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*Understanding complexity in ecosystem
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innovations in spatial analysis*

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“Look deep into nature, and then you will understand everything better.”

Albert Einstein

Understanding complexity in ecosystem service assessment: perspectives and innovations in spatial analysis

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SHORT ABSTRACT

Research efforts are increasingly driven toward assessing provision, use and demand of ecosystem services as interconnected components of complex social-ecological systems. The aim of this dissertation is to contribute to the literature about mapping and assessment of ecosystem services through a series of methodological applications under the paradigm of complexity. In the first paper, exploratory spatial data analysis is used to quantify the loss of information that occurs when upscaling spatial data to a coarser grain. The second paper explores temporal pattern and dynamics of land use change in the Alto Bellunese (South-Eastern Alps, Italy), to simulate the mechanistic evolution of forests and assess the provision of outdoor recreation opportunities over time. The third paper proposes a novel methodology for mapping summer non-rival demand for outdoor recreation, through spatial agent-based modeling.

ESTRATTO

Ricerche recenti tendono a valutare fornitura, uso e domanda di servizi ecosistemici in quanto componenti interconnesse di sistemi socio-ecologici complessi. Questa tesi ha lo scopo di contribuire alla letteratura in materia di mappatura e valutazione dei servizi ecosistemici mediante una serie di applicazioni metodologiche definite dal paradigma della complessità. Nel primo articolo, metodologie

di analisi esplorativa dei dati sono impiegate per quantificare la perdita di informazione che si verifica aggregando dati spaziali a risoluzioni inferiori. Il secondo articolo esplora dinamiche e pattern temporali di cambiamento dell'uso del suolo nell'Alto Bellunese (Alpi Sud-orientali, Italia), per simulare l'evoluzione meccanicistica delle foreste e valutare nel tempo la fornitura di opportunità ricreative all'aria aperta. Il terzo articolo propone una nuova metodologia per mappare la domanda estiva di attività ricreative in assenza di competizione, mediante modelli ad agenti spaziali.

EXTENDED ABSTRACT

Research efforts are increasingly driven toward assessing provision, use and demand of Ecosystem Services (ESs) as interconnected components of complex Social-Ecological Systems (SESs), entwined in a dynamic multi-scale spatial and temporal representation. The aim of this dissertation is to contribute to the literature about mapping and assessment of ESs through a series of innovative methodological applications under the paradigm of complexity. The first paper presents a novel methodology based on exploratory spatial data analysis to quantify the loss of information that occurs when upscaling spatial data to coarser scales. It is meant to avoid scale mismatches, information loss and statistical bias while mapping ESs and communicating spatial information. The methodology was tested on the ES "Outdoor Recreation" (OR), mapped at high resolution over three different areas in the eastern Alps. The related fine-grain ES pattern was iteratively upscaled to coarser scales where substantial information loss was detected, revealing hidden clusters and inconsistencies among aggregated data, compared to their fine-scale representation. The second paper explores temporal pattern and dynamics of land use change in the Alto Bellunese (South-Eastern Alps, Italy), combining classification algorithms and cellular automata Markov chains to simulate the mechanistic evolution of forests. The provision of OR was assessed on observed (2007) and projected land use (2017, 2030). Temperature and great soilscales were found to be the main drivers of the expansion of forests over grasslands but with decreasing impacts on existing open areas and, consequently, on the provision of OR opportunities over time. The third paper proposes a novel methodology for mapping summer non-rival demand for OR through spatial agent-based modeling. The model simulates the dynamic allocation of tourists' time invested in

OR activities over a georeferenced fine-grain representation of the SES under consideration, and returns a series of maps, showing OR demand for a simplified behavioral diversity of human agents. It was tested in the Alto Bellunese at 100 m resolution, by simulating a 1-day length time window referred to August 2017 and a significant, strong and positive correlation was detected between available tourists' overnight stay records and the spatially explicit simulated demand, after aggregation at municipality level. The modeling results of all these studies suggest that complexity is essential to bridge the gap between the evolving nature of SESs and the effective and reliable communication and visualization of spatial information in maps meant to help policymaking and management of natural resources and ESs e.g. under the influence of land use and climate change.

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ACRONYMS

ABM: Agent-Based Model/ing

AIC: Akaike Information Criteria

AlpES: Alpine Ecosystem Services

ARIES: ARtificial Intelligence for Ecosystem Services

AUC: Area Under the Curve

CA: Cellular Automata

CC: Climate Change

CD: Centroid Distance

CLC: Corine Land Cover

DEM: Digital Elevation Model

ES: Ecosystem Service

ESDA: Exploratory Spatial Data Analysis

GVIF: Generalized Variance Inflation Factor

k.LAB: Knowledge Laboratory (software)

LRT: Likelihood Ratio Test

LUC: Land Use Change

MAUP: Modifiable Areal Unit Problem

OR: Outdoor Recreation

OSM: OpenStreetMap

ROC: Receiver Operating Characteristic

SES: Social-Ecological System

WEDDA-RDM: Weather Driven Demand Analysis Regional Distribution Model

Introduction to the dissertation

Complexity theory deals with detection of system properties emerging from aggregation and non-linear interaction of individual elements. These elements compose complex systems, typically not at equilibrium and heterogenous over space and time, adaptive but also capable of sudden change in their state. They can show emergent properties, multiscale and hierarchical interactions, self-organization and unexpected behaviors which could not be either detected or analyzed under a reductionist perspective. Complexity itself can be defined as “*one property of several systems, from the physical to the ecological and social domains*” (Farina, 2006).

In human-environmental systems, Scholes et al. (2013) define ecosystem services (ESs) as “*the products of complex interconnected social–ecological systems [...] dependent on the interactions and feedback from multitude factors which can function at multiple scales*”. Social–Ecological Systems (SESs) in turn are defined as complex and adaptive systems where social and ecological individual entities (e.g. human and biophysical agents) interact at multiple spatial and temporal scales (Balbi and Giupponi, 2010; Lippe et al., 2019). Hence, being ESs products of SESs, their quantification through space and time should be carried out under the paradigm of complexity e.g. not assessing them on a single spatial scale and snapshot of time, in order to study emergent patterns and processes that underpin their provision, use and demand. Increasingly aware of the issue, the scientific community is approaching the science of complexity to pave the way for substantially improving the reliability of mapping and assessment studies of ESs. This may be crucial to providing reliable information to stakeholders and policymakers, hence using it to develop effective policies, e.g. to manage ESs under land use and climate change. Specifically, most of existing studies dealing with complexity focus on trade-offs among ESs (e.g. Laterra et al., 2012; Raudsepp-Hearne et al., 2010; Rodríguez et al., 2006; Schirpke et al., 2019; Spake et al., 2017); few studies try addressing scaling issues (e.g. Grêt-Regamey et al., 2014; Raudsepp-Hearne and Peterson, 2016; Roces-díaz et al., 2014); the time dimension is often not considered (e.g. Paracchini et al., 2014) or limited to few time steps (e.g. Hou et al., 2017); computational methods, such as agent-based models, are rarely used (e.g. Belem and Saqalli, 2017); at

last, machine learning is increasingly applied to deal with complexity issues (e.g. Schirpke et al., 2019; Willcock et al., 2018).

Given the above, this dissertation aims at studying ES mapping and assessment through a series of innovative methodological applications under the paradigm of complexity. Such applications are meant to address specific issues i.e. research gaps identified within each study, where the simplicity of traditional mapping approaches, typically adopted for fast communication to ease the integration of ESs in policy and management strategies, may neglect information that could be relevant to quantitatively assess ESs over space and time. Therefore, although each of the following studies has its own objective, the wider meaning of the dissertation is to contribute to the debate on the role of complexity in ES mapping and assessment, without claiming to exhaust the topic but by providing innovative methodological insights on complexity-related issues and opportunities for modeling ESs, i.e. as products of socio-economic and ecologic micro/macro level dynamics of SESs.

The present research activities draw on my contribution to the Interreg AlpES project, under the consulting role of the Economic Department of Ca' Foscari University for the Veneto Region, partner of the project. This contribution is partly summarized in a project report (available in the appendix of the dissertation) which focuses on the high-resolution spatial assessment of the ESs "Outdoor Recreation" (OR) and "Fodder provision from natural grassland", carried out in the Alto Bellunese, an area located in the northern part of the Veneto Region. Such publication sets the starting point of the core research activities of this dissertation, consisting of published and unpublished journal articles focused on OR in the context of the Eastern Alps.

The first paper has been published in the journal "Science of the Total Environment" and it represents one of the outputs of the AlpES project. It resulted from the collaboration between Ca' Foscari University and Eurac Research, the lead partner of the project. This work focuses on the complexity-related scale issues that arise when upscaling spatial data to administrative levels i.e. to avoid mismatches between the scale of the assessment of ESs and that of their level of management, but with potential significant losses of information.

The second (currently unpublished) paper aims at projecting land use pattern over time through a cellular automata Markov approach, being forest itself the dominant landscape element of the Alto

Bellunese, whose change may affect provision of OR in this region. Here, complexity arises from the micro-level mechanistic interactions of cellular automata that drive the evolution of forest over time.

The third (currently unpublished) paper aims at modeling demand for OR at high resolution through spatial agent-based modeling, to overcome common mapping approaches of demand based on statistical records e.g. population or tourists' overnight stays. Here, complexity is entwined with our understanding of the Alto Bellunese SES and the demand spatial pattern emerges from the simulated interactions among system components, i.e. between ES beneficiaries and providers, respectively defined by a simplified diversity of tourist agents, grounded on a set of behavioral assumptions, and geospatial information.

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Upscaling ecosystem service maps to administrative levels: beyond scale mismatches

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Abstract

As Ecosystem Services (ES) are the products of complex socio–ecological systems, their mapping requires a deep understanding of the spatial relationships and pattern that underpin ES provision. Upscaling ES maps is often carried out to avoid mismatches between the scale of ES assessment and that of their level of management. However, so far only a few efforts have been made to quantify how information loss occurs as data are aggregated to coarser scales. In the present study this was analyzed for three distinct case studies in the eastern Alps by comparing ES maps of outdoor recreation at the municipality level and at finer scales, i.e. high-resolution grids. Specifically, we adopt an innovative and flexible methodology based on Exploratory Spatial Data Analysis (ESDA), to disentangle the problem of the scale from the perspective of different levels of jurisdiction, by assessing in an iterative process how ES patterns change when upscaling high-resolution maps. Furthermore, we assess the sensitivity to the modifiable areal unit problem (MAUP) by calculating global statistics over three grid displacements. Our results demonstrate that spatial clusters tend to disappear when their extent becomes smaller than the features to which values are upscaled, leading to substantial information loss.

Moreover, cross-comparison among grids and the municipality level highlights local anomalies that global spatial autocorrelation indicators fail to detect, revealing hidden clusters and inconsistencies among multiple scales. We conclude that, whenever ES maps are aggregated to a coarser scale, our methodology represents a suitable and flexible approach to explore clustering trends, shape and position of upscaling units, through graphs and maps showing spatial autocorrelation statistics. This can be crucial to finding the best compromise among scale mismatches, information loss and statistical bias that can directly affect the targeted ES mapping.

Keywords: Scale mismatches; Management levels; Outdoor recreation; Spatial autocorrelation; Upscaling; MAUP

1 Introduction

Ecosystem services (ES) are the products of complex interconnected socio-ecological systems that operate and interact at multiple scales (Scholes et al., 2013). The spatial visualization of ESs in maps is an effective tool with great potential for the explanation of such complex phenomena (Burkhard et al., 2014), but spatial assessments are not often operationalized on solid or standardized frameworks (Primmer and Furman, 2012), neglecting, among others, important scale effects (Grêt-Regamey et al., 2014; Lü et al., 2013). A well-known scale-related issue is that policies can be effective only if their implementation matches the intrinsic scale of the problem under consideration (Wu and Li, 2006). Accordingly, several studies (Nahuelhual et al., 2015; Raudsepp-Hearne and Peterson, 2016) report that scale mismatches often arise when linking ES supply and related management objectives for societal needs, as the scale of environmental variation of an ES differs from the scale of the social organization that is responsible for its management (Cumming et al., 2006). Consequently, ES maps that are meant to drive ES management in policy-making need to prevent scale-related misinterpretation of their spatial pattern by selecting the scale, or the set of scales, that is both relevant for decision-makers and consistent with the mapped ES. The alignment of ES mapping outcomes to the related administrative unit (also referred to as “level of jurisdiction”) requires a solid knowledge of its management level and scaling

rules over space (Grêt-Regamey et al., 2015). This process is often carried out by calculating the mean or sum of grid-based continuous values overlapping the shape of administrative units, either on primary data (Meacham et al., 2016) or on the output of ES calculation procedures (Nelson et al., 2009; Schirpke et al., 2018). In doing so, it is assumed that the fine-grain process is well described by its coarser aggregate, but this holds only if the process scales linearly (Cushman and Huettmann, 2010; Scholes et al., 2013).

To date, only a few studies have addressed the scaling behavior of ES spatial patterns, evaluating differences in information when aggregating ES maps to a coarser grain. These studies (Grêt-Regamey et al., 2014; Raudsepp-Hearne and Peterson, 2016; Roces-Díaz et al., 2018) mainly assessed information loss through a family of techniques called Exploratory Spatial Data Analysis (ESDA). Thereby, the distribution and relationships among spatial features, i.e. spatial autocorrelation, can be analyzed using a series of indicators that highlight the level of spatial clustering of similar values (Anselin, 1996, 1995). These techniques were developed on the assumption that frequently spatial observations are clustered rather than independent, as explained by Tobler's first law of geography (Tobler, 1970). Like most spatial phenomena, ESs tend to be heterogeneously distributed over space, forming clusters of different size and shape (Raudsepp-Hearne and Peterson, 2016). Therefore, to detect and compare variations of ES values at different scales, the above-mentioned studies used autocorrelation as proxy of the inherent scale-dependent information. More specifically, Raudsepp-Hearne and Peterson (2016) calculated Moran's I global spatial autocorrelation (Goodchild, 1986) on a 1 km and 3 km grid map and at municipality level. They found that most of the assessed ESs show a high level of clustering and their pattern depends on the socio-ecological heterogeneity of the landscape. Both Grêt-Regamey et al. (2014) and Roces-Díaz et al. (2018) calculated Moran's I incremental spatial autocorrelation, showing correlograms for a set of ESs. They were able to show the spatial dependency per increasing distance class, respectively setting the bottom limit resolution at 25 m and at 1 km, where the upper lag sets the aggregation level. Despite the averaging effect that results in a loss of fine-grained information, both Raudsepp-Hearne and Peterson (2016) and Roces-Díaz et al. (2018) proved that the municipality level still reproduces the underlying spatial pattern with reasonable accuracy. However, these studies do not estimate grid-based local spatial autocorrelation, i.e. the contribution of each

individual cell with its neighbors to global indicators of spatial autocorrelation, such as Moran's I, which shows the overall degree of association of all features in a map (Anselin, 1996). In fact, when calculating global statistics, spatial autocorrelation is estimated through a single score per each scale of analysis, which intuitively represents a global trend that might be in conflict with local associations of values or features. Moreover, despite the mentioned studies that described and assessed scale effects of different ESs, practitioners in ES assessments still lack a common and standardized methodology to deal with the loss of information when upscaling maps from the scale of the ES process to the management level, i.e. aggregating information from finer scales (smaller grain size) to broader scales (larger grain size) (Wu and Li, 2006).

To enhance the understanding of scale in ES assessments, we draw on the outcomes of the Interreg Alpine Space project "AlpES - Alpine Ecosystem Services - mapping, maintenance and management", which produced a collection of ES maps for the entire European Alps (Schirpke et al., 2019). Using the example of the ES "Outdoor Recreation" (OR) we increase the spatial grain of the initial 100 m resolution map gradually to the municipality level, aiming to develop a novel, multi-step methodology based on existing ESDA techniques, in order to:

- evaluate whether statistically significant clusters of recreational values detected from a fine-grain representation (100 m grid) are consistent with their related coarser aggregates, up to the management level (in our example, the municipality level);
- understand how information loss occurs when upscaling grid-based data at local level i.e. if the aggregation process hides any important spatial pattern that might lead to a potential misinterpretation of spatial data when pursuing management objectives.

To evaluate the influence of site-specific characteristics, such as environmental variability, size and number of administrative units and socio-economic conditions, we test our approach in three distinct regions of the European Alps, namely Alto Bellunese, South Tyrol and Innsbruck. Related case-specific results are presented as a practical implementation of our methodology, which conceptually does not target specific objectives or ES. In fact it represents a novel multi-step approach meant to deal with the loss of information when increasing the spatial resolution of any type of ES from the scale of the ES process to the management level.

2 Materials and methods

In this section, we first present the spatial autocorrelation indicators of ESDA to provide an overview of the algorithms grounded in existing literature and relevant to our study. Secondly, we describe our methodology, i.e. how we use existing spatial autocorrelation indicators in our novel multi-step approach to address the research objectives. Before assessing spatial autocorrelation, the methodology replicates the same aggregation process that scientists usually carry out while averaging ES values overlapping spatial features (Nelson et al., 2009; Schirpke et al., 2018). Consequently, the interpretation of the main results is rather simple, as the methodology highlights spatial inconsistencies among scales through graphs and maps, e.g. where a cluster of values disappears in the upscaling process. The modifiable areal unit problem (MAUP) is also assessed through an iterative approach. Lastly, we introduce the case study areas and the ES we selected to present our methodology. Since the applicability of the presented methodology does not depend on specific objectives and it does not target a particular ES, in the present study, the concept of management objective has to be intended as a general purpose fulfilled by an action or policy drawn on the outcomes of an ES assessment. In fact, management objectives targeting ESs are often framed between a management level and one or multiple scales of observation that match the biophysical variability of the ES to be managed (Raudsepp-Hearne and Peterson, 2016). In this study, scale has to be intended as a hierarchical spatial representation of an ES pattern. Among all components that qualify scale, the grain represents:

- the smallest unit of variability of a spatial pattern at a targeted scale, within which homogeneity is assumed;
- the size and number of cells included within the extent of a targeted area (Wu and Li, 2006).

Therefore, the grain is applied here as a convenient metric to match scale with pattern of ESs. More specifically, in our analyses we refer to “scale” or “local level” when taking into consideration a spatial unit that is smaller, or at least comparable, with the size of a municipality. On the other hand, the term “municipality level” refers to municipalities as administrative units i.e. LAU2 level (Eurostat).

2.1 ESDA tools for spatial analyses

To explore spatial clustering over time, several indicators of spatial autocorrelation have been developed within the broader family of techniques called ESDA (Anselin, 1996): among these, Global Moran's, Local Moran's I and Getis-Ord G_i^* .

Global Moran's I statistic is a measure of the spatial dependency and non-stationarity of spatial features and indicates spatial clustering of similar values (Anselin, 1995). It can be interpreted as the degree of linear association between observed values and the weighted average (spatial lag) of their neighbors (Anselin, 1996). Moran's I values range between 1 and -1. Values close to 0 imply randomness; values close to 1 mean positive spatial autocorrelation, i.e. similarity among values; values close to -1 indicate negative spatial autocorrelation, i.e. dissimilarities among values. The spatial autocorrelation is an inferential statistic that is interpreted through hypothesis testing. The null hypothesis is the complete spatial randomness or, in other words, the independence of observed values from neighboring polygons or cells. The statistical significance of the presence of clusters is tested by comparing z-scores and p-values with the critical values of a normal distribution (Goodchild, 1986).

Anselin Moran's I local statistic differs from the Global Moran's I because it is calculated for each single deviation of observed values and not for their sum. Nevertheless, they share the same statistical interpretation. The Getis-Ord G_i^* statistic, also known as Hotspot Analysis, measures the degree of association resulting from the spatial concentration of the weighted values of each cell/polygon and its neighbors within a specified distance (Getis and Ord, 1992). The Getis-Ord G_i^* is already conceptualized as a Z-score (Getis and Ord, 1995) and implies positive spatial autocorrelation both for highly positive and negative Z-scores, i.e. high/high local relationships represent hotspots while low/low sets of values are coldspots. Both local statistics are calculated for every value x_i , resulting in a map where the clustering tendency can be visually explored to highlight local instabilities and multiple sources of spatial dependence (Anselin, 1996, 1995).

Further information and applied algorithms are reported in Supplementary material A.

2.2 The methodology

As reported by Cushman and Huettmann (2010), the upscaling of a spatial variable to a higher hierarchical level (i.e. municipality) can be carried out by calculating the mean of grid-based continuous values within the boundaries of selected administrative units. If we assume that grid-based cells are hypothetical sub-administrative units, even without a connection to any level of social organization, we can replicate the same aggregation process in an iterative and sequential procedure to monitor the loss of information across multiple scales. This is carried out with ESDA spatial autocorrelation statistics through global indicators and maps showing local statistics. With these tools we aim at detecting clusters with statistically significant p-values in order to reject the null hypothesis, i.e. the assumption of complete spatial randomness.

To find a suitable mapping scale, consistent with its related fine-scale pattern and useful for management purposes, our multi-step procedure includes three steps (Figure 1). First, ES values are aggregated to predefined grids with a sequentially increasing centroid distance (CD), covering a range of scales up to a grain size comparable with the mean of the areas of management units e.g. municipalities. Secondly, spatial indicators of autocorrelation are calculated over each scale of analysis as described in Section 2.1. The comparison of results among grids and with management units, and associated statistical inferences may reveal hidden patterns at coarser scales. At last, the MAUP can be assessed by displacing the original grids in alternative directions, to recalculate Global Moran's I and detect to which extent spatial indicators return different results. The methodology is flexible enough to be adjusted to the specificity of each individual study, e.g. selection of CD, targeted administrative level and ES to be assessed.

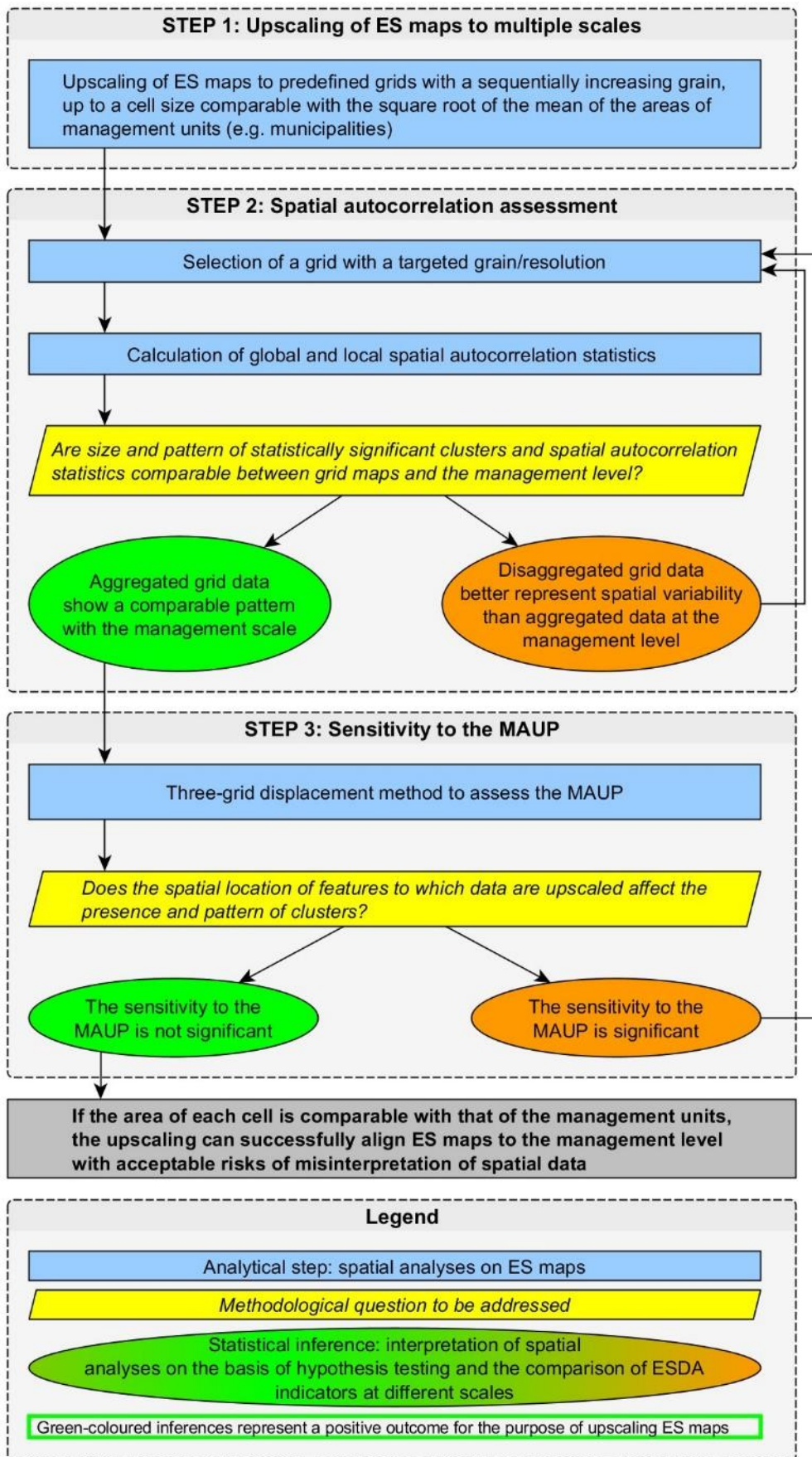


Figure 1. Conceptual approach to identify the suitable mapping scale consisting of three steps.

2.2.1 Aggregation of ES values

In our methodology, grid cells are assumed to be sub-administrative units with a regular shape, defined as an *a priori* level of jurisdiction without an existing connection with the real world. An empty grid is created with a targeted CD per each scale of analysis. The mean is calculated per each cell overlapping the raster map that displays the spatial variable to be upscaled. Control over borders is implemented, based on thresholds proposed by Raudsepp-Hearne and Peterson (2016): for CD equal or lower than 1 km, only the cells of the grid that entirely overlap the raster map are selected; for CD greater than 1 km, cells are kept if their area overlaps at least 50% of the raster map. The aggregation is carried out independently from the position of the grid. This is consistent with the fact that whenever the upscaling to a target organizational level is carried out, the shape and the position of administrative units cannot be chosen. As a general rule, the upper upscaling threshold is set to the CD that approximately equals the square of the mean of the administrative unit areas under investigation.

The aggregation procedures were coded in R, using the packages: `sp`, `raster`, `rgdal` and `rgeos` (R Core Team, 2018).

2.2.2 Calculation of spatial indicators of autocorrelation

The Global Moran's I spatial autocorrelation statistic is calculated per each scale of analysis. The approach is similar to that of correlograms, already explored by Grêt-Regamey et al. (2014) and Roces-Díaz et al. (2018). However, instead of estimating Moran's I over each distance class (spatial lag, i.e. the mean of values of neighboring cells within a bounded upper distance) the statistics are calculated over upscaled maps whose i^{th} cell is already the result of the aggregation process. Therefore, the statistic is calculated for a row-standardized spatial weight matrix based on first-order contiguity (Figure 2), as in the case study proposed by (Anselin, 1995).

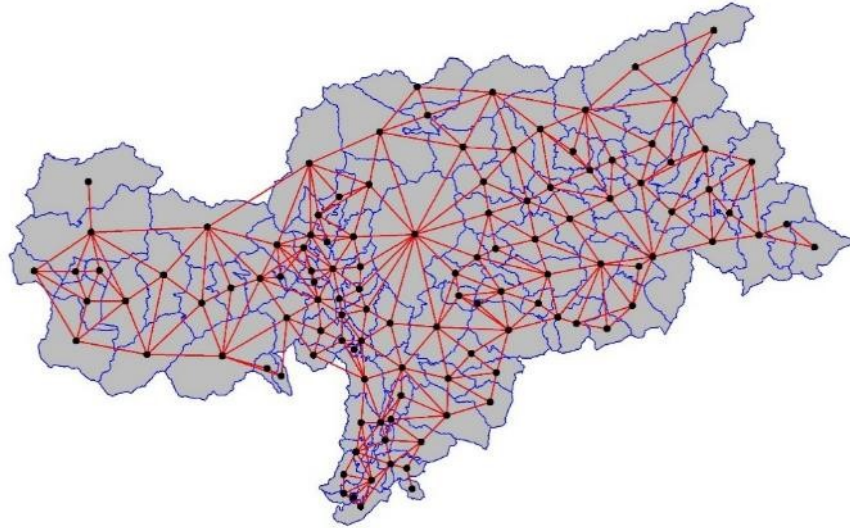


Figure 2. Visual representation of the first-order contiguity: spatial relationships among units having a common boundary.

Local statistics aim at decomposing the contribution of each single cell to global autocorrelation outcomes. This lets us visualize the presence of statistically significant clusters at multiple scales. Local Moran's I spatial autocorrelation and Getis-Ord G_i^* are calculated per each scale of the analysis, respectively using a row-standardized and binary spatial weight matrix based on first-order contiguity (Anselin, 1995; Getis and Ord, 1995). Resulting maps report Z-score and p-value that can be visually explored, in order to detect clusters, hotspots and coldspots of the upscaled variable. Cluster detection is enhanced by applying the "False Discovery Rate" correction to formerly calculated p-values (de Castro and Singer, 2006). The comparative target is the chosen administrative level, acknowledged to be the management level under investigation, over which spatial autocorrelation statistics can be calculated and compared with grid results.

The spatial analyses were carried out in R, using the package: `spdep` (R Core Team, 2018).

2.2.3 Assessment of the MAUP for randomly selected grids

The sequential step-by-step upscaling to bigger cells is affected by a methodological bias, which is intrinsic to any kind of aggregation procedure at administrative level. The shape, the position and the number of administrative units are always fixed. The consequence is that resulting aggregated values are affected by the MAUP, i.e. the outcomes of the upscaling process depend on shape and size of the aggregation units which might have strong implications on statistical analysis based on hypothesis

testing (Dark and Bram, 2007; Spake et al., 2017). To entirely avoid the MAUP problem, according to Jelinski and Wu (1996), one should analyze each individual element linked to the process that generates the assessed spatial pattern, rather than aggregate them at some kind of “artificial” unit. This is not feasible while working with large spatial datasets. In our case, having assessed spatial autocorrelation on a single grid, it is worth investigating *ex-post* if grids with different positioning might reduce information loss. Therefore, we displace the extent of the original grid in three directions: 1/2 CD up, 1/4 CD right and together in both directions i.e. diagonally. By including the main grid configuration, it is possible to aggregate data and calculate Global Moran’s I, on four different grids that overlap each other for 1/2 or 1/4 of their area. Moving the main grid in all Queen’s case directions would result in redundant grid configurations. Results can be presented in a boxplot, showing the range of variability per each scale and the performance of the main grid. This range is a subset of the one that would be obtained from iterating all theoretically infinite grid positions. The method is meant to highlight the impact of the MAUP concerning the grid position in each scale assessed or, in other words, the effect of the size component, with a reasonable computational effort. This is consistent with the sensitivity analysis approach described by Jelinski and Wu (1996) since the MAUP affects the spatial relationships of cells/polygons under investigation and consequently the detection of clusters through autocorrelation indicators.

2.3 Outdoor recreation activities in the regions of Alto Bellunese, South Tyrol and Innsbruck

We selected the regions of Alto Bellunese (IT), South Tyrol (IT) and Innsbruck (AT) as our test sites. They are located in the central-eastern part of the European Alps (Figure 3), straddling the border between Italy and Austria. The three areas represent contiguous territorial units subjected to different legislations and include municipalities with different size, topographic and socio-economic conditions. The overall region comprises 11,820 km² and spans an elevation gradient between 185 and 3851 m a. s. l. Its typical mountain geography considerably influences human activities, due to the high topographic variability and the harsh climate conditions. As a consequence, the land use composition

is characterized by a high presence of natural and semi-natural ecosystems interspersed with urbanized areas and agricultural lands, usually located in the fertile valley floors.

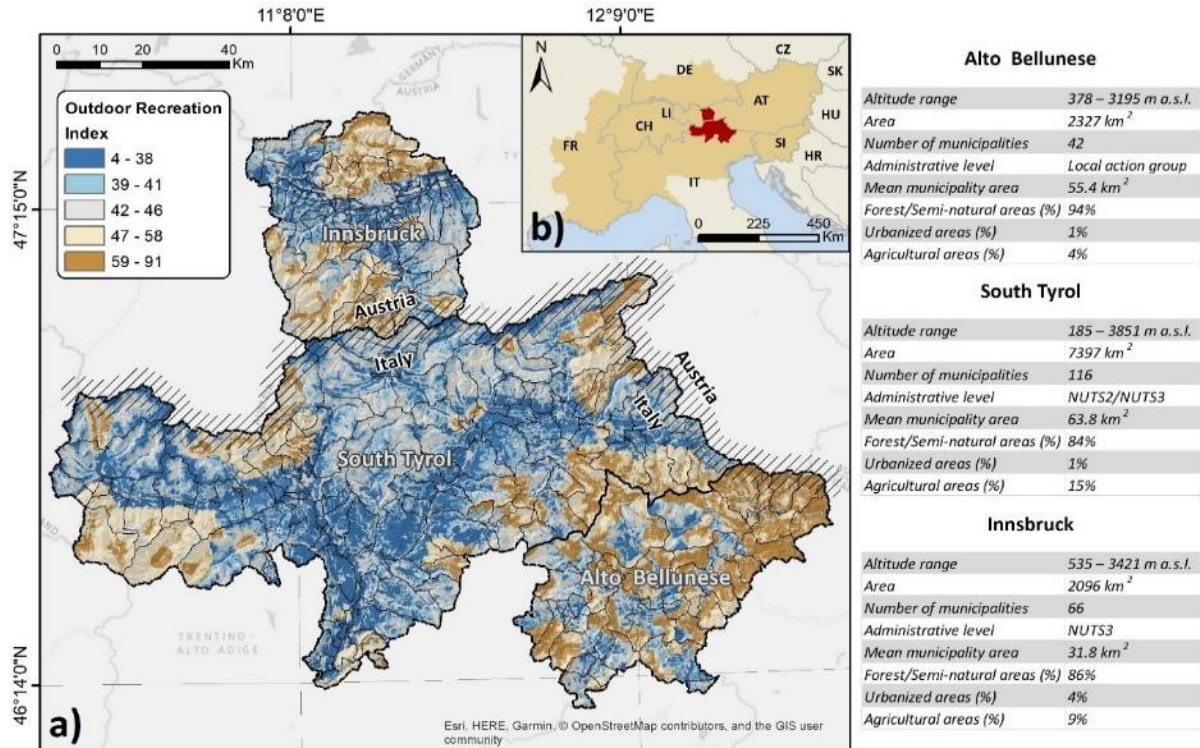


Figure 3. Selected test regions, the supply ES outdoor recreation index (a) and their localization in the Alpine space cooperation area (b).

The ES supply of OR activities that was used to assess the scale effects within the selected test regions, was mapped in terms of recreation opportunities (ES potential) provided by ecosystems and weighted by accessibility (Schirpke et al., 2018). Recreation opportunities were estimated on the basis of six spatial indicators: naturalness, protected areas, presence of water, landscape diversity, terrain ruggedness and density of mountain peaks. All spatial indicators were mapped as raster data with a spatial resolution of 100 m and overlaid after rescaling them to values between 0 and 100 (Figure 3). The level of accessibility was calculated on the basis of the road and trail network by using travel time from residential areas and was rescaled to values between 0 and 1. Recreation supply was finally mapped by multiplying the recreation potential by the level of accessibility. Full details on methods and data sources can be found in Schirpke et al. (2018).

3 Results

3.1 Scaling relationships and spatial autocorrelation indicators

As described in Section 2.2.1., the square root of the mean of the municipality areas sets the upper upscaling threshold. Table 1 reports these thresholds and grids with target CD, starting from the finest scale which equals the resolution of the maps showing OR activities in the three case study areas.

Table 1. CD of grids up to the chosen upper threshold based on the square root of the mean of the municipality areas, per case study.

Case study	Square root of the mean of the municipality areas (m)	Chosen upper CD threshold (m)	Grid cell CD
Alto Bellunese	7443.79	7500	<ul style="list-style-type: none"> • 100 m CD; • from 250 m to 4000 m CD with a step of 250 m; • from 4500 m to 7500 m CD with a step of 500 m.
South Tyrol	7985.61	8000	<ul style="list-style-type: none"> • 100 m CD; • from 250 m to 4000 m CD with a step of 250 m; • from 4500 m to 8000 m CD with a step of 500 m.
Innsbruck	5635.60	5750	<ul style="list-style-type: none"> • 100 m CD; • from 250 m to 5750 m CD with a step of 250 m;

Global statistics of grid aggregates are presented in Figure 4. Red points represent the Moran's I indices of the grids for which local statistics have been calculated. Each boxplot is created with four global results, the one of the grid in the original position and those whose cells are displaced in the Queen's case directions, as described in Section 2.2.3.

Global results at municipality level are shown in Table 2.

Table 2. Global Moran's I at municipality level.

Case study	Moran's I index	Z-score	p-value
Alto Bellunese	0.47	4.96	< 0.01
South Tyrol	0.51	8.73	< 0.01
Innsbruck	0.30	4.32	< 0.01

Figure 5 summarizes the main results of the hotspot analysis, individually carried out over each selected case study area: it shows the fine-grain hotspots of recreational values at 100 m and its corresponding aggregate at the municipality level. All the other maps displaying local statistics are shown in Supplementary material A. These include both Local Moran's I and Getis-Ord G_i^* Z-score maps, along with their related p-values for both each scale of analysis and each case study, as reported in Table 1. Furthermore, Supplementary material A also reports spatial autocorrelation statistics of the ES supply of OR activities over the whole Alpine arc. Despite being beyond the scope of this study, this analysis gives an overview of the hotspot pattern of recreational values at a higher hierarchical level, which share the same unit of variability as our test regions, i.e. the municipality level.

Since the presented methodology implies the upscaling of fine-grain data to a targeted administrative level, in the following sections we present our results from the finest to the coarsest scale, up to the comparative target.

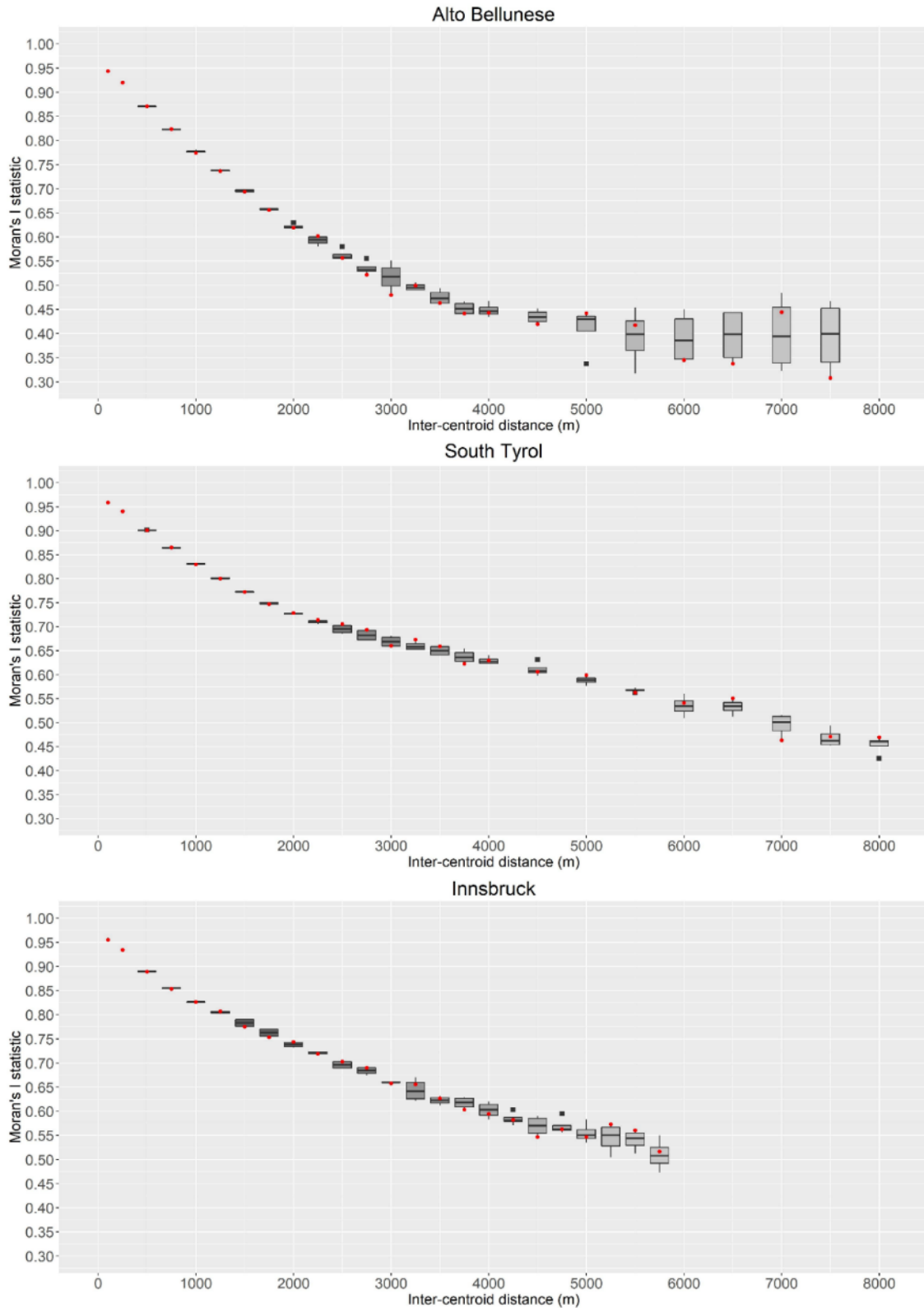


Figure 4. Moran's I statistic calculated over sequentially aggregated grids; each boxplot is built with four grids with different position and same dimension, starting from 500 m CD; red points represent the grids without displacement; black squares are values that are statistically distant from other data within the same CD.

