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Research Paper

Quantifying the urban gradient: A practical method for broad measurements

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HIGHLIGHTS

- Urbanization can be reliably quantified by manual scoring of land-cover features.
- A semi-automated scoring method is introduced to replace the manual processing.
- Both scoring methods and detailed geoinformatic measurements yield well-correlated results.
- All 3 alternative measures show similar urbanization effects in an ecological dataset.
- We provide software for scoring urbanization gradients from free aerial images.

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ABSTRACT

The process of habitat urbanization has intense and manifold effects on the biota that we need to better understand. The urbanization gradient approach is increasingly used in ecological research to study the responses of communities and populations of plants and animals to different degrees of landscape urbanization. However, the methods used for quantifying the urbanization gradient are heterogeneous. Here, first we validate a manual method designed for broad measures of landscape urbanization, based on major land-cover characteristics calculated from aerial images, that has been applied in former studies, and compare its results to measurements taken with a widely accepted geoinformatics software. Second, on the basis of this manual scoring method we introduce a recently developed, easily feasible, semi-automated method of measuring degree of urbanization, which uses only freely and worldwide accessible satellite imagery. Finally, we compare the results obtained by the three methods and the conclusions they yield within the framework of an ecological study conducted on birds. Our results show that the three methods quantify the urbanization gradient similarly, as the 'urbanization scores' they provide are strongly correlated and the results of the ecological analyses are highly repeatable across the three approaches. Since the semi-automated method grants this performance at far the lowest cost of time, we propose it as a useful tool for broad measurements of urbanization and its application can promote greater integrity between studies of urbanization effects on wildlife around the world. We also provide a download link to the free application of our semi-automated method.

1. Introduction

There is an ever growing need to detect and predict the effects of changes in our environment occurring either as a result of natural processes or human activity. One of the most pressing environmental changes is the escalating process of landscape urbanization. Our planet's human population is growing rapidly and alters natural landscapes at an accelerating rate throughout the world as the number and extent of urban settlements are increasing (Grimm et al., 2008; Hammond, Gyau, & Adiaba, 2011). The 'ecological footprint' of urban areas has become of great interest to wildlife researchers in the last decades, as urbanization turns natural landscapes into highly altered habitats with artificial surfaces, industrial pollution, anthropogenic disturbance, and severely altered energy

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flux and nutrient cycles (e.g. Lee, 2007; McDonnell & Hahs, 2008). This phenomenon is considered to be one of the most important causes of biodiversity loss, species endangerment and extinction (Lepczyk et al., 2008; McDonald & Marcotullio, 2012; McKinney, 2006). Thus, while researchers of basic ecological science endeavor to understand the complex effects of urbanization on animal and plant communities and populations, conservation biologists seek the causes and remedies when species cannot adapt to urbanized environments (Marlzuff, Bowman, & Donnelly, 2001; McKinney, 2006; Shochat, Warren, Faeth, McIntyre, & Hope, 2006). For both kinds of research, it is crucial to quantify the intensity of landscape urbanization in a way that is most relevant for the studied wildlife community or species.

Many animal-ecological studies on urbanization utilized simple comparisons of habitats labeled by various and poorly defined terms such as urban, suburban, and rural (e.g. reviewed by Marlzuff et al., 2001; Theobald, 2004). While this approach has the potential to reveal important differences between populations, it hinders the replication of such studies, the integration of their results, and the generalization of predictions and conservation recommendations because these terms carry different meanings in different regions of the Earth (Marlzuff et al., 2001). Although there were suggestions for standardized terminology for categories of differently urbanized landscapes (e.g. Marlzuff et al., 2001), such categories are relatively broad, not necessarily relevant for the studied system and certain habitats might not even fit into any category. Instead, explicit quantitative measures of relevant landscape characteristics can provide a more useful approach. Since the introduction of the concept of urbanization gradient (McDonnell & Pickett, 1990) it has become a frequently and effectively used framework for studying ecological issues of human settlements (McDonnell & Hahs, 2008). The term 'urbanization gradient' refers to the spatial variation of environmental factors in relation to the intensity of urbanization, from natural landscapes to the most heavily urbanized areas (McDonnell & Hahs, 2008). The simplest urban gradient would be a linear transect from the countryside to the city center whereby the intensity of urbanization and its environmental impacts decrease monotonically with distance from the center, but such a gradient approach would be an oversimplification (e.g. McKinney, 2006). Urban structures are rarely monocentric, with core regions being surrounded by asymmetric mosaics of differently urbanized landscapes such as industrial and residential outskirts (e.g. McDonnell & Hahs, 2008; McDonnell, Hahs, & Breuste, 2009). In this way the urban gradient is not necessarily a geographical transect but a continuum of a combination of landscape features that vary systematically as a result of anthropogenic environmental changes (McDonnell & Hahs, 2008).

