

Multi-criteria Evaluation vs Perceived Urban Quality: An Exploratory Comparison

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Abstract. This study compares a service-based and environmental evaluation of an urban area with that of its perceived walkability. The Pampulha region in Belo Horizonte, Brazil was first put through a multi-criteria spatial evaluation with respect to a set of spatial data considered relevant for liveability and quality of life in cities, and was subsequently assessed in terms of perceived walkability (using a machine learning procedure of a training set provided by local auditors). The two types of analysis were compared and qualitatively aggregated to obtain a joint spatial score of the urban environment. The findings provide useful insights for planning and urban policy.

Keywords: Urban quality · Spatial multi-criteria analysis · Walkability assessment · Machine learning

1 Introduction

In this study we conduct an exploratory analysis of factors of quality and attractiveness of urban environments and cityscapes. There are in general two ways in which such "quality" may be framed and assessed. One is centred on observable features sourced from available spatial data, represented through a series of indicators, and then in some way aggregated through a multi-criteria analysis. This framing can be said to follow the logic of a capability approach [1–3] insomuch as it attempts to analytically describe what there is, what it is like, what are the observable features of the urban environment, considered as enablers for people having certain capabilities in cities.

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The second way to frame the "quality" is to rely on subjective perceptions people have of the urban environment. Here the point is to survey declared preferences, based on their direct, "synthetic" perception of places.

Of course, the two ways of framing the urban quality are in principle related. One would assume that an urban environment endowed with valuable features, services, facilities, attractive and safe places would come out favourably in declared subjective judgements. But there are, in principle, also reasons for divergence between the two. One such reason is possibly of technical nature, the fact that it may not be easy to construct the statistical model capable to reduce with sufficient fidelity the synthetic subjective judgements to the available data and observable features.

However, there is another, more fundamental reason why one should not expect the two approaches entirely to match. The general point is that capabilities, while relevant for a normative definition of well-being and quality of life [1], do not necessarily nor perfectly map onto individual preference structures (say, as represented by a utility function). That is to say, when defining well-being, the capability approach emphasizes functional capabilities (which is urban context may mean access to certain services, places, public spaces, "right to the city", participation, safety and so on) which are construed in terms of what people have reason to value, instead of utility (happiness, desire-fulfilment or choice) or individual resources (e.g. income, commodities, assets). In other words, the focus on capabilities enables to acknowledge the existence of claims, like rights, which may empirically diverge from, and normatively dominate over utility-based claims [4].

In this study we take both routes and then perform an exploratory comparison between the two sets of evaluative outcomes. With a dose of agnosticism, we hold that both are informative from the perspective of urban policy and planning. Both how we may assume and model what the well-being and urban quality of people *should be* given the observable features of the urban environment, and what people themselves *believe* it to be. With such an agnostic attitude, our point is not so much to straitjacket one set of evaluations into the other, but to compare them, to see when they line up or differ, and perhaps to hint at why that may be so.

The remainder of this paper is organised as follows. In the next section we briefly present our case-study urban area – the Pampulha region in Belo Horizonte, Brazil.

For the multi-criteria evaluation, we use and aggregate 19 variables describing urban environment and landscape characteristics. The methodology and the results of that analysis are presented in Sect. 3.

In Sect. 4 we describe the methodology employed to assess the perceived urban quality, for which as we have employed a machine-learning classifier trained on a dataset of evaluative judgments on the perceived walkability of streets from Google Street View photography.

Finally, to streamline the comparison between the two sets of results, we define three levels (ordinal classes "low", "medium" and "high") of quality for each, yielding 3×3 possible combinations of outcomes. The discussion of these results and their qualitative comparison is presented in the concluding section.

2 Case-Study Area

The case urban area for our study was Pampulha, an urban region of about 145.000 inhabitants in the northwest of the city of Belo Horizonte, Brazil. The area (Fig. 1) is famous for its main attraction, the Pampulha Lake, and for its icons of Brazilian modern architecture designed by Oscar Niemeyer, the landmarks for leisure and sports, but also for important structures as the Federal University of Minas Gerais, the stadium, the first airport of the city and the zoo. In 2016 Pampulha Modern Ensemble was recognized by UNESCO as a World Heritage site.

Pampulha Region presents large variability in land uses: low density residential areas, with high and low land costs, as well as shantytowns; besides institutional, industrial and services and commerce areas. In comparison to other regions of the city, Pampulha is characterised by relatively abundant vegetation cover, flat area with low slope of roads, low density housing and just a few high-rise developments, good road infrastructure even though often lacking diffused commercial activities. Its variable character was one of the factors that guided choosing this study area, described by some numbers and characteristics: density (4.859 hab/km^2, relatively low density if compared to other areas of the city); topography (mostly flat, distinctively from most other areas of the city and more favourable for active mobility (walking, biking, …)), traffic (relatively less intense, with fewer traffic jams); vegetation (expressive amount of remaining green areas in parks and in private lots units); leisure (among the main destinations for open-air activities within Belo Horizonte); and available data (large amount of data of this Region available under a research's agreement signed between Belo Horizonte Council (PBH) and the Laboratory of Geoprocessing (LabGeo); also, LabGeo has developed previous studies of Pampulha Region, saving time of literature review to characterize it.

3 Features of Urban Quality: A Multi-criteria Analysis

The first part of the study was based on the use of a multi-criteria analysis to define and combine variables, in order to evaluate the conditions of urban quality resulting from a set of territorial features [5]. For that, we begin with 19 spatial variables, reported in Table 1 which, on our preliminary assessment, are relevant for the urban quality. These variables were demonstrative of urban infrastructure and landscape characteristics, for example roads width, visibility of waterbodies, presence of vegetation, composition of buildings.

