such as biodiversity conservation.

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Supplementary material

SM1 – Case study characteristics

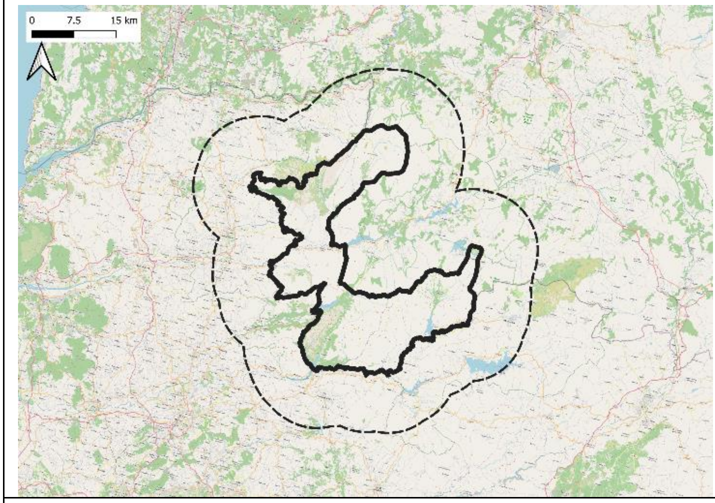
Abbreviations: Peneda-Geres National Park (PNP), UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM) and Kalkalpen National Park (KA-NP).

1. Area of the case studies

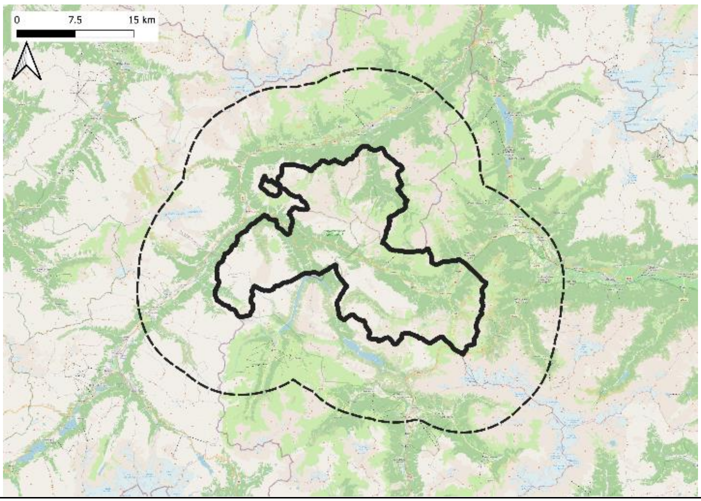
	Area (km^2)	
	Inner perimeter of PAs only	Whole case study area = inner PA perimeter and 10 km Buffer
Austria	208	1375 → KA-NP
Switzerland	448	1887 → UBREM
Portugal	696	2846 → PNP