When quantifying urban gradients, the number of measured environmental variables can vary at a wide scale depending on the purpose of study and our desired level of precision (Hahs & McDonnell, 2006). In landscape ecology for example, landscape composition (i.e. percentage of types of landscape cover) and heterogeneity (i.e. degree of contagion) are suitable predictors of ecological conditions for animals and serve as proxies for the structural characteristics of urbanization gradients (Alberti, Botsfort, & Cohen, 2001). Landscape gradients are often characterized by the proportion of areas covered by vegetation, buildings and roads (McDonnell & Hahs, 2008), and these metrics often predict animal communities' species composition, abundance and species richness along the urbanization gradient (e.g. Blair, 1996; Clergeau, Savard, Mennechez, & Falardeau, 1998; Germaine, Rosenstock, Schweinsburg, & Richardson, 1998; Germaine & Wakeling, 2001; Pillsbury & Miller, 2008). This is probably because these types of landscape cover reflect components of urbanization that are crucial for a wide range of species, e.g. more vegetation may provide more sites for foraging, nesting and roosting; the number and density of buildings is probably associated with altered native vegetation, disturbance by humans and pets, noise and light pollution; and roads may increase pollution by traffic and direct mortality by collision (Miller, Fraterrigo, Hobbs, Theobald, & Wiens, 2001; Van der Ree, 2009). The effects of these broad measures of landscape cover can be fine-tuned by more specific measures of urbanization for particular species. For example, the abundance of some bird species increases with median housing age in urban areas whereas other species show the opposite effect (Loss, Ruiz, & Brawn, 2009), and even factors as subtle as the density of trash bins can have important influence on the numbers of certain species (Jerzak, 2001). Measuring such specific aspects of urbanization can be a very powerful approach to identify the mechanisms responsible for observed ecological patterns such as the loss of species richness with increasing urbanization, and thereby to aid conservation efforts. However, such data are often location-specific, difficult and/or costly to obtain, or even non-available for various study sites, limiting the extent to which studies based on fine measurements can be reproduced at or extended to different locations. In contrast, broad measures of urban gradients using land-cover features can provide a common context and integrity between urban-ecology studies throughout the world (McDonnell & Hahs, 2008) while still capturing reasonably high amounts of variability in the patterns of urbanization (Hahs & McDonnell, 2006).