As the spatial unit of data, we used individual road tracks plus the frontal part of the lots (the first 15 m), representing the portion that a person captures with the observation while walking along the sidewalks.

All the variables were normalised in the range of values from 1 to 5, representing respectively the worst and best conditions. Examples of such evaluations on some variables are shown in Fig. 2.

Once all the variables were processed, we applied the aggregation procedure, the multi-criteria analysis based on weighted sum. In the first test, all the variables received the same weight. After that we applied the sensitivity analysis to suitability evaluation

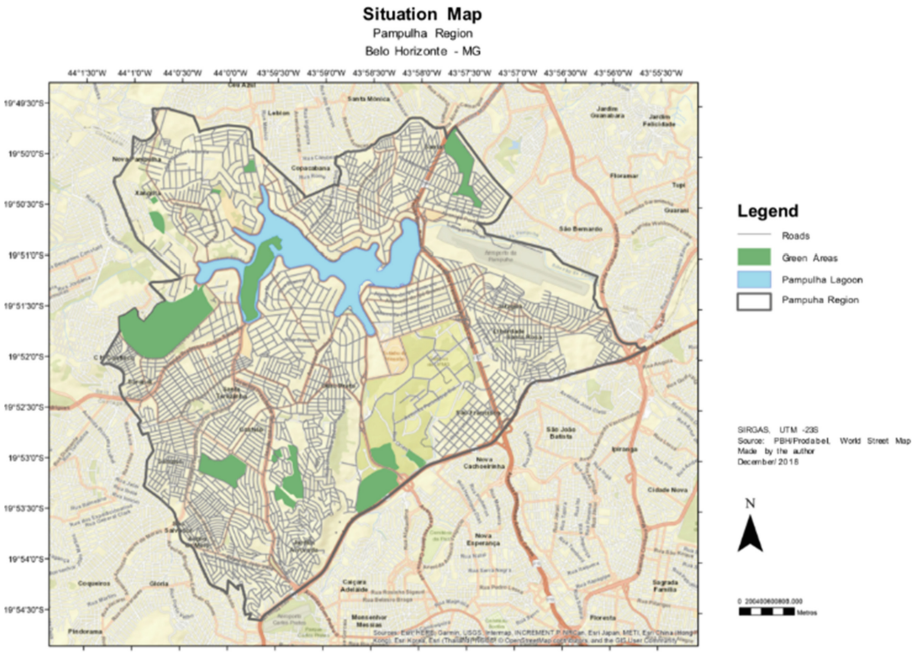

Fig. 1. The Pampulha Region (Color figure online)

(SASE) [6, 7], a method allowing a more robust analysis in comparison to the traditional multi-criteria analysis [8]. The method performs a Monte Carlo weighted sum simulation, using different weights delimited in a range from minimum to maximum values for each variable, and computes the degree of "doubt" on the performance of the variables. In our case, we can thus identify areas that are considered of high quality and without doubts (small uncertainty), areas of high quality but with doubts about the results (large uncertainty), areas of low quality and without doubts about that (small uncertainty), and areas of low quality but with doubts about the results (large uncertainty).

This analysis allowed to pinpoint the following three variables which were the greatest source of uncertainty:

- Residence's concentration: probably due to a specific characteristic of Pampulha Region that, for example, areas with low density have an ambiguous effect on walkability.
- Roads' Hierarchy: it is a technical nomenclature used by the City Hall that not necessarily express road's characteristics.
- Quantity of Bus Lines: Belo Horizonte's bus system (BRT/MOVE) works in a way not reflected by the values of the variable, generating an inconsistent data comparing main avenues (with few lines but regular services) and ordinary roads (with more lines but not so regular services).

Table 1. List of the starting variables used for in the MCA. In the first two columns the list of data and their spatialization in process maps.

Urban data	MCA - Delphi Method			MCA - Monte Carlo Weighted Sum + Uncertainty – SASE		
	Data	WT absolute	WT relative	Data	WT range	Variance
Bus stops	Bus stop concentration	7,8	6,00%	Bus stop concentration	4 to 8	−0.001
Cycle grid	Cycle grid	8	6,10%	Cycle grid	4,1 to 8,1	0.005
Urban parks, Green areas	Permeability percentage	9,1	6,90%	Permeability percentage	4,9 to 8,9	0.421
Land densification and buildings height	Building's height predominance	7	5,40%	Building's height predominance	3,4 to 7,4	0.003
	Building's height variability	5,1	4,00%	Building's height variability	2 to 6	0.04
Lots limits, block contours and land use	Commerce concentration	7	5,40%	Commerce concentration	3,4 to 7,4	0.002
	Industry concentration	8,7	6,70%	Industry concentration	4,7 to 8,7	0.001
Public and private equipment for leisure and tourism	Cultural attractions concentration	8,4	6,40%	Cultural attractions concentration	4,4 to 8,l4	0.005
Public and private urban equipment for health and education	Urban equipment concentration	7,5	5,80%	Urban equipment concentration	3,8 to 7,8	0.003
Roads grid, hierarchy, type, width and pavement	Roads width	9,3	7,10%	Roads width	5,1 to 9,1	0.011
	Roads type	8,6	6,60%	Roads type	4,6 to 8,6	0.004
	Roads paving type	8,4	6,40%	Roads paving type	4,4 to 8,4	0.093
Topography and roads grid	Roads slope	8,7	6,70%	Roads slope	4,7 to 8,7	0.054
Trees along the roads and in the frontal part of the lots	Trees concentration	9,4	7,20%	Trees concentration	5,2 to 9,2	0.295
Waterbodies	Waterbodies visibility	8,5	6,50%	Waterbodies visibility	4,5 to 8,5	0.005
Roads connection and urban services or commerce	Potential interaction of urban nodes	8,8	6,80%	Potential interaction of urban nodes		0.054
Bus lines	**x**	**x**	**x**	**x**	**x**	**x**
Lots limits, block contours and land use	**x**	**x**	**x**	**x**	**x**	**x**
Roads grid, hierarchy, type, width and pavement	**x**	**x**	**x**	**x**	**x**	**x**