2. Maps of the study areas - OSM data (© OpenStreetMap contributors)

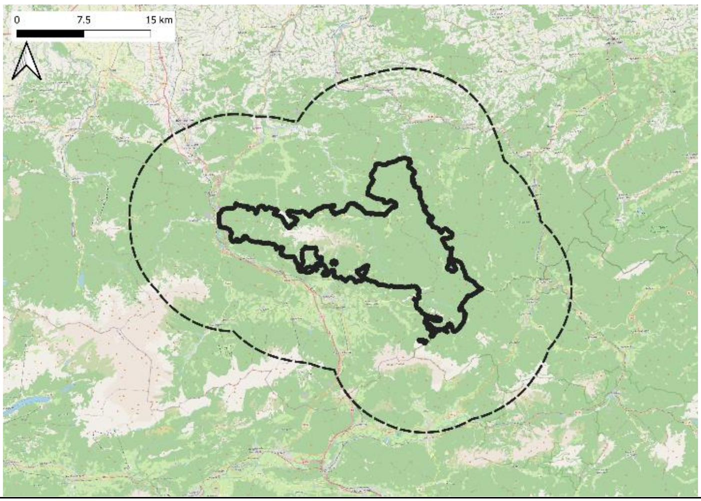
A. PNP



B. UBREM



C. KA-NP



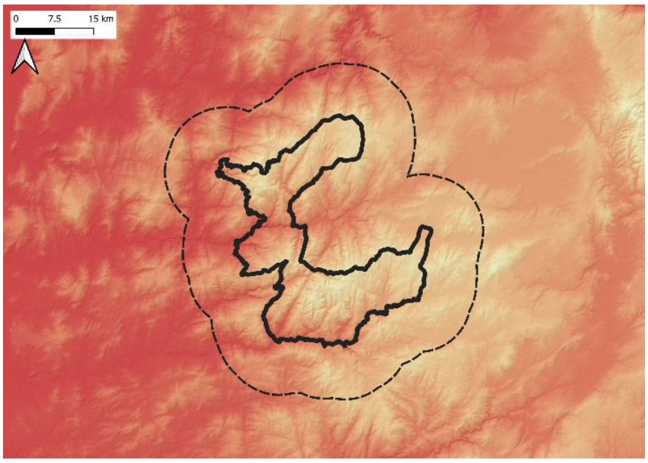
Legend

Protected area perimeter

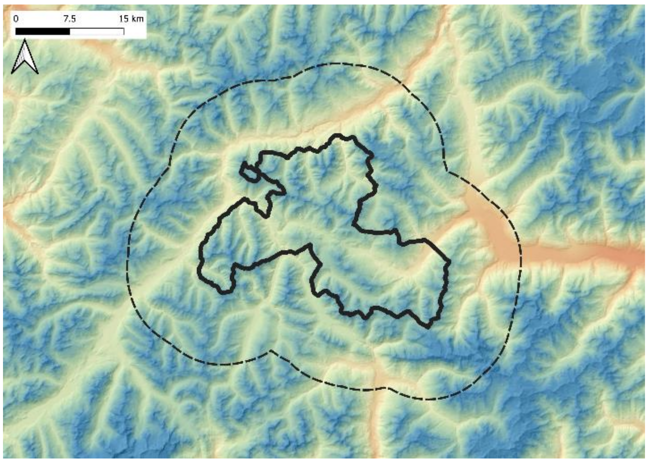
Buffer - 10 km

3. Maps of the study areas - Digital Elevation Model (© EU-DEM STRM-ASTER)

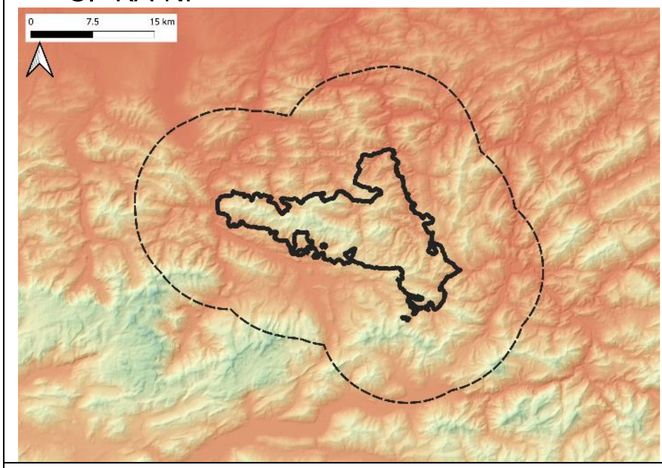
A. PNP



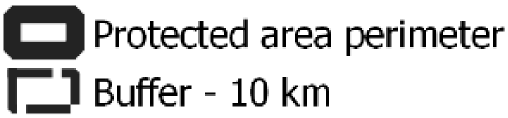
B. UBREM



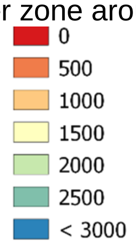
C. KA-NP

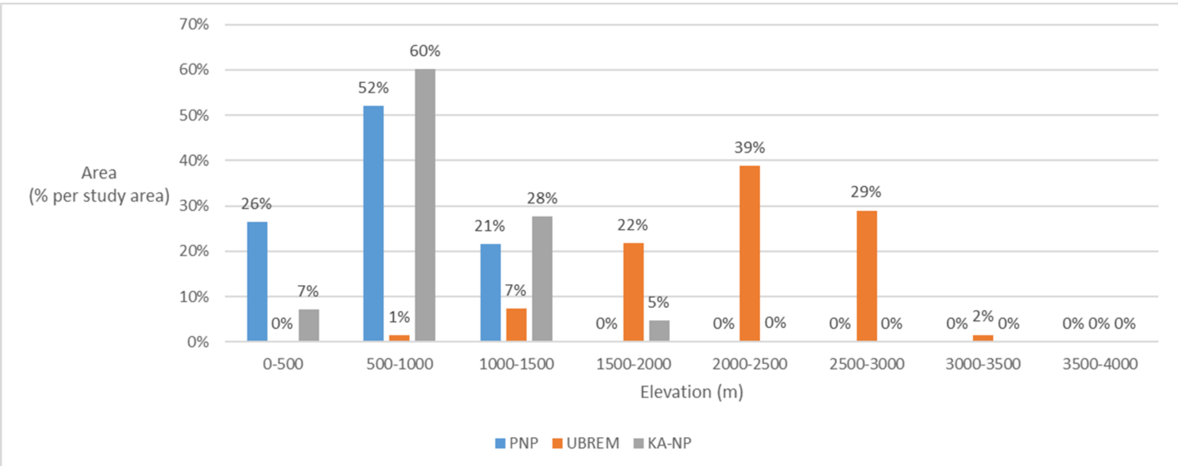


Legend



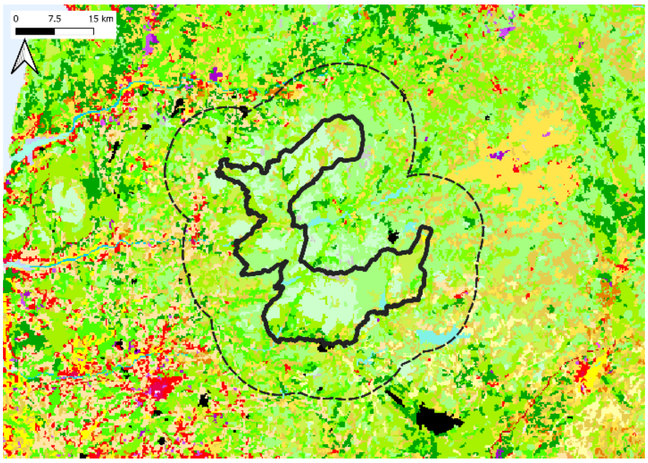
Distribution of altitude classes for the whole study areas (i.e. considering the inner zones and the buffer zone around)



