Biases in morphological landscape features:challenges for environmental purposes in GIScience and related fields

Valentin Chardon, Quentin Poterek, Cybill Staentzel

Cybergeo : European Journal of Geography
Cartographie, Imagerie, SIG | 2021

Biases in morphological landscape features: challenges for environmental purposes in GIScience and related fields

Biais dans les caractéristiques morphologiques du paysage : défis à relever à des fins environnementales dans les SIG et les domaines connexes

Sesgos en las características morfológicas del paisaje: desafíos ambientales en los SIG y campos a fin

Valentin Chardon, Quentin Poterek and Cybill Staentzel

Electronic version
URL: https://journals.openedition.org/cybergeo/36770
ISSN: 1278-3366

Publisher
UMR 8504 Géographie-cités

Electronic reference
Valentin Chardon, Quentin Poterek and Cybill Staentzel, "Biases in morphological landscape features: challenges for environmental purposes in GIScience and related fields", *Cybergeo : European Journal of Geography* [Online], Cartography, Images, GIS, document 979, Online since 05 May 2021, connection on 05 May 2021. URL: http://journals.openedition.org/cybergeo/36770

Biases in morphological landscape features: challenges for environmental purposes in GIScience and related fields

Biais dans les caractéristiques morphologiques du paysage : défis à relever à des fins environnementales dans les SIG et les domaines connexes

Sesgos en las características morfológicas del paisaje: desafíos ambientales en los SIG y campos a fin

Valentin Chardon, Quentin Poterek and Cybill Staentzel

Introduction

1 Environmental management is the heart of current scientific and societal concerns, notably in the context of global climate change. Plans frequently aim to change the structure of a landscape to achieve management goals, including ecological ones, supporting biodiversity and ecological processes (Haines-Young & Chopping, 1996). Landscape characterization is thus essential to assess ecological habitat changes within a multiscale approach, from fine (e.g, mesohabitats) to large scales (Staentzel et al., 2019). Historical topographic maps and remote sensing products (photographs, satellite and aerial images) are commonly used to evaluate short and long-term landscape changes from data that are manually digitized or extracted with semi-automatic or automatic procedures. For example, such datasets were used in fluvial geomorphology to evaluate diachronic planform changes (Bizzi et al., 2016; Eschbach et al., 2017; García et al., 2019, Brandolini et al., 2020), in ecology to assess landscape changes trajectories (Herrault, 2015; Poterek et al., 2020) or in urban geography to evaluate the dynamic of urban sprawl processes (Ji et al., 2001; Bhat Parvaiz et al., 2017). Most of these studies targeted the quantification of the land cover temporal evolution in a given landscape

solely by its composition, calculating average rates of change (Petit et al. 2002). A scarce of these studies integrated landscape changes in term of configuration (Li et al., 2015). Recently, two new indicators were recently proposed to quickly read landscape changes in terms of both configuration and composition features (Staentzel et al., 2019; Staentzel et al., 2020).

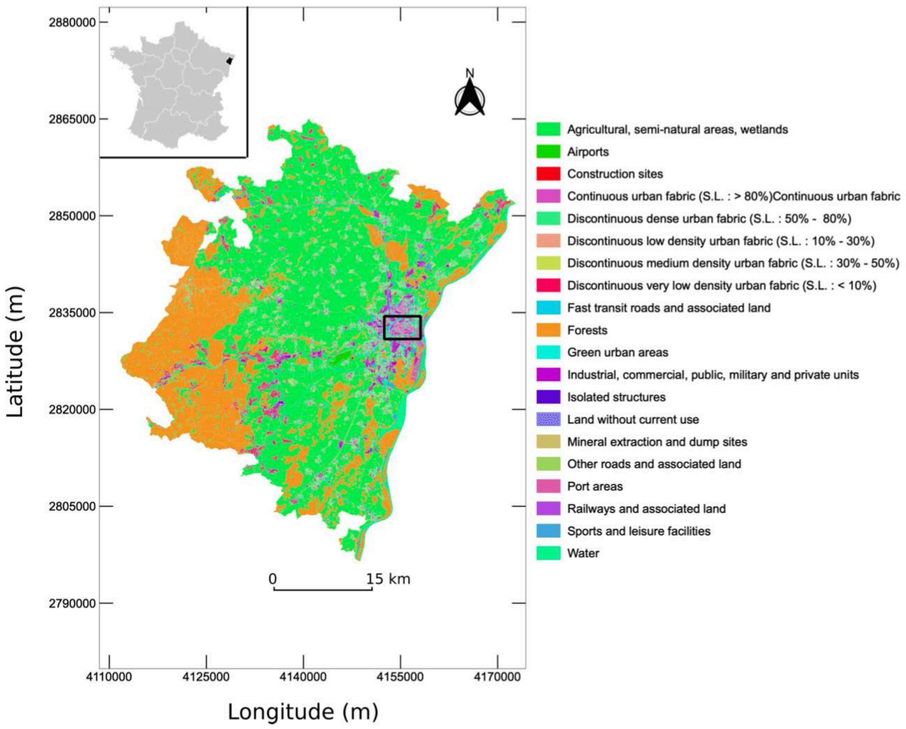
2 However, results about configuration and composition features may be biased by errors arising from various processing phases. These errors includes georeferencing mistakes, operator errors during the digitization step and spatial resolution effects (Fuller et al., 2003; Corry & Lafortezza, 2007). Numerous studies have attempted to assess such biases for each type of dataset in order to consider these errors during the analysis of results, and thus to reflect critically on landscape changes. In addition, some studies have evaluated the potential biases of rasterization step of vector dataset (Bettinger et al., 1996; Díaz-Varela et al., 2014). This step requires to use the software Fragstats and associated indicators (McGarigal and Marks, 1995; McGarigal, Cushman, & Ene, 2012) or compute transition matrix modelling, developed in 1990s, to apply on statistical models of plant succession (Usher, 1992). Poorly used in recent ecological studies, its interest has been demonstrated to quantify the percentage of change and define the transition nature within temporal trajectories of restored ecosystems (Gallet et al., 2014, Staentzel et al., 2019). Based on this method, Gallet et al. (2014) have developed dynamic vegetation models after rasterizing landscape data which consisted in transforming the vector dataset format to raster format. Transition matrix modelling also permitted to quantify the dynamic changes in plant communities following a restoration operation on the Rhine River (Staentzel et al., 2019). Nevertheless, the following question can still be asked: are the observed changes related to significant changes in land use or due to biases related to the mapping and/or rasterization step? The objective of this paper is to evaluate the potential biases during the rasterization step and to quantify them as a function of (i) the cell size used, and for the first time by (ii) the geometry of the studied features evaluated from five metrics using the Uniform Manifold Approximation and Projection (UMAP). Our main hypothesis is that the error produced during the rasterization of dataset can be affected by the size resolution used and the morphology of the studied geographic features. This study has been performed on the Urban Atlas 2006 dataset, focused on Bas-Rhin department (France).

