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Winescape aesthetic perception assessment

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Abstract

The term Winescape represents all the elements that are related to a wine landscape. The thesis investigates the aesthetic-perceptive characteristics present in the Winescape that affect consumers' behavior and intentions. Knowing what they are and their characteristics can support public decision-makers who want to increase their territory or cellar competitiveness, as these are some of the reasons that guide the choices of consumers and visitors.

The term Winescape has a dual meaning based on the relative reference scale: evaluating its macro-dimension, the term refers to the wine region, while taking into consideration its micro-dimension, it refers to the cellar environment.

The most frequently chosen method to identify users' aesthetic perceptual elements is the administration of surveys to the reference target. However, it is a procedure that has increasingly evident limits. Given their complexity, they are limited to a small number of participants and have a very high expenditure of time and resources. Furthermore, the user's response may not be completely impartial, marred by the awareness of being subjected to a questionnaire.

The thesis is based on the understanding of these limits to develop alternative solutions and methods. This, defining a diversified approach for each of the distinct meanings of the term Winescape.

The thesis's solution to identify the aesthetic components that influence user behavior in the macro-dimension of the term Winescape refers to the concept of cultural ecosystem services (CES) and the intangible benefits that both inhabitants and residents can enjoy. Tourists.

An indicator to get to know CES spontaneously by the general public is the analysis of photos shared and geotagged on Social Media, such as Flickr.

Furthermore, in the micro-dimension, the process is different: Neuromarketing turns out to be the most promising alternative in research on perception and emotions, which, thanks to this technology, are registered unconsciously and therefore free from preconceptions alterations that are instead inevitable in the traditional methodology. The focus is on providing the manager of a winery with a useful tool to enhance the wine product's quality and the environment and architecture of the winery itself. Offering a unique and emotional experience is the ultimate goal to establish a long relationship with visitors and induce the latter to repeat the visit and become loyal consumers.

Summary

CHAPTER 1

Introduction

Bitner defined servicescape concept in 1992, and he underlines that it is composed of three different dimensions 1) Environmental condition 2) spatial layout 3) signs, symbols, and artifacts; these elements influence the humor and behaviors of users. According to these aspects, users carry out behaviors of avoidance or approaching respect to "product" (Johnson & Bruwer, 2007)

Winescape derives from servicescape concept; it integrates the interaction between landscape, buildings, and heritage. With this term, we refer to physical elements present in the wine region as the vineyard, cellar door, landscape, and immaterial aspects, aesthetical values, and cultural heritage:

Very little research describe and measure the specific feature of Winescape that influence ecotourists or consumers' behavior and intention. These elements would be an essential support tool for public decision-makers who want to increase their territorial competitiveness.

Tourist choice is related to people's perception of aesthetic beauty, cultural heritage, spirituality, and inspiration(Getz & Brown, 2006). Aesthetic motivation motivates wine tourist behavior (Bruwer & Alant, 2009; Carmichael, 2005; Cohen & Ben-Nun, 2009). The wine tourism context's aesthetic experience is useful in predicting positive memories and develop destination loyalty (Quadri-Felitti & Fiore, 2013)). The winescape manages to visit aesthetically pleasing environments (Bruwer & Alant, 2009). More and more, a successful marketing strategy used to safeguard the landscape features is to invest in tourism's promotion based on identity feature of the landscape (D. B. Van Berkel & Verburg, 2011); quantifying the cultural services provided by landscapes can therefore help to understand the options for future development that preserve and develop tourism resources

The choice to buy wine depends not only on the quality of the wine itself but also on the perception that users have of the place of production (de Francesco et al., 2012; Jaeger, 2013; Yang & Paladino, 2015). The choice of wine depends on multiple factors, based on product and other links to regional value as landscape aesthetic perception, cultural heritage. A beautiful place can raise brand loyalty to a specific brand and influence the choice. The wine landscapes are a quality brand for the region (Daniel et al., 2012).
In winescape analysis, the term is also used to indicate two different approaches (Thomas et al., 2010): the macro approach, which looks at the wine landscape in the wine region or on the scale of a wine route (predominant in the literature on wine tourism, e.g. (Getz & Brown, 2006), and the micro approach, which focuses on the environment in a winery

Tourist and consumption choices of individual users are influenced by a positive perception both of the winescape intended as a wine region (macro approach) and intended as a cellar (micro approach). A positive experience within the wine-growing region entices users to come back again.
A positive experience inside the cellar increases the bond with the territory and brand loyalty towards the product.

A successful marketing strategy is not only wine, but all define its value and significance. Wine region and cellar door's perception is a focal point of these strategies.
To investigate which elements are positively perceived within the wine region, reference is made to CES's concept. Simultaneously, neuromarketing methods are used to study the positively perceived elements in a single winery.

WINESCAPE MACRO APPROACH

For the macro approach, there are few empirical studies aimed at identifying and measuring specific attributes of the winescape that influences the intentions and behavior of wine tourist

Winescape is strictly referred to the concept of Cultural landscapes, a landscape that has been affected, influenced, or shaped by traditional agricultural techniques, locally and historically adapted, by familiar. They often contribute to a unique aesthetic character and support a co-produced human-ecological system.

There is a strict link between the wine regions and cultural landscape; because the regional wine setting affords both material products as grapes and wine and a variety of CES that both inhabitants and tourists can benefit from it. Vineyards are an inspirational place where people can think and produce pieces of art; they have high aesthetic values; they have rural identity configurations that create landscapes representing cultural heritage. These intangibles material are classified as Cultural ecosystem services (CES).

CES are one of the four categories of ecosystem services defined in 20025 by the Millennium Ecosystem Assessment in 2005.

CES contain the non-material benefits people obtain from ecosystems. through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experience, and which include aesthetic, spiritual, educational, and recreational services (MA,2005)

Today, politicians do not consider CES in economic valuation and landscape planning (Winkler & Nicholas, 2016). However, for rising landscape awareness, it is fundamental to incorporate CES in decision making. For this reason, it is essential to provide tools providing public decision-makers with tools that quantify, identify, and map CES within the wine region.

Recently, in the literature, to overcome limits of stated preference measures, a substitute indicator to know the revealed preferences of the general public on panorama aesthetics and leisure activities is geotagged photos upload on Social Media.

Flickr is the most suitable for environmental sciences studies. Professional or amateur photographers exclusively use it because it was the first social media platforms to be created. Today, it has a photographic database size larger than Instagram. According to, (oded Nov, Mor Naaman, 2013), the photographic data uploaded on the Flickr platform imply an individual process that can be divided into two main phases: a) the technical-creative phase of taking the photo; b) the social phase of sharing this photo by associating commentary information to it. The sequence can be assimilated to a process of "selective attention" through which an individual discriminates between what she/he sees and what strikes her/him in a particular way. In this sense, the image taken and published in the web points out the relevant attributes in the person's preferences experiencing the landscape at that moment, highlighting those characteristics of the most evident territory at his/her sight.

Visitation rate based on Flickr's number of photos and users' information matched very well with empirical data collected from people (Keeler et al., 2015; Sonter et al., 2016; Wood et al., 2013). Therefore, the indicator's accuracy willingness can evaluate the demand for outdoor recreation and landscape aesthetics. To better understand CES, spatial information is necessary (Brown & Fagerholm, 2015; Crossman et al., 2013). Using geotagged photos is a relevant opportunity to quantify and map CES.(Weyand et al., 2016). Analysis of Crowdsourced photo can be divide into two categories: The former focuses on spatial and temporal information data of images (Casalegno et al., 2013; Gliozzo et al., 2016; Keeler et al., 2015; Tieskens et al., 2017), the latter is based on the statistical model that analyzes the correlation between the landscape and biophysical conditions with the position of photos (Oteros-Rozas et al., 2018; van Zanten et al., 2016). The first type of research is also applied in CES research (Keeler et al., 2015; Sonter et al., 2016) uses the restoration model of the Integrated Assessment of Ecosystem Services and Tradeoffs (InVEST) based on (Redhead et al., 2016) the total number of photos taken by each user (Wood et al., 2013). The second group of research uses the MaxEnt Model to estimate CES making a correlation between georeferenced photos of Flickr and the Ambiental features (Walden-Schreiner et al., 2018; Yoshimura & Hiura, 2017). However, both models have two problems to evaluate the visual quality of cultural and rural landscape; the first is that the probabilistic model considers only the territorial characteristics in an accurate position or the proximity of the area, the second is that the circumstances of landscape influence the photographic recreation (N. van Berkel et al., 2019)

WINESCAPE MICROAPPROACH

The high number of cellar doors and the development of wine tourism make the cellar door the focus of attracting tourists. The wineries manager wants to create a beautiful, impressive experience of cellar door to establish a long relationship with visitors to induce consumers to repeat visits and purchase wine. (Bruwer et al., 2013; Bruwer & Alant, 2009). To succeed in these mission managers, they have to consider, in addition to wine product quality, the environment, and the architecture of buildings and services. Purchase of wine is linked with experiential and hedonic motivation (Brodie et al., 2011).

The central part of wine tourists can be considered potential or effective wine consumers are searching for the hedonic experience made around wine products.

Alan e Bruwer (Alant & Bruwer, 2004)investigate ecotourist's motivation cellar door, have discovered that in addition to wine tasting or purchase, some motivations are linked to seak pleasant, quiet and beautiful place

Today, research on which elements influence the user's perceptive experience is carried out with questionnaires that reveal the user's conscious preferences and emotions.

A promising alternative in perception and emotion research is to use neuromarketing methods.

Among the Neuromarketing tools, we find electroencephalogram (EEG), eye tracking, functional magnetic resonance (FMI)

Neuromarketing tools allow you to analyze users' unconscious preferences. Traditional methods are considered wildly inaccurate because consumers can not reveal their underlying emotions. The rational answer to an interview is conditioned by several factors, more or less aware. From one hand the interviewer try to answer in the right way, on the other hand, what consumers believe to feel is not real, for these reasons do not match test made with neuromarketing method

The thesis aims to elaborate a methodology that provides a useful tool for mapping and identifying CES and architectural elements to help public administration in decision-making and provide helpful information for regional planning and rural development.

References

Alant, K., & Bruwer, J. (2004). Wine tourism behaviour in the context of a motivational framework for wine regions and cellar doors. *Journal of Wine Research*, *15*(1), 27–37. https://doi.org/10.1080/0957126042000300308

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research*, *14*(3), 252–271. https://doi.org/10.1177/1094670511411703

Brown, G., & Fagerholm, N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem Services*, *13*, 119–133. https://doi.org/10.1016/j.ecoser.2014.10.007

Bruwer, J., & Alant, K. (2009). The hedonic nature of wine tourism consumption: An experiential view. *International Journal of Wine Business Research*, *21*(3), 235–257. https://doi.org/10.1108/17511060910985962

Bruwer, J., Coode, M., Saliba, A., & Herbst, F. (2013). Wine tourism experience effects of the tasting room on consumer brand loyalty. *Tourism Analysis*, *18*(4), 399–414. https://doi.org/10.3727/108354213X13736372325957

Carmichael, B. A. (2005). Understanding the wine tourism experience for winery visitors in the Niagara region, Ontario, Canada. *Tourism Geographies*, *7*(2), 185–204. https://doi.org/10.1080/14616680500072414

Casalegno, S., Inger, R., DeSilvey, C., & Gaston, K. J. (2013). Spatial Covariance between Aesthetic Value & Other Ecosystem Services. *PLoS ONE*, *8*(6), 6–10. https://doi.org/10.1371/journal.pone.0068437

Cohen, E., & Ben-Nun, L. (2009). The Important Dimensions of Wine Tourism Experience from Potential Visitors' Perception. *Tourism and Hospitality Research*, *9*(1), 20–31. https://doi.org/10.1057/thr.2008.42

Crossman, N. D., Burkhard, B., Nedkov, S., Willemen, L., Petz, K., Palomo, I., Drakou, E. G., Martín-Lopez, B., McPhearson, T., Boyanova, K., Alkemade, R., Egoh, B., Dunbar, M. B., & Maes, J. (2013). A blueprint for mapping and modelling ecosystem services. *Ecosystem Services*, *4*, 4–14. https://doi.org/10.1016/j.ecoser.2013.02.001

Daniel, T. C., Muhar, A., Arnberger, A., Aznar, O., Boyd, J. W., Chan, K. M. A., Costanza, R., Elmqvist, T., Flint, C. G., Gobster, P. H., Grêt-Regamey, A., Lave, R., Muhar, S., Penker, M., Ribe, R. G., Schauppenlehner, T., Sikor, T., Soloviy, I., Spierenburg, M., … Von Der Dunk, A. (2012). Contributions of cultural services to the ecosystem services agenda. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(23), 8812–8819. https://doi.org/10.1073/pnas.1114773109 de Francesco, F., Radaelli, C. M., & Troeger, V. E. (2012). Implementing regulatory innovations in Europe: The case of impact assessment. *Journal of European Public Policy*, *19*(4), 491–511. https://doi.org/10.1080/13501763.2011.607342

Getz, D., & Brown, G. (2006). Critical success factors for wine tourism regions: A demand analysis. *Tourism Management*, *27*(1), 146–158. https://doi.org/10.1016/j.tourman.2004.08.002

Gliozzo, G., Pettorelli, N., & Muki Haklay, M. (2016). Using crowdsourced imagery to detect cultural ecosystem services: A case study in South Wales, UK. *Ecology and Society*, *21*(3). https://doi.org/10.5751/ES-08436-210306

Jaeger, T. F. (2013). Production preferences cannot be understood without reference to communication. *Frontiers in Psychology*, *4*(April), 1–4. https://doi.org/10.3389/fpsyg.2013.00230

Johnson, R., & Bruwer, J. (2007). Regional brand image and perceived wine quality: The consumer perspective. *International Journal of Wine Business Research*, *19*(4), 276–297. https://doi.org/10.1108/17511060710837427

Keeler, J. R., Roth, E. A., Neuser, B. L., Spitsbergen, J. M., Waters, D. J. M., & Vianney, J. M. (2015). The neurochemistry and social flow of singing: Bonding and oxytocin. *Frontiers in Human Neuroscience*, *9*(September), 1–10. https://doi.org/10.3389/fnhum.2015.00518

oded Nov, Mor Naaman, C. ye. (2013). Analysis of Participation in an Online Photo-Sharing Community: A Multidimensional Perspective. *Journal of the American Society for Information Science and Technology*, *64*(July), 1852–1863. https://doi.org/10.1002/asi

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., & Plieninger, T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecological Indicators*, *94*, 74–86. https://doi.org/10.1016/j.ecolind.2017.02.009

Quadri-Felitti, D. L., & Fiore, A. M. (2013). Destination loyalty: Effects of wine tourists' experiences, memories, and satisfaction on intentions. *Tourism and Hospitality Research*, *13*(1), 47–62. https://doi.org/10.1177/1467358413510017

Redhead, J. W., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T. H., & Bullock, J. M. (2016). Empirical validation of the InVEST water yield ecosystem service model at a national scale. *Science of the Total Environment*, *569–570*, 1418–1426. https://doi.org/10.1016/j.scitotenv.2016.06.227

Sonter, L. J., Watson, K. B., Wood, S. A., & Ricketts, T. H. (2016). Spatial and temporal dynamics and value of nature-based recreation, estimated via social media. *PLoS ONE*, *11*(9), 1–16. https://doi.org/10.1371/journal.pone.0162372

Thomas, B., Quintal, V. A., & Phau, I. (2010). Predictors of attitude and intention to revisit a winescape. *Australian & New Zealand Marketing Academy of Marketing Studies (ANZMAC) Conference Proceedings*.

Tieskens, K. F., Schulp, C. J. E., Levers, C., Lieskovský, J., Kuemmerle, T., Plieninger, T., & Verburg, P. H. (2017). Characterizing European cultural landscapes: Accounting for structure, management intensity and value of agricultural and forest landscapes. *Land Use Policy*, *62*, 29–39. https://doi.org/10.1016/j.landusepol.2016.12.001

Van Berkel, D. B., & Verburg, P. H. (2011). Sensitising rural policy: Assessing spatial variation in rural development options for Europe. *Land Use Policy*, *28*(3), 447–459. https://doi.org/10.1016/j.landusepol.2010.09.002

van Berkel, N., Goncalves, J., Lovén, L., Ferreira, D., Hosio, S., & Kostakos, V. (2019). Effect of experience sampling schedules on response rate and recall accuracy of objective self-reports. *International Journal of Human Computer Studies*, *125*(December), 118–128. https://doi.org/10.1016/j.ijhcs.2018.12.002

van Zanten, B. T., Zasada, I., Koetse, M. J., Ungaro, F., Häfner, K., & Verburg, P. H. (2016). A comparative approach to assess the contribution of landscape features to aesthetic and recreational values in agricultural landscapes. *Ecosystem Services*, *17*, 87–98. https://doi.org/10.1016/j.ecoser.2015.11.011

Walden-Schreiner, C., Leung, Y. F., & Tateosian, L. (2018). Digital footprints: Incorporating crowdsourced geographic information for protected area management. *Applied Geography*, *90*(December 2017), 44–54. https://doi.org/10.1016/j.apgeog.2017.11.004

Weyand, T., Kostrikov, I., & Philbin, J. (2016). Planet - photo geolocation with convolutional neural networks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9912 LNCS*, 37–55. https://doi.org/10.1007/978-3-319-46484-8_3

Winkler, K. J., & Nicholas, K. A. (2016). More than wine: Cultural ecosystem services in vineyard landscapes in England and California. *Ecological Economics*, *124*, 86–98. https://doi.org/10.1016/j.ecolecon.2016.01.013

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, *3*. https://doi.org/10.1038/srep02976

Yang, Y., & Paladino, A. (2015). The case of wine: understanding Chinese gift-giving behavior. In *Marketing Letters* (Vol. 26, Issue 3). https://doi.org/10.1007/s11002-015-9355-0

Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services*, *24*, 68–78. https://doi.org/10.1016/j.ecoser.2017.02.009

CHAPTER 2

Background, motivation, and aims

Papers collected discuss which elements of winescape in user perception, both in the macro and micro approaches, influence product purchase and tourism choice.

The papers [1-2-3] aim to help researchers, managers, and public planners develop projects, standards, and guidelines in the rural landscape.

The work's main objective is to propose a methodology to link the territory's environmental and cultural landscape characteristics with the concept of winescape to improve the image of wine tourism. Considering the limitations of the different approaches for the analysis of the potential supply of CESs highlighted in the literature, the present study integrates two theoretical approaches: one based on the indicators from the literature of the visual quality of the landscape and the other referring to the indicators from the existing literature on winescape.

All three works have the same structure divided into three phases:

- The demand for winescape- download photo, filtering, cumulative viewshed
- Supply of winescape-elaborate ecological indicators
- Identification of relevant attributes

The paper [4] aims to help managers of winery and architecture to develop projects, standards, and guidelines for the cellar door. This paper tries to analyze the winescape in micro approach using traditional method, survey, combine with neuromarketing method

PAPER1- RandomForest

The study aims to combine the cumulative viewshed calculated from geotagged photos shared on Flickr and landscape ecology metrics with the Random Forest statistical model in Chianti Classico.

The work is divided into two phases:

- In the first step, we calculate the demand for ecosystem services using trigger points of photos of Flickr point to elaborate cumulative.
- The second step relates to the ecological and historical landscape variables that define the supply of ecosystem services in the landscape.

Supply and demand were spatially modeled to assess the importance of different variables using a Random Forest model

PAPER 2- GWR

To investigate the presence of spatial variability in the relationships between the dependent variable (cumulative viewshed) and the explanatory variables (potential supply of CES), we implemented a spatial statistical approach using Geographically Weighted Regression (GWR)

The study area is Val di Cecina. Geographical methods can capture spatial variability, which is one of the main attributes able to explain local differences, and can solve the problem linked to one global average value by calibrating in each position a separate model that considers only the data of the neighborhood closest to the point of analysis

PAPER3-Maxent chianti classico

In this paper, each phase has a significant detail of the previous work. The study area is the Chianti Classico region

Step 1 Analysis of the winescape demand (dependent model variable). Also, we Classify automatically and identify the winescape user's clusters.

Step 2 analysis of the supply of ecosystem services (independent variables of the model). It is carried out by calculating the naturalistic and historical indices and identifying and calculating the winescape service indicators.

Step 3: Analysis of supply-demand balance: spatial modeling of photograph distributions. It is carried out by a) Computing maps of high-value location for the winescape user; b) Evaluating the marginal importance of the indicators.

PAPER 4 Micro approach assessment and neuromarketing

The research investigates which element of the cellar door's architecture influences consumers' behavior and intention. The study uses two different methods: the traditional method using survey and a neuromarketing method using eye-tracking and encephalogram to analyze which emotion users feel during the visit of the cellar door

CHAPTER 3

List of paper

Paper I

Veronica Alampi Sottini, Elena Barbierato, Iacopo Bernetti, Irene Capecchi, Sara Fabbrizzi, Silvio Menghini (2019) - The use of crowdsourced geographic information for spatial evaluation of cultural ecosystem services in the agricultural landscape: the case of Chianti Classico (Italy)

New Medit

DOI: https://doi.org/10.30682/nm1902g

Published online on: 15 June 2019

Paper II

Veronica Alampi Sottini,Elena Barbierato,Iacopo Bernetti, IreneCapecchi, Sara Fabbrizzi, Silvio Menghini (2019) - Rural environment and landscape quality: an evaluation model integrating social media analysis and geostatistics techniques

Aestimum

DOI: https://doi.org/10.13128/aestim-7379

Published on October 29, 2019

Paper III

Veronica Alampi Sottini, Elena Barbierato, Iacopo Bernetti, Irene Capecchi, Sara Fabbrizzi,

Silvio Menghini (2019) - Winescape perception and big data analysis: An assessment through social media photographs in the Chianti Classico region

Wine Economic and Policy

doi: https://doi.org/10.1016/j.wep.2019.07.001

Published online on: December 2019

Paper IV

Wine tourism, cellar Door perception and emotional response by Using VR, EEG and eye tracking technology

The use of crowdsourced geographic information for spatial evaluation of cultural ecosystem services in the agricultural landscape: the case of Chianti Classico (Italy)

veronica alampi sottini*, elena BarBierato*,iacopo Bernetti*, irene capeccHi*, sara FaBBrizzi*, silvio mengHini*

DOI: 10.30682/nm1902g JEL Codes:

Q57, Q56

Abstract

The use of geotagged photographs seems to be a promising alternative to assess Cultural Ecosystem Services CESs in respect to the traditional investigation when focusing on the study of the aesthetic appreciation of a protected area or natural landscape. The aim of this study is integrating the cumulative viewshed calculated from geotagged photo metadata publicly shared on Flickr with raster data on infrastructure, historical sites, and the natural environment, using landscape ecology metrics and RandomForest modelling. Crowdsourced data provided empirical assessments of the covariates associated with visitor distribution, highlighting how changes in infrastructure, crops and environmental factors can affect visitor's use. These data can help researchers, managers, and public planners to develop projects, and guidelines in the rural landscape for incresing the supply for CESs.

Keywords: *Ecosystem services, Landscape management, Geographical information systems.*

Introduction

The importance of Cultural Ecosystem Ser vices (CESs) to human wellbeing is widely recognised. However, quantifying these intangible benefits is difficult and thus it is often not assessed. Mapping approaches are increasingly used to understand the spatial distribution of different CESs, as well as to analyse how they are related to landscape characteristics and rural activities. CESs represent the intangible benefits that people receive from ecosystems through cultural heritage, spiritual enrichment, recreation and tourism, and aesthetic experiences. They are considered fundamental to wellbeing and are often at the heart of discussions on the protection of ecosystems (Bullock *et al*., 2018). CESs represent a framework that contribute to integrate the different types of ecosystem ser vices delivery and biodiversity conservation of the agroecosystems into synergistic strategies (Mace *et al*., 2012; Assandri *et al*., 2018); however, CESs very often fall victims to policy makers' preferences for economic, social or ecological values, as they are not included in economic evaluation and landscape planning., (Mileu *et al*., 2013; Winkler and Nicholas, 2016)

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Based on the existing features and traditions, promo tion of tourism and recreation is a preferred rural development option (Van Berkel and Verburg, 2014) creating opportunities to convert a part of the externalities produced in agriculture in productive resources for the sector and, consequently, inducing strong synergies between the economic and the socioenvironmental objectives. In particular, vineyard landscape provides several Cultural Ecosystem services, such as cultural heritage values, aesthetic values andrecreational opportunities (Winkler *et al*., 2017). The mapping of the preferred locations in the landscape allows for statistical and spatial analysis to be conducted to determine the relative importance of different factors for the delivery of CESs, considering the fundamental role of agriculture. Most studies evaluating ecosystem services have been limited to quantifying recreation and tour ism, leaving out the intrinsic qualities that are interrelated with tourism in the cultural service category. Some advances have been recently provided by Big Data and, specifically, by social media analysis. The use of geotagged photographs seems to be a promising alternative to assess CES in respect to the traditional investigation when focusing on the study of the aesthetic appreciation of a protected area or natural landscape (Tenerelli *et al*., 2016; Schirpke *et al*., 2017; Levin *et al*. 2017; Yoshimura and Hiura 2017; WaldenSchreiner *et al*. 2018).

The aim of this study is integrating the cumulative viewshed calculated from geotagged pho to metadata publicly shared on Flickr with raster data on infrastructure, historical sites, and the natural environment, using landscape ecology

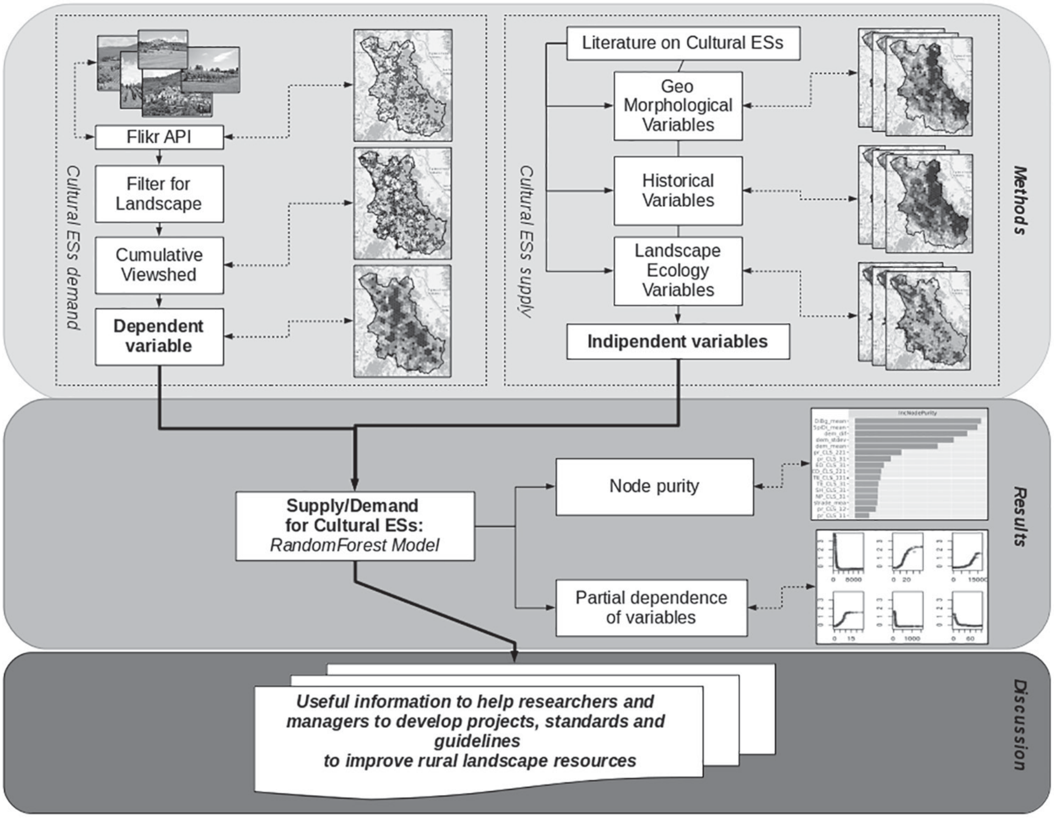


Figure 1 Flowchart of the work.

metrics and Random Forest modelling. Crowd sourced data provided empirical assessments of the covariates associated with visitor distribution, highlighting how changes in infrastructure, crops and environmental factors can affect visitor's use. These data can help researchers, managers, and public planners to develop projects, standards, and guidelines in the rural landscape, underlying how the evolution of the agricultural activities, and their land use, can influence their public contribution to the CESs. The results of the research of Torquati, Giacché and Venazi (2015) «indicate that in some contexts the preservation of the landscape can become an interesting marketing vehicle, enabling wine growers who produce quality wines to increase their income. This result demonstrates that landscape preservation can be a driving force for improvements in farm management and farm income, much more effective than the establishment of protected landscapes, and it confirms the importance of traditional landscapes as a driver of rural development».

Figure 1 shows the graphical abstract of the paper. The first phase of the work involved the development of two geodatabases. The first database is related to the demand for ecosystem services through the calculation of cumulative viewshed from the points from which the photos of agricultural landscapes shared on Flickr were taken. The second geodatabase relates to the ecological and historical landscape variables that make up the territorial offer of ecosystem services. Supply and demand were spatially modelled to assess the importance of different variables using a Random Forest model. By implementing the methods of the partially dependent areas and the thematic contribution areas it was possible to obtain very precise indications on the policies for the conservation and enhancement of the cultural ESs of the Chianti area.