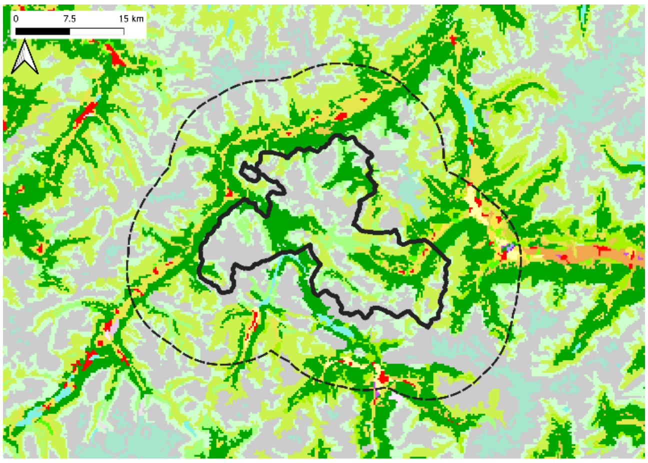


4. Maps of the study areas - Land cover classes (© https://land.copernicus.eu)

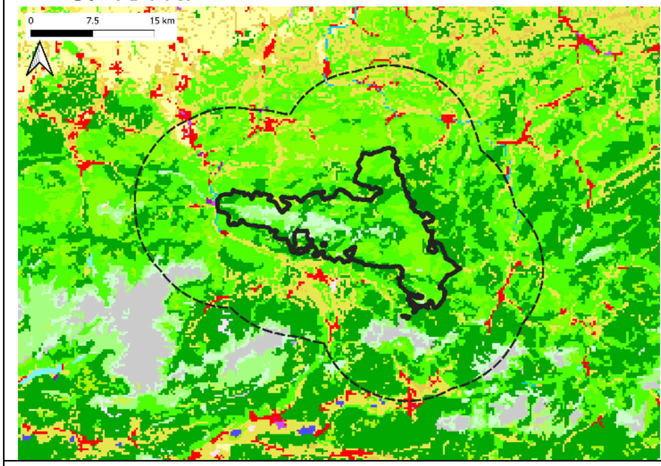
A. PNP



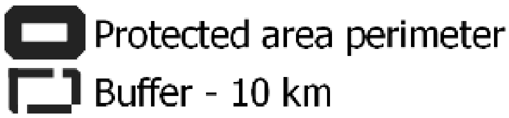
B. UBREM



C. KA-NP



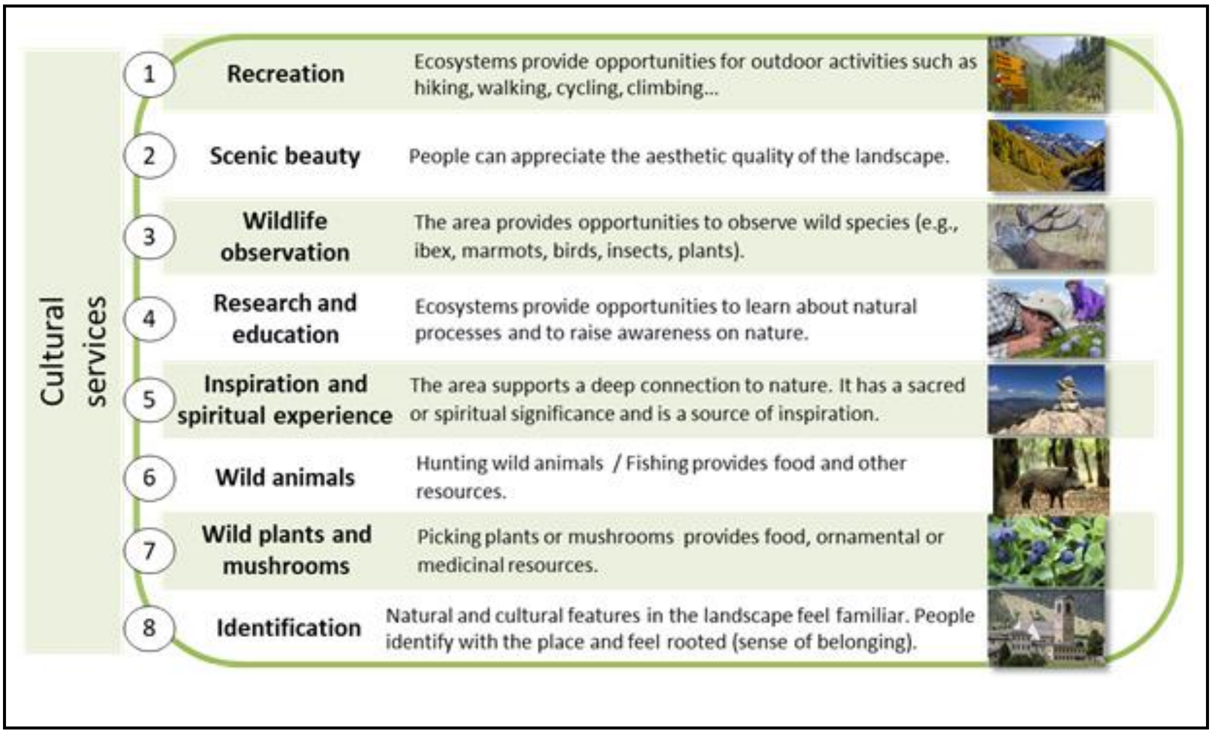
Legend



Distribution of CLC classes for the whole study areas (i.e. considering the inner protected perimeter and the buffer zone around)