Recently, the improving quality of remote sensing and image capturing techniques, and the increasing availability of airborne and satellite images enables these techniques to be used efficiently and extensively in biological surveys such as urban gradient measurements (e.g. Herold, Joseph, & Clarke, 2002; Schneider, Friedl, & Potere, 2010). The visual processing and evaluation of such imagery help us to analyze landscape characteristics accurately with consistent methodology for different areas around the world. However, accessing sufficiently high resolution and standard aerial or satellite images is often expensive, the images from different locations are not equally available or not comparable, and evaluating them by complex geoinformatics softwares requires special expertise. To date the continental-scale monitoring policy and environmental assessments differ between the North American continent, Europe and Australia. For example, the CORINE land-cover database provides comparable digital maps of land cover for each country for much of Europe based on spectral analysis of satellite imagery (Kleeschulte & Büttner, 2008). This database is widely used in national and international environmental studies, but its resolution (i.e. 25 hectares minimum mapping unit, 100 meters minimum width of linear elements) restricts its applicability for study systems that require relatively high spatial resolution. Its land-cover classes are different from the classes of the United States National Land Cover Dataset as well as from the Australian Land Cover and Land Use Dataset; furthermore, all three datasets are based on different data and different quality of satellite images (Barson, Lesslie, Smith, & Stewart, 2008; Homer, Dewitz, Fry, & Hossain, 2008). When standardized quantitative data are not available, researchers can rely on freely accessible imagery (e.g. GoogleEarth) and simple scoring methods to rank their study sites along the urban gradient (Bókony, Kulcsár, & Liker, 2010; Bókony, Kulcsár, Tóth, & Liker, 2012; Bókony, Seress, Nagy, Lendvai, & Liker, 2012; Liker, Papp, Bókony, & Lendvai, 2008; Zhang et al., 2011; Zhang & Zheng, 2010). This approach provides an easy, inexpensive way of measuring urbanization, but it is very time consuming and its adequacy has not been investigated yet.

In this study our aim is to introduce and validate a quickly feasible and freely available broad method for quantifying the intensity of urbanization based on landscape cover. This recently developed method (Czúni, Lipovits, & Seress, 2012) is a semi-automated approach based on the manual scoring system of Liker et al. (2008), requiring public satellite images or aerial photographs and some marginal manual work only. Using 21 study sites from an urban gradient, first we compare the 'urbanization scores' generated by both the original manual method and the newly developed semi-automated method to strictly quantitative measurements obtained by a widely accepted, expensive geoinformatics software. We also assess the measurement error of both the manual and semi-automated scoring methods. Finally, we investigate the ecological applicability of the scoring methods by repeating the analyses of a published study (Bókony et al., 2012) using each of the three methods and testing the repeatability of results. Bókony et al. (2012) studied the effects of urbanization on various measures of individual health condition in a bird species, the house sparrow (*Passer domesticus*) that is undergoing population declines in several parts of the world, especially in urban areas (De Laet & Summers-Smith, 2007; Seress et al., 2012). The authors measured 11 indices of environmental stress on adult birds to test whether individuals in more urbanized habitats are in worse physiological state. We chose this study because it includes several ecologically relevant variables that were examined in relation to urbanization and a relatively large number of study sites (i.e. the same 21 sites we focused on in this study), quantified by the manual scoring method of Liker et al. (2008), thus it provided a relatively large set of manual 'urbanization scores' to build upon.

2. Methods

For the 21 differently urbanized sites studied by Bókony et al. (2012), we took digital aerial images from GoogleMaps (Fig. A1). Each study site was represented by a 1 km × 1 km rectangular area with the location of bird captures in the center. We quantified the intensity of urbanization from these images by three approaches as described below.

2.1. Manual scoring

We applied the manual scoring method (Liker et al., 2008) on the images of 1 km × 1 km areas divided into 10 × 10 cells for each study site. We evaluated the content of each cell considering the type of three major land-cover characteristics, namely buildings (B), vegetation (V, including agricultural areas and brownfields), and paved surfaces (R, mostly roads and parking lots), as follows:

$$B = \begin{cases} 0 & \text{if} \quad \text{proportion of building cover is 0} \\ 1 & \text{if} \quad \text{proportion of building cover is between 0 and 50\%} \\ 2 & \text{if} \quad \text{proportion of building cover is above 50\%} \end{cases}$$

$$V = \begin{cases} 0 & \text{if} \quad \text{proportion of vegetation cover is 0} \\ 1 & \text{if} \quad \text{proportion of vegetation cover is between 0 and 50\%} \\ 2 & \text{if} \quad \text{proportion of vegetation cover is above 50\%} \end{cases}$$

$$R = \begin{cases} 0 & \text{if} \quad \text{no paved surface is present} \\ 1 & \text{if} \quad \text{paved surface is present} \end{cases}$$