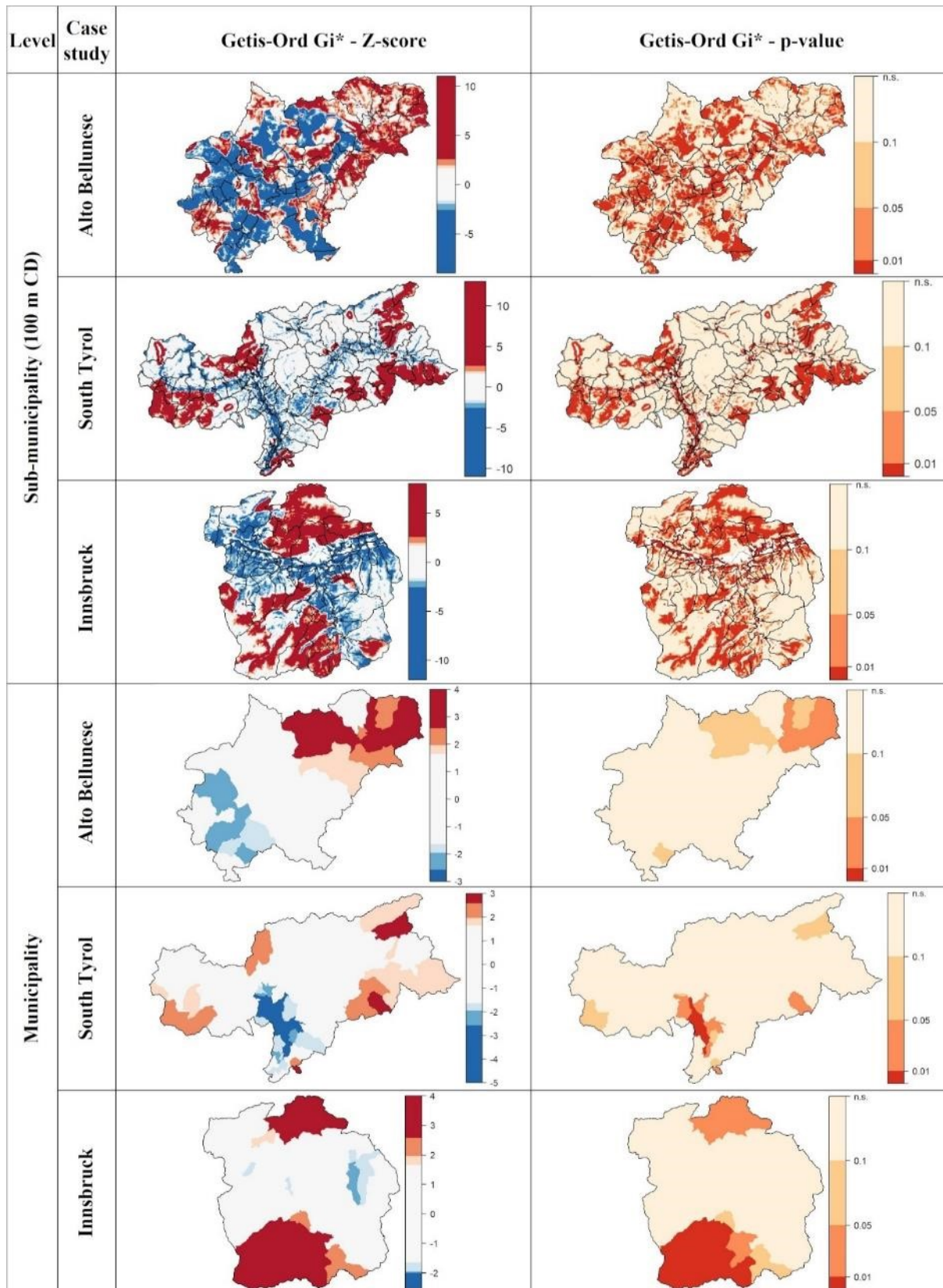


Figure 5. Getis-Ord G_i^* Z-score maps and related p-values for each case study area: hotspot pattern at 100 m CD (top) and after the upscaling of recreational values to the municipality level (bottom).

3.2 Alto Bellunese

In the area of Alto Bellunese, local spatial autocorrelation analyses at 100 m CD revealed a substantial heterogeneity of recreational values with hotspots and coldspots closely associated along the whole region, except for the north-eastern part. This area corresponds to a hotspot that is statistically significant over all the scales of analysis, including the municipality level (Figure 5). The aggregation implied a significant loss of information both in terms of quantity (the scale decreases together with the Z-score range) and allocation (the grain becomes unsuitable for providing spatial information concerning the hotspot location). Up to 1 km resolution, the smallest clusters were lost and the main hotspots and coldspots were still visible and increasingly easier to be identified. The information loss occurred almost linearly within 3000 m CD. After this threshold, it became non-linear and increasingly affected by the MAUP (Figure 4). The number of clusters exponentially dropped up to the grid with 7500 m CD despite the different number, distribution and shape of administrative features, resulting in a comparable cluster distribution between the grid with the biggest CD and the municipality level. From 2000 to 4750 m, the grids returned an overall deviation of around 0.05 Global Moran's I index units, but the MAUP became substantial only after 5000 m CD, resulting in a difference of up to 0.14 units. The MAUP was evident by comparing the hotspot analysis with global statistics at 6000, 6500, 7000 and 7500 m CD and at the municipality level (Figure 5 and Supplementary material A). The grid with 7000 m CD showed the presence of three coldspots, two with confidence intervals of 90% and one with 95%. At 6000, 6500 m CD and at the municipality level only one coldspot was visible (p -value > 0.1), while at 7500 m no coldspots could be found. The Global Moran's I statistic (red points in Figure 4 i.e. global results corresponding to grid maps in Figure 5 and Supplementary material A) was above the median only at 7500 m CD and it was the highest among considered grids. This means that the related configuration better captures the autocorrelation signal of the recreational pattern under investigation. Since the median across the top four scales showed comparable values, the spatial autocorrelation turned out to be particularly sensitive to the displacements within each scale. Surprisingly, the Global Moran's I indicator at municipality level was even higher than that of the grid with 7500 m CD: it means that the shape and the location of the municipalities are more suitable for representing local clusters

within Alto Bellunese. Practically, the local analysis returned that the fine-grain hotspot pattern in the south-western part was completely lost over 4000 m CD and in the municipality level.

3.3 South Tyrol

In South Tyrol, local spatial autocorrelation analyses showed a substantial agreement between the municipality level and the grids (Figure 5). Local statistics returned highly significant clusters, homogeneously distributed over space, meaning that the aggregation of hotspots and coldspots do not influence each other greatly. Up to 1000 m CD, the smallest clusters disappeared or became part of the main hotspots and coldspots, which were increasingly visible. Global Moran's I decreased linearly up to 2000 m CD, then once again almost linearly up to the threshold of 8000 m CD (Figure 4). The aggregation clearly implied a loss of information but, with some exceptions, the main hotspots and coldspots were still visible in the grids with the highest CD as well as, by comparison, at the municipality level. This was also due to the reduced impact of the MAUP which accounts for about 0.05 Global Moran's I index units in the worst case (7000 m CD). The main difference between the fine-grain pattern and its related aggregate at coarser scales was the evident reduction of the extent of coldspots. At municipality level, they are limited to the central part of South Tyrol, between the municipalities of Merano and Bolzano.

3.4 Innsbruck

As for South Tyrol, local statistics in the region of Innsbruck returned significant clusters homogeneously distributed over space, but with more closely associated hotspots and coldspots (Figure 5). The Global Moran's I decreased almost linearly up to the threshold of 5750 m CD (Figure 4), where local statistics returned four main clusters. The hotspots were clearly visible both in the grid and at the municipality level while no statistically significant coldspots were detected for the latter. Significant deviations were shown from 3250 m CD to 5750 m CD, reaching a maximum of 0.08 Global Moran's I index units. This means that the MAUP has some kind of impact in the aggregation, although smaller than in Alto Bellunese. Moreover, in the Innsbruck region, the grid-based aggregation performed better

than the municipality level: even in the worst case for the grid with 5750 CD, the Global Moran's I index did not fall below 0.45 units while, at the municipality level, it reached only 0.3 units. It appeared that the polygon configuration of administrative units loses a significant amount of information.

Unlike in the previous test regions, in the area of Innsbruck it can be observed that (Figure 4 and Table 2):

- the impact of the grid position is smaller than the difference between Global Moran's I values of the grids and the municipality level;
- the municipality level has a Global Moran's I smaller than the median of any other grids.

Since global statistics do not provide any information to explain these differences, local statistics were used to study global performances considering the local pattern. From Figure 6, it is evident that statistically significant hotspots at the municipality level are surrounded by other municipalities with a relatively high G_i^* Z-scores. At the same time, coldspots show weak values, in some cases due to the aggregation over polygons with a longitudinal trend that covers areas with opposite Z-scores. By comparison, in grid maps it was observed that the coldspot pattern is reduced along with the upscaling of recreational values. On the other hand, the main hotspots are still visible in the top scale of the grid-based aggregation, which explains the higher Global Moran's I value. The most evident change in spatial pattern occurs at 3500 m CD, where the main coldspot that crosses the Innsbruck region from West to East splits into two parts, i.e. the last cell connecting them and showing a statistically significant p-value disappears (Supplementary material A).

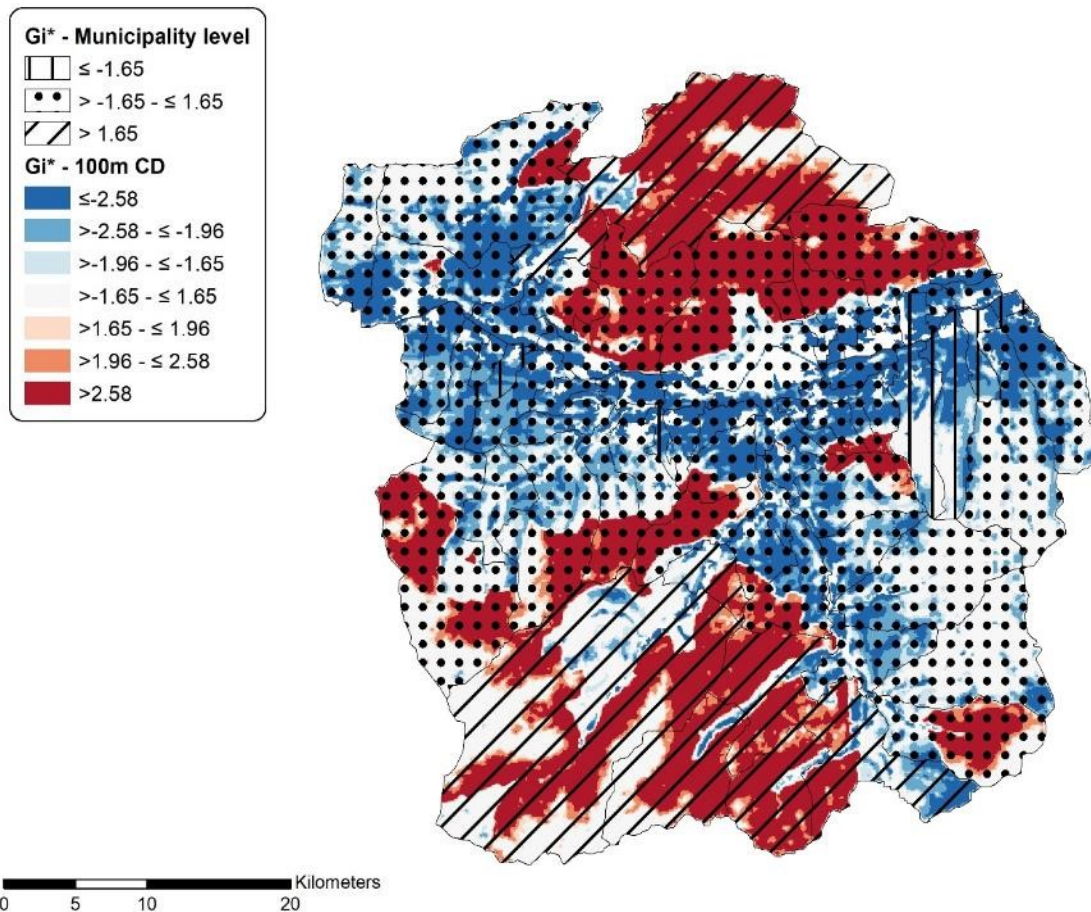


Figure 6. Getis-Ord G_i^* comparison between the grid with 100 m CD and the municipality level in the Innsbruck NUTS3 region.

4 Discussion and conclusion

ES maps are powerful tools that can drive the implementation of the ES framework in governance and decision-making processes. Specifically, to support management objectives and to be useful for policy-makers and stakeholders, maps must show the set of features/cells that represent the unit of variability over which a target organizational level might legislate, make decisions or act. In this study, we reinterpreted existing ESDA tools in a novel multi-step methodology to assess upscaling performance when mapping ESs at a targeted aggregated level. We focused only on the methodological issues without addressing specific targets, either management objectives or ESs. As ESDA can be applied to any spatial data, consequently our methodology can be applied to any spatial variable or ES. This is important because scaling effects affect the assessment of ESs depending on their unique relationship with terrain properties (Grêt-Regamey et al., 2014). For example, Grêt-Regamey et al. (2014) found

minor differences when assessing carbon sequestration and a difference of up to 329% by quantifying timber production at alternative scales. If geomorphology plays a key role in the spatial quantification of ESs, it is likely that sharp gradients would return a substantial spatial heterogeneity and consequently a loss of information when upscaling ES maps (Grêt-Regamey et al., 2014), as for OR. Thus, if significant, such heterogeneity would be detected while applying our methodology to ES maps. Therefore, through global and local spatial autocorrelation analyses and the evaluation of the sensitivity to the MAUP, it was possible to decompose the problem of scale in ES mapping from the perspective of different levels of jurisdiction. Specifically, ESDA techniques were used to highlight spatial clusters among administrative features and grids with a sequentially increasing grain. Afterwards, the comparison between global indices among grids and the municipality level was used to analyze whether the latter was hiding some important patterns. Lastly, multiple grid displacements were the strategy applied to estimate the impact of the MAUP.

The methodology was tested on the case study of OR in the Alps, where recreational values were aggregated prior to any spatial autocorrelation analysis, to address how spatial information of the selected ES behaves in the upscaling process. The first-order contiguity assumption helped us to simplify the interpretation of spatial autocorrelation statistics and enabled us to develop an iterative approach with reasonable computational effort that avoids sub-sampling procedures. The spatial pattern of the outdoor recreation ES at local level generally confirmed global outcomes, showing the step-by-step homogenization of the landscape of the assessed areas, from the finest to the coarsest scale. As the grain is expanded, the MAUP affects Global Moran's I results with an increasing magnitude. This was more evident in the area of Alto Bellunese where hotspots and coldspots were closely associated in a heterogeneous landscape with small and narrow valleys and sharp geomorphological gradients. Conversely, the South Tyrol region represents the example of an area where a linear aggregation shows a good performance due to relative homogeneity and clustering, with hotspots and coldspots that are not in opposition with each other. An intermediate situation was revealed in the Innsbruck region where, despite the fact that the main hotspots were detected, the municipality level was not able to show the presence of coldspots because of weak Z-scores and the MAUP. This seems to depend mainly on the shape of the municipalities, rather than on their location. In all three case studies, global spatial

autocorrelation analyses returned an approximately linear loss of information below 2000 m CD (Figure 4) and Moran's I indicators that converge to the same value among grids at equivalent scales. This CD accounts for roughly half of the range between the Global Moran's I indices of the coarsest and the finest scale considered, highlighting that at a finer scale the location of the grid is irrelevant to the result and that spatial processes are well described in terms of spatial allocation.

In our case study, and specifically in South Tyrol and in the region of Innsbruck, we can conclude that upscaled recreational values (and specifically, their statistically significant hotspots) are generally consistent with the related 100 m CD map. In Alto Bellunese, however, the heterogeneous pattern of relatively small clusters implies a substantial loss of information and either alternative aggregation strategies may be chosen to improve hotspot detection or the use of disaggregated data should be considered. A fine-grain spatial allocation of ESs might be suitable to pursue management objectives. In this case, upscaling could be used to highlight the main clusters, so as to spatially prioritize actions over sub-municipality areas and then switch to a more detailed cartography, e.g. for engineering purposes.

Although our methodology does not provide a unique solution to define the scale of detail for ES analysis, some generalizations can be inferred:

- clusters tend to disappear when their extent becomes smaller than the feature to which values are upscaled;
- the cross-comparison among grids and municipalities highlights local anomalies that grid displacements failed to detect through the Moran's I global spatial autocorrelation;
- in the grid-based approach, the median of the boxplots (Figure 4) can be considered as an indicator of the overall level of clustered information preserved within each scale;
- the magnitude of the MAUP can be estimated with few iterations but cannot be prevented, unless a different aggregation strategy is chosen.

On the basis of these points, we can conclude that our methodology is effective to choose a suitable mapping scale in ES assessment. The comparative analysis between grids and the municipality level, through boxplots and local assessments, helped us to define the quality of the upscaling by using the

spatial relationships as indicators of the change of the recreational pattern. This enabled us to estimate the loss of information through inferential statistics, using ESDA in a novel approach based on a multi-step procedure. Such a procedure is meant to provide a full set of data (maps and graphs) to study ES patterns in order to develop a global understanding of how spatial relationships scale up. This is crucial because avoiding scale mismatches to meet management objectives should not be the reason for information loss, which can lead to potential misinterpretation of mapping outcomes.

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Appendix A

ESDA tools for spatial analyses

Global Moran's I

Global Moran's I statistic provides an estimation of the spatial autocorrelation of all cells/polygons in a map. It is a measure of the spatial dependency and non-stationarity of spatial features and indicates spatial clustering of similar values (Anselin, 1995). It can be interpreted as the degree of linear association between observed values and the weighted average (spatial lag) of their neighbors (Anselin, 1996). The equations to calculate the Moran's I index and related statistics are shown in Box 1. Moran's I values range between 1 and -1. The weighted cross-product of the difference of the i^{th} value of a cell/polygon and the j^{th} values of its neighbors from the mean of the variable drive the sign of the index. Values close to 0 imply randomness; values close to 1 mean positive spatial autocorrelation i.e. similarity among values; values close to -1 indicate negative spatial autocorrelation i.e. dissimilarities among values. The expected value is a negative number that approximately equals zero for datasets with a large number of elements. It is calculated along with the variance of the variable to quantify the Z-score and its related p-value. The spatial autocorrelation is indeed an inferential statistic that is interpreted through hypothesis testing. The null hypothesis is the complete spatial randomness or, in other words, the independence of observed values from neighboring polygons or cells. The statistical significance of the presence of clusters is tested by comparing z-scores and p-values with the critical values of a normal distribution. Only the upper tail of the distribution is considered so as to reject the null hypothesis even when a strong dissimilarity is detected (lower tail). In this case the non-random pattern of cells/polygons is the result of a diverging process (Goodchild, 1986).

Global Moran's I index

$$I = \frac{\sum_i (x_i - \bar{x}) \sum_j (x_j - \bar{x}) w_{ij}}{\sum_i (x_i - \bar{x})^2} \frac{n}{\sum_i \sum_j w_{ij}}$$

with:

x_i = value of the i^{th} cell/polygon

x_j = value of the j^{th} neighbor

\bar{x} = mean of the values of all elements

w_{ij} = weight of x_j related to x_i

n = number of cells/polygons

Expected value

$$E = -1/(n - 1)$$

Variance

$$VAR = \frac{n[(n^2 - 3n + 3)S_1 - 2nS_2 + 3S_0^2] - K[(n^2 - n)S_1 - 2nS_2 + 6S_0^2]}{(n - 1)(n - 2)(n - 3)S_0^2} - E^2$$

with:

$$S_0 = \sum_i (x_i - \bar{x})^2$$

$$S_1 = (1/2) \sum_i \sum_j (w_{i,j} + w_{j,i})^2$$

$$S_2 = \sum_i \left(\sum_j w_{i,j} + \sum_j w_{j,i} \right)^2$$

$$K = \sum_i (x_i - \bar{x})^4 / [\sum_i (x_i - \bar{x})^2]^2$$

Z-score

$$Z = (I - E) / \sqrt{VAR}$$

Local Moran's I

Local statistics return a value for each cell/polygon and represent the decomposition of their contribution to global outcomes. Among these, Anselin Moran's I local statistic estimates local spatial autocorrelation (equations shown in Box 2), which differs from the global one because it is calculated for each single deviation of x_i and not for their sum. Its interpretation through hypothesis testing is the same as the global statistic. The output is a map (displaying any of the calculated statistics e.g. index or Z-score) where the clustering tendency can be visually explored so as to highlight local instabilities and multiple sources of spatial dependence, particularly useful within large datasets (Anselin, 1996, 1995).

Local Moran's I	$I_i = \frac{(x_i - \bar{x}) \sum_j (x_j - \bar{x}) w_{ij}}{\sum_i (x_i - \bar{x})^2} \frac{n}{\sum_i \sum_j w_{ij}}$
with:	
x_i	= value of the i^{th} cell/polygon
x_j	= value of the j^{th} neighbor
\bar{x}	= mean of the values of all elements
w_{ij}	= weight of x_j related to x_i
n	= number of cells/polygons
Expected value	$E_i = - \sum_j w_{ij} / (n - 1)$
Variance	$VAR_i = \left(\sum_{j \neq i} w_{ij}^2 \right) \frac{(n - K)}{n - 1} + \left(\sum_{k \neq i} \sum_{h \neq i} w_{ik} w_{ih} \right) \frac{(2K - n)}{(n - 1)(n - 2)} - \frac{(\sum_j w_{ij})^2}{(n - 1)^2}$
with	
K	= $\sum_i (x_i - \bar{x})^4 / \left[\sum_i (x_i - \bar{x})^2 \right]^2$
Z-score	$Z_i = (I_i - E_i) / \sqrt{VAR_i}$

Getis-Ord G_i^*

The Getis-Ord G_i^* statistic, also known as Hotspot Analysis, measures the degree of association resulting from the spatial concentration of the weighted values of each cell/polygon and its neighbors within a specified distance (Getis and Ord, 1992). It is reported to detect significant local clustering where global statistics do not provide signals of spatial association (Anselin, 1995). Box 3 reports the equation of the statistic which, once again, is interpreted through hypothesis testing. The Getis-Ord G_i^* is already conceptualized as a Z-score (Getis and Ord, 1995) and, as for Local Moran's I, it is calculated for every value x_i , resulting in a map. The main differences from Moran's I are:

- the weight of the main cell/polygon w_{ii} is included among those of neighbors w_{ij} ;
- for hypothesis testing, a two-tail test is applied because G_i^* implies positive spatial autocorrelation both for high positive and negative Z-scores i.e. high/high local relationships represent hotspots while low/low sets of values are coldspots (Anselin, 1995).

Getis-Ord G_i^*

$$G_i^* = \frac{\sum_j w_{ij} x_j - \left(\frac{\sum_j x_j}{n}\right) \sum_j w_{ij}}{\sqrt{\left[\frac{\sum_j x_j^2}{n} - \left(\frac{\sum_j x_j}{n}\right)^2\right] \frac{(n \sum_j w_{ij}^2) - (\sum_j w_{ij})^2}{n-1}}}$$

with:

x_j = value of the j^{th} neighbor

w_{ij} = weight of x_j related to x_i

n = number of cells/polygons

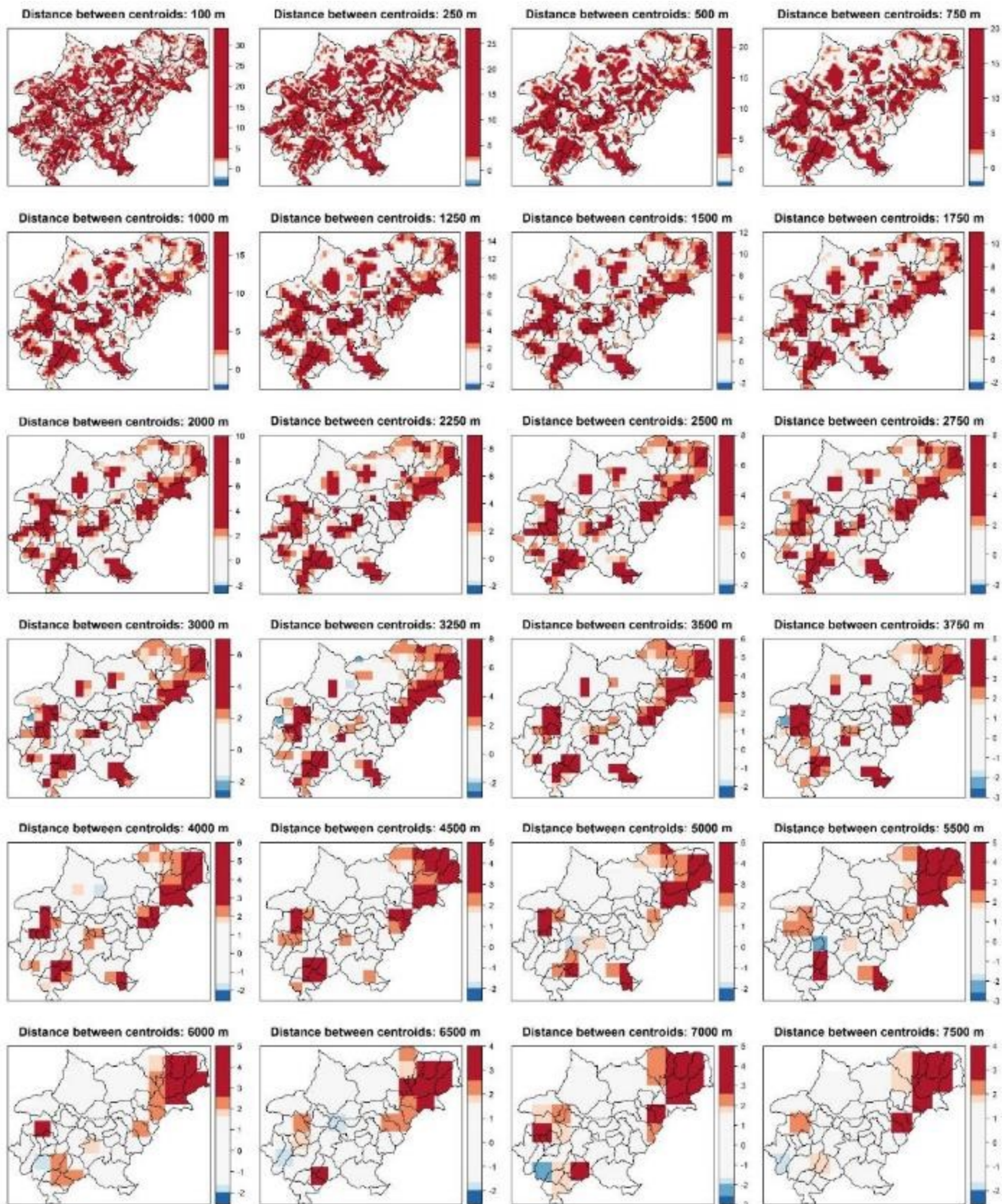
all j^{th} neighbors, including the weight of the i^{th} cell/polygon

References

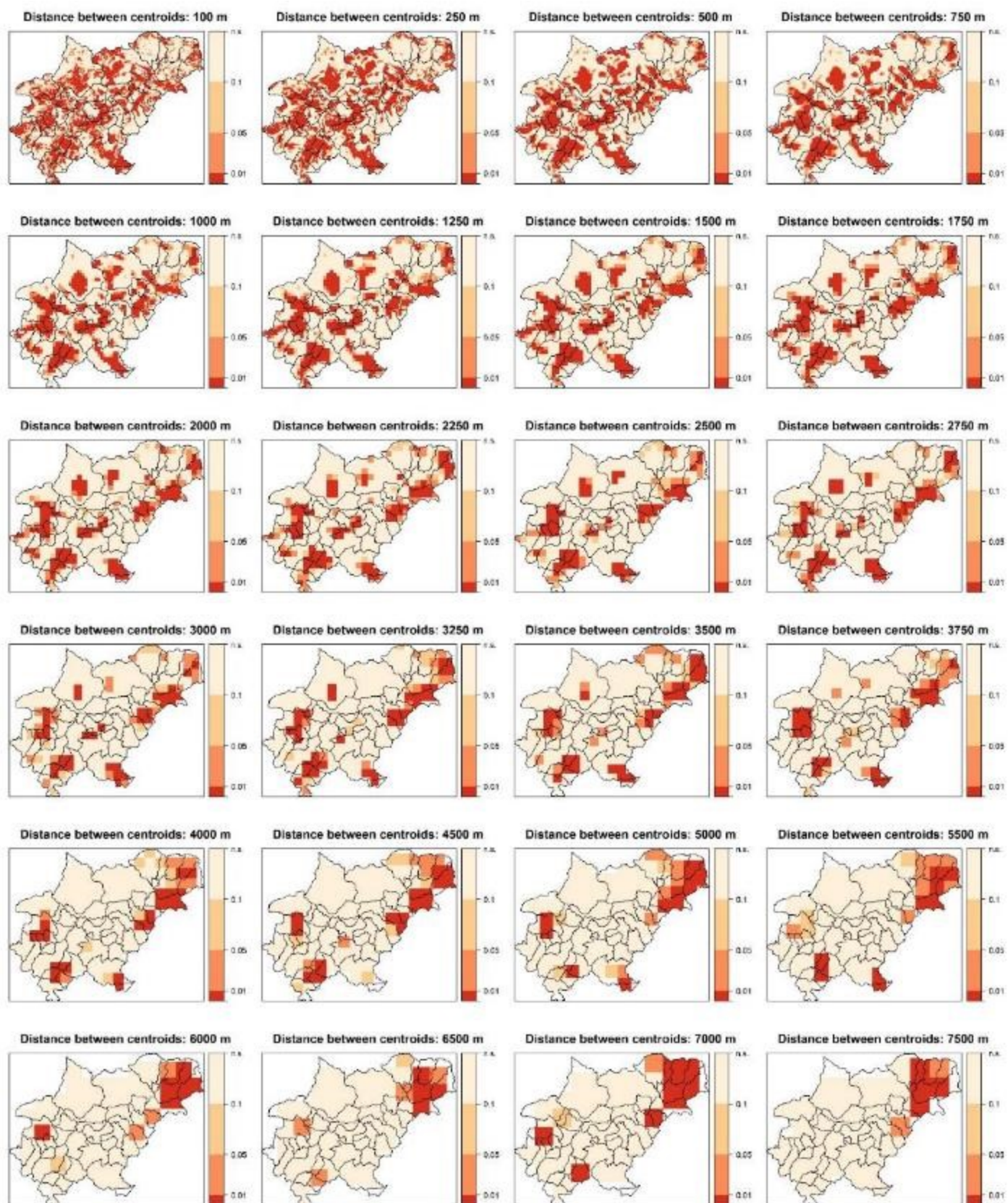
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Local spatial autocorrelation statistics at local level: Local Moran's I and Getis-Ord G_i^*

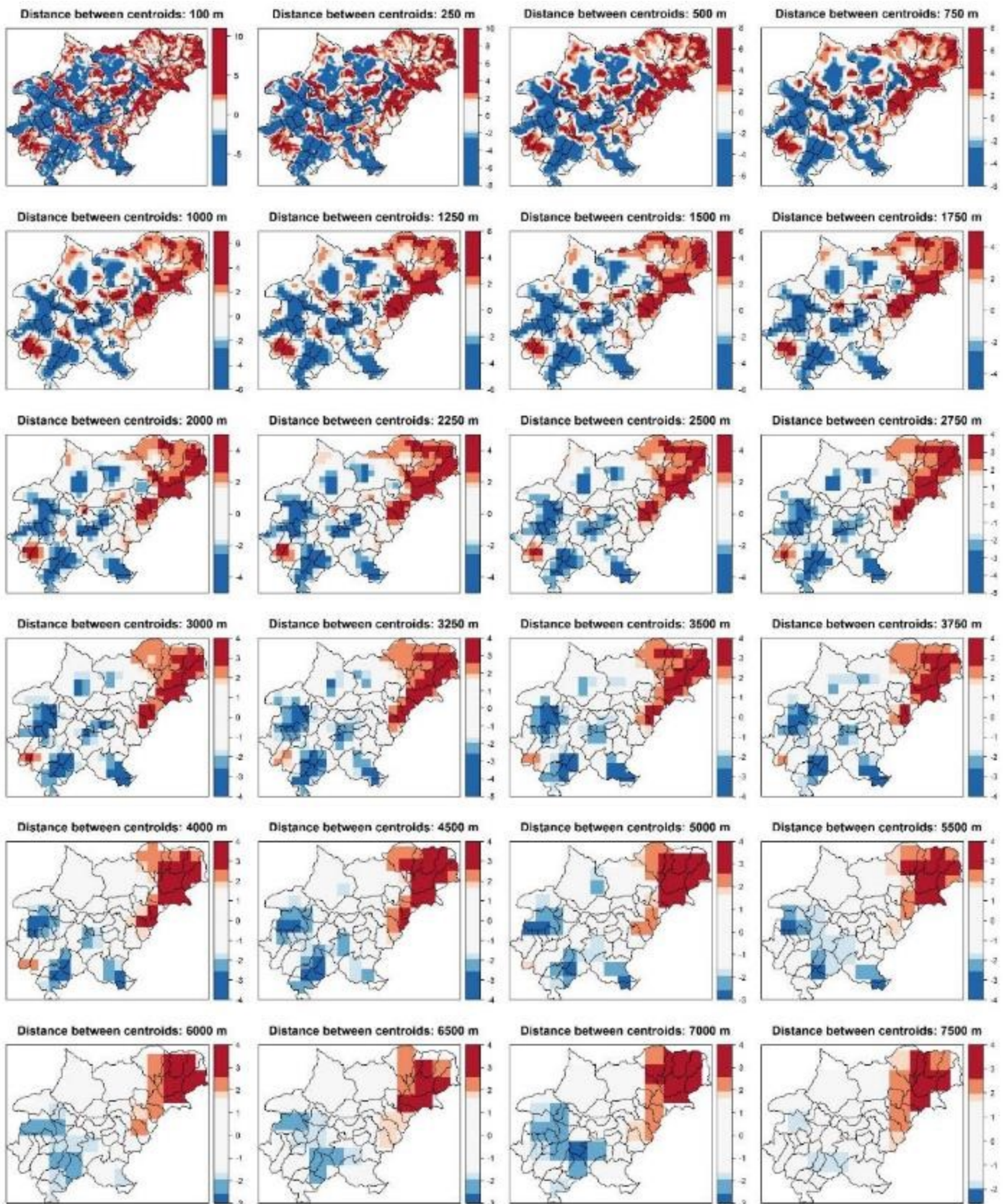
Alto Bellunese – Local Moran's I – Z-score



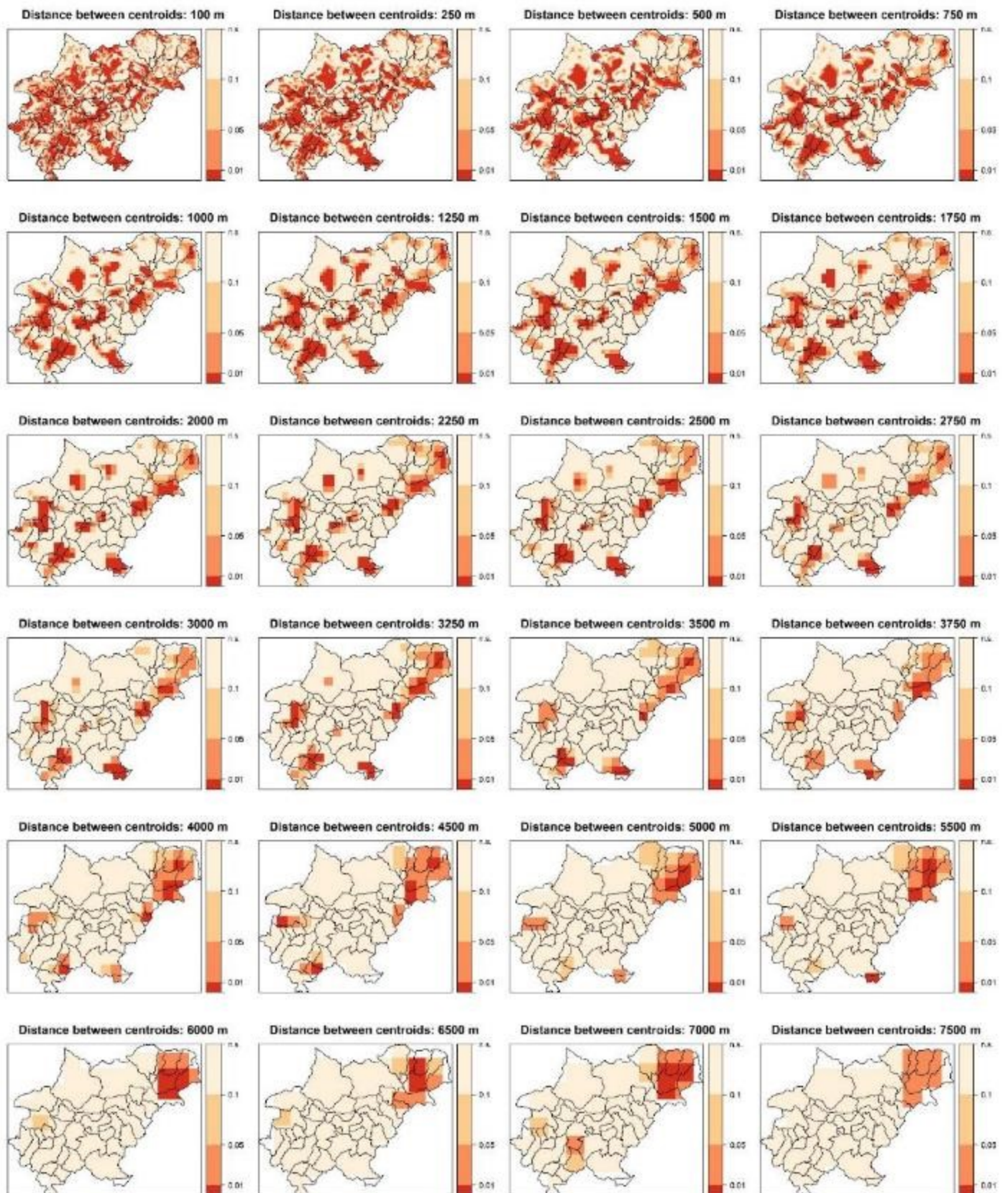
Alto Bellunese – Local Moran's I – p-value