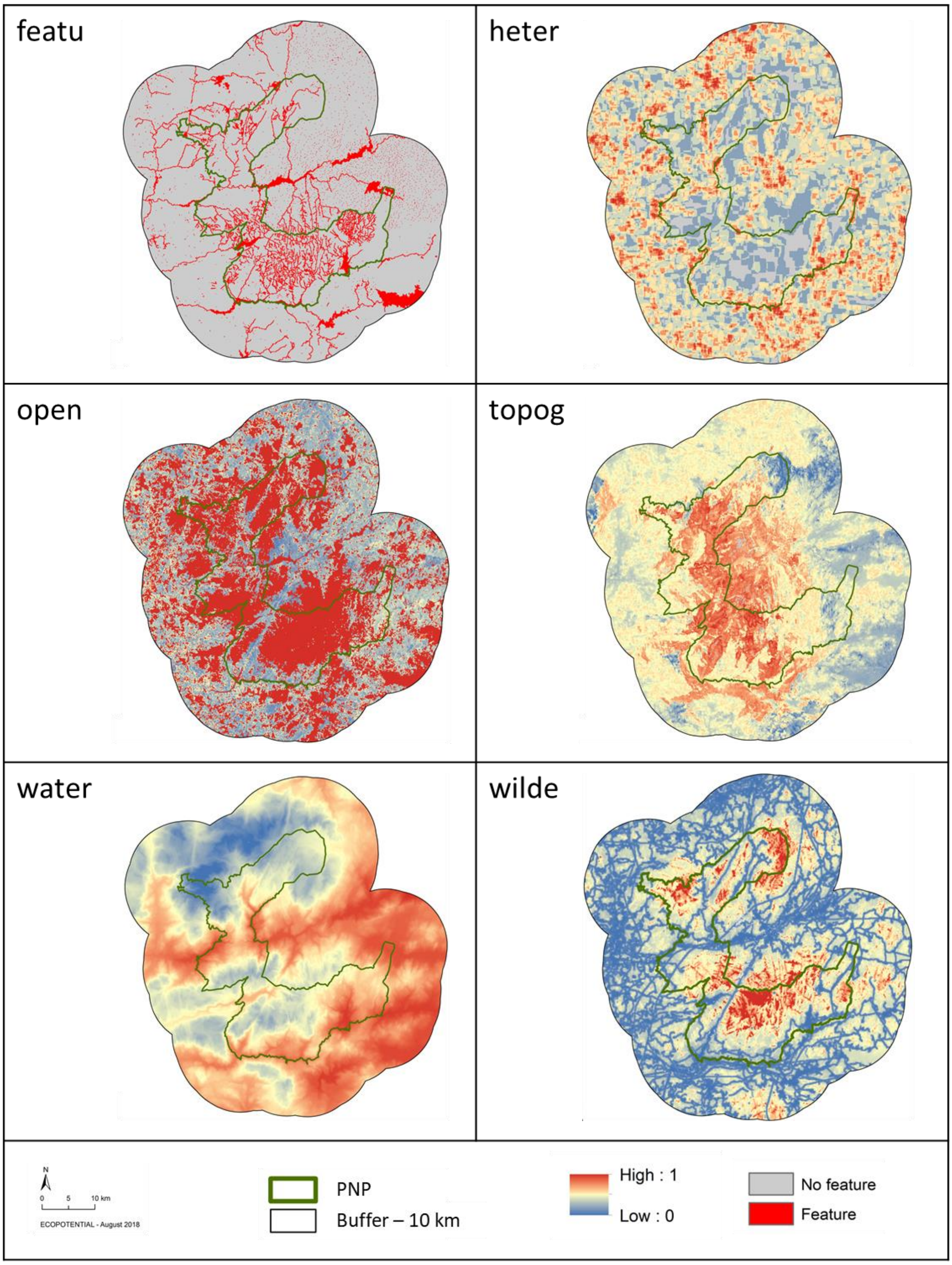
CLC code	CLC category (level 3)	KA-NP	PNP	UBREM
111	Continuous urban fabric	0,0%	0,0%	0,0%
112	Discontinuous urban fabric	1,9%	0,5%	0,7%
121	Industrial or commercial units	0,1%	0,0%	0,0%
122	Road and rail networks and associated land	0,0%	0,0%	0,0%
131	Mineral extraction sites	0,1%	0,0%	0,0%
142	Sport and leisure facilities	0,1%	0,0%	0,0%
211	Non-irrigated arable land	0,3%	1,5%	0,9%
212	Permanently irrigated land	0,0%	0,1%	0,0%
221	Vineyards	0,0%	0,1%	0,0%
222	Fruit trees and berry plantations	0,0%	0,0%	0,0%
231	Pastures	11,1%	1,6%	5,8%
241	Annual crops associated with permanent crops	0,0%	4,4%	0,0%
242	Complex cultivation patterns	0,1%	3,4%	0,4%
243	Land principally occupied by agriculture, with significant areas of natural vegetation	0,3%	7,7%	0,5%
311	Broad-leaved forest	17,8%	8,1%	0,1%
312	Coniferous forest	27,7%	3,6%	24,6%
313	Mixed forest	30,6%	6,4%	0,2%
321	Natural grasslands	1,9%	6,4%	18,2%
322	Moors and heathland	2,6%	27,0%	5,7%
324	Transitional woodland-shrub	0,9%	13,1%	1,8%
332	Bare rocks	1,4%	0,6%	24,1%
333	Sparsely vegetated areas	2,8%	13,0%	14,5%
334	Burnt areas	0,0%	0,4%	0,0%
335	Glaciers and perpetual snow	0,0%	0,0%	1,9%
411	Inland marshes	0,0%	0,0%	0,0%
511	Water courses	0,3%	0,1%	0,0%
512	Water bodies	0,0%	2,0%	0,5%

SM2 – Definition of Cultural Services in the field work material



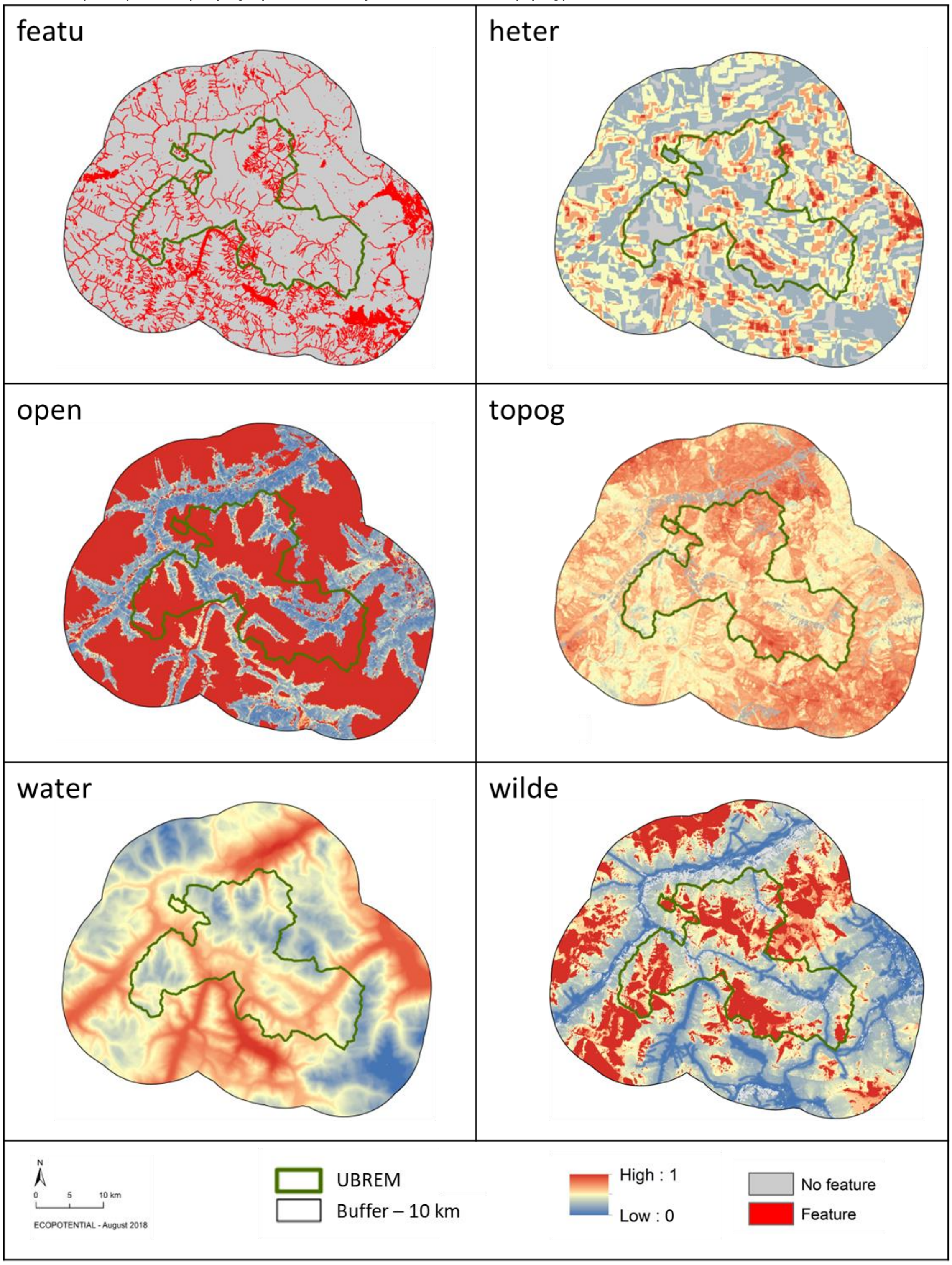
SM3 - CES potential supply indicators in Peneda-Geres National Park (PNP)