Methodology

Dataset rasterization

3 Distributed under the Copernicus Earth observation program, the Urban Atlas layer for 2006 (Fig. 1) was digitized using optical satellite imagery with a spatial resolution of 5 m or finer, and other ancillary data, such as OpenStreetMap and HRL Imperviousness (European Commission, 2016). This study focused on the south part of the Bas-Rhin department located in the Grand-Est Region in France state (Figure 1).

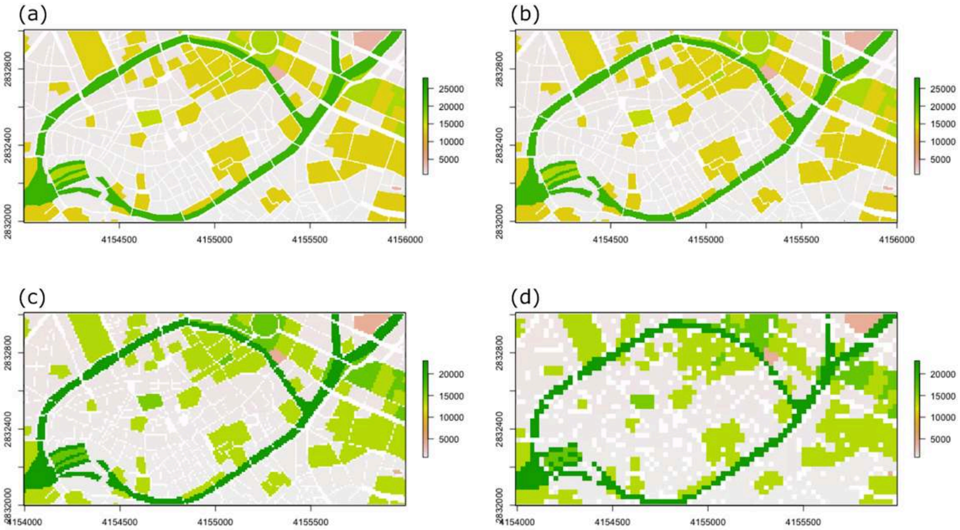
Figure 1 : Study area. The black rectangle corresponds to the example area presented in fig 2.



4 The minimum mapping unit, which determines the size of the smallest digitized feature, is of 0.25 ha for urban areas and 1 ha for rural areas. The recommended scale for usage is 1:10,000 (European Environment Agency, 2015).

5 The Urban Atlas layer 2006 was rasterized using the conversion tool implemented in the ArcMap software (v10.3; ESRI) to assess the consequence of rasterization on landscape analysis. Rasterization was performed using the cell center option, implying that the entity located at the center of each raster cell determines the LULC class to the corresponding pixel. We tested various cell sizes as 1 m, 5 m, 10 m and 25 m to evaluate the size influence on both area and perimeter error estimation (Figure 2).

Figure 2 : Example of rasterization step performed on the Strasbourg urban area city at cell size equal to 1 m (a), 5 m (b), 10 m (c) et 25 m (d).



Morphological metrics

6 For each cell size, we evaluated the number of missing features and the effect of geographic features morphology on both area and perimeter estimation errors. The morphology of the geographic features was evaluated using five morphological metrics in order to relate them to area and perimeter estimation errors. The metrics were calculated using the QGIS v3.4.7 software (QGIS Development Team, 2014) and based on the equations developed by Zdila et al. (2016) (Figure 3). Described mathematically by equation 1 to equation 5, they reflect respectively the aspect ratio, the circularity, the compactness, the roundness and the solidity. So as to better identify and visualize the relationship between rasterization parameters, i.e. morphology and errors, the five metrics that were previously computed were embedded into two dimensions using the UMAP algorithm (McInnes et al., 2018). UMAP analysis is a new multiple learning technique to reduce the size of large dataset with provide the advantage to low run time processing and conserve the global structure (McInnes et al., 2018). Moreover, this analysis allows to capture the non-linear structure at the contrary of the Principal Component Analysis (PCA) (McInnes et al., 2018).