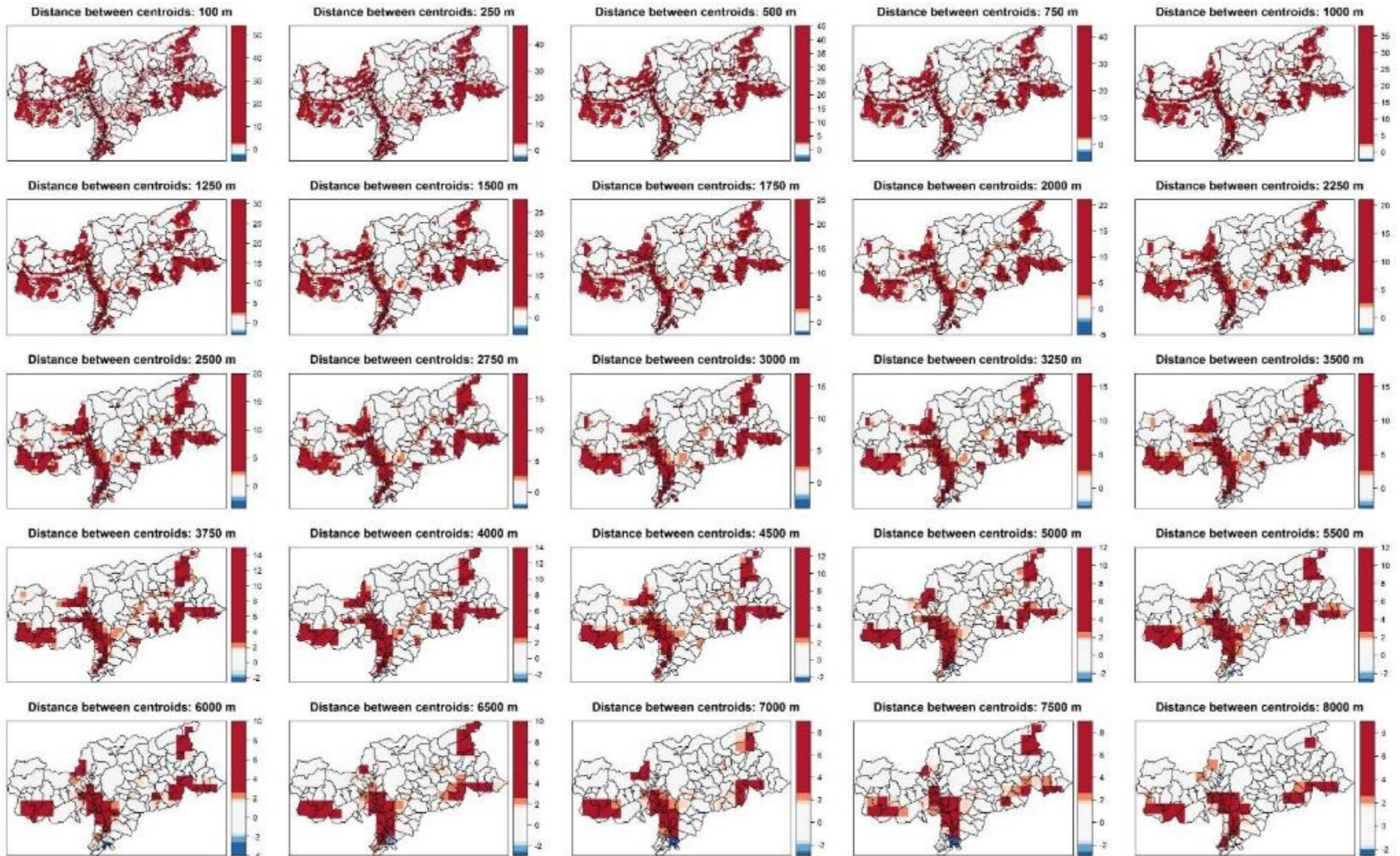
Alto Bellunese – Getis-Ord G_i^* – Z-score



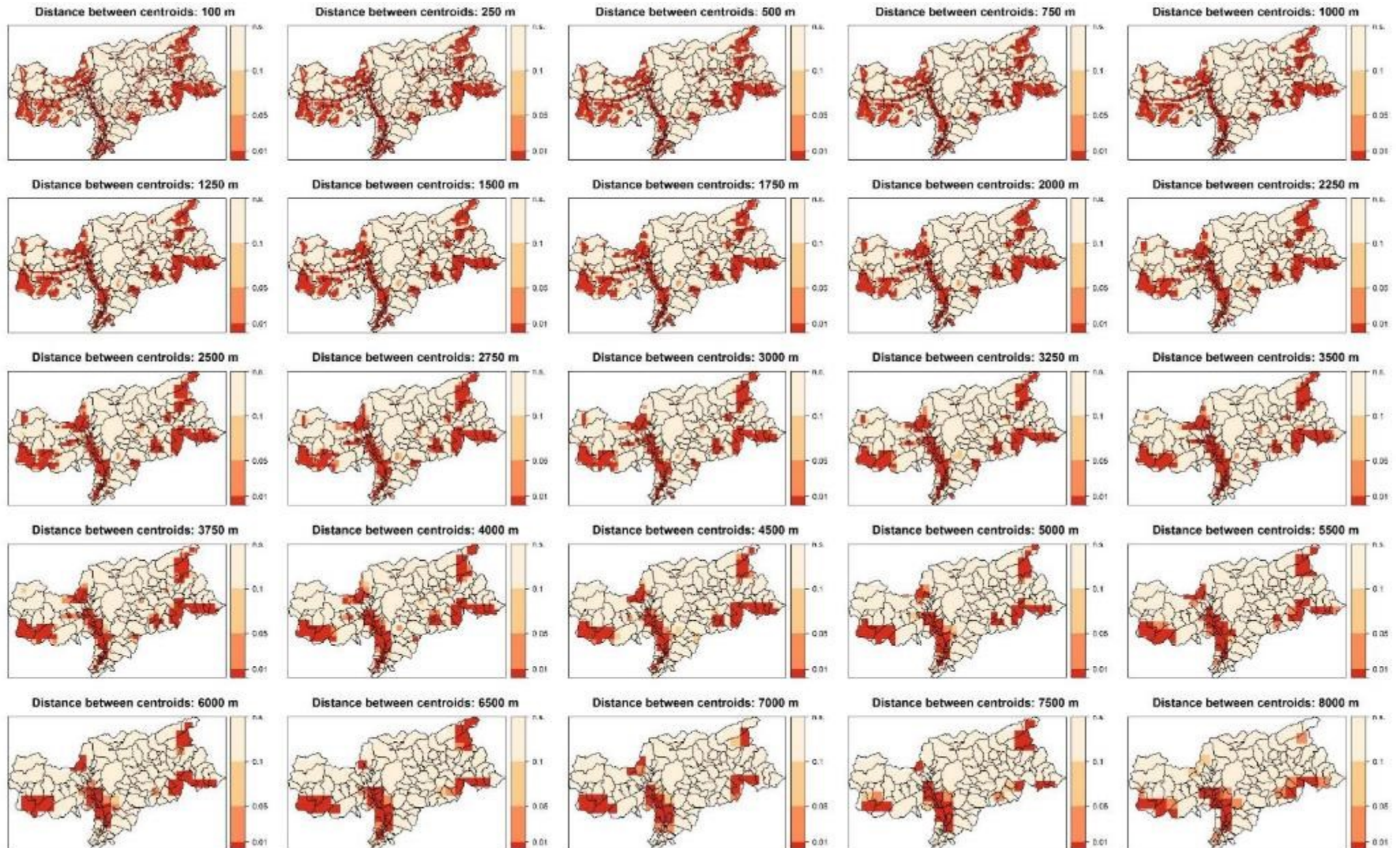
Alto Bellunese – Getis-Ord G_i^* – p-value



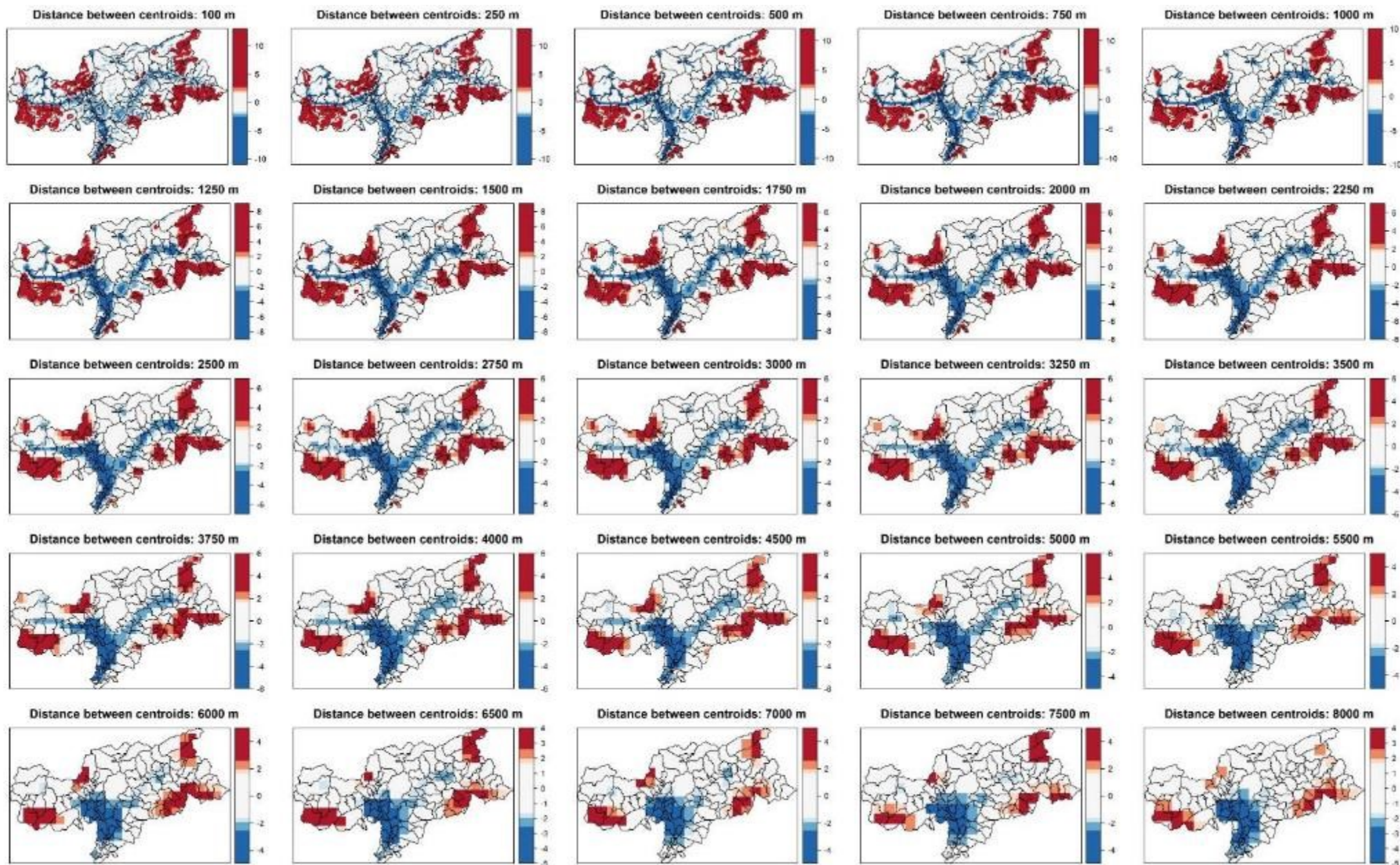
South Tyrol – Local Moran's I – Z-score



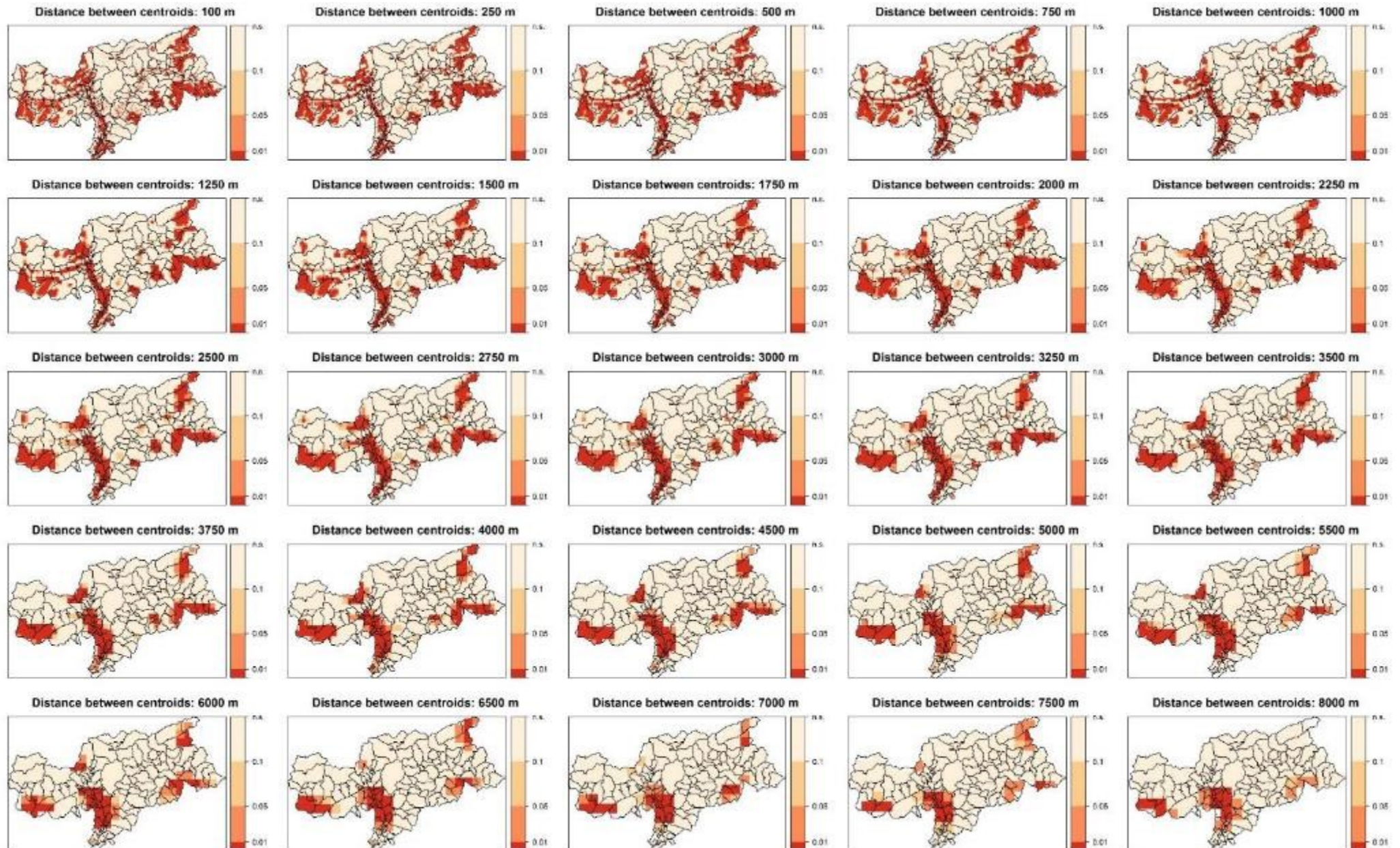
South Tyrol – Local Moran's I – p-value



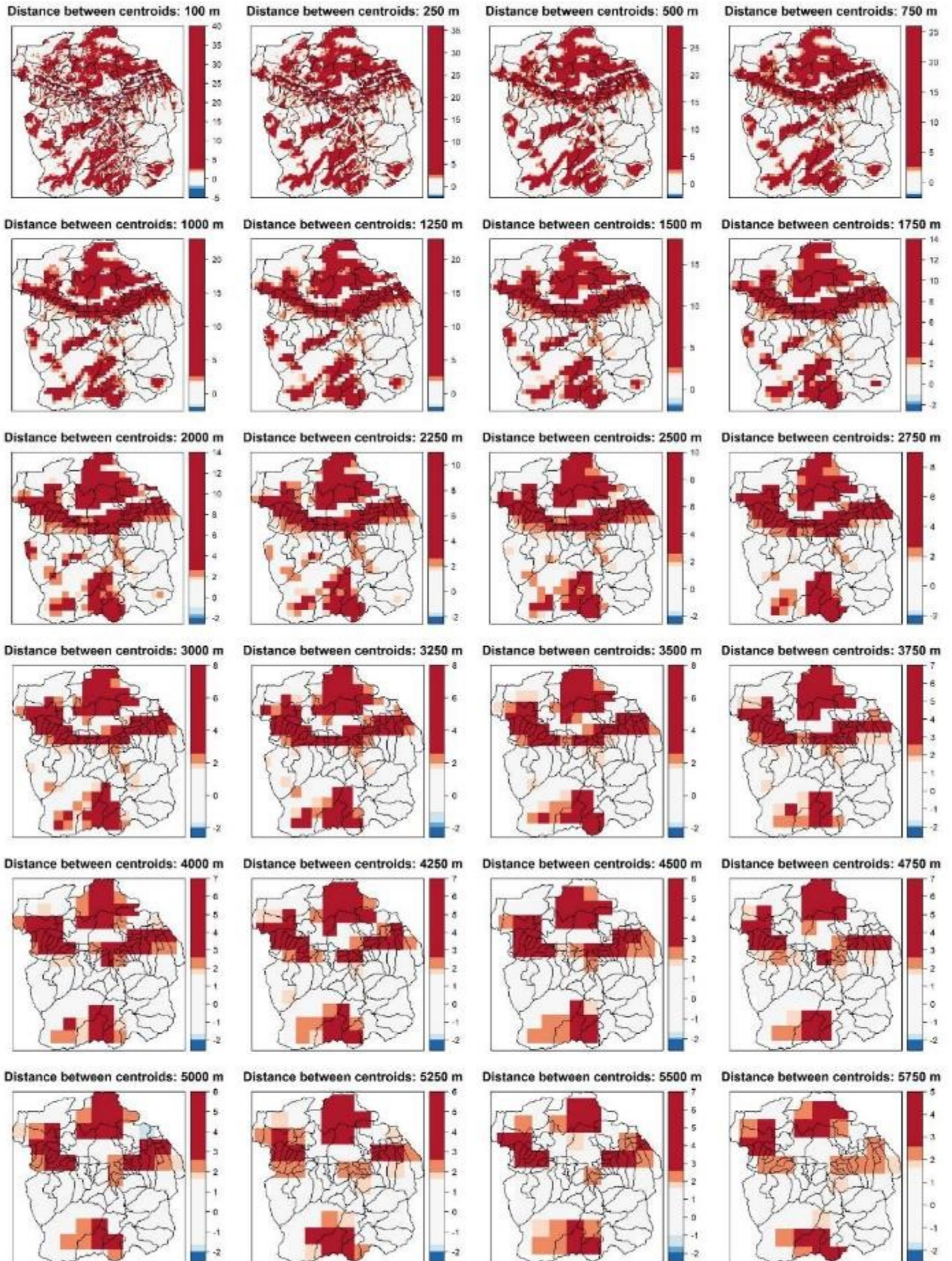
South Tyrol – Getis-Ord G_i^* – Z-score



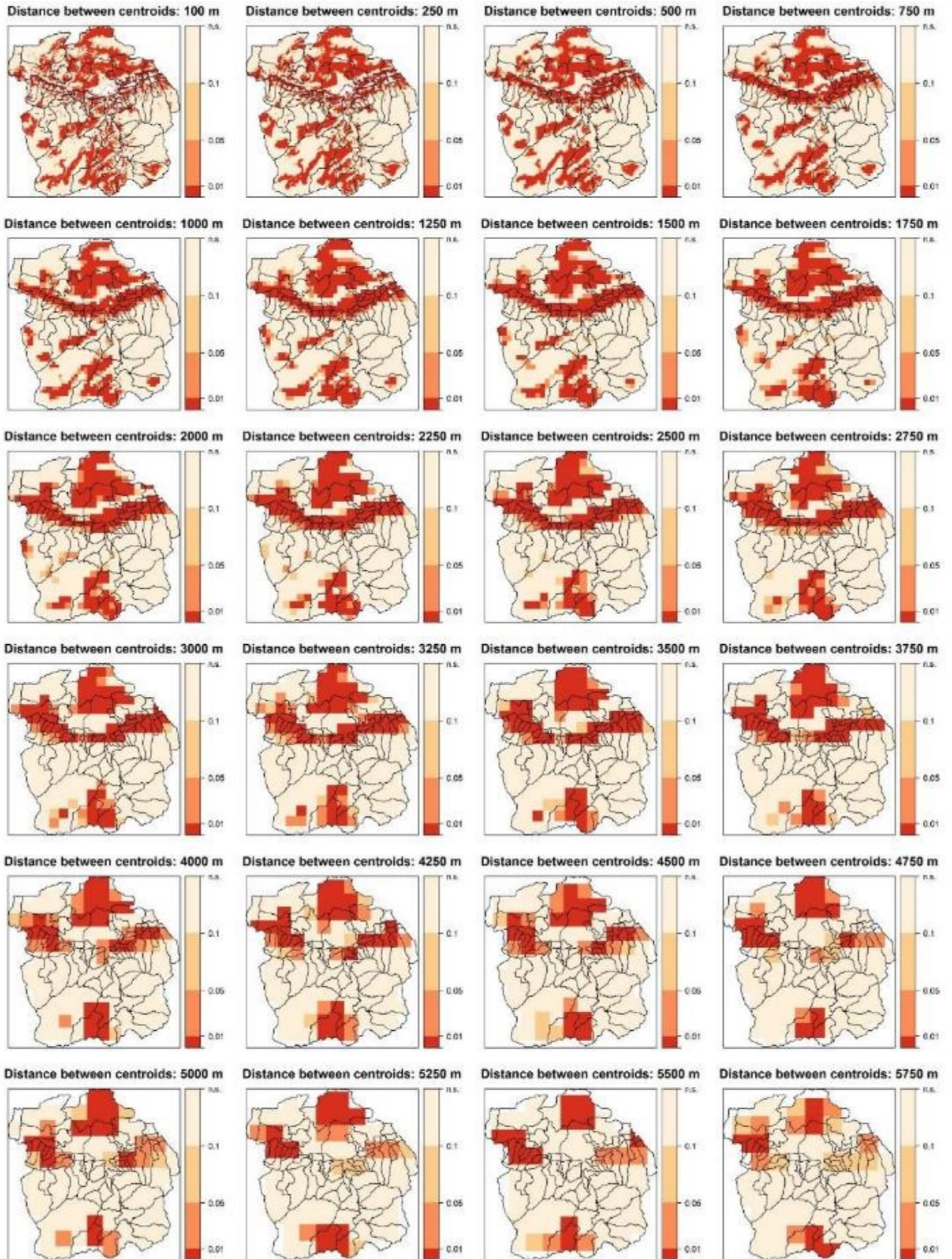
South Tyrol – Getis-Ord G_i^* – p-value



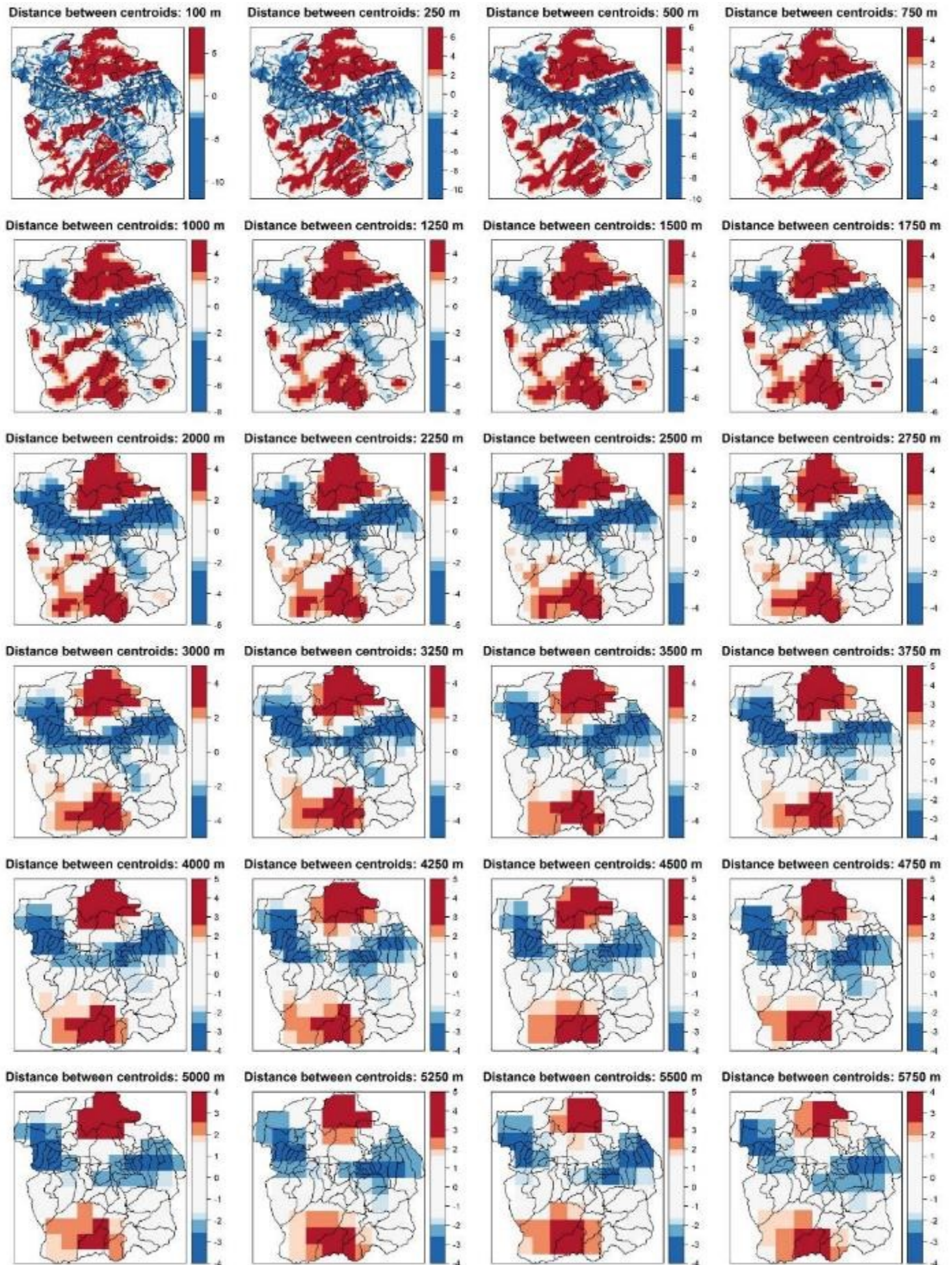
Innsbruck – Local Moran's I – Z-score



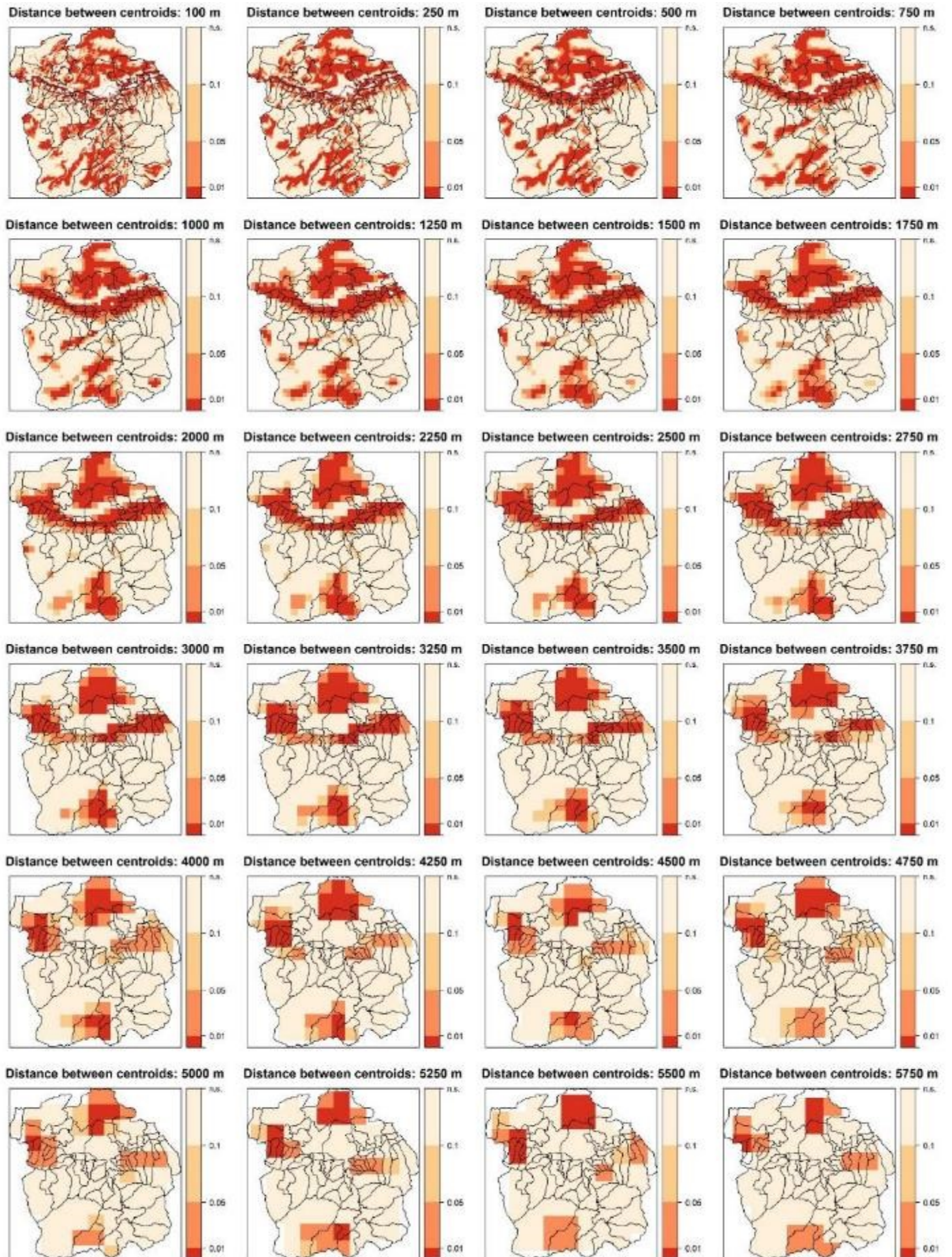
Innsbruck – Local Moran's I – Z-score



Innsbruck – Getis-Ord G_i^* – Z-score

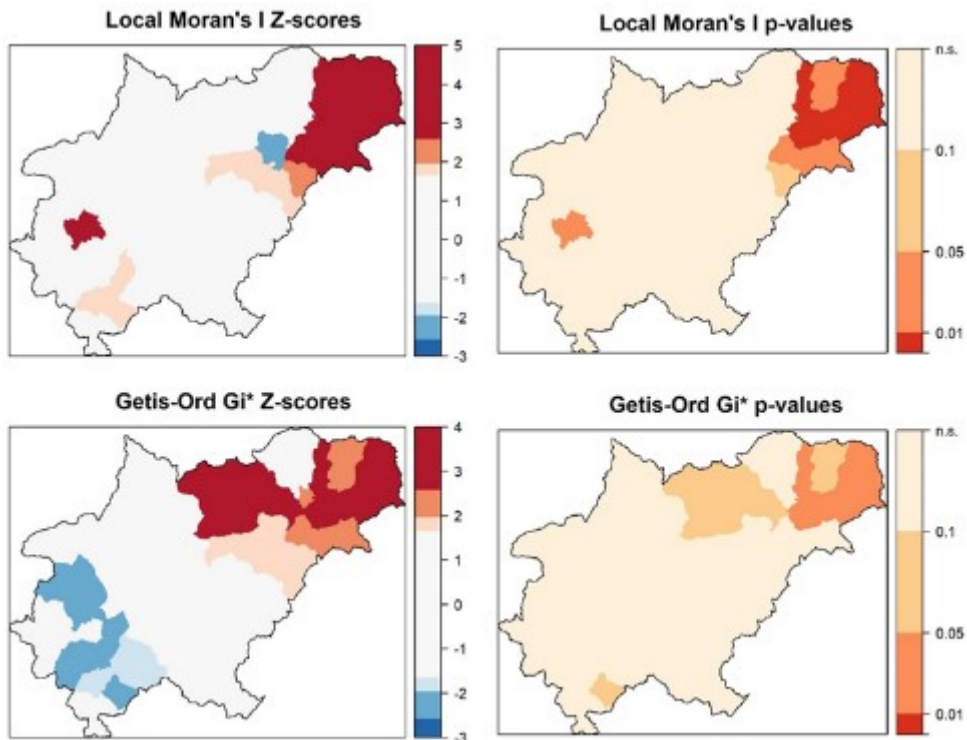


Innsbruck – Getis-Ord G_i^* – p-value

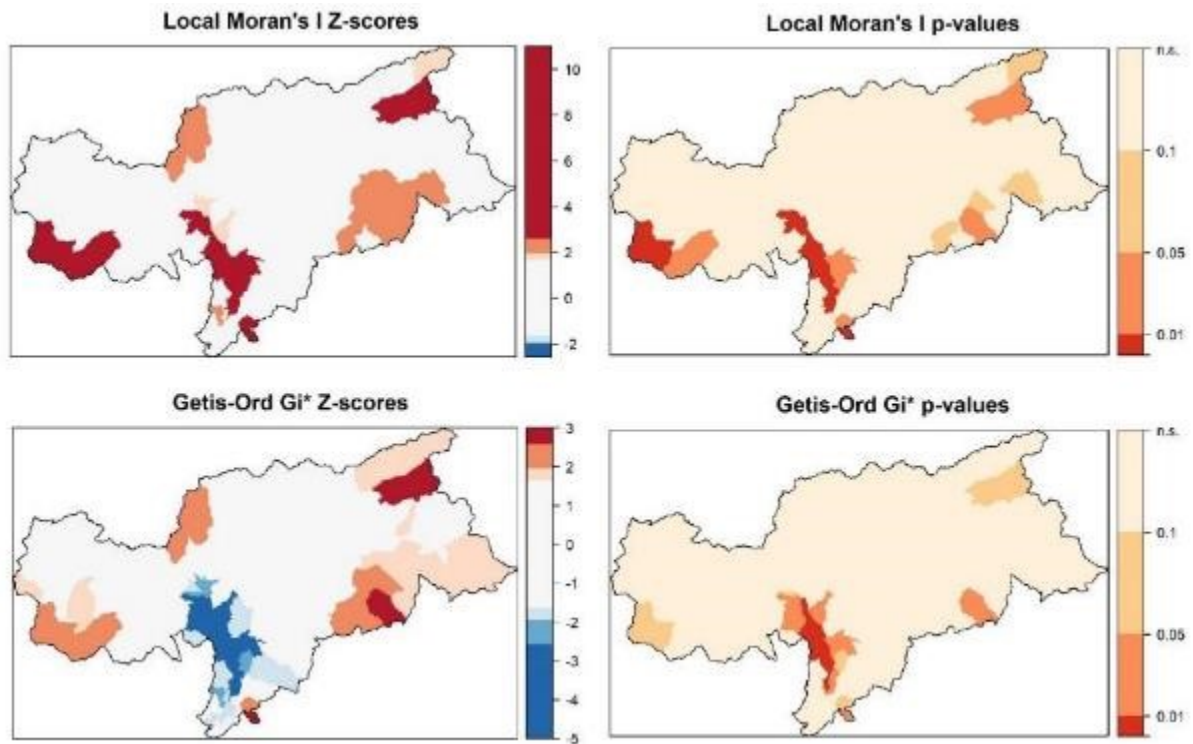


Local spatial autocorrelation statistics at the municipality level: Local Moran's I and Getis-Ord Gi*

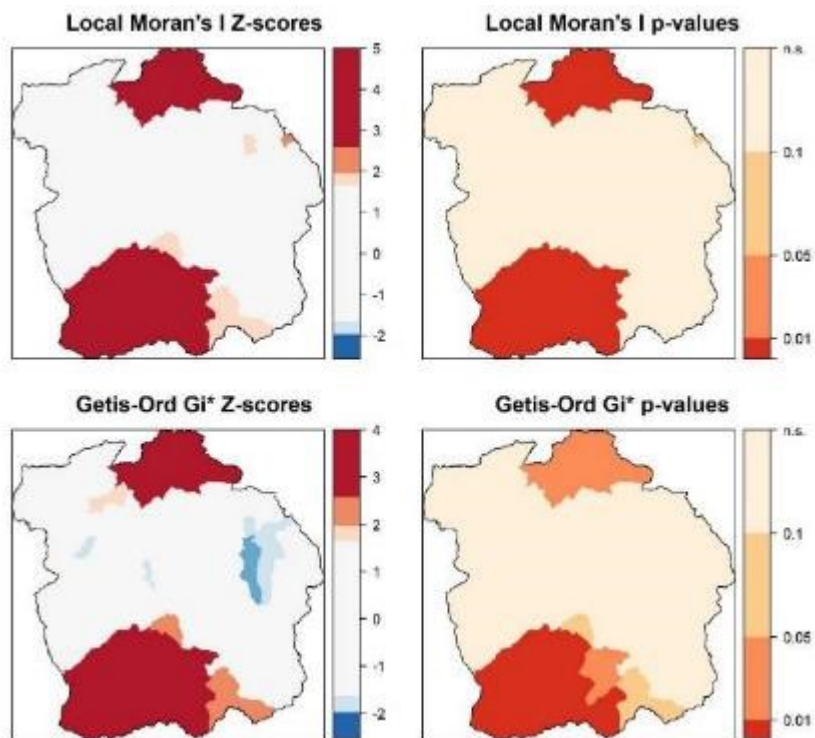
Alto Bellunese



South Tyrol



Innsbruck



Spatial autocorrelation statistics at the pan-Alpine level

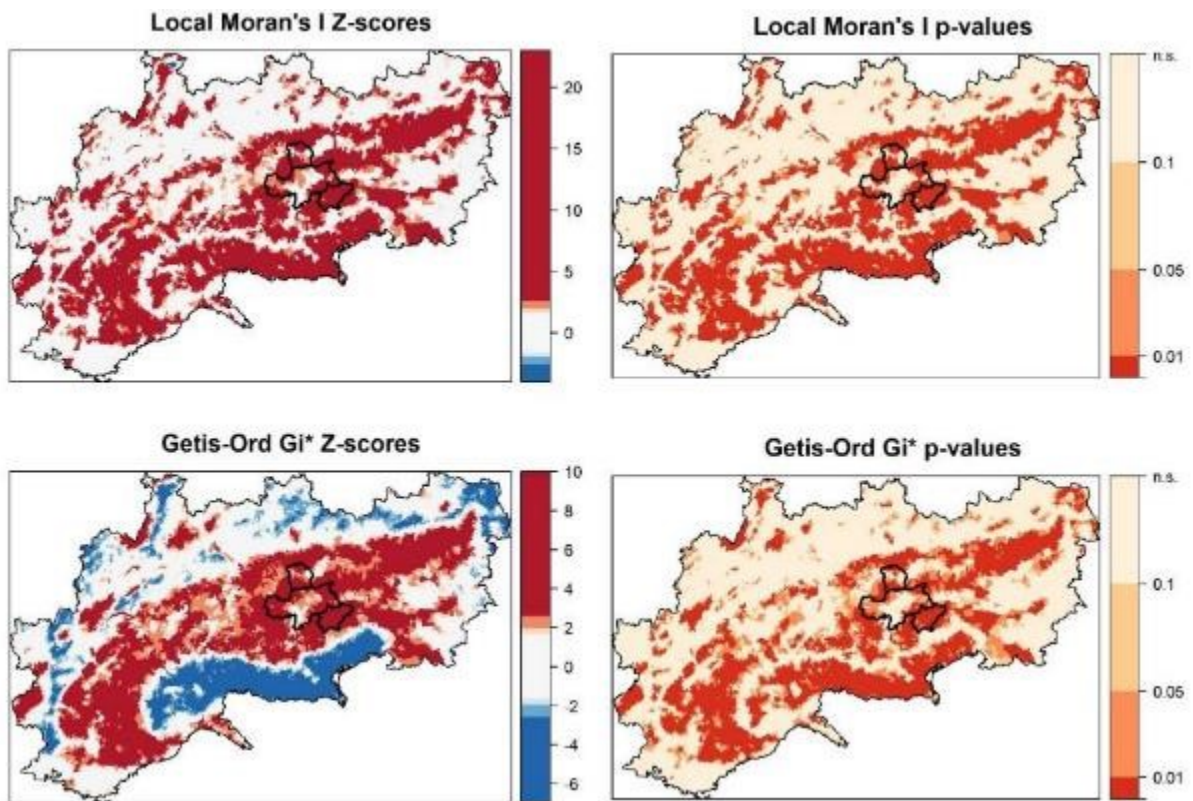
Since a transnational ES assessment was carried out in the framework of the Interreg AlpES project, we applied ESDA techniques at the Pan-alpine level to highlight spatial autocorrelation, cluster presence and pattern of the ES “Outdoor recreation”. We estimated a Global Moran’s I index of 0.82 with a p-value lower than 0.01. Since the geomorphology played an important role in the methodology to quantify the selected ES (Schirpke et al., 2018¹), the hotspot analysis clearly revealed the whole Alpine arc, surrounded by statistically significant coldspots located in flat areas.

At the pan-Alpine level:

- Alto Bellunese is included in a wider hotspot with p-values smaller than 0.001 for almost all its area; the internal pattern revealed at higher scale is totally hidden;
- South Tyrol and the region of Innsbruck exhibit a substantial variability depending on the local pattern, quite consistent with local analyses at coarser scales, although no statistically significant coldspots were detected.

The lack of coldspots within the case study regions at this level of analysis depends on the spatial range of variability of the recreational values. Consequently, negative Z-score were assigned to mainly flat areas. On the other hand, these regions show a wide and extensive hotspot presence depending on their belonging to bigger clusters, representing the geomorphological gradients of the eastern Alps.

¹ Schirpke, U., Meisch, C., Marsoner, T., Tappeiner, U., 2018. Revealing spatial and temporal patterns of outdoor recreation in the European Alps and their surroundings. *Ecosyst. Serv.* 31C, 336–350. <https://doi.org/10.1016/j.ecoser.2017.11.017>



Modeling impact of forest expansion on outdoor recreation: a CA-Markov approach

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Abstract

Exploring temporal pattern and dynamics of alpine socio-ecosystems is becoming more and more relevant as land use change and climate change affect landscape attributes that underpin provision of many cultural ecosystem services, including outdoor recreation activities. Archetypal is the case of the Alto Bellunese area, in which the decline of traditional agricultural businesses has led to a substantial expansion of forests over grasslands, historically limited by livestock farming. In this context, the objective of this study is to assess the close-term impact of land use change on outdoor recreation opportunities in the Alto Bellunese. We first coupled a classification algorithm i.e. logistic regression model, with Markov chains and cellular automata to project land use and simulate the expansion of forests over grasslands from 2007 to 2030. Secondly, we used the observed land use map of 2007 and projected maps of 2017 and 2030 to map the spatial pattern of outdoor recreation opportunities over time. We found that temperature is the main variable that drives the evolution of forest pattern, followed by great soilscapes, while proxies of human impact appear to have little effect on land conversion, although statistically significant. By comparing the loss of provision between 2007-2017 and 2007-2030, we found that major impacts already occurred in the first period. Here, among other predictors, observed temperature records drove most land conversions before the projected increase (+0.025°C per year from 2018, i.e. the second period) has had any impact on forest pattern and landscape

heterogeneity, under current modeling infrastructure and data. We concluded it is not likely to expect relevant close-term consequences from temperature change on existing open areas and consequently on the provision of outdoor recreation opportunities in the Alto Bellunese.