From these cell scores we calculated the following summary land-cover measures for each study site: mean building density score (potential range 0–2), number of cells with high building density (>50% cover; range 0–100), number of cells with paved surfaces (range 0–100), mean vegetation density score (range 0–2), and number of cells with high vegetation density (>50% cover; range 0–100). For each study site, we then calculated the 'urbanization score' using the PC1 score from a principal component analysis (PCA) of the five variables described above. We will refer to this measure as manual scores henceforth.

The manual scores of the 21 study sites published by Bókony et al. (2012) were compiled by 3 observers (i.e. each observer scored a non-overlapping subset of the 21 sites). Their PCA extracted one principal component (PC1) that accounted for 92.2% of the total variance and correlated strongly with reduced vegetation cover and increased density of buildings and roads (Bókony et al., 2012). To assess the measurement error of this method, two of us (G.S. and V.B.) scored each site twice (with ca. 2 weeks between each observer's first and second scorings) and generated 2 × 2 sets of manual 'urbanization scores' (denoted as GS1, GS2, VB1, and VB2, respectively) by PCA (Table A1). We used these scores to test the repeatability of 'urbanization scores' (i.e. the relative ranking of sites along the urban gradient) both within and between observers (see below). Furthermore, to assess measurement error at the level of image cells, we chose one suburban site situated in the middle part of the urban gradient (the Veszprém campus) and obtained manual scores for it from 10 independent observers not aware of the aims of our study, and from the two previously mentioned researchers with experience in manual scoring (i.e. 12 observers in total). We used these scores to test the agreement of manual scoring between observers at the level of image cells, and to compare this to the agreement between semi-automated and manual scoring (see below). Additionally, 10 observers (including G.S. and V.B.) scored this single site twice, with at least 5 days between their first and second scoring. We used these data to test the within-observer repeatability of manual scoring at the level of image cells (see below). Note that manual scoring is very labor intensive and time consuming so re-scoring of all sites by many observers was not feasible.

2.2. Semi-automated scoring

The semi-automated scoring method, based on the approach of Liker et al. (2008), was developed by Czúni et al. (2012). This method is a trained classification method based on analysis of several image features; its aim is to greatly reduce the time required for scoring while retaining as much precision as possible.

First we created the appropriate general classification model which ultimately generates the cell scores for B, V and R categories (Fig. 1). We took satellite images in .jpeg format from GoogleMaps of the 1 km × 1 km areas studied by Bókony et al. (2012). Since these satellite images have different resolution, we normalized image size for 164 cm/pixel, and divided each image to 100 image cells; these cells served as the units of analysis for the classifications (100 m × 100 m of physical terrain size). We took the 21 sites in the order as ranked by the manual scores of Bókony et al. (2012) and chose every second image to represent the entire urban–rural gradient. For these selected images we extracted relevant image features by image processing methods to obtain high-dimensional data vectors for our classification models as follows. For each image cell we measured the values of 52 different features based on color, texture, and local contrast (edges and corners) information, as described in detail by Czúni et al. (2012). Briefly, we calculated the following features: number of edge points detected by the Canny edge detector (Canny, 1986) applied in 19 different settings (19 values); number of points belonging to each of the 5 specified segment classes: grass, tree/bush, building, road, others, with 4 different window size settings of the Laws classifier (20 values; Laws, 1980); number of corner points detected by the Harris corner detector (Harris & Stephens, 1988) applied in 6 different settings (6 values); average value of Red, Green and Blue channels within an image cell (3 values), average and modus of Hue (of the HVS color space), and the corresponding variance of Hue (4 values).