Study area

The territory of the appellation of the Chianti Classico (Figure 2) extends for 71,800 hectares located between the provinces of Siena and Florence. The characteristics of the climate, the soil and the different altitudes make the Chianti area a region suited to produce quality wines. The characteristic element of the Chianti agricultural landscape are the rows of vines that al ternate with the olive groves. With over 7,200 hectares of vineyards registered in the D.O.C.G. register, Chianti Classico is one of the most important appellations in Italy. The enhancement

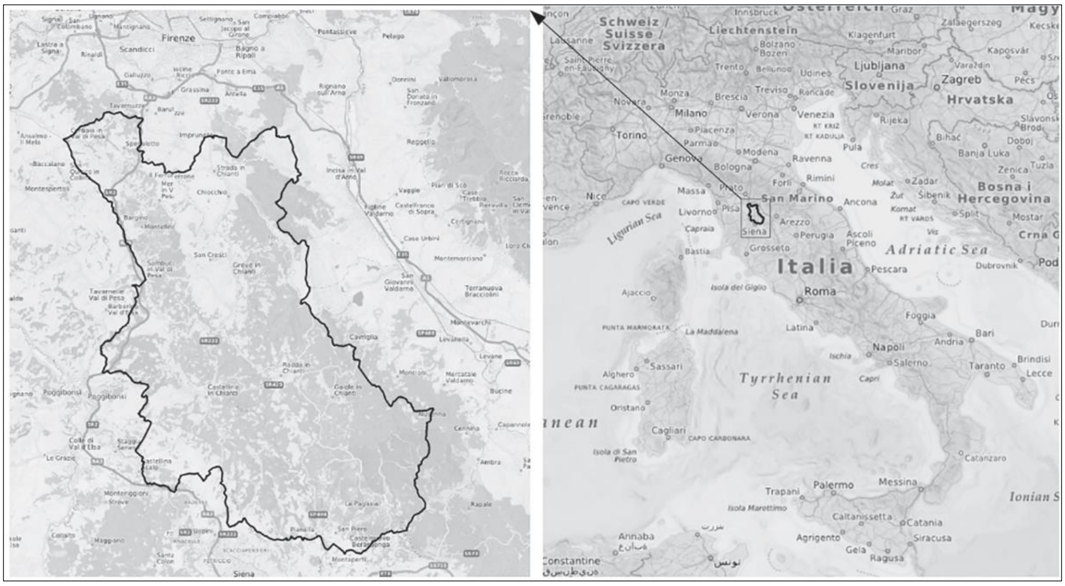


Figure 2 Study area

of the territory and landscape of Chianti has its origins since the sixteenth century when, with the conversion of the Florentine Lordship into the Grand Duchy of Tuscany, banking and commercial activities went into crisis and many investments were directed to strengthening the primary production. Some forms of production still present today originated from that period (Marone and Menghini, 1991).Torquati, Giacché and Venanzi (2015, p. 122) have defined Chianti as a «Traditional Cultural Vineyard Landscape (TCVL) because the viticulture sector is the one most integrated with the kind of tourism that is interested in quality food products associated with a specific place of origin, and also the sector that, more than others, has responded to market changes by increasing the appeal of their products». Vineyards are one of the most powerful territorial markers as they act as carriers of rural identity. The typical landscape of Chianti reflects itself in the highly specialized wine production. Even the most inexperienced observer can easily recognize the link between the landscape and the typical product of the area. These two specific characteristics allow us to go beyond the concept of TCVL towards a viticultural landscape, underlining the relations between the final product (the wine) and the territory, thus bringing the well-known opportunities for commercial differentiation that in the sector are defined in the concept of terroir and in specific production areas with an appellation of origin.

Methods

Demand for CESs

According to the scientific literature, demand for CESs can be estimated from the territorial density of the shooting points of the photos published on Flickr. Photo sharing sites, such as Flickr, allow users to cloud storage the photos and to view the geotagged and map based photo locations. Studies also indicate that Flickr data can be spatially accurate and timely. Many stud ies showed that the number of uploaded photos was positively correlated with other methods of monitoring visitors and that it could be used to provide information on the movements, itinerary and distribution of the visitors. Using an algorithm based on Flickr's *Application Programming Interface*, the coordinates of the shooting points of shared photos from 2005 to 2017 were downloaded. The photos containing the tags "wine", "vineyard", "Chianti", and related words, were filtered. Then, specific filters were applied to avoid distortions due to photos being repeated several times in a single location by a single photographer. The records were downloaded and analysed in R and converted into shapefiles for geospatial analysis using QGIS.

When analysed in combination with spatial data, the spatial patterns of photo density can reveal the preference for different landscape at tributes (Van Zanten *et al*., 2016) or the consequences of landuse change (Sonter *et al*., 2016). From the point of view of statistical modelling, the most used approach is the Maximum Entro py model (Braunisch *et al*., 2011; Westcott and Andrew, 2015; Coppes and Braunisch, 2013; Richards and Friess, 2015; Yoshimura and Hiura, 2017; WaldenSchreiner *et al*., 2018). Recently Tenerelli, Püffel and Luque (2017) used the cluster analysis to integrate visual characters of the landscape and visiting users' preferences and Van Berkel *et al*. (2018) developed a model where the response variable is assumed to follow a negative binomial (NB) distribution. These studies allowed us to take advantage of social media for analysing landscape preferences. However, the different approaches still show some limitations as for the setting up of a decision support system, of projects and plans for the preservation and for the development of cultural ecosystem services of the rural landscape. The approaches based on the probabilistic models (MaxEnt and NB distribution) relate the probability of having a preference on a landscape (that leads to a photo shared on Flickr) with the territorial characteristics that occur in a single pixel or in its close spatial proximity. The photographic recovery, on the other hand, is influenced by the entire surrounding landscape (Van Berkel *et al*., 2018). In this regard, the calculation of the views had is a potentially useful geographic instrument able to capture the perception of the landscape. A viewshed is the 360° area that is visible from a discrete location (Vukomanovic *et al*., 2018). It includes all the surrounding points within the line of sight of an assumed viewer's location and excludes points that are obstructed by the terrain or by other features. Viewshed research has been instrumental to the understanding of the scenic values associated with residential development (Vukomanovic and Orr, 2014) and to the relationship between aesthetic values and landscape patterns (Schirpke *et al*., 2016). However, the difficulty in identifying the subject of appreciation within the viewshed has unfortunately led many studies to resort to the best guess regarding the precise location of the appreciated areas (Schirpke *et al*., 2016; Yoshimura and Hiura, 2017). Combining georeferenced photos provided voluntarily by social media users with viewshed analysis represents a unique opportunity to evaluate the landscape qualities and visible attributes associated with highly valued areas. In our work, as a proxy for the demand for CESs, an index using cumulative viewsheds calculated from photographing positions was developed. Visibility analysis is increasingly implemented by landscape planners in effective decision support systems for the best possible spatial arrangement of land uses and for assessing the visual impact of certain features on the landscape (Palmer and Hoffman, 2001; Bell, 2001; Bryan, 2003; Hernández *et al*., 2004). Perhaps the most popular concept used to explore visual space in a landscape has been the cumulative viewshed (Wheatley, 1995; Martín Ramos and Otero Pastor, 2012), sometimes called total viewshed or intrinsic viewshed (FranchPardo *et al*., 2017). In general, cumulative viewsheds are created by repeatedly calculating the viewshed from various viewpoint locations, and then adding them together one at a time using the map algebra to produce a single image. We defined and calculated each viewshed using a 10 m digital DTM from a height of 165 cm and within a maximum radius of 5 km (Willemen *et al*., 2008; Chesnokova, Nowak and Purves, 2017; Brad bury *et al*., 2018). To obtain a cumulative views had, the single viewsheds were added together. The result was transferred into a hexagonal grid theme with a cell size of 1 km (Willemen *et al*., 2008; Chesnokova, Nowak and Purves, 2017; Bradbury *et al*., 2018) with visibility attributes assigned to each cell.

The potential supply of CESs

We define potential supply as the set of intrinsic territorial characteristics that contribute to determining the offer of cultural ecosystem ser vices. Potential supply differs from the real one as it includes locations with intrinsic characteristics that can potentially satisfy demand, but at the same time it has limitations that do not allow the matching between supply and demand. The aim of the potential supply model is to identify these locations that represent the most interesting places for the development of targeted territorial policies.

It is possible to map the potential supply of CESs by analysing the relationship between the demand area and its environmental factors as the demand map represents the visitors' aesthetic preferences.

Analysing the explanatory variables used in the different studies it is possible to highlight that:

- the model of Richards and Friess (2015) adopted four environmental factors: (1) the distance from the nearest footpath (including the boardwalk), (2) the distance from focal points (rest shelters and a viewing tower), (3) the dis tance from the site entrance, and (4) the dominant habitat type within the neighbouring 30 m;
- the model of Yoshimura, and Hiura (2017) used vegetation type, distances from rivers, lakes, or coastline as explanatory variables and 10 classes of topography features;
- Richards and Tunçer (2017) used four explanatory variables: (1) the distance from the nearest major outdoor attraction, (2) the presence of parks, including nature reserves, (3) the proportional coverage of forest within 50 m, and

(4) the proportional coverage of managed vegetation within 0.01 km, 2 grid squares;

- in the MaxEnt model used by WaldenSchrein er *et al*. (2018) visitor infrastructure (i.e., distance to buildings, parking, roads, trails, and campsites) and environmental characteristics (i.e., vegetation type, elevation, slope, and distance to water) served as independent variables. These studies allowed us to take advantage of social media for analysing landscape preferences. However, the different approaches still show some limitations as for the setting up of a decision support system, of projects and plans for the preservation and for the development of cultural ecosystem services of the rural landscape.

Our approach for assessing CESs provided by viticultural landscapes is based on spatially ex plicit quantitative indicators mainly represent ed by landscape ecology metrics. The analysis of the relationships between the visual quality of the landscape and its structural properties is an active area of research in the field of environmental perception. For the assessment of landscape quality, reference was made to the exhaustive classification of indicators proposed by Ode, Tveit and Fry, 2008. The conceptual framework developed by these authors allows to link each indicator to concepts described by different aesthetic theories of landscape: (a) the concept of complexity can be explained by several theories that include the Biophilia evolutionary theory (Ulrich, Kellert and Wilson, 1993); (b) naturalness is related to the degree of naturality (or naturalness) of the environment observed and it is explained by the restorative and therapeutic role of nature (Kaplan, 1995); (c) historicity is linked to the presence of historical and temporal elements in the landscape and to man’s ability to recognize his identity in the landscape according to the theory of Genius Loci (NorbergSchulz, 1980); (d) the concept of coherence is explained by the legibility aspects of the theories of Information Processing (Kaplan and Kaplan, 1989); (e) the concept of visual scale derives from the Evolutionary theory developed by Appleton (1996) that link preferences to the opportunity of prospect (ability to see) and refuge (not being seen).

According to the above, the following visual quality indicators were selected and were divided into five conceptual categories:

Complexity indicators:

number of different land cover per view; Shannon index.

Naturalness indicators:

percentage area, edge density, and number of patches of natural and seminatural vegetation;

percentage area, edge density, and number of patches of water bodies.

Historicity indicators:

distance from historic villages; distance from historic roads.

Coherence indicators:

percentage area, edge density, and number of patches of vineyards;

percentage area, edge density, and number of patches of olive groves;

percentage area, edge density, and number of patches of arable land.

Visual scale indicators:

elevation, standard deviation of elevation, range of elevation.

According to the classification proposed by Ode *et al.*, 2009, indicators related to the category of visual disturbance, also called indica tors of lack of consistency (Kaplan and Kaplan, 1989), should also be considered. This category includes, for example, the density of modern buildings and infrastructures with a high visual impact. However, in the area under consideration these elements are absent or scarcely significant and are therefore not relevant for the definition of the potential supply.

The indicators were calculated at landscape level using the Frastag software. The maps of the indicators, such as the cumulative viewshed, were also sampled using a hexagonal grid. The hexagonal grid is recommended by the authors of the FRAGSTATS Patch Analyst implementation (McGarigal and Marks, 1995) as the form of stacking that, being closer to a circle, minimizes angular effects. A nonparametric multivariate approach was used to determine the most important landscape variable to be associated with the cumulative viewshed variable. Nonparametric approaches do not assume normality in the distributions of the variables and, consequently, complex data are better analysed in this way. Since many metrics were evaluated, an ensemble decision tree approach was selected to regress biodiversity variables many times against all possible metrics using random forest regression (Breiman, 2001). To estimate the spatial distribution of the potential supply of Cultural SEs, a RandomForest (RF) model was used with cumulative viewshed as the dependent variable and potential offer indicators as independent variables. RF is a popular and useful tool for nonlinear multivariate classification and regression, which produces a good tradeoff between robustness (low variance) and adaptiveness (low bias). Direct interpretation of a RF model is difficult, as the explicit ensemble model of hundreds of deep trees is complex. In the case of linear regression, we can gain a remarkable understanding of the structure and interpretation of the model by examining its coefficients. For more complex models, such as random forests, a relatively simple parametric description is not available, which makes them more difficult to interpret. To overcome this difficulty

Friedman (2001) proposed the use of *partial dependence plots* that allow visualizing a suitable RF model through its mapping from feature space to prediction space. Welling *et al*. (2016) propose a new methodology, forest floor, to first use feature contributions (FC), a meth od to decompose trees by splitting features and then performing projections. The advantages of forest floor over partial dependence plots is that interactions are not masked as averaging. As a result, interactions that are not visualized in a given projection can be located. Forest floor was implemented in the forest Floor library for the statistical programming language R.

Results

The raw database contained about 28,815 pho to localizations taken in the period 20052017. Only photos taken in the rural landscape were selected for analysis. Subsequently, the pictures that contained the tags “wine”, “vineyard”, “Chi anti” and related words, were filtered. Finally, specific filters were applied to avoid distortions due to photos repeated many times in a single lo cation by a single photographer. The final dataset contained 9,304 photographic points. Figure 3 shows a demand map based on the cumulative viewshed index. This map provides an overview and a detailed distribution of the aesthetic demand. The cumulative viewshed index recorded a maximum value of 600 with an average value of 60 and a median value of 20, thus with a frequency distribution that is very asymmetrical.

Figure 3 Demand for Cultural Ecosystem Service

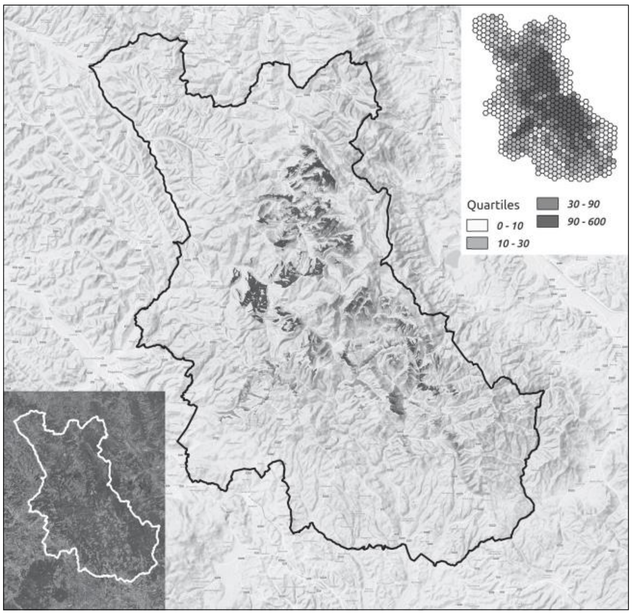
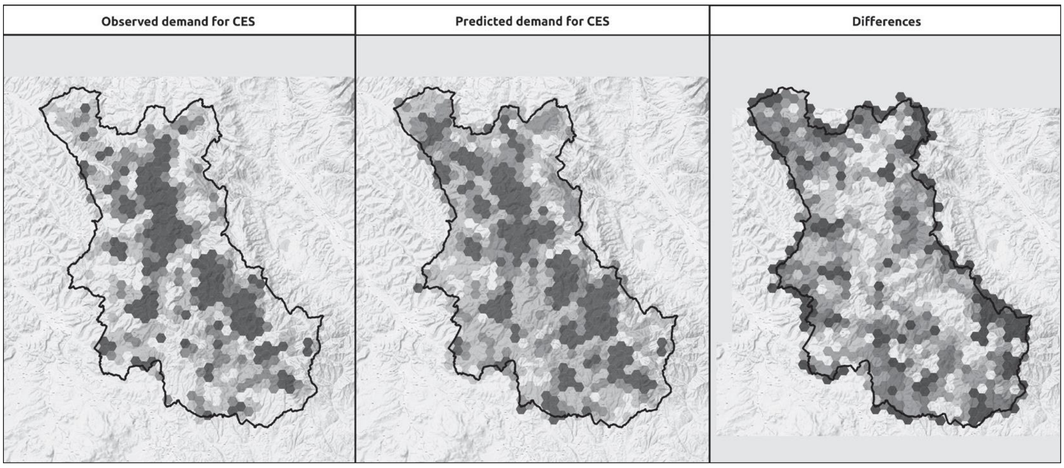


Figure 4 Observed and predicted values and differences in demand for CES.



The areas with the highest demand for CES are in the cultivated hill characterized by a complex mosaic of vineyards, fields and wooded areas. Figure 4 shows the observed, predicted and relative error percentage values of the demand estimation model for Cultural ES. The figure shows that the most significant percentage errors are localized in areas with low demand (mainly at the edge of the map due to the weak effect of variables localized just outside the boundary of the area), confirming the reliability of the model in identifying

Table 1 Importance of the variables

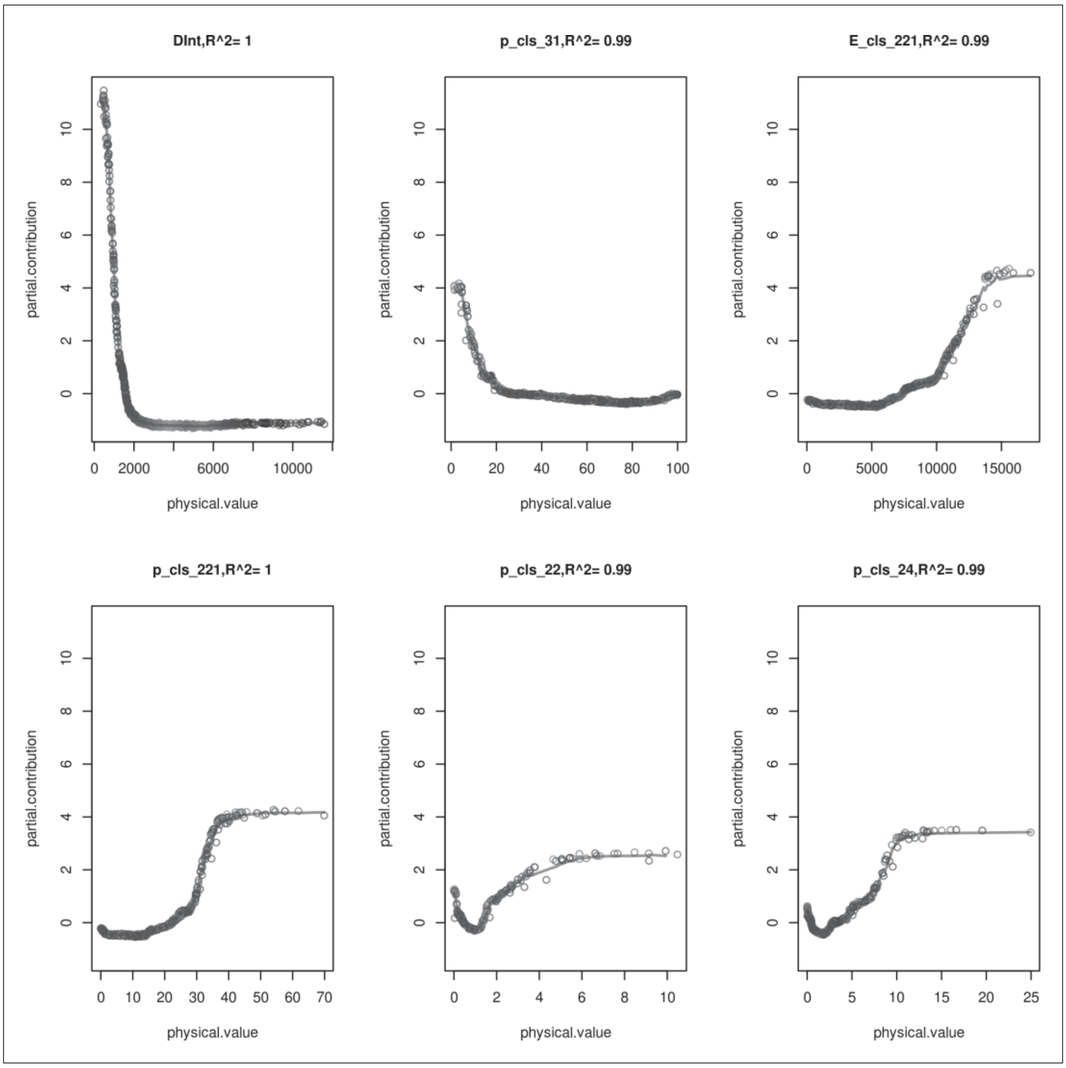
Variable	*Symbol*	*IncNodePurity*
Distance from historical village	DInt	1559,11
Perc of forest area	p_cls_31	832,76
Edge density of vineyards	E_cls_221	670,64
Perc of vineyards	p_cls_221	670,06
Perc. of heterogeneous agricultural area	p_cls_24	604,10
Edge density of olive groves	E_cls_223	560,39
Shannon index	SHDI	543,74
Distance of historical path	DTrack	496,69
Perc. of olive groves area	p_cls_223	471,43

Edge density of forest areas	E_cls_31	448,00
Perc. of pastures	p_cls_23	320,41
Perc. of permanet crops	p_cls_22	301,30
Edge density of scrubs and/or herbaceosus vegetation association	E_cls_32	293,31
Perc. of scrubs and/or herbaceosus vegetation association	p_cls_32	251,43
Elevation range	Elevrange	113,31
Mean of elevation	Elevmean	112,48
Standard deviation of elevation	Elevstdev	106,19
Perc. of arable land	p_cls_21	67,32

the relevant environmental factors in the locations with the highest value. The pseudo R^2 of the Random Forest model was 0.89 so the predictive accuracy is considered high. Table 1 shows the environmental factors that contributed most to the model. In order, they were: distance from historic villages, percentage of forest, vineyard edge density, distance from historical path, percentage of heterogeneous agricultural areas and percentage of vineyards.To understand the effect of the environmental characteristics on the demand for CESs the partial contribution graph of the characteristics is used. Figure 5 shows the FC plots of the 9 variables with the highest importance in the model. FC plots are very useful for understanding the effect of environmental characteristics on the demand for CESs. The analysis of the FC plot of the distance from historical villages allows assessing that the variable's contribution to the de mand for CES decreases as the distance increases

and becomes irrelevant beyond 1,000 meters. The percentage of forest is inversely proportion al to the demand for CESs too, as well as to the distance from the historical paths. On the other hand, the margin density of the vineyards is positively correlated with the demand for CES with optimal values between 10,000 and 15,000 meters of margin per hectare. The percentage of vineyard also makes a positive contribution up to a maximum limit of 40% of the total area. The FC graphs allow evaluating the interaction between two environmental variables. Figure 6 shows examples of bivariate FC charts: it can be noted that the cross combinations that most contribute to the demand for ESCs, are related to landscapes with up to 20% of forests and up to 5060% of vineyards with a density of margins of 15,000 meters per hectare.

Figure 5 FC plots for the 9 most important variables. Panel titles designate which variable is being plot along the xaxis: (DInt) distance from historic village, (p_cls_31) % of forest area, (E_cls_221) edge density of vine yard, (p_cls_221) % of vineyards , (p_cls_24) % of heterogeneous agricultural area, (E_cls_223) edge density of olive groves, (SHDI) Shannon index, (Dtrack) distance from historical path, (p_cls_223) % of olive groves. Panel titles also include the R^2 (leaveoneout goodness of fit) of the average Feature Contribution line (denoted in black). The colour gradient is applied in all panels along the distance from the historical village axis



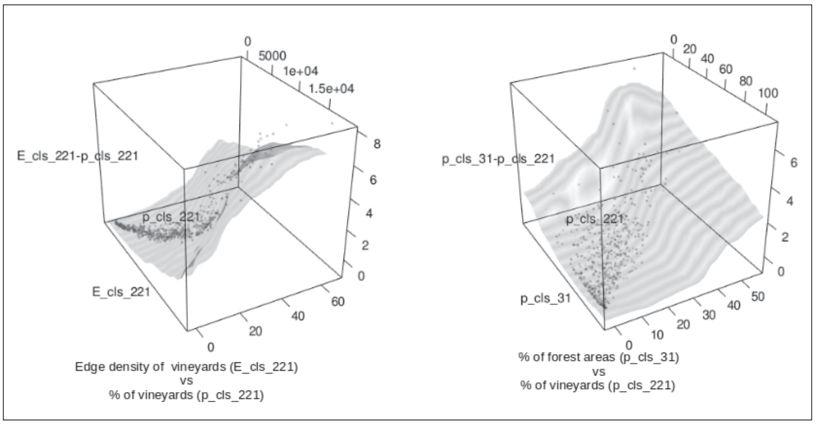


Figure 6 Bivariate par tial dependence plots.

Discussion

The results of the models highlight that vine yards and arable land separated by hedges and vegetation strips contribute to a higher value of CESs. The results indicate that approximately half of the variation in scenic perceptions can be explained by spatial landscape metrics. These results give landscape planners and de signers some insight into the preferred composition and configuration of human landscapes. They provide additional support for the contribution of natural appearing landscapes with a complex pattern of edges to the landscape quality of a community. The use of partial dependent graphs also provides useful indications for rural policy interventions that maintain and/or increase the supply of ESCs, avoiding excessive specialization in land regulations, which are more difficult to manage. This aspect also involves the hydraulic arrangements of the slopes, on which practically the entire cultivation of vines develops in the area under examination. In addition, areas with a positive difference between the expected and observed values in the Random forest model represent areas with a good probability of having a high potential CESs value. Figure 7 shows localizations with both high values (beyond the third quartile) in the observed demand for CESs and high per centage difference (above the third quartile) between observed and predicted demand. These localizations are hotspot areas not adequately exploited either because the tourist flows are external to them or because of the presence of visual detractors that could be removed through landscape restoration projects. On the other hand, for the locations shown in Figure 7, it is necessary to consider actions to increase the attractiveness of places, removing the limiting causes. For locations with both high values in the observed demand and minimal deviations between expected and observed values, safe guard and/or consolidation measures of an already satisfactory situation should be implemented. Lastly, localizations with a high value of the observed demand and a low value of the predicted demand represent places where there are landscape characteristics not considered by the present model, but which have a significant local importance. These characteristics must be identified singularly and safeguarded.

The models applied confirmed the importance of agricultural cultivations for the value of the landscape and allowed to obtain a spatial assessment of the consistency of the externalities produced by agriculture, providing clear bene fits for the choices of territorial government and rural development. The analysis showed that the correlation between cumulative viewshed and the indicators of landscape ecology gives useful information for the definition of rural policies for the enhancement of rural landscape in Mediterranean region. The FC plot analysis allowed identifying the territorial relationship among historical buildings, roads and rural land scape elements, thus defining the localizations to be preserved and enhanced through events. The FC curves allowed the definition of specific agricultural land planning interventions. As an example, Figure 5 shows the FC curves for the following variables: percentage of vineyards, percentage of olive groves, edge density of olive groves, and edge density of vineyards; these curves allowed the outlining of a model of identity landscape consisting of a mosaic made with up to 20% of forests, up to 3040% of olive grows and up to 3040% of vineyards with a density of margins such as to lead to a Shannon Index of approximately 3.

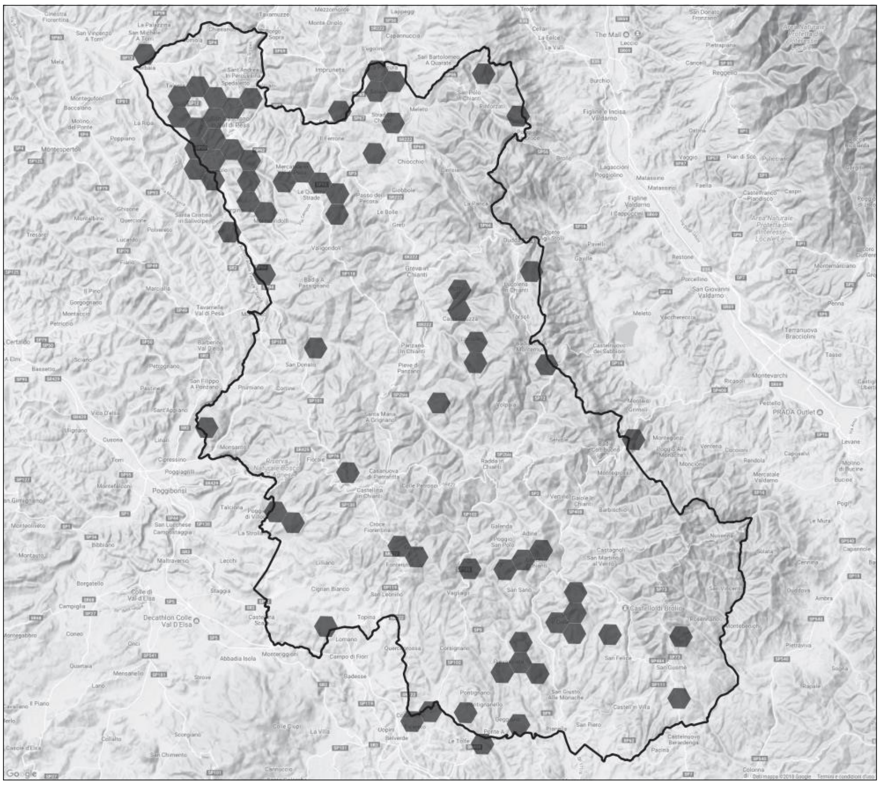


Figure 7 Hot spot areas not ad equately valued.