Abbreviation of biophysical indicators are the following: i) water inder (*water*), ii) presence of distinctive natural or cultural landscape features (*featu*), iii) openness of the landscape (*openn*), iv) heterogeneity of landscape (*heter*), v) wilderness of the view shed (*wilde*), and vi) topographic variability of the view shed (*topog*).



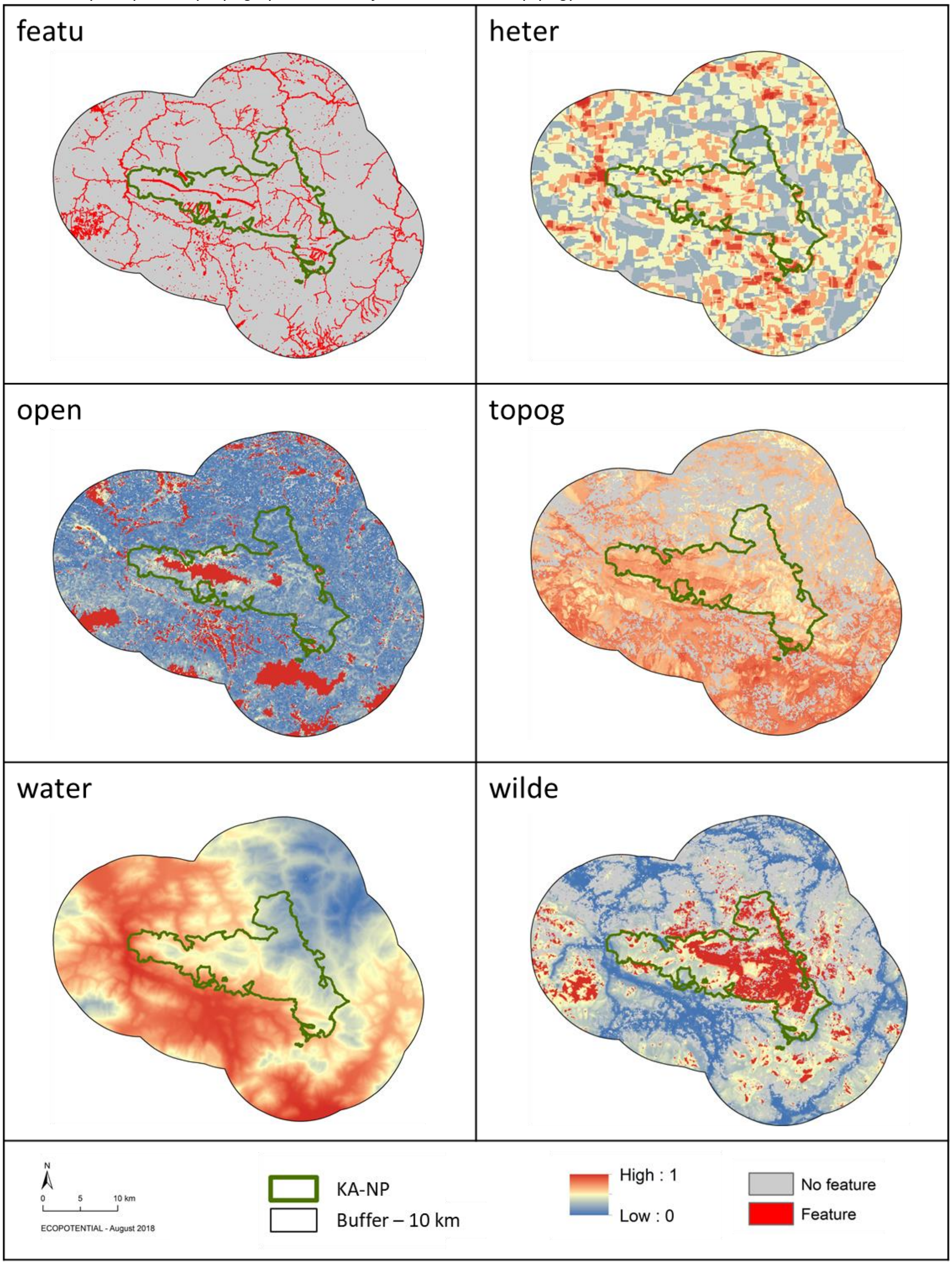
SM4 - CES potential supply indicators in UNESCO Biosphere Reserve Engiadina Val Müstair (UBREM)

Abbreviation of biophysical indicators are the following: i) water inder (*water*), ii) presence of distinctive natural or cultural landscape features (*featu*), iii) openness of the landscape (*openn*), iv) heterogeneity of landscape (*heter*), v) wilderness of the view shed (*wilde*), and vi) topographic variability of the view shed (*topog*).



SM5 - CES potential supply indicators in Kalkalpen National Park (KA-NP)

Abbreviation of biophysical indicators are the following: i) water inder (*water*), ii) presence of distinctive natural or cultural landscape features (*featu*), iii) openness of the landscape (*openn*), iv) heterogeneity of landscape (*heter*), v) wilderness of the view shed (*wilde*), and vi) topographic variability of the view shed (*topog*).



SM6 – Workflows for CES individual indicators

The grid resolution for each indicator matches the European INSPIRE reference grid (downloaded from https://www.eea.europa.eu/data-and-maps/data/eea-reference-grids-2).