Keywords: South Eastern Alps; Mountain Socio-Ecosystems; Forest Expansion; Cellular Automata; Outdoor Recreation; Spatial Mapping

1 Introduction

Outdoor recreation (OR) is a cultural ecosystem service (ES) that plays a fundamental role in human well-being. Mountains are typical destinations that offer a range of outdoor activities e.g. hiking, biking and climbing, in this way providing several opportunities for mental and physical health recovery. Assessing provision of OR is therefore relevant for policymaking and landscape planning to manage land, sustaining nature-based tourism and ecotourism in mountain areas. Potential provision of OR is commonly mapped through survey-based and proxy-based static approaches. Temporal dynamics and patterns are rarely considered in quantifying OR opportunities (Schirpke et al., 2018). Some exceptions are: Guo et al. (2010) explore the relationship between economic growth i.e. tourism development, and provision of ESs over time; Wood et al. (2013) and Schirpke et al., (2018) use crowd-sourced information from online social media to study seasonal patterns of visitation rates and OR, respectively; Sonter et al. (2016) study the statistical relationship between landscape attributes and temporal changes of visitation rates. Nowadays, exploring temporal pattern and dynamics of alpine socio-ecosystems is becoming more and more relevant as Land Use Change (LUC) affects:

- landscape attributes (e.g. natural elements, landscape diversity, panoramas, etc.) that underpin provision of many cultural services, including OR;
- mountain local communities which mainly depend on revenues from tourism-related businesses (Schirpke et al., 2016).

Archetypal is the case of the Alto Bellunese, a mountainous area framed within alpine landscapes of the Dolomites, thus mainly covered with forests, natural and semi-natural environments. The area

covers 42² municipalities of the Belluno NUTS 3 area, an Italian province located in the Veneto Region, South Eastern Alps. The Alto Bellunese is a well-known tourism destination, acknowledged as a UNESCO World Heritage Site. It has a high environmental value, with 58% of its area recognized as Natura 2000 site. The local economy is mainly based on tourism and non-intensive livestock farming. Acknowledged trends in the area include decline of traditional agricultural businesses and demographic decrease. Their macroscopic trade-off is the natural expansion of forests, limited in the past by human activities e.g. grazing pressure over natural grasslands from livestock pasture. Well-known from the literature (Cocca et al., 2012; Giupponi et al., 2006) and acknowledged from the experts of the Veneto Region (see Zen et al., 2018), land abandonment is considered the main driver of mountain landscape change in the Alps. Last but not least, the whole alpine area is experiencing dramatic consequences of climate change (CC). Climate simulations from the EU FP6 Integrated Project ENSEMBLES³ return a regional warming of about 0.25 °C per decade until the mid of the 21st century, under the A1B emission scenario of the IPCC Fourth Assessment Report (AR4). Other expected consequences are changes in the seasonality of precipitation, global radiation, relative humidity and an increasing frequency of extreme events, such as droughts, floods and storms (Gobiet et al., 2014).

Given the above, the objective of this study is therefore to expand the work carried out by the Veneto Region in the Interreg Alpine Space project “AlpES - Alpine Ecosystem Services - mapping, maintenance and management” (full details in Zen et al. (2018)), to simulate the close-term impact of LUC on OR opportunities in the Alto Bellunese. We simulate the acknowledged trend of forest expansion driven by land abandonment and demographic decline up to 2030. In this way, we include temporal dynamics, thus quantifying pattern and change of the provision of OR where forests are more likely to develop. We assume natural forest expansion over grasslands driven by biophysical and socio-economic variables acknowledged from the literature.

² The municipality of Sappada became part of Friuli-Venezia Giulia Region on October 29th, 2018. At the time of writing, the Alto Bellunese includes 41 municipalities.

³ An ensemble of 17 different regional climate models driven by lateral boundary conditions from 8 different global climate models is used to carry out 22 high resolution simulations until 2050, 15 of them ranging to 2100 (Gobiet et al., 2014).

2 Materials and methods

The methodology includes classification algorithms and stochastic cellular automata (CA) to model forest expansion over time and quantify future OR services based on observed LUC trends and the A1B emission scenario. The following sections (2.1, 2.2 and 2.3) introduce data and concepts necessary to understand the architecture of the model developed in this study. Then, the model itself is explained (Section 2.4). Finally, an overview about the software and tools used to implement the model is presented (Section 2.5).

2.1 Logistic regression model

Logistic regression is a classification algorithm that estimates the probability (p) of observing a binary (or categorical) response, based on one or more independent variables. It uses the maximum likelihood estimation to calculate the best combination of model parameters that maximizes the probability of observing a given dataset. Logistic regression is formalized as a logistic function (Equation 1), known as link function of a linear combination of input variables (Equation 2).

$$p = \frac{e^y}{1 + e^y} = \frac{1}{1 + e^{-y}} \quad (Eq. 1)$$

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n \quad (Eq. 2)$$

The dependent variable (y) of the linear model is not directly observed and equals the so-called log odds of the probability (Equation 3):

$$y = \ln \frac{p}{1 - p} \quad (Eq. 3)$$

Therefore, a logistic regression model is calibrated by using binary (or Boolean) observations and a set of continuous and/or categorical independent variables. The calibration aims at finding the set of variables that maximizes the goodness of fit of the fitted model (Ghatak, 2017). Among others, Wald test, likelihood ratio test (LRT), pseudo R^2 and Akaike Information Criteria (AIC) are all different statistics that help to find significant predictors, dropping those not significant, hence comparing different combinations of input variables:

- Hypothesis testing (Wald test; LRT): it can be used to detect if there is a statistically significant relationship between the dependent variable and each individual predictor i.e. if the estimated model parameters are significantly different from zero; it is also used to test the goodness of fit as twice the difference of the fitted model (which includes all selected predictors) and a restricted model (without one or more predictors or eventually with only the intercept, hereafter referred to as null model) which approximately follows a chi-squared distribution under the null hypothesis (Equation 4) (Ghatak, 2017; Wooldridge, 2012):

$$2 * (LL_{fitted} - LL_{null}) \sim \chi^2 \quad (Eq. 4)$$

with:

- LL_{fitted} : maximized value of the log-likelihood function of the fitted model;
- LL_{null} : maximized value of the log-likelihood function of the null model.
- Pseudo R^2 : the maximized log-likelihood of the null and the fitted model are compared i.e. it estimates the improved goodness of fit over the null model; Hemmert et al. (2018) review several indicators, among which Horowitz's pseudo R^2 is reported to be the one less sensitive to sample size and asymmetry of binary observations (Equation 5):

$$R_{Horowitz}^2 = 1 - \frac{LL_{fitted} - \frac{p}{2}}{LL_{null}} \quad (Eq. 5)$$

with:

- p : number of estimated parameters.
- AIC (Equation 6): it penalizes complex models and helps to avoid overfitting i.e. its value increases with the number of parameters and decreases with the sample size (Aho et al., 2014).

$$AIC = -2LL_{fitted} + 2p \quad (Eq. 6)$$

Logistic regression is typically validated by estimating its discriminatory power among the observed test data. Standard accuracy can be calculated as the number of times that estimated probabilities exceeding a fixed threshold (0.5 for two symmetric classes) match observed values. For imbalanced data, however, Receiver Operating Characteristic (ROC) is the preferred accuracy measure because it does not depend on observed proportion of classes. It is the curve drawn by plotting false positive rate

(predicted FALSE where observed values are TRUE i.e. 1-specificity) against true positive rate (predicted TRUE where observed values are TRUE i.e. sensitivity). The Area Under the Curve (AUC) of the ROC curve represents the performance of the classifier and ranges between 0.5 and 1, where 0.5 indicates random chance while 1 means perfect discriminatory power (Ghatak, 2017).

2.2 Cellular automata

CA are discrete dynamic systems. They are arranged into lattices of grids of regularly spaced cells, eventually georeferenced in a geographical space. CA are simple entities whose location is always fixed over time (Heppenstall et al., 2011). Their shape can be rectangular or circular, respectively based on Moore and Von Neumann neighborhood configuration (Ghosh et al., 2017). Their size typically ranges from 3x3 to 9x9 (Shafizadeh-Moghadam et al., 2017; Verburg et al., 2004). CA can have only one attribute and two possible states: either 0 or 1. The state of each automaton depends on: its previous state, the previous state of surrounding cells and a set of local rules that enable state transition over time (Heppenstall et al., 2011). These transitions make CA models able to spread information over space via neighboring cells, resulting in adaptive and self-organizing behavior (Boavida-Portugal et al., 2016). CA are often used with Markov chains to model LUC. In a Markov process it is assumed that the cells' future state only depends on their previous state. If the cells represent georeferenced land units, Markov chain models provide the expected number of land use transitions between two subsequent time steps, while CA constrain these transitions depending on the neighboring cell states. Hence, CA allocate expected land units by considering proximity of geospatial phenomena (Ghosh et al., 2017).

2.3 Input data and pre-processing

The available input data are listed in Table 1. Pre-processing is required on input data to derive land use maps and spatial predictors for the statistical models used in this study. Spatial information of forest pattern is obtained from the forest map of the Veneto Region of 2000 (vegetation types matching Corine Land Cover (CLC) categories of 311, 312 and 313). It is compared with the land use map of the Veneto Region of 2007 to quantify the expected number of cell conversions between considered time steps.

These data represent the most precise spatial representation of forests (2000) and land use pattern (2007) in the Alto Bellunese currently available. Disaggregated Corine-like land use categories of the 2007 map are aggregated as reported in Table 2, to model overall forest cover, including coniferous, broadleaf and mixed forests. Temperature drives vegetation pattern and types along altitudinal gradients and determines the length of the growing season (Cudlín et al., 2017). Here, temperature maps are obtained by regressing 2 m temperature records (from local weather stations) over a Digital Elevation Model (DEM) as they strongly depend on altitudinal gradients (Gobiet et al., 2014). Because the Alto Bellunese is a small mountain area with typical alpine climate, horizontal temperature differences are considered not significant. Slope is a geomorphological constraint to vegetation growth, but it also locally limits accessibility for human activities (Gellrich et al., 2007) e.g. tourism and livestock farming. Distance from natural grassland areas is used as proxy of livestock. Forests are indeed more likely to develop over shrublands or, in general, where grazing pressure of cattle is limited. Because such activity is not static over space, we argue that distance is a better predictor than the simple presence of natural grasslands, as used by Gellrich et al. (2007). Distance from roads and villages is used as proxy of global accessibility to human activities. Distant areas from settlements and paved roads are expected to undergo a reduced pressure from human activities, under current socio-economic trends (Gellrich et al., 2007; Giupponi et al., 2006). Both slope and Euclidean distances are here calculated with standard GDAL algorithms, respectively using a DEM and CLC maps. Finally, soil categories that overlap forests and grasslands in the Alto Bellunese are extracted from the soil map of the Veneto Region: DA1, DA2, DA3, DB1, DB2, DB3, DB4, DB5, DB6, GA2, MA1, MB1, VB1. Full details about soil categories are available in Supplementary material A. They represent great soilscapes i.e. soil subsystems with homogeneous features, e.g. location, origin of parent material, depth, stoniness and presence of specific chemicals. Such information is highly relevant because forest soils are formed by vegetation remains, and recycling of organic matter through litter decomposition is essential for forest productivity, which depends on soil conditions e.g. water-holding and nutrient-supplying capacity (Boyle, 2005).

Table 1. Input datasets and maps.

Name	Data typology	Description	File ID	Source
Temperature records	Dataset	Meteorological parameters (including temperature, humidity and wind) detected through a monitoring system consisting of a network of automatic stations, covering the entire Veneto Region.	arpa_ve:c0306010_DatiMeteo	GeoPortale of the Veneto Region
DEM	Raster	European digital elevation model at 25 m resolution	DEM-v1.1	Copernicus Land Monitoring Service
Forest in 2000	Vector	Delimitation of forest areas of the Veneto Region by vegetation typology	r_veneto:c0605011_CategForestali	GeoPortale of the Veneto Region
Land use in 2006	Vector	3-level land use map of Europe, only used to rebuild incorrect spatial data of 2007, as reported in Section 4.1	CLC2012_CLC2006_V2018_20b2	Copernicus Land Monitoring Service
Land use in 2007	Vector	5-level land use map of the Veneto Region	r_veneto:c0506111_CCS2007SPLUS	GeoPortale of the Veneto Region
Road network	Vector	Paved and unpaved roads, accessible and not accessible paths to motorized vehicles and footpaths of mountain areas of the Veneto Region	r_veneto:c01070740011_ViaSilvoPast	GeoPortale of the Veneto Region
Great soilscapes – L3	Vector	Third hierarchical level of the soil map of the Veneto Region. Soils are classified by main environmental, morphological and lithological features.	arpa_ve:c0507021_CartaSuoliVen	GeoPortale of the Veneto Region

Table 2. Customized reclassification of land use categories.

3-level CLC categories	Aggregated classification used in this study
112, 113, 121, 122, 124, 131, 132, 133, 134, 141, 142	1 – Urban areas
211, 221, 222, 224, 231, 232, 242, 243	2 – Agricultural land
311, 312, 313	31 – Forests
321, 322, 324	32 – Natural grasslands
331, 332, 333, 334, 335	33 – Land without vegetation
412	4 – Wetlands
511, 512	5 – Waterbodies

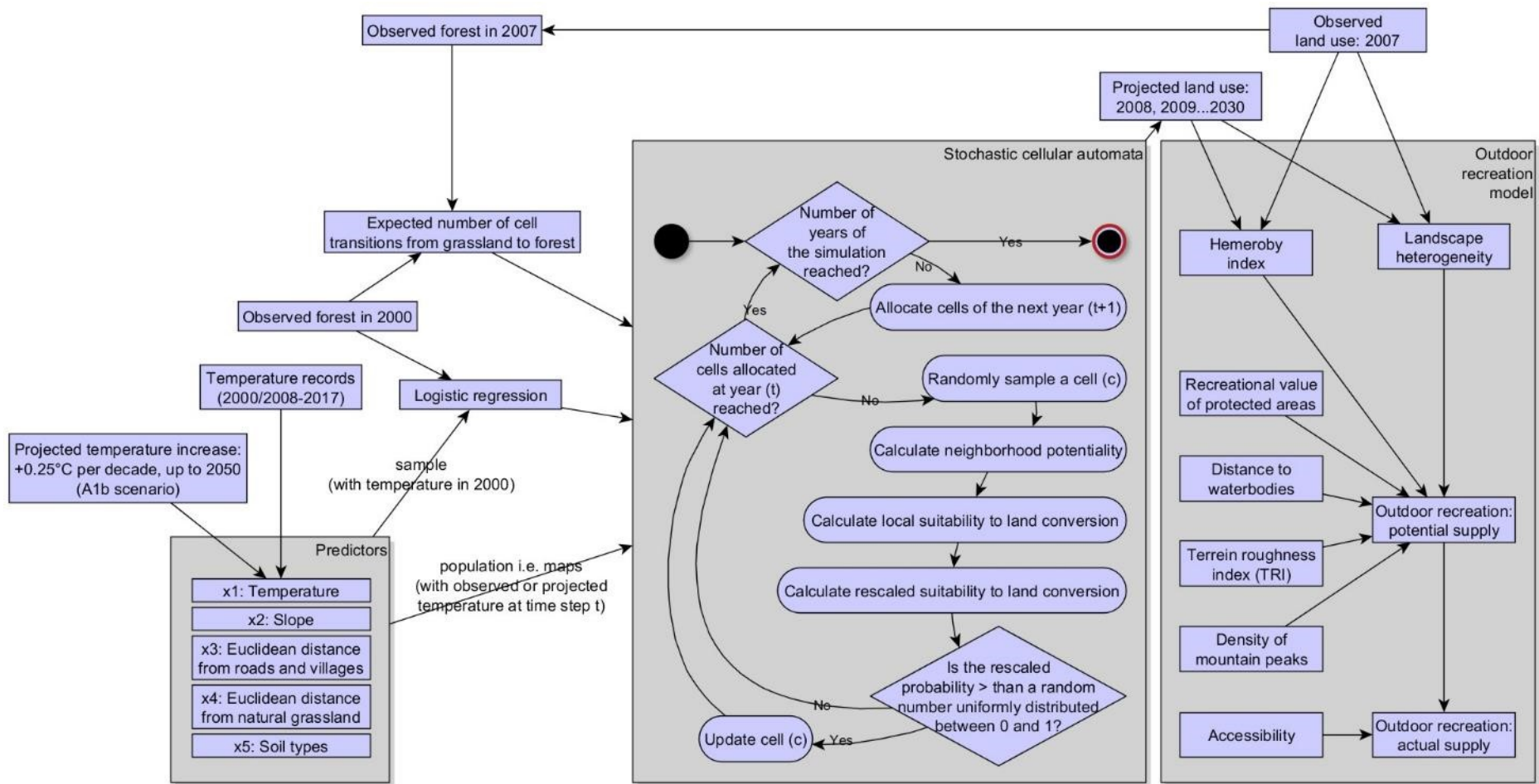


Figure 1. Conceptual framework: a logistic regression model is used to parametrize stochastic CA, to model expected forest expansion over space and along a Markovian sequence of yearly time steps; projected land use maps are used to quantify the impact of forest expansion on OR opportunities.

2.4 Model architecture and specifications

Methodology and equations are mainly derived from Wu (2002) and Schirpke et al., (2018). The model architecture is shown in Figure 1. The biophysical and socio-economic predictors listed in Section 2.3 and the observed presence/absence of forests in 2000 are used as inputs in a logistic regression. In these data, a cell is classified as forest if covered for at least 30% of its extent by coniferous or broad-leaf forests. Geospatial data are filtered in order to extract only forest and grassland cells (and related predictors for the same geographical coordinates). A systematic sampling is carried out to sample 50% of the datasets, hence converting spatial raster data into tabular shape of sampled cells (presence/absence of forest and related predictors). The systematic sampling grants coverage of the whole filtered area while reducing spatial dependency and is commonly used in logistic regression models (Arsanjani et al., 2013). The sampled dataset is shuffled and then divided into two subsets, a training set and a test set, respectively with proportion 80-20. Logistic regression is then calibrated over the training data, following the specifications described in Section 2.1. i.e. maximizing the pseudo R^2 , minimizing the AIC and verifying the p-value of each predictor. Moreover, the Generalized Variance Inflation Factor (GVIF) is calculated in order to avoid multicollinearity. The logistic regression model is then validated using the test set, by calculating the AUC of the ROC curve. It is preferred over the standard measure of accuracy because in our study observations are unbalanced and forest cells outnumber grassland cells by approximately three times. Once validated, the logistic regression model can be used to map suitable areas (hereafter referred to as suitability map) i.e. where it is likely new forest land units would develop in a hypothetical Markov process, given the set of predictors listed in Section 2.3 which are used to maximize the probability of detecting observed forest in 2000. Then, by using Markovian logic, the proportion of expected grassland-to-forest transitions is calculated by comparing the presence of forest between alternative time steps (in our case, 2000 and 2007) and projected over time as follows. Coupled CA-Markov chains typically update land units in discrete time steps amounting from some months to a year (Ghosh et al., 2017). Discrete time units are indeed very useful to simplify the dynamic representation of the real world. However, as Markovian logic assumes CA's constant land states at each time step, it fails to consider that multiple feedbacks from surrounding

neighbors can strengthen land conversion, even within the same time unit. For practical reasons, however, multiple comparisons are usually preferred i.e. all cells of a map are simultaneously updated (Wu, 2002). Unfortunately, this logic does not appear to be suitable to model the presence or absence of forest because land units are classified on the percentage of cover compared to a fixed threshold (30%). In other words, e.g. we would not expect to simulate 100% cover where forest was totally absent the year before, but multiple grassland patches with sparse trees, close to each other, could evolve into forest on a different time scale from the one of the chosen discrete time unit. For this reason, in our study, multiple comparisons are avoided i.e. CA do not update their state simultaneously, but individually with feedbacks from previous iterations within the same time unit. Specifically, through a Monte Carlo simulation, an unknown set of iterations is run to allocate expected land transitions within a single time step. Then the process is repeated for all time steps according to the standard Markovian logic. Intuitively, this means that iterations are not defined by a specific temporal resolution except for the fact that we know they occur within a specific time step of the Markov chain. We consider this a realistic assumption because vegetation growth continuously and slowly occurs and, in this way, each automaton's surrounding cells strengthen forest expansion independently from the time sequence of the Markov process. However, time thresholds are needed for practical reasons i.e. to allocate expected land use transitions and to map land use for ES assessment at specific time thresholds. Therefore, in our study we model forest expansion at yearly time steps: the observed land use in 2007 is projected year-by-year up to 2030. Suitability at each time step is calculated by using available temperature records, up to 2017. The projected temperature is derived by averaging the observed data between 2013 and 2017, and a linear increase of 0.025°C per year is applied up to 2030, according to the A1B emission scenario, as described in Section 1. The climatological treeline is set to 2200 m of altitude in the Alto Bellunese as in Cocca et al. (2012). Although affected by CC, the observed treeline is well below the theoretical one, therefore its altitudinal change is not considered.

The iteration loop includes the set of equations and conditional instructions that define the rules of our CA, triggering land conversion. It is described as follows:

1. Every iteration starts with the sampling of an automaton i.e. by randomly selecting a couple of spatial coordinates to sample a grassland cell that could potentially evolve into forest. In this

study, CA are implemented with a 5x5 size and circular neighborhood shape (12 neighbors and a central cell). States of surrounding cells are collected and used to calculate neighborhood potentiality (np) of the automaton sampled in the current iteration. Neighborhood potentiality can be here interpreted as forest density and is calculated as follows (Equations 7 and 8):

$$s_c^i = \begin{cases} \textit{presence of forest}, & s_c^i = 1 \\ \textit{absence of forest}, & s_c^i = 0 \end{cases} \quad (\textit{Eq. 7})$$

$$np^i = \frac{\sum_{c=1}^n s_c^i}{n - 1} \quad (\textit{Eq. 8})$$

with:

- s_c^i : state of the neighbor with index c allocated within the circular extent of the sampled automaton for the current i^{th} iteration;
 - n: number of cells within the circular extent of the sampled automaton.
2. Global suitability (gp) of the sampled automaton is then obtained from the suitability map previously generated with the logistic regression model for the current iteration and for all other iterations belonging to the same time step of the Markovian sequence.
 3. Global suitability and neighborhood potentiality are used to quantify the constrained local suitability (lp), which can be calculated as follows (Equation 9):

$$lp^i = gp^i * np^i \quad (\textit{Eq. 9})$$

with:

- gp^i : global probability of transition (output of the logistic regression) of the sampled automaton for the current i^{th} iteration;
 - np^i : neighborhood potentiality of the sampled automaton for the current i^{th} iteration.
4. Because in Equation 8 neighborhood potentiality applies a restriction based on forest density and changes the transition probability estimated with the logistic regression model, quantity of land conversions is no more expected to be consistent with the observed data. Moreover, local agglomeration may create too many potential sites (Wu, 2002). Wu (2002) suggests comparing the probability at each iteration with the most suitable site at that particular iteration. In our case, since we avoid multiple comparisons, it is not computationally feasible to recalculate the

most suitable site after each iteration is run. On the other hand, because in this study the time reference of the Markov process is the year, we rescale (rp) the local suitability on the most suitable site for the current year, by using the following distance-decay function (Equation 10):

$$rp^i = lp^i * \exp\left(-dd^t \left(\frac{1 - lp^i}{\max(lp^i)}\right)\right) \quad (Eq. 10)$$

with:

lp^i : local suitability calculated with Equation 9;

dd^t : a dispersion parameter calculated for the current and all other iterations belonging to time step t of the Markov sequence.

The exponential part of Equation 10 represents the distance between the suitability of the sampled automaton and the most suitable site at time step t . The dispersion parameter (dd) can range between 1 and 10. Wu (2002) suggests setting it at 5, which returns a quite strict distance constraint. For computational reasons, because high dispersion parameters slow down the speed of the simulation, the dispersion parameter is calculated on the basis of Equation 11:

$$dd^t = -\frac{\ln \frac{0.08}{\max(lp^i)}}{0.75} \quad (Eq. 11)$$

With Equation 11, assuming the limit case $\max(lp^i)= 1$ and a hypothetical automaton with $lp^i=0.25$ (thus, having an average global suitability and an average neighborhood potentiality), its local suitability would be rescaled to 0.02. Thus, probability of land conversion significantly decreases for all cells with weak to average local suitability. This criterion is procedurally applied to quantify what we consider a good trade-off between rescaling performance and computational needs. Equation 11 returns values around 3, decreasing together with maximum local suitability detected at each time step t of the Markov sequence.

5. The rescaled suitability is finally compared with a random number uniformly distributed between 0 and 1, to decide whether the state of the automaton, i.e. the originally sampled grassland cell, is converted to forest (Equation 12):

$$s^t = \begin{cases} forest, & rand(i) < rp^i \\ grassland, & rand(i) \geq rp^i \end{cases} \quad (Eq. 12)$$

Therefore, the iteration loop is triggered multiple times per year to allocate projected land transitions, hence projecting future land use up to a targeted time horizon compared to a reference base year, respectively 2030 and 2007 in this study. Projected land use maps are composed by using simulated forest and grassland pattern and other land categories as observed in 2007. Simulated land use maps are therefore used to map projected OR activities. These are quantified by means of six spatial indicators: presence of protected areas, hemeroby i.e. the level of human influence, distance to water bodies, landscape heterogeneity, terrain ruggedness and density of mountain peaks. Forest presence and pattern affect hemeroby and landscape heterogeneity, whose quantification depends on land use categories. Potential OR is calculated through simple additive weighting of normalized spatial indicators (between 0 and 1), by using equal weights. The level of accessibility is calculated considering the road and trail network and using travel time from urban areas. Actual OR supply is mapped by multiplying the recreation potential by the normalized level of accessibility. The methodology to map OR opportunities is derived from Schirpke et al. (2018) and reported in Section 2.3.1 of Zen et al. (2018). The provision of OR activities is then mapped at selected time steps, by using observed (2007) and projected (2017, 2030) land use data.

2.5 Software and tools

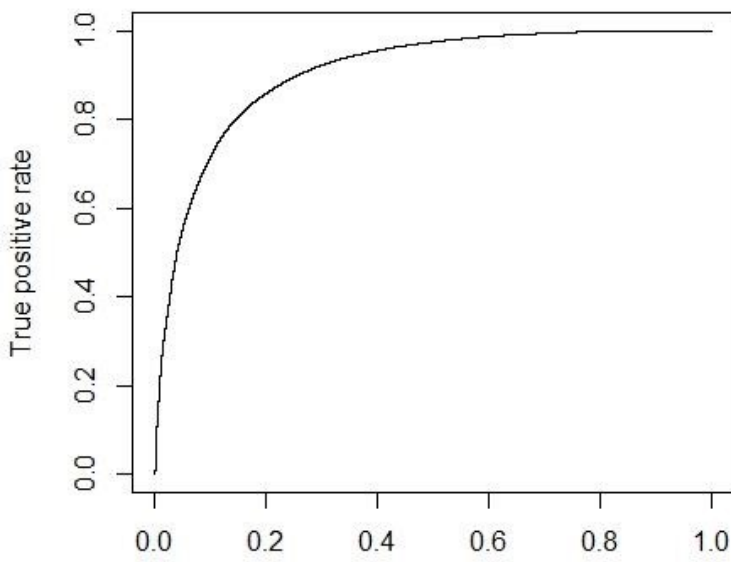
The methodology is implemented through multiple tools. All procedures aimed at pre-processing data and projecting land use i.e. the logistic regression model and the CA algorithm, are developed in the R language (R Core Team, 2019). OR is instead assessed through a semantic meta-modeling approach, using the k.IM language in the Knowledge Laboratory (k.LAB) software, which powers the ARTificial Intelligence for Ecosystem Services (ARIES) project, to make efficient use of spatial information and models. It enables ES modeling through customizable methods e.g. at multiple scales, using simple to complex approaches (Martínez-López et al., 2019; Villa et al., 2017, 2014). In this way, in our study, the OR model is customized with the available data at 25 m resolution, according to specifications of Schirpke et al. (2018), in the context of the Alto Bellunese.

3 Results

Statistics of calibration and validation of the logistic regression model are shown in Table 3. Refer to Section 2.1 for their theoretical explanations and to Section 2.4 for their implementation in the modeling infrastructure.

Multicollinearity is not detected ($\text{GVIF}^{1/(2 \cdot \text{Df})} < 2$), therefore predictors are found not to be correlated with each other. All predictors are statistically significant ($p\text{-values} < 2e^{-16}$), including great soilscape except for soil category GA2. They were selected so as to minimize the AIC and the residual deviance (through the LRT). Calculated Horowitz pseudo R^2 indicates excellent fit according to Hemmert et al. (2018), considering benchmarks for sample size > 200 and asymmetry > 1.6 of binary observations. LRT returns a statistically significant p -value, so the fitted model shows an improved performance over the null model. Validation was carried out in the test set by using the ROC and its AUC indicates an excellent discriminatory power in detecting forest presence. It means that estimated probabilities through the logistic regression model can be used to map cells where forests are more likely to develop. Forests expand on the most suitable areas of the Alto Bellunese, as classified by the logistic regression model. CA spread forests over grasslands through an iterative loop that converts the state of 7218 cells per year, i.e. the expected number of land conversions. In this way, land use was projected from 2007 to 2030, to quantify OR opportunities under the A1B scenario and considering the observed LUC trend in the period 2000-2007. Because LUC affects spatial heterogeneity and hemeroby, these criteria were quantified at selected time steps (2007, 2017 and 2030) from observed and projected land use maps, and the provision of OR opportunities was finally mapped (Figure 2). Comparison with OR quantified on observed land use was made by subtracting the 2007 map from the projected OR in 2017 and 2030, returning an overall negative impact on the provision of this ES. The sum of all values of the cells of the difference maps for the period 2007-2017 (-16938.2) and 2007-2030 (-21897.9), returned a loss in the first period that approximately equals three times the loss of the second period. Similar ratios can be found by comparing differences of normalized criteria in the same periods i.e. hemeroby and landscape heterogeneity.

Table 3. Calibration and validation statistics of the logistic regression model.

Calibration						
	Estimate	Standard Error	Z value	p-value	GVIF ^{1/(2*Df)}	
Intercept (reference: DB2)	-1.068	1.607e-02	-66.450	<2e-16	-	
Temperature (°C)	9.084e-01	2.749e-03	330.487	<2e-16	1.291	
Slope (°)	-1.927e-02	2.652e-04	-72.652	<2e-16	1.112	
Distance from roads and villages (m)	-8.033e-04	5.436e-06	-147.775	<2e-16	1.080	
Distance from natural grasslands (m)	-5.093e-05	2.436e-06	-20.908	<2e-16	1.195	
Great soilscapes - DA1	-1.698	1.434e-02	-118.408	<2e-16	1.028	
Great soilscapes - DA2	-1.174	1.666e-02	-70.460	<2e-16		
Great soilscapes - DA3	-1.746	5.320e-02	-32.819	<2e-16		
Great soilscapes - DB1	-1.586	1.259e-02	-125.963	<2e-16		
Great soilscapes - DB3	3.856e-01	1.691e-02	22.808	<2e-16		
Great soilscapes - DB4	-2.907e-01	1.658e-02	-17.538	<2e-16		
Great soilscapes - DB5	-3.697e-01	1.461e-02	-25.301	<2e-16		
Great soilscapes - DB6	-4.576e-01	1.765e-02	-25.925	<2e-16		
Great soilscapes - GA2	5.561	1.691e+01	0.329	0.742		
Great soilscapes - MA1	-2.413	2.492e-02	-96.843	<2e-16		
Great soilscapes - MB1	2.741e-01	1.854e-02	14.784	<2e-16		
Great soilscapes - VB1	-1.543	3.059e-02	-50.451	<2e-16		
Horowitz pseudo R ²	4.406e-01					
Validation						
Accuracy	0.860					
AUC	0.907					
ROC						

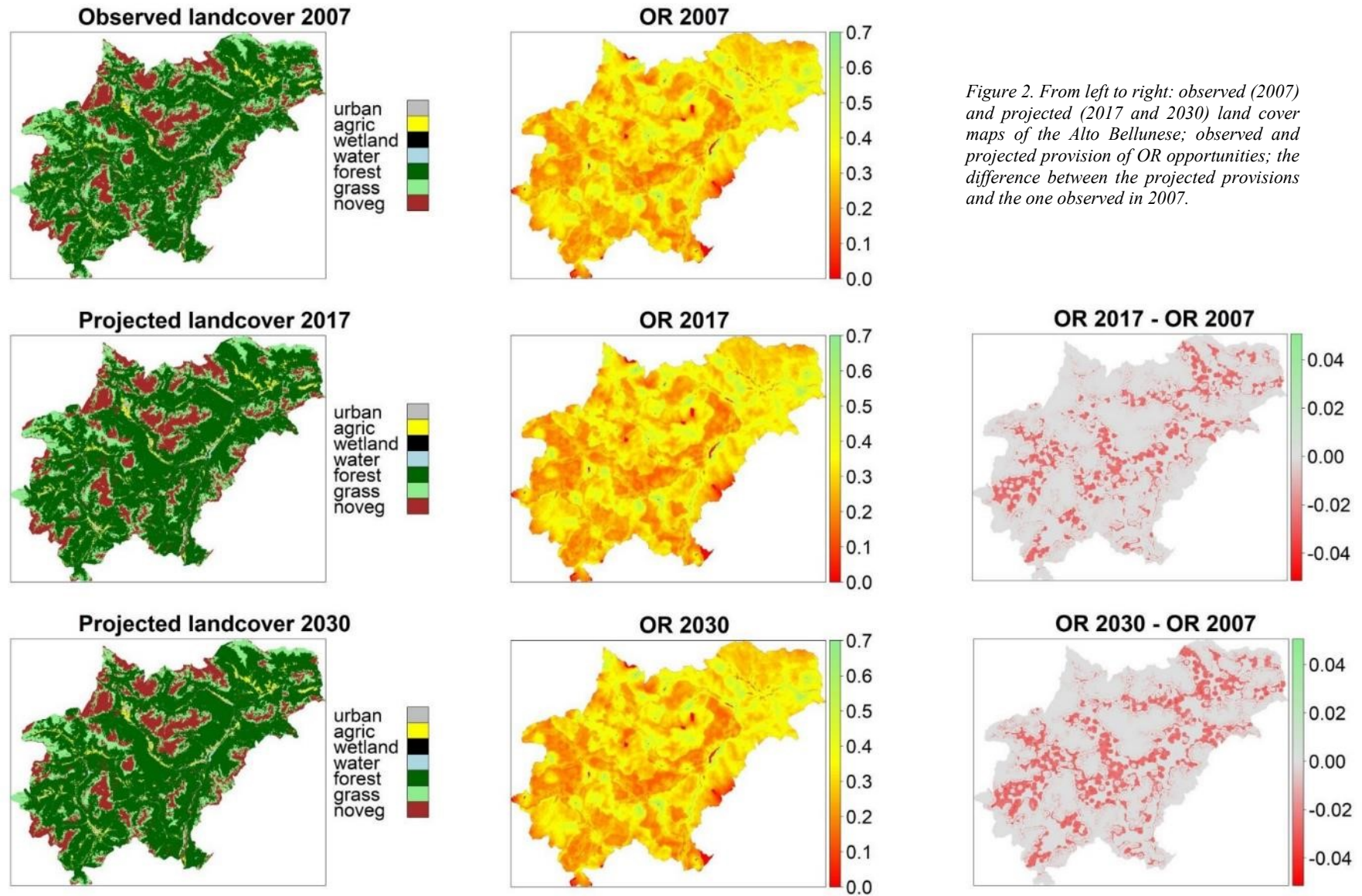


Figure 2. From left to right: observed (2007) and projected (2017 and 2030) land cover maps of the Alto Bellunese; observed and projected provision of OR opportunities; the difference between the projected provisions and the one observed in 2007.

4 Discussion and conclusion

4.1 Data selection and model development

In this study we expanded the assessment of the provision of OR opportunities in the Alto Bellunese, carried out in the framework of the Interreg AlpES project, to include LUC dynamics, focusing on the expansion of forests. This macroscopic trend is acknowledged from the literature not only in this area (Cocca et al., 2012; Giupponi et al., 2006) but also in other alpine regions, where the relationship among landscape management, land abandonment, forest cover change and recreation (Sonter et al., 2016) or aesthetic value of landscapes (Schirpke et al., 2016) is not trivial. We used a classification algorithm i.e. logistic regression model, to detect where forest is more likely to develop. We tried to avoid classification problems by using the forest map of 2000 of the Veneto Region (Table 1) which reports vegetation types and percentage of cover rather than just Corine-like categories. In this way, the logistic regression model was calibrated on the best available data and run at multiple time steps to estimate changes in the suitability of developing forest (if e.g. the annual average temperature increases). Because logistic regression is static (Wu, 2002), it was coupled with Markov Chains and CA to spread forest over time and space, respectively. Markov chains are indeed a convenient solution to constrain observed LUC within time units consistent with the phenomenon to be simulated. CA reproduce neighborhood effects of geospatial phenomena i.e. forests are more likely to develop near existing forests. In this study, within each step of the Markovian sequence, cells are not updated simultaneously but individually with feedbacks from previous iterations. This choice was made on the assumption that we do not model sharp land conversions as, in the existing physical world, vegetation growth occurs continuously and slowly. Moreover, forests are commonly classified in terms of dominant cover or depending on a percentage of cover. In this way, in our model, at each iteration, each automaton's surrounding cells strengthen forest expansion independently from the time sequence of the Markov process. This logic is implemented by applying a Monte Carlo simulation to allocate expected land conversion grassland-to-forest (observed between 2000 and 2007) within and between yearly time units, to project forest expansion over time from 2007 (base year of the simulation) to 2030. The observed

land use map of 2007 and the projected maps of 2017 and 2030, were used to model OR opportunities over time. Specifically, 2017 was chosen for two reasons:

- annual average temperature records were available up to 2017;
- in October 2018 an unprecedented extreme storm event destroyed about 100000 hectares of forest in the Veneto Region and most damages occurred in the Belluno Province; this event made existing land cover datasets obsolete; it changed the way people perceive forests i.e. not only as consequence of land abandonment but also as a resource threatened by CC; it also reopened the debate about management of forest heritage in the region (for further information see “Veneto in ginocchio. Maltempo ottobre/novembre 2018”).

For these reasons we can consider OR in 2017 as the result of the potential evolution of forests in the Alto Bellunese, given the set of independent variables used to calibrate the logistic regression model, available temperature records and the observed number of conversions i.e. forest cells in 2007 overlapping cells not classified as forest in 2000 (vegetation types corresponding to CLC categories 311, 312 and 313). OR in 2030 instead can be considered a theoretical exercise to study projected OR trend, given a temperature increase of 0.025 °C per year, well being aware that the simulated forest pattern will never be comparable with future land use pattern in the Alto Bellunese, after the extreme events of 2018. Hence, we assumed global interregional convergence of economic growth according to the A1B scenario of the IPCC AR4 (Gobiet et al., 2014), together with local intraregional divergence of opportunities for economic development (observed LUC trend), as land abandonment depends on local environmental and socio-economic issues.

It is worth noting that the logistic regression could have been calibrated on land use differences between subsequent time steps, e.g. as performed by Gellrich et al. (2007). In this study, it was not feasible because of errors found in the land use data of 2007. On the one hand, we could use the most precise 5-level land use map available for the area; on the other hand, we found classification errors e.g. in the municipalities of Rocca Pietore and Livinallongo del Col di Lana, later confirmed by experts of the Veneto Region through photointerpretation. Incorrect spatial data were rebuilt with the 3-level European land use map of 2006 (Table 1). Therefore, we used observed land conversions between 2000 and 2007 as a quantitative reference to project forest expansion but, instead of calibrating the model on

differences between time steps that might suffer from hidden classification problems or bias from vector drawing, we decided to train the logistic regression model on data covering the whole Alto Bellunese. The AUC of 0.907 (Table 3) suggests that the overall forest pattern can be detected with excellent classification performance, meaning that it might be less affected by mapping errors compared to intertemporal differences.