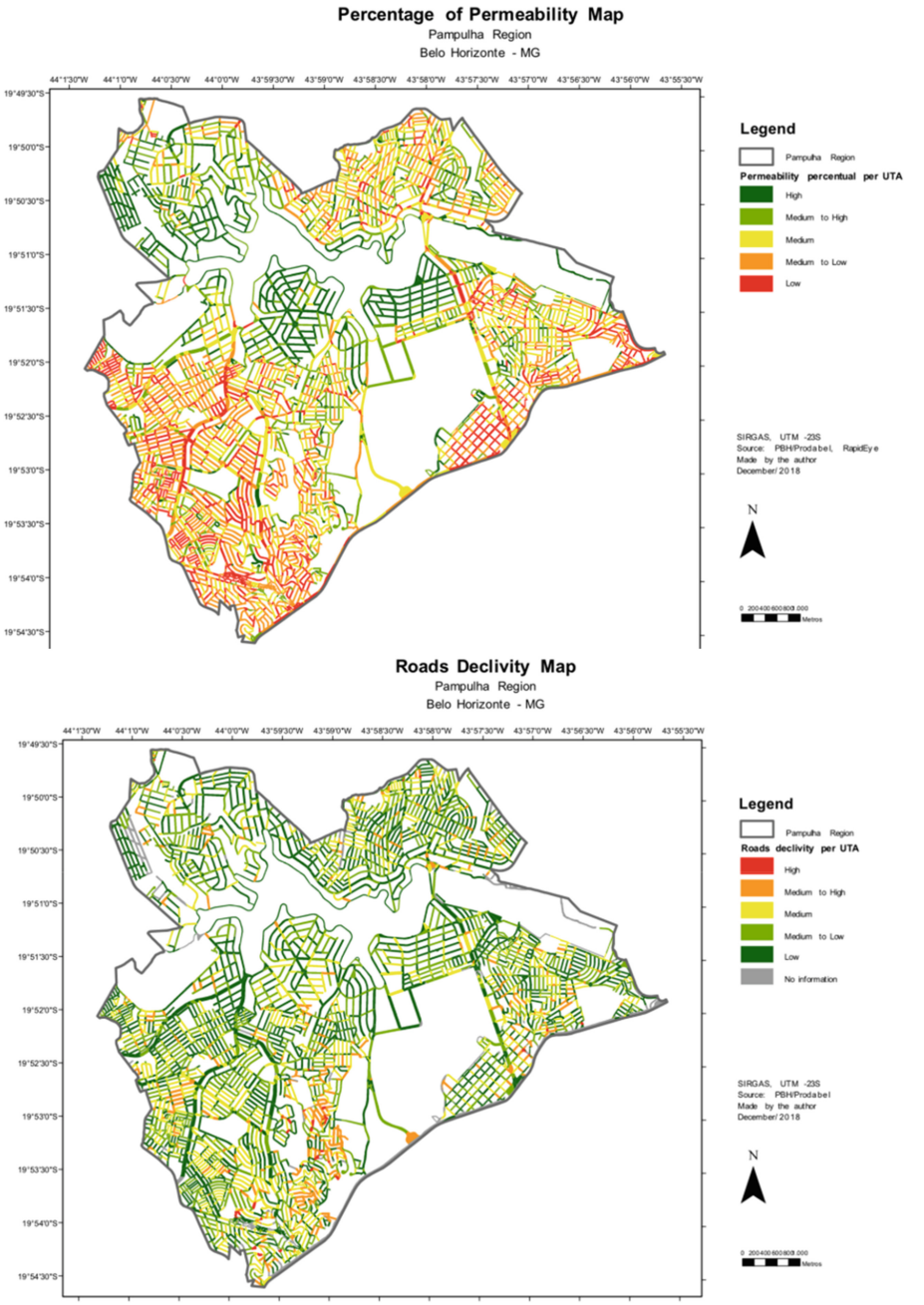

Fig. 2. Examples of evaluation maps for variables used in the MCA.

