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MACHINE LEARNING AND LANDSCAPE QUALITY. REPRESENTING VISUAL INFORMATION USING DEEP LEARNING-BASED IMAGE SEGMENTATION FROM STREET VIEW PHOTOS

Fabio Bianconi, Marco Filippucci*, Marco Seccaroni*, Andrea Rolando**, Domenico D'Uva****

*Università degli Studi di Perugia, Dipartimento di Ingegneria Civile ed Ambientale – Perugia, Italy
**Politecnico di Milano, Dipartimento di Architettura e Studi Urbani – Milano, Italy
***Politecnico di Milano, Dipartimento di Architettura, Ingegneria delle Costruzioni e Ambiente Costruito – Milano, Italy

Abstract

The study is centered on the value of visual perception in the measurement of landscape quality. The research aims to define a digital methodological process and criterion for assessing the quality of a landscape, using along a road georeferenced image as open source big data. Artificial intelligence system, trained to recognize and quantify the elements present, processes these images associating area data, therefore converted them into values according to specific criteria. In each image, it evaluates positive or negative characteristics of the path, and the sum of all big data values generates an index (L-value). This approach is tested in different case studies, validating AI results with Collective Intelligence, using anonymous questionnaires. The proposed process transforms the perceptual data inherent in the photographs into information, from which it extrapolates a knowledge path synthesized in map, representation of perceived qualities of the landscape.

Keywords

Big data, visual quality, street view images, image segmentation, landscape quality

1. Introduction

1.1 Objectives

The research aims to create a procedure to evaluate landscape quality, using open-source big data.

Starting from perceptual data derived by street view imagery, testing the analytic value of semantic segmentation filtered by criteria, the objective is to represent and share landscape evaluation in map. Therefore, the research is inside the field of representation, according to its ability to acquire and share knowledge.

Landscape is too often an aulic and virtual concept, something connected to "beauty" but not measurable. It is related to space, to territory, but firstly to the study of perception. In fact, the European Landscape Convention (2000), stated the landscape as "an area, as perceived by people, whose character is the result of the action and interaction of natural and/or human factors" (ELC art. 1, para. 38), marking the perception process (Bianconi & Filippucci, 2019) as the real center of the question: connected to visuality (Arnheim, 1954), landscape can be measured using new digital tools (Yin & Wang, 2016), to be included in scientific analysis. The hypothesis is to extract human perception data from photos (J. He, Zhang, Yao, & Li, 2023; F. Zhang et al., 2018), using open big data (Srivastava & Vargas-, 2018; Yuan, Wang, Niu, & Liu, 2023). In this way, it is possible to register the needs of assessing and measuring landscape (Dunkel, 2015), searching for a place value (Carmona, 2019) or a landscape value (Solecka, 2019).

The aim is to define a methodological process, related to digital procedures, and a criterion to interpret in a map the quality of a landscape from its georeferenced images. The research approach is characterized by an automatization in digital process of landscape valuation, effects of a criterion, results that must be verified. In this context the definition of the Convention of landscape is useful, centered in the term perception but also in the value of "people". For this reason, it is possible to compare the results obtained researching the interpretation of "territorial intelligence" (Laurini, Servigne, &

Favetta, 2020), related to participation (Smith, Bossen, & Kanstrup, 2017) and codesign (Bianconi, Filippucci, & Cornacchini, 2020), collecting Volunteered Geographic Information (VGI) (Goodchild, Fu, & Rich, 2007).

According to these hypotheses, the field of application of this research is the evaluation of landscape quality index (Gavrilidis, Ciocănea, Niţă, Onose, & Năstase, 2016) using an automatic methodology from georeferenced photos. This index integrates infrastructures and landscape (Shannon & Smets, 2011), creating an innovative spatial information, and particularly identifying the best route in term of bikeable (Kellstedt, Spengler, Foster, Lee, & Maddock, 2021; Muhs & Clifton, 2016) and walkable (Middleton, 2021; Moudon et al., 2006; Shamsuddin, Hassan, & Bilyamin, 2012), in pedestrian or compromised areas.

1.2 State of art

The proposed path is linked to visual culture (Jenks, 2002), subverting landscape analysis assessed from a zenithal viewpoint (Bianchi, D'Uva, & Rolando, 2020), and no scientific data related to empirical approaches according to observer's point of view (Lynch, 1960). Often landscape evaluations dependfrom the use of the GIS ecosystem, which works with georeferenced databases to assess the presence and type of elements characterizing the landscape (Scandiffio, 2019; 2021). It is possible to combine GIS and ML methodology (Bianchi Alessandro, D'Uva Domenico, Rolando Andrea, 2020; Liang, D'Uva, Scandiffio, & Rolando, 2022), to acquire information that would be difficult to obtain by limiting the ground survey activity. The related quality can be recorded in a synthetic map extracted by empirical interview (Lynch, 1960), or in sequences of drawings as in Gordon Cullen studies (Cullen, 1961), but also in the immediacy of the photography (Mitchell, 1980). The culture of connectivity (van Dijck, 2013) and digital democracy (Iafrate, 2018), emphasizes a sharing culture and in particular billions number of photos are uploaded online, representing an important data source to represent landscape conceptualization (Dunkel, 2015).