4.2 Outdoor recreation opportunities in the Alto Bellunese

Odds can be calculated by applying the exponential function to predictor coefficients in Table 3, as they are easier to be interpreted. *Ceteris paribus*, probability of land conversion increases with temperature (148 % increase in the odds per one-unit increase of the variable) and with presence of certain soilscapes (47 % and 32 % increase in the odds of detecting forest over soil categories DB3 and MB1, respectively), the latter assuming DB2 as reference category (see Supplementary material A for soil descriptions). Other soilscapes have odds smaller than 1, meaning that they are associated with a lower probability of detecting forest. This is particularly relevant for soils VB1, DB1, DA1, DA3 and MA1 (more than 78 % decrease in the odds of detecting forest over these soils). Hence, we found that temperature is the main variable that drives the evolution of forest pattern, followed by great soilscapes which can be considered as a synthetic semi-qualitative representation of different biophysical and environmental information. By comparing the loss of OR provision between 2007-2017 (10 years) and 2007-2030 (23 years), we found that major impacts on OR already occurred in the first period, through landscape heterogeneity and hemeroby, as a result of the loss of open areas. This suggests that open areas in 2007 may have been located where the logistic regression model returned the most suitable areas i.e. where transitions grassland-to-forest were more likely. Moreover, although the projected temperature increase (+0.025°C per year) in the second period globally raised the suitability of developing new forests, in the simulation most land conversions took place in the first period. Therefore, we concluded it is not likely to expect relevant close-term consequences of temperature change on existing open areas and consequently on the provision of OR opportunities. In addition, although significant, proxies of human impact (slope and distances from grasslands, urban areas and roads)

appeared to have very little effect on land conversion (less than 2 % decrease in the odds per one-unit increase in the variables). Last but not least, the event of 2018 left several open issues. First, an updated assessment of OR opportunities would require spatial data that are currently not available. Secondly, having thousands of hectares of forests “removed” by natural events does not mean that the problem of the loss of open areas is solved, because the relationship between land use and OR is not trivial. Sonter et al. (2016) e.g. proved that clearing forests does not necessarily increase visitation rates in recreational sites, while Schirpke et al. (2016) reported that the aesthetic value of forests cannot be objectively quantified as perception depends on cultural background, origin and age. Moreover, CC will exacerbate land abandonment and public investments to actively manage forests will exponentially increase. Therefore, either for conservation, protection or recreation, forest use and its role in the socio-ecosystem of the Alto Bellunese will strongly depend on future land management by public authorities. From our findings and under current modeling infrastructure and data, we can argue that OR provision is expected to decrease over time but with a smaller decrease in the period 2018-2030 compared to the period 2007-2017. Storm damages add a further degree of complexity in modeling ES, by modifying landscape components and pattern over time. Further research could be driven in the direction of simulating impact of storm damages on forests and then integrating it with our methodology. Because in this study a Monte Carlo simulation is used to individually update cells within Markovian time steps, it might be easier to integrate processes that occur at different time scales i.e. forest growth is typically represented on a yearly time scale while storm damages occur within few days or weeks. In this way, it would be possible to project land use by considering both storm damages and socio-economic issues i.e. land abandonment.

Acknowledgments

This study draws on the outcomes of the contribution of the Veneto Region to the Interreg AlpES project (‘AlpES’ project, CUP: D52I16000220007), which aimed at mapping the provision of OR and fodder from alpine grasslands at high resolution within the Alto Bellunese, i.e. one of the pilot regions of the project.

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Appendix A

Great soilscapes (otherwise known as soil subsystems) represent the third level in the classification of the soil map of the Veneto Region (1:250000), describing main environmental factors, geomorphology, lithology and soil features. Here, we report a synthetic description of all great soilscapes detected within the boundaries of the Alto Bellunese area. Full details can be found at the following URL:

http://www.arpa.veneto.it/temi-ambientali/suolo/file-e-allegati/carta-dei-suoli/leg_250k.pdf

DA1: Soils formed by carbonate lithotypes. Typically located on high slopes and summits of main mountain ranges (> 1600 m), they can be covered in glacial and slope deposits. They are thin and very stony, with a weak profile differentiation and accumulation of organic matter over the topsoil layer (Rendzic Leptosols). Typical related land uses are natural grasslands, pastures, shrublands and secondarily forests i.e. woods of larches, stone pines and scots pines, occasionally with extensive areas covered in rocks and debris.

DA2: Soils formed by silicate lithotypes. Typically located on high slopes and summits of main mountain ranges (> 1600 m), they can be covered in glacial and slope deposits. They are moderately deep and stony. They have either a moderate profile differentiation, locally with moderate translocation of aluminum and iron sesquioxides (Dystric Cambisols) or a strong profile differentiation, with translocation of sesquioxides and organic substance (Entic Podzols). Typical related land uses are natural grasslands, pastures and secondarily spruce woods, with rocky surfaces and debris up to 20 %.

DA3: Soils formed by carbonate lithotypes. Typically located on high slopes and summits of main mountain ranges (> 1700 m), they can be covered in glacial and slope deposits. They are either thin and very stony, with a weak profile differentiation over eroded and/or steep surfaces (Rendzic Leptosols) or moderately stony, with a strong profile differentiation and clay leaching over stable surfaces (Skeletal Luvisols). Typical related land uses are natural grasslands and pastures, with rocky surfaces and debris up to 30 %.

DB1: Soils formed by carbonate lithotypes. Typically located on low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are thin and very stony with a weak profile differentiation (Calcaric Leptosols). Typical related land uses are shrublands and forests of different kind i.e. spruces, scots pines, beeches and larches, with rocky surfaces and debris up to 15 %.

DB2: Soils formed by carbonate lithotypes. Typically located on low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are thin and very stony with a weak profile differentiation (Rendzic Leptosols) over steep surfaces or moderately deep and stony with a moderate profile differentiation (Calcaric Cambisols) on stable surfaces. Typical related land uses are forests of different kind i.e. spruces, stone pines, silver firs, larches and beeches.

DB3: Soils formed by silicate lithotypes. Typically located on low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are moderately deep and stony, with a moderate profile differentiation, locally with moderate translocation of aluminum and iron sesquioxides (Dystric Cambisols). Typical related land uses are forests i.e. spruce woods and secondarily natural grasslands and pastures.

DB4: Soils formed by carbonate lithotypes. Typically located on steep and/or eroded low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are either deep and stony, with a strong profile differentiation and deep clay accumulation (Skeleti-Cutanic Luvisols) or moderately deep and stony, with a moderate profile differentiation (Calcaric Cambisols). Typical related land uses are natural grasslands and forests i.e. spruces, beeches, hop-hornbeams, ash trees and oaks, with rocky surfaces and debris up to 10 %.

DB5: Soils formed by carbonate lithotypes. Typically located on low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are moderately or very deep, stony, with a strong profile differentiation and deep clay accumulation (Cutanic Luvisols). Typical related land uses are natural grasslands, pastures and forests i.e. spruces, secondarily larches, beeches, hop-hornbeams, ash trees and shrublands in general.

DB6: Soils formed by carbonate and terrigenous lithotypes. Typically located on low slopes and wide basins, they are extensively covered in glacial and slope deposits. They are moderately deep, stony with

a moderate profile differentiation and evident hydromorphism (Gleyic Cambisols). Typical related land uses are meadows and forests of different kind i.e. stone pines, larches, spruces and silver firs, with rocky surfaces and debris up to 10 %. Human influence is also significant with urban cover up to 10 %.

GA2: Soils typically located on slopes with glacial deposits and limestone or marly limestone substrates. They are moderately deep, with strong profile differentiation and deep clay accumulation (Leptic Luvisols) when located over marly limestone substrates. Alternatively, they are moderately deep, with a moderate profile differentiation (Calcaric Cambisols) over glacial deposits. Only soil GA2.1. is detected in a very small area i.e. 0.009 % of the Alto Bellunese. This sub-category is reported to be mainly covered in beech woods.

MA1: Soils formed by silicate lithotypes. Typically located on high slopes and summit of main mountain ranges (> 1900 m), they can be covered in glacial and slope deposits. They are moderately deep and stony. They have either moderate profile differentiation, locally with a moderate translocation of aluminum and iron sesquioxides (Dystric Cambisols) or a strong profile differentiation, with translocation of sesquioxides and organic substance (Entic Podzols). Typical related land uses are natural grasslands with rocky surfaces and debris up to 50 %.

MB1: Soils formed by silicate lithotypes. Typically located on low to medium slopes of primary and secondary mountain ranges, they are extensively covered in glacial and slope deposits. They are moderately deep and stony with a moderate profile differentiation and translocation of aluminum and iron sesquioxides (Dystric Cambisols). Typical related land covers are forests i.e. spruce and silver fir woods and secondarily natural grasslands.

VB1: Soils located in valleys mainly with fluvial and locally glacial deposits. They are either very thin and gravelly, with a weak profile differentiation (Calcaric Leptosols) on the most recent surfaces or moderately deep, gravelly, with a moderate profile differentiation (Calcaric Cambisols) on stable areas. Typical related land uses are meadows, riparian vegetation and secondarily forests i.e. stone pines, larches, spruces, dwarf pines, beeches, with debris up to 50 %. Human influence is also significant with urban cover up to 15 %.

An agent-based approach to mapping outdoor recreation demand: the case study of Alto Bellunese

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Abstract

In view of the global environmental changes that human societies are facing, mapping and assessment of provision and demand of ecosystem services (ES) are becoming essential for environmental management and policymaking in sustainable landscape planning. ESs are products of interconnected components of complex social-ecological systems (SES) and therefore their quantification requires integrating spatial information, temporal dynamics and behavioral complexity of human agents and social organizations. In this study we propose a spatial agent-based model (ABM) for mapping the summer non-rival demand for outdoor recreation (OR) activities, by integrating geospatial information of a SES with its own provision of recreational opportunities and a simplified diversity of agents, displaced over space and time depending on a set of behavioral assumptions. As in the literature tourism demand is commonly mapped through statistical records at administrative levels i.e. number of overnight stays, the rationale of our model is to break down these records into smaller time units, to dynamically allocate agents' time invested in recreational activities over a georeferenced fine-grain representation of the SES under consideration. The model returns a series of maps, showing the OR demand per agents' behavioral typology, allocated within a reference time window. It was tested in the Alto Bellunese, a mountain region located in the South Eastern Alps, by simulating a 1-day length time window referred to August 2017. A significant, strong and positive correlation was detected between

the simulated demand and available tourists' overnight stay records at municipality level. We concluded that the current modeling infrastructure shows promising results for future applications, but it may substantially benefit from further research activities to ground behavioral assumptions and improve the spatial representation of the SES under consideration. We therefore propose our spatial ABM as a prototype of a core technology that can be enhanced and customized in many ways, depending on specific research needs.

Keywords: spatial agent-based model, outdoor recreation, tourism demand, mapping and assessment, spatial complexity, mountain socio-ecological system

1 Introduction

Mapping and assessment of provision and demand of ESs have a high applicability in function-oriented landscape planning approaches, environmental management strategies and in policymaking. The demand-side is essential to integrate societal needs for goods and services into ES assessments (Burkhard et al., 2014) as individuals and social organizations are important actors of social-ecological systems (SESs). ESs are indeed the products of complex interconnected SESs (Scholes et al., 2013) and the demand for such services is only one among several system components. The interplay between social and ecological components is established by a multitude of factors that interact at multiple spatial and temporal scales, e.g. socio-economic conditions, behavioral norms, marketing, demographic changes and technological innovations. Societal preferences and individual needs of potential beneficiaries affect the way people consume and use ESs. Opportunities for and costs of accessing ESs are also relevant, e.g. physical accessibility to spatially confined ESs or individual awareness of the provision of ESs under imperfect information (Schröter et al., 2014; Wolff et al., 2015). Such complexity is typically addressed with simple and easy-to-apply GIS-based spatial analyses. Maps themselves have indeed both high potential and risks for the explanation of complex phenomena (Burkhard et al., 2014). Moreover, the inherent complexity of social system components makes it difficult to ground a solid and shared definition of the concept of demand for ESs. Focusing on cultural

ESs, demand for such services can be assessed either through proxies of their direct use and consumption or through stated individual and collective preferences that can reveal the quantity and type of demand required for personal well-being and quality of life (Wolff et al., 2015). Among cultural ESs, the demand for outdoor recreation (OR) activities is typically mapped where people spend most of their time (Burkhard et al., 2014), by using population density (Paracchini et al., 2014; Vallecillo et al., 2018) or statistical records e.g. number of inhabitants and tourists' overnight stays per administrative unit (Burkhard et al., 2012; Schirpke et al., 2018; Schröter et al., 2014). This represents the potential theoretical demand which differs from the actual use or consumption of an ES. Burkhard et al. (2012) define the potential demand as ecosystem goods and services currently consumed or used in a particular area over a given time period, not considering where ecosystem services are actually provided. We define actual use the one expressed by beneficiaries that carry out OR activities where such recreational opportunities are provided. This is consistent with Schröter et al. (2012), who suggest mapping demand where the actual use occurs, and with Burkhard et al.'s (2014) definition of ES flow. It represents the simple direct relationship between providers and users taking place in accessible areas that are actually used for recreation (Schröter et al., 2012). Unlike the theoretical potential demand, the users' side of the flow, i.e. the actual demand, is assessed without considering individual and societal preferences, such as biophysical characteristics, location and timing of availability, opportunities and costs (Schröter et al., 2014).

As ESs are products of SESs, their quantification requires integrating spatial information, temporal dynamics and behavioral complexity of human agents and social organizations. To this purpose, Agent-Based Modeling (ABM) is a computational method that enables scientists to model the spatial and temporal dynamics between agents, e.g. individuals or groups of people, and the environment, in this way exploring the inherent mechanisms that underpin system components e.g. provision, flow and demand of ESs. With ABM, scientists deal with complexity theory and try to detect emergent properties that cannot be analytically dealt with and which arise from synergies and interdependencies among lower level system components (Balbi and Giupponi, 2010). On the other hand, supply, flow, actual and potential demand for ESs are defined in order to assess and map individual system components from a reductionist perspective or at most compared in relative terms through a simple balance

(Burkhard et al., 2012). In practice, as they represent an aggregated level of abstraction of the environment and its interplay with human societies, their quantification could be reconciled and modeled by simulating SESs, trying to reproduce the complexity of the real world. Indeed, e.g. when an individual recreates, s/he has a demand for recreational opportunities based on his/her own preferences; next, s/he has the ability and/or the opportunity to reach a certain destination; finally, s/he has limited information about space so that the choice of a new destination is typically a second-best option compared to expectations. Moreover, OR is dynamic over space and time e.g. how people decide to spend their time, given the assumption they would try to satisfy their demand with the available provision of OR opportunities. Social and ecological complexity cannot be modeled with common GIS-based spatial analyses but, geospatial simulations with ABM integrate potential and advantages of both approaches, thus enabling scientists to dynamically model agents' interactions, displacements and decisions within a georeferenced environment (Heppenstall et al., 2011).

In the field of ESs, ABM has been rarely used (Belem and Saqalli, 2017). Some studies were carried out in the tourism sector (Balbi et al., 2013; Boavida-Portugal et al., 2017). To our knowledge no applications of ABM exist to assess OR activities in a geographical context. The objective of this study is therefore to develop the prototype of a spatial ABM for mapping the spatially-explicit summer non-rival demand for OR activities, by integrating system components into a georeferenced space with its own provision of OR opportunities and a simplified diversity of agents that are displaced over space and time, depending on a set of behavioral assumptions. This ABM is proposed to assess demand for OR activities in the Alto Bellunese, a mountain region located in the South Eastern Alps, through a set of 10 simulations. Each simulation returns a series of maps, showing demand in terms of agents' time dynamically allocated within a reference time window. In accordance with the above-mentioned definitions, these maps would represent the users' side of the flow but they are simulated with information that is meant to map the theoretical potential demand. Therefore, in our modeling infrastructure, the words "potential demand" and "actual demand" lose their meaning and hereafter we simply refer to them as "demand".

2 Material and methods

In this section, we first present the rationale of our model. Secondly, we provide an overview of the case study area on which the model is tested. Then, we explain the ABM parametrization, including behavioral dynamics and assumptions. Finally, we conclude with an overview about the software and tools used for the current implementation of the model.

2.1 An agent-based approach to modeling demand for outdoor recreation services

When trying to satisfy their demand for OR activities, people move over space and time. Their spatial allocation or displacement is assumed to be rational, meaning that its cost has been minimized. The cost of spending a certain period of time in a place is intuitively related to the willingness of paying for such opportunity. However, time itself is a cost since people carefully invest their free time in OR activities. Demand is dynamically expressed by people over space and time and, in fact, when tourists move (or don't move) from a certain area they are continuously investing their time. Every choice (move or stay) and any displacement can be modeled by parametrizing agents' surrounding landscape with the shortest paths between the agents' locations (e.g. accommodation) and targets (e.g. OR activity providers). Thus, in this study, the cost of spending a certain fraction of time per day in a specific place, either travelling or staying at recreational locations, represents our interpretation of OR demand in a continuous space and in a defined time interval. The higher the time spent by an agent in these places is, the higher the demand for recreational services is. Therefore, by simulating agents' movement in a study region, we can map demand within a reference time window.

2.2 The Alto Bellunese

The Alto Bellunese area is located in the Belluno NUTS 3 area, within the Veneto Region, South Eastern Alps and it covers 42⁴ municipalities. It corresponds to the old local tourist sector Dolomiti-Cortina (Partnership GAL Alto Bellunese, 2016). The area is framed in the alpine landscapes of the Dolomites

⁴ The municipality of Sappada became part of Friuli-Venezia Giulia Region on October 29th, 2018. At the time of writing, the Alto Bellunese includes 41 municipalities.

and mainly covered in forests, natural and semi-natural environment. It is in fact a well-known tourism destination area, acknowledged as a UNESCO World Heritage Site. It has a high environmental value, with 58% of its area recognized as Natura 2000 site. The local economy of the Alto Bellunese is mainly based on tourism and suffers decline of non-intensive livestock farming as well as demographic decrease. In 2018, in the wider framework of the Interreg Alpine Space project “AlpES - Alpine Ecosystem Services - mapping, maintenance and management”, the Veneto Region with support of Ca’ Foscari University carried out a high-resolution mapping study of OR services in the Alto Bellunese. Full details about this study and further information on the area can be found in Zen et al. (2018). The current work has been drawn from the outcome of the contribution of the Veneto Region to the AlpES project (Zen et al., 2018), where demand was not quantified in a spatially-explicit way but only using statistical records, i.e. census data and sum of tourists’ overnight stays at municipality level.

2.3 Model parametrization

The ABM is parametrized by spatially allocating a sample of observed overnight stays i.e. number of tourists per time unit, within the geospatial representation of a given study region, including OR opportunities and topographical elements. Topographic barriers and accessibility are taken into account through a cost-distance algorithm which sets least-cost paths i.e. minimum travel time, to reach agents’ recreational destination. Figure 1 shows the conceptual representation of the spatial ABM prototype. Full details are specified in the following subsections.

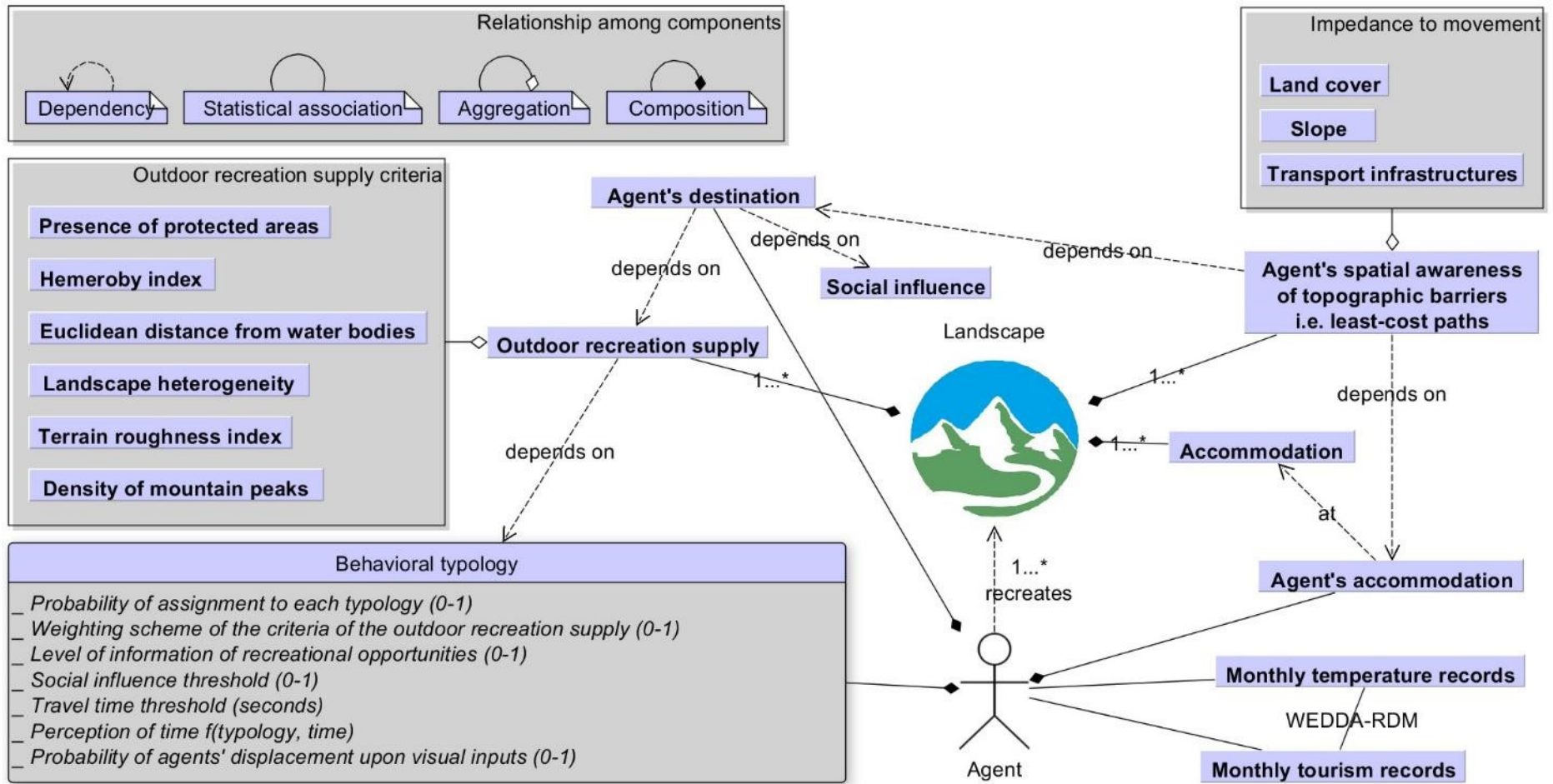


Figure 1. Conceptual representation of the prototype of our spatial ABM; top left legend of model components. "1...*" indicates "multiplicity"; spatial data, either raster maps or geodatabases, are reported in bold.

2.3.1 Provision of outdoor recreation activities in the Alto Bellunese

In the AlpES project, OR activities were quantified by means of six indicators (hereafter referred to as “criteria”): presence of protected areas, hemeroby i.e. the level of human influence, distance from water bodies, landscape heterogeneity, terrain roughness and density of mountain peaks. The potential provision was calculated by averaging normalized spatial criteria (between 0 and 1), using equal weights. The level of accessibility was calculated considering the road and trail network, by using travel time from urban areas. The actual OR supply was finally quantified by multiplying the recreation potential by the normalized level of accessibility. The methodology used to map OR opportunities was derived from Schirpke et al. (2018) and is reported in Section 2.3.1 of Zen et al. (2018). In this study we use the abovementioned criteria⁵ to quantify potential OR, but they are not aggregated with equal weights, as described in Section 2.3.3. Moreover, the level of accessibility also considers the type of land use⁵ and the origin could be any random existing accommodation facilities rather than the centroid of closest urban area, as reported in Section 2.3.4.

2.3.2 The WEDDA Regional Distribution Model

In ABM, fine-scale models can be nested into models that run at coarser scales and define the boundary conditions (Lippe et al., 2019). In our model, we need to define the number of tourists per day that visit the Alto Bellunese, coming from any potential external origin. Therefore, a customized version of the WEDDA-RDM is derived from Cavallaro et al. (2017). It can be applied to model the share of tourists p (Equation 1) i.e. the probability of stay, of each month i within a set of months I of a targeted year, for a single origin (rest of the world) and a single destination (the targeted region), possibly under alternative climate scenarios.

$$p_i = \frac{e^{(g_i + \varepsilon_i)}}{\sum_{i \in I} e^{(g_i + \varepsilon_i)}} \quad (Eq. 1)$$

⁵ To model OR criteria, we used a land use map available from the second work of the current dissertation: *Modeling Impact of Forest Expansion on Outdoor Recreation: A Ca-Markov Approach*. The OR criteria supplied to the agents were those projected by using the land use map of 2017. This also affected accessibility as a consequence of the expansion of forests.

For a set of months I of a targeted year:

- p_i is the share of tourists of month i;
- g_i is the climate score of month i;
- ε_i is the attractiveness score of month i.

The impact function g_i (Equation 2) is designed for summer tourism and aggregates monthly mean temperature and cloud cover to model the suitability of climatic and environmental conditions to carry out recreational activities in open spaces.

$$g_i = 25 + 0.5 * ts_i + 0.25 * ss_i \quad (Eq. 2)$$

For each month i of a targeted year:

- g_i is the impact function i.e. the climate dependent part of the WEDDA-RDM model;
- ts_i is the temperature score;
- ss_i is the sunshine score.

The temperature score ts_i ranges in a scale between 0 and 100 and is calculated on the suitability of the perceived temperature while recreating (e.g. through Equation 3): the score is monotonic increasing up to 25.3 °C i.e. 100, then monotonic decreasing.

$$ts_i = 100 * e^{-\frac{(t_i - 25.3)^2}{128}} \quad (Eq. 3)$$

For each month i of a targeted year:

- ts_i is the temperature score;
- t_i is the monthly mean temperature.

The sunshine score ss_i ranges in a scale between 0 and 100 and represents the cloud cover, monotonic decreasing over 25% (e.g. Equation 4).

$$\begin{cases} s_i \leq 25 \Rightarrow ss_i = 100 \\ s_i > 25 \Rightarrow ss_i = -\frac{4}{3} * s_i + \frac{400}{3} \end{cases} \quad (Eq. 4)$$

For each month i of a targeted year:

- ss_i is the sunshine score;
- s_i is the monthly percentage of cloud cover.

The attractiveness of each specific month ε_i (in Equation 1) is estimated from the observed share of tourists compared to all presences of all months I . Hence, the number of overnight stays in a specific month OV_i equals the utility function (Equation 5) and consequently ε_i can be quantified (Equation 6):

$$OV_i = e^{(g_i + \varepsilon_i)} \quad (Eq. 5)$$

$$\varepsilon_i = \log OV_i - g_i \quad (Eq. 6)$$

For each month i of a targeted year:

- OV_i is the number of observed overnight stays of month i ;
- g_i is the climate score of month i ;
- ε_i is the attractiveness score of month i .

At last, the projected number of overnight stays can be quantified with Equation 7, where the superscript c denotes the estimated share of tourists and the number of overnight stays under alternative climate scenarios.

$$OV_i^c = \frac{p_i^c}{p_i} * OV_i \quad (Eq. 7)$$

2.3.3 Parametrization of the agents

The WEDDA-RDM returns the probability of having an agent within the targeted destination region during a specific month, on the basis of climate parameters and statistical records. However, in our study the spatial ABM is developed on a daily temporal resolution. Thus, the number of tourists per month (Veneto Region, 2019) is divided by the number of days of the considered month i . Secondly, because of technical and computational reasons, only a sample of the observed tourists per day can be modeled and they are arranged into groups, known as super-individuals from the literature (Lippe et al., 2019). Therefore, in our spatial ABM, each agent is assumed to be a group of 2.4 people on average, which could be a family or otherwise. It represents the average number of individuals of an Italian family according to ISTAT (2018) and we also consider it a reasonable value to model tourists sharing a collective recreational target in the Alto Bellunese. So, each group is generated from a normal distribution with mean 2.4 and standard deviation 1. They are created so that the sum of all tourists approximately equals the number of observed tourists per day in the sample. Taking all of this into

account, Box 1 reports an example of the parametrization of a sample of agents for a single run of the ABM.

Box 1. Example of parametrization using tourism presences of 2017 in the Alto Bellunese (Veneto Region, 2019).

- Overall number of tourists = 3336393
- Number of tourists in August = 851063
- Share of tourists in August (p_i) = 0.2550848
- Average number of tourists per day in August (rounded) = 27454
- Sample of 1% of the number of tourists in August (rounded) = 275
- Assumed average composition in tourists per group = 2.4
- Number of groups/agents in August in the sample = 108

In Box 1 the sum of the number of tourists of all groups in the model equals 1 % of the number of tourists of August 2017 i.e. 275 people. Clearly, one might choose to model bigger tourist samples or even the whole population (27454 tourists), given the computational load that can be simultaneously executed.

So far, behavioral implications were not considered in the creation of groups. In ABM, agents' roles, attributes and attitudes are defined to represent the real-world human and social complexity under a simplified diversity of behavioral typologies (Lippe et al., 2019). Hence, a typology is randomly assigned to each group of tourists, to qualify their behavior when interacting with the surrounding environment. In this study we model three different behavioral typologies based on Cohen's recreational motivations (Cohen, 1979) (Table 1). As described in Section 2.1, agents try to satisfy their own demand for recreational services depending on their behavioral typology. In doing so, tourists perceive the surrounding landscape in a different way i.e. they weigh the criteria that quantify the OR service differently. Therefore, the six criteria reported in Section 2.3.1 are matched with the chosen behavioral typology on the basis of tourists' landscape preferences (from Komossa et al., 2018), by assigning a different weight to each criterion (Table 2). Worth noting, we assigned a weight of 0.0 to the density of mountain peaks as we consider it a quantitative criterion beyond spatial human perception. Among Cohen's categories, the "Recreational mode" and the "Diversionary mode" represent the typical

behavior of most mass tourists and, in our narrative, they compose 80 % of the sample of the agents (Table 1). The other 20 % is assigned to the “Experimental mode”, a minority of people seeking for wilderness, trained to travel to reach off-road remote areas.

Table 1. Matching of Cohen’s behavioral modes with tourists’ landscape preferences, identified by Komossa et al. (2018).

Cohen’s behavioral mode	The recreational mode	The diversionary mode	The experimental mode
Rationality of behavioral modes (Cohen, 1979)	<ul style="list-style-type: none"> • Typical modern tourist, entertainment and recreation oriented • Aims at restoring physical and mental well-being • Not interested in authenticity 	<ul style="list-style-type: none"> • Escapes from the stressful everyday life • Aims at restoring physical and mental well-being without actually enjoying recreation opportunities 	<ul style="list-style-type: none"> • Nonconformist • Seeks to experiment alternatives • Spiritual meaning of physical activities
Landscape preferences (Komossa et al., 2018)	<ul style="list-style-type: none"> • Flat, accessible landscapes • Forest for recreation • Water-dominated areas • Multiple landcover types close to each other • Areas that can be reached without intense physical efforts 	<ul style="list-style-type: none"> • Natural landscapes intended as “sporting facilities” for outdoor recreation activities, e.g. water bodies for kayaking, canoeing and surfing; high altitude and slopes for paragliding and climbing • Preference for multiple landscapes e.g. meadows and hedgerows, watercourses, mixed forests, pastureland 	<ul style="list-style-type: none"> • Remote places, hardly accessible • Harsh surfaces with substantial roughness, often at high altitude • Wild, unexplored areas • Avoid human disturbance
Interpretation in the framework of this study	People that enjoy relaxing but rather undynamic activities close to easily accessible areas, e.g. families with small children, elderly people.	Sporty people of different kind, not necessarily experts in the activities they carry out; they rely on existing infrastructures and accessible areas to recreate	Expert trekkers properly equipped to travel along off-road untraced paths
Ratio in the sample	0.4	0.4	0.2

Table 2. Matching of OR criteria with a set of weights on the basis of our interpretation of Cohen's behavioral modes in Table 1.

		Cohen's behavioral modes		
		The recreational mode	The diversionary mode	The experimental mode
OR criteria	Presence of protected areas	0.0	0.1	0.3
	Hemeroby index	0.1	0.2	0.4
	Euclidean distance from water bodies	0.5	0.2	0.0
	Landscape diversity	0.4	0.1	0.0
	TRI – Terrain Roughness Index	0.0	0.4	0.3
	Density of mountain peaks	0.0	0.0	0.0

2.3.4 Parametrization of the environment

ABMs of SESs require the incorporation of biophysical and technical geospatial information to allow for geographical understanding of the interaction between human behavior and the environment (Lippe et al., 2019), which in this study is represented by the Alto Bellunese. Agents are parametrized at the existing accommodation (hotels, apartments, chalets, guesthouses, hostels, camping and caravan sites, available from OpenStreetMap (OSM) through the Overpass API) and they can choose where to recreate depending on their behavioral typology, i.e. how they weigh OR criteria. Thus, accommodation and criteria are parametrized in the model, being essential spatially-explicit components in it. Additional geospatial information is included in the ABM to inform agents about their surrounding space, providing them with the capability of moving to and from their targeted destination in a realistic and rational way. Agents' movement is driven by:

- a friction map which is developed to set the time cost required to move across each cell of the spatial representation of the area under consideration; it is created by using transport infrastructures, landcover features and slopes;
- maps of least-cost paths, matching each agent with the targeted destination or accommodation and calculated on the basis of the friction map.

The procedure to generate least-cost paths is based on Nelson (2008) and is meant to develop the agents' spatial awareness, so as to make their movement consistent with the topography of the environment in which they act and with the temporal resolution of the ABM. Least-cost paths represent the cumulative

time cost of moving to a targeted destination and can be calculated by taking into account all elements that are considered relevant to model the impedance of a geographical space to agents' movement. Specifically, roads and paths are parametrized in km/h (Table 3) and then converted into the minutes required to cross each single cell at the chosen resolution, i.e. 100 m in this study.

Table 3. Roads and paths downloaded from OSM by using the key "highway" and the selected values. Speed values are assigned in km/h depending on the type of road, then converted to minutes to cross each cell of 100 m side.

Key	Value	Speed (km/h)	Time cost (min)
highway	primary	70	0.0857
highway	secondary	40	0.15
highway	tertiary	40	0.15
highway	minor	40	0.15
highway	residential	30	0.2
highway	path	5	1.2

By following the same rationale, each off-road cell is parametrized on the basis of the related land cover type⁵. In this case, the time cost in minutes per cell can be directly assigned according to Nelson (2008) (Table 4).

Table 4. Look-up table used to parametrize each off-road cell on the basis of customized land cover classes (modified from Nelson, 2008); to our purposes, water bodies are considered barriers to agents' displacement and a value 9999.0 is assigned.

Land cover	Time cost (min)
landcover:ArtificialSurface	1.2
landcover:AgriculturalVegetation	3.6
landcover:Forest	4.8
landcover:NaturalGrassland	3.6
landcover:BareArea	2.4
landcover:Wetland	6.0
landcover:WaterBody	9999.0

Outside the boundaries of the Alto Bellunese, the time cost is mapped up to a distance of 5 km, not including off-road cells. The friction map can be then refined in two ways: by including barriers or inaccessible places; by refining the cost estimation on the basis of biophysical parameters, e.g. slope and elevation (Nelson, 2008). In our case, the spatial allocation of water bodies (as barriers to agents' motion) is improved with OSM features. Then, since slope affects agents' displacements on foot along

paths and off-road areas, a reduction factor is applied to improve the estimation of the time cost (Nelson, 2008; van Wagtendonk and Benedict, 1980). The base walking speed (5 km/h) is first corrected for the slope on the basis of Equation 9:

$$v = v_0 * e^{-\tan\left(\frac{s*\pi}{180}\right)*k} \quad (Eq. 9)$$

where:

- v = corrected speed
- v_0 = walking speed over a flat surface
- s = slope in angular degrees
- $k = 2.47$ – a constant parameter for uphill and downhill travel

The corrected speed is converted into a friction factor and then used as a multiplier against the time cost calculated under the assumption of a walking speed of 5 km/h over a flat surface (Equation 10):

$$t = \frac{v_0}{v} * \frac{1}{\frac{v_0*10}{60}} \quad \text{which can be simplified to} \quad t = \frac{6}{v} \quad (Eq. 10)$$

where:

- t = time cost in minutes
- v = corrected speed
- v_0 = walking speed over a flat surface

Before generating least-cost paths to any selected destination i.e. tourism destinations and accommodation, the friction map is converted into seconds as it is the time unit of the spatial ABM prototype developed in this study.

2.4 Behavioral assumptions and dynamics

All maps of least-cost paths are generated from the same friction map consistent with existing landscape elements and geomorphology. The result is that tourists can “query” the environment to move along transport infrastructure, paths and possibly off-road areas in a realistic space and time representation. This is essential because time invested by agents represents their spatially-explicit demand for OR opportunities, simulated in the time window of one day of stay within the Alto Bellunese. Specifically,

in the morning (from 7.00 AM), tourists leave their lodging and move to a destination randomly chosen among those with an acceptable provision of OR for the specific behavioral typology. Human agents have limited cognitive abilities i.e. “bounded rationality” (Heppenstall et al., 2011), therefore the chosen destination is likely to be a second-best option rather than the best site. On the other hand, their spatial awareness can be considered as nearly perfect because people’s movement over space is nowadays enhanced by GPS navigation devices, e.g. mobile devices and automotive navigation systems. Social media might also play a major role in shaping tourists’ choices through information and experiences shared by other people. Taking all this into account, for each agent the destination is chosen as follows:

1. criteria maps are aggregated by using the weighting scheme of the related behavioral typology (Table 2), resulting in a map of the potential OR;
2. the destination is chosen from the top 25 % of the area that provides the highest potential OR, hence all cells below the third quartile of the map are filtered out;
3. the destination is chosen within an acceptable travel time threshold from agents’ accommodation (Table 5A), hence all cells perceived as too distant are filtered out;
4. the destination is more likely to be chosen among well-known and popular places if a behavioral typology is to some extent susceptible to social influence e.g. through information available on social media; therefore, unattractive areas are filtered out, if applicable (Table 5B);
5. hence the destination is randomly chosen among reachable cells above the third quartile of the potential OR provision and possibly known from social media.

Worth noting, flow of OR activities from Schirpke et al. (2018) (full details in Section 2.3.2 of Zen et al. (2018)) is here reinterpreted as an indicator for mapping popular and renowned areas for summer tourism. It represents the normalized count of summer tourists per day in a circular moving window with radius 1500 m, averaged from 2008 to 2016. It is estimated through the social media Flickr, on metadata related to the photos shared by the website users and georeferenced in the Alto Bellunese. So, recreational and diversionary agents choose their destination in the top 50% of the area with the highest count of tourists per day, provided it has an acceptable and accessible OR provision. Supplementary material A shows the OR provision per behavioral typology, not including accessibility.

Table 5. (A) Assumed top travel time thresholds, used to subset potential destinations among all cells of the landscape that provide acceptable recreational opportunities depending on behavioral modes; (B) threshold of social influence that shapes agents' decisions by filtering out unpopular places; (C) probability of stay after the agents have reached their destination.

Behavioral typologies	(A) Travel time threshold (hours)	(B) Social influence threshold (0-1)	(C) Probability of stay after reaching agents' destination (0-1)	Interpretation of agents' behavior on the basis of Table 1
The recreational mode	0.5	0.5	0.9	The chosen destination is ideally close, well-known and must provide all kinds of recreational opportunities; travel to distant locations and physically intensive displacements are avoided
The diversionary mode	1.5	0.5	0.4	Travelling is one among a set of recreational experiences; their movement depends on various activities e.g. sports, which are likely to be carried out after the destination is reached; facilities for such activities are likely to be located in renowned and popular areas
The experimental mode	2.5	0.0	0.1	They spend most of their time on travelling which is itself part of the recreational experience; even after having reached the destination it is likely they move around to explore the surrounding area; they seek for opportunities to discover unexplored areas which are never <i>a priori</i> considered unattractive i.e. no areas are filtered out.

Departures to the recreational destination occur with an increasing probability as time moves forward, depending on the behavioral typology. Such probability becomes higher than 0 after 7.00 a.m., when agents leave their lodging and after 3.00 p.m., when they go back. Departures are triggered if the probability calculated at time step (t) with Equations 11 to 16 in Table 6 is equal or higher than a random number uniformly distributed between 0 and 1. Each potential departure is an independent event and their cumulative probability over time can be controlled with Equation 17 e.g. agents that belong to the recreational mode have a little yet increasing cumulative probability to leave their accommodation which approximately equals 0.632 out of 1 after 9000 seconds (9.30 a.m.) but only 0.007 after 5400 seconds (8.30 a.m.), from the beginning of the simulation. Then, the exponential equations rapidly diverge to ensure the departure of all remaining agents.

Table 6. Equations (11 to 16) are used to simulate the probability “p” of triggering agents’ departures from and to accommodation as time “t” (in seconds) move forward. Parameter “a” equals 0.001388889 within each equation. Parameters “b” are iteratively calculated at each time step. Equation 17 can be used to control the cumulative probability over time.