$$\text{Aspect ratio} = \frac{\text{majoraxis}}{\text{minoraxis}} \quad (1)$$

7 Aspect ratio ranges between 1 and +inf. A shape with an aspect ratio of 1 corresponds to a circle.

$$\text{Circularity} = 4\pi\frac{\text{area}}{\text{perimeter}^2} \quad (2)$$

8 Circularity ranges between 0 and 1. A shape with a circularity of 1 corresponds to a circle.

$$\text{Compactness} = \frac{\text{area}}{\text{perimeter}} \quad (3)$$

9 Compactness ranges between 0.001 and 466.52. The higher the compactness, the more complex a shape is.

$$\text{Roundness} = 4\frac{\text{area}}{\pi^{*}(\text{majoraxis})^{2}} \quad (4)$$

10 Roundness ranges between 0 and 1. A shape with a roundness of 1 corresponds to a circle. Unlike circularity, it is insensitive to irregular borders, since perimeter is not used for calculation.

$$\text{Solidity} = \frac{\text{area}}{\text{convexarea}} \quad (5)$$

11 Solidity ranges between 1 and +inf. A shape with a solidity of 1 is convex. The higher the solidity, the more concave it is.

12 Finally, for each geographic feature (i), the relative error and the absolute error (%) for the area and perimeter parameters were calculated for each cell size. The relative and absolute error for the area and perimeter was calculated as following :

$$\text{Relative error}_{(\text{area})} = (\boxed{1 - (\frac{area_{(i)}}{area_{(shapefile)}})})*100 \quad (6)$$

$$\text{Relative error}_{(\text{perimeter})} = (\boxed{1 - (\frac{perimeter_{(i)}}{perimeter_{(shapefile)}})})*100 \quad (7)$$

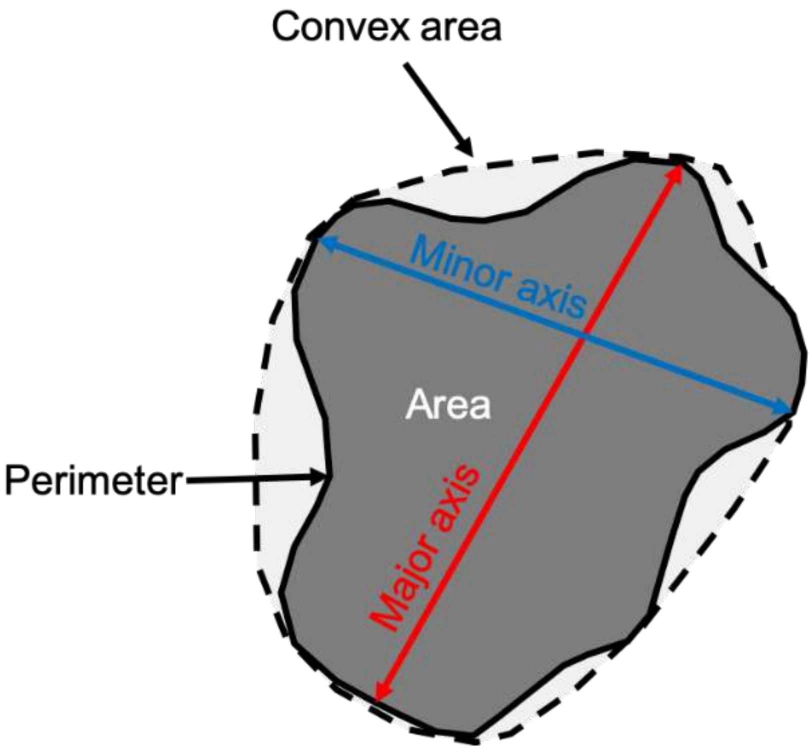
where i corresponds to the cell size used for dataset rasterization.

$$\text{Absolute error}_{(\text{area})} = |\text{Relativeerror}_{(\text{area})}|) \quad (8)$$

$$\text{Absolute error}_{(\text{perimeter})} = |\text{Relativeerror}_{(\text{perimeter})}|) \quad (9)$$

13 We performed multiple linear regressions between morphological metrics, and the relative error measurements for area and perimeter for all cell size to identify relationships between these variables. All statistical analyses were performed using the R v.3.6.2 software.

Figure 3 : Illustration of the main variables used to calculate the five morphological metrics described by Eq. 1 to Eq. 5 (modified from Matsumoto et al., 2015).

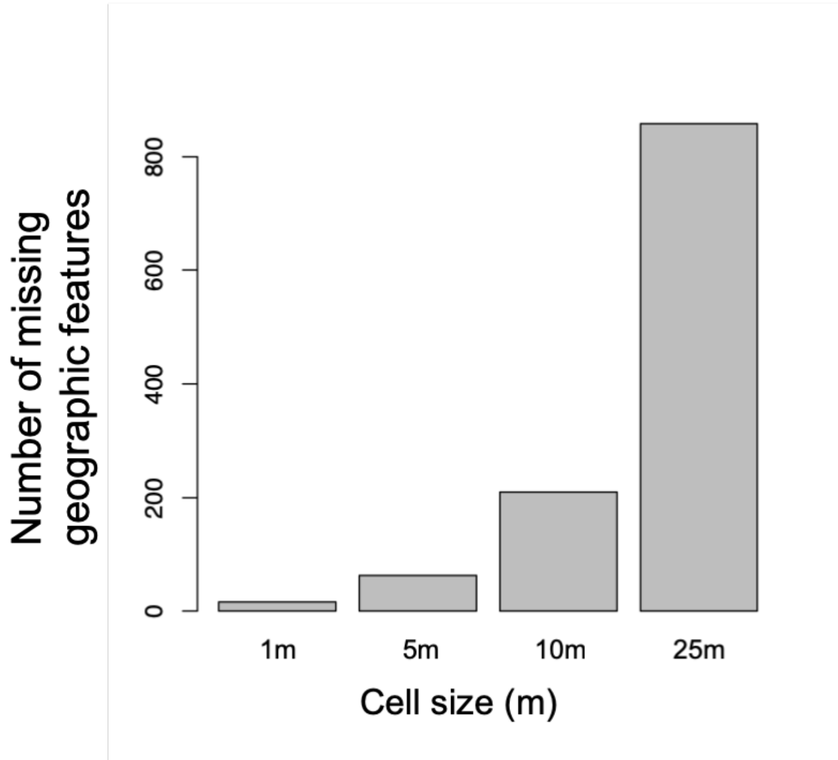


Results

14 The results showed a positive relationship between the cell size chosen during the rasterization step and the number of missing geographic features (Figure 4). This highlighting a loss of information by enlarging the size of the raster cells. Missing geographic features mainly included linear entities, such as roads, highways, and watercourses.