This big data generated by the bottom-up revolution reinforced by the Internet of People, Thing and Service (IOPTS), find in deep learning a disruptive process. Machine Learning (ML) represents the new tool and the new design approach that improves automatically through experience and by using big data and the billions of images in the internet, which are a central resource, where the open source world represents an important value (C. Wang, Antos, & Triveno, 2021). Digital ecosystems attributable to ML systems (Zhu et al., 2020) allow for recognizing elements previously identified through Image Segmentation (IS) technology (Ye, Zeng, Shen, Zhang, & Lu, 2019), assigning a percentage value of occupation of the whole field of view. This approach represents one of the most interesting frontiers in deep learning application in landscape analysis, computational models composed of multiple processing layers to learn representation of data with multiple levels of abstraction (LeCun, Bengio, & Hinton, 2015).

1.3 Related works

The use of street view image processing increased rapidly from 2010 to 2020, focusing on five main areas: thermal environment (Ren, Liu, & Zhang, 2022), neighborhood morphology (Chiang, Sullivan, & Larsen, 2017), socio-economic factors (Meng, Xing, Yuan, Wong, & Fan, 2020), landscape design (Bianconi, Filippucci, Ceccaroni, & Seccaroni, 2022; Shao, Yin, Xue, & Ma, 2023; Y. Wang, Fang, Liu, & Jadoon, 2022; A. Zhang, Zhai, Liu, Song, & Feng, 2022), environmental evaluation (Li et al., 2015; Seiferling, Naik, Ratti, & Proulx, 2017; Xing et al., 2023), environmental perception (Bibri et al., 2022; Sass, 2012), also in favor of autonomous driving (Tang, Li, & Wei, 2023). Research methods used include experiments, simulations, deep learning and data analysis (N. He & Li, 2021). In environmental perception and environmental evaluation, this type of images was used to evaluate walkability (Kang, Kim, Park, & Lee, 2023) and urban quality (Wen, Liu, & Yu, 2022; Ye et al., 2019)

While developing and refining this algorithm, related case studies were examined (Seiferling et al., 2017), in particular to mark the bikeability index analysis system used for the city of Munich (Schmid-Querg, Keler, & Grigoropoulos, 2021). The procedures are able to value independently every element along the possible paths connecting the start and endpoints, generating a general value, which is applicable to any context. A possible application of the study is the selection of the best cycling routes among the already existing roads, a topic related to the finding of the scenic routes (Alivand & Hochmair, 2013). Different studies have analyzed the value of walkable cities (Muhs & Clifton, 2016). Walkability and bikeability are both connected to a different timing in the evaluation of a place quality (Muhs & Clifton, 2016), both related to a multi-criteria methodology (Kellstedt et al., 2021) a question that pertains to a more limited number of studies. Still, this concept is essential to distinguish features that increase the quality of travel for bicycling purposes versus a predominant use for walking. In fact, the hypothesis is that walkability and bikeability are not only a matter of infrastructures, but they are related to landscape analysis (Badland & Pearce, 2019) and to the qualification of the context (Ewing et al., 2013), analyzable by an overview of variables and measures of physical environments. In this context, the shortest path is not necessarily the best path (Quercia, Schifanella, & Aiello, 2014), as the possibility of introducing deviations to the most efficient trajectory (Salazar Miranda, Fan, Duarte, & Ratti, 2021) to increase the quality of the path is worthy of analysis, according to the need to evaluating the images perceived.

2. Method

The proposed path is based on customized algorithm, that valorizes the potential of imagery platform and support images segmentations, identifying categories of elements (instances). Information are organized in a bidimensional data structure, a Data Frame, which organizes data into a two-dimensional table of rows and columns, much like a spreadsheet. Through this structure, which links image interpretation to geographical references, it is possible to interpret data using customized criteria, according to the need of transforming information in knowledge, of perceptive data in landscape interpretations. The criteria represent a hypothesis of data interpretation, tested, and verified in different case studies valorizing the territorial intelligence.

2.1 Imagery platform

Images are analyzed and segmented using Mapillary, maybe the first platform to provide detailed geotagged street photos based on crowdsourcing, adding to the list of Web 2.0 applications that administer and facilitate, able to interpretate also photo captured in sub-optimal conditions for structure-from-motion such as low framerate, non-orbital trajectories, and under-constrained camera parameters, and to create effectively train deep neural networks with data from many heterogeneous camera sources (Warburg et al., 2020). This system has been preferred to other because it allows the availability of an open-source platform for sharing input data, and for those output (Neuhold, Ollmann, Rota Bulò, & Kontschieder, 2017). Compared to Google Street View (GSV), images on the Mapillary platform follow the CC BY SA 4.0 License, which everyone can use for free. Mapillary images have been widely applied to the construction of street-level datasets for detecting cars, skies, and other object categories to achieve a semantic understanding of street scenes (Neuhold et al., 2017).