Departures	from accommodation (beginning of a trip)	to accommodation (end of a trip)	Interpretation of agents’ behavior on the basis of Table 1
The recreational mode	$p = e^{(t-9000)*a} + b$ (equation 11)	$p = e^{(t-37800)*a} + b$ (equation 12)	Agents’ departures never occur early; they do not reach remote places; they can recreate as much as they want
The diversionary mode	$p = e^{(t-5400)*a} + b$ (equation 13)	$p = e^{(t-34200)*a} + b$ (equation 14)	Agents’ departures occur earlier in the morning than in the recreational mode; they do not reach remote places, but they carry out physically intense activities, which typically occur well before sunset
The experimental mode	$p = e^{(t-1800)*a} + b$ (equation 15)	$p = e^{(t-30600)*a} + b$ (equation 16)	Agents’ departures strictly depend on travel plans to achieve remote destinations; they leave in the early morning and start to go back in the early afternoon
Cumulative probability at time step (t)	$cp^t = 1 - [(1 - p^1) * (1 - p^2) * \dots * (1 - p^t)]$ (equation 17) with: cp ^t = cumulative probability at time step (t) p ^t = probability calculated with equations 10 to 15, at time step (t)		

So, after a random amount of time from the beginning of the simulation each group of tourists is displaced to the chosen destination through their related least-cost path. Once the destination is reached, the visual input from the surrounding environment drives tourists to explore and continue satisfying their demand for OR activities. In the time window between reaching the destination and before going back, agents’ movement is driven by five rules:

- they move to surrounding cells that provide acceptable recreational opportunities on the basis of a threshold that corresponds to the third quartile of the potential OR of the related behavioral typology;
- they always stay within a distance from their accommodation calculated on the cumulative time threshold that enables them to go back by the end of the simulated day;
- before any displacement (or further stay), they have to pay for the time cost to leave the current cell or, in other words, the invested time in OR activities;

- they move to a surrounding cell with a probability that depends on their behavioral typology i.e. a displacement is triggered if the probability of stay in Table 5C is smaller than a random number uniformly distributed between 0 and 1;
- they do not recreate outside the boundaries of the Alto Bellunese.

Finally, after 3.00 p.m., departures to accommodation are randomly triggered on the basis of equations in Table 6, once again depending on agents' behavioral typology. OR is assumed not to occur outside the Alto Bellunese but agents are allowed to cross the boundaries up to a distance of 5 km. This is admitted for the sole purpose of reaching recreational destinations or accommodation sites within the Alto Bellunese i.e. to simulate a realistic cross-boundary usage of transport infrastructures. Agents' dynamics are summarized in Figure 2.

2.5 Time allocation and outputs of the model

As explained in Section 2.1, time is the cost that tourists invest while visiting the Alto Bellunese. Hence, the time invested in recreational activities can be dynamically allocated and mapped while running a simulation of our spatial ABM. More specifically, the time cost paid by an agent to move or stay in a cell of the environment of the model is multiplied by the number of tourists that compose the agent and are “virtually” allocated in their current space. Further time investments can be later allocated by other agents and added to the previous demand, if belonging to the same behavioral typology. Time spent at accommodation is not mapped as it is assumed not to be invested in recreational activities. Time spent outside the boundaries of the Alto Bellunese is not mapped as well, simply because it is beyond the scope of the study. Therefore, to sum up, demand for OR opportunities equals the sum of the time cost in seconds locally invested by agents of the same behavioral typology within the time window of a day, from 7.00 a.m. to 8.00 p.m. (46800 seconds), in the Alto Bellunese. Such information can be directly and easily converted into a series of maps, one per each behavioral typology and all together. Moreover, in the time window of the simulation the normalized supply that meets tourists' demand is dynamically traced so as to both control the overall agents' behavior and monitor the average level of use of OR opportunities.

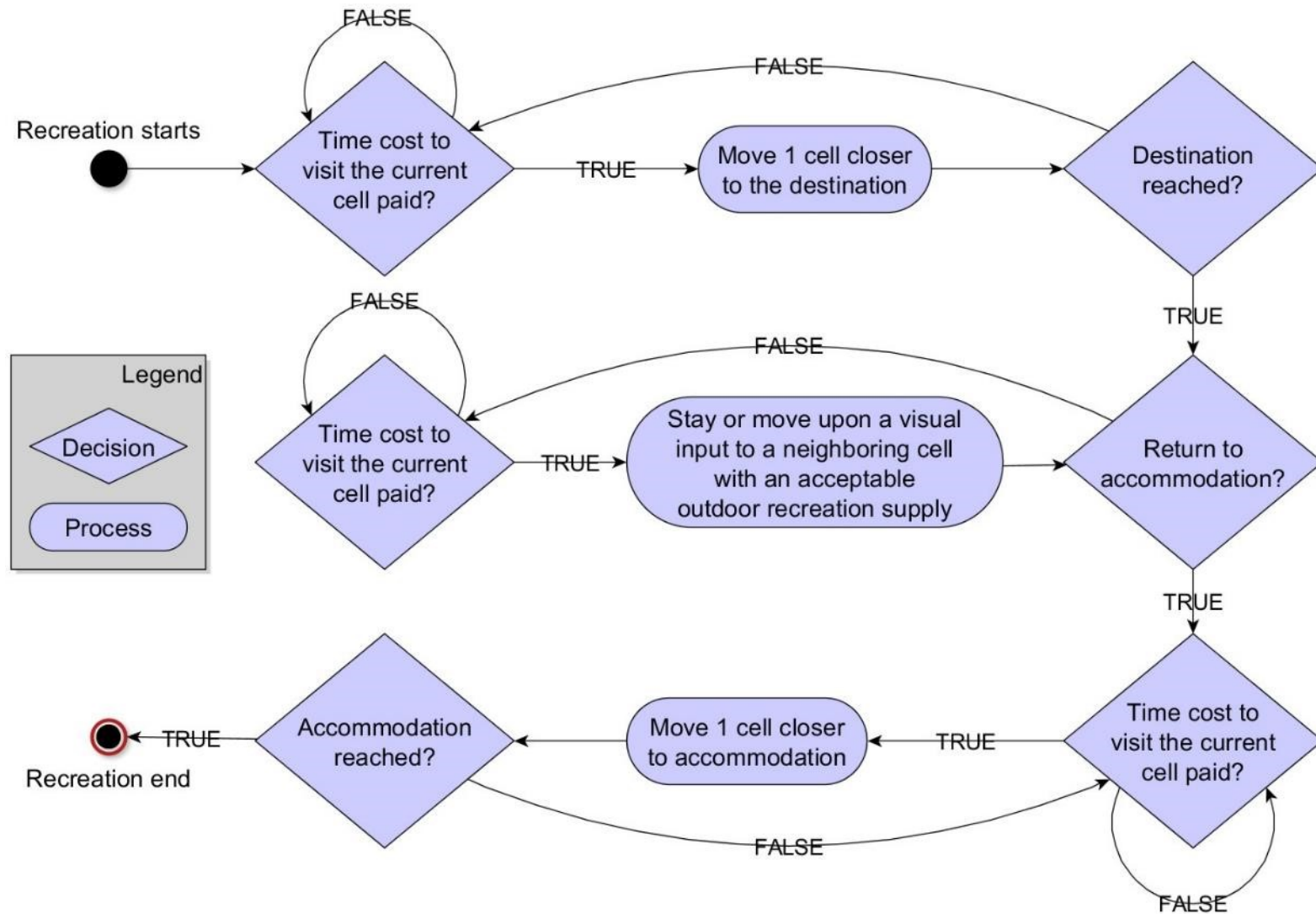


Figure 2. Agents' dynamics in the spatial ABM: three loops enable agents to invest their time to reach a targeted recreational destination, to recreate and finally to return to accommodation.

2.6 Tools and technical insights

The methodology is implemented through a series of software tools. The OR criteria are mapped using the Knowledge Laboratory (k.LAB) software, which powers the ARTificial Intelligence for Ecosystem Services (ARIES) project, to access and integrate data from multiple sources and customize ES modeling (Villa et al., 2014). The platform was used also in the framework of the AlpES project to map the provision of OR services within the Alto Bellunese (Zen et al., 2018). The friction map, showing the time cost of leaving each cell of the environment, is developed as well with k.LAB because with this platform it is possible to query and manage OSM data via the Overpass API. The OR criteria and the friction map serve as input data, processed with a customized R script together with other spatial data and behavioral parameters (see Figure 1) to build the infrastructure of information of our ABM. Specifically, the “raster” (Hijmans, 2019) and the “rgdal” (Bivand, 2018) packages are used to manipulate geodata. The calculation of the cumulative time cost is carried out with the “accCost()” function of the “gdistance” package (van Etten, 2018), under Queen’s case spatial contiguity. Such information is parametrized into NetLogo, a modular framework for ABM (Lippe et al., 2019), with a collection of R functions included in the “RNetLogo” package (Thiele, 2014). Specifically, the “NLCommand()” is a general purpose command to execute NetLogo codes implemented as strings and thus nested into R codes. It can be used to parametrize NetLogo directly from the R environment or from local resources e.g. by using the GIS extension of NetLogo (NetLogo Gis Extension, 2019). The “NLSetAgentSet()” command is instead specifically meant to parametrize agents. The dynamical loops that enable agents to invest time in recreational activities are developed as a collection of strings, once again nested into R codes but automatically printed into NetLogo with the “NLSourceFromString()” command. The latter is a second-best choice since it requires automatic print of Netlogo codes every time a new simulation is run. For the time being, this solution is applied in order to model each agent independently. Typically, in ABM with NetLogo, agents sharing attributes are collectively modeled as breeds (NetLogo Programming Guide, 2019) and, in our study, these could correspond to Cohen’s behavioral modes. However, each individual agent has a subjective spatial awareness of the environment i.e. a combination of least-cost paths to tourists’ accommodation and destination which

are parametrized in the environment with unique variable identifiers targeting only one agent. Therefore, each agent is not modeled as belonging to a breed but with his own piece of code, automatically printed into NetLogo with a FOR loop. The interface of the NetLogo environment is developed with a simple design to get control over dynamics and agents' behavior (Figure 3), within a georeferenced space showing the Alto Bellunese, accommodation and agents. After that a simulation is started through the "GO" button, agents' movement can be monitored in the model environment and the average supply is dynamically traced as explained in Section 2.5. Once the simulation is completed, spatial data can be exported from NetLogo into R with the function "NLGetPatches()". Further analyses on the outputs of the spatial ABM are carried out with standard R statistical packages (R Core Team, 2019).

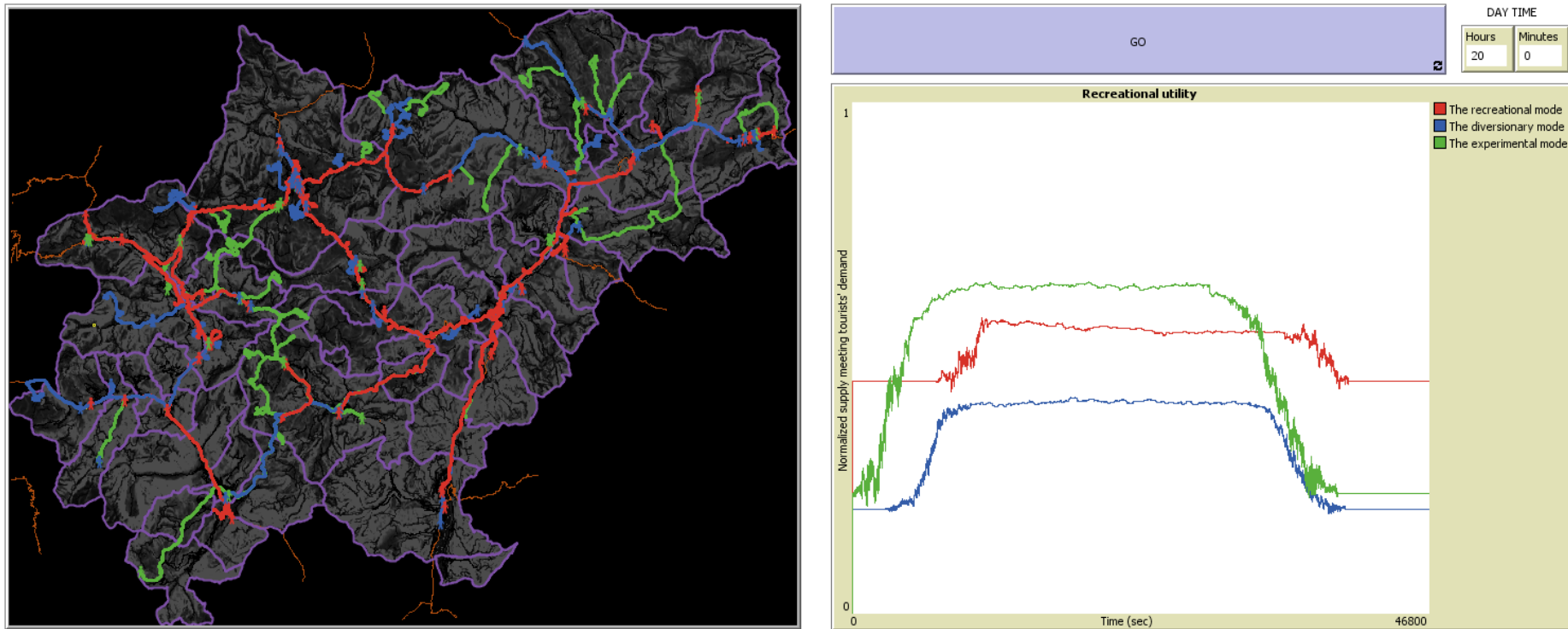


Figure 3. Interface of Netlogo: (left) the Alto Bellunese in a georeferenced space at 100 m resolution, showing the boundaries of municipalities in purple, main roads in orange and a grayscale raster in the background (the darker the color, the smaller the time cost of moving outside a cell is); (right) normalized OR supply meeting tourists' demand per behavioral typology, dynamically traced into a graph so as to monitor the average level of use of the ES along the day; (left and right) agents belonging to the recreational mode are shown in red, agents belonging to the diversionary mode are shown in blue and agents belonging to the experimental mode are shown in green; (top-right) the GO button starts the simulation and the display keeps track of the time flow from 7.00 a.m. to 8.00 p.m.

3 Results

Geospatial data were generated from a series of 10 simulations, executed on the basis of the ABM infrastructure and parametrization reported in Section 2. Results include four maps per simulation (available in Supplementary material B, together with their summary statistics), one per behavioral typology and a map including all agents. These maps show the tourists' OR demand quantified in terms of agents' time locally spent within the Alto Bellunese, hence dynamically allocated in the ABM environment. Figure 4, 5 and 6 show the 10-simulation sum of the OR demand per behavioral typology, i.e. the aggregation of maps from individual simulations. Their overlap represents the demand of all typologies and is shown in Figure 7. Log-lin frequency histograms of these maps are shown in Figure 8 to help visualization.

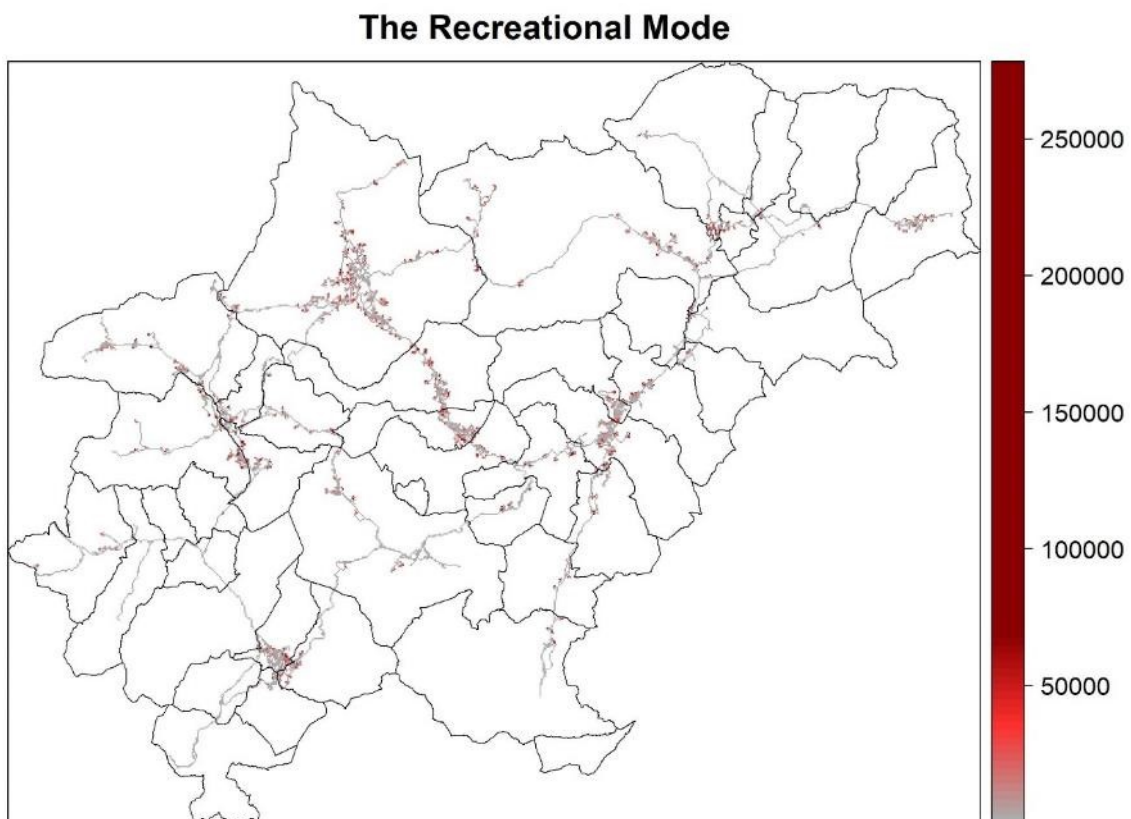


Figure 4. 10-simulation sum of the OR demand for the recreational typology, quantified as time investment in seconds spatially allocated by tourists in the Alto Bellunese, along the 1-day length time window of each simulation.

The Diversionary Mode

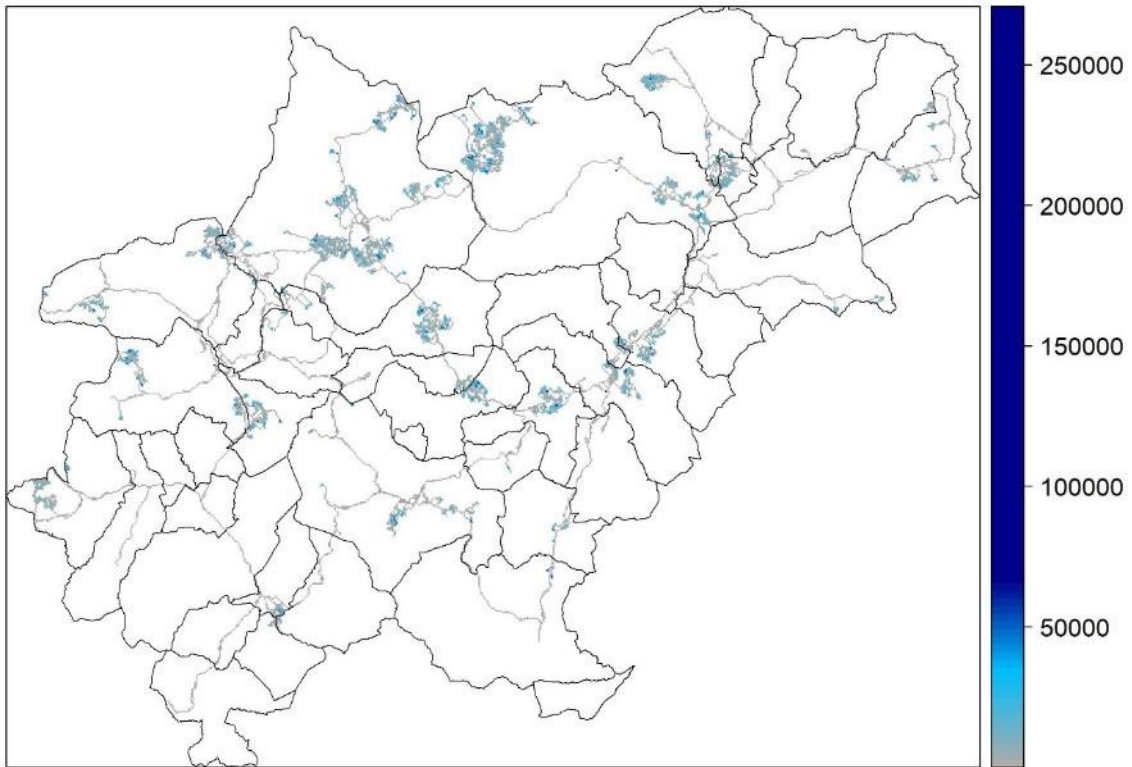


Figure 5. 10-simulation sum of the OR demand for the diversionary typology, quantified as time investment in seconds spatially allocated by tourists in the Alto Bellunese, along the 1-day length time window of each simulation.

The Experimental Mode

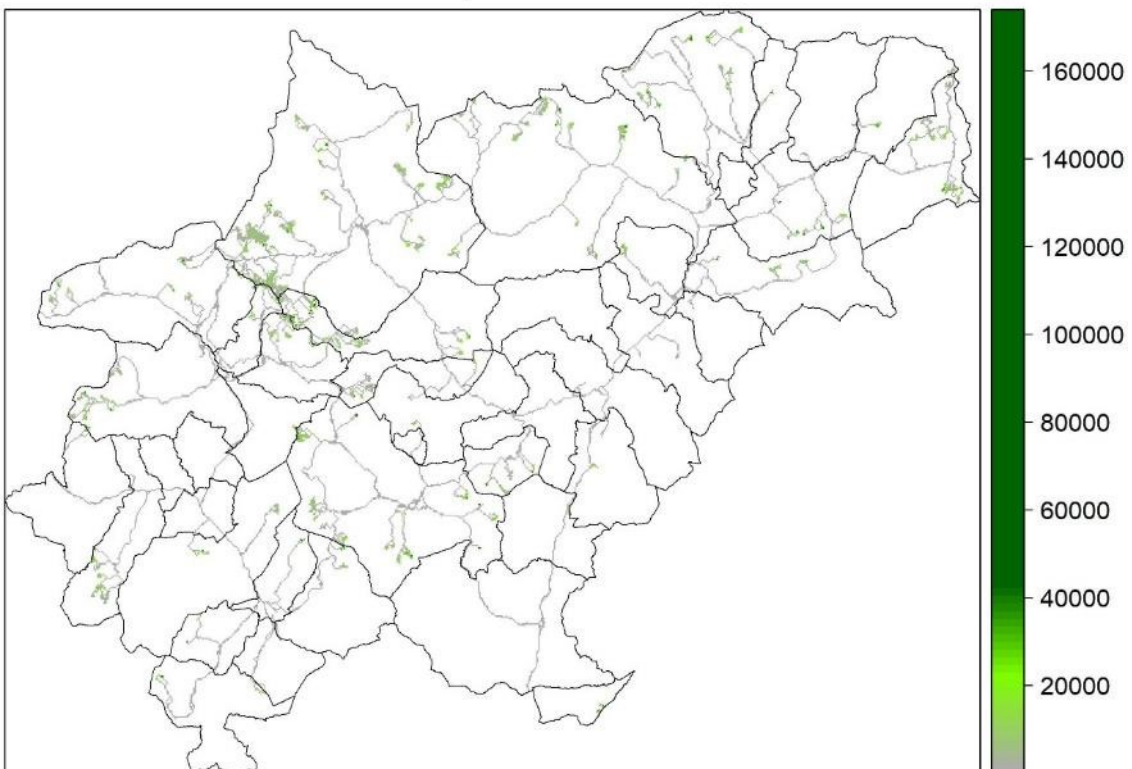


Figure 6. 10-simulation sum of the OR demand for the experimental typology, quantified as time investment in seconds spatially allocated by tourists in the Alto Bellunese, along the 1-day length time window of each simulation.

All behavioral typologies

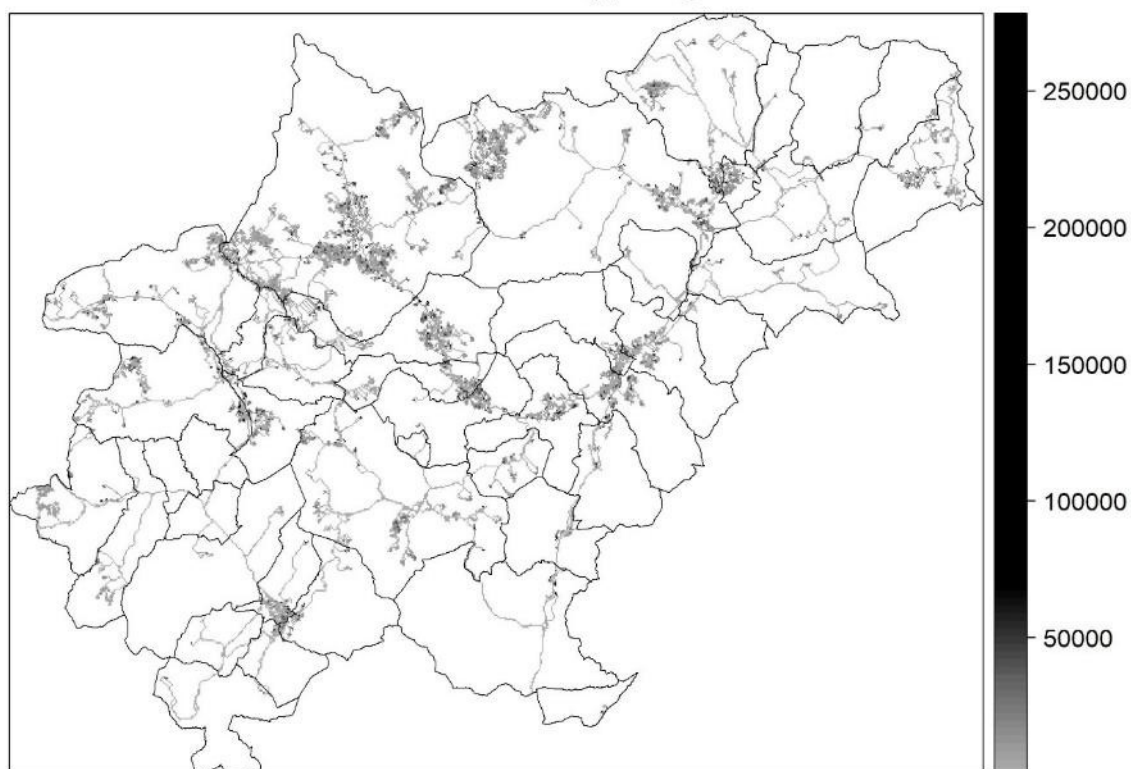


Figure 7. 10-simulation sum of the OR demand, quantified as time investment in seconds spatially allocated by all tourists (2751 individuals arranged into 1093 groups i.e. 108 to 111 agents per simulation) in the Alto Bellunese, along the 1-day length time window of each simulation.

Figure 9 reports correlation analyses between normalized statistical records of tourists' overnight stays (yearly data provided by the Veneto Region at municipality level, available through Zen et al. (2018) and used in the AlpES project together with population data to map the demand for OR opportunities) and:

- the simulated time investment of all tourists from the 10-simulation sum of the OR demand, aggregated by municipality and then normalized (a);
- the simulated time investment of recreational (c), diversionary (d) and experimental (e) tourists from the 10-simulation sum of the OR demand weighted by the local provision for their typology, aggregated by municipality and then normalized.

Figure 9 also reports a correlation analysis between the normalized amount of accommodation per municipality and the simulated time investment of all tourists from the 10-simulation sum of the OR demand, aggregated by municipality and then normalized (b).

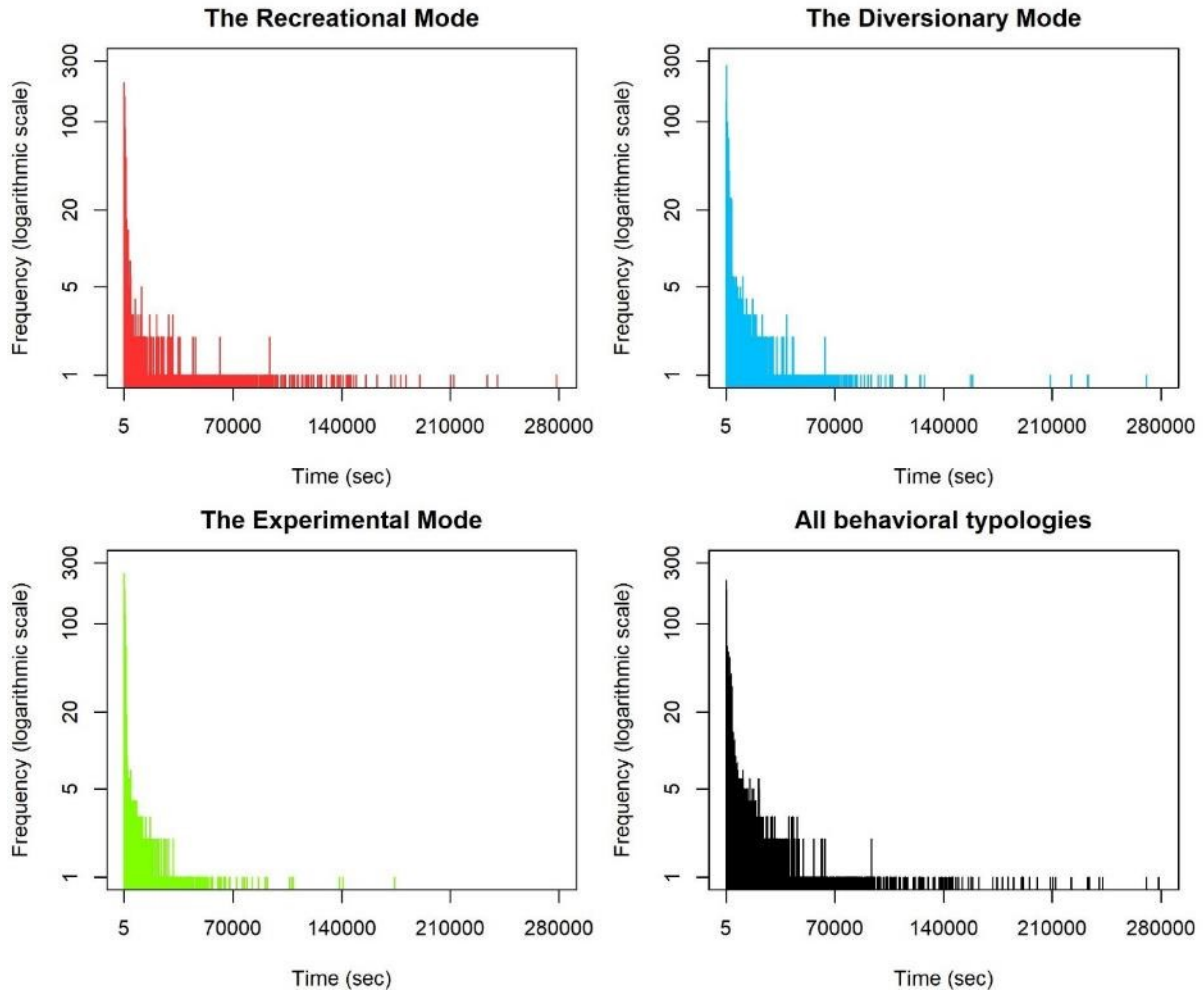


Figure 8. Log-lin frequency histograms of maps in Figures 4, 5, 6 and 7.

In Zen et al. (2018), the tourism component of the demand for OR activities refers to the annual average of tourist presences in the period 2008-2014 per municipality and it is divided by 365 days to quantify the so-called “permanent resident equivalents” (methodology from Schirpke et al. (2018)). On the contrary, in our study monthly records used to parametrize the ABM cover the whole Alto Bellunese (Veneto Region, 2019) and the simulated demand refers to the month of August. Despite these differences, in Figure 9 we decided to compare observed and simulated demand in relative terms because, to our knowledge, in the Alto Bellunese summer tourism prevails over winter tourism. This is proved over large parts of the Alps (Schirpke et al., 2018) and acknowledged in the local tourism sector Cortina-Dolomiti by the Veneto Region (2019b). So, we did not consider the recreational demand from locals, and tourists’ overnight stay records from Zen et al. (2018) were directly normalized to provide a relative indication of tourist presences per municipality, represented in the vertical axis of graphs (a),

(c), (d) and (e). Concerning the simulated demand i.e. the variables in the horizontal axis of graphs (a), (b), (c), (d) and (e), aggregation from the 100 m resolution OR demand maps to the municipality level was carried out through arithmetic sum, i.e. one second spent in a cell of a municipality is a second spent in that municipality. Time was also weighted by the local provision per behavioral typology (c, d, e) to represent the quality of time per cell i.e. one second invested in a cell is more valuable if in that cell there is a high OR potential. To sum up, demand from the AlpES project (not including population data) was correlated with overall quantity (a) and behavioral related quantity and quality (c, d, e) of time, to verify the consistency between simulated and observed demand from Zen et al. (2018) at the municipality level. A significant, strong and positive Pearson's correlation coefficient was detected for all considered variables (statistics shown in Figure 9).

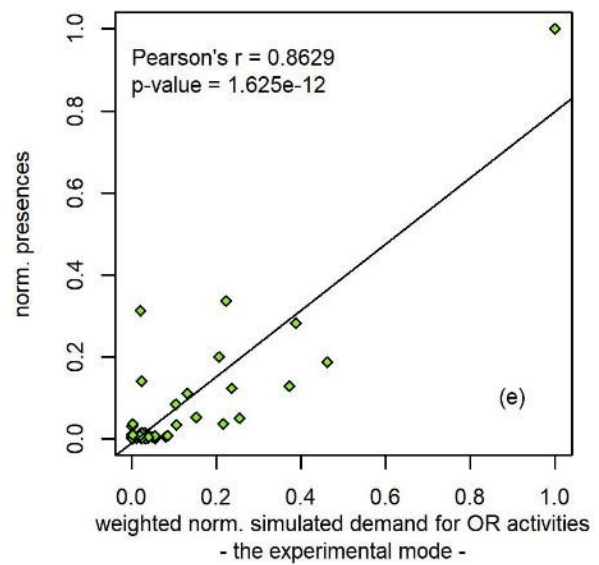
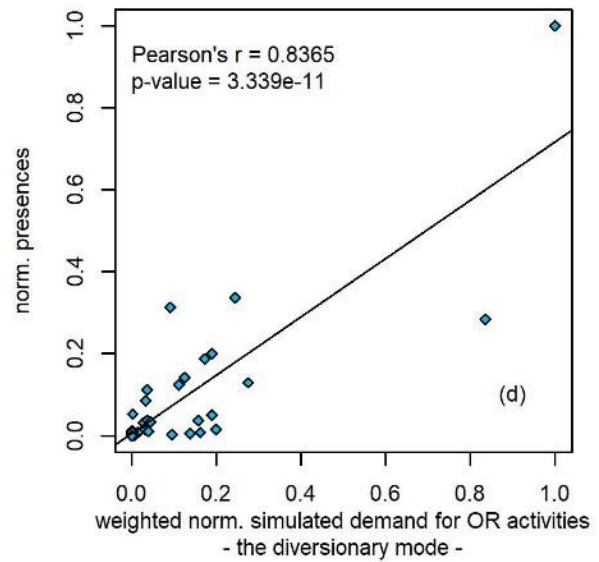
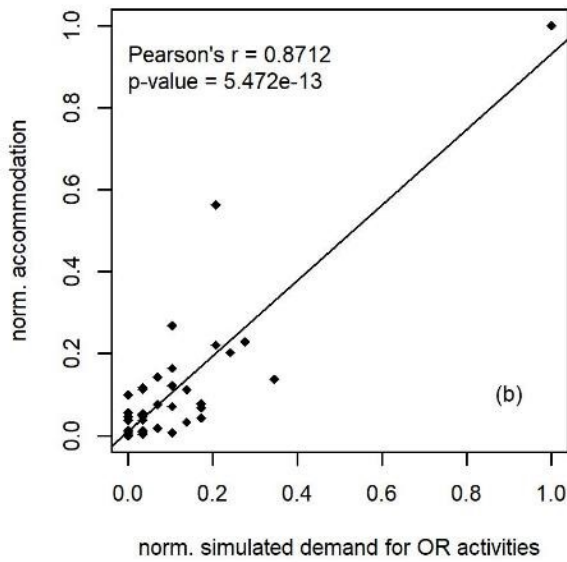
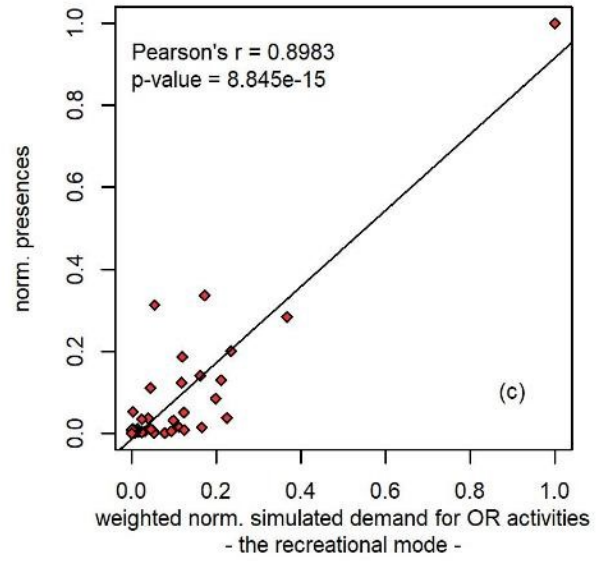
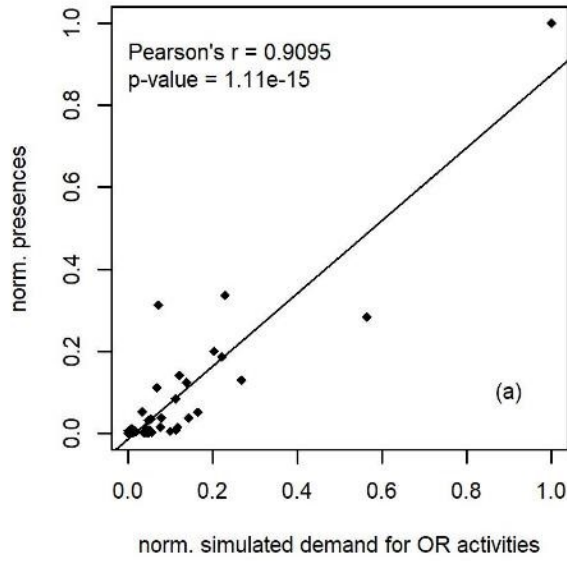


Figure 9. Correlation analyses between the observed demand and the overall quantity (a) and behavioral related quality (c, d, e) of time invested by the agents in the simulations; correlation analysis between the amount of accommodation and the overall quantity of time (b); analyses carried out on normalized aggregated data (arithmetic sum) at municipality level; numerical records of graph (a) reported in Supplementary material C.

4 Discussion

The study is meant to present a novel spatial ABM approach to mapping the summer non-rival demand for OR activities by breaking down the concept of tourists' overnight stays, typically available as statistical records, into smaller time units dynamically allocated over space. Time is invested in recreational activities depending on the tourists' behavioral typologies, their bounded cognition and limited information. Provision of recreational activities, topography and geomorphological information compose the 100 m resolution grid-based environment of the ABM, making it possible for agents to process spatial information and "recreate" in a realistic time and space representation, i.e. in the case study, one day of August 2017 in the Alto Bellunese. In this section the reliability of the spatial ABM in mapping demand for OR activities is discussed by assessing the results of our application. Then, the current infrastructure, its strengths, weaknesses and potential improvements are explored in detail.

4.1 Analysis of outdoor recreation activities in the Alto Bellunese

Simulations are executed under the same parametrization of the model and resulting OR demand maps show the allocated time during the 46800 seconds of the simulated time window. Their summary statistics (available in Supplementary material B) represent an indication of the stochasticity that arises from the agents' random yet rather rational movement in space. Means, maximum values and standard deviations differ among simulations as they depend on the time spent by the agents at their accommodation or outside the Alto Bellunese, therefore not invested in OR activities. Stochasticity arises also from the likelihood of staying in a cell after having reached the targeted recreational location, which depends on agents' behavioral typologies. Most times the minimum value is 5 seconds and represents the time investment of an agent composed of a single tourist that spends that amount of time to leave a cell of the road network i.e. primary roads. In this case, time is allocated once and during the simulation no other agents cross the same cell. In general, mass tourism is evident as recreational and diversionary agents collectively represent 80 % of the simulated sample. Experimental agents instead allocate less time, globally because they account only for 20 % in the sample and locally because they are parametrized to be frequently displaced. Agents' spatially-explicit time allocation or, in other words,

their demand for OR activities dynamically emerge from the simulations, resulting in different patterns that are shown by overlapping results from the 10 simulations (Figure 4, 5, 6 and 7). Such patterns can be interpreted by considering specifications of the behavioral modes:

- recreational agents move along roads, around settlements and popular areas and main paths nearby to enjoy mountain landscapes without intense physical efforts;
- diversionary agents seek for suitable environmental condition for OR activities e.g. slopes, areas near water bodies, yet rather accessible and therefore close to roads, paths and around settlements and popular areas;
- experimental agents seek for remote and unexplored land, without being limited in their choices by harsh geomorphological or topographic conditions.

In these maps, cells showing a low time allocation (Figure 8) have the highest frequencies and represent flat urban surfaces and connections, typically only crossed by agents for reaching recreational places. Time spent around recreational destinations is instead represented by cells with small frequencies because it is very unlikely that the stochasticity in the model would return the same time allocation in different places.