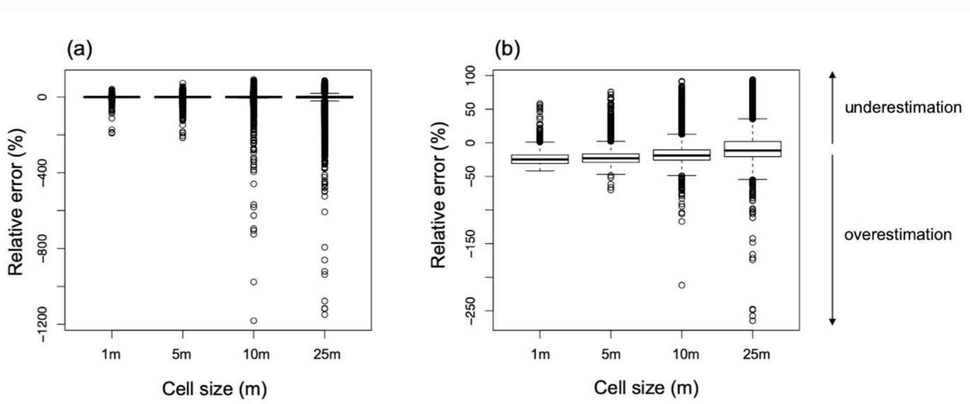
15 The relative mean error values for the area parameter were equal to 0.06 % (standard deviation as sd = ± 2.67 %), -0.11% (sd = ± 4.88 %), -0.66% (sd = ± 18.39 %) and -2.67% (sd = ± 31.29 %) for 1 m, 5 m, 10 m and 25 m, respectively (Fig. 5.a). The absolute mean error values for the area parameter were equal to 0.22% (standard deviation as sd = ± 2.67 %), 1.31% (sd = ± 4.88 %), 3.98 % (sd = ± 18.39 %) and 11.37% (sd = ± 31.29 %) for 1 m, 5 m, 10 m and 25 m, respectively (Figure 5.a).

Figure 4 : Number of missing geographic features according to the size scale.



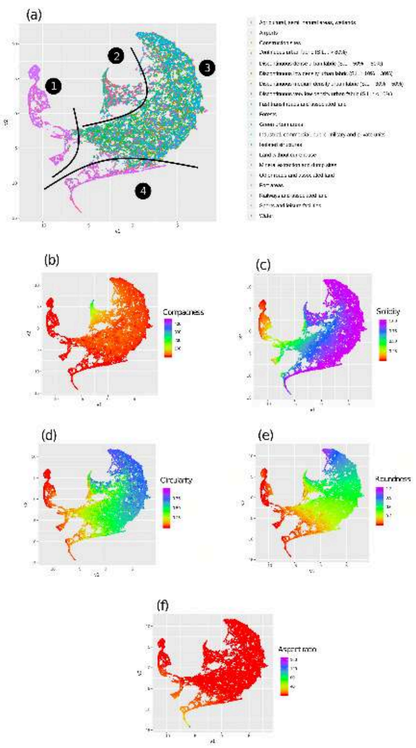
16 Both relative and absolute errors showed a low evolution in mean, frequently close to 0 all along the size scale. However, the standard deviation showed an increase in the variability of the relative error, with a distinct overestimation tendency (Figure 5.a). By comparison, the mean relative error values for the perimeter parameter were equal to -24.25 % (sd = ± 8.77 %), -22.37 % (sd = ± 9.32 %), -16.52 % (sd = ± 14.47 %) and -4.80 % (sd = ± 20.25 %) for 1 m, 5 m, 10 m and 25 m, respectively. The mean absolute error values for the perimeter parameter were equal to 24.54 % (sd = ± 8.77 %), 23.25 % (sd = ± 9.32 %), 19.63 % (sd = ± 14.47 %) and 17.00 % (sd = ± 20.25 %) for 1 m, 5 m, 10 m and 25 m, respectively. An overestimation tendency was observed along the whole size scale, with an increase in relative error variability (Figure 5.b) and a decrease of mean absolute error.

Figure 5 : Relative errors of area (a) and perimeter (b) parameters along the size scale.