This platform for feature recognition, according to the official statistics, since the beginning of 2014, collects a total of 543.8 million images, and the database is easily increasable, including non-common paths that other IS system, as Google, do not consider.

The digital path developed is able to use its API as a code created entirely using Python programming language, representing the real value added of the path.

2.2 Imagery platform

A Seamless Scene Segmentation typology developed by Mapilary, with a CNN-based architecture, was used for semantic segmentation. The used architecture takes advantage of a novel segmentation head that seamlessly integrates multi-scale features generated by a Feature Pyramid Network with contextual information conveyed by a light-weight DeepLab-like module. For the semantic segmentation model, Mapillary obtained a baseline segmentation result of 73.8% (mean Intersection- over-Union), which is comparable to 75.2% reported using a DenseNet-169 backbone, 73.6% using DeepLab2 in combination with a ResNet-101, or 74.6% with a ResNet-152.

The instance-segmentation mAP (mean average precision on masks) results of Mapillary single model baseline are 31.9%, which is slightly above the reported baseline score in Mask R-CNN (31.5% w/o COCO pre-training) (Porzi, Bulò, Colovic, & Kontschieder, 2019; Porzi, Hofinger, et al., 2019).

2.3 Algorithm developed

The first phase of the Python script interfaces with the Mapillary database through the proprietary API. Through these, it is possible to query the database with a request and limit it to a well-defined portion of the territory using the parameter defined with the lower left vertex and the upper right vertex, corresponding to the geographical coordinates of the area. Mapillary returns an ordered list of sequences of images present in the filtered pane. By breaking down the sequences, it is possible to identify the unique key image of each image. Using a new request and imposing the key image as a parameter, Mapillary returns a json type file.

Within the file, the geographical position of the shot and what the API calls "value", with the relative area of the semantic segmentation of the image, are selected for each photo: in fact, Mapillary can recognize from a raster image 152 categories of elements identified as "instances", to which it attributes an area, with the sum of the found instances approaching unity.

By using Python, for each photo analyzed a list has been created with a Database inside: this is composed of a unique code of the image for Mapillary, necessary for its identification, the geographical coordinates of the taken photo, fundamental for spatial representation, the value, describing the interpretation of the represented landscape, the relative areas of the segmentation, at the basis of the quantification of the relationships between the parts.

The Database created is functional to the selection of the individual elements identified, which are recomposed according to an experimental criterion resulting from research evaluations in the context of landscape. The goal is therefore to read the interpretation of the segmentation in relation to the values and areas identified, in order to map out a landscape interpretation that concerns perceptual values enriching the territorial data.

With the interpretation provided by the criteria, associated with the geographical coordinates, at the end of the path, it is possible to associate the segment that joins two consecutive photos with a graphic attribute that varies according to the specific score Lvalue. The positive values with Lvalue>1 are represented in green (HSB = 104, 1, 0.55), then the color is desaturated in a linear way until Lvalue=0 (HSB = 104, 0, 0.55).

Then the brightness is decreased in a linear way for negative values until Lvalue< -1 (HSB = 104, 0, 0).

In the representation a check of the Sky is made, i.e., if it has an area greater than 65% it is represented in light blue (HSB = 202, 0.90), this is because if the photo is not horizontal, the Lvalue may not be correct.

To overcome the problem of a calculation that with the available APIs does not guarantee optimal responses in the event of a request with all the available values, a recursive procedure has been developed, starting from a first set of 31 values, the most present in images. If, with this request, the segmented area is less than 98%, the algorithm requires to query the Mapillary database again by increasing the elements of the parameter "values" with the complementary excluded, in order to obtain an area close to unity. Although, if before or after the verification, the sum of the segmented areas is greater than 98%, the second step is to calculate the areas of the elements of equal value. The next passage is to identify all those images that present a substantial reduction in the representation of the landscape, often caused by the presence of the dashboard in the photograph: in these cases, these areas are removed from the summation and the remainder are proportionally extended to always obtain a sum next to unity (Figure 1).

2.4 Criteria

For the creation of the criterion, related to perceptive quality of landscape, the categories used to determine the information were taken into account, first selecting those that are most present in the survey areas: Sky, Vegetation, Buildings and Roads.

The criterion proposed to determine the "score" Lvalue is the following:

$$\mathrm{L_{value}} = \alpha_1 \mathrm{V} + \alpha_2 \mathrm{S} + \alpha_3 \mathrm{B} + \alpha_4 \mathrm{R} + \beta_1 \sum VAP + \beta_2 \sum VAN + \beta_3 \sum VDP + \beta_4 \sum VDN$$

The four main values are first addressed: Vegetation (V), Sky (S), Buildings (B) and Roads (R). Starting from the consideration that "Vegetation" value is always a positive element, α1=1 if the segmented area is less than 60%; if it is higher the applied parameter is lower: α_1=0.75.