The reliability of the modeling results was investigated by comparing them with tourist overnight stay records used in the AlpES project by Zen et al., (2018) to map demand at municipality level. Because our spatial ABM breaks down time from a single day of stay within a municipality to 46800 seconds at 100 m resolution within and outside municipalities, we expected a weak to average correlation between the simulated results and the observed demand from the AlpES project. Time is indeed no more a statistical record “constrained” within a single municipality. We found instead a significant, positive and strong correlation among considered variables (Figure 9). We interpret these results on the basis of the following information:

- there is a substantial asymmetry in the areas of the municipalities of the Alto Bellunese i.e. the wider they are, the more likely it is for an agent to invest time within their boundaries; this occurs even if the invested time is weighted by the local supply per behavioral typology (Figure 9c, d, e);

- in the ABM mass tourism is driven by social media information and thus people choose their recreational destination within renowned tourism places (in our model, top 50% of the area), where typically it is more likely to find accommodation;
- we found a statistically significant correlation between the amount of accommodation per municipality and the simulated aggregated results of our model (Figure 9b) i.e. agents invest more time in OR activities within these municipalities even though time allocation at accommodation is prevented.

To sum up, in the Alto Bellunese yearly statistical records of tourist presences are correlated with the simulated demand, which in turn is correlated with the amount of accommodation. This suggests that simple statistical records at the municipality level might be a good representation of demand for OR activities if these mainly occur within dominant and renowned areas e.g. Cortina d'Ampezzo or Auronzo di Cadore in the Alto Bellunese. Otherwise, the number of presences per municipality might not provide useful information because in the real world tourists do not recreate at their accommodation place and this is why, in the beginning, we expected a weak correlation with the simulated demand. Further research on different areas would be required in order to generalize these findings. For the time being, however, results from correlation analyses validate our spatial ABM as the simulated demand was found to be consistent with existing statistical records at the municipality level and no spatially-explicit data do exist for such purpose, as far as we know. Full sensitivity analysis was not performed because of the computational load that is required to parametrize each single run of the spatial ABM (further details in Section 4.2.1).

4.2 Agent-based modeling for mapping recreational opportunities

Bearing in mind definitions in the introduction section, in our model demand would represent the actual request that take place where recreational services are provided. Such strict definition can be useful from a reductionist perspective to model individual system components. In the ABM approach, however, demand is simulated so that we can set a virtual population of agents that can match existing demand, theoretical beneficiaries or alternative scenarios e.g. the expected increase of summer tourism

demand together with summer temperature (Cavallaro et al., 2017). This advantage is achieved at the expenses of the efforts required to model the complexity of the real world, both the environment and agents' behavioral rules. As with the spatial ABM we aimed at modeling time, geomorphology and topographical elements, the way people perceive the surrounding space, their willingness to move and recreate, all these features play a role in allocating time to map demand for OR activities, not to mention the stochasticity behind equations that trigger agents' movement. Given the level of complexity of the representation of the Alto Bellunese SES that underpins our modeling exercise i.e. geospatial information and behavioral assumptions, we argue that the current modeling infrastructure is already capable of mapping demand for OR activities, as shown in Figures 4, 5, 6 and 7 (10 simulation sum) and in Supplementary material B (individual simulations). At the same time, we are aware of its several limitations and in the following sections we suggest potential enhancement, from simple to radical improvements.

4.2.1 Technical and practical limitations of the current implementation of the ABM

The computational load that is required to parametrize the model limits the exploration of parameter space for sensitivity analysis. Such computational bottleneck mainly depends on the generation of agents' least-cost paths. In the current implementation, assuming e.g. 108 agents (from Box 1), with an Intel® Core™ i7-4720HQ CPU (2.60GHz base frequency), the R code requires about 5 hours to generate 216 maps (two per agent, one to reach the destination and the other to return to the accommodation). The other parametrization steps, the automatic print of the code from R into Netlogo and the simulation itself run in the order of minutes. This is still very far from our being able to map the whole population of agents e.g. 27454 tourists (from Box 1), whose parametrization would require much more time. Secondly, the higher the number of agents and geospatial data uploaded in the Netlogo space is, the more likely it is to run out of RAM memory. In our case it was not a problem because we worked with small samples of agents at 100 m resolution. As we mapped non-rival demand, we could run multiple simulations and add the results up together (Figure 4, 5, 6 and 7), which overall represent 10% of the demand of an average day of August 2017. Considerable computational power and RAM

memory would be required to model the whole demand with a single or few executions of the model e.g. through cloud and high performance computing (Lippe et al., 2019). In addition, future revisions of the code of the spatial ABM prototype should move toward increasing the efficiency of the use of computational and memory resources.

4.2.2 Improvement of the geospatial representation of the environment

In our study, the grid-based environment of Netlogo was set to 100 m resolution as it was considered a good compromise between the computational load required to generate least-cost paths and the quality of resulting maps. The spatial resolution of the environment also affects the speed of the simulation and the amount of geospatial data that can be simultaneously parametrized in the Netlogo environment, given the available RAM memory capacity. While parametrizing roads with an average speed might be a reasonable assumption over flat land, a finer grid would be preferable to model mountain regions. This could improve the spatial representation of the cumulative time cost over transport infrastructures, in the Alps typically composed by narrow roads with hairpin bends. A 25 m or even higher resolution might be appropriate. To address the computational bottleneck, one might model smaller areas at higher resolution e.g. 1 municipality instead of 42 as in our case study, if consistent with the research question. However, most spatial ABMs are developed at municipality or regional scale and research efforts should be made toward large-scale modeling over broader geographical areas (Lippe et al., 2019). In our case, it may be worth modeling the surrounding space of the Alto Bellunese, e.g. to improve the cross-boundary dynamics of agents' movement far beyond the 5 km we have considered in our study. Although computationally demanding, such enhancement may also pave the way for dynamically modeling demand from visitors coming on daily trips from their homes outside the region under consideration. In the current implementation of the model, demand for OR activities over the road network can be mapped simply by overlapping them and filtering out the time allocated over roads, but results would be partial since they would not include cross-boundary traffic from daily trips. Anyway, roads grant accessibility to recreational sites and so we consider it as time indirectly invested in recreational activities. Concerning instead agents' time spent along footpaths and off-road areas, beyond

increasing the spatial resolution, the ABM environment can be enhanced by improving the parametrization of the friction map. The effect of slope on time cost depends on the coefficient k of Equation 9, defined by Nelson (2008) as a constant parameter for downhill and uphill travel. Since they model accessibility to major cities at global level, they choose a value of 3.00. We reduced this value to 2.47 to slightly decrease the impedance of the land as we assume that tourists that move along steep slopes are to some extent trained for such activities because they belong to the diversionary or experimental typology. Anyway, time cost exponentially diverges for slopes greater than 60° . Given the above, agents' time perception may be improved by generating a friction map per behavioral mode. In this way, the time cost to cross a cell would be different among typologies i.e. by assigning different k coefficients.

4.2.3 Fine-tuning of behavioral parameters

Parameters describing agents' typologies, such as size of groups, level of information shaping their cognition, the way the agents weigh ES criteria, the likelihood of their displacement and all other behavioral assumptions provide a solid base for the realism of the social component in the simulation. The way current ABM infrastructure can map demand is promising because the simulated pattern was found to be correlated with observed tourists' overnight stays at municipality level. However, at local scale, time allocation would definitely benefit from fine-tuning of behavioral parameters through expert judgement, to better represent the spatially-explicit demand for OR activities.

4.2.4 Modeling of rival summer demand for outdoor recreation activities

As mentioned in Section 4.2.1, for the time being we decided to model non-rival summer demand for OR activities, in this way neglecting competition for land among agents. This is consistent with the literature since OR activities can be considered non-rival as long as the carrying capacity of a region is not taken into account, e.g. number of visitors per recreational facility or rooms per hotel (Burkhard et al., 2014; Schröter et al., 2014). However, while recreating a high tourist density might be negatively perceived e.g. by tourists that according to our interpretation belong to the experimental typology. In

addition, we argue there might be some kind of threshold to the physical space that a group of people can occupy. It may not be relevant at 100 m resolution but, when working with finer grids, it definitely has some impact on the way people spend their time on recreation e.g. people may spread around over space in an area locally dense of tourists instead of converging toward the cell that represent their “first best” choice. Anyway, to include competition for land in our spatial ABM, it is first necessary to simultaneously model all tourists for the time window under consideration, as described in Section 4.2.1, otherwise competition might be underestimated. Secondly, minor improvements would be required in the code that executes the dynamical loop and drives agents’ movement (Figure 2).

4.2.5 Full application of the WEDDA-RDM

The impact function (Equation 2) of the WEDDA-RDM requires that the temperature component (Equation 3) of the destination region for the time window under consideration is set, which may not be trivial. Because tourists typically adopt coping strategies for adverse weather conditions (McCreary et al., 2019) e.g. low temperatures at high altitude, we suggest using reference temperatures from the bottom of mountain valleys or sites close to settlements. For such purpose, as a first approximation we propose averaging the elevation of cells of the road network of the region under consideration (not including settlements themselves where people do not recreate). In this way, monthly temperature records e.g. available from local weather stations, can be regressed to the representative elevation for the area and then averaged to get the temperature value required for the climate component of the WEDDA-RDM. In the case of the Alto Bellunese, the average elevation of the road network is 1136.29 m and its average temperature during August 2017 was 17.1 °C. The WEDDA-RDM returns an increased probability of tourist presences up to an average temperature of 25.3°C, which represents an optimal climate condition for OR activities (Cavallaro et al., 2017). In the Alto Bellunese, by considering alternative temperature scenarios e.g. seasonal extremes, the trivial result would be a progressive increase of demand for such activities (Equation 5). Less obvious would be instead the impact that might arise from the competition for land resulting from seasonal peaks of tourism density driven by climate change. This is the case in which the spatial ABM would benefit from its being

coupled with the WEDDA-RDM i.e. multiple increasing temperature scenarios from which different demand spatial patterns might emerge because of the competition for OR opportunities. Anyway, computational and memory issues should be first addressed, as reported in Section 4.2.1, to simultaneously model all tourists for the time window under consideration. Last but not least, concerning the impact function (Equation 2), it can be customized by complementing the temperature component (Equation 3) with further parameters e.g. cloud cover percentage, precipitation or snow water equivalent in case of winter tourism (Equation 4) (Cavallaro et al., 2017), that can be used to simulate demand for OR activities under alternative weather conditions or different seasons.

4.2.6 From the ecosystem service framework toward the complexity of the real world

The ABM could be enhanced in many different directions according to research objectives, by improving in this way the spatial and temporal representation of the SES under consideration. However, all the improvements discussed so far fall into the ES framework that operates within some level of abstraction and is specifically suited for wide geographical areas, regional to continental scales (e.g. Paracchini et al., 2014; Schirpke et al., 2018). ABMs instead are typically developed at local to regional scale and most of them lack feedbacks from large scale processes (Lippe et al., 2019). Therefore, by assuming that the computational and memory resource requirements were addressed, the environment of the spatial ABM might be expanded to include individual elements that compose the SES under consideration e.g. accommodation with number of tourists per facility and recreational sites with their own carrying capacity. Economic models might be also embodied in the ABM to represent individual businesses. The opportunity cost for accessing recreational areas might be modeled through the allocation of money, complementing in this way agents' time investments. The listed potential major enhancements are not comprehensive as complexity has no limits other than those defined by research questions that underpin modeling requirements. Therefore, we limit the discussion to the following points.

- Cohen's (1979) other categories i.e. the "Experiential mode" and the "Existential mode", were not included in the current study. OR criteria were considered as not suitable to meet the

demand of these kinds of tourists because their recreational motivations lie in the specific spiritual, cultural, historical or scientific meaning of landscape elements. These should be parametrized as individual sites into the environment of the ABM, in case it is necessary to map the OR demand of the abovementioned categories.

- In the current implementation of the spatial ABM, recreational destinations are randomly chosen among those cells that meet the requirements of the behavioral typology; the algorithm requires only a friction map and a couple of coordinates to generate the map of least-cost paths to the targeted destination; therefore, by supplying a set of coordinates (as in our case for agents' accommodation), the current technology is already capable of driving agents to individual landscape elements rather than random cells.
- Fine-scale dynamics of agents with individual landscape features might be used to model the whole tourism sector where OR represents one among several activities. Such hypothetical infrastructure might simultaneously operate and complement a large-scale ES-based framework where demand might be mapped at the chosen grain from feature-level information. In this case, radical improvements to the agents' behavioral rules and the model infrastructure would be required in comparison with our study, as we considered only roads, paths and accommodation among landscape countable elements, only to map demand for OR activities.

5 Conclusion

In this study we developed a spatial ABM to model and map the summer non-rival demand for OR activities, by integrating geospatial information of a SES with its own provision of OR opportunities and a simplified diversity of agents that are displaced over space and time, depending on a set of behavioral assumptions. We proposed the spatial ABM as a modeling exercise to assess OR services in the case study of the Alto Bellunese, a mountain region located in the South Eastern Alps. The model returns a series of maps, showing the OR demand in terms of local time investment dynamically allocated by agents while recreating. Our findings for the Alto Bellunese show that the approach may be promising for future applications. Indeed, our spatial ABM may substantially benefit from further

research activities to ground behavioral assumptions and improve the spatial representation of the SES under consideration. We therefore propose our model as the prototype of a core technology that can be enhanced and customized in many ways, depending on specific research needs. We also hope to have succeeded in inspiring future applications of ABMs in the field of ESs.

Acknowledgements

This study draws on the outcomes of the contribution of the Veneto Region to the Interreg AlpES project ('AlpES' project, CUP: D52I16000220007), which aimed at mapping the provision of OR and fodder from alpine grasslands at high resolution within the Alto Bellunese, i.e. one of the pilot regions of the project.

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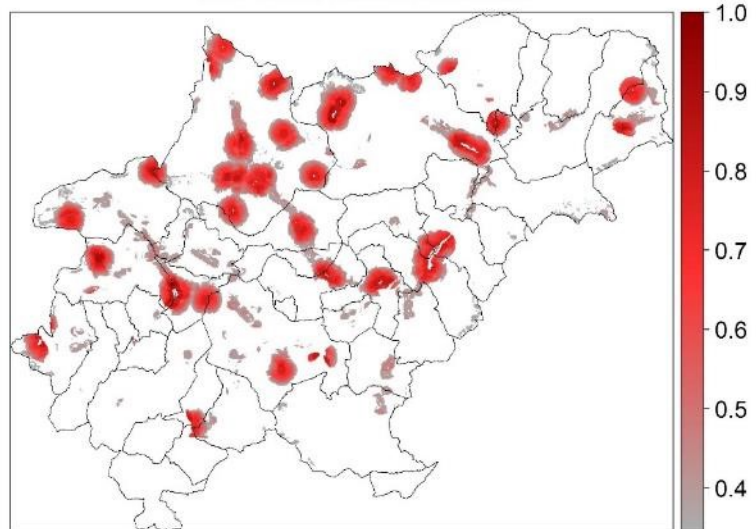
Appendix A

From the top, OR supply maps for recreational, diversionary and experimental agents. Colored cells of these maps represent potential tourism destinations.

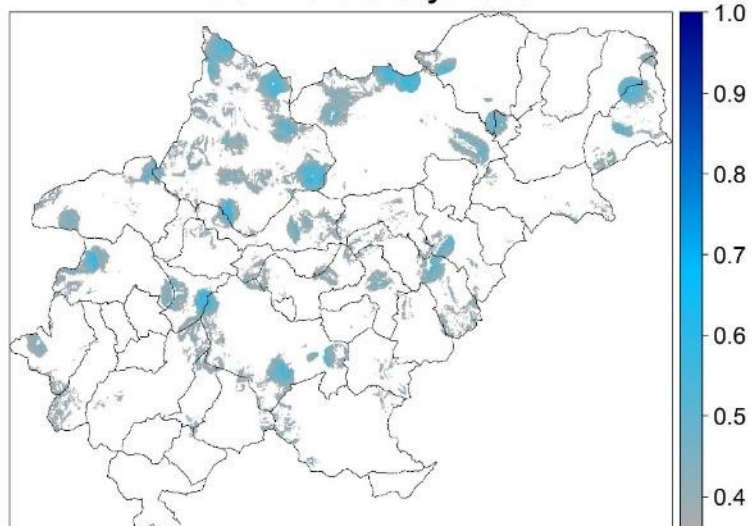
In case of recreational and diversionary agents, destinations are randomly chosen in the top 25 % of the area of the Alto Bellunese that provide the highest provision of OR and fall into the top 50% of the area with the highest count of tourists per day.

In case of experimental agents, destinations are chosen in the top 25 % of the area of the Alto Bellunese, without further constraints.

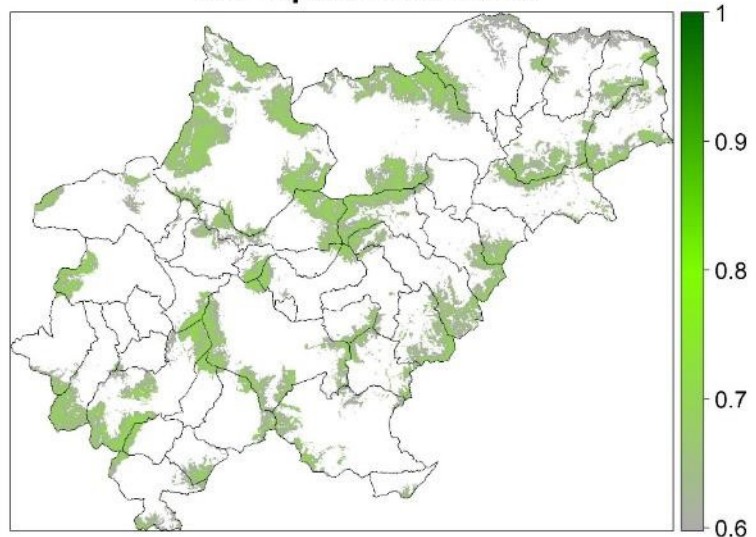
The Recreational Mode



The Diversionary Mode



The Experimental Mode



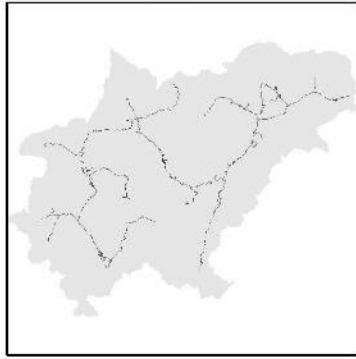
Appendix B

Figures 4, 5, 6 and 7 in this paper report the 10-simulation sum of the OR demand per behavioral typology and for all of them together, quantified in terms of time locally spent and dynamically allocated by tourists within the Alto Bellunese, along a 1-day length time window. Here, disaggregated results from individual simulations are presented with the same rationale, together with summary statistics, i.e. mean, min/max value and standard deviation (of non-zero cells). Because of visualization purposes, only presence/absence of demand is shown, respectively by recreational agents, diversionary agents, experimental agents and by all typologies.

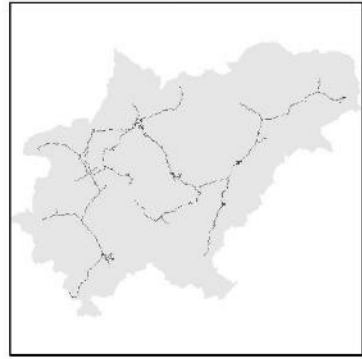
Sim. 1



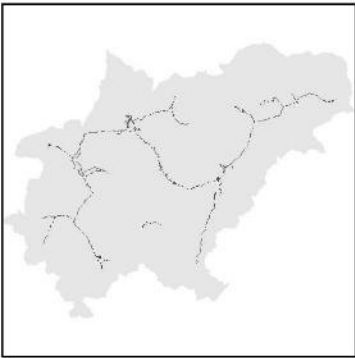
Sim. 2



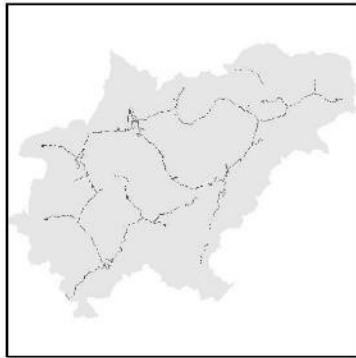
Sim. 3



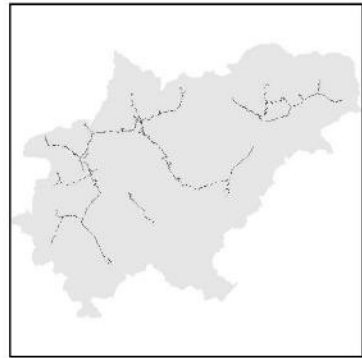
Sim. 4



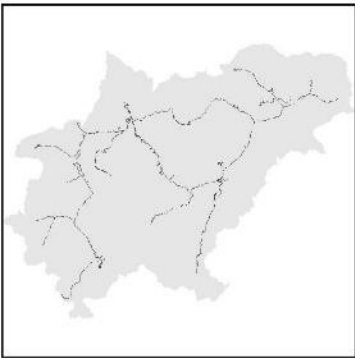
Sim. 5



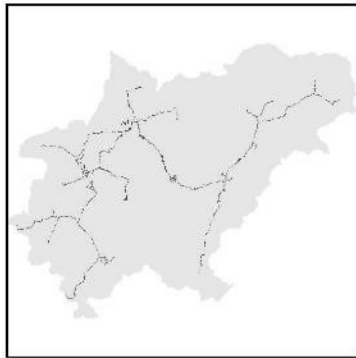
Sim. 6



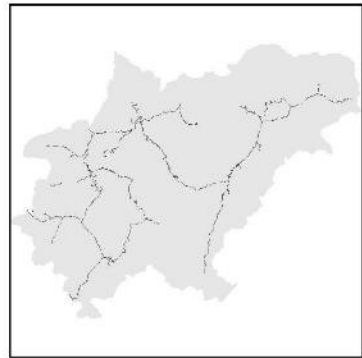
Sim. 7



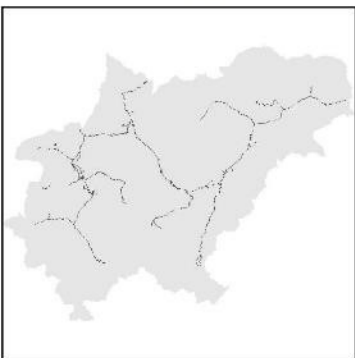
Sim. 8



Sim. 9



Sim. 10

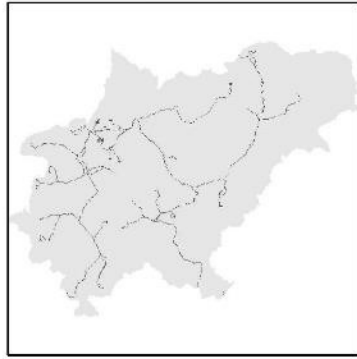


The
Recreational
Mode

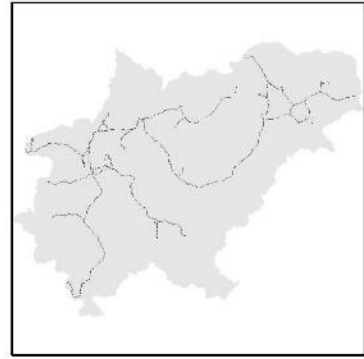
Sim. 1



Sim. 2



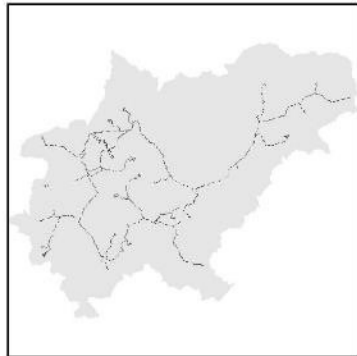
Sim. 3



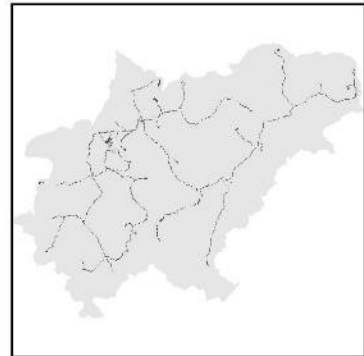
Sim. 4



Sim. 5



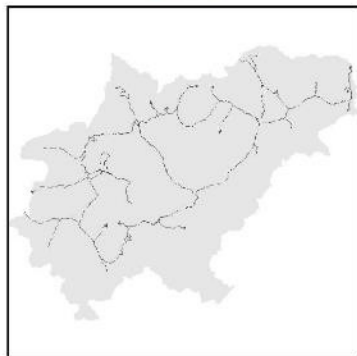
Sim. 6



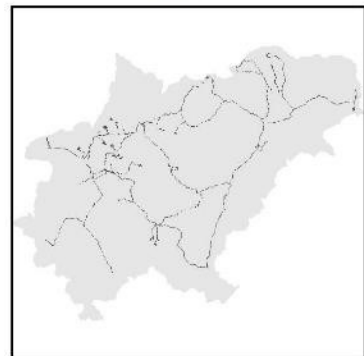
Sim. 7



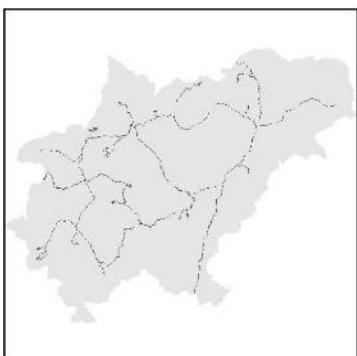
Sim. 8



Sim. 9

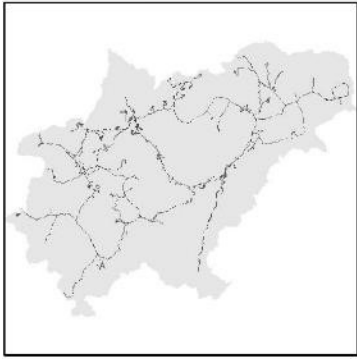


Sim. 10

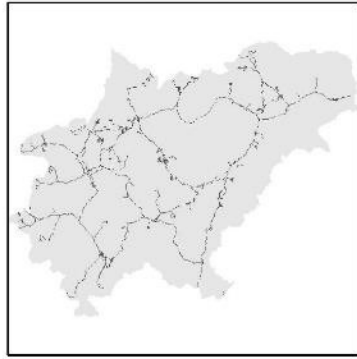


The
Experimental
Mode

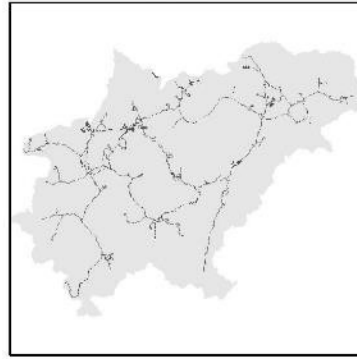
Sim. 1



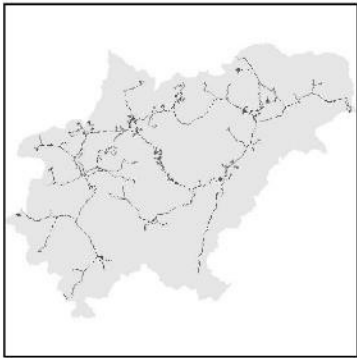
Sim. 2



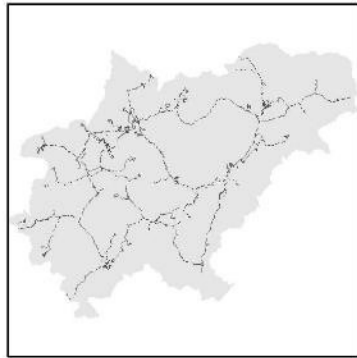
Sim. 3



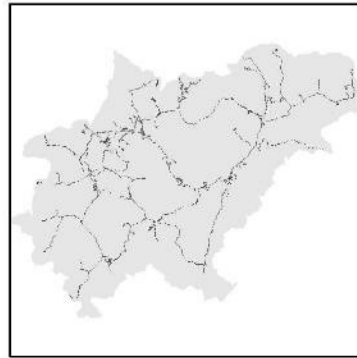
Sim. 4



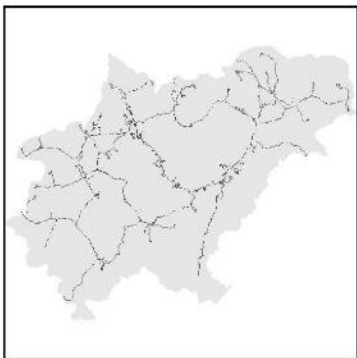
Sim. 5



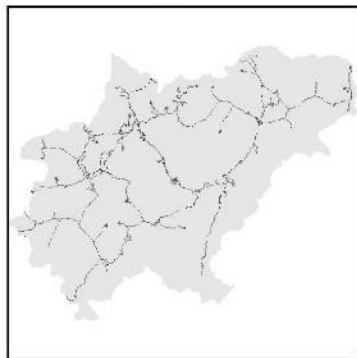
Sim. 6



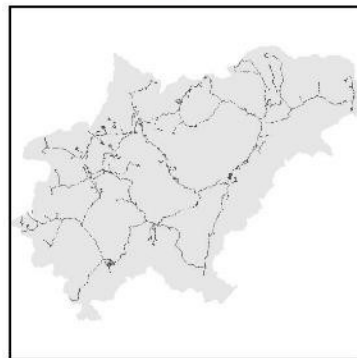
Sim. 7



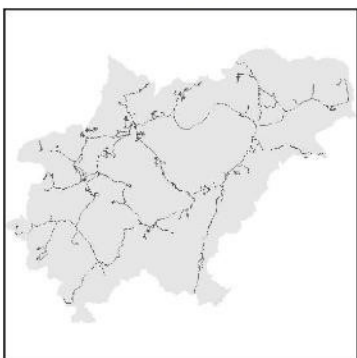
Sim. 8



Sim. 9



Sim. 10



All
Behavioral
Typologies

The recreational mode				
Simulation	Min	Max	Mean	Standard deviation
1	5	171640	2115.79	10569.59
2	5	179655	1919.66	9786.87
3	5	240120	1674.74	9950.73
4	5	154985	2098.81	10125.18
5	5	181420	2129.88	9969.33
6	5	146055	1936.41	9619.12
7	5	190550	1650.23	8718.92
8	5	133320	1978.98	9078.56
9	5	155748	1889.64	10038.12
10	5	103980	1730.29	8771.58
The diversionary mode				
Simulation	Min	Max	Mean	Standard deviation
1	5	102663	1429.58	4871.57
2	5	208528	1301.00	5428.63
3	5	270705	1687.31	7468.77
4	5	86934	1613.93	4842.42
5	5	231764	1207.40	5305.43
6	5	222272	1498.51	6550.85
7	5	75668	1514.96	5160.68
8	5	103360	1406.45	5356.26
9	5	127611	1315.13	5348.49
10	5	101592	1638.52	5597.65
The experimental mode				
Simulation	Min	Max	Mean	Standard deviation
1	5	72309	893.33	3619.91
2	5	78912	973.45	3919.08
3	9	140853	861.43	4696.92
4	5	77480	768.06	3666.78
5	9	108044	879.11	4326.55
6	5	138504	856.79	4274.28
7	5	56540	852.55	3453.43
8	5	173955	844.03	4361.86
9	5	67428	858.47	3171.69
10	5	91968	713.35	3614.93
All behavioral typologies				
Simulation	Min	Max	Mean	Standard deviation
1	5	171640	2350.06	8448.16
2	5	208528	2319.01	8516.32
3	5	270705	2481.90	9913.32
4	5	154985	2448.46	8060.10
5	5	231764	2376.32	8878.33
6	5	222272	2325.92	8697.55
7	5	190550	2331.57	7842.00
8	5	173955	2418.14	8355.65
9	5	155748	2294.01	8497.53
10	5	103980	2370.42	7897.67

Appendix C

Numerical records of graph (a) in Figure 9.

- (i) Simulated normalized time investment aggregated by municipality from the 10-simulation sum of the actual OR demand
- (ii) Normalized statistical records of tourists' observed overnight stays, from the AlpES project (data from the municipalities of Soverzene and Ospitale di Cadore were not available)

Municipalities by ISTAT code	Simulated demand (i)	Observed demand (ii)
25001	0.0755	0.0147
25003	0.1210	0.1410
25005	0.5633	0.2832
25007	0.1118	0.0844
25008	0.0469	0.0314
25010	0.0035	0.0041
25013	0.0381	0.0048
25014	0.0494	0.0079
25015	0.1640	0.0508
25016	1.0000	1.0000
25017	0.0552	0.0020
25018	0.1167	0.0149
25019	0.0709	0.3128
25023	0.0325	0.0526
25025	0.0101	0.0051
25027	0.0462	0.0007
25030	0.2283	0.3366
25032	0.0072	0.0113
25033	0.0173	0.0025
25037	0.0377	0.0012
25039	0.1423	0.0368
25043	0.0116	0.0019
25044	0.2025	0.1998
25046	0.0081	0.0014
25047	0.0093	0.0105
25049	0.0046	0.0014
25050	0.0778	0.0369
25051	0.2677	0.1292
25052	0.1376	0.1237
25054	0.0677	0.1110
25059	0.0134	0.0072
25062	0.0005	0.0061
25063	0.1129	0.0077
25065	0.0531	0.0341
25066	0.0988	0.0048
25067	0.0043	0.0087
25069	0.0000	0.0000
25071	0.0434	0.0103
25073	0.2207	0.1871

Discussion and conclusion to the dissertation

Efforts of the scientific community are increasingly driven toward assessing ESs under the paradigm of complexity as they are not individual and isolated entities but products of SES interconnected components in a multi-level infrastructure of multiple social and ecological elements. Traditional mapping and assessment approaches often lack such a wider and holistic perspective and neglect complexity, in this way leading to potential misunderstanding of the spatial pattern of ES provision, use or flow and demand, of their relationship and dynamics over time. This affects the way experts and researchers can effectively communicate spatial information to stakeholders and policymakers for developing policies, e.g. to manage ESs under the influence of land use and climate change. Therefore, this dissertation has aimed at studying ES mapping and assessment under the paradigm of complexity, starting from the wider context of my participation to the Interreg AlpES project.

The first paper of this dissertation was published as one task of the project, together with Eurac Research. We developed a novel methodology based on exploratory spatial data analysis to quantify the loss of information that occurs when upscaling spatial data to a coarser resolution, exploring in this way clustering trends, shape and position of aggregated units at multiple scales. In this study complexity is an issue that arises from the aggregation of spatial units in such a way that relevant information may be lost and therefore specific attention should be paid in the upscaling process. The methodology was in fact developed to avoid scale mismatches, information loss and statistical bias while mapping ESs and communicating spatial information to stakeholders and policymakers. Although aggregating heterogeneous real-world spatial data without affecting information pattern is a challenge far from being addressed, experts and researchers should always be aware of how ES pattern changes across scales. Specifically, the trade-off between information loss and upscaling for avoiding scale mismatches should be carefully considered in order to effectively integrate ESs in policymaking and land management strategies.

The second paper aimed at exploring temporal pattern and dynamics of the Alto Bellunese SES through a logistic regression model coupled with Markov chains and cellular automata to project land use and simulate the expansion of forests over grasslands up to 2030. In this study complexity was considered in the opportunity of modeling the mechanistic evolution of forests over time through cellular automata, which were applied to spread forest from existing land patches covered in woods to surrounding grasslands. This led us to infer that it is not likely to expect any relevant close-term consequences from temperature change on the provision of OR opportunities in the Alto Bellunese, on the basis of the land use pattern preceding the impact of the storm event of November 2018. Therefore, in this case, complexity behind LUC dynamics was essential to map the spatial pattern of the provision of OR over time under the current socio-economic trend, modeling infrastructure and available data.

The third paper aimed at mapping the summer non-rival demand for OR through spatial agent-based modeling, a methodology suitable to model emergent features of complex systems. In this study an ABM was developed to overcome traditional OR mapping approaches based on statistical records by dynamically allocating tourists' time invested in OR activities over a georeferenced fine-grain representation of the SES under consideration. Demand spatial pattern for OR emerged from the simulated complex interactions between ES beneficiaries, i.e. a set of tourist agents with a simplified behavioral diversity, and providers i.e. landscape units, along a 1-day length time window representing a typical summer day. Substantial agreement was found in the Alto Bellunese SES between the simulated demand and tourists' overnight stay records available at municipality level. Such results are promising for future applications of our ABM, e.g. for scenario analysis under climate change, and the suggested potential enhancements define a "road map" from the ES framework toward representing the complexity of an existing mountain SES.

To sum up, complexity played a major role in modeling OR provision and demand across all studies in the dissertation, trying to pave the way for ES modeling in the wider perspective of SES. In this sense, provision, use or flow and demand of ESs can no more be considered as standalone georeferenced elements but products of interconnected components of SESs, entwined in a dynamic multi-scale spatial and temporal representation. The methodologies developed in these studies aimed at discovering emergent features to help understand the complex systems under consideration and not neglecting

information that affects ES spatial patterns. Thus, the paradigm of complexity proved to be essential to bridge the gap between the complex evolving nature of SESs and the effective and reliable communication and visualization of spatial information in maps for policymaking and management of natural resources and ESs. Although relevant for advancing science in ES mapping and, in general, in sustainable landscape planning, research in this field is still in its infancy. As a matter of fact moving from spatial mapping in GIS towards spatio-temporal analysis of SESs requires high level technical skills i.e. programming e.g. R, the use of specific software e.g. Netlogo and k.Lab, computational resources and methodologies not yet fully exploited in the field. Among these, ABM proved its potential in the third paper where the discussion section deeply covered strength and limitations of the current modeling infrastructure and a series of potential enhancements to provide a glimpse in the complexity implicitly entwined in an existing SES and its dynamics (the Alto Bellunese case study). Ultimately, the dissertation hopefully has succeeded in inspiring the development of computational models for ES mapping and assessment and specifically ABMs for understanding the environment, its relationships with human societies and their dynamics over space and time.

Appendix to the dissertation I

Authors' contributions

Manuscript title: *Upscaling ecosystem service maps to administrative levels: beyond scale mismatches*

(published in Science of The Total Environment, Volume 660, 10 April 2019, Pages 1565-1575)

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- Conceived and designed the analysis
- Collected the data
- Contributed data or analysis tools
- Performed the analysis
- Wrote the paper
- Other contribution

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- Performed the analysis
- Wrote the paper
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- Contributed data or analysis tools
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Revised the draft and helped to improve its quality
- Other contribution

Manuscript title: *Modeling impact of forest expansion on outdoor recreation: a CA-Markov approach*

(currently unpublished)

Author 1: Michele Zen

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- Contributed data or analysis tools
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Author 2: Stefano Balbi

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Manuscript title: *An agent-based approach to mapping outdoor recreation demand: the case study of Alto Bellunese (currently unpublished)*

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Appendix to the dissertation II

Report of the contribution of the Veneto Region to the Interreg AlpES project ('AlpES' project, CUP: D52I16000220007), which aimed at mapping the provision of OR and fodder from alpine grasslands at high resolution within the Alto Bellunese, i.e. one of the pilot regions of the project. The publication is framed in collaboration between the Veneto Region (partner of the AlpES project), the Department of Economics of Ca' Foscari University and Etifor S.r.l., and it is cited in the dissertation as follows:

Zen, M., Giupponi, C., Pasutto, I., Burlando, C., Gallo, D., Da Deppo, I., 2018. Mapping and stakeholder engagement in the Alto Bellunese, Veneto Region, north-eastern Italy. Pilot activity in the Alto Bellunese. Report of Work Package 2. Region of Veneto, Venice, Italy.

Mapping and stakeholder engagement in the Alto Bellunese, Veneto Region, north- eastern Italy

– Final report –



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AlpES – mapping, maintenance and management

The Alpine Space (AS) is an important provider of ecosystem services (ES). These ES are one of the main pillars of a Green Economy in the Alps, a key driver of Alpine development and the focus of the next State of the Alps report. The population and different economic sectors such as tourism, forestry, agriculture, energy and transport in- and outside the AS derive benefits from ES. However, sectoral conflicts are becoming increasingly complex. AlpES builds on and provides testing and implementation opportunities for the ES concept, which is already established at EU level and can help in resolving conflicts among different interests, particularly in transnational contexts.

AlpES lasts from December 2015 to December 2018 and is co-financed by the European Regional Development Fund through the Interreg Alpine Space programme.

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1. Introduction

The present report focuses on two activities that the Parks and Forests division of the Veneto Region led in the pilot test area Alto Bellunese as part of the Interreg Alpine Space project AlpES “Mapping, Management and Conservation of Alpine Ecosystem Services”. After a short description of the Alto Bellunese, Chapter 2 reports on the methodology and results of the mapping and assessment of two selected ecosystem services in the Alto Bellunese. This work was led by the University of Ca’ Foscari. Chapter 3 reports on the participatory activities that were carried out in Val di Zoldo, Alto Bellunese, to raise awareness and inform the community about two selected ecosystem services. This work was led by Etifor, spin off of the University of Padova and the Local Action Group Alto Bellunese.