Conclusion

The results of the work show that a reliable estimate of the demand for Cultural ESs can be assessed by calculating the cumulative views had from the shooting points of the photos shared on Flickr social media. This method is easily transferable to other territories with limited repricing costs. The relationship between the demand for Cultural ESs and the historical and environmental characteristics of the land scape can be effectively estimated through a Random Forest regression model. Moreover, the analysis of the results of the model implementing the Feature Contribution plots meth od allows having important and very detailed quantitative information for the implementation of rural policies to enhance the rural territory. As highlighted in the results, the model provides a useful analysis to distinguish those areas that already fully express their attractive ness from those that have a good potential but is still unexpressed. Thanks to the spatialization of the results, the suggested model offers the planner the possibility of identifying the areas in which to intervene with priority implementing safeguard projects, starting from the containment of the anthropic pressure. At the same time, the model detects those areas in which it is necessary to stimulate a certain attractiveness, both in favour of primary production activities – which help to generate and maintain some essential landscape components – and in favour of external visitors. This study can stimulate further research aimed at detecting the perception of individuals on the ecosystem services that a landscape can provide, helping planners and policy makers to optimise choices for the effective management of the agricultural landscape (SanchezZamora *et al*., 2014). In recent years, an increasing share of budgetary resources has been used for measures aimed at protecting the visual quality of agricultural landscapes (Howley *et al*., 2012). Thus, understanding of the perceptions of individuals on landscapes becomes an essential cognitive element for the effective planning of rural development policies, in line with the promotion of bottom up approaches of territorial governance (De Vreese *et al*., 2016). Lastly, the 20142020 CAP presented policies focused on the efficient provision of ecosystem services from agricultural land. The capacity of agroforestry practices to improve the provision of cultural ecosystem services can be encouraged through public policies such as the EU biodiversity strategy to 2020, but the separation between agriculture and forestry in the current EU perspective is a limit to a support frame work for agroforestation. Therefore, the results of the present study can provide information for designing a new CAP with combined rural and forest planning measures.

References

Appleton J., 1996. The experience of landscape. Chichester: Wiley, pp. 6667.

Assandri G., Bogliani G., Pedrini P. and Brambilla M., 2018. Beautiful agricultural landscapes pro mote cultural ecosystem services and biodiversity conservation. *Agriculture, Ecosystems and Envi ronment*, 256: 200210.

Bell S., 2001. Landscape pattern, perception and visualisation in the visual management of forests. Landscape and Urban planning, 54(14): 201211. Bradbury R., Ridding L.E., Redhead J.W., Oliver T.H., Schmucki R., McGinlay J., Graves A.R., Morris J., Bradbury R.B., King H. and Bullock J.M., 2018. The importance of landscape characteristics for the delivery of cultural ecosystem services. J EnvironManage, 206: 11451154.

Braunisch V., Patthey P. and Arlettaz R., 2011. Spa tially explicit modeling of conflict zones between wildlife and snow sports: prioritizing areas for winter refuges. *Ecological Applications*, 21(3): 955967.

Breiman L., 2001. Random forests. *Machine learn ing*, 45: 532.

Bryan B.A., 2003. Physical environmental modeling, visualization and query for supporting landscape planning decisions. *Landscape and urban planning*, 65(4): 237259.

Bullock C., Joyce D. and Collier M., 2018. An explo ration of the relationships between cultural ecosys tem services, sociocultural values and wellbeing. *Ecosystem Services*, 31: 142152.

Chesnokova O., Nowak M. and Purves R.S., 2017. A crowdsourced model of landscape preference. In *LIPIcsLeibniz International Proceedings in Informatics*, Schloss DagstuhlLeibnizZentrum fuer Informatik, Vol. 86.

Coppes J. and Braunisch V., 2013. Managing visitors in nature areas: where do they leave the trails? A spatial model. *Wildlife biology*, 19(1): 111.

De Vreese R., Leys M., Fontaine C.M. and Dendon cker N., 2016. Social mapping of perceived ecosys tem services supply – The role of social landscape metrics and social hotspots for integrated ecosys tem services assessment, landscape planning and management. *Ecological Indicators*, 66, 517533.

cience, 24(7): 581592.

FranchPardo I., CancerPomar L. and Napoletano B.M., 2017. Visibility analysis and landscape eval uation in Martin river cultural park (Aragon, Spain) integrating biophysical and visual units. *Journal of Maps*, 13(2): 415424, DOI:10.1080/17445647.207.1319881.

Friedman J.H., 2001. Greedy function approximation: a gradient boosting machine. *Annals of statistics*, 11891232.

Hernández J., Garcıa L. and Ayuga F., 2004. Assess ment of the visual impact made on the landscape by new buildings: a methodology for site selection. *Landscape and Urban Planning*, 68(1): 1528.

Howley P., Donoghue C.O. and Hynes S., 2012. Ex ploring public preferences for traditional farming landscapes. *Landscape and Urban Planning*, 104: 6674.

Kaplan R. and Kaplan S., 1989. The experience of nature: A psychological perspective. *CUP Archive*. Kaplan S., 1995. The restorative benefits of nature: Toward an integrative framework. *Journal of environmental psychology*, 15(3): 169182.

Levin N., Lechner A.M. and Brown G., 2017. An evaluation of crowdsourced information for assess ing the visitation and perceived importance of pro tected areas. *Applied geography*, 79: 115126.

Mace G.M., Norris K. and Fitter A.H., 2012. Biodi versity and ecosystem services: a multilayered re lationship. *Trends in ecology & evolution*, 27(1): 1926.

Marone E., Menghini S., 1991. Sviluppo sostenibile: il caso di Greve in Chianti e del Chianti Classico. In *Atti XXI Incontro CeSET "Sviluppo sostenibile nel territorio: valutazioni di scenari e di possibilità"*, Perugia 8 marzo 1991.

Martín Ramos B. and Otero Pastor I., 2012. Mapping the visual landscape quality in Europe using phys ical attributes, *Journal of Maps*, 8(1): 5661, DOI: 10.1080/17445647.2012.668763.

McGarigal K. and Marks B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantify ing landscape structure. Gen. Tech. Rep. PNW GTR351. Portland, OR: US Department of Agri culture, Forest Service, Pacific Northwest Research Station, 122 p.

Mileu A.I., Hanspach L., Abson D.J. and Fischer J., 2013. Cultural ecosystem services: a literature re view and prospects for future research. *Ecology and Society*, 18(3), art. 44.

NorbergSchulz C., 1980. *Genius loci*. New York: Rizzoli.

Ode Å., Fry G., Tveit M.S., Messager P. and Miller D., 2009. Indicators of perceived naturalness as drivers of landscape preference. *Journal of envi ronmental management*, 90(1): 375383.

Ode Å., Tveit M.S. and Fry G., 2008. Capturing land scape visual character using indicators: touching base with landscape aesthetic theory. *Landscape research*, 33(1): 89117.

Palmer J.F. and Hoffman R.E., 2001. Rating reliabil ity and representation validity in scenic landscape assessments. *Landscape and urban planning*, 54(1): 149161.

Richards D.R. and Friess D.A., 2015. A rapid indi cator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media pho tographs. *Ecological Indicators*, 53: 187195.

Richards D.R. and Tunçer B., 2017. Using image rec ognition to automate assessment of cultural ecosys tem services from social media photographs. *Eco system Services*, 31: 318325.

SanchezZamora P., GallardoCobos R. and CenaDel gado F., 2014. Rural areas face the economic crisis: Analyzing the determinants of successful territorial dynamics. *Journal of Rural Studies*, 35: 1125.

Schirpke U., Meisch C., Marsoner T. and Tappeiner U., 2017. Revealing spatial and temporal patterns of outdoor recreation in the European Alps and their surroundings. *Ecosystem Services*, 31: 336350.

Schirpke U., Timmermann F., Tappeiner U. and Tasser E., 2016. Cultural ecosystem services of mountain regions: Modelling the aesthetic value. *Ecological Indicators*, 69: 7890.

Sonter L.J., Watson K.B., Wood S.A. and Ricketts T.H., 2016. Spatial and temporal dynamics and val ue of naturebased recreation, estimated via social media. *PLoS one*, 11(9), e0162372.

Tenerelli P., Demšar U. and Luque S., 2016. Crowd sourcing indicators for cultural ecosystem services: a geographically weighted approach for mountain landscapes. *Ecological Indicators*, 64: 237248.

Tenerelli P., Püffel C. and Luque S., 2017. Spatial as sessment of aesthetic services in a complex moun tain region: combining visual landscape properties with crowdsourced geographic information. *Land scape ecology*, 32(5): 10971115.

Torquati B., Giacchè G. and Venanzi S., 2015. Eco nomic analysis of the traditional cultural vineyard landscapes in Italy. *Journal of Rural Studies*, 39: 122132.

Ulrich R.S., 1993. Biophilia, biophobia, and natural landscapes. In: Kellert S.R., Wilson E.O. (eds.), *The Biophilia Hypothesis*. Washington, DC: Island Press, 73137.

Van Berkel D.B. and Verburg P.H., 2014. Spatial quantification and valuation of cultural ecosystem services in an agricultural landscape. *Ecological indicators*, 37: 163174.

Van Berkel D.B., Tabrizian P., Dorning M.A., Smart L., Newcomb D., Mehaffey M., Neale A. and Meentemeyer R.K., 2018. Quantifying the visualsensory landscape qualities that contribute tocultural ecosystem services using social media and LiDAR. *Ecosystem Services*, 31: 326335.

Van Zanten B.T., Van Berkel D.B., Meentemeyer R.K., Smith J.W., Tieskens K.F. and Verburg P.H., 2016. Continentalscale quantification of landscape values using social media data. *Proceedings of the National Academy of Sciences*, 113(46): 1297412979.

Vukomanovic J. and Orr B.J., 2014. Landscape aes thetics and the scenic drivers of amenity migration in the new west: naturalness, visual scale, and com plexity. *Land*, 3(2): 390413.

Vukomanovic J., Singh K.K., Petrasova A. and Vogler J.B., 2018. Not seeing the forest for the trees: Mod eling exurban viewscapes with LiDAR. *Landscape and Urban Planning*, 170: 169176.

WaldenSchreiner C., Leung Y.F. and Tateosian L., 2018. Digital footprints: Incorporating crowd sourced geographic information for protected area management. *Applied Geography*, 90: 4454.

Welling S.H., Refsgaard H.H., Brockhoff P.B. and Clemmensen L.H., 2016. Forest floor visualizations of random forests. Preprint arXiv:1605.09196.

Westcott F. and Andrew M.E., 2015. Spatial and en vironmental patterns of offroad vehicle recreation in a semiarid woodland. *Applied Geography*, 62: 97106.

Wheatley D., 1995. Cumulative viewshed analysis: A GISbased method for investigating intervisibility, and its archaeological application. In: Lock G. and Stancic Z. (eds.), *Archaeology and geographical information systems*. London: Taylor and Francis, 171186.

Willemen L., Verburg P.H., Hein L. and van Mens voort M.E., 2008. Spatial characterization of land scape functions. *Landscape and Urban Planning*, 88(1): 3443.

Winkler K.J. and Nicholas K.A., 2016. More than wine: Cultural ecosystem services in vineyard landscapes in England and California. *Ecological Economics*, 124: 8698.

Yoshimura N. and Hiura T., 2017. Demand and supply of cultural ecosystem services: Use of Geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services*, 24: 6878.

Rural environment and landscape quality: an evaluation model integrating social media analysis and geostatistics techniques

The use of geo-tagged photographs seems to be a promising alternative for assessing the scenic beauty of the agricultural landscape compared to the traditional investigation based on expert and perceptual approaches. The aim of this study is integrating the cumulative viewshed calculated from geotagged photo metadata publicly shared on Flickr with raster data on geomorphology, historical sites, and the natural environment, using landscape ecology metrics and Geographically Weighted Regression model- ling. Crowdsourced data provided empirical assessments of the covariates associated with visitor distribution, high- lighting how changes in infrastructure, crops and environmental factors can affect visitor's use. This information can help researchers, managers, and public planners to develop projects, plans and guidelines to increase the visual quality of the agricultural landscape.

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JEL: *C14, Q15*

Introduction

Humans benefit from the many services that rural ecosystems deliver wheth- er it is food supply, clean water regulation or inspiration invoked by a beautiful landscape. The Millennium Ecosystem Assessment (MA, 2003) in the early 2000s popularized this concept as "ecosystem services". The main reference for ecosys- tem services assessment in public policies for rural landscapes remains the ecosys- tem services cascade model defined by de Groot (2006). It classifies ecosystem ser- vices into four classes, identifying for each class the ecosystem functions relevant for human needs: regulating or regulation services, supporting or habitat services, provisioning or production and cultural ecosystem services (CES). The Millenni- um Ecosystem Assessment (MA, 2003) defined "cultural ecosystem services" as the nonmaterial benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences. In Europe, many agricultural landscapes are hot spots in the provision of CES (Pinto-Correia *et al.*, 2006; Stenseke, 2009). These agricultural landscapes are often referred to as cultural landscapes, which are generally defined as landscapes man- aged by traditional agricultural techniques, locally and historically adapted, by fa- miliar and/or subsistence methods (IEEP, 2007). They often contribute to a unique aesthetic character and support a co-produced human-ecological system. Over the past twenty years, much attention has been paid to maintaining spatial and economic synergies between ecosystem functions in rural areas in the context of development planning. The promotion of tourism based on territorial characters and traditions is increasingly a winning strategy (Van Berkel and Ver- burg, 2011) as it allows the generation of income outside the intensification of ag- ricultural production and promotes the conservation of rural landscape features (Buijs *et al.*, 2006). Tourism attractions are related to people's perception of aesthet- ic beauty, cultural heritage, spirituality and inspiration (Brown, 2006). These char- acteristics are non-material benefits related to land management and therefore not exclusive. Failure to provide sufficient incentives to maintain cultural landscapes can result in loss and/or degradation (Swinton *et al.*, 2007). The quantification of cultural services provided by landscapes can therefore help to understand the op- tions for future development that maintain and develop tourism resources. Values that emerge from cultural services are often estimated using stated preferences (e.g., van Berkel and Verburg, 2013; Plieningeretal, 2013). Moreover, a difficult in spatialisation of monetary values with proper detail (resolution) is highlighted in literature (Carvalho-Ribeiro *et al.,* 2016). To cope with this troubles a series of al- ternative methods in respect to economic analysis have been applied to quantify CES (see Fontana *et al.,* 2013; Nahuelhual *et al.,* 2013; Brown & Fagerholm, 2015; Saarikoski *et al.,* 2016; Rovai *et al.,* 2016; Pastorella *et al.,* 2017; Dunford *et al.,* 2018). The above researches have the merit of having laid the foundations for CES anal- ysis allowing for subjectivity evaluation in participative processes.

Many studies use crowd-sourced images in the analysis of CES, and we can group them into two categories. The first group focuses on the spatial and tem- poral information of photos (Casalegno *et al.*, 2013; Keeler *et al.*, 2015; Gliozzo *et al.*, 2016; Tieskens *et al.*, 2017). The emphasis of these studies was on the location and the users who took and uploaded the photos. The Integrated Valuation recre- ation model of Ecosystem Services and Tradeoffs (InVEST) applies the concept of photo-user-days (Redhead *et al.*, 2016), which considers the total number of days the users took photos (at least one photo from a user) in each mapping (Wood *et al.*, 2013). The InVEST recreation model started to be applied to several CES analy- ses (Keeler *et al.*, 2015; Sonter *et al.*, 2016). The second group of studies aims to correlate the landscape context and the biophysical settings with the positions of georeferenced photos (Pastur *et al.*, 2016; Tenerelli *et al.*, 2016; van Zanten *et al.*, 2016; Oteros-Rozas *et al.*, 2017), using geostatistical analysis methods derived from biology, such as the Maximum entropy models (MaxEnt). The researchers applied MaxEnt model to manage visitor impacts on natural resources, including human- nature interactions (Braunisch *et al.*, 2011), and off-piste recreational behaviour prediction (Coppes and Braunisch, 2013; Westcott and Andrew, 2015; Richards and Friess, 2015). The authors implemented MaxEnt model to the estimate CES corre- lating the locations of Flickr geo-referenced photos with the environmental char- acteristics of the territory (Yoshimura and Hiura, 2017; Walden-Schreiner, *et al.*, 2018). However, the models highlighted have two critical limits in the assessment of the visual quality of complex cultural rural landscapes. On the one hand, the approaches based on the probabilistic models (MaxEnt and Negative Bernoulli distribution) consider only the territorial characteristics that occur in a single location or close to its spatial proximity. On the other hand, the entire surrounding landscape influences photographic recovery (Van Berkel *et al.*, 2018). In this regard, the calculation of the views is potentially useful to cap- ture the perception of the landscape. Moreover, the hypothesis at the basis of the two approaches is that the sta- tistical relationship between explanatory variables of landscape quality and con- centration of shared photos is constant in space. In complex landscapes, it seems reasonable to assume that there may be intrinsic differences regarding space that occur in terms of spatially variable parameters. In both cases, it seems preferable to use geostatistical techniques to describe and map these spatial variations as an exploratory tool to develop a better understanding of the relationships studied.The aim of this paper is integrating the geotagged photo metadata publicly shared on Flickr with raster data on geomorphology, historic sites and the natural environment, using landscape ecology indexes and Geographically Weighted Re- gression (GWR) modelling. Figure 1 shows the workflow of the approach.

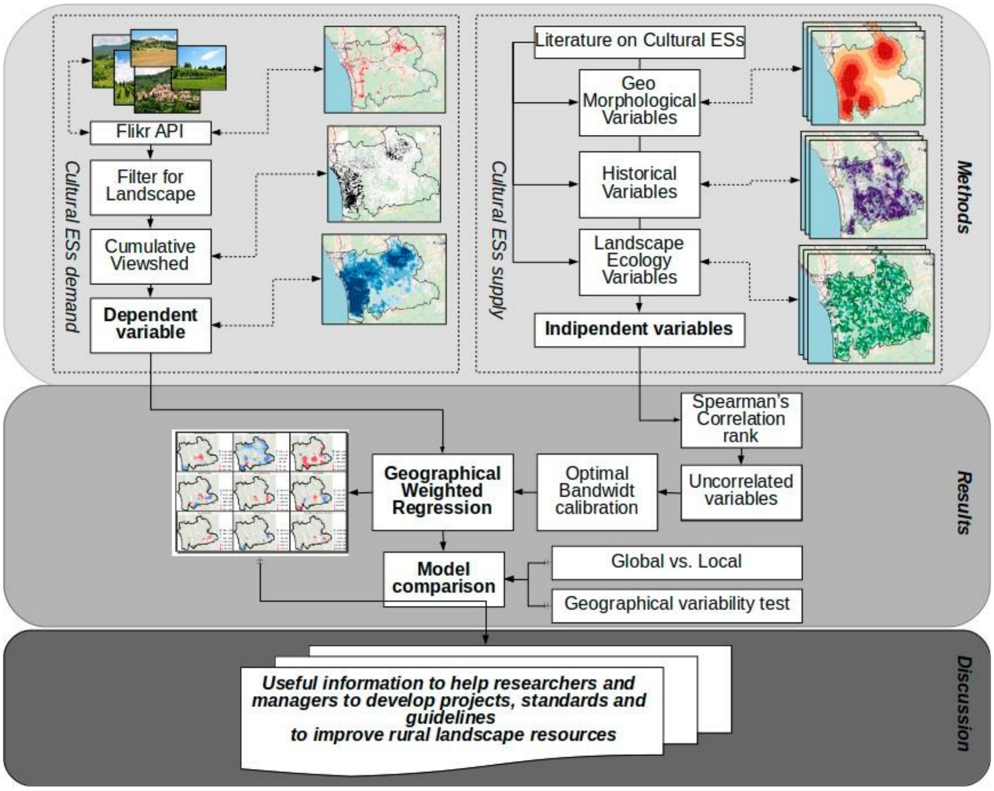
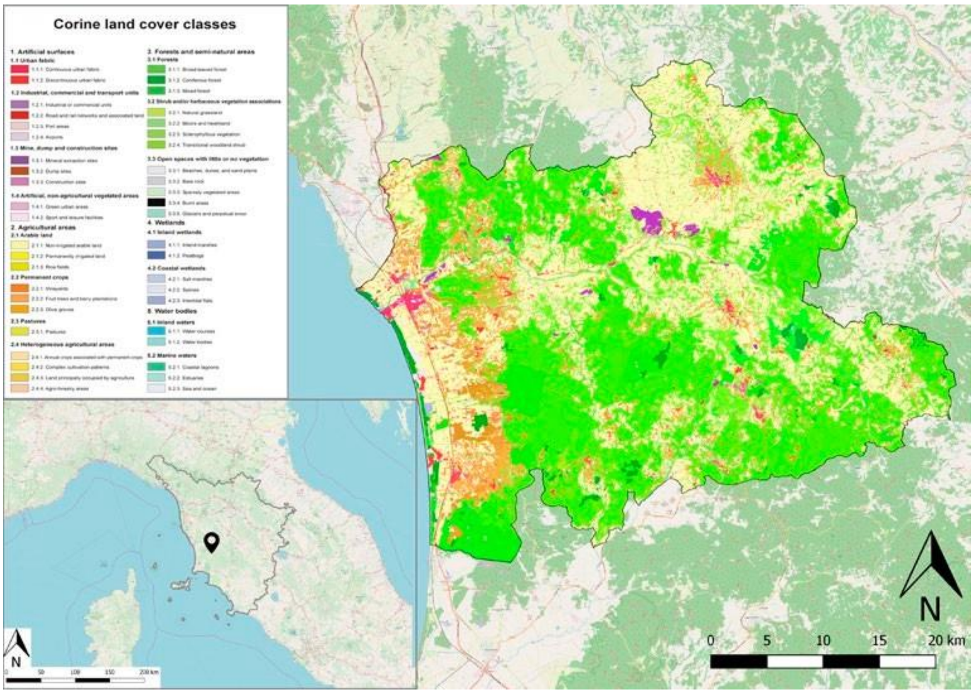


Figure 1. Flow-chart of the work.

Study area

The study area is located on the river basin of the Cecina River, located along the coast of Livorno and Pisa. Forest and crops make up the landscape. Today, the coastal strip is characterised by prevalent agriculture of plains (with arable crops and horticultural crops) and hills (with olive groves, promiscuous crops and specialised vineyards), and by widespread and concentrated urbanisation, par- ticularly relevant in some places dedicated to summer tourism. Although it is a context of high anthropization, the coastal territory shows significant naturalistic areas of value linked to the presence of humid areas and back-dunal woods, on the one side, and continuous sandy coastal system of dune habitats and natural pine groves of domestic pine, on the other. Agro-forest-pastoral landscapes of high naturalistic value, crossed by the course of the Cecina River and by a dense hydrographic network, dominate the internal hilly territory. Vast sclerophyllous and broad-leaved thermophile woods alternate with traditional agricultural land- scapes. On one of the hills lies the historic city of Volterra, surrounded by beauti- ful scenic hills characterised by extensive agriculture (arable crops). About 50,000 inhabitants live in Val di Cecina. The area covers more than 200,000 hectares, 43% of which is forest and 35% arable land. Figure 2 shows the study area.

Figure 2. Study area.



Methods

1.1 Demand for cultural ecosystem services

In our research, the geotagged photos were queried from the Flickr Appli- cation Programming Interface using the statistical software program R. The raw database contained about 35,000 localizations of photos taken in the period 2005- 2017. The pictures containing in the tags the “agriculture”, “rural landscape”, “vineyard”, “olive”, “grassland”, and the related words were filtered. Finally, spe- cific filters were applied to avoid distortions due to photos repeated many times in a single location by a single photographer. The final database counted 11,296 photographic points. The analysis of the spatial distribution of the Cultural ESs application was carried out through the following elaborations.

As a proxy for the demand for Cultural ESs, we develop an index using cu- mulative viewsheds calculated from photographing positions. Visibility analysis is increasingly applied by landscape planners as well, being useful as a decision support system, since it deals with the best possible spatial arrangement of land uses and it assesses the visual impact of given features in the landscape (e.g., Bell, 2001; Bryan, 2003; Hernández *et al.*, 2004; Palmer and Hoffman, 2001). Perhaps the most popular concept used to explore visual space in a landscape has been the cumulative viewshed (Wheatley 1995; Ramos and Pastor, 2012), sometimes called total viewshed or intrinsic viewshed (Franch-Pardo, Cancer-

Pomar and Napole- tano, 2017). In general, cumulative viewsheds are created by repeatedly calculating the viewshed from various viewpoint locations and then adding them up one at a time using map algebra, in order to produce a single image. We defined and calculated each viewshed using a digital elevation model (DEM) of 10 m from a height of 165 cm and within a maximum radius of 5 km (Willemen *et al.*, 2008; Chesnokova *et al.*, 2017). The single viewsheds were added together to obtain a cumulative viewshed. The result was transferred into a hexagonal grid theme with a cell size of 1 km, with visibility attributes assigned to each cell. We chose the hexagonal grid because of its topological and geometric properties (Feick and Robertson, 2015). The maps of the indicators, such as the cumulative viewshed, were sampled using a hexagonal grid with a 1-kilometre side, resulting in 1,444 statistical observations.

1.2 *Potential supply of cultural ecosystem services*

It is possible to map the potential supply of CES by analysing the relation- ship between the demand area and its environmental factors as the demand map shows the visitors' aesthetic preferences.

The analysis of the relationships between the visual quality of the landscape and its structural properties is an active area of research in the field of environ- mental perception. The following visual quality indicators were selected, and, according to Ode, Tveit and Fry (2008), divided into five conceptual categories:

1. indicators of complexity: number of different land covers per view, Shannon index.
2. indicators of naturalness: percentage area, edge density, and number of patch- es of natural and semi-natural vegetation; percentage area, edge density, and number of patches of water bodies, Shannon index, number of patches, land- scape shape index;
3. indicators of historicity: distance from historic villages; distance from historical roads;
4. indicators of coherence: percentage area, edge density, and number of patches of vineyards; percentage area, edge density, and number of patches of the olive grove; percentage area, edge density, and number of patches of arable land;
5. indicators of visual scale: elevation, the standard deviation of elevation, the range of elevation.

The indicators at points 1, 2 and 4 were calculated at landscape level using the Fragstats software. According to the standards legend Corine Land Cover level 2, we calculated the indicators of naturalness and complexity for each land use class. The indicator at point 3 derives from historical territorial geodatabases of the Tus- cany Region. Finally the indicators at point 5 derive from our elaboration using the DEM of Tuscany Region. The initial set results to be composed of 78 explana- tory variables.

To estimate the spatial distribution of the potential supply of Cultural SEs, a Geographically Weighted Regression model was used with the cumulative views- hed as the dependent variable and the potential offer indicators as independent variables.

1.3 Geographically Weighted Regression model for cultural ecosystem services

To investigate the presence of spatial variability in the relationships between the dependent variable (cumulative viewshed) and the explanatory variables (po- tential supply of CES), we implemented a spatial statistical approach using Geo-graphically Weighted Regression (GWR) (Fotheringham *et al.*, 2002). Classical sta- tistical methods, such as multivariate regression, assume that the same relation-ship occurs everywhere in space and, thus, they generate a global average value valid for the entire data set, even though, in reality, it can not be valid anywhere. Geographical methods can capture spatial variability, which is one of the main at- tributes able to explain local differences, and can solve the problem linked to one global average value by calibrating in each position a separate model that consid-ers only the data of the neighbourhood closest to the point of analysis. Moreover, the data are weighted according to their geographical distance from each local re- gression point so that the closer they are to the point of analysis the more impor- tant they are. The result is a set of local models, one for each point, that capture any spatial variability in the relationships. The first "law" of geography states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). This is the key concept of spatial data analysis and is related to the concept of spatial cor- relation. GWR is a local spatial statistical technique used to analyse and map spatial non-stationarity, i.e., the measurement of relationships among variables that may differ at different locations. Unlike conventional regression, which produces a single regression equation to summarize global relationships among the explana- tory and dependent variables, GWR provides a calibration of separate regression equations for each observation of dataset, consisting of a dependent (response) variable y and a set of k independent (explanatory) variables x_k, k=1 … m, and of n observations with known geographical coordinates. Each equation is calibrated using a different weighting of the observations contained in the dataset. The equation for a typical GWR model is (Fotheringham *et al.*, 2001, Fotheringham *et al.*, 1998):

$$y_i(u) = \beta_{0i}(u,v) + \beta_{1i}(u,v)x_{1i} + \ldots + \beta_{mi}(u,v)x_{mi}$$

As GWR generally (but not necessarily) assumes that Tobler 's first law is veri- fied to a given dataset, the calibration of the GWR model requires a decision re- garding the size of the subset of n observations to be included in the neighbour- hood of the predicted values. This is referred to as the bandwidth size for estimat- ing the local regression parameters (Brunsdon *et al.*, 1998). Thus, the weighting scheme is that the values near to point i have more influence in the estimated re- gression values than values located far away from that same point (Fotheringham *et al.*, 2001). In this study we adopt the Gaussian kernel type that weights con- tinuously and gradually decreases from the centre of the kernel but never reaches zero. The kernel shape is defined by the following equation, which takes into ac- count only the *nth* nearest neighbours:

$$w_{ij} = \exp\frac{-d_{ij\,2}}{b_2}$$

where *i* is the regression point index; *j* is the locational index; w_{ij} is the weight val- ue of observation at location j for estimating the coefficient at location *i*; d_{ij} is the Euclidean distance between *i* and *j*; *b* is a bandwidth size defined by a distance metric measure. Bandwidths for GWR models can be user-specified or found via some auto- mated (e.g., cross-validation) procedure provided some objective function exists. Different methods are proposed to define the finest bandwidth value or the ap- propriate value of n (Hurvich *et al.*, 1998; Akaike, 1974; Fotheringham *et al.*, 2003). Many studies have applied GWR in human and political geography (Mansley and Demšar, 2015; Brunsdon *et al.*, 1996; Fotheringham *et al.*, 2013), as well as in physical geography and ecology (Atkinson *et al.*, 2003; Clement *et al.*, 2009; Har- ris *et al.*, 2010; Jetz *et al.*, 2005), proving the suitability of this tool to provide an explanatory approach in spatially varying relationships (Páez *et al.*, 2011). For the valuation of CES, Tenerelli *et al.* (2016) used a GWR method to study the relation- ship between the geo-tagged images account and the landscape settings, whose spatial variation may affect the cultural service. Schirpke *et al.* (2018) used a GWR model to analyse how spatial and temporal patterns correlate spatially explicit indicators and crowd-sourced information from social media. The estimation of the GWR models was carried out through the GWmodel library of the statistical program R (Gollini *et al.*, 2013; Lu *et al.*, 2013). Fotheringham and Park (2018) in- vestigates both spatial and temporal elements of the apartment pricing process by modelling the determinants of apartment prices. Riccioli *et al.* (2018) analysed and tested the spatial non-stationarity of the relationship between ungulates and hu- man activities. The GWR approach uses a moving window weighting technique, where lo- calised models are at target locations. Here, for a single model in a specific tar- get location, we weight all neighbouring observations according to a certain distance-decay kernel function and then locally apply the model to the weight- ed data. The bandwidth controls the size of the window over which this local- ised model might apply. A fundamental element in GW modelling is the spatial weighting function (Fotheringham *et al.*, 2002) that quantifies (or sets) the spatial relationship or spatial dependency between the observed variables. There are three critical elements in structuring this weighting system: (i) the type of dis- tance, (ii) the kernel function and (iii) its bandwidth. According to Gollini *et al.* (2013), we adopted the Euclidean distance with a bi-square kernel. Having the data set organised on a regular hexagonal tessellation, we set an adaptive kernel bandwidth that to include the N hexagons closest to the observation/calibration hex. When an objective function exists (e.g., when the model can predict it), we can find an optimal bandwidth, using cross-validation and related approaches. We can find an optimum kernel bandwidth for GW regression by minimising some diagnostic models of adaptation, such as a leave-one-out cross-validation (CV) score (Bowman, 1984), which represents the accuracy of the model predic- tion; or the Akaike Information Criterion (AIC) (Akaike, 1973), which represents the parsimony of the model (i.e., a compromise between prediction accuracy and complexity). Once we calibrated our local model, we evaluated the spatial variability in the relationships through a visual representation of the parameter estimate surfaces. The surfaces were cross-mapped with the local t-values for each parameter estimate to identify areas where the relationships are significant. We also mapped the local percentage of explained deviance to identify areas where the model is performing better (percentage of explained deviance higher than the average) or worse, and we relate these patterns with the most significant local parameter estimates. Finally, we tested the spatial distribution of the local and global residuals both through visual representation and using Moran'sI measure of spatial autocorrelation. The level of spatial autocorrelation can be investigated visually by mapping the standardised residuals for both models as well as calculating measures of spatial autocorrelation, such as Moran's I (Good- child, 1986; Moran, 1950).