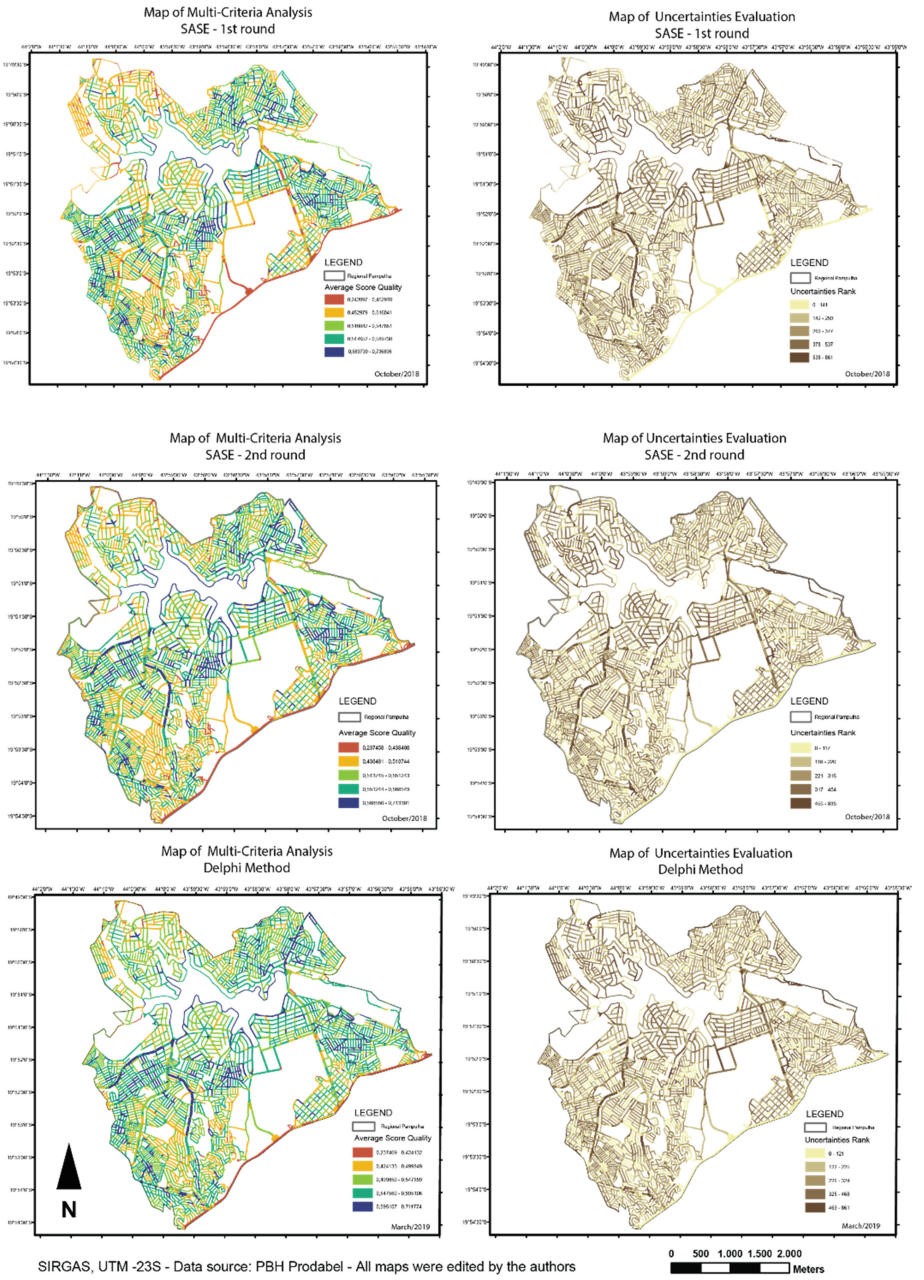

Fig. 3. Multi-Criteria (Suitability) and Uncertainty (Sensitivity) Evaluation Maps.

The Multi-Criteria Analysis Map and the Uncertainties Map generated with all the 19 variables are presented in Fig. 3, first row (maps *a* and *b*), applying the same weight to all variables. Uncertainty calculation demonstrated that 3 variables were quite irregular in their performance and were therefore excluded from the subsequent evaluation. Another round of analysis with the remaining 16 variables are presented in Fig. 3, second row (maps *c* and *d*).

To further improve the analysis, citizens' preferences were integrated through a Delphi Method [9, 10]. For that, 15 people we interviewed, presenting their opinion about the importance of the variables to their preferences to walk along a road, considering not only Pampulha, but a urban area in a general sense in Brazil. They composed a group including different ages, different social and economic conditions and different education level. After collecting these opinions, new variables weights were defined. Then, it was once more processed by the SASE Multi-Criteria evaluation tool because it was able to test a range of weights instead of just the final average value of voluntaries votes. The range was defined according to probability function, what means the value of the standard deviation of the votes to the lower and to the higher limit of the range. The results were presented in Fig. 3, third row (maps *e* and *f*), MCA (Suitability) and Uncertainty (Sensitivity).

Following the above described procedure, the multi-criteria analysis produced the evaluation maps with their "level of trust", presenting thus more robust results.

4 Perceived Urban Quality: Walkability Evaluation Based on Deep Learning

For the assessment of perceived urban quality through walkability evaluation, we used the machine learning technique presented in [11], based on a deep convolutional neural network (CNN) trained on a dataset of georeferenced street images from Google Street View. In brief, the adopted approach is based on the following two steps: first, the CNN is trained on a set of labelled images; then, the trained CNN can be used for predicting the perceived walkability on a different set of street-level images, so allowing a massive and fast evaluation of urban landscapes.

From the work described in [11], we had already trained a CNN on a dataset composed of images from some Italian cities. Nevertheless, to apply the CNN-based methodology to the Pampulha Region, and potentially to other areas with similar characteristics, we extended that pre-existent dataset with new training samples from the current area of study. In fact, as the result of the training phase, the CNN learns to classify effectively the specific types of urban landscapes that are included in the training set. However, cities in different parts of the world can be characterized by significantly different urban landscapes. For these reasons, adding new and different examples to the training set can be crucial to enhance the generalization ability of the CNN with the aim of classifying unseen street-level images belonging to different places of the world.

More in detail, the pre-existing dataset was built by downloading, at 5.300 different street points, four images with headings shifted by 90° so to roughly describe the 360-degree panorama (see Fig. 4). Each group of four images was classified by trained observers in terms of perceived quality of walkability on the relatively narrow rating scale of five values (from 1 → low walkability to 5 → high walkability).