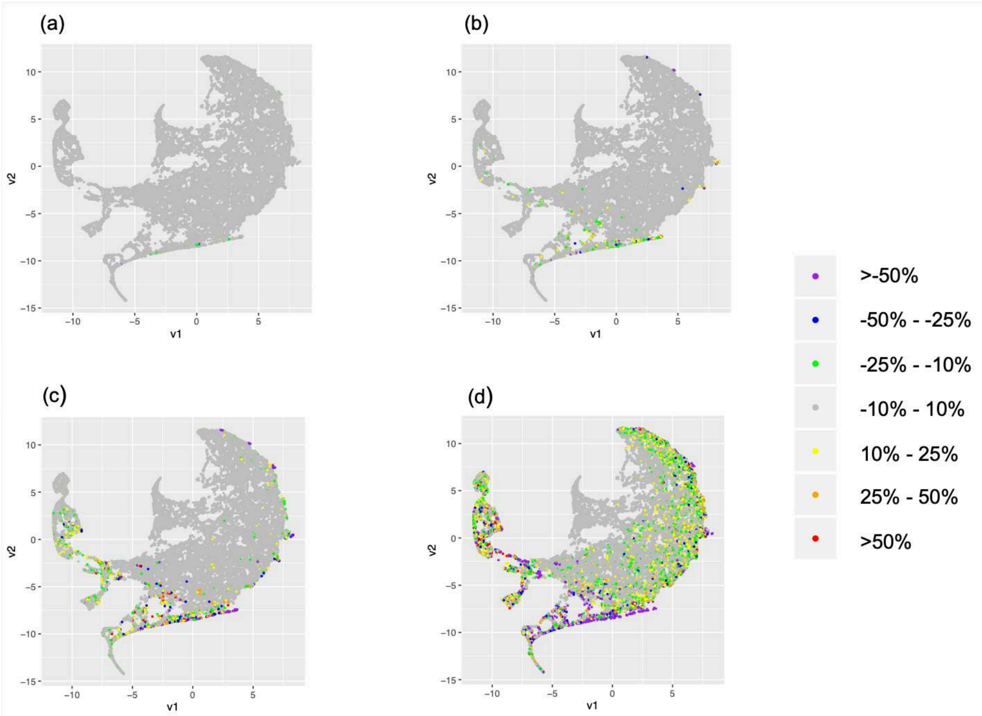
17 The UMAP algorithm highlighted four main groups (Figure 6.a). The first group was characterized by low values of all metrics and composed of linear geographic features, such as line communications (roads, railways, regulated rivers). The second group was characterized by low values for aspect ratio, moderate values for solidity, circularity and roundness, and high values for compactness. It was mostly composed of agricultural, semi-natural and wetland areas. The third group was characterized by low values for aspect ratio and compactness, and moderate to high values for solidity, circularity, roundness. It was mostly composed of urban fabric geographic features and forests. The fourth group was characterized by low values for circularity, roundness and compactness, moderate to high values for aspect ratio, and high values for solidity. It was composed by large geographic features, such as water bodies or sport/leisure facilities.

Figure 6 : (a) Groups issued from the UMAP algorithm performed on the five shape descriptors (b to f) results for each descriptor. The numbers in (a) indicated the groups highlighted by the UMAP algorithm.



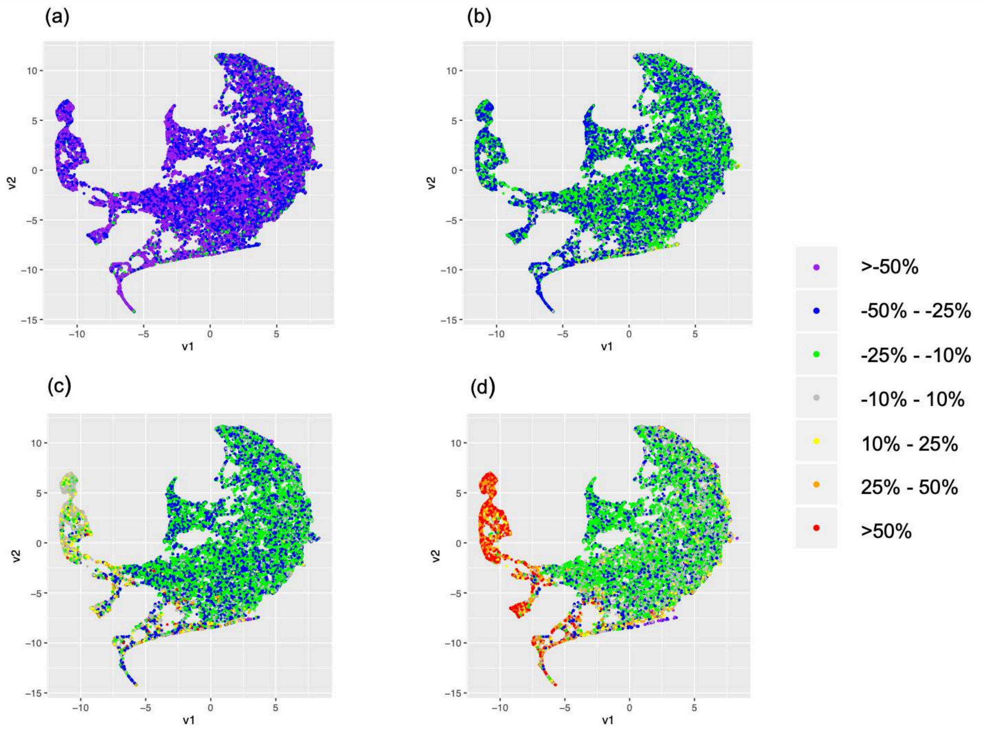
18 No specific effects were noted for the 1 m cell size (Figure 7.a). At 5 m or more, the relative errors for the area parameter were influenced by the shape of geographic features (Figure 7.b). The highest values for relative errors of the area estimation at 5 m occurred for group 4 with a global overestimation of the area (Figure 7.b), and at 10 m for groups 1 and 4 (Figure 7.c). At 25 m, an overestimation was mainly observed for all groups, except for group 2 where values of the relative error not exceeded ± 10% for all scale size (Figure 7).

Figure 7 : Relative estimated errors of the area parameter along the size scale: 1 m (a), 5 m (b), 10 m (c) and 25 m (d).