4. Results

The first step in the GWR procedure was to test the multicollinearity between the variables using Spearman's correlation rank. We kept all the variables as they showed a Spearman's correlation lower than 0.7. In the end, we considered a final set of 9 variables. Figure 3 shows the map of the explanatory variable (cumulative viewsheds) and Figure 4 the 6 maps of the independent variables.

Table 1 shows the results for the global Generalized Last Squares (GLS) model. The results suggest that all parameter estimates are significant except the patch richness value. The explained deviation is only about 41%, with an AICc coeffi- cient of 17,389. The model significance is assessed by the F-Statistic. The F-Statistic is trustworthy only when the Koenker's studentized Breusch-Pagan (KBP) statis- tic is not statistically significant (Breusch and Pagan, 1979; Koenker, 1981). In this case, the KBP statistic is significant (*cfr.* Tab. 1). Furthermore, the KBP statistic de- termines whether the explanatory variables in the model have a consistent rela- tionship to the dependent variable, both in geographic space and in data space. When the model is consistent in geographic space, the spatial processes represent- ed by the explanatory variables behave the same everywhere in the study area (the processes are stationary). When the model is consistent in data space, the variation in the relationship between predicted values and each explanatory variable

Figure 3. Maps of cumulative viewsheds (explanatory variable).

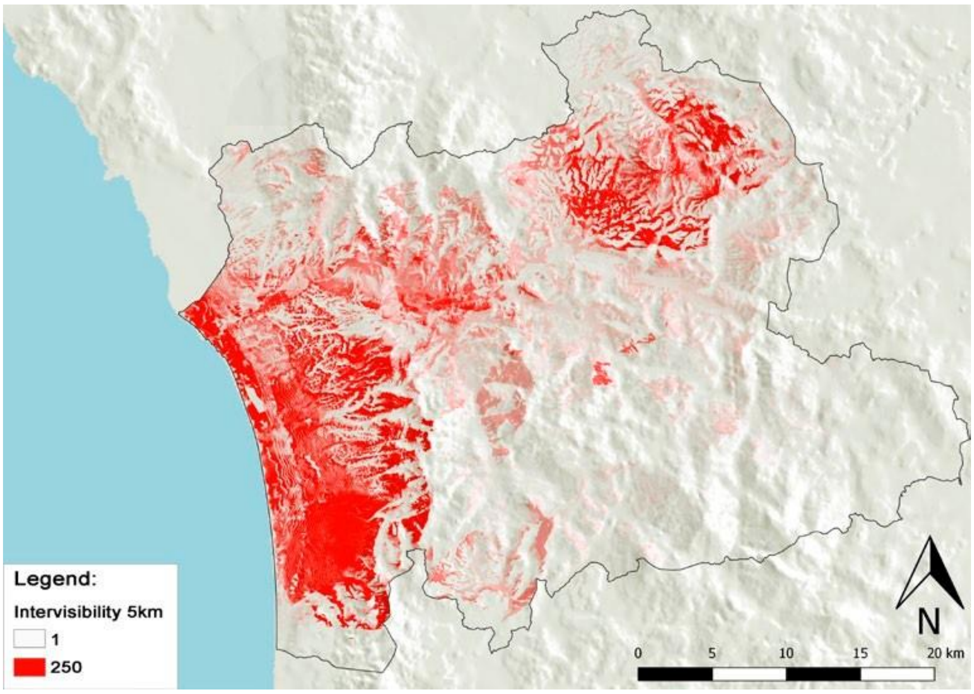
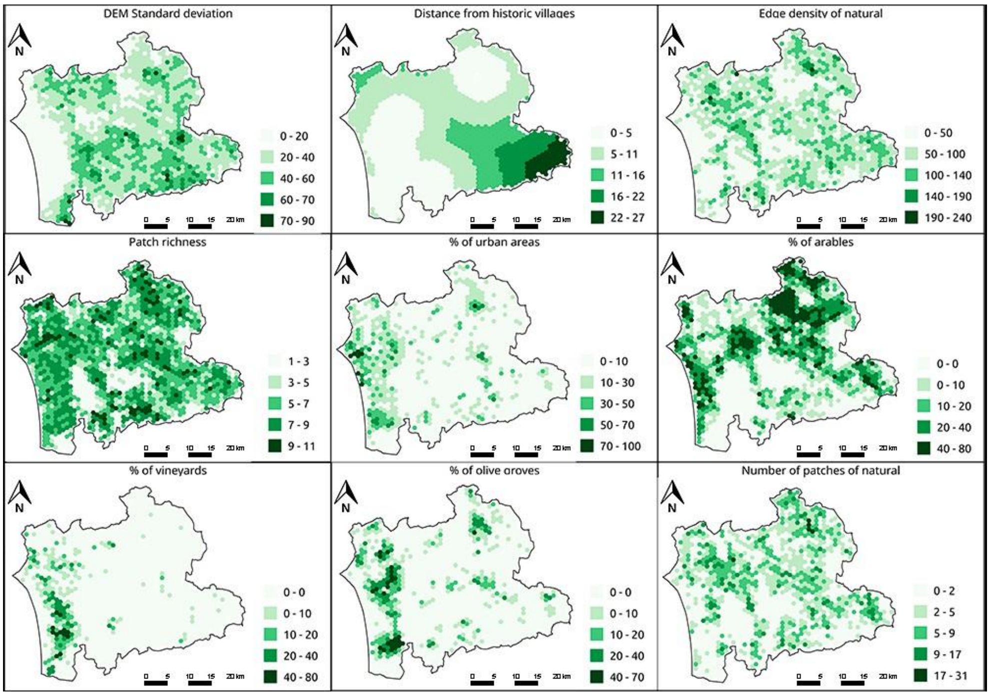


Figure 4. Maps of independents variables.



does not change with changes in explanatory variable magnitudes (there is no heteroscedasticity in the model). We performs the Breusch-Pagan test for het- eroskedasticity on the least squares fit of the spatial models using the procedure bptest.sarlm of the statistical program R (Bivand *et al.*, 2018). The significance of the KBP statistic indicates heteroscedasticity and/or non-stationarity of the model; this model is, therefore, a good candidate for Geographically Weighted Regression analysis.

In the next step, we first built an entirely local GWR model. The result of the bandwidth optimization suggested an optimal bandwidth of 86 cells (i.e. for each of the 1,444 cells, a local model was calibrated using data from the nearest 86 cells). The adaptation of the model was much improved compared to the local model (Table 3) with an average 78.6% of deviance explained (i.e. a significant increase from the global model) and with an AICc of 15.773. The improvement in the quality of the model from global to local shows that there is indeed a spatial variability in the data and that it is essential to unravel it.

According to Lu *et al.* (2015), we performed a model specification exercise to find an independent variables subset for our GW regression. To support this pro- cedure, we implemented a pseudo stepwise procedure, going in a forward direc- tion. The following four steps, where the results are displayed using plots with the AICc values of each model, describe this procedure:

Table 1. Generalized Last Square model.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
Intercept	164.6	12.25	13.432	< 2e-16	***
DEM standard deviation	-1.07	0.2207	-4.847	.000001390000	***
Distance from hystoric village	-0.005395	0.0004906	-10.998	< 2e-16	***
Edge density of natural areas	-0.3562	0.08907	- 4	.000066700000	***
Patch richness	-2.231	1.57	-1.421	.155000000000	
Percent of urban areas	1.851	0.4493	4.119	.000040300000	***
Percent of arables	0.6574	0.1298	5.064	.000000463000	***
Percent of vineyards	5.74	0.424	13.536	< 2e-16	***
Percent of olive grow	2.023	0.3581	5.648	.000000019500	***
Number of natural patches	-6.67	1.083	-6.159	.000000000948	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 99.3 on 1434 degrees of freedom
Multiple R-squared: 0.4221
Adjusted R-squared: 0.4185
F-statistic: 116.4 on 9 and 1434 DF, p-value: < 2.2e-16
Diagnostic information
Residual sum of squares: 14139488

Sigma(hat): 99.02258
AIC: 17389.26
AICc: 17389.44
Koenker (BP) Statistic 39.543, df = 9, p-value = 9.194e-06

1. Calibration of all possible bivariate geographically weighted regressions by se- quential regression of a single independent variable to the dependent variable.
2. Detection of the best performing model that produces the minimum AICc, and permanent incorporation of the corresponding independent variable in subsequent models.
3. Sequential introduction of a variable of the remaining group of independent variables for the creation of new models with the independent variables per- manently included, and determination of the following permanently included variable from the best fitting model that has the minimum AICc.
4. Reiteration of step 3 until the model includes permanently all independent variables.

These steps were performed using the package GWmodel of the statistical software R (Lu e al, 2014). Figure 5 shows a circle view of the 45 geographically weighted regressions (numbered 1 to 45) that result from the stepwise procedure.In the figure, the dependent variable is located in the center of the chart and the independent variables are represented as nodes differentiated by shapes and color. The first independent variable permanently included is "distance from his- toric villages", the second one is "edge density of naturals", the third one is "percentage of arable land" and the last one is "numbers of patches". Moreover, figure 5 shows the corresponding AICc values for the same fits. The two graphs together explain the model performance when we introduce an increasing number of vari- ables. As can be expected, AICc values continue to fall until all independent vari- ables are included. The results suggest that it is worth continuing with all eight independent variables. To interpret the spatial relationships resulting from GWR, we represented the local parameter estimate surfaces, and we analysed the spatial distribution of local coefficients and their relative significance levels (Figure 6 and 7). In general, the parameters are not significant in the south-east area of the ter- ritory under study, characterised by low photo density (see also Figure 3). We no- tice that there are two distinct areas. In the north-west area (the area around the city of Volterra), the standard deviation of the elevations, the distance from his- toric villages, the percentage of olive groves, the density of margins from natu- ral areas and the percentage of arable land are significant. In the East area, close to the coast, the DEM standard deviation, the distance from the historic villages, the margins density of the natural areas, the percentage of area affected by ar- able land, vineyards and olive groves and the number of natural patches are sig- nificant on a vast area. About the signs of the coefficient, the distance from the historic villages and the standard deviation of the DEM are both negative in the two areas characterized by the highest concentration of photos. For the dependent variables of landscape ecology instead, the signs of the coefficient are different in the two areas. The perception of the landscape of Volterra is positively correlated to the percentage of olive groves, and the edge density of natural areas, while it is negatively correlated to the patch richness and the percentage of vineyards. In the area near the coast, the perception of the landscape is positively correlated to the patch richness, to the percentage of arable land and it is inversely proportional to the density of margins and the number of patches of natural areas. In general terms, therefore, the GWR highlights the presence of highly differentiated areas relating to the appreciation of the characteristics of the landscape. To analyse the local variability of the relationships between the photo count- ing and the explanatory variables, we mapped the local percentage of explained deviance. Figure 8 shows the explained deviance, highlighting that it is every- where higher than in the global model.

Table 2. Results of Geographically Weigthed Regression model.

	Min.	1st Qu.	Median	3rd Qu.	Max.
Intercept	-170.47	11.225	68.895	204.27	981.7019
DEM standard deviation	-92.992	-0.38785	0.011412	0.29064	8.81
Distance from hystoric village	-0.15695	-0.016151	-0.0052386	-0.00028583	0.0765
Edge density of natural areas	-4.4125	-0.17754	-0.0033543	0.052348	2.7686
Patch richness	-28.059	-1.8661	-0.086415	1.3978	54.715
Percent of urban areas	-27.009	-0.085966	0.6723	2.3271	27.3817
Percent of arables	-5.9141	-0.077748	0.02702	0.58779	14.0546
Percent of vineyards	-33.376	-0.5068	0.074384	1.6036	22.7161
Percent of olive grow	-13.962	-0.43454	-0.015489	0.47527	17.3402
Number of natural patches	-25.306	-2.1949	-0.18176	0.30492	21.8281

AICc : 16274.47
AIC: 15773.28
R-square value: 0.8462371 Adjusted R-square
value: 0.786029

Figure 5. Model view of the stepwise specification procedure.

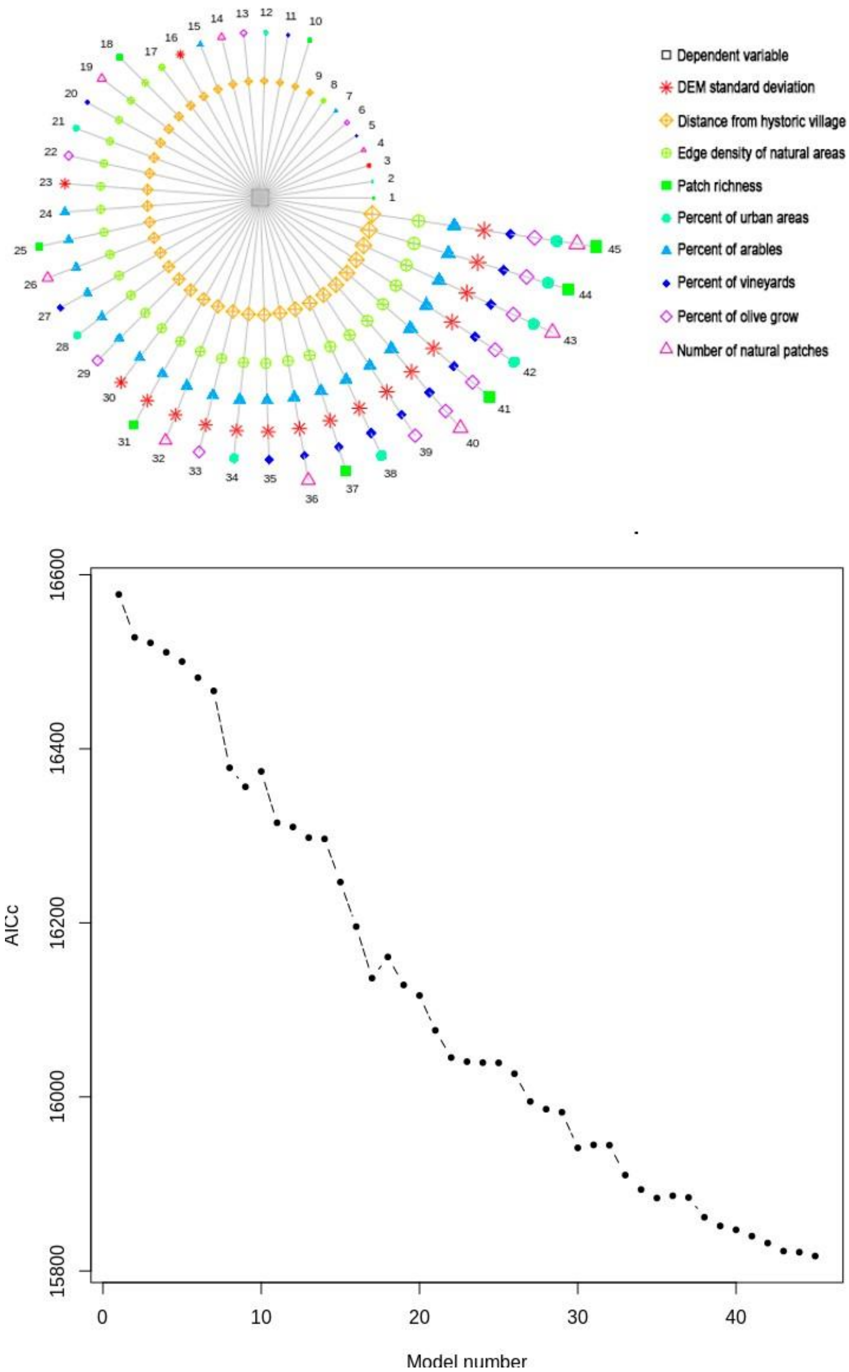


Figure 6. Maps of spatial distribution of local coefficients.

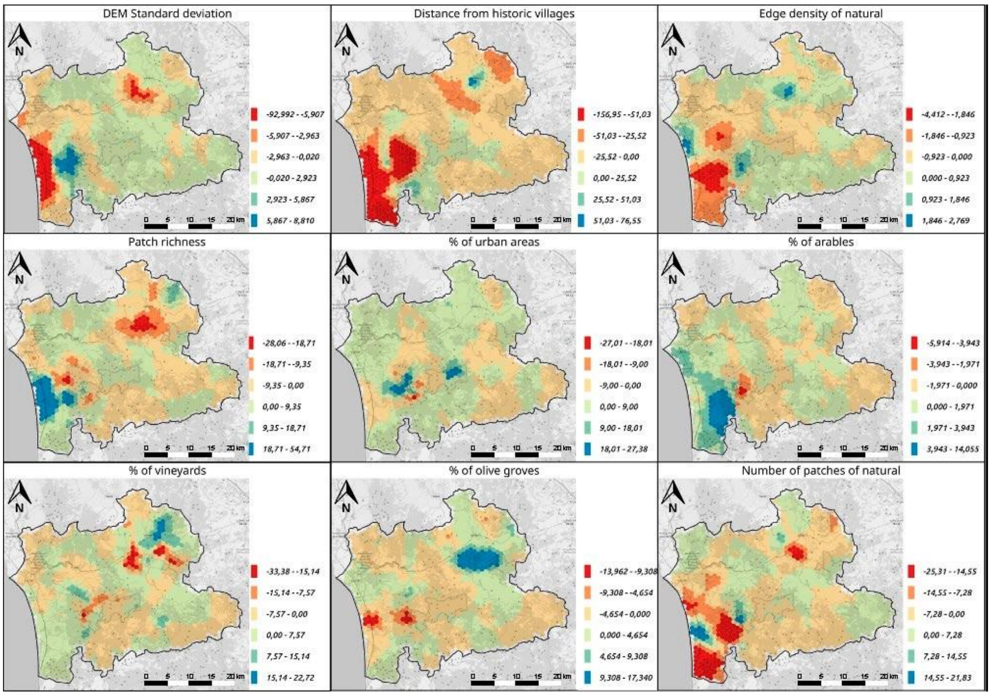


Figure 7. Maps of spatial distribution of significance levels.

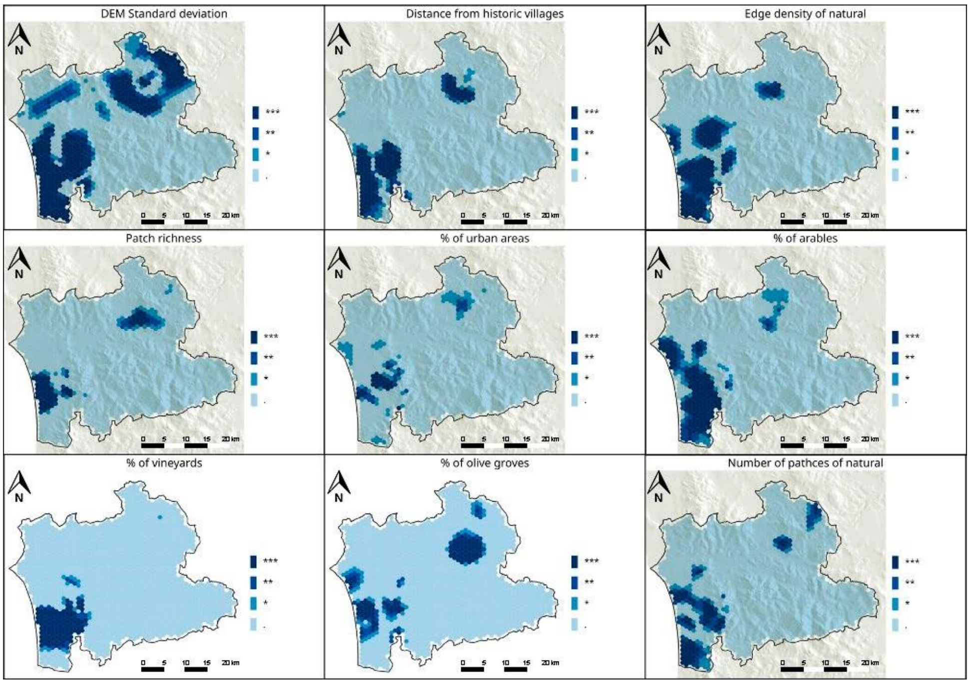
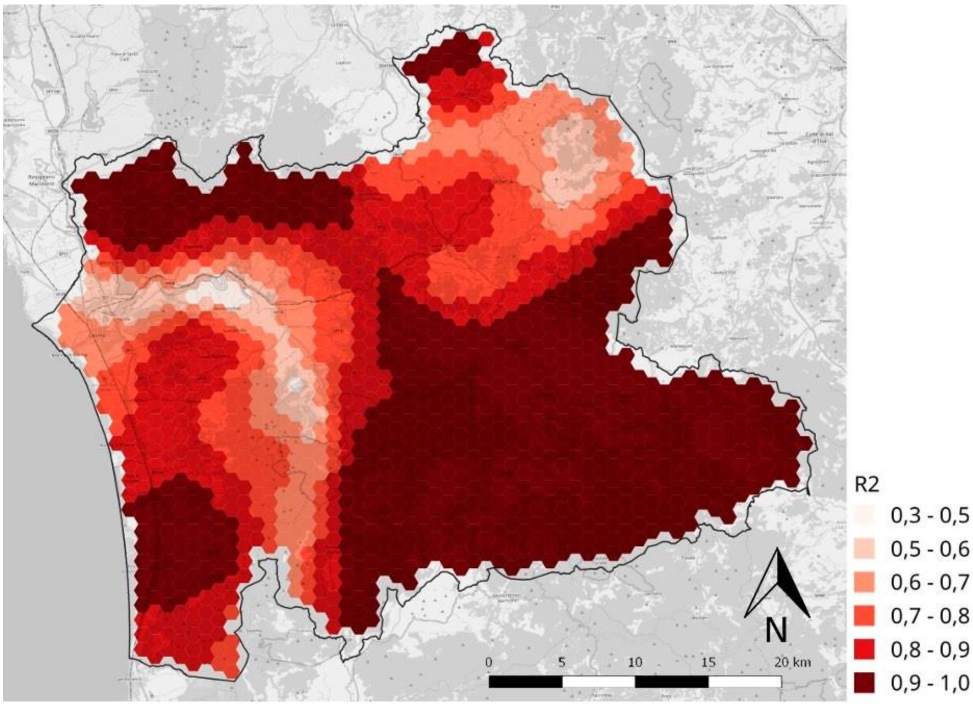


Figure 8. Map of explained deviance.



Discussion and conclusion

The implemented models confirmed the importance of agricultural cultiva- tions for the value of the landscape and allowed to obtain a spatial evaluation of the consistency of the externalities produced by agriculture, with obvious benefits for the choices of territorial government and rural development.

Furthermore, Flickr provides a free, up-to-date, and high spatial and tempo- ral resolution information source. However, as our analyses revealed, each crowdsourced database has limitations in terms of spatial data quality and sampling bias. The results of the spatial analysis of the photographic series indicate specific models of visit preferences and how the perception of the agricultural landscape is influenced both by the complementary characteristics of the rural landscape and by the agronomic choices at different scales of analysis. The spatial distribu- tion of visit preferences provides an indicator of the social benefits of agriculture, allowing a local analysis of the areas providing services and addressing the lack of quantitative indicators. Our explanatory analysis allows the identification of areas of interest in which land use planning and management strategies of the agricultural ecosystem should take into account the actual provision of non-material benefits related to the landscape. The analysis performed supports setting landscape planning pri- orities by providing an understanding of how changes in specific environmental settings can influence the supply of landscape in certain areas. Therefore, the proposed method represents a significant first step in informing stakeholders and policymakers about priority areas. A further improvement of this study is to conduct interviews and surveys with questionnaires to visitors. It would allow us to evaluate the benefits and the different values relating to the landscape. Validating these data sources and addressing uncertainty in data deriving from social media represents an important area of future research as as it is necessary before crowd- sourced data achieves acceptance for use in protected area planning and manage- ment, and for quantifying and qualifying the characteristics and values of cultural ecosystem services in rural areas.

References

Akaike H (1973). “Information Theory and an Extension of the Maximum Likelihood Principle.” In BN Petrov, F Csaki (eds.), 2nd Symposium on Information Theory, pp. 267–281. Akademiai Kiado, Budapest.

Akaike H. (1974). A new look at the statistical model identification. In Selected Papers of Hiro- tugu Akaike (pp. 215-222). Springer, New York, NY.

Atkinson P.M., German, S.E., Sear, D.A., Clark, M.J., 2003. Exploring the relations between river- bank erosion and geomorphological controls using geographically weighted logistic regres- sion. *Geogr. Anal*. 35(1): 58-82.

Bell S. (2001). Landscape pattern, perception and visualisation in the visual management of for- ests. *Landscape and Urban planning* 54(1-4): 201-211.

Bivand R.S. and Wong D.W. S. (2018). Comparing implementations of global and local indicators of spatial association. *TEST* 27(3): 716-748. doi.org/10.1007/s11749-018-0599-x

Bowman A (1984). An Alternative Method of Cross-Validation for the Smoothing of Density Esti- mates. *Biometrika* 71: 353-360.

Braunisch V., Patthey P. and Arlettaz R. (2011). Spatially explicit modeling of conflict zones be- tween wildlife and snow sports: prioritizing areas for winter refuges. *Ecological Applications* 21(3): 955-967.

Brown G, Fagerholm N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem Services* 13: 119-133.

Brown G. 2006. Mapping landscape values and development preferences: a method for tourism and residential development planning. *Int. J. Tourism Res*. 8: 101-113.

Brunsdon C., Fotheringham A.S. and Charlton M.E. (1996). Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical analysis* 28(4): 281-298.

Brunsdon C., Fotheringham S. and Charlton M. (1998). Geographically weighted regression. *Jour- nal of the Royal Statistical Society: Series D (The Statistician)* 47(3): 431-443.

Bryan B.A. (2003). Physical environmental modeling, visualization and query for supporting landscape planning decisions. *Landscape and urban planning* 65(4): 237-259.

Breusch T.S. and Pagan A.R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society* 1287-1294.

Buijs A.E., Pedroli B. and Luginbühl Y. (2006). From hiking through farmland to farming in a leisure landscape: changing social perceptions of the European landscape. *Landscape ecology* 21(3): 375-389.

Campello R.J., Moulavi D., Zimek A., Sander J. (2015). Hierarchical density estimates for data clustering, visualization, and outlier detection. *ACM Transactions on Knowledge Discovery from Data (TKDD)* 10(1): 5.

Carvalho-Ribeiro S., Ramos I.L., Madeira L., Barroso F., Menezes H. and Correia T.P. (2013). Is land cover an important asset for addressing the subjective landscape dimensions? *Land Use Policy* 35: 50-60.

Casalegno S., Inger R., DeSilvey C. and Gaston K.J. (2013). Spatial covariance between aesthetic value and other ecosystem services. *PloS one* 8(6): e68437.

Chesnokova O., Nowak M. and Purves R.S. (2017). *A crowdsourced model of landscape preference*. In LIPIcs-Leibniz International Proceedings in Informatics (Vol. 86). Schloss Dagstuhl-Leibniz- Zentrum fuer Informatik.

Clement F., Orange D., Williams M., Mulley C., Epprecht M. (2009). Drivers of afforestation in Northern Vietnam: assessing local variations using geographically weighted regression. *Appl. Geogr*. 29(4): 561-576,

Coppes J. and Braunisch V. (2013). Managing visitors in nature areas: where do they leave the trails? A spatial model. *Wildlife biology* 19(1): 1-11.