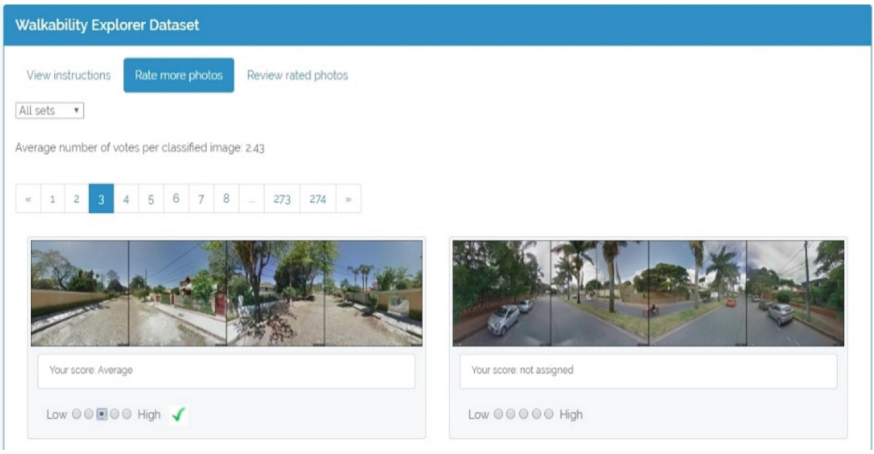

Fig. 4. Web user interface for the assessment of perceived walkability

Following the approach described in [11], we then performed an additional assessment of human-perceived walkability, specific for the Pampulha Region, through the web user interface represented in Fig. 4, on a random set of images downloaded

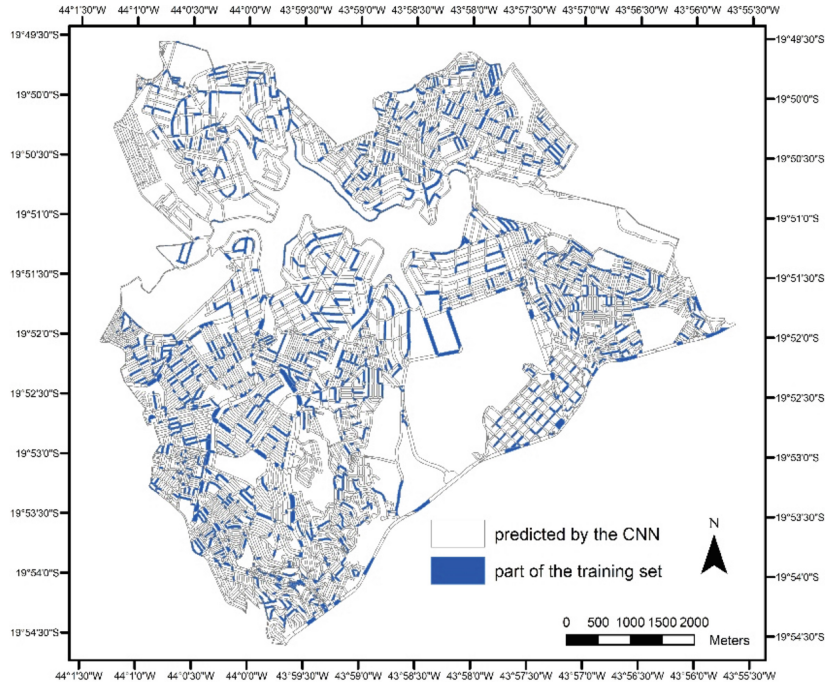

Fig. 5. Streets of the Pampulha Region used for the CNN training process (i.e. those evaluated by at least three people)

from Google Street View. At the end of the process, we extended the original dataset with the 1.757 photos that collected at least three votes, which were averaged. In Fig. 5 we show the map of Pampulha Region in which the highlighted streets used in the training process are highlighted.

As a result, the whole dataset of 7.057 images was partitioned into the adopted five classes as follows: 606 images in class 1, 2.331 in class 2, 2.706 in class 3, 1.048 in class 4 and the remaining 366 in class 5.

4.1 Adopted CNN Architecture and Implementation

As already done in [11], given the relatively small amount of data available for training, we use *transfer learning* in order to train a CNN capable to classify an input image from Google Street View into one of the five ordinal categories of perceived walkability mentioned above. In practice, such an approach consists of using a certain number of the first convolutional blocks of a deep CNN, pre-trained on a large dataset, to build a different neural network characterized by much less parameters to learn. In practice, the outputs of the pre-trained CNN layers can be considered as features extracted from the input image that are used to feed a relatively simpler neural network. Only the latter is actually trained with the available data. More in detail, also in the present study we adopted a feature extractor based on the VGG16 model pre-trained on the Places dataset with 365 scene categories (i.e. Places365), which is made available by the MIT Computer Vision Group [12].

The VGG16 model [13] is a deep neural network composed of 13 convolutional layers followed by 3 fully connected layers. In particular, the RGB image is used as input for a stack of convolutional layers endowed with small receptive fields based on 3×3 filters. Some of the convolutional layers are followed by a spatial max-pooling performed over a 2×2 pixel window. The CNN architecture adopted in the present work exploits the features extracted at the end of the thirteenth VGG16 layer, which corresponds to a $7 \times 7 \times 512$ tensor after max pooling. However, instead of flattening the 25088 features to connect the convolutional structure to a traditional neural network classifier, in order to minimise over-fitting by reducing the total number of parameters in the model we adopted the approach proposed in [14], which consists of using a global average pooling operator. The latter takes the tensor of dimension $7 \times 7 \times 512$ and gives a tensor of size $1 \times 1 \times 512$. In practice each 7×7 feature is reduced to a single scalar by simply taking the average of all 7×7 values. Therefore, for each input image we have 512 scalar features extracted and used as input for two fully-connected ReLU layers with 512 and 256 channels respectively. Finally, the last layer of our network is composed of four outputs, each in the interval [0, 1]. However, instead of using the classical softmax function for the output nodes, which would force the sum of outputs to be 1, we use a standard sigmoid function.