1.1. The Alto Bellunese pilot test region

The Alto Bellunese is in the Belluno Province, in the south eastern Alps. It has a population of 67,198 inhabitants, covers an area of 2,328.21 km² with a mean surface per municipality of 55.4 km² and has a density of 28.9 inhabitants/km² (2011 population census). It comprises the northernmost area of the Veneto region, and it includes 41 municipalities⁶ within five Mountain Unions (Comelico Sappada, Centro Cadore, Valle del Boite, Agordo, Cadore Longarone Zoldo). The local population is ageing and there is demographic decline (e.g. 24,42% are over 65 years of age; – 4,9% between 2001-2011). The territory is mainly covered with forests and semi-natural environments (94%), while the soil used for agricultural purposes is 4% and the urbanized area is 1%. Recent trends include increasing forest cover (over 60%) and decreasing pastures, associated with decreasing businesses in forestry, agriculture and husbandry (-52% Total Agricultural Area between 2000-2010; -47,3% of businesses in agriculture). Environmental values are high, with 58% of the area recognised as a Natura 2000 site. The natural values and beautiful landscape of the Belluno Dolomites make it a famous tourist destination. The area is recognized as a UNESCO World Heritage site and includes the Ampezzo Dolomites Regional Park and partially the National Park of the Belluno Dolomites.⁷

⁶ The municipalities represented in the study followed the criteria adopted at the pan-Alpine level in the framework of the AlpES Project. However, during the project, two administrative modifications occurred: the municipalities of Zoldo Alto and Forno di Zoldo were fused into the municipality of Val di Zoldo (February, 2016); while the municipality of Sappada became part of the Friuli-Venezia Giulia Region (December, 2017).

⁷ On October 29th, 2018, the Dolomites were affected by gale force winds and higher than normal rainfalls. This event has greatly impacted the landscape even though the impacts have not yet quantified. It is estimated that over two million cubic meters of wood were affected by the windfall.

1.2. The Local Action Group Alto Bellunese

Local Action Groups (LAGs) operate locally as part of the regional Rural Development Programme, identifying and implementing a local development strategy, which includes decisions on the allocation of its financial resources and the management. In the Alto Bellunese, the LAG Alto Bellunese manages a local development strategy and implements the 'Community-Led Local Development (CLLD) Dolomiti Live' as part of the Interreg V-A Italy – Austria. The LAG Alto Bellunese is an observer of the Veneto Region in the AlpES project and participated in the planning and organisation of the activities carried out in the municipality of Zoldo.

2. Mapping and assessment of two selected ecosystem services in the Alto Bellunese

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In the framework of the transnational Interreg AlpES project, the mapping and assessment of ecosystem services was carried out on two specific ecosystem services: fodder production and outdoor recreation activities. These were selected from a list of 8 ecosystem services identified by EURAC for mapping across the Alpine Space area during an initial workshop among all partners. To align with EURAC's definition of selected ecosystem services, Ca' Foscari and the Veneto Region decided to focus a more in-depth study on fodder production from high-altitude grassland for grazing and harvesting. Natural fodder production supports the fragile production system of the so-called "malghe" and, in general, of all livestock farms that adopt traditional and sustainable production methods. From past studies⁸, there has been a progressive reduction in the number of livestock farms in the Alto Bellunese, along with a reduced management of pastures and meadows, preserved through the ancient practice known as "alpeggio", i.e. summer transhumance to high elevation pastures. The decreasing use of pastures has led to a subsequent uncontrolled expansion of the forest, whose management is of primary concern yet requires economic investments and supportive policies.

In the Alto Bellunese, tourism plays a fundamental role in the local economy. Spatial mapping of locations where it is possible to enjoy recreational activities such as hiking, cycling and sports at recreational facilities, enables to identify areas important both for conservation and management as well as for the local economy. Therefore, spatial mapping of recreational services may inform local decision-makers on current uses and status of the territory for recreational purposes. It also enables comparison of relative performance among different municipalities of the area.

This chapter presents a simplified description of the methodologies developed by Eurac Research, the coordinator of AlpES, and their application at the municipality level across the pan-Alpine area. Within the Eurac methodology, each ES is quantified with a single value for each municipality. Eurac's methodology was then adapted to carry out a more accurate spatial analysis using locally available data. Thus, the work reported in this chapter aims at showing the mapping of the two ES with a spatial unit smaller than the municipality scale, and more specifically at a 25 m resolution (1

⁸ Giupponi, C., Ramanzin, M., Sturaro, E., Fuser, S., 2006. Climate and land use changes, biodiversity and agri-environmental measures in the Belluno province, Italy. *Environ. Sci. Policy* 9, 163–173. <https://doi.org/10.1016/j.envsci.2005.11.007>

pixel or cell of a map equals 25 m in the real world) or using spatial units with an equivalent geometrical accuracy (known as “vectors”). Lastly, a collaboration between Eurac Research and the Veneto Region enabled to assess the quality of the results concerning the Alto Bellunese at the pan-Alpine level for the outdoor recreation service. This step was necessary to understand the limitations and potential of quantifying ES at the municipality scale in a relatively small area such as the Alto Bellunese. We suggest referring to the scientific literature for further information about the topic⁹.

2.1. Methodology for mapping fodder production

Ecosystem Services represent the benefits for humans of the environment, as the goods and services that support the economy of our society. Understanding the processes and interactions between humans and the environment that affect the state and dynamics of ES, has become a priority for the development of local policies, with the aim of managing natural resources, landscapes or simply preserving the functionality of ES. Despite their complexity, ES can be quantified through numerical and measurable variables that define their provision, flow and demand at a given time interval:

- provision refers to the quantity of goods and services provided by an ES to society;
- flow refers to the actual quantity of goods and services used by human beings;
- demand refers to the quantity of goods and services that would be necessary to fulfil the needs of the society.

The cartographic representation of provision, flow and demand enables us to show the spatial quantification of ES. These can be used to implement the ES concept in decision-making processes and local policies.

2.1.1. Provision

Provision is estimated from a series of biophysical parameters – altitude, slope, temperature and precipitations – that quantify:

- the potential production of biomass from meadows and pastures;
- the actual production that can be used through grazing or harvesting.

The length of the period in which the metabolic activity of plants produces new biomass, defined as “growing season”, is assumed to be the number of subsequent days per year with mean daily temperature equal to or higher than 5°C. Sequentially, the mean in the period 1993-2016 of the number of days per year with mean temperature equal to or higher than 5°C is:

⁹ Grêt-Regamey, A., Weibel, B., Bagstad, K.J., Ferrari, M., Geneletti, D., Klug, H., Schirpke, U., Tappeiner, U., 2014. On the effects of scale for ecosystem services mapping. PLoS One 9, 1–26. <https://doi.org/10.1371/journal.pone.0112601>

- estimated at the sea level through a regression with the elevation of the Arpav weather stations;
- estimated at the sea level over the whole region at 25 m resolution, through a geostatistical procedure known as “ordinary kriging”;
- estimated at the actual altitude over the whole region.

The potential production is therefore calculated with statistical methods depending on the growing season, by considering different kinds of fodders (**Table 1**) derived from the land use map of the Veneto Region (year 2007, 3 level).

Table 1. Types of fodders related to the land uses detected in the assessed region.

Land use	CLC code	Forage type
Grass surfaces not subject to rotation	23100	4
Permanent meadows with spontaneous grass, not normally subject to man’s work	23200	4
Pastures located around “malghe”	32120	3
Different kinds of grazing grounds	32130	3
Shrubland	32211	2
Wetland	41200	2

Source: Land use map of the Veneto Region, level 3 (2007)

Potential production mainly depends on temperature, but it is also affected by other biophysical and climatic factors which set the effectiveness of biomass production in plant communities:

- precipitations: if the sum of rainfalls (estimated through ordinary kriging from Arpav data in the period 1993-2016) during the growing season is lower than 3.33 times the number of days per year with mean temperature equal to or higher than 5°C, the potential production is reduced by 10 times;
- slope: if the slope exceeds 10°, the biomass production is reduced by one factor (1-(slope/100));
- aspect: the exposure of mountain slopes to the sun trajectory around the earth is considered by reducing the biomass production of up to 20%.

Precipitation, slope and aspect are used to quantify the actual fodder productivity in the assessed region, starting from the potential one. Both potential and actual productivities are calculated in deci-tonnes of dry matter per hectare.

2.1.2. Flow

Flow is quantified over natural grasslands starting from the energy content (in Mega Joule NEL - Net Energy of Lactation per tonne of dry matter) of the forage types reported in **Table 1**. High-altitude pastures and meadows are derived from the land cover map of the Veneto Region (2007), considering all surfaces associated with the CLC codes 32120 and 32130. Flow is therefore calculated by multiplying the energy content by the actual productivity of the natural grassland at a 25 m resolution. An overall reduction of 15% is calculated to consider storage losses and those that occur while feeding cattle.

2.1.3. Demand

Fodder demand is quantified in Giga Joule NEL at the municipality level on the number of cattle detected within the municipalities (database ISTAT, 2010). The metabolic consumption depends on species and age classes. The demand is therefore estimated through the product of the number of cattle divided per species, the composition in terms of age classes for each species and their related daily metabolic consumption.

2.2. Results of mapping fodder production

Fodder provision from grasslands at a 25 m resolution is shown in **Figure 1**. Natural pastures are located along the high-altitude slopes (over 750 m of elevation) and have an overall low productivity. Pastures and meadows located in the valleys are limited in extent yet have a high productivity because of the presence of milder temperatures and geomorphological conditions suitable for the growth of vegetation. The flow and demand of fodder are estimated on available data. It was not possible to quantify them in a spatially explicit way (at 25 m resolution) because of the lack of updated information concerning:

- the location of high-altitude livestock farms;
- the cattle composition per each livestock farm.

Flow was calculated at a 25 m resolution. It is an overestimation because we could not consider the presence of topographic barriers that might limit the accessibility of cattle to pastures. Flow is therefore limited by the accessibility to pastures and meadows, which depends on the location of livestock farms. Demand was calculated on available cattle census data per municipality. The composition of the class “bovine animals” was estimated by drawing on South Tyrol data as they were considered representative for the same socio-economic conditions as the livestock farms within Alto Bellunese (majority of dairy farming).

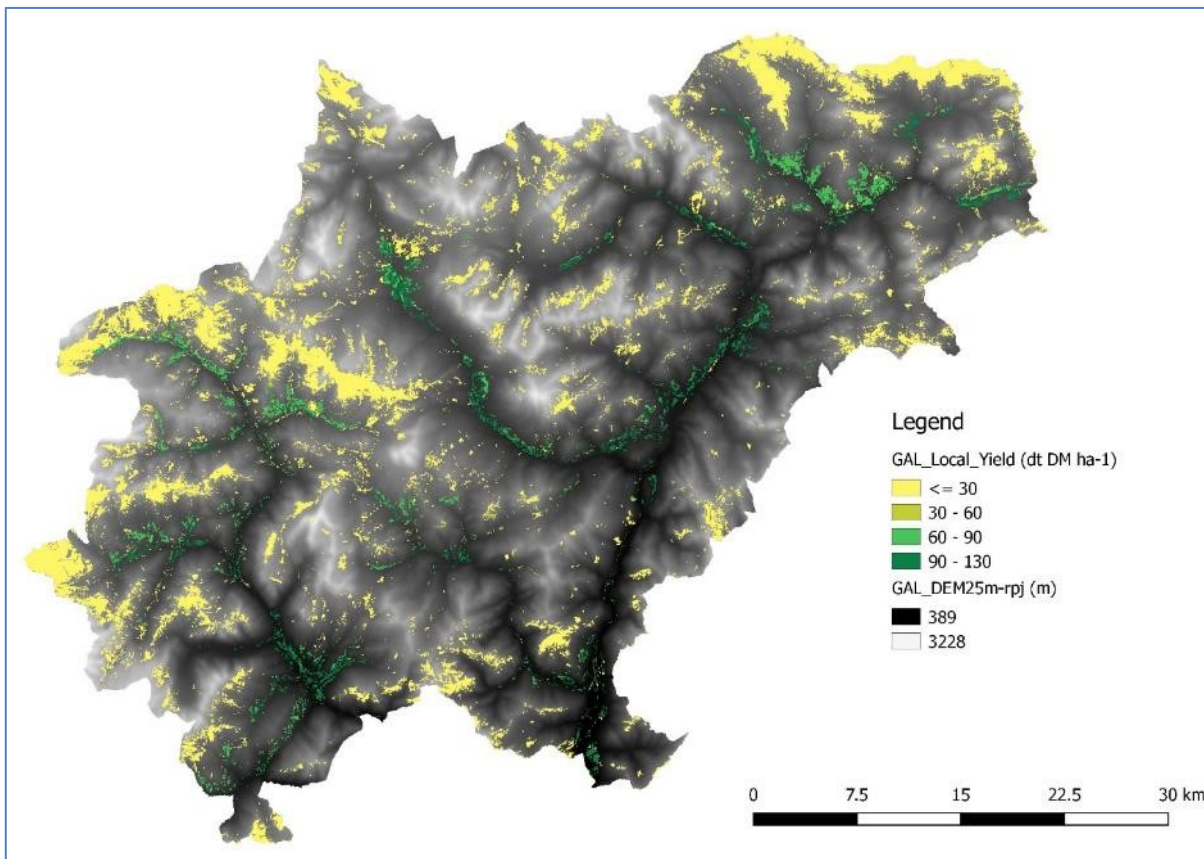


Figure 1. Index of the provision of fodder (deci-tonnes of dry matter per hectare); altitude (m).

2.3. Methodology for mapping outdoor recreation activities

2.3.1. Provision

Outdoor recreation activities are quantified through six indicators. Each one defines a component of the recreational potential of the assessed region:

- presence of protected areas: reclassification of protected areas (database CDDA10 i.e. nationally designated areas) and Natura 2000 network areas through the assignment of values between 0 and 1, where 0 implies lack of protected areas or inaccessibility, while 1 represents the highest value of recreational opportunities;
- degree of anthropization of the territory, also known as “Hemeroby index”: reclassification of land use classes drawn from a land cover map of the Veneto Region (year 2012, level 3), through the assignment of values between 1 and 7, where 1 represent the lowest level of anthropization while 7 defines the highest level of human influence;
- distance from water bodies: calculation of the Euclidean distance (length in meters) from the main water bodies (lakes) present in the studied area;

¹⁰ <https://www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-12>

- degree of landscape heterogeneity: number of land use classes located in a squared window of 1 km per side in the surrounding of each pixel of a land use map;
- terrain roughness index (TRI): the roughness is given by the differences among adjacent elevations in an altitude map;
- peak density: combination of altitude, TRI and curvature (second derivative of the elevation that represents the local morphology of valleys and mountain slopes), to identify the number and the location of the main mountain peaks.

The maps associated with each listed indicator are rescaled to make their range vary between 0 and 1 (where 1 defines the highest contribution to the recreational potential). This procedure is referred to as “normalization”. Normalized maps are averaged by assigning equal weight to each indicator. The result is the outdoor recreational potential, calculated without accounting for the actual enjoyment of benefits from the ES. The recreational potential is therefore recalculated by considering the accessibility or, in other words, the time required to travel within the assessed region from the main urban areas. Accessibility is normalized between 0 and 1 and multiplied with the potential to quantify the actual provision of recreational services.

2.3.2. Flow

The flow of recreational services is estimated through the social media Flickr, on metadata related to the photos shared by the website users and georeferenced in the assessed region. Data is elaborated in such a way as to remove photos taken in urban areas and duplicated photos (e.g. two photos taken in sequence from the same user in the same place), depending on unique combinations of username, day and location. The elaborated data represents the spatially discrete estimation of the number of tourists in a defined time interval within the assessed region (tourists per day in the period 2008-2016). Data on the actual presence of tourists identified by their related unique combination is then converted into maps by assigning to each pixel the number of tourists located within 1500 m around each pixel. The count is worked out separately for each year in the time interval 2008-2016 by considering: the whole number of tourists per year; those only detected in the summer period; those detected in the winter period. The values of each map are normalized between 0 and 1 and aggregated in the time interval 2008-2016 to obtain three maps, each one representative for one period of the year: annual flow, summer flow and winter flow.

2.3.3. Demand

Demand is estimated on the overall number of overnight stays, annually recorded within the municipalities. Recreational demand from tourists is thus quantified in the period 2008-2014, proportionally to the number of days spent in the location. Consequently, tourists are equated to residents and their recreational demand is added to the local population. The overall demand is calculated at the municipality level, normalized and, at last, divided by the area (m²) of each

municipality. This way, recreational demand is quantified both in absolute terms and proportionally to the surface of municipalities.

2.4. Results of mapping outdoor recreation activities

The recreational potential is concentrated in remote areas, near lakes or where there is a high roughness. In the north eastern part of the Alto Bellunese, several protected areas strengthen the overall recreational potential of the area. In other areas, the biophysical and functional factors identified by the six indicators described in the methodology section provide a greater heterogeneity of recreational opportunities. Provision of recreational services (**Figure 2**) depends on potential and distance from villages. Accessibility is clearly opposite to the level of human influence, so the highest values of actual provision are found in areas that show both a high recreational potential and a high level of accessibility.

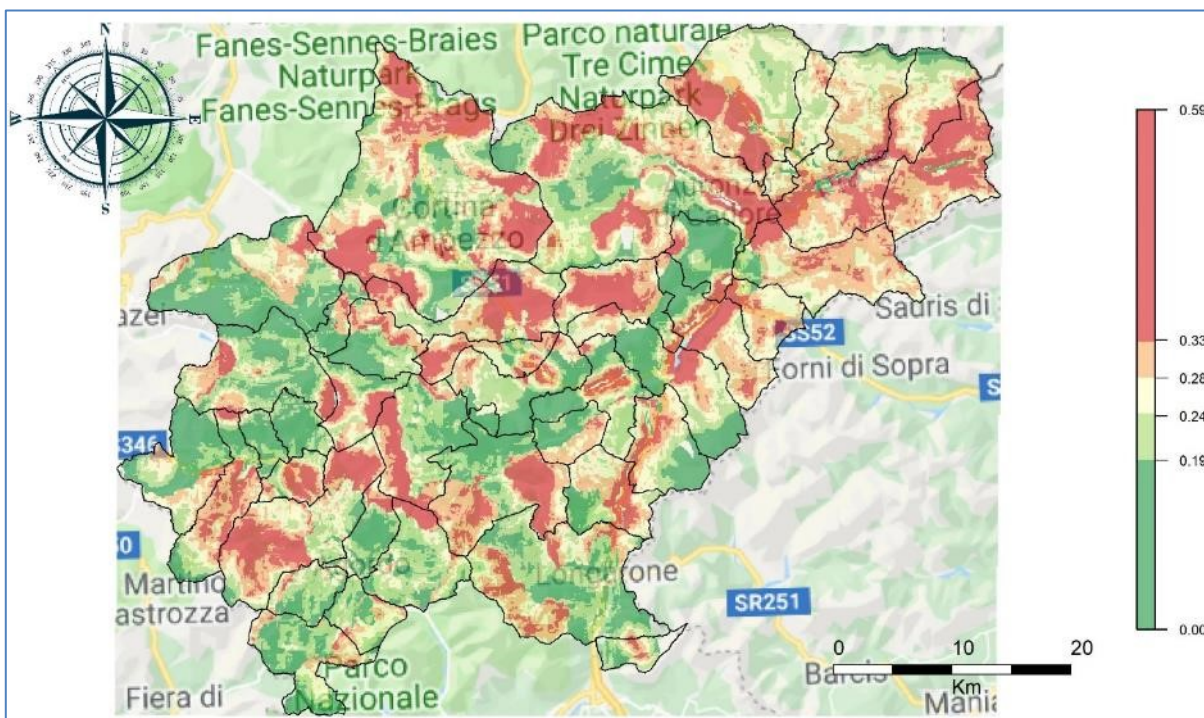


Figure 2. Index of the provision of recreational services (0-1); background picture taken from Google Maps.

Flow of recreational services (**Figure 3**) is concentrated near villages, roads, cycling paths and footpaths, and near main recreational facilities (e.g. ski resorts). Proximity to urban areas and roads is substantial in the winter period while in the summer period, the presence of visitors is more widespread across the region.

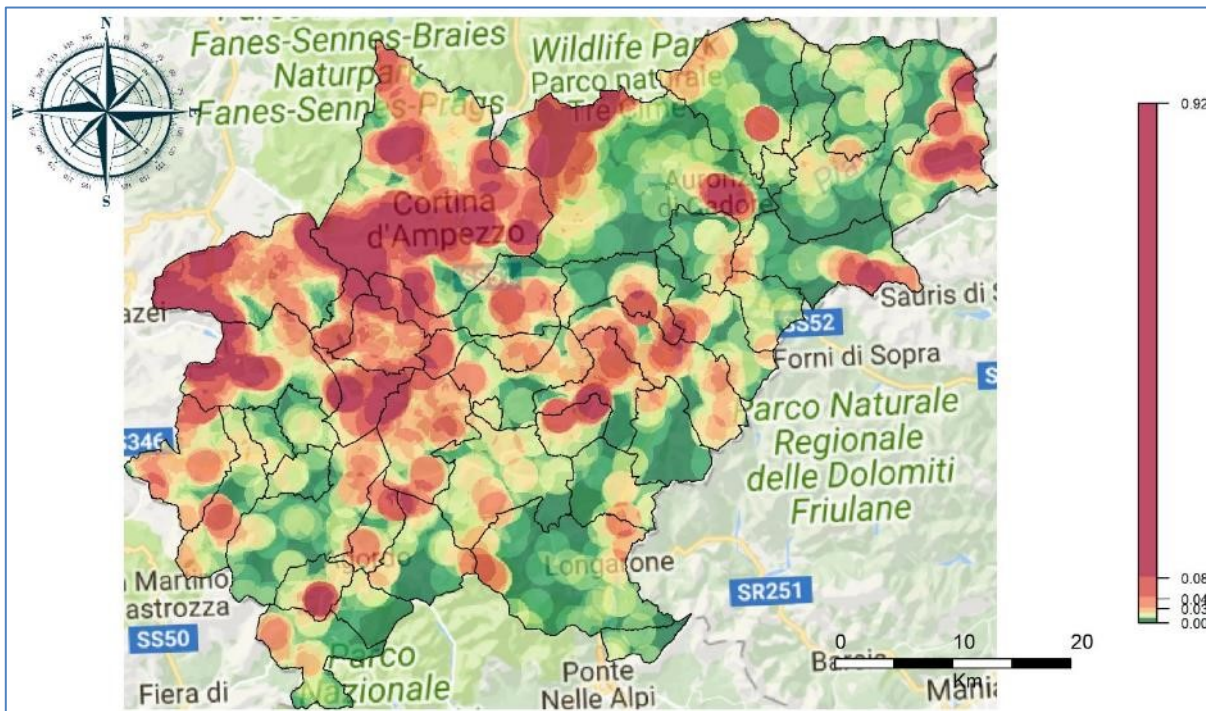


Figure 3. Index of the flow of recreational services (0-1); background picture taken from Google Maps.

In absolute terms, demand for recreational services is concentrated in the municipalities of Cortina d'Ampezzo because of a high number of tourists, and Longarone, because of a high number of residents. Proportionally to the municipality area (**Figure 4**), the municipalities of Agordo and Cencenighe Agordino show the highest demand per m². Demand data for the municipalities of Soverzene and Ospitale di Cadore were not available. Finally, the lack of spatially discrete data such as the location of the number of overnight stays per hotel made it impossible to quantify the outdoor recreation demand at a 25 m resolution.

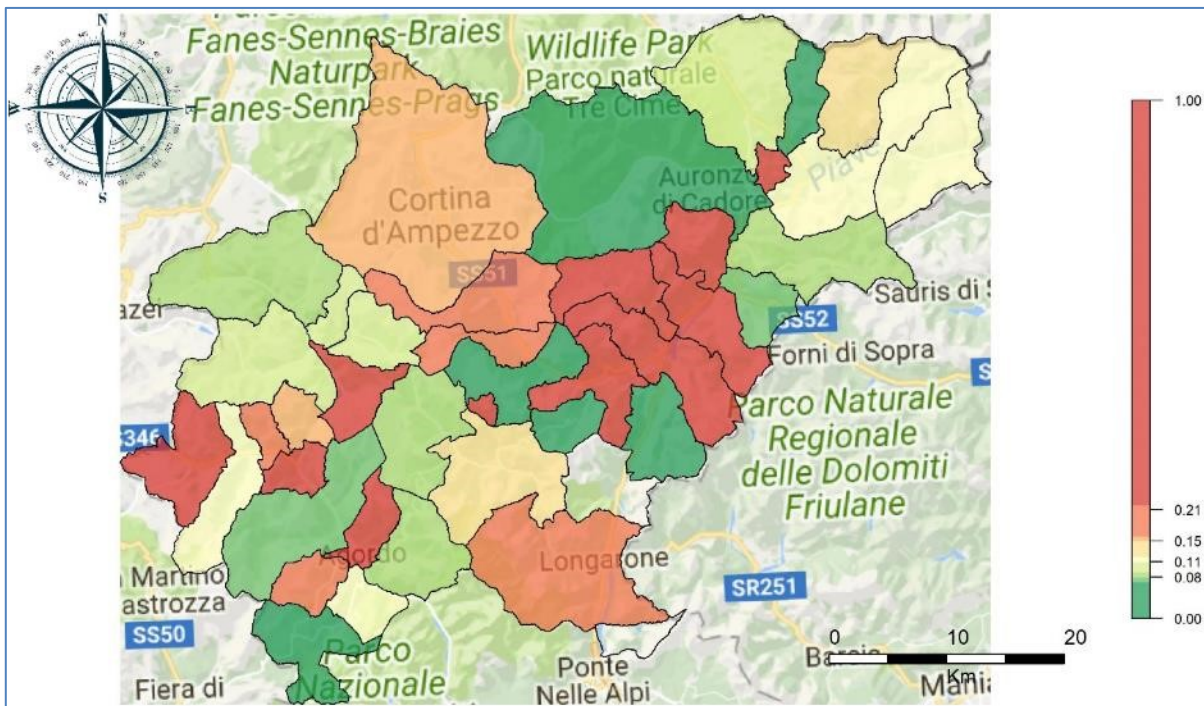


Figure 4. Index of the demand for recreational services per m² (0-1); background picture taken from Google Maps.

2.5. From the municipality to the local level: potential and limitations of the pan-Alpine approach in the Alto Bellunese

The AlpES project had the objective of quantifying a selection of ES at the municipality level. A single value was calculated per each municipality, representing the performance of a certain ES within its area. This estimation aimed at quantifying provision, flow and demand at the municipality level, which is the administrative level to which one or more authorities responsible for the management of ES can be matched. On the one hand, the aggregation, or the arithmetic mean, of spatially explicit values (each one matched to a pixel) to the municipality level simplifies the implementation of the concept of ES in local policies. On the other hand, it leads to a loss of spatial variability of the mapped ES.

The methodology and the results of the study carried out in the Alto Bellunese enabled to present the spatial variability of two selected ES at high resolution within the Alto Bellunese, in such a way as to compare them with the ES estimated at the pan-Alpine level. This comparison was implemented by applying exploratory spatial data analysis techniques to estimate the spatial autocorrelation per each sequential aggregation step, between disaggregated results at 100 m resolution and the municipality level. The study was carried out in collaboration with Eurac Research

over three different regions of the Alps and specifically on the outdoor recreation activities. Concerning the Alto Bellunese, the results show that the high roughness interspersed with narrow valleys results in a mosaic of geomorphological features and consequently in a wide heterogeneity of recreational values. These take the shape of small clusters (associations of similar values) distributed over space that can be detected only in high resolution maps. Nevertheless, the widest clusters proved to be comparable with those detected at a municipality level. By extending these considerations to a pan-Alpine level, we may conclude that:

- the aggregation of the outdoor recreation values at the municipality level implies the loss of the local heterogeneity;
- the municipality scale can represent the general trend of recreational opportunities over wider areas (such as the whole Alpine arc);
- the quality of the aggregation depends on the specific geomorphological features of the region being assessed.

3. Stakeholder engagement in Val di Zoldo, Alto Bellunese

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^bRegione Veneto, ^cEtifor, ^dLocal Action Group Alto Bellunese

Stakeholders hold different knowledge and understandings about nature and ecosystem services, with different views on best ways to manage, conserve and support their valorisation. In the Veneto Region, the AlpES project supported awareness-raising activities on the concept of ecosystem services, selecting forest expansion and recreation as key themes to facilitate in-depth workshops related to best ways to valorise mountain landscapes. The Veneto Region, a partner of the AlpES consortium, collaborated with the University of Padova, the Local Action Group (LAG) Alto Bellunese, the Municipality of the Val di Zoldo, and Etifor, spinoff of the University of Padova, to promote awareness and identify development projects aimed at the valorisation of ecosystem services. This final report documents the participatory approaches that were carried out in Val di Zoldo, a selected focus area of the pilot region Alto Bellunese, to better inform about ecosystem services in the local context.

The Veneto Region teamed up with University of Padova and Etifor, a spinoff, to develop the stakeholder engagement strategy in the Alto Bellunese. In early 2017, the Region and its team held meetings with the LAG to introduce the concept of ecosystem services, rank the relevant ones for the territory of the Alto Bellunese, and co-develop an approach to inform about and communicate the ES concept to a wider territorial audience. Further, the selected ecosystem services, the area for conducting the information and awareness-building activities and the specific communication target were decided. Specifically, a series of community-based workshops were planned in Val di Zoldo to inform the community (e.g., public institutions, private entrepreneurs and citizens) about two ecosystem services from the list of eight ES identified by Eurac Research: biomass production from grasslands (ES 2) and outdoor recreation activities (ES 7). Both ES were identified as a potential issue on which to develop new opportunities for better management and local development. In the case of ES 2 (biomass production), the LAG specifically identified forest expansion, rather than biomass use, as a theme on which to base community workshops.

Several meetings were then carried out with the LAG Alto Bellunese and the mayor of the municipality of Val di Zoldo. The workshops were all organized in the municipality. The first set of workshops was carried out between June and July 2017 and focused on forest values and management of forest expansion, while the second set was carried out in October and November 2017 and centred on recreational services. Following community-based engagement, the LAG

expressed support for ongoing work on the identified activities through the CLLD Dolomiti Live programme, beyond and independently of the AlpES project, while in 2018 the Veneto Region supported a continuation of the discussion on recreation and tourism with public and private stakeholders. Etifor thus conducted four meetings with the local private and public stakeholders involved in the tourism system, including the municipality, the tourism consortium, the association of hotels, and the alpine club, to identify the tourism products, their strengths and weaknesses, and present a plan of action to the Destination Management Organisation (DMO) Dolomiti, in the Province of Belluno.

3.1. Community-based engagement on the theme of forest expansion

The first set of three workshops was carried in the municipality to discuss issues related to forest resources and management in the widest possible terms. The local municipality was contacted to explain the rationale of the workshop within the AlpES project. The municipality offered a meeting space and widely advertised the event of the three meetings both online and in print. The first meeting was promoted as a conference-show, designed to introduce the theme of the ‘forest’ to a wider audience from anthropological, cultural and literary perspectives. It was titled: [“Follow me, there’s a path in the woods”](#) (Figure 5). Actors Paola Brolati and Charly Gamba masterfully performed a selection of literary excerpts on the cultural values of the forests.



Figure 5. Flyer and scenes from the performance in Fusine di Val di Zoldo. Photo credits: A. Pra

The performance was followed by two technical workshops. While the first show was attended by close to 80 people, the workshops were attended by 15-20 people each.

The first workshop focused on an overview of the changing dimensions of mountain forests, highlighting the abandonment of both agricultural and forest lands, with a consequent doubling of forest lands and halving of forest harvest in Italy. Ecosystem services were introduced as a new emergent theme which could help support forest management. The example of Payment for Ecosystem Services was used to show how ecosystem services could be managed through a variety of different public-private approaches, including compensation measures. The second workshop focused on opportunities for developing short value chains from non-timber forest products.

In the round table discussions, participants highlighted the need to identify and develop the non-timber forest products from the valley, promote the idea of ‘cultivating biodiversity’ (also in terms of heritage species), as well as share knowledge and best practices. Some entrepreneurs saw potential in combining a productive activity such as timber harvesting, with a cultural activity, such as telling stories about timber harvesting. On the other hand, lack of entrepreneurship and a detailed analysis of the potential opportunities were identified as two key challenges. Participants also highlighted complex issues around timber harvesting, and import-export relations. Land fragmentation was also highlighted as an issue, although new legislation could support common management including of private lands. Participants discussed the roles of the municipality, private entrepreneurs and the University for providing common vision and a strategy for moving forward.

The results of the discussions highlighted how, despite a rich endowment of forest resources and a potential opportunity, temporal trends in forest expansion and the consequent decline in grasslands are seen as a missed opportunity for local development. While analysing these complex relationships was beyond the scope of the AlpES project in Val di Zoldo, the results showed how forest landscapes are either unmanaged, underutilized or benefits flow outside of the territory. Future activities in this sector could be supported beyond the scope of the AlpES project through the LAG’s CLLD Dolomiti Live programme.

3.2. Community-based engagement on the theme of tourism

A series of three workshops were held in the fall to discuss the relevance of recreational services. These workshops were advertised both through the municipality’s newsletter as well as in print (**Figure 6**). Trees with the title “Cultivating tourism to develop the territory” were placed in two of the major towns of the valley to ask community members their own thoughts on the sentence: “Tourism in Val di Zoldo is...”. Over 45 responses were received. Residents and tourists first provided a written comment to the survey by proposing key words such as *nature*, *culture*, *family*, as well as *resource*,

opportunity and maintenance of the territory. These themes were then used as the basis for discussing local needs and necessary steps to organize the tourism product.



Figure 6. Flyer and survey for promoting the workshops on recreation and tourism. Photo credits: C. Burlando.

During the first meeting, a first introduction to the AlpES project and the rationale for connecting the recreational ecosystem service to tourism was followed by a round table discussion with the Region, the Destination Management Organisation (DMO), the LAG, the municipality of Val di Zoldo and the tourism consortium. The representatives were invited to reflect on:

- The contributions of the AlpES project to the tourism destination Val di Zoldo;
- The type of tourism required for supporting local development;
- The needs of the municipality within a tourism system;
- The needs of private entrepreneurs;
- The functions of the DMO.

During the second meeting, participants were invited to reflect on tourism as a common good, which depends on the territory and can no longer develop disjointed from its resident community. Two round tables were carried out with entrepreneurs and the community to discuss the needs of the

tourism system. Both discussions highlighted awareness of the need to work together and share ideas, as well as the need to ensure better organization, professionalism and engagement of youth. During the third meeting, participants were invited to reflect on the tourism product as the “expression, and not the addition, of a series of goods and services which render the experience of the tourist accessible in space and guaranteed over time”. Participants were then asked to discuss on the resources, organisation, themes and products in the valley (**Figure 7**).

The series of meetings that the Veneto Region and the LAG Alto Bellunese developed within AlpES aimed at identifying possible projects for local development, based on the valorisation of the recreational ecosystem service through the LAG’s CLLD Dolomiti Live programme.



Figure 7. Round table at Fusine di Val di Zoldo and roundtable discussions. Photo credits: I. Da Deppo

Over the course of the three meetings, the project enabled to highlight opportunities for developing a tourism quality product while identifying possible obstacles. Following the meeting, the LAG Alto

Bellunese, the municipality of Val di Zoldo, the Veneto Region and Etifor met to take stock of the workshops. The LAG and the municipality identified two cooperation projects:

- A pilot project to address public mobility in the valley for both residents and tourists, based on knowledge exchange with from other areas in Austria with similar territorial challenges, analysing actual needs and testing possible solutions;
- A project to valorise the Unesco site Mount Pelmo and its dinosaur footprints through a cooperation project with northern Germany.

Both projects emerged from the workshops and were a concrete response to community needs. Finally, the Region also proposed a continuation of the AlpES activities to strengthen the organisation of the tourism system in the municipality of Val di Zoldo, and develop a constructive dialogue with the DMO Dolomiti, which was engaged in the implementation of the Territorial Marketing Plan for the Province of Belluno.

3.3. Towards a strengthened organization of tourism in Val di Zoldo

The need to improve the tourism organisation in Val di Zoldo led to four meetings with both public and private stakeholders to identify the products and priorities for tourism management. Specifically:

- development and sharing of a new tourism concept for the valley;
- identification and development of the tourism products that valorise the specificities, the community and the resources of the Val di Zoldo;
- a governance model to support local sustainable tourism;
- an action plan to valorise the proposals raised during the community meetings.

The dialogue enabled to identify the strengths and weaknesses of two of the key tourism products in the valley – family and trekking – and to prioritise management interventions. The latter included: a) the development of a corporate identity for communication and marketing, b) the day-to-day management of the tourism office and the implementation of the tourism tax, c) the training of new professionals and d) the strengthening of protocols ensuring the quality of the tourism products. Lastly, the meeting with the DMO Dolomiti served to discuss responsibilities and synergies between levels of governance on issues such as divisions of functions, marketing and promotion.

3.4. Concluding remarks

Stakeholder engagement activities first focused on introducing the ecosystem services terminology, sharing information and promoting community perspectives on the ES identified as relevant for Val di Zoldo. To do this, the discussion on ecosystem services was narrowed to two ES that are of relevance to the area, namely biomass production from grasslands and tourism. The first theme was discussed in the community in terms of forest expansion. These discussions were developed through participatory community workshops. The first set of workshops focused on innovative management of forests. The second set of workshops focused on tourism.

The discussions that emerged from the workshops provided the LAG with the opportunity to identify those activities and actions that could support rural development projects, specifically, actions for the future valorisation of tourism in the valley. The local development agency was able to draw on emergent needs and propose two cooperation projects promoting local public mobility and the valorisation of a Unesco World Heritage site located in the Pelmo Mountain. These projects have been developed together with the local municipality.

The ecosystem services concept was also important to highlight the values of natural resources in the management of forests and in the organisation of a tourism destination. Forests, nature and landscapes are an opportunity for local development. Within the ecosystem services literature, payment for ecosystem services enable the valorisation of services and benefits to humans which would otherwise not be recognised. Similarly, the organisation of a tourism destination – and more specifically the organisation of public and private actors – is the first competitive factor in a destination. Within current destination management models, payments rendered through the tourism tax (if levied from the visitor) or operator tax (if levied from the operator) are used to support the day-to-day management of the destination. In the case of AlpES, discussions on the theme of tourism were clearer when using the more internationally recognised terminology of destination management and destination marketing as an approach which supports the community, local development through private and public partnership and collaborations across different levels of governance.

The evolution of tourism demonstrates that resources are not the only ingredient for the success of a territory. The combination of an ecosystem services approach and a destination management can help focus attention on the social values of the recreational ecosystem service and on the mechanisms that can support their proper management. Through AlpES, stakeholder engagement activities in Val di Zoldo contributed to raise attention on the need for a clear organisational governance structure for tourism. Interactions with the Destination Management Organisation Dolomiti have enabled this discussion to move forward.

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To conclude, not less important, I'd like to thank the administrative staff of the Department of Economics and of the PhD course in Science and Management of Climate Change, for their amazing support in managing and organizing students' activities.

Estratto per riassunto della tesi di dottorato

L'estratto (max. 1000 battute) deve essere redatto sia in lingua italiana che in lingua inglese e nella lingua straniera eventualmente indicata dal Collegio dei docenti.

L'estratto va firmato e rilegato come ultimo foglio della tesi.

Studente: Michele Zen _____ matricola: 822947 _____

Dottorato: Scienza e Gestione dei Cambiamenti Climatici _____

Ciclo: 32° _____

Titolo della tesi: Understanding complexity in ecosystem service assessment: perspectives and innovations in spatial analysis _____

Abstract:

Research efforts are increasingly driven toward assessing provision, use and demand of ecosystem services as interconnected components of complex social-ecological systems. The aim of this dissertation is to contribute to the literature about mapping and assessment of ecosystem services through a series of methodological applications under the paradigm of complexity. In the first paper, exploratory spatial data analysis is used to quantify the loss of information that occurs when upscaling spatial data to a coarser grain. The second paper explores temporal pattern and dynamics of land use change in the Alto Bellunese (South-Eastern Alps, Italy), to simulate the mechanistic evolution of forests and assess the provision of outdoor recreation opportunities over time. The third paper proposes a novel methodology for mapping summer non-rival demand for outdoor recreation, through spatial agent-based modeling.

Estratto:

Ricerche recenti tendono a valutare fornitura, uso e domanda di servizi ecosistemici in quanto componenti interconnesse di sistemi socio-ecologici complessi. Questa tesi ha lo scopo di contribuire alla letteratura in materia di mappatura e valutazione dei servizi ecosistemici mediante una serie di applicazioni metodologiche definite dal paradigma della complessità. Nel primo articolo, metodologie di analisi esplorativa dei dati sono impiegate per quantificare la perdita di informazione che si verifica aggregando dati spaziali a risoluzioni inferiori. Il secondo articolo esplora dinamiche e pattern temporali di cambiamento dell'uso del suolo nell'Alto Bellunese (Alpi Sud-orientali, Italia), per simulare l'evoluzione meccanicistica delle foreste e valutare nel tempo la fornitura di opportunità ricreative all'aria aperta. Il terzo articolo propone una nuova metodologia per mappare la domanda estiva di attività ricreative in assenza di competizione, mediante modelli ad agenti spaziali.

Firma dello studente