De Groot R. (2006). Function-analysis and valuation as a tool to assess land use conflicts in plan- ning for sustainable, multi-functional landscapes. *Landscape and urban planning* 75(3-4): 175- 186.

Dunford R., Harrison P., Smith A., Dick J., Barton D.N., Martin-Lopez B., Kelemen E., Jacobs S., Saarikoski H., Turkelboom F., Verheyden W., Hauck J., Antunes P., Aszalós R., Badea O., Baró F., Berry P., Carvalho L., Conte G., Czúcz B., Garcia Blanco G., Howard D., Giuca R., Gomez- Baggethun E., Grizetti B., Izakovicova Z., Kopperoinen L., Langemeyer J., Luque S., Lapo- la D.M., Martinez-Pastur G., Mukhopadhyay R., Roy S.B., Niemelä J., Norton L., Ochieng J., Odee D., Palomo I., Pinho P., Priess J., Rusch G., Saarela S.R., Santos R., van der Wal J.T., Vadineanu A., Vári A., Woods H., Yli-Pelkonen V. (2013). Integrating methods forecosystem service assessment: Experiences from real world situations. *Ecosystem Services* 29: 499-514

Feick R. and Robertson C. (2015). A multi-scale approach to exploring urban places in geotagged photographs. *Computers, Environment and Urban Systems* 53: 96-109.

Fontana V., Radtke A., Bossi Fedrigotti V., Tappeiner U., Tasser E., Zerbe S., Buchholz T. (2013). Comparing land-use alternatives: Using the ecosystem services concept to define a multi-cri- teria decision analysis. *Ecological Economics* 93: 128-136.

Fotheringham A.S. and Park B. (2018). Localized spatiotemporal effects in the determinants of property prices: A case study of Seoul. *Applied Spatial Analysis and Policy* 11(3): 581-598.

Fotheringham A.S., Brunsdon C. and Charlton M. (2003). *Geographically weighted regression: the analysis of spatially varying relationships*. John Wiley & Sons.

Fotheringham A.S., Charlton M.E. and Brunsdon C. (1998). Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. *Environment and plan- ning A* 30(11): 1905-1927.

Fotheringham A.S., Charlton M.E. and Brunsdon C. (2001). Spatial variations in school perfor- mance: a local analysis using geographically weighted regression. *Geographical and Environ- mental Modelling* 5(1): 43-66.

Fotheringham A.S., Brunsdon C. and Charlton M. (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley, Chichester, England/Hoboken, NJ, USA.

Fotheringham A.S., Kelly M.H. and Charlton M. (2013). The demographic impacts of the Irish famine: towards a greater geographical understanding: the demographic impacts of the Irish famine. *Trans. Inst. Br. Geogr*. 38(2): 221-237.

Franch-Pardo I., Cancer-Pomar L. and Napoletano B. M. (2017). Visibility analysis and landscape evaluation in Martin river cultural park (Aragon, Spain) integrating biophysical and visual units. *Journal of Maps* 13(2): 415-424. DOI: 10.1080/17445647.2017.1319881

Gliozzo G., Pettorelli N. and Haklay M. (2016). Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. *Ecology and Society* 21(3).

Gollini I., Lu B., Charlton M., Brunsdon C. and Harris P. (2013). GWmodel: an R package for exploring spatial heterogeneity using geographically weighted models. *arXiv preprint* arXiv:1306.0413.

Goodchild M.F. (1986). *Spatial Autocorrelation*. Geo Books, Norwich.

Harris P., Fotheringham A.S., Juggins S. (2010). Robust geographically weighted regression: a technique for quantifying spatial relationships between freshwater acidification critical loads and catchment attributes. *Ann. Assoc. Am. Geogr*. 100(2): 286-306.

Hernández J., Garcıa L. and Ayuga F. (2004). Assessment of the visual impact made on the land- scape by new buildings: a methodology for site selection. *Landscape and Urban Planning* 68(1): 15-28.

Hurvich C.M., Simonoff J.S. and Tsai C.L. (1998). Smoothing parameter selection in nonparamet- ric regression using an improved Akaike information criterion. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 60(2): 271-293.

IEEP (Institute for European Environmental Policy) (2007). *Final Report on the Study of HNV Indi- cators for Evaluation*. European Commission, DG Agriculture, Brussels.

Jetz W., Rahbek C. and Lichstein J.W. (2005). Local and global approaches to spatial data analysis in ecology. *Global Ecol. Biogeogr*. 14(1): 97-98.

Keeler B.L., Wood S.A., Polasky S., Kling C., Filstrup C.T. and Downing J.A. (2015). Recreational demand for clean water: evidence from geotagged photographs by visitors to lakes. *Frontiers in Ecology and the Environment* 13(2): 76-81.

Koenker R. (1981). A note on studentizing a test for heteroscedasticity. *Journal of Econometrics*

17(1): 107-112.

Levin N., Lechner A.M. and Brown G. (2017). An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. *Applied geography* 79: 115-126.

Li D., Zhou X. and Wang M. (2018). Analyzing and visualizing the spatial interactions between tourists and locals: A Flickr study in ten US cities. *Cities*.

Lu B., Harris P., Charlton M., Brunsdon C., Nakaya T. and Gollini I. (2015). Package 'Gwmodel'. Lu B., Harris P., Gollini I., Charlton M. and Brunsdon C. (2013). GWmodel: an R package for ex-

ploring spatial heterogeneity. GISRUK 2013, 3-5.

MA, 2003. *Millennium Ecosystem Assessment, Ecosystems and Human Well-being: A Framework for Assessment*. Island Press, Washington.

Mansley E. and Demšar U. (2015). Space matters: Geographic variability of electoral turnout determinants in the 2012 London mayoral election. *Electoral Studies* 40: 322-334.

Moran P.A.P. (1950). Notes on continuous stochastic phenomena. *Biometrika* 37: 17-23.

Nahuelhual L., Carmona A., Lozada P., Jaramillo A. and Aguayo M. (2013). Mapping recreation and ecotourism as a cultural ecosystem service: An application at the local level in Southern Chile. *Applied Geography* 40: 71-82.

Ode Å., Tveit M.S. and Fry G. (2008). Capturing landscape visual character using indicators: touching base with landscape aesthetic theory. *Landscape research* 33(1): 89-117.

Oteros-Rozas E., Martín-López B., Fagerholm N., Bieling C. and Plieninger T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape fea- tures across five European sites. *Ecological Indicators* 94: 74-86.Páez A., Farber S., Wheeler D. (2011). A simulation-based study of geographically weighted re- gression as a method for investigating spatially varying relationships. *Environ. Plan. A* 43(12): 2992-3010.

Palmer J.F. and Hoffman R.E. (2001). Rating reliability and representation validity in scenic land- scape assessments. *Landscape and urban planning* 54(1): 149-161.

Pastorella F., Giacovelli G., De Meo I., Paletto A. (2017). People's preferences for Alpine forest landscapes: Results of an internet-based survey. *Journal of Forest Research* 22(1): 36-43.

Pastur G.M., Peri P.L., Lencinas M.V., García-Llorente M. and Martín-López B. (2016). Spatial pat- terns of cultural ecosystem services provision in Southern Patagonia. *Landscape Ecology* 31(2): 383-399.

Pinto-Correia T., Gustavsson R. and Pirnat J. (2006). Bridging the gap between centrally defined policies and local decisions–Towards more sensitive and creative rural landscape manage- ment. *Landscape ecology* 21(3): 333-346.

Ramos B.M. and Pastor I.O. (2012). Mapping the visual landscape quality in Europe using physi- cal attributes. *Journal of Maps*, 8(1), 56-61.

Redhead J.W., Stratford C., Sharps K., Jones L., Ziv G., Clarke D., … and Bullock J. M. (2016). Empirical validation of the InVEST water yield ecosystem service model at a national scale. *Science of the Total Environment* 569: 1418-1426.

Riccioli F., Boncinelli F., Fratini R. and Casini L. (2018). Geographical Relationship between Ungu- lates, Human Pressure and Territory. *Applied Spatial Analysis and Policy* 1-24.

Richards D.R. and Friess D.A. (2015). A rapid indicator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media photographs. *Ecological Indicators* 53: 187- 195.

Rovai M., Andreoli M., Gorelli G., Jussila H. (2016). A DSS model for the governance of sustain- able rural landscape: A first application to the cultural landscape of Orcia Valley (Tuscany, Italy). *Land Use Policy* 56: 217-237.

Saarikoski H., Mustajoki J., Barton D.N., Geneletti D., Langemeyer J., Gomez-Baggethun E., Mar- ttunen M., Antunes P., Keune H. (2016). Multi-Criteria Decision Analysis and Cost-Benefit Analysis: Comparing alternative frameworks for integrated valuation of ecosystem services. *Ecosystem Services* 22B: 238-249.

Schirpke U., Meisch C., Marsoner T. and Tappeiner U. (2018). Revealing spatial and temporal pat- terns of outdoor recreation in the European Alps and their surroundings. *Ecosystem services* 31: 336-350.

Sonter L.J., Watson K.B., Wood S.A. and Ricketts T.H. (2016). Spatial and temporal dynamics and value of nature-based recreation, estimated via social media. *PLoS one* 11(9): e0162372.

Stenseke M. (2009). Local participation in cultural landscape maintenance: Lessons from Sweden.

Land Use Policy 26(2): 214-223.

Swinton S.M., Lupi F., Robertson G.P., Hamilton S.K., 2007. Ecosystem services and agriculture: cultivating agricultural ecosystems for diverse benefits. *Ecol. Econ*. 64: 245-252.

Tenerelli P., Demšar U. and Luque S. (2016). Crowdsourcing indicators for cultural ecosystem ser- vices: A geographically weighted approach for mountain landscapes. *Ecological Indicators* 64: 237-248.

Tieskens K.F., Schulp C.J., Levers C., Lieskovský J., Kuemmerle T., Plieninger T. and Verburg P.H. (2017). Characterizing European cultural landscapes: Accounting for structure, management intensity and value of agricultural and forest landscapes. *Land use policy* 62: 29-39.

Tobler W. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Ge- ography* 46: 234-240.

van Berkel D.B. and Verburg P.H. (2011). Sensitising rural policy: Assessing spatial variation in rural development options for Europe. *Land Use Policy* 28(3): 447-459.

van Zanten B.T., Van Berkel D.B., Meentemeyer R.K., Smith J.W., Tieskens K.F. and Verburg P.H. (2016). Continental-scale quantification of landscape values using social media data. *Proceed- ings of the National Academy of Sciences* 113(46): 12974-12979.

Walden-Schreiner C., Leung Y.F. and Tateosian L. (2018). Digital footprints: Incorporating crowd-sourced geographic information for protected area management. *Applied Geography* 90: 44-54.
Welling S.H., Refsgaard H.H., Brockhoff P.B. and Clemmensen L.H. (2016). Forest floor visualizations of random forests. *arXiv preprint* arXiv:1605.09196.

Westcott F. and Andrew M.E. (2015). Spatial and environmental patterns of off-road vehicle rec- reation in a semi-arid woodland. *Applied Geography* 62: 97-106.

Wheatley D. (1995). *Cumulative viewshed analysis: A GIS-based method for investigating intervisibility, and its archaeological application*. In G. Lock and Z. Stancic (Eds.), Archaeology and geographi- cal information systems (pp. 171-186). London: Taylor and Francis.

Willemen L., Verburg P.H., Hein L. and van Mensvoort M.E. (2008). Spatial characterization of landscape functions. *Landscape and Urban Planning* 88(1): 34-43.

Wood S.A., Guerry A.D., Silver J.M. and Lacayo M. (2013). Using social media to quantify nature- based tourism and recreation. *Scientific reports* 3: 2976.

Yoshimura N. and Hiura T. (2017). Demand and supply of cultural ecosystem services: Use of Geo-tagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services* 24: 68-78.

Winescape perception and big data analysis: An assessment through social media photographs in the Chianti Classico region

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Abstract

Quantifying and mapping the relevant landscape attributes of winescape is difficult due to both the complex identity characterization of the places and the multidimensionality of the pursued perceptive experience on the emotional level. Although the quality of the rural landscape is recognized as an essential element of winescape, in the literature there are no methodological and applicative studies on the identification of the most significant characteristics of a wine region that are fundamental attributes in the preferences of visitors. The aim of the work is to propose a methodology to link the environmental and cultural landscape characteristics of the territory with the concept of winescape to improve the image of wine tourism adopting a systematic approach for territorial branding starting from the analysis of the visitors' preferences. The analysis is conducted through the geographical information data shared on the social media Flickr. Different methods of analysis are applied in an integrated way to:

a) analyze the demand for winescape in its different dimensions;
b) identify the territorial variables that are part of the winescape supply;
c) build a spatial relationship model between winescape demand and supply to quantify the territorial suitability and provide useful information for rural development strategies.

Keywords: Winescape; Big data; Landscape quality; Image clustering; Maxent; Wine tourism: territorial marketing

Introduction

The landscape is a classic example of mixed good, as it guarantees both positive externalities and private benefits. In the case of the rural landscape, and in the light of a growing neo-archaism, this characteristic has become increasingly important as the people expectations have grown and the rural world was rediscovered for its positive elements, moving away from a prejudicial vision of absolute negativity lasted until the seventies (Menghini, 2009). Today the rural landscape is linked to specific choices in terms of both local governance and economic development policies (Antrop, 2005). These policies focus on an increasingly integrated approach, based on "rural development". From a physical place, passively designated to host human activities, the territory is increasingly seen as a more complex resource made up of tangible and intangible assets, and able to orientate and ensure specific goods and local services (public and private ones) for residents and external users (Sidali et al., 2015). This different vision of the territory has led to in-depth revisions of the principles of local governance and rural development policies. The former no longer considers the management of the rural areas to support urban growth in a residual way, while the latter explores new business development strategies according to the concept of multifunctional diversification (Morgan et al., 2010).

1.1. *Literature review*

The term "winescape" derives from the concept of servicescape introduced by (Bitner, 1992); p.65). Within this specific case, servicescape identifies those activities complementary to the product that facilitate the marketing of services. Within the different dimensions that can be identified when dealing with servicescape, Bitner highlights three composite dimensions as being particularly relevant: 1) ambient conditions; (2) spatial layout and functionality; and (3) signs, symbols and artefacts. According to the author, these attributes merge to influence the mood and attitude of customers and employees, leading to approach or avoidance behaviors.

Some recent empirical studies have extended this theory to space services. For example, for cruise travel marketing, Kwortnik (2008) identifies a broader range of space services:

(1) natural environment (ocean); (2) environmental conditions (smell, music, cleanliness and lighting); (3) ship design; (4) social factors (human relationships, congestion, relationships with service personnel). Similarly, for Johnson and Bruwer (2007); p. 277), "*the "winescape" in turn encapsulates the interplay of: vineyards; wineries and other physical structures; wines; natural landscape and setting; people; and heritage, town(s) and buildings and their architecture and artefacts within, and more*." In the study of winescape, Thomas, Quintal and Phau (Thomas et al., 2010) define two approaches: the macro

approach, which considers the wine- scape at the wine region or at a wine route scale (predominant in the literature on wine tourism, e.g. (Getz and Brown, 2006), and the micro approach, which focuses on the environment in a specific estate or winery. As for the macro approach, the authors point out that there are few empirical studies aimed at identifying and measuring specific attributes of the winescape according to their influence on the attitude of the wine tourist and his/her subsequent behavioral intentions. Among them, in his study on wine farms in the Niagara region, Carmichael (2005) highlights that "*Overall, the rural landscape is found to be highly important in visitor enjoyment of the wine tourism experience*". Getz and Brown (2006) identify four dimensions for wine tourism, but only "the cultural product" characterized by "*traditional wine villages, unique accommodation with regional character and fine dining and gourmet restaurants*" can be related to the concept of winescape (Getz and Brown, 2006); p. 153). In one research aimed at the conceptualization of the image of a wine region into the concept of winescape as it is perceived by tourists, Bruwer and Joy (2017) note that "*The most important winescape dimension is the destination's natural beauty/geographical setting of its landscape*". According to Bruwer et al. (2013); the landscape itself, with its characteristics of rurality and naturalness, is a fundamental part of the concept of winescape, especially with wine tourism. "*During the aesthetic experience of landscape, there are four levels of aesthetic cognition: the perceptual (senses are involved, viewing, hearing or smelling), expressive (feelings and emotions associated with), symptomatic (object signs are symptomatic of something else) and symbolic (ideas and imaginations created in the viewers mind) …. It should be noted that the winescape translates into the destination region's identity and eventually into its brand image, once operationalized accordingly*." (p. 5). More recently, Bruwer, Gross and Lee (Bruwer et al., 2016) point out that "*the scenic location … makes it a dramatic nature experience for visitors.*" and that "*The landscape itself, and ultimately the entire winescape, therefore "seduced" the visitor into engaging in a total experience and forming a cognitive and affective perception of a fairly hedonic nature.*" The authors conclude that "*The impact of the nature-related dimension (i.e., scenery and/or natural settings) outweighs all other dimensions of the wine region's winescape, whether from a distance from the destination region (in-state vs. out-of-state) perspective or wine tourism as the primary reason for visiting the region (wine tourists vs. non-wine tourists). Both in-state and out-of-state visitors, but more so out-of-state visitors, exhibit hedonic pleasure-seeking needs expression and actions in their actual wine tourism consumption behavior. This resonates with* Williams (2001) *work, which suggested a diminishing importance of the industrial features of wine tourist destination image with a trend toward more experiential aspects*".

Overall, in different ways all the authors underline the strong characterization of a wine-growing landscape both for the physical relevance of the vines, as a permanent cultivation, and for the ploughing and type of farming chosen. Within the wine sector, this is even more evident in the increasingly specialized local agri-food systems, as it is also set forth by the various territorial certifications. The physical presence of the vines is unequivocally linked to a specific production, wine, and represents an element of strong characterization for the identity of a place. In Italy, as in many other parts of the world, this evidence becomes the pivot around which processes of elevation of the attractiveness of the place, differentiation strategies and effective positioning of the wines are generated, according to a product-territory relationship among the most distinctive within the range of Italian agri-food quality products. To fully understand the real recreational tourist opportunities of a winescape according to both the strong identity of the places and the local communities (their cultural values and traditions) is fundamental to consider how the preferences of the tourist demand evolved. In recent years, the tourist demand went towards an evident segmentation, differentiating into “charter” and “mass” tourism, on the one hand, and “elite” and “exploration” tourism, on the other (Cohen, 1979; Smith, 1977; Gubert and Pollini, 2002). In the first segments, composed of large groups, the mere visit of the place represents the primary aim, while the second segments, being inspired by post-modern behavioral patterns (Menghini, 2009), focus on a more engaging experience, willing to live the overall atmosphere of a place, such as in the case of winescape. In the post-modern vision, the tourist, searching for fulfilment in a winescape, needs to perceive his recreational tourist experience as a guest and not as a customer, living the trip with a much deeper intensity than a simple stay. Traditional surveys through questionnaires are largely used to analyze the preferences and perceptions of complex phenomena such as wine tourism (Boatto et al., 2013; Alebaki et al., 2015; Alampi Sottini et al., 2009; Hervé et al., 2018; Eustice et al., 2019). However, in recent years, additional techniques using the data shared through social media spread as a complementary tool to direct surveys. As Cinelli Colombini (Cinelli Colombini, 2013) highlighted in her article “*the web is the key for tourism […]10% of all the tourism business and 30% of the bookings happen online […] mobile phones or smartphones will be crucial for orienting visitors during their travel experience. Future travellers will not ask for information anymore and will look at the web for guidance on what to see, where to eat or sleep and what to do. In other words, all the useful information to turn a tour into something unique will be available online*” (p. 112). Numerous studies describe how social media can influence wine consumers and may represent an important opportunity for wineries. Reyneke, Pitt and Berthon (Reyneke et al., 2011) used data from the website howsociable.com to portray similar luxury wine brands in multi-dimensional space. Wilson and Quinton (2012); p. 282) conducted interesting research on Twitter's contribution to winery revenues. The authors found that "*The embracing of social media moves wine businesses beyond engaging with consumers through winery visits, email or direct mail marketing campaigns and offline tastings and into the social realm of connecting, sharing and extending audiences through social media*". Capitello, Agnoli, Begalli and Codurri (Capitello et al., 2014) explored the best practices adopted by Italian wineries in increasing wine brand visibility using social media as a low-cost tool in their marketing stra-tegies. More recently, Sogari et al. (2017) studied the role of social media in the consumer purchasing behavior for wine between the millennial and non-millennial generations. Galati et al. (2017) analyzed the Facebook activities of a sample of Sicilian wineries and explored the relationships between these engagement activities and some primary features of the firms and their entrepreneurs. In the food tourism sector, Liu et al. (2013) studied the online image-sharing community Flickr to profile the users who are fond of online food photography as well as to explore the role of online food photography in their traveling planning process. When focusing on the study of aesthetic appreciation of a specific rural area or landscape, the use of geo-tagged photo- graphs seems to be a promising alternative to appraise landscape perception in respect to traditional investigation through questionnaires (Tempesta and Vecchiato, 2015); the evaluation of landscape through photographs has developed in the last decades as a method for the analysis of rural landscapes and natural areas. Levin et al. (2017) found "*strong and significant correlations between all crowdsourced data and visitation statistics, demonstrating the potential to use crowdsourced data to characterize the social and perceived importance of protected areas and as proxy for visitation statistics*". The same authors also demonstrated the advantages of combining remote sensing data with geo-tagged photos of Flickr social media to identify the tourist frequency and monitor the impacts of overloading. Yoshimura and Hiura (2017) and Walden-Schreiner et al. (2018) analyzed the relationships between shooting locations of geo-referenced photos of Flickr with both the environmental characteristics of the territory and the presence of infrastructures; the aim of the authors was to deliver management strategies for the preservation of natural resources, while providing opportunities for tourism and recreation.

1.2. *Aim of the work*

Quantifying and mapping the relevant landscape attributes of winescape is difficult because of the complex identity characterization of the places (the type of cultivation, the production methods, the types of wines, the traditions of local consumption, etc..), and the multidimensionality of the pursued perceptive experience on the emotional level.

During the aesthetic experience of the landscape, there are four levels of aesthetic cognition: perceptive (the senses such as sight, hearing, smell are involved), expressive (feelings and emotions associated with the identity of the places), symptomatic (objective signs are symptomatic of something else) and symbolic (ideas and imaginations created in the minds of the viewers) (Nohl, 2001). The strong evidence of the relationships among vineyards, wine production and local traditions has the highest expression in the Chianti region, as the name of the territory indicates at the same time both a product and a specific geographic area. This strong relationship is the basis of the "winescape" concept. The most important practical consequence is that the interest in a territory is closely linked to the demand for wine. Mitchell et al. (2012) emphasized this multidimensionality introducing the concept of "cultural geography" and stated that "*rural landscapes, regardless of their use, are perceived differently by different groups of people*" (p. 315). It means that the image of a destination is a function defined by those who visit the destination and by those who live in and around the wine region of destination. In conclusion, although the quality of the rural landscape is recognized as an essential element of winescape, in the literature there are no methodological and applicative studies on the identification and characterization of the significant attributes used to detect the identity elements of the image of a wine region as the visitor perceives them. The studies mentioned above, carried out through direct surveys, allowed to identify the relevant characteristics of winescape in terms of services to wine tourists, but they are very vague and generic in the determination of landscape and environmental attributes.

In the present study, the potential supply of winescape was considered instead of the real one. The former is defined as the (interconnected) set of intrinsic territorial characteristics that contribute determining the offer of Cultural Ecosystem Ser- vices (CESs). The contribution that CESs make to well-being can be understood considering three main elements: *the "identities" they help frame, the "experiences" they help enable and the "capabilities" they help equip. By making these distinctions the framework is designed to avoid describing benefits in purely intangible terms* (Fish et al., 2016); p. 213). The potential supply of CESs can be mapped analyzing the relationship between the demand area and its environmental factors, as the demand map represents the visitors' aesthetic preferences. With specific reference to the wine landscape, the paper highlights how this new vision of the territory requires different analytical approaches for the assessment of the resources, integrating analyses based on the quantification of the consistency of landscape resources with the preferences of individuals. How- ever, the exploration of an individual's preferences must be carried out considering the nature of the landscape, which is not associated with a specific place and time of "exchange". According to the above, the present research proposes an analysis of the quality of the landscape as visitors to a given territory perceive it. The analytical phase of the study, ac- cording to the concept of "winescape", investigates the preferences of visitors to the specific territory of Chianti, offering survey tools capable of monitoring the characteristics of the demand and the supply. The main objective of the work is to propose a methodology to link the environmental, and cultural landscape characteristics of the territory with the concept of winescape to improve the image of wine tourism. Considering the limitations of the different approaches for the analysis of the potential supply of CESs highlighted in the literature, the present study integrates two theoretical approaches: one based on the indicators from the literature of the visual quality of the landscape and the other referring to the indicators from the existing literature on winescape. For this purpose, different methods of analysis presented in the literature were applied in an integrated way to pursue the following specific objectives:

(i) analyze the demand for winescape in its different dimensions;
(ii) identify the territorial characteristics, and their measurable variables, that define the supply of winescape;
(iii) create a spatial relationship model between demand and supply for winescape to quantify the territorial suit- ability and provide useful information for regional planning and rural development.

Within a local development plan framed in the most modern territorial marketing approaches, this methodological proposal represents a preliminary analysis of the demand through which to formulate development strategy able to combine the local attitudes (vocations) with the behavior of winescape users (see Fig. 1).

2. Study area

The Chianti Classico region (Fig. 2) stretches over 70,000 ha between Florence and Siena. It is covered by about 10,000 ha of vineyards, 7200 of which registered in the Chianti Classico PGDO appellation. In this territory, even though the vine covers only 15% of the total area, viticulture represents the key element of both the local landscape and the entire local socio-economic identity: the term Chianti indistinctly identifies both the geographical area and the most relevant product of the area, its wine. After a period of massive rural exodus, since the seventies, the territory has become the center of a variety of interest, especially for the tourist-recreational potential of the area which now has one of the most extensive net- works of farm tourism throughout Europe. The Chianti Classico region has a specific vocation to host forms of tourism characterized by predominantly individual behavior, aimed at the search for recreational opportunities far from mass tourism and willing to visit places with a level of discretion able to capture the most hidden and intangible elements.

3. Methods

3.1. *Introduction*

In summary, the proposed methodology is divided into the following phases:

Step 1: Analysis of the winescape demand (dependent model variable). It is carried out by:

a) Downloading both the photos taken in the study area and their geographical coordinates;

b) Filtering the photos to identify images related to the concept of winescape;

c) Classifying the photos automatically and identifying the winescape user's clusters.

Step 2: Analysis of the supply of ecosystem services (independent variables of the model). It is carried out by:

a) Calculating the naturalistic and historical indices;

b) Identifying and calculating the winescape service indicators.

Step 3: Analysis of supply-demand balance: spatial modelling of photograph distributions. It is carried out by:

a) Computing maps of high-value location for the winescape user;

b) Evaluating the marginal importance of the indicators.

Fig. 2 shows the flow chart of the proposed methodology.

3.2. *Demand for winescape services*

We are currently experiencing a rapid increase in available data sources regarding voluntary geographical information. The term "Volunteered Geographic Information" (VGI) means the range of content, provided through the Web by its users which allow the generation of geographical information (Goodchild, 2007). Social media applications, such as Twitter, Flickr or Facebook, provide a source of geographical information that can be queried via public Programming Interfaces (APIs). At the same time, people are showing a growing willingness to actively share their experiences of living the urban, rural and natural spaces, in a context of use that falls under the broad term of “People as sensors”. In addition, geotagging (i.e. to associate geo-localization information to a piece of information) becomes increasingly popular for photos. According to Nov et al. (2010); the photographic data uploaded on the Flickr platform implies an individual process that can be divided into two main phases:

a) the technical-creative phase of taking the photo;

b) the social phase of sharing this photo by associating commentary information to it.

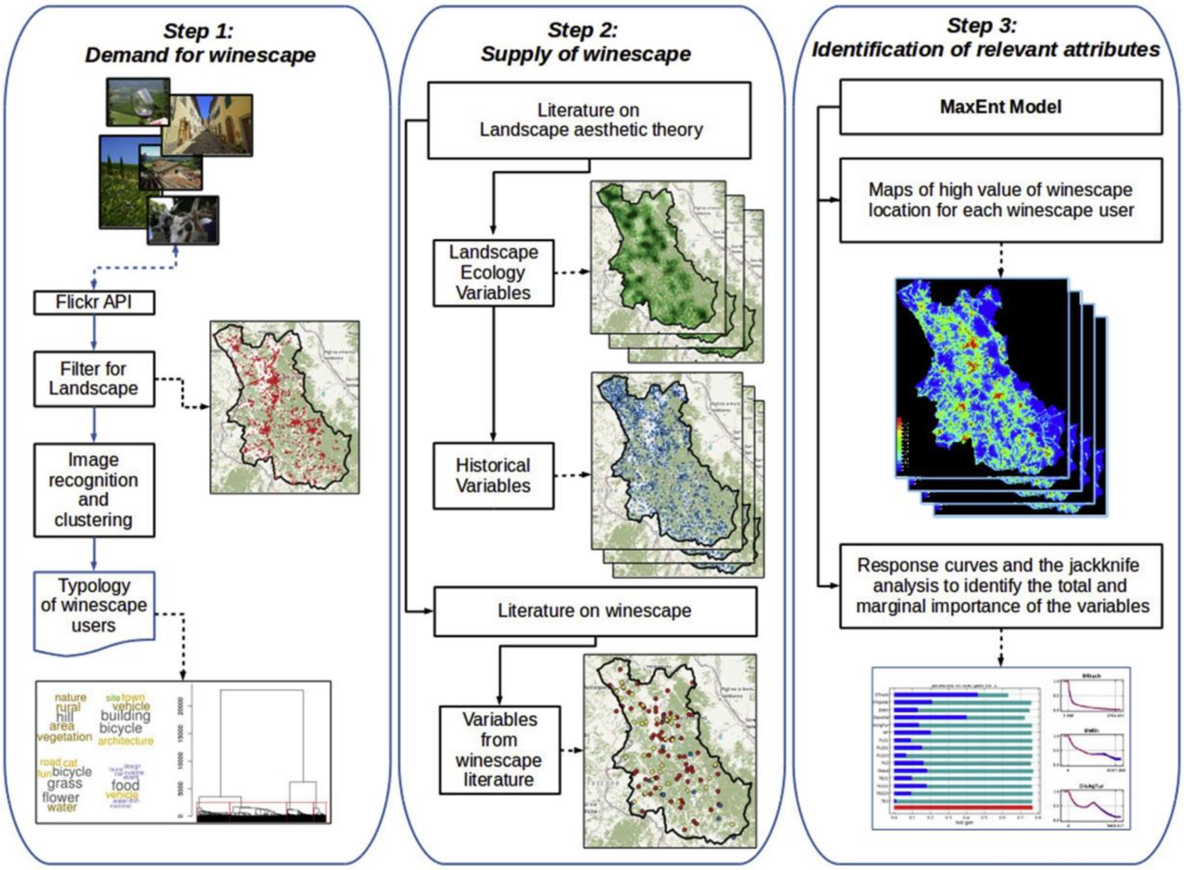

Fig. 1. Flow chart of the work.