In order to classify each image into one of the five ordered categories, we use a generalisation of ordinal perceptron learning approach [15] proposed in [16]. In the adopted method, the class 1 correspond to the CNN output (0, 0, 0, 0), the class 2 is encoded as (1, 0, 0, 0), the class 3 as (1, 1, 0, 0) and so on. To convert an output vector

to its category, the method scans the output nodes from left to right and stops when the output of a node is smaller than a predefined threshold T (we use $T = 0.5$) or no nodes are left.

The implementation was carried out by using the Keras framework [17], with Tensorflow backend [18], and executed on a workstation equipped with a NVidia Quadro P6000 GPU.

4.2 CNN Training and Application

The 7.057 labelled images composing the dataset were randomly partitioned into a training set (70%), validation set (10%) and test set (20%). The training was performed using some standard data augmentation techniques to artificially enlarges the training and to prevent overfitting. In particular, for each original image in the training set we generated five new images by using a horizontal flip, a random zooming with scale in the range [0.6, 0.8], a shearing in counter-clockwise direction with a random angle up to 0.5° and a random rotation with angle up to 5°. Therefore, the training process of the CNN was carried out based on 24.700 images, while 706 images were used for controlling overfitting (validation set) and the remaining 1.411 images were used for testing the results after training.

The learning phase was performed using the mean squared error (MSE) as loss function and the *adadelta* [19] optimiser with its default parameters provided in Keras. Moreover, to prevent overfitting, the learning process was stopped after ten epochs without improvements of the loss function in the validation set. During the learning phase we stored the CNN weights corresponding to the minimum validation loss, which was 0.28.

The obtained CNN was evaluated on the 706 images included in the test set and the results are reported in the confusion matrix of Table 2. The overall accuracy (i.e. number of patterns correctly classified) was 71% while the achieved accuracy within one class was 98% (i.e. only 2% of the images were affected by an error greater than one class).

Table 2. Confusion matrix obtained on the test set

Human perception	CNN classification				
	1	2	3	4	5
1	**102**	11	0	0	0
2	29	**396**	103	3	0
3	5	51	**331**	43	0
4	0	13	97	**136**	23
5	2	0	10	18	**39**

After the evaluation of accuracy described above, we retrained the CNN using 90% of the available data and leaving the remaining 10% for validation and overfitting control. Then, we applied the CNN to 7.662 Google Street View photos that covers the

street network of the Pampulha Region. As explained above, each input image processed by the CNN is composed of four photos with headings differing by 90°, in such a way to describe the 360° view from the centre of the edge. After applying the CNN to each image, the classification of the streets is computed as the average score predicted by the CNN for each image belonging to that street. The results of this classification are shown in Fig. 6.

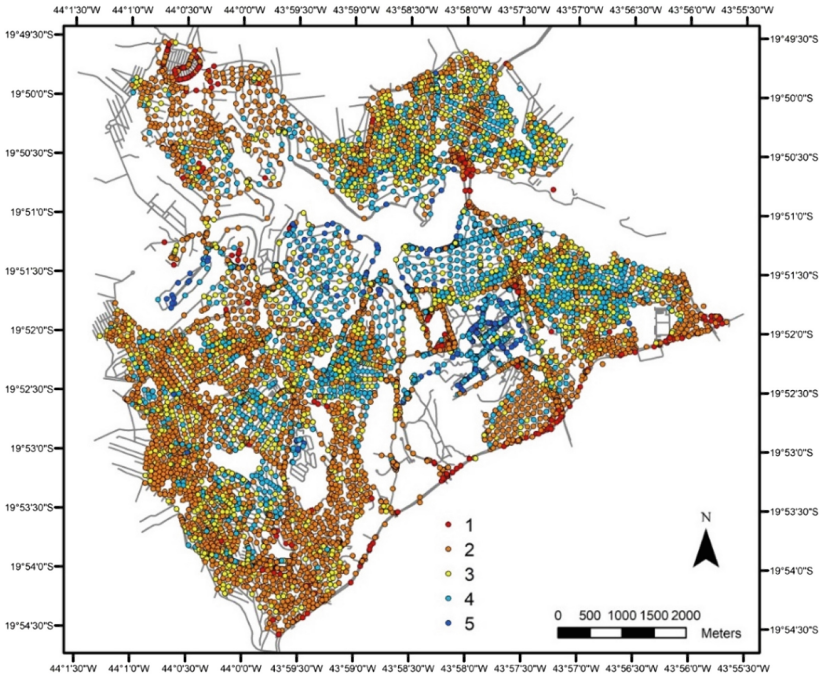

Fig. 6. CNN-classification of expected perceived walkability, with levels from 1 (low) to 5 (high).

5 Comparison and Discussion of Results

As anticipated in the introduction, to simplify and streamline the qualitative comparison between the two sets of results, we defined three levels ("low", "medium" and "high") of quality for each analysis, using uniform-interval thresholds values for the MCA values, and setting walkability levels 1 and 2 as "low", 3 as "medium", and 4 and 5 as "high". We report these classifications in Fig. 7.