9.6.1 Water index

- Definition: Inverse euclidean distance to water bodies, weighted by importance of water body types (lakes, rivers, streams) and affected by slope
- Abbreviation: *water*
- Metric: Index between 0 (*no large water bodies easily reachable*) to 1 (*large water bodies easily reachable*)
- Workflow:
  - Compute slope by transforming the DEM at 100*100m (Copernicus product) with ArcGIS function *Slope*
  - Calculate cost distance to water bodies using ArcGIS function *Cost distance* with the slope raster as input
  - Reclass EU-Hydro River Network (Copernicus product) and sum up distance rasters using the following categories à weights:
    - Rivers with Strahler Index 1 and 2 and Ditch = weight 1
    - Rivers with Strahler Index >= 3 and River = weight 2
    - Inland water with area up to 10 ha and Small lake = weight 2
    - Inland water with area up to 10 ha and Major lake = weight 3
  - Standardize the inverse index between 0 and 1

9.6.2 Presence of natural and cultural features

- Definition: Presence of natural and cultural attractive landscape elements
- Abbreviation: *featu*
- Metric: Binary index: 0 (*no attractive feature*), 1 (*presence of at least on attractive feature*)
- Workflow:
  - Extract natural and cultural features from OSM data:
    - Amenity: baking_oven, crypt, kneipp_water_cure place_of_worship, public_bath, shelter
    - Barrier: hedge
    - Building: chapel, shrine, cabin, hut, ruins
    - Geological: palaeontological_site
    - Historic: aqueduct, archaeological_site, castle, church, citywalls, farm, fort, milestone, monument, ruins, rune_stone, tree_shrine, wayside_cross, wayside_shrine
    - Landuse: farmland, farmyard, military, reservoir, village_green
    - Leisure: garden, swimming_area
    - Man_made: cross, watermill, windmill
    - Mountain_pass: yes
    - Natural: water, glacier, spring, hot_spring, geyser, peak, ridge, arete, cliff, saddle, rock, stone, sinkhole, cave_entrance
    - Place: locality
    - Railway: funicular, preserved

  - Tourism: attraction, viewpoint
  - Waterway: river, riverbank, stream, wadi, drystream, waterfall
- Calculate sum of points in each pixel base on spatial joint between OSM points and base raster layer using ArcGIS functions *Spatial Join* and *Union*
- Reclass output as binary values: 0->0 and ≥1-> 1

9.6.3 Openness of the landscape

- Definition: Density of open space per pixel (based on tree cover), to inform the local feeling of space and openness
- Abbreviation: *open*
- Metric: Index between 0 (1*00% tree cover in the pixel*) to 1 (*0% tree cover in the pixel*)
- Workflow:
  - Raster Tree Cover Density (Copernicus product)
  - Convert raster values to index ([0-100%] to [0-1])

9.6.4 Landscape heterogeneity

- Definition: Variety of land cover types in the surrounding 1*1km window of each pixel
- Abbreviation: *heter*
- Metric: Index between 0 (*homogeneous land cover types in the surrounding window*) to 1 (*high diversity of land cover types in the surrounding window*)
- Workflow:
  - Raster at 100*100m of Corine Land Cover data at level 3 (Copernicus product)
  - Apply ArcGIS function *Focal Statistics*. Specification: Rectangle, Height 10, Width 10, StatType: Variety
  - Standardize index between 0 and 1

9.6.5 Wilderness of the view shed

- Definition: Natural character of the view shed, unaffected by human visual disturbances such as artificial areas and roads, for each stand point (tree cover < 90%)
- Abbreviation: *wilde*
- Metric: Index between 0 (*viewshed is highly artificial, or no view point*) to 1 (*viewshed is highly natural*)
- Workflow:
  - Extract artificial features from Corine Land cover (code 100, 110, 111, 112, 120, 121, 122, 123, 124)
  - Extract artificial features from OSM data
    - Aerialway: cable_car, gondola, chair_lift, mixed_lift, drag_lift, t-bar, j-bar, platter, rope_tow, magic_carpet, zip_line, pylon, station, good
    - Aeroway: aerodrome, apron, hangar, helipad, heliport, runway, terminal
    - Highway: motorway, trunk, primary, secondary, tertiary, unclassified, residential, service, motorway_link, trunk_link, primary_link, secondary_link, tertiary_link, bus_guideway, escape, raceway, road
    - Landuse: brownfield, commercial, depot, garages, greenhouse_horticulture, industrial, landfill, peat_cutting, plant_nursery, port, quarry, railway, reservoir, residential, retail

    - Man_made: communications_tower, cutline, clearcut, mast, snow_fence, snow_net, works
    - Military: airfield
    - Place: city, town
    - Power: plant, generator, line, minor_line, pole, portal, tower
    - Railway: disused, light_rail, monorail, narrow_gauge, rail
    - Route: pipeline
    - Waterway: dam, weir
    - Cutting: yes / left / right
  - Reclass each pixel as artificial or not based on spatial join between artificial data and base raster layer using ArcGIS functions *Spatial Join* and *Union*
  - Reclass pixels as stand points depending on the Tree Cover Density (Copernicus product):
    - Tree cover ≥ 90% set pixel to 0 value
    - Tree cover < 90% set pixel to 1 value, i.e. stand point.
  - Use of Viewshed Explorer software to assign view shed pixels to each stand point, based on the DEM at 100*100m (Copernicus product) within a 15km radius.
  - Calculate proportion of view shed considered as artificial for each pixel
  - Standardize index between 0 and 1

9.6.6 Topographic variability of the view shed

- Definition: Variability of the altitudinal profile of the view shed for each stand point (tree cover < 90%)
- Abbreviation: *topog*
- Metric: Index between 0 (*view shed is completely flat, or no view point*) to 1 (*topography in the view shed is very heterogeneous*)
- Workflow:
  - Reclass pixels as stand points depending on the Tree Cover Density (Copernicus product):
    - Tree cover ≥ 90% à set pixel to 0 value
    - Tree cover < 90% à set pixel to 1 value, i.e. stand point.
  - Based on the DEM at 100*100m (Copernicus product), compute terrain roughness index (TRI) after Riley et al. 1999, using QGIS function *ruggednessindex* in each view shed and attribute value to the initial stand point pixel.
  - Use of Voxel viewshed software to assign view shed pixels to each stand point, based on the DEM at 100*100m (Copernicus product).
  - Calculate TRI variability in the view shed of each pixel.
  - Standardize index.
  - Reference: Riley, S. J., DeGloria, S. D., & Elliot, R. (1999). Index that quantifies topographic heterogeneity. Intermountain *Journal of Sciences*, 5(1-4), 23-27.