Another positive element is "Sky" value, but it has been taken into consideration that the photos are sometimes disproportionate due to the random photographic taking, with an area of the sky that can alter the final value if depicting a too large or too small portion of the sky, or in case of absence of horizontality, a condition that imposes the need to decrease the weight of this value in the interpretative criterion, therefore $\alpha_2 = 0.75$. "Buildings", on the other hand, can have a null or

Fig. 2: San Vito Chietino – Photo survey and Image Segmentation of most frequent elements and the segmentation of the dashboard

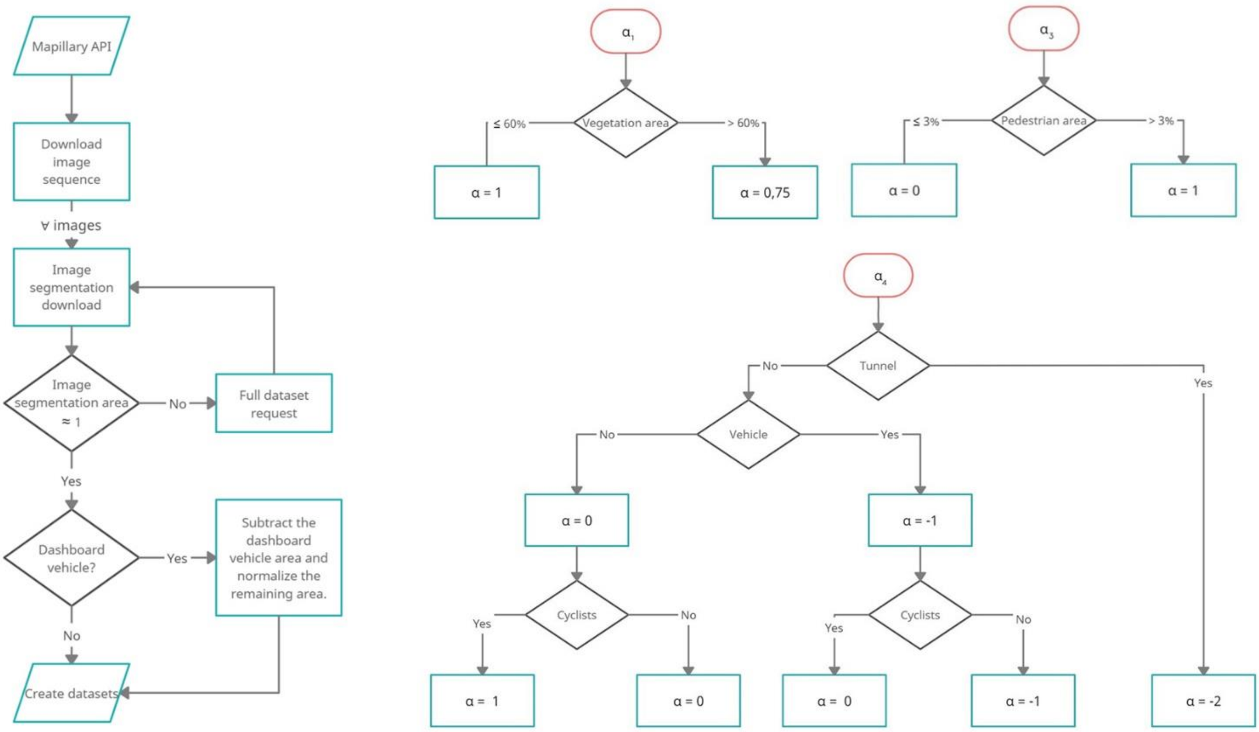

Fig. 1: Flowchart of the first part of the algorithm. From Mapillary AP\I to Dataset and Flowchart of coefficients α

positive value, because the semantic segmentation fails to classify them by their qualities (if they are cultural, ruined, residential, illegal, colored ...), which is why a reduction coefficient α_3 is inserted: a positive value (α_3=1) is attributed to all those buildings that generally overlook squares or pedestrian areas with an area greater than 0.03 assuming an architectural value, while a null value is attributed (α_3=0) for all other cases, thus excluding the class from the evaluations. Finally, "Road" value can assume a positive, negative or null value, expressed by a coefficient α_4, due to its relationship with other secondary "values" (e.g. tunnels, vehicles and cyclists...) identified by the segmentation: specifically, the presence of a tunnel causes the road to have a double negative value (α_4=-2), just as the presence of vehicles is associated with a negative value (α_4=-1), the simultaneous presence of cyclists and vehicles on the road gives it a neutral value (α_4=0) and finally the mere presence of cyclists makes the road positive (α_4=1), while in the event of the absence of a relationship between the road value and the secondary values, it is not considered (α_4=0)(Figure 2).

In addition to the main "values", the secondary "values" that are able to characterize the scene have also been identified. These have been divided in two categories: "areal" for those that are considered on the basis of their area, and "determinants" are those for which their only presence is decisive. These categories are also divided due to the attribution to the "secondary value" of a positive (Table 1) or negative (Table 2) connotation for slow mobility. All residual values excluded from the main ones are organized according to the four categories, to which a parameter β is associated:

Positive Areal Values (VAP) | for each value, β_1= 1, and VAP is equal to the area of the present elements;

Negative Areal Values (VPN) | for each value, β_2=-1, and NPV is equal to the area of the elements present;

Positive Determining Values (VDP) | for each element, β_3= 1, VDP increases by 0.05 for each present element;

Negative Determining Values (VDN) | for each element, β_4 = 1, VDN increases by -0.09 or -0.07 except for tunnels it increases -0.8.