19 Concerning perimeter measurements, no particular difference was observed between groups for the 1 m and 5 m cell sizes, with a net overestimation of the parameter (Figure 8.a-b). Starting from the 10 m spatial resolution, an underestimation of the values was observed for group 1 (Figure 8.c). At 25 m, an underestimation was observed for groups 1 and 4, and an overestimation for groups 2 and 3 (Figure 8.d).

Figure 8 : Relative estimated errors for the perimeter parameter along the size scale: 1 m (a), 5 m (b), 10 m (c) and 25 m (d).



Discussion

20 Our results showed that the rasterization procedure can generate high biases in area and perimeter estimations. The intensity and tendency of errors depend on both the cell size used for raster computation (Figure 4), but also by the morphology of the geographic features. In some cases, a loss of information with a deletion of some geographic features may result as for linear geographic features. In our database, these were the finest structures in the landscape. As since observed by Díaz-Varela et al, (2014), the choice of cell size during the rasterization step must be suitable for the minimum mapping unit of the studied dataset. This implies that the processing time may rise sharply in case of large study area. As expected, our results showed a strong positive relationship between the cell size used during the rasterization step and the relative mean error for area and perimeter estimation. Nevertheless, the nature of errors was not similar between the two parameters (Figure 5). Regarding the area parameter, we noticed a quasi-systematic and increasing overestimation (Figure 5.a). Indeed, for cell sizes equal to 5 m and 10 m, the overestimates impact a large number of geographic features belonging mainly to groups 1 and 4, which correspond to linear geographic features (Figure 6; Figure 7). These results differ from obtained by Bellinger et al. (1996) due to low variability in terms of geographic features in their case.

21 Concerning the perimeter parameter, the results were more nuanced, with an overestimation for almost all geographic features with a cell size of 1 m (Figure 5.b; Figure 8.a). This overestimation tended to decrease when spatial resolution was around 5 m. From 10 m onwards, an underestimation appeared for the geographic features of groups 1 and 4, and amplified with the increase of cell size to 25 m. A decreasing of the

overestimation occurred for the other geographic features (Figure 5.b; Figure 8.c-d). The error estimates for this metric were incrementally correlated with the geometry of the geographic features as the raster cell size increased. However, no relationships were found that might explain error measurements for area, based on raster cell size. Corry & Lafortezza (2007) also showed that area as well as cohesion, interspersion or juxtaposition metrics are robust to changes in spatial resolution, while others exhibit erratic results. Landscape analyses based on the area parameter as transition matrix modelling were thus not concerned by such biases even if landscapes are represented by similar scaled data. Conversely, the high error of perimeter estimation for all cell sizes stressed that metrics based on a such parameter must be used cautiously in case of rasterization of a vector dataset. Linear structures (group 1) and water bodies (group 4) were the most affected (Fig. 8). Thus, before any rasterization step of vector dataset preliminary analyses must be performed on the geometry of geographic features to define the best spatial resolution to reduce the errors on landscape metrics estimations.

22 In our study, we applied the rasterization step using the cell center option. Other rasterization methods are available in standard GIS software, such as the maximum area or the maximum combined area. However, the latter methods are frequently preferred in ecological studies, maximizing the dominance within one pixel. Hence, further works will be performed to evaluate their influence following the same framework proposed here.

Conclusion

23 The rasterization procedure can induce severe errors in the estimation of usual shape parameters, mainly on the perimeter parameter. This study reveals using UMAP analysis that landscape indices based on perimeter can be subjected to significant errors and must be interpreted cautiously. Sensitivity analyses could be performed to prevent errors in defining the best raster cell size. So as to keep consistency and accuracy in the assessment of spatial-temporal landscape changes, we thus recommend to consider (i) the degree of shape complexity (i.e. morphology of geographical features), (ii) the alignment of temporal vector datasets, and (iii) a relevant selection of landscape metrics or tools, all this taking in consideration the tolerated computation time.

BIBLIOGRAPHY

Bettinger P., Bradshaw G. A., Weaver G. W, 1996,"Effects of geographic information system vector–raster–vector data conversion on landscape indices", *Canadian Journal of Forest Research*, Vol.26, No.8, 1416-1425.

Bhat Parvaiz A., Mifta ul Shafiq Abaas A. Mir, Pervez Ahmed, 2017, "Urban Sprawl and Its Impact on Landuse/Land Cover Dynamics of Dehradun City, India", *International Journal of Sustainable Built Environment,* Vol.6, No.2, 513-521.

Bizzi S., Demarchi L., Grabowski R. C., 2016, "The use of remote sensing to characterise hydromorphological properties of European rivers", *Aquatic Sciences*, Vol.78, No.1, 57-70.

Brandolini F., Reynar E., Pelfini M., 2020, "Multi-Temporal Mapping of the Upper Rhone Valley (Valais, Switzerland): Fluvial Landscape Changes at the End of the Little Ice Age (18th–19th Centuries)", *Journal of Maps*, Vol.16, No.2, 212-221.

Corry R., Lafortezza R., 2007, "Sensitivity of landscape measurements to changing grain size for fine-scale design and management", *Landscape and Ecological Engineering*, Vol.3, No.1 ,47-53.

Díaz-Varela E. R., Marey-Pérez, M. F., Riveiro-Valiño, J. A., & Alvarez-Lopez, C. J., 2010, "Preservation of Spatial Information in Rasterization Processes: A Practical Approach Using Real Categorical Data and Landscape Metrics", *GIScience & Remote Sensing*, Vol.47, No.3, 425-442.

European Environment Agency, 2015, "Copernicus Land Monitoring Service –Local Component", *Urban Atlas*, 2 p.

European Commission, 2016, "Mapping Guide v4.7 for a European Urban Atlas", 42 p.