9.6.7 Accessibility (acces)

- Select features from OSM data
  - Aerialway: cable_car, gondola, chair_lift, mixed_lift, station
  - Amenity: bus_station, ferry_terminal, motorcycle_parking, parking, parking_space

  - Highway: primary, secondary, tertiary, unclassified, residential, service, living_street, pedestrian, track, road, footway, bridleway, steps, path, cycleway, bus_stop
  - Place: town, village, hamlet
  - Public_transport: stop_position, station
  - Railway: halt, station, tram_stop
  - Route: hiking, horse, mtb, nordic_walking, running
- Use OSM points and polygons data as starting points and OSM line data as possible trails (convert to raster using ArcGIS functions *Spatial Join* and *Union*).
- Compute slope by transforming the DEM at 100*100m (Copernicus product) with ArcGIS function *Slope*
- Combine with equal weights the influence of slope (through Tobler's function) and of type of trail (impedance, inspired by Doherty et al. 2014) to prepare the Vertical factor table.
- Use ArcGIS *Path distance* function with the starting point raster as input layer, the combined 'Impedance + Tobler' dataset as Vertical factor (cost raster), and the DEM (Copernicus product) as surface layer.
- Standardized the inverse index.
- Reference: Doherty, P. J., Guo, Q., Doke, J., & Ferguson, D. (2014). An analysis of probability of area techniques for missing persons in Yosemite National Park. *Applied Geography*, 47, 99-110.

SM7 – GAMMs for Research Question 1 – whole case study areas (inner zone + buffer)

RQ1 - GAMM - PNP

A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.766	0.6648	-4.161	<0.001	***
CES_supply	3.107	1.3210	2.352	0.019	*
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	17.02	17.02	4.453	<0.001	***
Observations: 1148					
Adjusted R^2: 0.297					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ1 - GAMM - UBREM

A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.516	0.34504	-4.392	<0.001	***
CES_supply	0.085	0.6666	0.128	0.8980	
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	20.39	20.39	4.16	<0.001	***
Observations: 2438					
Adjusted R^2: 0.186					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ1 - GAMM - KA-NP

A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.486	0.3525	-7.053	<0.001	***
CES_supply	2.673	0.787	3.396	<0.001	***
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	16.78	16.78	6.547	<0.001	***
Observations: 1888					
Adjusted R^2: 0.287					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

SM8 – GAMMs for Research Question 2 – whole case study areas (inner zone + buffer)

RQ2 - GAMM - PNP without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.590	0.2856	-12.569	<0.001	***
featu	5.062	0.3657	13.840	<0.001	***
topog	1.229	0.3783	3.249	0.0012	**
wilde	-1.846	0.3490	-5.289	<0.001	***

Observations: 1148

Adjusted R^2: 0.757

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - PNP with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-4.490	0.3697	-12.14	<0.001	***
featu	5.949	0.4719	12.61	<0.001	***
acces	5.979	0.5903	10.13	<0.001	***

Observations: 1148

Adjusted R^2: 0.876

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - PNP with only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.525	0.2093	-7.288	<0.001	***
acces	4.806	0.4725	10.171	<0.001	***

Observations: 1148

Adjusted R^2: 0.538

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.352	0.1809	-18.531	<0.001	***
featu	3.895	0.2241	17.382	<0.001	***
water	0.614	0.2223	2.764	0.006	**
wilde	-0.606	0.2256	-2.687	0.007	**

Observations: 2438

Adjusted R^2: 0.599

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.144	0.2158	-14.574	<0.001	***
featu	3.711	0.2566	14.464	<0.001	***
heter	-0.447	0.2222	-2.013	0.044	*
acces	3.642	0.253	14.394	<0.001	***
Observations: 2438					
Adjusted R^2: 0.757					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM with only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.139	0.1148	-9.915	<0.001	***
acces	3.933	0.2196	17.909	<0.001	***
Observations: 2438					
Adjusted R^2: 0.554					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - KA-NP without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.162	0.1958	-16.153	<0.001	***
featu	4.612	0.2768	16.659	<0.001	***
water	-0.937	0.5303	-1.767	0.077	
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	15.13	15.13	5.526	<0.001	***
Observations: 1888					
Adjusted R^2: 0.751					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - KA-NP with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.320	0.2515	-13.199	<0.001	***
featu	4.198	0.3024	13.886	<0.001	***
openn	0.698	0.3088	2.261	0.0239	**
water	-3.361	0.7033	-4.779	<0.001	***
acces	4.035	0.525	7.686	<0.001	***

B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	14.89	14.89	6.253	<0.001	***
Observations: 1888					
Adjusted R^2: 0.805					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - KA-NP with only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.412	0.1435	-9.842	<0.001	***
acces	3.189	0.3096	10.300	<0.001	***
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	18.4	18.4	6.634	<0.001	***
Observations: 1888					
Adjusted R^2: 0.494					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

SM9 – GAMMs for Research Question 3 – whole case study areas (inner zone + buffer)

RQ3 - GAMM PNP without *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.4073	0.4788	-7.116	<0.001	***
featu	2.9496	0.7284	4.05	<0.001	***

Observations: 316

Adjusted R^2: 0.377

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM PNP with *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.4325	0.5484	-6.259	<0.001	***
featu	3.7174	0.889	4.181	<0.001	***
acces	2.6212	0.8479	3.091	0.002	**

Observations: 316

Adjusted R^2: 0.551

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM PNP only *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.4722	0.4074	-6.068	<0.001	***
acces	1.6971	0.6361	2.668	0.008	**

Observations: 316

Adjusted R^2: 0.116

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM without *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.7374	0.4793	-7.798	<0.001	***
featu	2.7607	0.6558	4.21	<0.001	***
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	2	2	1.34	0.263	

Observations: 426

Adjusted R^2: 0.332

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM with *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.2717	0.5025	-6.51	<0.001	***
featu	2.4069	0.689	3.493	<0.001	***
acces	1.8232	0.6628	2.751	0.006	**
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	2	2	1.18	0.308	

Observations: 426

Adjusted R^2: 0.495

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM only *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.4556	0.3932	-6.245	<0.001	***
acces	2.2786	0.6231	3.657	<0.001	***
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	2	2	0.839	0.433	