The first two elements of the criterion are the summations of the areas in the positive and negative Area Values list.

The list of positive point elements is used to calculate the parameter β_3 and for each element present in the DataFrame 0.05 is added.

Through the list of negative point elements, it is possible to calculate the parameter β_4: in fact, the value 0.09 is added to each point element present in the image DataFrame if a vehicle is present, while is added 0.07 for all other elements. Furthermore, if the tunnel is also present this value is increased by 0.8 (Figure 3).

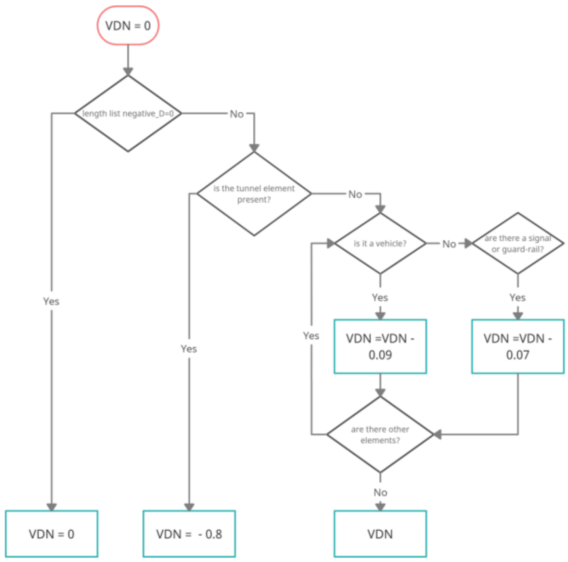

Fig. 3: Flowchart of Negative Determining Values (VDN)

Tab. 1: Items identified through segmentation subdivided according to criterion classes

Positive Areal Values	Positive Determining Values (+0.05)
construction--flat--bike-lane	animal--ground-animal
construction--flat--pedestrian-area	human--person
construction--flat--sidewalk	human--rider--bicyclist
nature--beach	object--bike-rack
nature--mountain	object--traffic-light--cyclists
nature--sand	object--vehicle--bicycle
nature--terrain	
nature--water	
object--bench	
void--ground	

Tab. 2: Items identified through segmentation subdivided according to criterion classes

Negative Areal Values	Negative Determining Values (-0.07)	Negative Determing Values (-0.09)
construction--barrier--curb	construction--barrier--guard-rail	object--vehicle--bus
construction--barrier--fence	object--support--traffic-sign-frame	object--vehicle--car
construction--barrier--guard-rail	object--traffic-cone	object--vehicle--caravan
construction--barrier--separator	object--traffic-light	object--vehicle--motorcycle
construction--barrier--wall	object--traffic-light--general-upright-front	object--vehicle--on-rails
construction--barrier--other-barrier	object--traffic-sign	object--vehicle—other-vehicle
construction--flat--traffic-island	object--traffic-sign--front	object--vehicle--trailer
construction--flat--rail-track		object--vehicle--truck
construction--structure--bridge		object--vehicle--wheeled-slow
object--banner		
object--billboard		
object--trash-can		

2.5 Validation of the criteria

The process of image segmentation makes it possible to estimate a landscape index in relation to the data extrapolated from the pixels in an automated process obtained with the aid of artificial intelligence. If landscape value can be considered in algorithmic terms as a massive use of data abstracted from the person's capacity for interpretation, to validate the process results it is necessary to propose a comparison with different people interpretations, defining a common application. The canonical approach in surveys uses questionnaire, useful to bring out the approach through territorial intelligence to validate the criterion.

The questionnaire proposed for all the case studies presents a similar logic, analysing emblematic routes among the many represented in the map by the script. Therefore, five routes were chosen, with a number that could be used to make several comparisons, all of which were compared individually to identify the order of preference of the route to valorise, verifying whether it corresponded to the evaluations obtained with the algorithm.

The questionnaire that circulated online, in fact, provided for a brief qualification of the subject in identifying his age, knowledge of the place, and use of the bicycle. Subsequently, the routes identified on the map represented with three images, in order to provide a clear reference to the subject, were evaluated among themselves, asking the tester which one of the paths he would prefer to ride in or which one he would like to see enhanced, thus opening up also to the design sphere.

3. Result

3.1. The case studies

The implemented path can be applied in any area represented in a photo inside the Mapillary site.

In a paradigmatic way, three case studies are chosen to verify the effectiveness of the proposed path and the designed criteria. The case studies are selected in relation to the possibility to verify the results using a partecipatory process, moreover, representing different typology of landscape, to be read in relation to the increasing gradient of urbanization.