Lynch suggests that "[...] *the generalized mental picture of the exterior physical world that is held by an in- dividual [...] is the product both of immediate sensation and of the memory of past experience, and it is used to*

interpret information and to guide action" (Lynch, 1960):p. 4). Speaking generally (Collier, 1967; Sontag, 1977; Dakin, 2003; Scott and Canter, 1997), the action of taking a picture is not only linked to the characteristics of the surrounding environment, but involves all of the aspects of the interpretative cognition that the individual applies to that space (personal preferences, memories, opinions, etc.). So, both the act of taking a picture in a specific place and the consequent action of choosing which photos to share on the social network platform reflect the quality of the perception that the individual has of that place.

For the present research, different sources of information were initially considered: Instagram, Facebook, Twitter, Panoramio and Flickr. We decided to choose Flickr for the following reasons: a) it is broadly used as a data source in GIScience, landscape, geography and tourism literature (Dunkel, 2015; Gliozzo et al., 2016; Oteros-Rozas et al., 2017); b) it offers an accessible API that has been widely experimented (Alivand and Hochmair, 2017); c) it provides a source of free, updated, and with good spatial as well as temporal resolution information (Levin et al., 2017).

Fig. 2. The study area.

The density of pictures taken in each location can be considered an indicator of the interest in the territorial services of the winescape. However, interpreting the information in the photographs can be a challenge for the investigation on the cultural uses of the environment, since the choice of what to photograph is naturally subjective. The subject of the photo can provide very useful information to characterize the geographical and cultural identity variables of a location. Manual classification of the content of the photographs is not an easily applicable solution since the investment in terms of time required to compare a large number of sites would be substantial. To allow a rapid evaluation of territorial cultural services over large areas, automated analysis of the contents of the photographs from social media is necessary. To solve this problem, Richards and Tunçer (2017) applied an online machine learning algorithm - Google Cloud Vision - and used hierarchical clustering to group the photos. This method turned out to give good correspondence compared with manual classification.

Based on this approach, in the present study, each down- loaded image was analyzed by the learning algorithm (Google Cloud Vision, 2017), obtaining a specific description of the context, encoded in specific keywords. This analysis was carried out by automatic access to the Google Cloud Vision API via the R package {RoogleVision}. A maximum of five keywords per image was returned. After this analysis, a hierarchical clustering algorithm was applied to group photographs according to their keywords (Oteros-Rozas et al., 2017). Then, a distance matrix was generated by building a document-term matrix with photos as documents and keywords assigned to photos as terms. After- wards, hierarchical clustering was applied to the matrix using the Ward distance, implemented in the "hclust" function for the statistical programming language R (R Core Team, 2018). We choose the elbow method to determine the optimal number of clusters. It optimizes the sums of squares within the clusters (Kassambara, 2017).Clusters identified by hierarchical grouping were then used to categorize photographs. Lastly, to give meaning to each of the resulting clusters, we considered the fifteen words most commonly attributed to the photographs in each group. This number of words was considered adequate to let us define the type of photographs included in each cluster.

3.3. *Supply of winescape: the choice of explanatory variables*

Differently from the real supply, the potential supply of CESs includes locations with intrinsic characteristics that can potentially satisfy the demand but has limitations that do not allow the matching of supply and demand. The potential supply analysis aims to go beyond the current situation, suggesting strategies for the future.

As for the assessment of landscape quality, the exhaustive classification of indicators proposed by Ode, Tveit and Fry (Ode et al., 2008) was used as a reference. The conceptual framework developed by these authors links each indicator to concepts described by different aesthetic theories of landscape:

(a) complexity indicators are referred to the Biophilia evolutionary theory (Ulrich et al., 1993);
(b) naturalness indicators are related to the degree of naturality (or naturalness) of the examined environment, and they are explained by the restorative and therapeutic role of nature (Kaplan, 1995);
(c) coherence indicators are explained by the legibility aspects of the theories of Information Processing (Kaplan and Kaplan, 1989).

According to the above, in the present study, three main conceptual categories were identified and linked with five different visual quality indicators:

1) Complexity indicators
- Number of different land covers per view in a radius of 1000 m;
- Shannon index in a radius of 1000 m.

2) Naturalness indicators
- percentage area, edge density, and number of patches of natural and semi-natural vegetation.

3) Coherence indicators
- percentage area, edge density, and number of patches of vineyards in a radius of 1000 m;
- percentage area, edge density, and number of patches of olive groves in a radius of 1000 m.

As for the indices deriving from the specific literature on winescape, the experimental studies of Echtner and Ritchie (1991); Winkler and Nicholas (2016); and, in particular, Getz and Brown (2006); were considered. According to Getz and Brown, the expectations of enotourist are at the same time related to the product (wine), the essential destination features and the cultural values. According to the authors, the 'core wine product'' considers both the product and the wineries (the hospitality of places, the frequency of events, the expertise of the staff, the size of the winery, etc.); the 'core destination appeal'' includes attractive scenery with well marked wine trails; the 'cultural product'' encompasses unique accommodation with regional character, fine dining and gourmet restaurants, and traditional wine villages.

In the present paper, the following indicators have been identified, which fall within the dimensions 'core destination appeal' and 'cultural product':

- core destination appeal
  - distance from historic villages in a radius of 1000 m;

- territorial density of traditional and historical buildings (reference year: 1954), calculated using a Gaussian filter, with a radius of 1000 m;
- proximity to historic travel paths.

- cultural product
  - proximity to the best restaurants based on the ratings shared on the TripAdvisor social network;
  - proximity to cellars included in the first best 100 places in Italy according to the magazine Wine Spectator.

The indicators were calculated at landscape level using the Frastag and QGIS software.

3.4. *Supply-demand balance: spatial modelling of photograph distributions*

The final step of the research was the analysis of the cor- relations between the shooting locations of Flickr geo- referenced photos with the environmental characteristics of the territory. This analysis was carried out by the MaxEnt model (Yoshimura and Hiura, 2017; Walden-Schreiner et al., 2018). The method is based on an automatic learning procedure to estimate the probability of the presence of a wine- scape user in a specific location according to territorial characteristics. This model integrates continuous and categorical predictive variables, minimizes over-treatment, and evaluates the influence of each covariate.

In present study, the model runs on 15 replicas. The maximum number of background points was set to 10,000,8with a convergence threshold of 0.00001 (Merow et al., 2013; Phillips et al., 2006; Poor et al., 2012). The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) graph was used as the first parameter to validate the MaxEnt model (Phillips and Dudík, 2008).The ROC can measure the efficiency of a binary classifier, such as the MaxEnt model, and the AUC represents the prob- ability of sensitivity. An AUC value of 0.5 indicates a random pattern, while a value of 1 indicates a model that perfectly classifies the presence of data. An AUC value between 0.50 and 0.70 suggests a reasonably accurate model; a value between 0.70 and 0.90 suggests an accurate model, and a value higher than 0.90 indicates an extremely accurate model (Swets, 1988). The response curves are another useful evidence given by the MaxEnt model. The curves show how the probability of predicted presence varies according to each environmental variable, keeping all the other environmental variables at the average value of the sample. Then, the Jackknife analysis was used to indicate the most informative variables. The Jackknife test obtained from MaxEnt allowed the contribution of each environ- mental variable to be analyzed; this approach excludes one variable at a time when running the model. Thus, it provides information on the performance of each variable in the model in terms of how important each variable is in explaining the distribution of species and how much unique information each variable provides. The Jackknife test determined the contribution of all variables to the distribution of the Flickr points. The MaxEnt methodology was applied separately for each cluster identified in par. 2. A probability map for each cluster was obtained. Lastly, the different maps were aggregated into a single map of prevailing probability. To each geographical location, the cluster with the highest probability was assigned.

4. Results

4.1. Image recognition and clustering

Using the algorithm based on Flickr's *Application Programming Interface* (par. 2), the coordinates of 28,815 shooting points of shared photos were downloaded from 2005 to 2017.

Afterwards, the pictures with the tags containing the words, and related terms, “wine”, “vineyard”, “Chianti”, were selected. Lastly, specific filters were applied to avoid distortions due to photos repeated many times in a single location by a single photographer. The final dataset contained 9304 photographic points. The records were downloaded and analyzed in R and converted into shapefiles for geospatial analysis using QGIS.

Then, on the 9304 records, the *Google Cloud Vision API* assigned at least one descriptive label to 9228 photos; the remaining 76 not labelled photos were excluded from further analysis. Fig. 3 shows the dendrogram and the results of the elbow method used for determining the optimal number of clusters. The elbow method suggests 4 clusters. Through hierarchical clustering, the following groups of photo points were identified for each cluster: cluster 1 counting 2657 points, cluster 2 1100 points, cluster 3 4693 points and cluster 4778 points.

The contents of the images were classified considering the 15 most frequent labels for each cluster (Table 1). Cluster 1, named “Landscape”, was characterized by open panorama photographs mainly belonging to winegrowing areas, with a combination of rural, natural and artificial historical elements typical of the Chianti landscape. Cluster 2, named “Miscellaneous” collected a mix of photos, with a relative prevalence of images taken during the international cycling event "*L'eroica*". Cluster 3, named “Villages”, comprised photos of urban spaces of historical villages and photos of architectural details (gates, fountains, arches, etc..) belonging to them. Cluster 4, named “Events”, was mainly made up of photos of food, places (wine cellars and restaurants), and events (wed- dings, conferences, etc.).

4.2. Spatial modelling of photograph distributions

The probability of occurrence for photographs of the "Landscape", "Miscellaneous", "Villages" and "Events" was modelled separately for each cluster. The AUC was high for all models: in "Landscape" the AUC, calculated through the training set, was 0.82 and the standard deviation was 0.023; in "Miscellaneous", the average test AUC for the replicate runs was 0.811 and the standard deviation 0.024; in "Villages", the

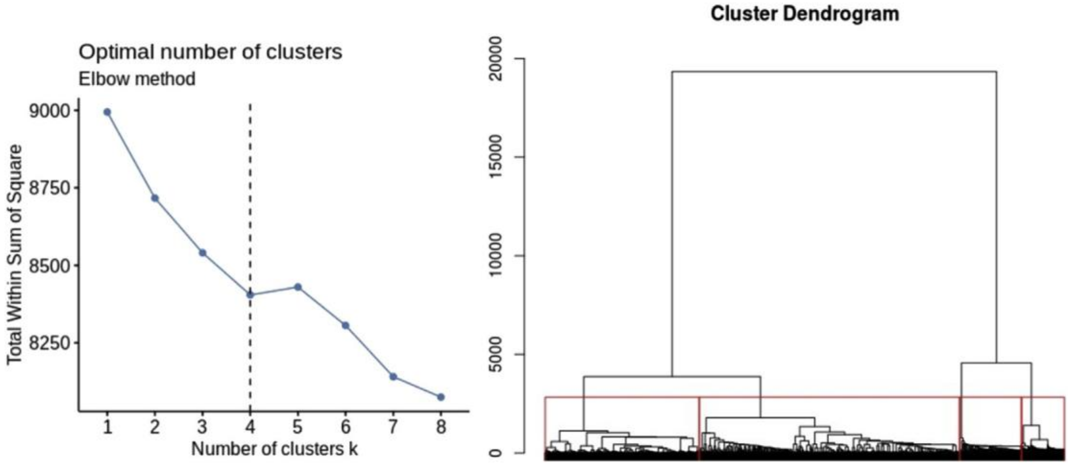

Fig. 3. Results for the elbow method and the cluster dendrogram.

Table 1 Most common descriptive labels of the photographic content in the identified clusters.

	Cluster 1			Cluster 2			Cluster 3			Cluster 4		
	words	freq	%	words	freq	%	words	freq	%	words	freq	%
1	hill	653	24.59%	bicycle	81	7.36%	building	704	15.00%	food	144	18.51%
2	agriculture	624	23.49%	flower	74	6.73%	vehicle	583	12.42%	event	54	6.94%
3	rural	560	21.08%	water	70	6.36%	town	521	11.10%	cuisine	51	6.56%
4	vegetation	531	19.99%	design	68	6.18%	architecture	503	10.72%	water	49	6.30%
5	nature	500	18.83%	building	68	6.18%	history	442	9.42%	design	48	6.17%
6	vineyard	391	14.72%	cat	60	5.45%	site	421	8.97%	dish	46	5.91%
7	town	382	14.38%	road	58	5.27%	road	391	8.33%	mammal	44	5.66%
8	leaf	347	13.06%	fun	58	5.27%	property	365	7.78%	flower	41	5.27%
9	landforms	277	10.43%	vehicle	56	5.09%	historic	361	7.69%	product	40	5.14%
10	grassland	269	10.13%	vegetation	54	4.91%	house	360	7.67%	motor	32	4.11%
11	house	266	10.02%	leaf	53	4.82%	medieval	358	7.63%	wood	32	4.11%
12	property	253	9.53%	girl	51	4.64%	village	314	6.69%	family	31	3.98%
13	village	241	9.07%	interior	51	4.64%	rural	308	6.56%	flora	31	3.98%
14	alley	213	8.02%	wood	50	4.55%	nature	296	6.31%	like	31	3.98%
15	neighbourhood	198	7.45%	mammal	48	4.36%	agriculture	289	6.16%	recreation	31	3.98%
	N. of images	2656			1100			4693			778	

AUC was 0.885 and the standard deviation 0.042; in “Events”, the AUC was 0.857 and the standard deviation 0.047. To examine the territorial localizations where it is more likely to have geotagged photos classified in the different clusters, the prevalent probability map was calculated. Fig. 4

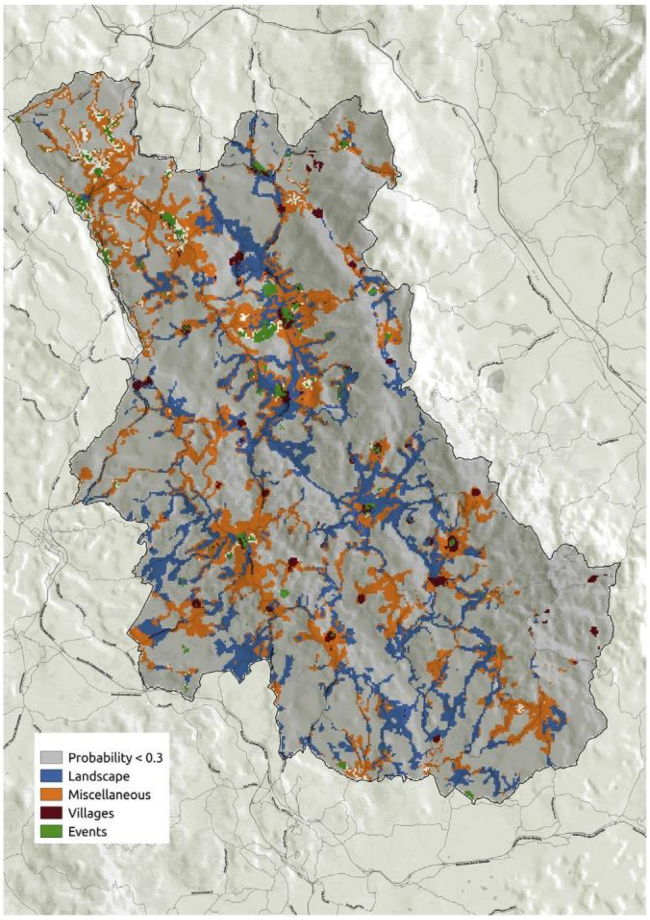

Fig. 4. Map of the prevailing probability of photos classified in the different clusters.

shows the map of the prevailing probability of photos classified in the four different clusters. Near the historical villages, we identify the maximum probability of having users classified in the “Villages” and “Events” clusters. However, the overlap between the two clusters is limited. The “Events” cluster is concentrated in the larger villages while the users belonging to the cluster “Villages” also visit scattered villages and historic houses. Visitors belonging to the clusters “Land- scape” and “Miscellaneous” visit Chianti in a more wide- spread way. The places where the probability of having users of the cluster “Landscape” is higher are located near the historic Chiantigiana road. On the other hand, the “Miscellaneous” cluster is characterized by users that explore the territory also using unpaved roads. The importance of the variables evaluated by the Jackknife test is showed in Fig. 5. In detail, the most significant variables for the cluster “Events” are, in descending order, the density of traditional and historical buildings, the distance from travel path and the number of different land covers per view. For the cluster “Villages”, the most important variables are the density of historical and traditional buildings, the distance from travel path and the distance from farm holidays. For the cluster “Miscellaneous” the most essential variable is the distance from travel path, followed by the density of traditional and historical buildings and the Shannon index. Lastly, for the Cluster “Landscape” the most significant variables are, again, the distance from travel path and the density of traditional and historical buildings, and the ecology and landscape indicators referring to crops (edge density of vineyards, percentage of vineyards and percentage of natural areas). To be noted that many variables have a jackknife test value higher than 0.65, demonstrating an excellent predictive capacity. Lastly, the response curves give interesting information. As an example, Fig. 6 shows the curves relative to some variables of the model. On the one hand, distance from travel paths indicates a high logistic probability of infrastructure being present within five hundred meters.

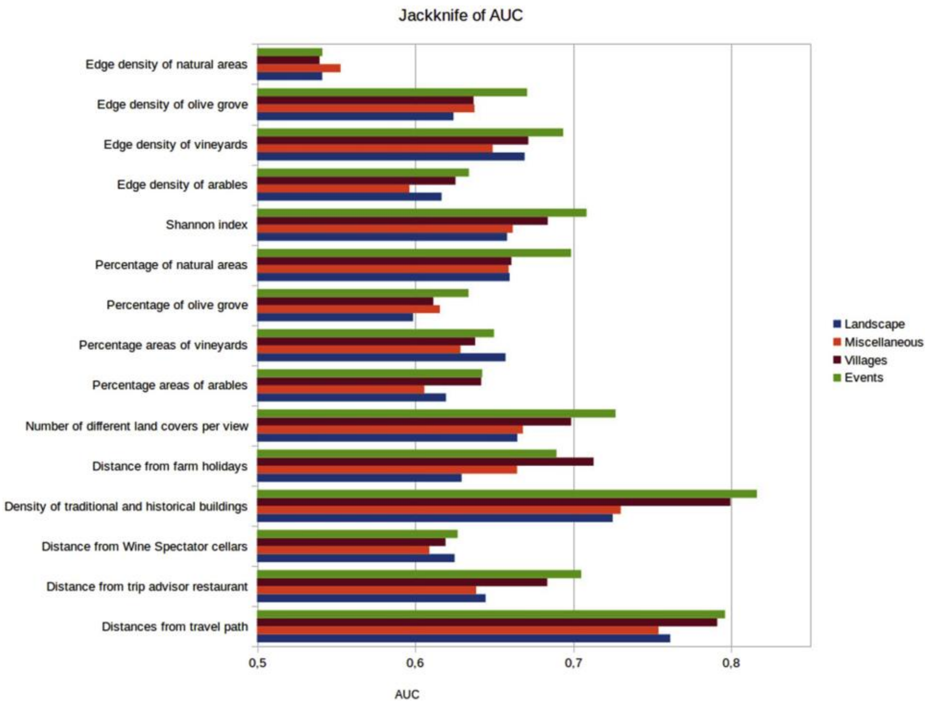

Fig. 5. Jackknife test.

On the other hand, the logistic probability is directly proportional to the percentage of vineyard for all image clusters up to at least 30 per cent; beyond this value the probability is stable for the "Landscape" cluster, slightly decreases for the "Miscellaneous" and "Events" clusters and sharply decreases for the "Villages" cluster. The MaxEnt procedure output reports are available as supplementary materials. They also contain all the calculated response curves.

The response curves allowed the definition of specific agricultural land planning interventions. As an example, Fig. 5 shows the response curves for the following variables: percentage of vineyard, percentage of olive grove, edge density of olive groves, and edge density of vineyards. These curves allowed the outlining of a model of identity landscape consisting of a mosaic made up of about 50e60%

of vine- yards and 25e30% of olive groves, with 30,000 m of vine- yard margins in a radius of 1000 m (95 m/ha) and about 40,000 m of vineyard margin (127 m/ha). These parameters can be implemented as prescriptions or guidelines for the provision of payments, encouraging farmers to enhance the environment and landscape services on their farmland within the framework of rural development programs (Bernetti and Marinelli, 2010).

5. Discussion

Winescape is a fundamental emotional attribute able to influence consumer behavior by elevating the perceived quality of the product. Tempesta et al. (2010) p. 833) proved that «*''Evocative*" *landscape obtained the highest partial preference level, and was without doubt the factor capable of most greatly influencing the liking of a wine. Clearly linking wine production to cultural heritage and, therefore, implicitly to the most noble regional viticulture traditions … had a significant effect on preferences*». Moreover, Sillani et al. (2017) proved that the combination of viticulture and wine-making, on the one side, and landscape, history and culture, on the other, can be a powerful tool to convert externalities into relevant attributes within a marketing strategy. Therefore, the territorial elements highlighted by the analysis of winescape perception can be considered as tangible elements of landscape that become intangible

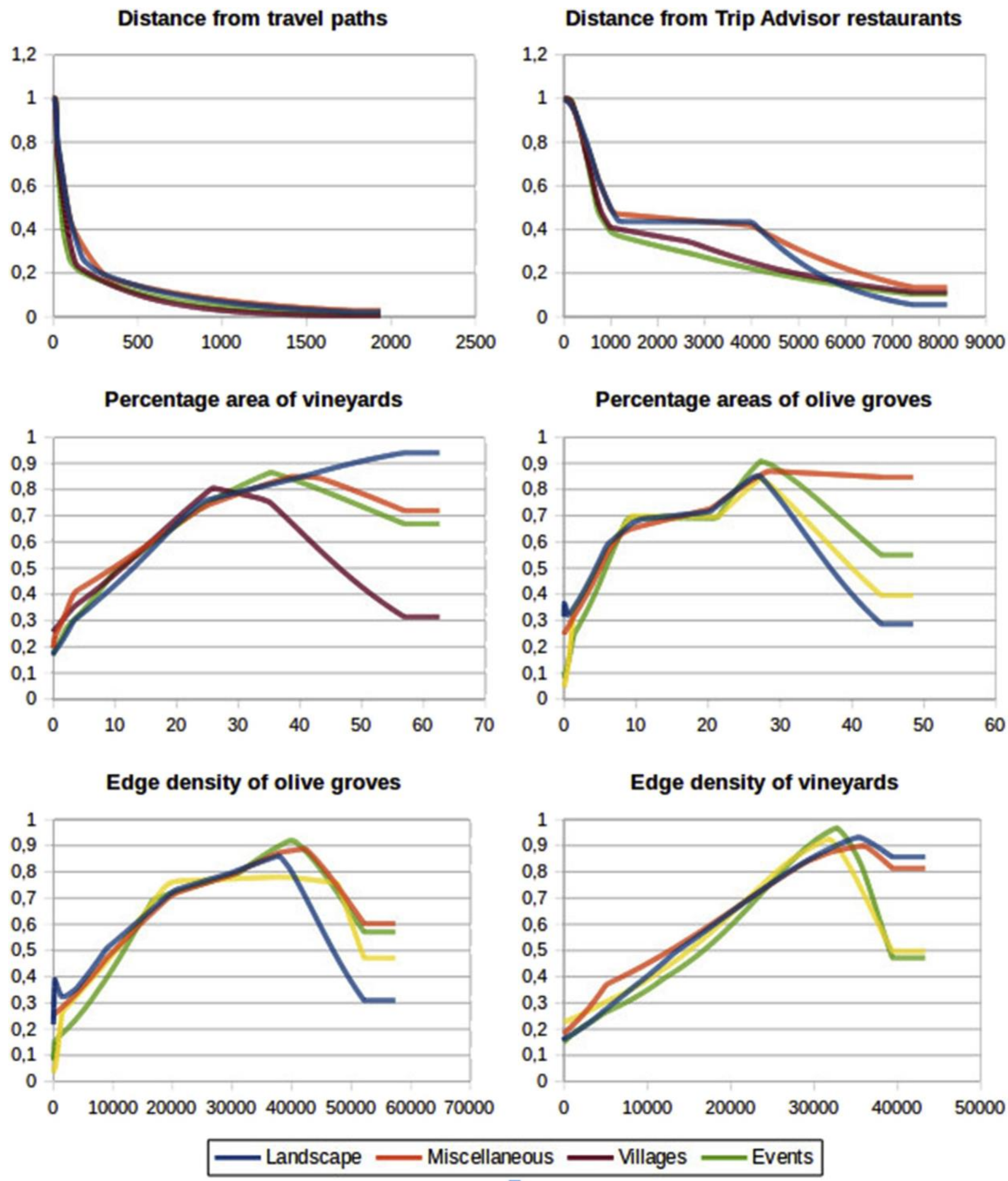

Fig. 6. Response curves for some variables.

components of the wine product, thus useful for its differentiation. In addition, according to Fish (Fish et al., 2016) the four different clusters can be interpreted considering three different aspects: i) the identity of the places, ii) the lived experiences; iii) the individual capabilities. Even if these three aspects can be identified in each cluster, it is possible to point out how:

i) The identity of the places are mostly related to Cluster 1, “Landscape”, being the wine landscape full of suggestions that immediately evoke the relationship between the product and the places;
ii) The lived experiences mainly characterize Cluster 4 “Events” and Cluster 2 “Miscellaneous”; in this case, the relationship between winescape and the product is given by events. Mason and Paggiaro (2012) highlighted the importance of festivalscapes in determining emotions, satisfaction and future behavior of participants at food and wine events;
iii) The individual capabilities characterize Cluster 3 “Villages” and Cluster 4 “Events”; winescape is used in knowledge acquisition processes at the level of intellectual advancement through both tasting and wine- food pairing or the connection of wine with architecture.

The elaboration of a spatial model for each cluster offers the planner the possibility of identifying the areas in which to intervene with priority, implementing safeguard projects starting from the most important and critical situations, e.g. the containment of the anthropic pressure where needed. Furthermore, in recent years, an increasing share of budgetary resources has been used for measures aimed at protecting the visual quality of agricultural landscapes (Howley et al., 2012). The understanding of the individual perception of the land- scape becomes an essential cognitive element for the effective planning of rural development policies, in line with the pro- motion of bottom-up approaches of territorial governance (De Vreese et al., 2016). The analyses carried out in the present study allow us to create a theoretical-methodological framework useful for the definition, planning, and development of winescape on a geographical scale. The overall approach adopted in the pre- sent study in Chianti Classico demonstrates that big data derived from Flickr platform are a valid source of information to identify the elements that characterize the territory, ac- cording to both the "macro" scale of Thomas, Quintal and Phau (Thomas et al., 2010) and the vision of winescape as a "cultural product" (Getz and Brown, 2006). In particular, the results highlight how winescape determines a specific territorial brand thanks to the contribution of the different tangible and intangible territorial elements, which act as both goods and services. The present study can be a useful analytical tool for both farms and public decision makers that are involved in the definition of rural development strategies based on sustain- able territorial marketing approaches. Through the correct management of the rural landscape, the approach proposed is a valid support for implementing the conditionality measures, regarding the provisions of the Italian National Strategic Plan and the regional rural development plans. After the introduction of decoupling and conditionality (EC Reg. 1782/2003), farms were asked to adopt agri-environmental measures preserving and improving the quality of the landscape. This attention on the landscape has been confirmed and even increased with the CAP strategies for 2014e2020, which aim at strengthening rural development objectives. However, the paper is not without limitations. It has been demonstrated that the number of Flickr users has been positively correlated with the number of visitors (Wood et al., 2013), but, probably, the representativeness of the sample in sharing the appreciation of the landscape is influenced by some technological aspects (the rate of Internet use, the diffusion of cameras and smartphones with GPS, ...). Moreover, the sample could be distorted depending on the age, the level of education and the tendency of using the social platform. However, methods based on questionnaires or interviews show the problem of representativeness as well (Tenerelli et al., 2016). A further drawback in the use of the Flickr platform is the difficulty in distinguishing the photos taken by residents from those taken by tourists since most Flickr user profiles do not have detailed home address information. Zheng et al. (2015) proposed a method for predicting places of residence and vacation locations, merging the visual content of the photos and the spatial and temporal characteristics of people's mobility patterns. In this direction, the future development of this research will be the updating of this methodology with additional information about the origin of Flickr users and their itineraries. The occurrence and density of photo- graphs of the wine landscape can provide an indicator of public interest for a specific please, but there is a mismatch between such an indicator and the measurement of the value of the winescape service. The motivations for people to photograph the landscape and historic villages vary. In some cases, people take photographs to record positive attributes of the environment they find attractive, while in other cases, visitors take photographs to record negative environmental attributes (Dorwart et al., 2009). Furthermore, photographs can be taken to represent a place as a physical object or, otherwise, to be interpreted through the lens of a person's memories and the experiences surrounding a place (Scott and Canter, 1997). Therefore, it is complex to attribute a winescape value to the indicator showed in the paper. People can take photographs in a place while they use it for recreational purposes (i.e. while they are creating art or while they are documenting what they see as an important cultural heritage). The analysis of the content of social media pho- tographs to evaluate the services of the wine landscape should be aware of the uncertainty belonging to the content of the photograph. In our approach, we considered the occurrence of landscape photographs as general indicators of public interest for that specific place. To understand more clearly why people take photographs in a particular place, and what cultural ecosystem services are provided, more information on the context may be needed. It may be possible to get a context on the use of rural spaces through metadata, as the latter is sometimes provided together with the social media photos (i.e. the title, notes, comments and tags) (Bernetti et al., 2019). Alternatively, interviews or surveys with people in a specific place may provide an additional context on the most popular cultural ecosystem services (Pleasant et al., 2014). Therefore, the analysis of social media photographs should not be the only approach used when trying to quantify the services of the cultural ecosystem. It can represent a useful tool for providing quantitative data on large spatial scales, which can integrate more in-depth qualitative analyses (Richards and Friess, 2015; Thiagarajah et al., 2015).