Comparing the results of the two final maps, the first thing to observe is that both methods presented very few areas with "low" interest for walkability or quality of cityscape (roads in red). Probably this is because Pampulha is a relatively appreciated region of the city, in comparison to other areas. It has a large lake, expressive vegetation cover, not so dense housing areas, and roads with good conditions to walk. The

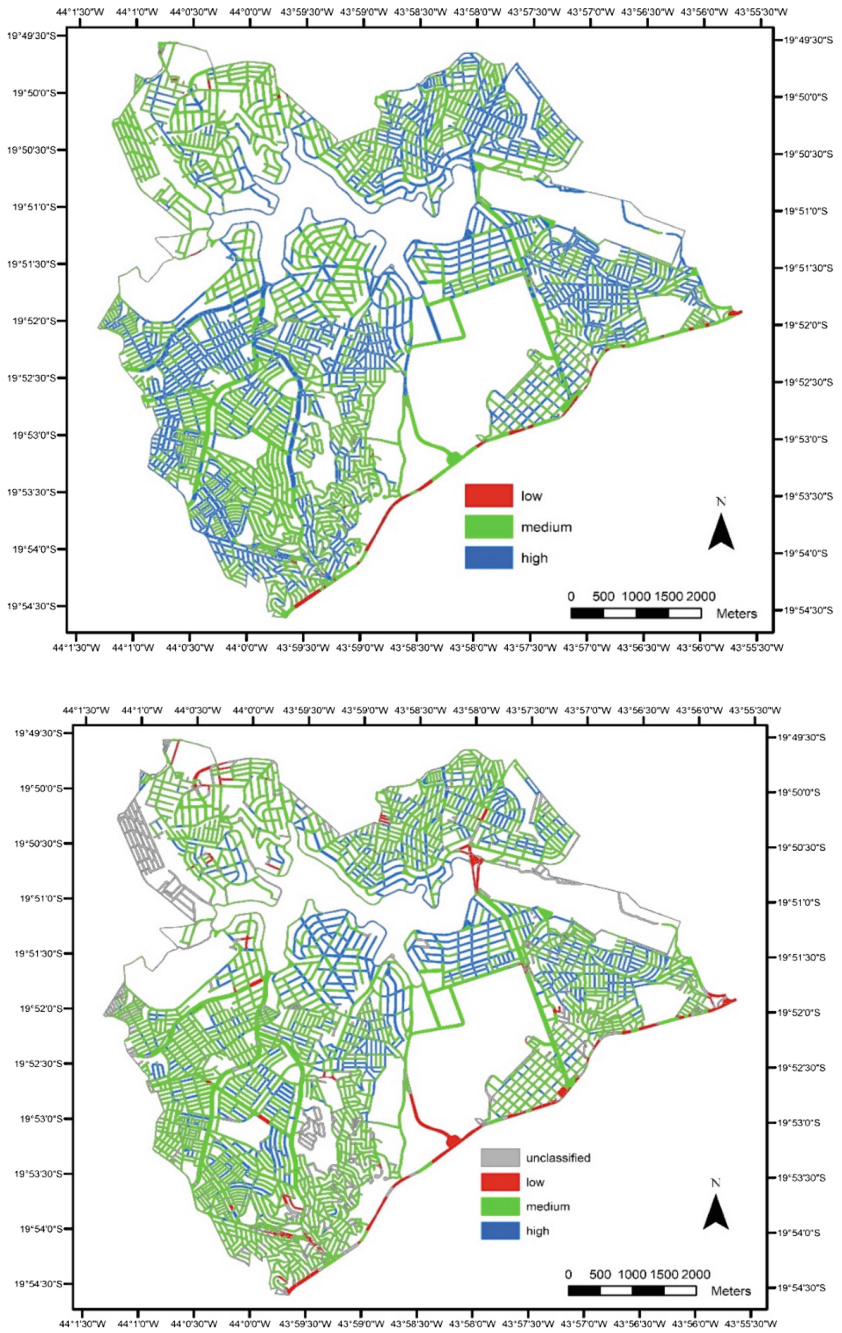

Fig. 7. MCA (above) vs. CNN classified perceived urban quality: three levels (Color figure online)

results confirm the anecdotal impression of the place as one of the more attractive areas of the city of Belo Horizonte. From both evaluative approaches, it is possible to conclude that the place is good for walking. However, previous studies and observations of peoples' behaviour showed that they are not too much walked, even having very good conditions for that. Besides perhaps being related to more general cultural attitudes, studies have shown that it may also be related to widespread caution and worry for the (perceived) lack of safety along the streets [20].

Looking at the "high" conditions, the technical approach provided by multi-criteria analysis, based on the selection of main variables according to a knowledge-driven suggestion by the expert opinions (the main variables were defined by the planning experts who know the area, while the importance of each variable, composing the weights to be used in weighted-sum MCA were defined by representatives of the local residents, consulted through a Delphi method) presented a larger number of roads with good conditions in comparison to CNN method. That may possibly be so because the MCA considered many variables, for many of which Pampulha presents relatively good scores. Comparing the two results, where the MCA tells there are the best conditions, CNN also recognises it, but in a smaller portion of the same area. To use Daniel Kahneman's distinction [21] we could say that MCA is based on a "slow thinking", more analytical and calculating, trying to integrate many variables in the evaluation, while CNN classification is driven by "fast thinking", guided by more intuitive, emotional reaction of people to places.