The first case study selected for application of the detailed methodology is the system of slow mobility connections of the Trabocchi coast, in Abruzzo, Italy (Marino, et al., 2018) where the route of the Adriatic railway has been decommissioned, to make way for a 40 km long greenway. The choice of an area far from the metropolis (Festa & Forciniti, 2019) is consistent with the methodology of the analysis suitable for routes outside urban centres. The proposed study is helpful in elaborating connections between different urban centres (Karanikola, Panagopoulos, Tampakis, & Tsantopoulos, 2018) rough slow mobility strategies. The node of San Vito Chietino in the northern portion of this cycle route has explicitly been analysed in its system. In this case study, 1840 images.

Fig. 4: San Vito Chietino, Termoli and Perugia – L_{value} index mapping of the whole area. Positive values are green. Negative Values are grey

From the 1860 photographs processed for this case study, it was possible to analyze the values divided in 21 tracks: in this set, sky value was present in 1845 images, road value in 1852, buildings value in 1531, and vegetation value in 1858. On average, the area of the sky value was 34%, the area of the road value was 21%, the area of the buildings value was 2%, and the area of the vegetation value was 15% (Figure 4).

Tab. 3: Summary of data analysed in the three case studies

Case study	Total photos	Building area	Photos with building	Road area	Photos with road	Sky area	Photos with sky	Vegetation area	Photos with vegetation	Total Area (V,S,B,R)
San Vito Chietino	1860	0.02	1531	0.21	1852	0.34	1845	0.15	1858	0.72
Termoli	6920	0.11	6390	0.21	6763	0.33	6827	0.14	6784	0.79
Perugia	3115	0.22	3095	0.19	2998	0.11	2906	0.18	2949	0.70

In addition, the area of Termoli, a case with homologous spatial configurations to the previous case stady, was selected to verify the correct functioning of the analysis method. The interpolated images were 6920 divided in 41 paths (Figure 4).

The third case study was a residential district of Perugia, named Fontivegge. The area is very different from the second case study, in fact the building area is about double (11% against 22%). Interpolated images were 3115 divided into 29 paths (Figure 4).

Comparing the three case studies and analysing in this way around 10.000 images, it was possible to mark the elements selected for the criteria: Vegetation (V), Sky (S), Building (B) and Road (R) represent the 76% of the elements and they were present on average respectively in 15.1%, 27.6%, 12.8%, 20.5%. These data help to understand the reasonableness of the criteria proposed (Table 3).

3.2. Criterion validation

The results of the interpretation of the images through segmentation are translated into the planimetric drawing of a representation capable of bringing out the quality of the tracks. Through the developed algorithm, interactive maps in HTLM format have been elaborated, one for each case study, where the interpretation of the track is graphically synthesized with a gradient of colours with respect to the synthesis value Lvalues, and where it is possible to interrogate all the other values estimated by the algorithm.

The maps show the different quality of the tracks and allow the identification, even at a glance, of those tracks with better quality. In the three case studies, as it can be assumed, it is possible to see a different level of landscape quality, corresponding to the gradient of urbanization that underlies the selection of the case studies (Figure 5). The results obtained were validated through the questionnaire. The five routes were selected in correspondence with values marked by an evident gap and compared in the questionnaire with each other (Figure 6). The survey found the answers of 37 people for the Trabocchi coast, 108 people for Termoli, 122 people for Perugia. By comparing two by two the routes, we can draw up a ranking of preference among the chosen routes in the sample and compare it with the one processed with Lvalue, therefore we will see that in all the case studies, there is a flat coincidence with the ranking resulting from the values of the algorithm (Tables 4-5-6-7). Hence, in the case studies, it is verified that the algorithmic construction and the criteria drawn up allows an interpretation to be attributed to the quality of the places and the landscape experienced.

Tab. 4: Average L_{value} of the paths obtained by applying the criterion

	Path 01	Path 02	Path 03	Path 04	Path 05
San Vito Chietino L_{value}	+0,75	+0,21	+0,18	-0,15	/
Termoli L_{value}	+0,78	+0,62	+0,57	+0,15	-0,27
Perugia L_{value}	+0.15	+0.08	-0.35	+0.88	+0.75

Tab. 5: Ranking of Perugia tracks by preference with the survey and according to L_{value}

Survey	Lvalue
04	04
05	05
01	01
02	02
03	03

Tab. 6: Ranking of San Vito Chietino tracks by preference with the survey and according to Lvalue

Survey	Lvalue
01	01
02	02
03	03
04	04

Tab. 7: Ranking of Termoli tracks by preference with the survey and according to Lvalue