Observations: 426

Adjusted R^2: 0.237

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP without *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.8722	0.4428	-6.487	<0.001	***
featu	2.692	0.7158	3.761	<0.001	***

Observations: 248

Adjusted R^2: 0.408

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP with *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.8722	0.4428	-6.487	<0.001	***
featu	2.692	0.7158	3.761	<0.001	***

Observations: 248

Adjusted R^2: 0.408

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP only *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.2013	0.4084	-5.39	<0.001	***

acces	1.545	0.6796	2.273	0.024	*
Observations: 248					
Adjusted R^2: 0.0834					

Dependent variable: CES actual use. Significant codes (Sign.): *** $p<0.001$; ** $p<0.01$; * $p<0.05$

SM10 - GAMMs for Research Question 1 - inner zones only (excluding points in the buffer zones)

RQ1 - GAMM - PNP					
A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-0.948	0.836	-1 133	0.257	
CES_supply	0.178	1.590	0.112	0.911	
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	23.36	23.36	2.748	<0.001	***

Observations: 784

Adjusted R^2: 0.386

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ1 - GAMM - UBREM					
A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-0.956	0.467	-2 044	0.041	*
CES_supply	0.314	0.903	0.348	0.728	
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	21.96	21.96	4.137	<0.001	***

Observations: 1086

Adjusted R^2: 0.285

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ1 - GAMM – KA-NP					
A. parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.590	0.611	-4.241	<0.001	***
CES_supply	4.590	1.270	3.613	<0.001	***
B. smooth terms	edf	Ref.df	F-value	p-value	
s(x,y)	24.86	24.86	4.704	<0.001	***

Observations: 910

Adjusted R^2: 0.465

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

1184 SM11 - GAMMs for Research Question 2 - inner zones 1185 only (excluding points in the buffer zones)

RQ2 - GAMM - PNP without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.686	0.383	-9.627	<0.001	***
featu	4.992	0.453	11.010	<0.001	***
heter	0.951	0.430	2.209	0.027	*
wilde	-2.804	0.495	-5.664	<0.001	***

Observations: 784

Adjusted R^2: 0.769

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - PNP with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-4.423	0.505	-8.753	<0.001	***
featu	5.116	0.547	9.355	<0.001	***
acces	6.408	0.720	8.899	<0.001	***

Observations: 784

Adjusted R^2: 0.882

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - PNP only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.259	0.278	-4.533	<0.001	***
acces	6.208	0.621	10.001	<0.001	***

Observations: 784

Adjusted R^2: 0.722

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.735	0.211	-12.967		***
featu	3.962	0.275	14.385		***
water	1.852	0.285	6.498		***

Observations: 1086

Adjusted R^2: 0.651

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.538	0.273	-9.307	<0.001	***
featu	3.868	0.356	10.854	<0.001	***

acces	4.380	0.359	12.183	<0.001	***

Observations: 1086

Adjusted R^2: 0.792

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM - UBREM only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-0.480	0.143	-3.359	<0.001	***
acces	4.604	0.282	16.354	<0.001	***

Observations: 1086

Adjusted R^2: 0.665

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM – KA-NP without acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.108	0.253	-12.265	<0.001	***
featu	4.582	0.329	13.948	<0.001	***
heter	1.274	0.319	3.992	<0.001	***

Observations: 910

Adjusted R^2: 0.694

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM – KA-NP with acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.022	0.330	-9.157	<0.001	***
featu	3.975	0.397	10.017	<0.001	***
heter	0.861	0.404	2.129	0.033	*
openn	1.222	0.333	3.664	<0.001	***
water	-0.927	0.391	-2.375	0.018	*
acces	4.706	0.544	8.646	<0.001	***

Observations: 910

Adjusted R^2: 0.83

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ2 - GAMM – KA-NP only acces

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-0.904	0.169	-5.348	<0.001	***
acces	4.479	0.369	12.133	<0.001	***

Observations: 910

Adjusted R^2: 0.545

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

SM12 - GAMMs for Research Question 3 - inner zones only (excluding points in the buffer zones)

RQ3 - GAMM PNP without *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.290	0.536	-6.139	<0.001	***
featu	2.565	0.719	3.567	<0.001	***

Observations: 244

Adjusted R^2: 0.308

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM PNP with *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.225	0.616	-5.232	<0.001	***
featu	3.052	0.846	3.606	<0.001	***
acces	2.601	0.839	3.099	0.002	**

Observations: 244

Adjusted R^2: 0.533

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM PNP only *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.083	0.428	-4.870	<0.001	***
acces	2.041	0.675	3.024	0.003	**

Observations: 244

Adjusted R^2: 0.206

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM without *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.600	0.528	-6.820	<0.001	***
featu	3.285	0.723	4.542	<0.001	***

Observations: 302

Adjusted R^2: 0.439

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM with *acces*

Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-3.121	0.587	-5.320	<0.001	***
featu	2.946	0.782	3.770	<0.001	***
acces	2.643	0.787	3.359	<0.001	***

Observations: 302

Adjusted R^2: 0.60

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM UBREM only *acces*					
Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.014	0.424	-4.756	<0.001	***
acces	3.014	0.725	4.157	<0.001	***
Observations: 302					
Adjusted R^2: 0.359					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP without *acces*					
Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-2.735	0.511	-5.350	<0.001	***
featu	1.853	0.691	2.683	0.008	**
Observations: 188					
Adjusted R^2: 0.203					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP with *acces*					
Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.736	0.456	-3.807	<0.001	***
acces	2.583	0.791	3.267	0.001	**
Observations: 188					
Adjusted R^2: 0.297					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

RQ3 - GAMM KA-NP only *acces*					
Parametric coefficients	Estimate	Std. Error	t-value	p-value	Sign.
(Intercept)	-1.736	0.456	-3.807	<0.001	***
acces	2.583	0.791	3.267	0.001	**
Observations: 188					
Adjusted R^2: 0.297					

Dependent variable: CES actual use. Significant codes (Sign.): *** p<0.001; ** p<0.01; * p<0.05

SM13 – Median distances - inner zones only (excluding points in the buffer zones)

Median of the distances (m)	PNP	UBREM	KA-NP
Observed	555.8	326.8	833.2
Random	1171.7	818.2	764.3
p-values	<0.001	<0.001	0.2318