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6. Conclusion

The rural dimension is revealed in the territorial values of both the tangible (detectable with the senses in the physical evidence of a landscape, and perceivable on a visual, olfactory and acoustic level) and the intangible elements (culture, tradition, health, state of mind, etc …).The methodology described in the paper aims to be original, to classical GIS analysis (i.e. ROS models), qualifying the landscape not through the measurement of objective territorial characteristics but through the visitors' preferences revealed by Flickr. The proposed model measures what visitors notice and what strikes them most both when they decide to take a picture (an aspect that is increasingly relevant in the digital age) and when they select what to upload and share in the web, adding precise "tags" that specify the object on which they have placed their attention. This sequence can be assimilated to a process of "selective attention" through which an individual discriminates between what she/he sees and what strikes her/him in a particular way. In this sense, the image taken and published in the web points out the relevant attributes in the preferences of the person who is experiencing the landscape at that moment, highlighting those characteristics of the territory that are most evident at his/her sight. Once the possible macroscopic dissonances between the territorial characteristics (not included in the analyses carried out in this research) and the predominant attributes pointed out by the visual preferences have been assessed, the model provides public decision-makers with precise indications on the main attractions of the winescape and indicates how to promote certain specific characteristics, if poorly perceived by the final user, by informing and educating him/her according to a communicative mix that constitutes a priority lever of any territorial marketing strategy. Furthermore, the big data information shows the precise moment in which the photo was taken, and it allows the researcher to get some essential indications about the situation. For instance, it is possible to associate whether and to what extent the attention on specific landscape features is due to specific events or routes. This wide range of information is the starting point for the development of sound territorial marketing strategies, which are based on a thorough knowledge of the preferences of the visitors and not on a simple collection of places and events from calendars and documentation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wep.2019.07.001.

References

Alampi Sottini, V., Travaglini, I., Scozzafava, G., 2009. "L'indagine diretta". In: Menghini, S. (Ed.), Risorse rurali e turismo: il ruolo dell'agricoltura nel sistema economico senese", vols. 128e162. FrancoAngeli, Milano. ISBN 978-88-568-1739-3.

Alebaki, M., Menexes, G., Koutsouris, A., 2015. Developing a multidimen- sional framework for wine tourist behavior: evidence from Greece. Wine Econ. Policy 4 (2), 98e109.

Alivand, M., Hochmair, H.H., 2017. Spatiotemporal analysis of photo contribution patterns to Panoramio and Flickr. Cartogr. Geogr. Inf. Sci. 44 (2), 170e184.

Antrop, M., 2005. Why landscapes of the past are important for the future.

Landsc. Urban Plan. 70 (1), 21e34.

Bernetti, I., Marinelli, N., 2010. Evaluation of landscape impacts and land use change: a Tuscan case study for CAP reform scenarios. Aestimum (56), 1e29.

Bernetti, I., Chirici, G., Sacchelli, S., 2019. Big data and evaluation of cultural ecosystem services: an analysis based on geotagged photo- graphs from social media in Tuscan forest (Italy). iFor. Biogeosci. For. 12 (1), 98.

Bitner, M.J., 1992. Servicescapes: the impact of physical surroundings on customers and employees. J. Mark. 57e71.

Boatto, V., Galletto, L., Barisan, L., Bianchin, F., 2013. The development of wine tourism in the Conegliano Valdobbiadene area. Wine Econ. Policy 2 (2), 93e101.

Bruwer, J., Joy, A., 2017. Tourism destination image (TDI) perception of a Canadian regional winescape: a free-text macro approach. Tour. Recreat. Res. 42 (3), 367e379.

Bruwer, J., Lesschaeve, I., Gray, D., Sottini, V.A., 2013. Regional brand perception by wine tourists within a winescape framework. In: 7th AWBR International Conference (St. Catherines).

Bruwer, J., Gross, M.J., Lee, H.C., 2016. Tourism destination image (TDI) perception within a regional winescape context. Tour. Anal. 21 (2e3), 173e187.

Capitello, R., Agnoli, L., Begalli, D., Codurri, S., 2014. Social media strate- gies and corporate brand visibility in the wine industry: lessons from an Italian case study. EuroMed J. Bus. 9 (2), 129e148.

Carmichael, B., 2005. Understanding the wine tourism experience for winery visitors in the Niagara region, Ontario, Canada. Tour. Geogr. 7 (2), 185e204.

Cinelli Colombini, D., 2013. Italian wine tourism and the web: a necessary wedding. Wine Econ. Policy 2 (2), 111e113.

Cohen, E., 1979. Rethinking the sociology of tourism. Ann. Tourism Res. 6 (1). January/March 1979.

Collier, J., 1967. Visual Anthropology: Photography as a Research Method (New York).

Dakin, S., 2003. There's more to landscape than meets the eye: towards in- clusive landscape assessment in resource and environmental management. Canadian Geographer/Le Géographe Canadien 47 (2), 185e200.

De Vreese, R., Leys, M., Fontaine, C.M., Dendoncker, 2016. Social mapping of perceived ecosystem services supply eThe role of social landscape metrics and social hotspots for integrated ecosystem services assessment, landscape planning and management. Ecol. Indicat. 66, 517e533 science, 24(7), 581-592.

Dorwart, C.E., Moore, R.L., Leung, Y.F., 2009. Visitors' perceptions of a trail environment and effects on experiences: a model for nature-based recre- ation experiences. Leis. Sci. 32 (1), 33e54.

Dunkel, A., 2015. Visualizing the perceived environment using crowdsourced photo geodata. Landsc. Urban Plan. 142, 173e186.

Echtner, C.M., Ritchie, J.B., 1991. The meaning and measurement of desti- nation image. J. Tour. Stud. 2 (2), 2e12.

Eustice, C., McCole, D., Rutty, M., 2019. The impact of different product messages on wine tourists' willingness to pay: a non-hypothetical experi- ment. Tour. Manag. 72, 242e248.

Fish, R., Church, A., Winter, M., 2016. Conceptualising cultural ecosystem services: a novel framework for research and critical engagement. Ecosyst. Serv. 21, 208e217.

Galati, A., Crescimanno, M., Tinervia, S., Fagnani, F., 2017. Social media as a strategic marketing tool in the Sicilian wine industry: evidence from Facebook. Wine Econ. Policy 6 (1), 40e47.

Getz, D., Brown, G., 2006. Critical success factors for wine tourism regions: a demand analysis. Tour. Manag. 27 (1), 146e158.

Gliozzo, G., Pettorelli, N., Haklay, M., 2016. Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. Ecol. Soc. 21 (3).

Goodchild, M.F., 2007. Citizens as sensors: the world of volunteered geog- raphy. Geojournal 69 (4), 211e221.

Gubert, R., Pollini, G., 2002. Turismo, fluidità relazionale e appartenenza territoriale. FrancoAngeli, Milano.

Hervé, M.E., Boudes, P., Cieslik, C., Montembault, D., Jung, V., Burel, F.,, et al., 2018. Landscape complexity perception and representation in a wine-growing region with the designation of origin in the Loire Valley (France): a cultural ecosystem service? Renew. Agric. Food Syst. 1e13.

Howley, P., Donoghue, C.O., Hynes, S., 2012. Exploring public preferences for traditional farming landscapes. Landsc. Urban Plan. 104, 66e74.

Johnson, R., Bruwer, J., 2007. Regional brand image and perceived wine quality: the consumer perspective. Int. J. Wine Bus. Res. 19 (4), 276e297.

Kaplan, S., 1995. The restorative benefits of nature: toward an integrative framework. J. Environ. Psychol. 15 (3), 169e182.

Kaplan, R., Kaplan, S., 1989. The Experience of Nature: A Psychological Perspective. CUP Archive.

Kassambara, A., 2017. Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning, vol. 1. STHDA.

Kwortnik, R.J., 2008. Shipscape influence on the leisure cruise experience. Int. J. Cult. Tour. Hosp. Res. 2 (4), 289e311.

Levin, N., Lechner, A.M., Brown, G., 2017. An evaluation of crowdsourced information for assessing the visitation and perceived importance of pro- tected areas. Appl. Geogr. 79, 115e126.

Liu, I., Norman, W.C., Pennington-Gray, L., 2013. A flash of culinary tourism: understanding the influences of online food photography on people's travel planning process on Flickr. Tour. Cult. Commun. 13 (1), 5e18.

Lynch, K., 1960. The Image of the City, vol. 11. MIT press.

Mason, M.C., Paggiaro, A., 2012. Investigating the role of festivalscape in culinary tourism: the case of food and wine events. Tour. Manag. 33 (6), 1329e1336.

Menghini, S., 2009. Risorse rurali e turismo. Il ruolo dell’agricoltura nel sistema economico senese. FrancoAngeli, Milano.

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36 (10), 1058e1069.

Mitchell, R., Charters, S., Albrecht, J.N., 2012. Cultural systems and the wine tourism product. Ann. Tourism Res. 39 (1), 311e335.

Morgan, S.L., Marsden, T., Miele, M., Morley, A., 2010. Agricultural multi- functionality and farmers' entrepreneurial skills: a study of Tuscan and Welsh farmers. J. Rural Stud. 26 (2), 116e129.

Nohl, W., 2001. Sustainable landscape use and aesthetic perceptionepreli-

minary reflections on future landscape aesthetics. Landsc. Urban Plan. 54 (1e4), 223e237.

Nov, O., Naaman, M., Ye, C., 2010. Analysis of participation in an online photo-sharing community: a multidimensional perspective. J. Am. Soc. Inf. Sci. Technol. 61 (3), 555e566.

Ode, Å., Tveit, M.S., Fry, G., 2008. Capturing landscape visual character using indicators: touching base with landscape aesthetic theory. Landsc. Res. 33 (1), 89e117.

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., Plieninger, T., 2017. Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. Ecol. Indicat. 94, 74e86.

Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31 (2), 161e175.

Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190 (3e4), 231e259.

Poor, E.E., Loucks, C., Jakes, A., Urban, D.L., 2012. Comparing habitat suitability and connectivity modeling methods for conserving pronghorn migrations. PLoS One 7 (11), e49390.

R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. URL. https://www.R-project.org/.

Reyneke, M., Pitt, L., Berthon, P.R., 2011. Luxury wine brand visibility in social media: an exploratory study. Int. J. Wine Bus. Res. 23 (1), 21e35. Richards, D.R., Friess, D.A., 2015. A rapid indicator of cultural ecosystem service usage at a fine spatial scale: content analysis of social media photographs. Ecol. Indicat. 53, 187e195.

Richards, D.R., Tunçer, B., 2017. Using Image Recognition to Automate Assessment of Cultural Ecosystem Services from Social Media Photo- graphs. Ecosystem Services.

Scott, M.J., Canter, D.V., 1997. Picture or place? A multiple sorting study of landscape. J. Environ. Psychol. 17 (4), 263e281.

Sidali, K.L., Kastenholz, E., Bianchi, R., 2015. Food tourism, niche markets and products in rural tourism: combining the intimacy model and the experience economy as a rural development strategy. J. Sustain. Tour. 23 (8e9), 1179e1197.

Sillani, S., Miccoli, A., Nassivera, F., 2017. Different preferences for wine communication. Wine Econ. Policy 6 (1), 28e39.

Smith, V.L., 1977. Host and Guest. The Anthropology of Tourism. University of Pennsylvania Press, Philadelphia.

Sogari, G., Pucci, T., Aquilani, B., Zanni, L., 2017. Millennial generation and environmental sustainability: the role of social media in the consumer purchasing behavior for wine. Sustainability 9 (10), 1911.

Sontag, S., 1977. On Photography. Farrar, Straus and Giroux, New York.

Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240 (4857), 1285e1293.

Tempesta, T., Vecchiato, D., 2015. Testing the difference between experts' and lay people's landscape preferences. Aestimum (66), 1e41.

Tempesta, T., Giancristofaro, R.A., Corain, L., Salmaso, L., Tomasi, D., Boatto, V., 2010. The importance of landscape in wine quality perception: an integrated approach using choice-based conjoint analysis and combination-based permutation tests. Food Qual. Prefer. 21 (7), 827e836.

Tenerelli, P., Demšar, U., Luque, S., 2016. Crowdsourcing indicators for cultural ecosystem services: a geographically weighted approach for mountain landscapes. Ecol. Indicat. 64, 237e248.

Thiagarajah, J., Wong, S.K., Richards, D.R., Friess, D.A., 2015. Historical and contemporary cultural ecosystem service values in the rapidly urbanizing city state of Singapore. Ambio 44 (7), 666e677.

Thomas, B., Quintal, V., Phau, I., 2010. Predictors of attitudes and intention to revisit a winescape. In: Proceedings of Australian and New Zealand Marketing Academy Conference. Australian and New Zealand Marketing Academy.

Ulrich, R.S., Kellert, S.R., Wilson, E.O., 1993. The Biophilia Hypothesis.

Biophilia, Biophobia, Nat. Landsc. 73e137.

Walden-Schreiner, C., Leung, Y.F., Tateosian, L., 2018. Digital footprints: incorporating crowdsourced geographic information for protected area management. Appl. Geogr. 90, 44e54.

Wilson, D., Quinton, S., 2012. Let's talk about wine: does Twitter have value?

Int. J. Wine Bus. Res. 24 (4), 271e286.

Williams, P., 2001. Positioning wine tourism destinations: an image analysis.

Int. J. Wine Mark. 13 (3), 42e58.

Winkler, K.J., Nicholas, K.A., 2016. More than wine: cultural ecosystem services in vineyard landscapes in England and California. Ecol. Econ. 124, 86e98.

Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Sci. Rep. 3, 2976.

Yoshimura, N., Hiura, T., 2017. Demand and supply of cultural ecosystem services: use of Geo-tagged photos to map the aesthetic value of land- scapes in Hokkaido. Ecosyst. Serv. 24, 68e78.

Zheng, D., Hu, T., You, Q., Kautz, H.A., Luo, J., 2015. May). Towards lifestyle understanding: predicting home and vacation locations from user's online photo collections. In: ICWSM, pp. 553e561.

Wine tourism, cellar Door perception, and emotional response by using VR, EEG, and eye-tracking technology

Keywords: Wine tourism; Cellar door; Tourists' Experience; Virtual Reality; Neuromarketing

Introduction

The Millennial generation, which 35% is a consumer of wine, replaced the negative idea of landscape linked to hard work, which belonged to the previous generation, with a positive one linked to leisure. This new approach significantly influenced the development of rural and wine tourism

In recent years, a type of tourism that became more attractive and famous is Wine tourism (Hall et al., 2000; O'Neill et al., 2002; Yuan et al., 2005).

The winery's tourist experience affects the choices of consumption and purchase of wine (Investigator & Bruwer, 2014). It makes it possible to transform a non-consumer into a wine consumer. A positive tourist experience generates brand loyalty among its visitors (Quintal et al., 2015). It evokes willingness to revisit the place, buy the product, and share the experience

The essential aspect for wine tourists is the visit to Cellar door. The cellar door experience is unique because users can get in touch with tangible elements, wine, vineyard, and intangible product, as history, tradition, atmosphere. A memorable and complete experience at the winery includes wine tasting, wine sales, and interaction with employees, the environment itself.

Consumption of Wine, respect for other liquor implies social and hedonic motivation (Brodie et al., 2011). Visitors of the cellar door look for an "extra value" as hedonic experience, emotion, and relaxation. (O'Neill, Palmer & Charters, 2002). Some researchers underline that some users visit the cellar door not to purchase wine but to have a touristic experience or inform themselves about wine. Thanks to cellar door experience, the winery can develop long relationships with clients to generate positive word-of-mouth and customer loyalty. (Bruwer & Alant, 2009) (Bruwer et al., 2013)

The wineries' manager wants to create a beautiful, impressive cellar door experience to establish a long relationship with visitors to induce consumers to repeat visits and purchase wine. (Bruwer et al., 2013) The importance of cellar door underlines the necessity of understanding how it can influence visitors' behaviors and intentions.

Alant e Bruwer (Alant & Bruwer, 2004) investigate ecotourist's motivation cellar door, have discovered that in addition to wine tasting or purchase, some motivations are linked to seak pleasant, quiet and beautiful place

To succeed in these mission managers, they have to consider, in addition to wine product quality, the environment and the architecture of the building that create the right atmosphere.

Today, researches focus on how servicescape influences the user's perceptive experience is carried out with questionnaires that reveal the user's conscious preferences and emotions.

A promising alternative in perception and emotion research is to use neuromarketing methods.

Among the Neuromarketing tools, we find electroencephalogram (EEG), eye tracking, functional magnetic resonance (FMI)

Neuromarketing tools allow you to analyze users' unconscious preferences. Traditional methods are considered wildly inaccurate because consumers can not reveal their underlying emotions. The rational answer to an interview is conditioned by several factors, more or less aware. On the one hand, the interviewer tries to answer in the right way; on the other hand, what consumers believe in feeling is not real, for these reasons do not match test made with neuromarketing method.

Based on winery as a catalyst of wine consumption and purchase choices, the research project investigates how and how much the servicescape, particularly spatial layout, contributes to having a positive tourist experience and influencing the consumers' behaviors.

The study aims to understand which feature of the spatial layout of the cellar door is related to tourists' emotions, choice of purchase, and connection through the use of new technologies as virtual reality, eye-tracking, and electroencephalogram to elaborate on marketing strategies that enhance the product and improve tourist experience.

Two research hypotheses are drawn to be examined by this study:

H1: Do Cellars with different architectural types can arouse emotions in visitors?

H2. Which elements of a winery and its context influence the user's emotions?

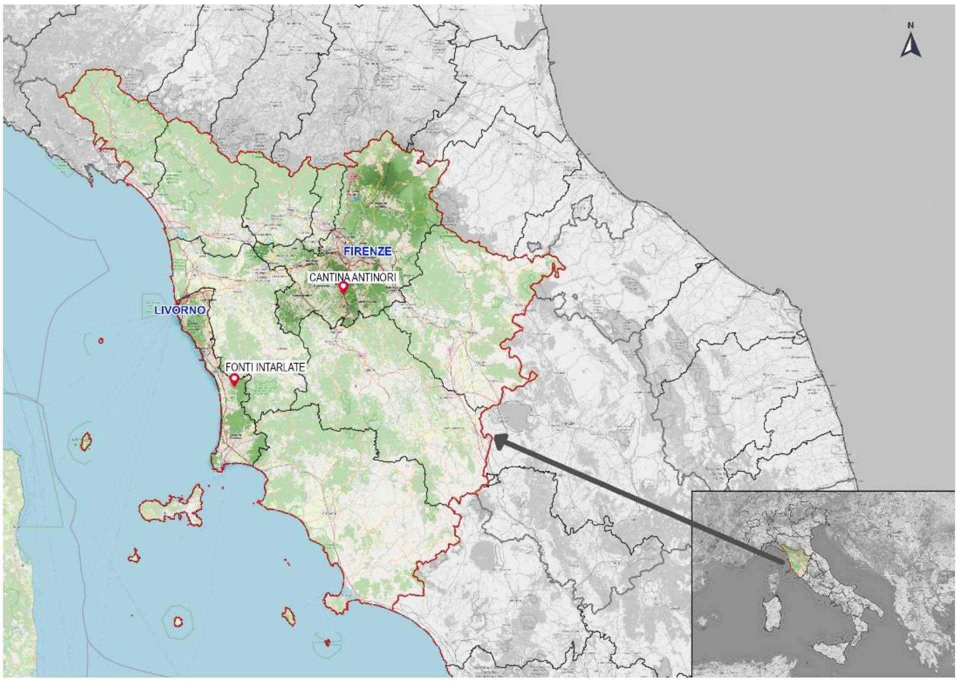
Study area

The Fonti Intarlate farm is located in Bibbona, a village place in Livorno, in the Bolgheri wine region. Fonti Intarlate is a family company, born from the Pacini family's will to cultivate in a specialized way. The company covers 10 hectares planted with both olive trees, typical Tuscan varieties, and vineyards, mainly red grapes. Inside the farm, there are two buildings characterized by traditional architecture: the main one, in Tuscan style, is used for processing, conservation, and tasting with the sale of products; the other, smaller, called "La Stallina," is successfully used for agritourism.

The Antinori Winery is located in San Casciano Val di Pesa, a town in Florence in the Chianti area lead by Antinori noble Family. The cellar door's architecture was entrusted to the Archea studio, which decided to design an underground architecture. It is projected to be a recognizable landmark integrated into the territory. The Antinori wineries extend for 12 hectares and reduce the environmental impact that all industrial sites have on the territory; it is decided to cover all the infrastructural systems and the building's services under the green. Antinori cellar door is an architecture experiment that is almost invisible from the outside. The building is revealed through two cuts in the earth that identify the terraces.

The cellars were chosen because they represent different architectural styles, inlaid sources for the Tuscan region's traditional architectural style and identity, while Antinori is an example of modern architecture.

Figure 1-Study area



Material and method

The proposed methodology uses a traditional method mixed with neuromarketing technologies. The former directly measured consumers' thoughts, feelings, and intentions; it *analyzes only the rational part of users'* *decision-making processes*. In contrast, the latter measured underlying feelings and intentions *responsible for most purchasing decisions. 95% of purchasing decisions are made irrationally.*

In the traditional method, we use a self-reported questionnaire, the Positive and Negative Affect Schedule (PANAS). PANAS (Watson et al., 1988) is one of the most used tools to evaluate positive and negative affective states. PANAS measures two distinct and independent dimensions: positive affect and negative affect. The questionnaire consists of 20 adjectives, 10 for the positive affect scale (PA), and 10 for the negative affect scale (NA). The PA subscale reflects the degree to which a person feels enthusiastic, active, and determined; the NA subscale refers to some general unpleasant states such as anger, guilt, and fear. The subject must evaluate how he generally feels according to the adjective, responding on a 5-point Likert scale (1 = not at all, 2 = little, 3 = moderately, 40 enough, 5 = a lot). The original version was developed and validated by Watson, Clark, and Tellegen in 1988 and had excellent psychometric properties. PANAS has been translated into several languages; the Italian version has been validated by Terracciano (Terracciano, McCrae, & Costa, 2003) on a sample of 600 subjects and has replicated the psychometric characteristics of the American study.

	Positive adjective	**Negative adjective**
1	Interested	Distressed
2	Excited	Upset
3	Strong	Guilty
4	Enthusiastic	Scared
5	Proud	Hostile
6	Inspired	Irritable
7	Determined	Ashamed
8	Attentive	Nervous
9	Active □	Afraid
10	Focus	Jittery

Table 1 - PANAS' adjectives

In Neuromarketing technologies, we use eye-tracking and EEG devices. Eye-tracking is a process that monitors eye movements to determine where a test subject is looking, what he is looking at, and how long his gaze lingers at a certain point of space. Eye-tracking is an effective consolidated methodology applicable to a variety of contexts. Principal Eye tracking data output are: number of blinks, fixations, and pupil dilation. Blinking is often an involuntary act of shutting and opening the eyelid; in these moments, there is a blackout of information and a drop of attention. Fixations and gaze points are the basic output measures of interest and often the most used terms. Gaze points show what the eyes are looking at. If a series of gaze points is very close – in time and/or space – this gaze cluster constitutes a fixation, denoting a period where the eyes are locked towards an object. Fixations are excellent measures of visual attention, and research in this field has been continually growing.

The tracking of eye movements occurs through special devices. In our research, we use pupil lab hardware, a binocular 200Hz eye tracking. The electroencephalogram (EEG) is a device capable of recording and measuring the brain's electrical activity through special electrodes positioned on the test subject's head.

The EEG allows us to measure and record the emotions and moods (concentration, stress, calm, fun, etc.) of a user. It can be used to discover the emotional involvement. We use Muse wearable brain sensing headband. The device measures brain activity through four electrodes TP9-TP10-AF8-AF7 by y 10-20 international standards. The output of EEG data is five waves of different frequencies, gamma(32-100Hz), beta(13-32Hz), alpha(8-13HZ), Theta (4-8Hz), Delta(0.5-aHz), each link to an emotional state. We decide to use only two waves: alpha wave and beta wave; the alpha wave is related to a relaxed state of the subjects while the beta wave is linked to an excited state of respondents.

Subject *and stimuli*

Subjects interviewed are students of architecture specializing in Planning of the City, Territory, and Landscape or architecture. The type of panel is chosen because they are familiar with the architecture study. We administered 360-degree photos, Antinori's photos are downloaded by Google street. In contrast, the photos of intaralate sources were taken via a Nikon 360 during an inspection, view through Virtual Reality(VR) HTC VIVE head-mounted display. 360-degree photos are three for each cellar door. The photos chosen are based on specific space: Entrance, building and its context, and retail or production zone.

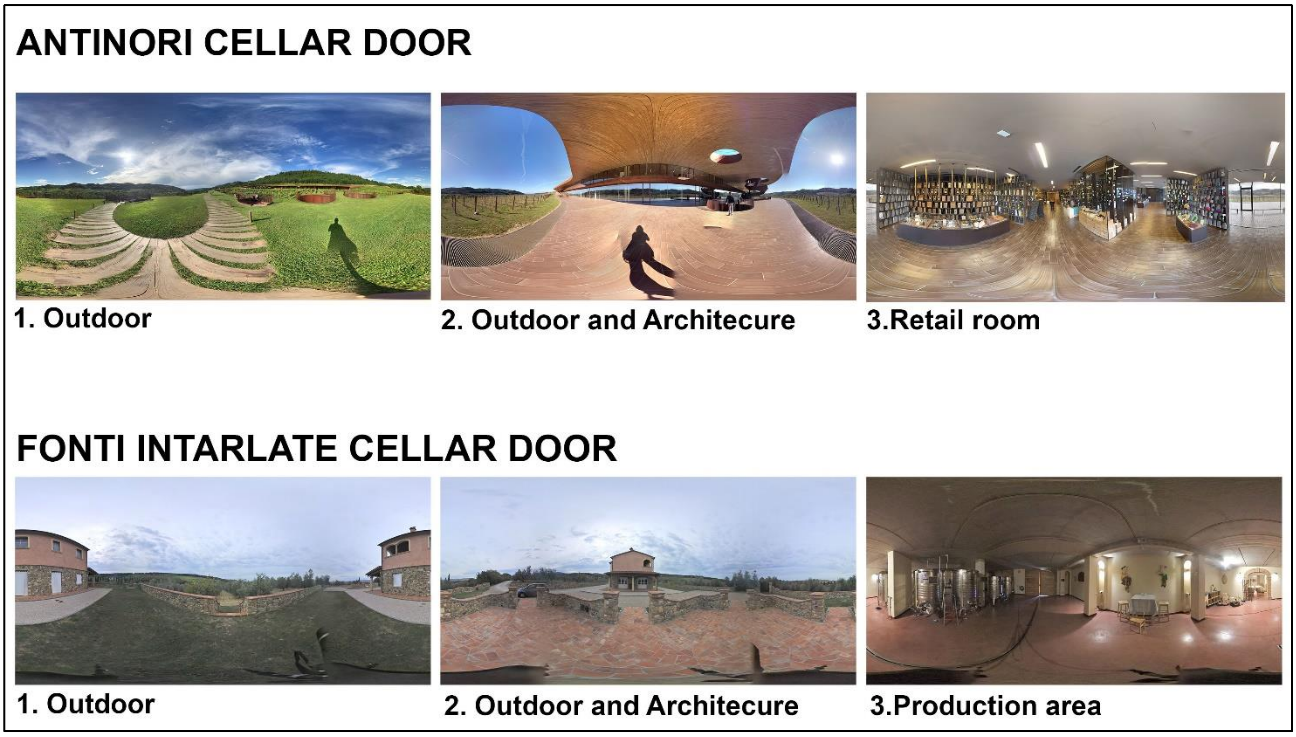


Figure 2-360 degree photo sample

Virtual Reality (VR) is the term used to indicate a simulated reality, built on the computer, within which the user can move freely. Through Unity software, we project the survey app; each photo appears for 30 seconds, and after this, the 20 adjectives of the PANAS are shown. The experiment lasts overall 40 minutes.

In this way, a simulated and three-dimensional world is created that appears as real. Moreover, just like in reality, the virtual environment in which you immerse yourself can be explored in every single centimeter and in every direction. It is advantageous, especially for the study of emotions, since VR can arouse more emotions and emotional changes by reproducing more realistic experimental settings. Many positive aspects of surveying with virtual reality, VR, and photo 360 reproduces places in the same conditions, a snapshot of a precise moment. These avoid the problem of assessments influenced by weather conditions. The advantages are also economic, as, through VR, different stimuli are tested without moving the subject, which would require greater economic expenses and time.