Survey	Lvalue
01	01
02	02
03	03
04	04
05	05

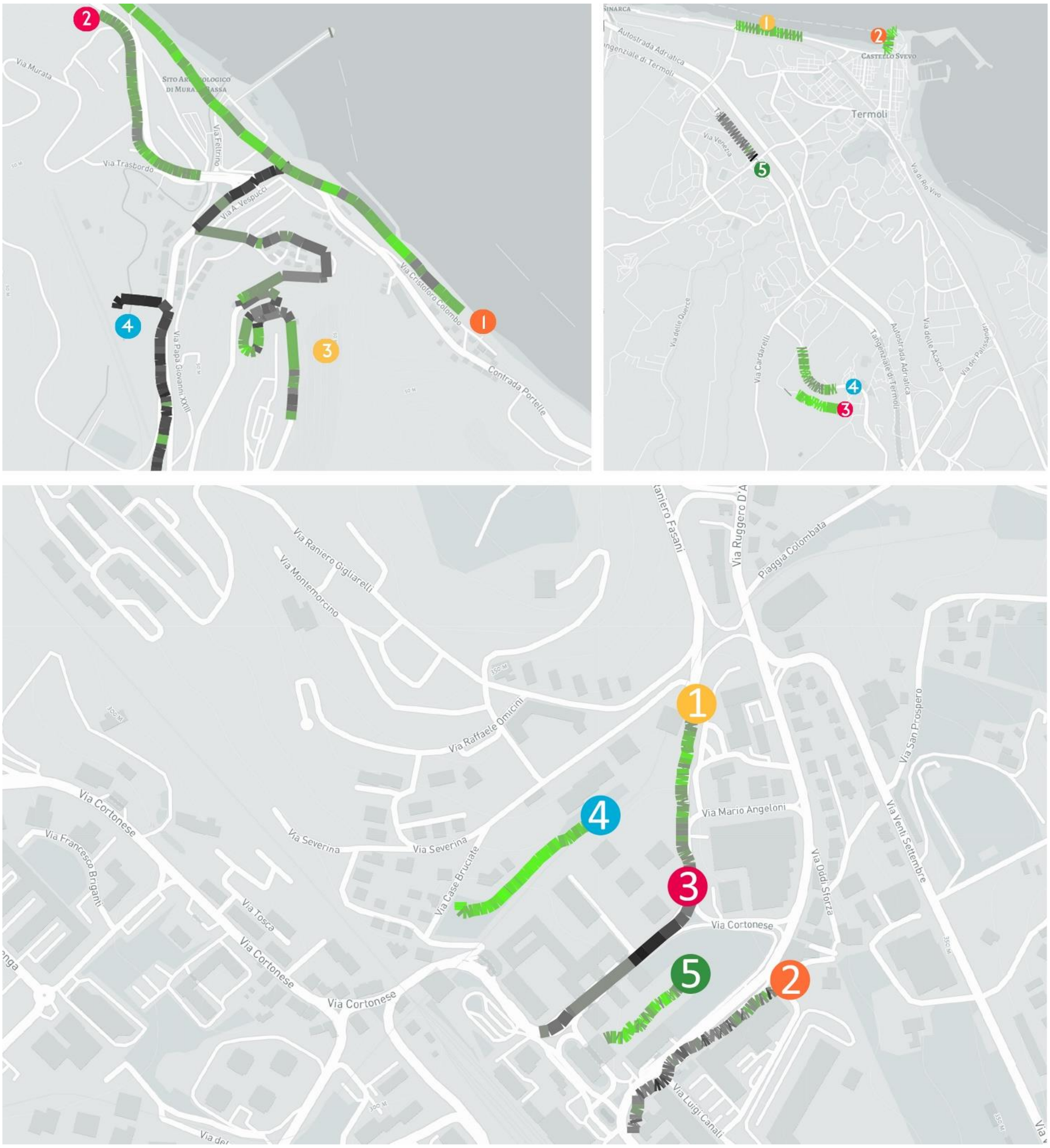

Fig. 5: San Vito Chietino, Termoli and Perugia – Lvalue index mapping along specific paths following criteria application