Eschbach D., Schmitt L., Imfeld G., May J-H., Payraudeau S., Preusser F., Trauerstein M., Skupinski G., 2018, "Long-Term Temporal Trajectories to Enhance Restoration Efficiency and Sustainability on Large Rivers: An Interdisciplinary Study", *Hydrology and Earth System Sciences*, Vol.22, 2717-2737.

Fuller R. M., Smith G. M., Devereux B. J., 2003, "The Characterisation and Measurement of Land Cover Change through Remote Sensing: Problems in Operational Applications?", *International Journal of Applied Earth Observation and Geoinformation,* Vol.4, No.3, 243-253.

Gallet S., Sawtschuk J., 2014, "Restoration Dynamics Evaluation by Vegetation Mapping and Transition Matrix Modelling: Analysis of 20 Yr of Restoration and Management at the Megalithic Site of Carnac (Brittany, France)", *Applied Vegetation Science,* Vol.17, No.2, 225-235.

García J. H., Dunesme S., Piégay H., 2019. "Can We Characterize River Corridor Evolution at a Continental Scale from Historical Topographic Maps? A First Assessment from the Comparison of Four Countries", *River Research and Applications*, Vol.36, 934-946.

Haines-Young R., Chopping M., 1996, "Quantifying landscape structure: a review of landscape indices and their application to forested landscapes", *Progress in physical geography,* Vol.20, No.4, 418-445.

Herrault P.A., 2015, "Extraction de fragments forestiers et caractérisation de leurs évolutions spatio-temporelles pour évaluer l'effet de l'histoire sur la biodiversité : Une approche multi-sources", Thesis at: Université Toulouse le Mirail - Toulouse II, 407 p.

Ji C. Y., Liu Q., Sun D., Wang S., Lin P., Li X., 2001, "Monitoring Urban Expansion with Remote Sensing in China", *International Journal of Remote Sensing,* Vol.22, No.8, 1441–1455.

Li W., Chen Q., Cai D., Li R., 2015, "Determination of an Appropriate Ecological Hydrograph for a Rare Fish Species Using an Improved Fish Habitat Suitability Model Introducing Landscape Ecology Index", *Ecological Modelling,* Vol.311, 31-38.

Matsumoto N., Ogawa M., Takayasu K., Hirayama M., Miura T., Shiozawa K., Masahisa, Nakagawara H., Moriyama M., Udagawa S., 2015, "Quantitative Sonographic Image Analysis for Hepatic Nodules: A Pilot Study", *Journal of Medical Ultrasonics,* Vol.42, No.4, 505-512.

McInnes L., Healy J., Melville J., 2018, "UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction", 64 p.

McGarigal K., Cushman S.A., Ene, E., 2012, "FRAGSTATS v4: spatial pattern analysis program for categorical and continuous maps", *Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: http://www.Umass.edu/landeco/research/fragstats/fragstats.html.*

McGarigal K., Marks B.J., 1995, "Spatial pattern analysis program for quantifying landscape structure", *Gen. Tech. Rep. PNW-GTR-351. US Department of Agriculture, Forest Service, Pacific Northwest Research Station*, 1-122.

Petit C., Lambin E. F., 2002, "Impact of Data Integration Technique on Historical Land-Use/Land-Cover Change: Comparing Historical Maps with Remote Sensing Data in the Belgian Ardennes", *Landscape Ecology,* Vol.17, No.2, 117-132.

Poterek Q., Herrault P.-A., Skupinski G., Corpetti T., Sheeren D., 2020, "Deep Learning for Automatic Colorization of Legacy Grayscale Aerial Photographs", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote sensing,* Vol.13, 2899-2915.

QGIS Development Team, 2014, *"QGIS Geographic Information System. Open Source Geospatial Foundation Project".*

Staentzel C., Combroux I., Barillier A., Beisel J.N., 2020, "L'étude temporelle des transitions paysagères et de l'hétérogénéité dans la mosaïque d'habitats comme outil d'évaluation des opérations de restauration écologique ? Retours d'expériences et analyse comparative", *Techniques Sciences Méthodes,* 15-29.

Staentzel C., Beisel J.N., Gallet S., Hardion L., Barillier A., Combroux I., 2018, "A Multiscale Assessment Protocol to Quantify Effects of Restoration Works on Alluvial Vegetation Communities", *Ecological Indicators,* Vol.90 ,643-652.

Zdilla M.J., Scott A. H., McLean K.A., Cyrus L.M, Laslo J.M, Lambert H.W., 2016, "Circularity, Solidity, Axes of a Best Fit Ellipse, Aspect Ratio, and Roundness of the Foramen Ovale: A Morphometric Analysis with Neurosurgical Considerations", *Journal of Craniofacial Surgery,* Vol.1, No.1, 222-228.

ABSTRACTS

During the last two decades, a wide range of geographical tools including the calculation of landscape metrics were transposed to ecological studies to build models for land-use dynamics. Currently, few studies have evaluated the biases which can occur during the rasterization step which could influence the results. The purpose of this study was to evaluate the influence of dataset rasterization on area and perimeter variables, which are frequently used to calculate landscape indices, according to (i) the rasterization cell size and (ii) the shape of geographic features. The Urban Atlas 2006 dataset focused on Bas-Rhin department (France) was used as a vector reference layer. Rasterization was performed for various cell sizes to evaluate the influence of spatial resolution on the errors injected into shape descriptors. Five morphological metrics were calculated for all geographic features. For the first time, a UMAP algorithm was performed to relate the rasterization relative errors at all spatial resolutions with morphological attributes. Results showed that low values of area errors were obtained for cell sizes lower than 5 m (<10%). For higher cell sizes, errors exceeding 10% appeared for linear and low width geographic features. For perimeter, significant errors were observed for cell sizes between 1 and

5 m (>10%) with an overestimation tendency. For cell sizes greater to 10 m, overestimations and underestimations were occurring according to the shape of geographic features. This study showed that sensitivity analyses must be performed before any study carried out on landscape changes estimation to define the best raster cell size as function to the morphological attributes of the geographic features, the predefined error threshold.