The parts in which the results were very different are explained by the variables chosen and the objectives of the analysis. In the centre part of the region, there is a neighbourhood in the shape of a star, to the south of the lake. This area is called "Bandeirantes" and it is characterised by large lots (around 1000 m^2), expressive vegetation, large roads of low slope, which makes it to be perceived as a very pleasant area, due to these spatial characteristics. But, considering the list of variables used in MCA (that also represents a "list of desires" to a Brazilian to feel secure to walk along the road), the area is very empty in terms of housing density, commerce, services and so one, which make the perception of those places not so interesting and secure as they are pleasant from the point of view of their visual values.

Further studies should be developed in other parts of the city with the same methods. A next step of the research can be the selection of the "high" values in CNN results, to be compared with the results of MCA, in order to identify with are the main variables that are present in those areas. This next step can be based on data-mining and the extraction of the variables that compose the best conditions in the territory, as the signature of the array of variables, what can be used as a guiding reference for urban planning and policy.

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References

1. Sen, A.: The Idea of Justice. Harvard University Press, Cambridge (2009)
2. Blečić, I., Cecchini, A., Talu, V.: Capability approach and urban planning. Fertile urban capabilities and quality of urban life of the most disadvantaged inhabitants [Approccio delle capacità e pianificazione urbana. Capacità urbane feconde e qualità della vita urbana degli abitanti più svantaggiati]. Archivio di Studi Urbani e Regionali **48**, 34–52 (2018). https://doi.org/10.3280/ASUR2018-122003
3. Brighouse, H., Robeyns, I.: Measuring Justice: Primary Goods and Capabilities. Cambridge University Press, Cambridge (2010)
4. Sen, A.: Utilitarianism and welfarism. J. Philos. **76**, 463–489 (1979). https://doi.org/10.2307/2025934
5. Rocha, N.A., Moura, A.C.M., Casagrande, P.: Análise combinatória e pesos de evidência na produção de análise de multicritérios em modelos de avaliação. Geogr. y Sistemas de Información Geográfica (GEOSIG) **11**, 49–74 (2018). https://docs.wixstatic.com/ugd/79758e_4d6e3e3aa4394cb99da67962a23aa240.pdf
6. Ligmann-Zielinska, A., Jankowski, P.: Impact of proximity-adjusted preferences on rank-order stability in geographical multicriteria decision analysis. J. Geogr. Syst. **14**, 167–187 (2012). https://doi.org/10.1007/s10109-010-0140-6
7. Ligmann-Zielinska, A., Jankowski, P.: Spatially-explicit integrated uncertainty and sensitivity analysis of criteria weights in multicriteria land suitability evaluation. Environ. Model Softw. **57**, 235–247 (2014). https://doi.org/10.1016/j.envsoft.2014.03.007
8. Moura, A.C.M., Jankowski, P.L.: Contribuições aos estudos de análises de incertezas como complementação às análises multicritérios - "sensitivity analysis to suitability evaluation". Revista Brasileira de Cartografi **68**, 665–684 (2016). http://www.seer.ufu.br/index.php/revistabrasileiracartografia/article/view/44274
9. Dalkey, N., Helmer, O.: An experimental application of the DELPHI method to the use of experts. Manag. Sci. **9**, 458–467 (1963). https://doi.org/10.1287/mnsc.9.3.458
10. Moura, A.C.M.: Reflexões metodológicas como subsídio para estudos ambientais baseados em análise multicritérios. In: Anais XIII Simpósio Brasileiro de Sensoriamento Remoto, pp. 2899–2906. INPE, Florianópolis (2007). http://marte.sid.inpe.br/col/dpi.inpe.br/sbsr@80/2006/11.13.14.41/doc/2899-2906.pdf
11. Blečić, I., Cecchini, A., Trunfio, G.A.: Towards automatic assessment of perceived walkability. In: Gervasi, O., et al. (eds.) ICCSA 2018. LNCS, vol. 10962, pp. 351–365. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-95168-3_24
12. Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., Torralba, A.: Places: a 10 million image database for scene recognition. IEEE Trans. Pattern Anal. Mach. Intell. **40**, 1452–1464 (2018). https://doi.org/10.1109/TPAMI.2017.2723009
13. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition (2014)
14. Lin, M., Chen, Q., Yan, S.: Network in network (2013). https://arxiv.org/abs/1312.4400v3
15. Crammer, K., Singer, Y.: Pranking with ranking. In: Dietterich, T.G., Becker, S., Ghahramani, Z. (eds.) Advances in Neural Information Processing Systems, vol. 14, pp. 641–647. MIT Press (2002)
16. da Costa, J.P., Cardoso, J.S.: Classification of ordinal data using neural networks. In: Gama, J., Camacho, R., Brazdil, P.B., Jorge, A.M., Torgo, L. (eds.) ECML 2005. LNCS (LNAI), vol. 3720, pp. 690–697. Springer, Heidelberg (2005). https://doi.org/10.1007/11564096_70
17. Chollet, F., et. al.: Keras (2015). https://github.com/fchollet/keras

18. TensorFlow: Large-scale machine learning on heterogeneous systems. https://www.tensorflow.org/
19. Zeiler, M.D.: ADADELTA: an adaptive learning rate method (2012). https://arxiv.org/abs/1212.5701v1
20. Moura, A.C.M., Ramos, V., Faria, D., Freitas, V.: Geodesign no ensino de planejamento urbano em escala local: a construção compartilhada de ideias para projetos e políticas. Geogr. y Sistemas de Información Geográfica (GEOSIG) **11**, 127–152 (2018). https://docs.wixstatic.com/ugd/79758e_17fda28772a247458c4f086b58e33281.pdf
21. Kahneman, D.: Thinking, Fast and Slow. Farrar, Straus and Giroux, New York (2011)