While the users live the 3D experience, we scan and record the eye movement and the brain activity

The research produces three different output data: EEG, eye tracking, and PANAS data.

Figure 3-Devices

The PANAS and EEG data are analyzed with descriptive statistical analysis; the eye-tracking data is analyzed by computing specific indices.

At least, we combine this three-output using a Hierarchical Multi Factorial Analysis. Hierarchical multiple factor analysis (HMFA) is the most direct extension of multiple factor analysis (MFA): it is used with tables in which the variables are structured according to a hierarchy. In practice, this means a sequence of nested partitions.

Results

Twelve subjects compose the sample, 58% of male and 42% of female, 80% belong to the millennial generation, and 20% belonged to baby boomers.

PANAS analysis

For each photo is calculated the positive and negative scores of PANAS. The positive score is the sum of all positive adjective values, while the negative score is the sum of the negative adjective. The score has a range between 10 to 50. In PANAS's analysis, the positive score is higher than the negative score for both cellar door. However, the Antinori cellar door has a positive score higher than Fonti Intrarlate, and it has a negative score smaller value than Fonti Intarlate.

	Cantina Antinori	
	Positive score	*Negative score*
foto1	*34.33*	*12.08*
foto2	*35.33*	*12.58*
foto3	*31.75*	*11.66*

	Cantina Fonti Intarlate	
	Positive score	*Negative score*
foto1	*29.83*	*11.58*
foto2	*27.66*	*15.08*
foto3	*25.66*	*14.5*

Table 2 - Positive and Negative Score PANAS

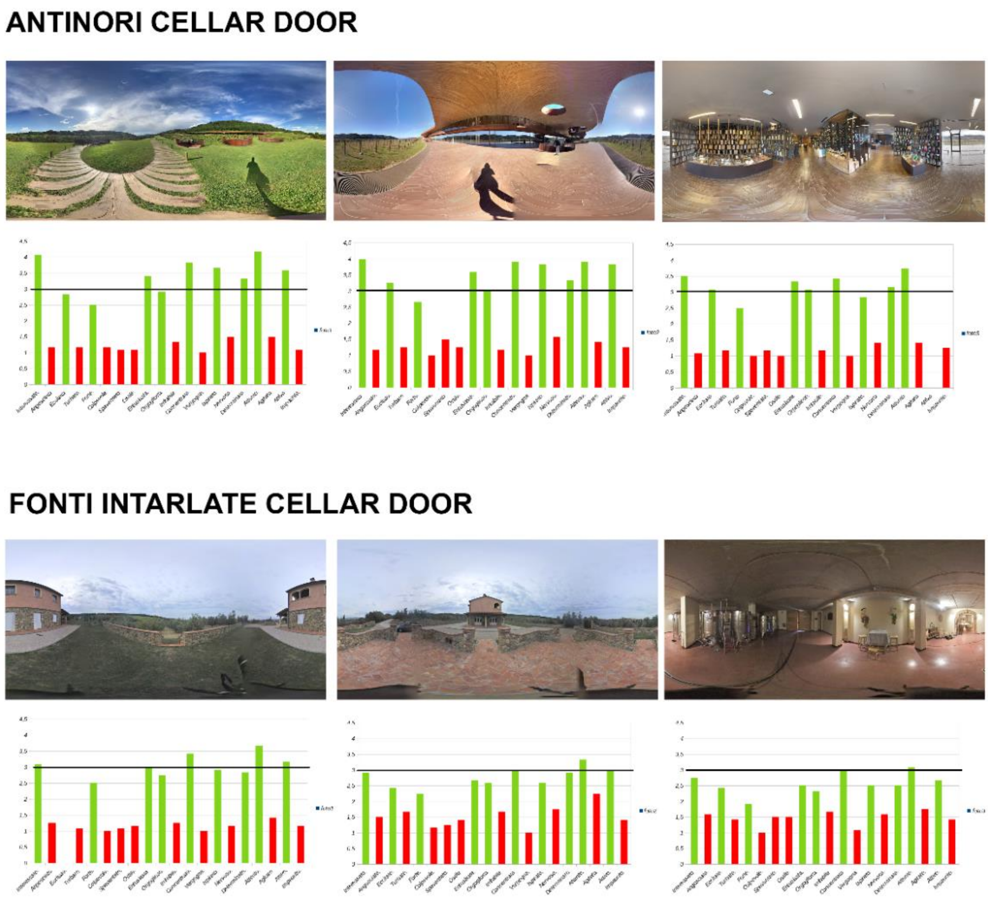


Figure 4- Panas' analysis

Eye-tracking analysis

The analysis of the eye-tracking data has two types of processing, a table that for each photo has calculated a series of cumulative indices of all the participants(average of diameter pupil average fixation duration (ms) the average count of fixation media, count of blink, Average blink duration (ms), and a visual that returns cumulative diameter-weighted heatmaps to identify fixation points. The index of eye tracking is higher for Antinori cellar doors. The cumulative heatmap determines important visual focusing points divided into three groups: the architectural component and landscape component.

	1		*2*		*3*		*4*		*5*		*6*	
	M	(sd)	M	sd	M	sd	M	sd	M	sd	M	sd
average of diameter (px)	46,34	(14,88)	44,32	(16,03)	45.68	(15.96)	42,80	(14,34)	42,57	(15,67)	42,74	(14,0)2
average fixation duration (ms)	395,87	(206,99)	401,75	(157,99)	331.90	(231.58)	343,89	(221,48)	293,88	(223,52)	308,10	(203,18)
average count of fixation media	9,83	(8,10)	7,25	(6,27)	4.75	6.27	5,08	7,04	4,83	6,15	5,33	6,85
count of blink	25,50	(64,38)	27,00	(63,83)	24.33	58.66	26,08	64,60	23,67	57,16	24,25	58,05
Average blink duration (ms)	3,25	(2,90)	2,49	(1,50)	3.56	3.23	2,95	2,75	3,38	2,61	2,36	2,06

Table 3-Eye indicator

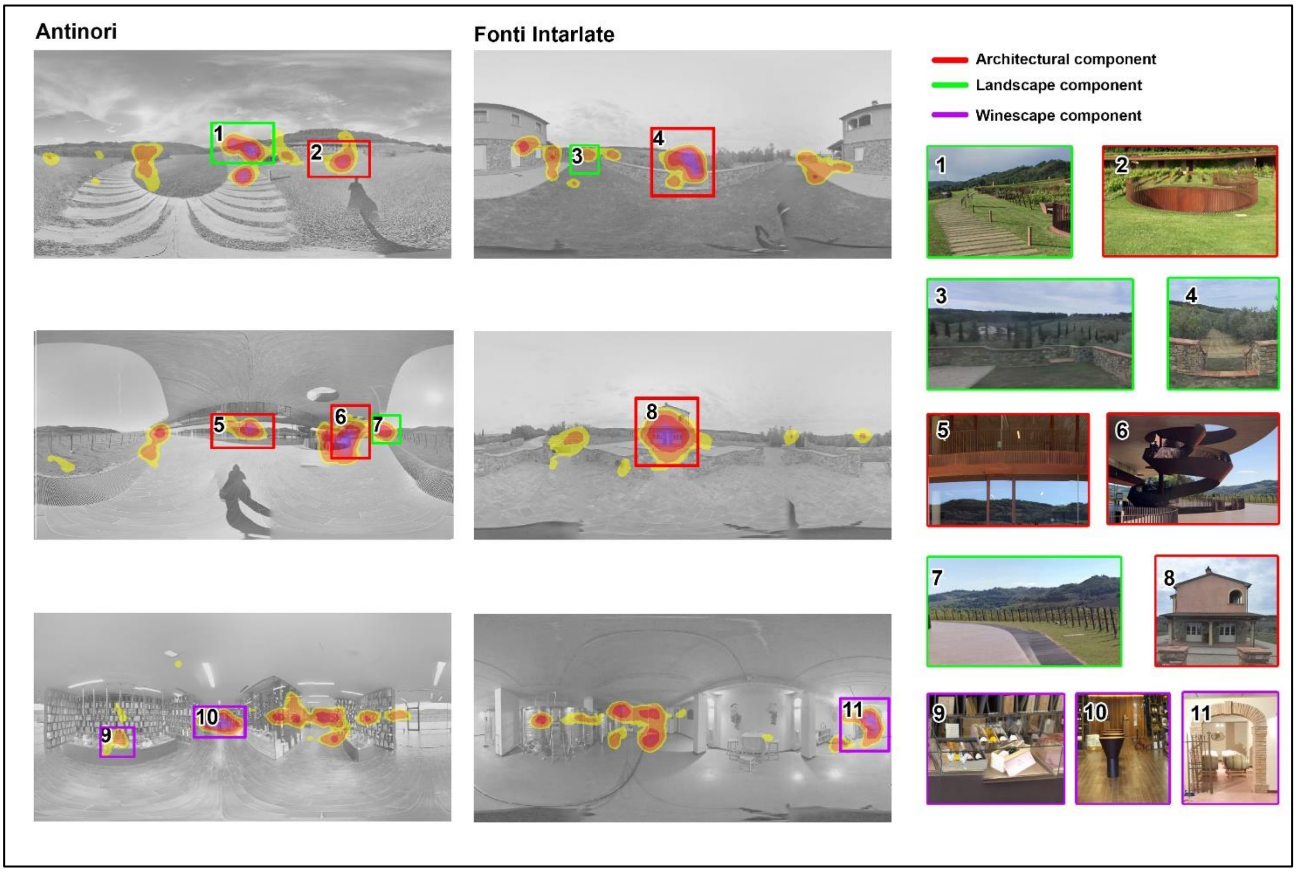


Figure 5-Heatmap weighted on diameter

EEG analysis

We extracted all five waves from EEG screening, alpha, beta, delta, gamma, and theta of 4 electrodes AF7 AF8 TP9 TP10 for all participants. The data is merged with an average and is grouped by brain area; data from AF7 and AF8 is a group in anterior-frontal and TP9-TP10 tempo parietal. The result is shown with kviat diagram each vertex are a wave and the line are the different photos of the different cellar door. The value of the delta is higher.

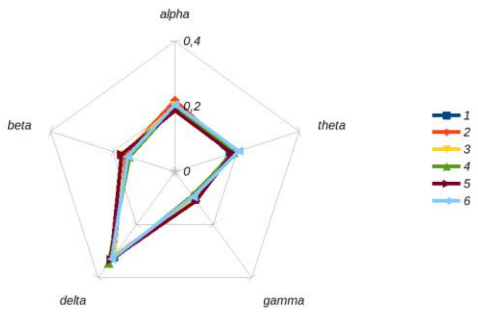


Figure 6-TemporalParietal

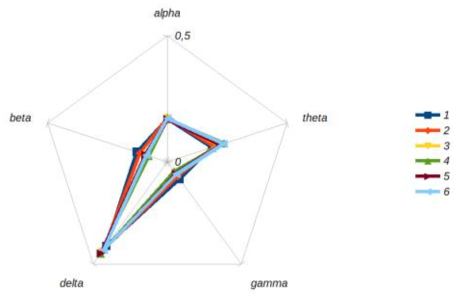


Figure 7-Frontal

HMFA analysis

We elaborate an HMFA that returns with two dimensions, the first dimension with an *eigenvalue of* 29% while the second dimension with an *eigenvalue of* 17%. The first dimension is positively correlated with blink and with beta and gamma waves, while it is negatively correlated to the eye-tracking blinks (attention). The second dimension is positively related to the pupil diameter (pleasure) and negatively correlated to beta and gamma waves (excitement, anxiety). In the space of the two dimensions, both cellar doors demonstrate positive emotions.

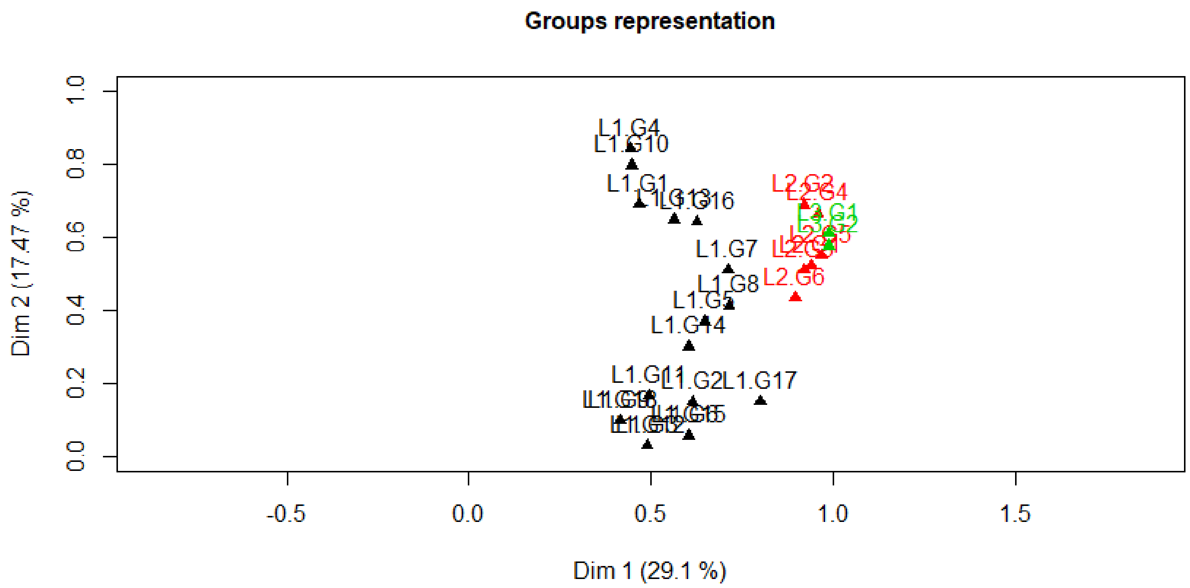
	eigenvalue	*percentage of variance*	*cumulative percentage of variance*
comp 1	*1,98*	*29,10*	*29,10*
comp 2	*1,19*	*17,47*	*46,57*
comp 3	*0,95*	*14,06*	*60,63*
comp 4	*0,62*	*9,12*	*69,75*
comp 5	*0,59*	*8,63*	*78,37*
comp 6	*0,38*	*5,61*	*83,98*
comp 7	*0,36*	*5,31*	*89,30*
comp 8	*0,25*	*3,66*	*92,96*
comp 9	*0,20*	*2,96*	*95,91*
comp 10	*0,17*	*2,47*	*98,38*
comp 11	*0,11*	*1,62*	*100,00*

Table 4- HMFA eingevalues

	correlation	*p.value*
anteriore_beta.2	*0,95*	*0,00*
anteriore_gamma.2	*0,94*	*0,00*
anteriore_gamma.5	*0,93*	*0,00*
anteriore_beta.5	*0,92*	*0,00*
anteriore_beta.4	*0,90*	*0,00*
anteriore_gamma.4	*0,87*	*0,00*
anteriore_beta.1	*0,86*	*0,00*
n_blink_6	*0,84*	*0,00*
n_blink_1	*0,84*	*0,00*
anteriore_gamma.1	*0,84*	*0,00*
n_blink_3	*0,84*	*0,00*
n_blink_5	*0,83*	*0,00*
anteriore_beta	*0,83*	*0,00*
n_blink_4	*0,83*	*0,00*
n_blink_2	*0,83*	*0,00*
anteriore_beta.3	*0,82*	*0,00*
anteriore_gamma	*0,78*	*0,00*
anteriore_gamma.3	*0,72*	*0,01*
nfix_3	*0,68*	*0,02*
posteriore_beta.5	*0,64*	*0,03*
posteriore_beta	*0,64*	*0,03*
anteriore_alpha.5	*-0,60*	*0,04*
anteriore_theta.2	*-0,62*	*0,03*

anteriore_delta.2	*-0,63*	*0,03*
anteriore_theta.4	*-0,63*	*0,03*
anteriore_theta.5	*-0,66*	*0,02*
anteriore_theta	*-0,67*	*0,02*
posteriore_theta.5	*-0,67*	*0,02*
anteriore_delta	*-0,69*	*0,01*
f_foto3_positive_m	*-0,69*	*0,01*
a_foto3_positive_m	*-0,69*	*0,01*
anteriore_delta.5	*-0,72*	*0,01*
anteriore_delta.1	*-0,74*	*0,01*
anteriore_theta.1	*-0,75*	*0,00*
f_foto2_positive_m	*-0,79*	*0,00*
a_foto2_positive_m	*-0,79*	*0,00*
f_foto1_positive_m	*-0,85*	*0,00*
a_foto1_positive_m	*-0,85*	*0,00*

	correlation	*p.value*
diam_medio_1	*0,92*	*0,00*
diam_medio_6	*0,90*	*0,00*
diam_medio_3	*0,89*	*0,00*
diam_medio_2	*0,89*	*0,00*
diam_medio_4	*0,88*	*0,00*
diam_medio_5	*0,88*	*0,00*
posteriore_theta.1	*0,71*	*0,01*
posteriore_alpha.4	*0,65*	*0,02*
posteriore_delta.1	*0,61*	*0,04*
posteriore_gamma.1	*-0,61*	*0,03*
posteriore_gamma.2	*-0,64*	*0,03*
posteriore_beta.2	*-0,67*	*0,02*
fix_dur_med_4	*-0,68*	*0,01*
posteriore_beta.1	*-0,69*	*0,01*
fix_dur_med_2	*-0,83*	*0,00*



Discussion and Conclusion

PANAS and EEG results confirm that there is not a significant emotional difference between the two cellar door. In the Kviat diagram's EEG analysis, the graph's trend is similar for the two cellar door. Both PANAS and EEG values are more significant for Aninoti Cellar Door, which is more willing than Fonti Intarlate. Although, Both of the cellar doors make positive emotions.

The eye-tracking results underline that the fixation point is similar and that it can be subdivided into three categories:

Landscape; Architecture; Element link to the winery. The element of fixation in the landscape group is, in particular, the skyline and vegetation element. In architecture, the main attractive point is the landmark, the ladder for Antinori, and the building for the Fonti Intarlate least the winery element are barrels ora retail element.

The HMFA analysis mixes all these three analyses and finds the correlation between elements. In the first dimension, the number of blinks is positively correlated with the gamma e beta waves. The number of blinks is one of the indexes of attention, and gamma e beta waves are linked with an emotional state of activity and interest. In the second dimension, the diameter is linked with alpha waves. The diameter dimension is an approval rating of pleasure, and alpha waves are related to the user's relaxing emotion.

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Research implications and limitations

The pro of the research is that there is a positive correlation between neuromarketing technologies and traditional methods. The cons are that neuromarketing technologies require specific skills to analyse output data and require a neutral place to administer the questionnaire to avoid external interferences.

The field of study taken into consideration in this work is continuously in progress. It will be exciting to continue to analyze developments from a theoretical point of view and in the field's implementation.

In the future, we want to increase the number of samples, including an expertise sample. We want to choose more different cellar doors (e.g, industrial cellar door) to differentiate the results.
Also, it could be interesting to implement this research with the evaluation of the tour experience.

References

Alant, K., & Bruwer, J. (2004). Wine tourism behaviour in the context of a motivational framework for wine regions and cellar doors. Journal of Wine Research, 15(1), 27–37. https://doi.org/10.1080/0957126042000300308

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement: Conceptual domain, fundamental propositions, and implications for research. Journal of Service Research, 14(3), 252–271. https://doi.org/10.1177/1094670511411703

Brown, G., & Fagerholm, N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem Services*, *13*, 119–133. https://doi.org/10.1016/j.ecoser.2014.10.007

Bruwer, J., & Alant, K. (2009). The hedonic nature of wine tourism consumption: An experiential view. International Journal of Wine Business Research, 21(3), 235–257. https://doi.org/10.1108/17511060910985962

Bruwer, J., Coode, M., Saliba, A., & Herbst, F. (2013). Wine tourism experience effects of the tasting room on consumer brand loyalty. Tourism Analysis, 18(4), 399–414. https://doi.org/10.3727/108354213X13736372325957

Carmichael, B. A. (2005). Understanding the wine tourism experience for winery visitors in the Niagara region, Ontario, Canada. *Tourism Geographies*, *7*(2), 185–204. https://doi.org/10.1080/14616680500072414

Casalegno, S., Inger, R., DeSilvey, C., & Gaston, K. J. (2013). Spatial Covariance between Aesthetic Value & Other Ecosystem Services. *PLoS ONE*, *8*(6), 6–10. https://doi.org/10.1371/journal.pone.0068437

Cohen, E., & Ben-Nun, L. (2009). The Important Dimensions of Wine Tourism Experience from Potential Visitors' Perception. *Tourism and Hospitality Research*, *9*(1), 20–31. https://doi.org/10.1057/thr.2008.42

Crossman, N. D., Burkhard, B., Nedkov, S., Willemen, L., Petz, K., Palomo, I., Drakou, E. G., Martín-Lopez, B., McPhearson, T., Boyanova, K., Alkemade, R., Egoh, B., Dunbar, M. B., & Maes, J. (2013). A blueprint for mapping and modelling ecosystem services. *Ecosystem Services*, *4*, 4–14. https://doi.org/10.1016/j.ecoser.2013.02.001

Daniel, T. C., Muhar, A., Arnberger, A., Aznar, O., Boyd, J. W., Chan, K. M. A., Costanza, R., Elmqvist, T., Flint, C. G., Gobster, P. H., Grêt-Regamey, A., Lave, R., Muhar, S., Penker, M., Ribe, R. G., Schauppenlehner, T., Sikor, T., Soloviy, I., Spierenburg, M., … Von Der Dunk, A. (2012). Contributions of cultural services to the ecosystem services agenda. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(23), 8812–8819. https://doi.org/10.1073/pnas.1114773109

de Francesco, F., Radaelli, C. M., & Troeger, V. E. (2012). Implementing regulatory innovations in Europe: The case of impact assessment. *Journal of European Public Policy*, *19*(4), 491–511. https://doi.org/10.1080/13501763.2011.607342

Getz, D., & Brown, G. (2006). Critical success factors for wine tourism regions: A demand analysis. *Tourism Management*, *27*(1), 146–158. https://doi.org/10.1016/j.tourman.2004.08.002

Gliozzo, G., Pettorelli, N., & Muki Haklay, M. (2016). Using crowdsourced imagery to detect cultural ecosystem services: A case study in South Wales, UK. *Ecology and Society*, *21*(3). https://doi.org/10.5751/ES-08436-210306

Investigator, P., & Bruwer, A. J. (2014). *AUSTRALIAN WINE INDUSTRY CELLAR DOOR RESEARCH STUDY 2013 INTERIM REPORT to Project Number : USA-1204 Date : January 2014*. *January*.

Jaeger, T. F. (2013). Production preferences cannot be understood without reference to communication. *Frontiers in Psychology*, *4*(April), 1–4. https://doi.org/10.3389/fpsyg.2013.00230

Johnson, R., & Bruwer, J. (2007). Regional brand image and perceived wine quality: The consumer perspective. *International Journal of Wine Business Research*, *19*(4), 276–297. https://doi.org/10.1108/17511060710837427

Keeler, J. R., Roth, E. A., Neuser, B. L., Spitsbergen, J. M., Waters, D. J. M., & Vianney, J. M. (2015). The neurochemistry and social flow of singing: Bonding and oxytocin. *Frontiers in Human Neuroscience*, *9*(September), 1–10. https://doi.org/10.3389/fnhum.2015.00518

oded Nov, Mor Naaman, C. ye. (2013). Analysis of Participation in an Online Photo-Sharing Community: A Multidimensional Perspective. *Journal of the American Society for Information Science and Technology*, *64*(July), 1852–1863. https://doi.org/10.1002/asi

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., & Plieninger, T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecological Indicators*, *94*, 74–86. https://doi.org/10.1016/j.ecolind.2017.02.009

Quadri-Felitti, D. L., & Fiore, A. M. (2013). Destination loyalty: Effects of wine tourists' experiences, memories, and satisfaction on intentions. *Tourism and Hospitality Research*, *13*(1), 47–62. https://doi.org/10.1177/1467358413510017

Quintal, V. A., Thomas, B., & Phau, I. (2015). Incorporating the winescape into the theory of planned behaviour: Examining “new world” wineries. *Tourism Management*, *46*, 596–609. https://doi.org/10.1016/j.tourman.2014.08.013

Redhead, J. W., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T. H., & Bullock, J. M. (2016). Empirical validation of the InVEST water yield ecosystem service model at a national scale. *Science of the Total Environment*, *569–570*, 1418–1426. https://doi.org/10.1016/j.scitotenv.2016.06.227

Sonter, L. J., Watson, K. B., Wood, S. A., & Ricketts, T. H. (2016). Spatial and temporal dynamics and value of nature-based recreation, estimated via social media. *PLoS ONE*, *11*(9), 1–16. https://doi.org/10.1371/journal.pone.0162372

Thomas, B., Quintal, V. A., & Phau, I. (2010). Predictors of attitude and intention to revisit a winescape. *Australian & New Zealand Marketing Academy of Marketing Studies (ANZMAC) Conference Proceedings*.

Tieskens, K. F., Schulp, C. J. E., Levers, C., Lieskovský, J., Kuemmerle, T., Plieninger, T., & Verburg, P. H. (2017). Characterizing European cultural landscapes: Accounting for structure, management intensity and value of agricultural and forest landscapes. *Land Use Policy*, *62*, 29–39. https://doi.org/10.1016/j.landusepol.2016.12.001

Van Berkel, D. B., & Verburg, P. H. (2011). Sensitising rural policy: Assessing spatial variation in rural development options for Europe. *Land Use Policy*, *28*(3), 447–459. https://doi.org/10.1016/j.landusepol.2010.09.002

van Berkel, N., Goncalves, J., Lovén, L., Ferreira, D., Hosio, S., & Kostakos, V. (2019). Effect of experience sampling schedules on response rate and recall accuracy of objective self-reports. *International Journal of Human Computer Studies*, *125*(December), 118–128. https://doi.org/10.1016/j.ijhcs.2018.12.002

van Zanten, B. T., Zasada, I., Koetse, M. J., Ungaro, F., Häfner, K., & Verburg, P. H. (2016). A comparative approach to assess the contribution of landscape features to aesthetic and recreational values in agricultural landscapes. *Ecosystem Services*, *17*, 87–98. https://doi.org/10.1016/j.ecoser.2015.11.011

Walden-Schreiner, C., Leung, Y. F., & Tateosian, L. (2018). Digital footprints: Incorporating crowdsourced geographic information for protected area management. *Applied Geography*, *90*(December 2017), 44–54. https://doi.org/10.1016/j.apgeog.2017.11.004

Weyand, T., Kostrikov, I., & Philbin, J. (2016). Planet - photo geolocation with convolutional neural networks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9912 LNCS*, 37–55. https://doi.org/10.1007/978-3-319-46484-8_3

Winkler, K. J., & Nicholas, K. A. (2016). More than wine: Cultural ecosystem services in vineyard landscapes in

England and California. *Ecological Economics*, *124*, 86–98. https://doi.org/10.1016/j.ecolecon.2016.01.013

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, *3*. https://doi.org/10.1038/srep02976

Yang, Y., & Paladino, A. (2015). The case of wine: understanding Chinese gift-giving behavior. In *Marketing Letters* (Vol. 26, Issue 3). https://doi.org/10.1007/s11002-015-9355-0

Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services*, *24*, 68–78. https://doi.org/10.1016/j.ecoser.2017.02.009

CHAPTER 4

Conclusion

Macroapproach

All Models confirm the importance of crops in landscape perception afford to have a spatial valuation of positive externalities. The results underline that vineyard and crop divided by edges and vegetation stripes contribute to a higher CES value. The approaches underline that using big data, photo from Flickr can be a good source of information to identify the elements that characterized the territory and map ces

Analysis in the paper I e II shows that correlation between cumulative viewshed and indicator provides useful information to identify the rural politics to valorize the landscape.

Analysis in paper III Willigness that the combination between vineyard and landscape can be a powerful tool to convert externalities into relevant attribute in marketing strategies

Our explanatory analysis identifies the area of interest in which the landscape planner had to apply strategies to manage the territory. The analysis identifies the priority areas of intervention and explains how some environmental feature changes influence landscape supply. The method proposed is the first step to inform stakeholders on the prioritization of the area.

In paper one and paper two, the comparison between observed demand forces and predicted demand highlights three possible scenarios.

1. The areas with high value in both cases, where protection and safeguard measures must be implemented

2. Hotspot areas predicted by the model but not observed, where enhancement projects must be implemented through landscape restoration projects for the removal of limiting causes

3. high value in the observed map but low in the predicted value since the model did not detect the landscape features present as relevant. In these cases, it is necessary to identify these characteristics promptly to protect

In paper three, the implementation of a cluster gives more information to planner to manage the territory.

In Cluster one, landscape, winescape perception is related to genius loci aspect of area, cluster two, other, and four, event, winescape perception is linked to event, for example, wine festival influences the emotion of consumers, at least cluster three, buildings, underline the correlation between winescape perception and architecture

Future development of research can be to lead interviews with visitors to face big data uncertainty. This implementation allows validating social media data to evaluate more landscape value and convince the administration of the reliability of using crowdsourcing data in land management.

Micro approach

In paper 4, results confirm emotions, detected both through the PANAS method and with eye-tracking and EEG, show an active involvement of the interviewees; they seem to connect wine to a psychological condition of interest, relaxation, and attention. The eye-tracking data, which makes it possible to find the visitors' points of visual attraction, can provide useful information to architects to design a new cellar door or renovate old one that enhances the integration with the winescape. The eye-tracking underlines which element of the landscape and architecture had to be taken into account in the design project. One element is the panorama and the skyline that users can see from the cellar door; another element is an architectural landmark, which makes the place identity and attracts people's attention.

Different styles of architecture generate the same positive emotions as PANAS and EEG's willingness. These cellar doors do not generate different emotional states; they make the same emotion in users with different intensities. Future development can compare more different cellar doors, as industrial cellar doors with traditional ones, to verify if the generated emotion is different.