Fig. 6: San Vito Chietino, Termoli and Perugia – Photo Survey along the paths

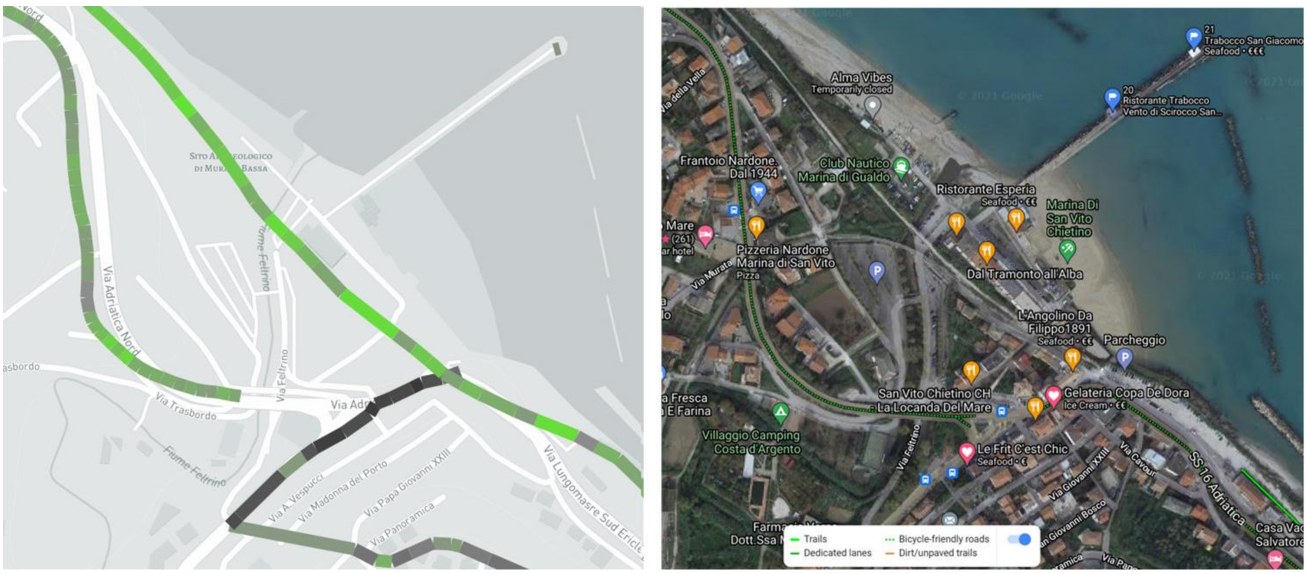

Fig. 7: San Vito Chietino - Google comparison with the algorithm

The case studies were compared with Google tools in order to check out the best rout in terms of spatial quality. Google routes are in the two case studies San Vito Chietino and Termoli. Therefore, it is demonstrated that the adopted procedure succeeds, with the selected criteria, in identifying elements that are useful for understanding the potential of a place.

The results obtained in the path evaluation are then evaluated with the cycle-friendly road recognition recently made available by Google. A comparison has been implemented by checking the selected paths between the two processes in the areas in question and critically analysing whether the selection leads to congruent results with the reality experienced.
Google points out the roads that can be considered cyclable, through ML techniques, by means of a classification that divides the routes into different categories. In figure 7, SS16 road (left curved) is valued as bicycle-friendly, where traffic is considerable throughout the year and the greenway of the green coast of the Trabocchi running along the sea, is not entirely surveyed. The methodology in this paper, on the contrary, correctly detects the poor cyclability of the state road by assigning a value of 0.2 while, the same methodology assigns a value of 0.75 to the greenway.

4. Conclusions

The research developed is based on the aim of transforming in information the big data of the open-source maps and of data sharing, for the billions of photos in internet, a step that imposes a first interpretation left to digital with its machine learning. The proposal shows the transition that occurs through interpretation from data, to information and then to knowledge: the data (pixels) in the photo become entities (segmentation) and then information, resulting in a map (criterion) that shows a knowledge of the qualities of places. Through the comparison between Artificial and Collective Intelligence, it is possible to measure landscape quality using visual data, as proposed in the research objectives. Identify the best walkable or bikeable path is an implicit evaluation of perceptual information, able to consider users wellness in their interaction with environment and territory, which is the landscape experience.

The technical novelty of this work is the development of an automated methodology that from georeferenced images allows a GIS representation of the processed data.

The proposal shows the result on the possibility of using open data, and specifically images, to provide interpretations on the landscape, enhancing a clear connection in a theme that remains random, subjective, therefore not scientifically searchable, and which instead it is here addressed in a process that is substantiated by the value of digital and that opens up to new research fields. This condition specifically corresponds to the cycling of the paths, but the value of the methodology designed is broader than the peculiar specificity. However, the support provided by digital remains basic in providing calculations on data that would otherwise fail to produce similar analytical results.

The technical approach is addressed to an innovative approach in the definition of innovative criteria to quantify the analysis: landscape assessment is a path derived by selection, identification, and interpretation of data. Machine Learning shows how images become the revolutionary condition of observation, already made discrete, and already filtered into categories, then interpretable with criteria. A methodological process is thus configured, which can be replicated, redesigned for other objectives through a transformation of the criteria based on observation and the definition of hypotheses and theses that can be replicated for other realities.

This path therefore leads to providing assessments still linked to the sphere of the person and not of the machine, which is instead fundamental for calculating and organizing data through cataloguing in what are called "values". The subtended key theme is to be able to simulate the judgment process that is inherent in perception and is in the foundation of the landscape concept: it is a matter of building criteria, which in digital process must still be translated into numbers and relationships, due to the specific researched objectives. The proposed algorithm generates knowledge, it allows to correlate the interpretation inherent in the information to make the path to be taken. The results obtained by the capacity of the artificial intelligence trained to learn how to recognize by comparative calculation have been screened by criteria that prove valid by the statistical comparison made with the territorial intelligence, with those who live in and implicitly interpret that place and know its potential.

Landscape value derived by this path can support a full interpretation of landscape if it is integrated with additional sources of data. In the next steps of the research, it is helpful to think that the index as defined is a component of a much broader analog/digital ecosystem. It is possible to consider as elements of development, in addition to the already mentioned GIS system, the big data generated by the bottom-up contribution of users, the Remote Sensing tools for the interpretation of satellite databases. In addition, cultural interpretations of the landscape, such as photographs, paintings, literature, become essential evaluation elements if they have not already been integrated into existing tools.

In conclusion, the research differs from others in creating a new criterion for landscape interpretation using open-source data.

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