Au cours des deux dernières décennies, un large éventail d'outils géographiques a été transposé aux études écologiques afin de construire des modèles permettant d’étudier les dynamiques de changement des milieux naturels. Très fréquemment, une étape de rastérisation de données vectorielles est utilisée dans ce cadre. Encore peu d'études ont évalué les biais qui peuvent survenir lors de cette étape de rastérisation. L'objectif de cette étude est d'évaluer l'influence de la rastérisation, à partir d’un ensemble de jeu de données, sur les variables de surface et de périmètre, métriques fréquemment utilisées pour calculer les indices de paysage en fonction (i) de la taille de la cellule lors de la rastérisation et (ii) de la forme des caractéristiques géographiques. Le jeu de données de l'Atlas urbain 2006, centré sur le Bas-Rhin (France), a été utilisé comme couche vectorielle de référence. La rastérisation a été effectuée pour différentes tailles de cellule afin d'évaluer l'influence de la résolution spatiale sur les erreurs d’estimation des descripteurs de forme. Cinq métriques morphologiques ont été calculées pour toutes les entités géographiques. Pour la première fois, un algorithme UMAP a été réalisé pour relier les erreurs relatives de rastérisation à toutes les résolutions spatiales avec les attributs morphologiques de chaque entité géographique. Les résultats ont montré que de faibles valeurs d'erreurs de surface ont été obtenues pour des tailles de cellules inférieures à 5 m (<10%). Pour des tailles de cellules plus élevées, des erreurs supérieures à 10 % sont apparues pour les entités géographiques linéaires et de faible largeur. Pour le périmètre, des erreurs significatives ont été observées pour les tailles de cellules entre 1 et 5 m (>10%) avec une tendance à la surestimation. Pour les tailles de cellule supérieures à 10 m, des surestimations et des sous-estimations se produisaient en fonction de la forme des entités géographiques. L'étude a montré que des analyses de sensibilité doivent être effectuées au préalable avant une estimation des changements de paysage afin de définir la meilleure taille de cellule matricielle en fonction des attributs morphologiques des caractéristiques géographiques et du seuil d'erreur prédéfini.

Durante las últimas dos décadas, una amplia gama de herramientas geográficas han sido empleadas en estudios de la métrica del paisaje, con la finalidad de construir modelos aplicados en las dinámicas del cambio en el medio natural y donde frecuentemente se rasterizan los datos vectoriales. Actualmente, no existe una robusta literatura que haya evaluado los sesgos que pueden ocurrir durante tal proceso de rasterización y que podrían influir en los resultados. El objetivo de este estudio, fue evaluar la influencia de la rasterización a partir de un juego de datos sobre las variables de superficie y perímetro, métricas que se utilizan con frecuencia para calcular índices de paisaje en función de (i) el tamaño de la celda de rasterización y (ii) la forma de las características geográficas. Se utiliza el conjunto de datos “Atlas urbano” 2006, centrado en el departamento de Bas-Rhin (Francia) como capa vectorial de referencia. La rasterización se realizó para varios tamaños de celda, con la finalidad de evaluar la influencia de la resolución espacial sobre los errores de estimación de descriptores de forma. Se calcularon cinco métricas morfológicas para todas las entidades geográficas. Por primera vez, se realizó un algoritmo UMAP, para relacionar los errores relativos a la rasterización en todas las resoluciones espaciales, con los atributos morfológicos de cada entidad. Los resultados expresan que se obtuvieron bajos valores de error en la superficie para tamaños de celda menores a 5 m (<10%). Para tamaños de celda más elevados, emergen errores superiores al 10% en las entidades geográficas lineales y con un reducido ancho. Respecto al perímetro, se observaron errores significativos para tamaños de celda entre 1 y 5 m (> 10%) con una tendencia a la sobre estimación. Para los tamaños de celda superiores a 10 m, se produjeron sobre y sub estimaciones según la forma de las entidades

geográficas. Este estudio deja en evidencia la necesidad de llevar a cabo análisis de sensibilidad, antes de aplicar cualquier estimación de cambios en el paisaje, con la finalidad de definir el mejor tamaño de la celda ráster en función de los atributos morfológicos de las características geográficas y del umbral de error predefinido.

INDEX

Mots-clés: résolution spatiale, analyse structurelle (morphologie), métrique paysagère, matrices de transition, transformation
Keywords: spatial resolution, structural analysis (morphology), landscape metric, transition matrices, transformation
Palabras claves: resolución espacial, análisis estructural (morfología), métrica del paisaje, transformación

AUTHORS

VALENTIN CHARDON

Post-doctorant CNRS
Université de Strasbourg, CNRS, Laboratoire Image Ville Environnement, UMR 7362, F-67000, Strasbourg, France
valentin.chardon@live-cnrs.unistra.fr

QUENTIN POTEREK

Doctorant,
Université de Strasbourg, CNRS, Laboratoire Image Ville Environnement, UMR 7362, F-67000, Strasbourg, France
quentin.poterek@live-cnrs.unistra.fr

CYBILL STAENTZEL

MCF contractuelle, ENGEES
Université de Strasbourg, CNRS, Laboratoire Image Ville Environnement, UMR 7362, F-67000, Strasbourg, France
ENGEES, F-67000, Strasbourg, France
cybill.staentzel@live-cnrs.unistra.fr