Finally, we established the relation, by three independent classification models, between the high-dimensional data vectors and the cell scores obtained by manually scoring the values of B, V and R, respectively. For this purpose, we used a set of manual scores (GS3) by a single observer (G.S.) who has extensive practice with manual scoring. For the classification task we used the

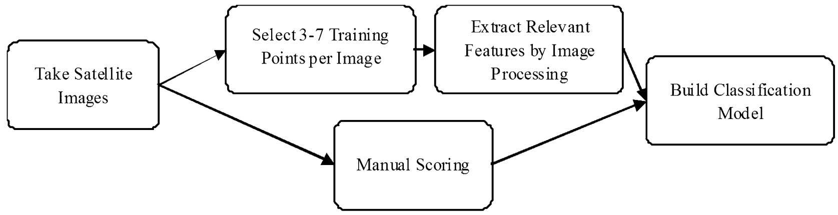

Fig. 1. Process of the building of the classification model in the semi-automated scoring method.

Support Vector Machine (SVM) algorithm (Vapnik, 2006), which is a robust classification and regression technique that maximizes the predictive accuracy of a model without overfitting the training data. After establishing the models (i.e. training), we used the remaining images to compare the manually assigned scores with the scores predicted by the SVM model (i.e. testing).

Once the classification model is established, it can be used to generate the 'urbanization scores' for other areas the user wishes to study (Fig. 2); here we simply applied the SVM model to the 21 images (100% of cells) we had used for training and testing the model. As landscape objects of the same type can highly vary in appearance both within and between images (e.g. buildings may look very different), we improved the SVM model's classification efficiency by adapting the Laws classifier with manually selecting a very few, typically 1–5, training points for each of the three major land-cover characteristics (*B*, *V* and *R*) per image. Then we predicted the values of *B*, *V* and *R* for each cell by applying the three respective SVM models, calculated the five summary land-cover measures of Liker et al. (2008) from the predicted values of *B*, *V* and *R*, and used them in a PCA to obtain the 'urbanization score' (Table A1). We will refer to the 'urbanization scores' gained from this measure as semi-automated scores henceforth.

Our classification models obtained by the above training process can be used to generate the semi-automated scores of urbanization for any 1 km × 1 km area by our application, written in C++ and C# languages and using 'OpenCV' library (Bradski & Kaehler, 2008). It can be downloaded freely, along with a users' guide, from the following URL: http://keplab.mik.uni-pannon.hu/en/urbanization-index

2.3. Geoinformatics measurements

To obtain strictly quantitative measurements of land-cover characteristics of each study site, we conducted measurements using the ArcGIS 10.0 (ESRI, 2010) geoinformatics software. All measurements were done by a single person who had previous experience with ArcGIS and was not aware of the aims of our study. In each image all polygons of landscape objects were traced and categorized as vegetation, buildings, paved surfaces, or other (e.g. railway lines, water bodies). Then we calculated the total percentage area of each cover type by summing the area of the polygons of each of the four categories. Finally, we extracted an 'urbanization score' from a PCA including the percentage cover of the three relevant categories (i.e. vegetation, buildings, and paved surfaces; Table A1). We will refer to this measure as 'ArcGIS scores' henceforth. To compare the ArcGIS scores with the manual scores at the level of image cells, we converted the proportion of cover by buildings, vegetation and paved surfaces for each cell into values of 0, 1, or 2 according to Liker et al. (2008).

2.4. Data analysis

We assessed the measurement error of both scoring methods by several approaches. For the manual scoring, first we tested the agreement within and between observers at the level of image cell scores for the Veszprém campus site using the kappa statistic, i.e. Cohen's kappa with squared weights for the agreement between two sets of scores by the same observer ($N = 10$), and Fleiss' kappa for the agreement between observers ($N = 12$; Peat, 2001). We express the level of agreement as the % of cells receiving the same score from the observer's 1st and 2nd scoring (within-observer repeatability) for each observer, and the % of cells receiving the modal value of the 12 observers' 1st scores for that cell (between-observer repeatability).

Secondly, we tested the repeatability of the manual scoring at the level of images (sites) both within and between observers (i.e. 'urbanization scores' GS1, GS2, VB1, and VB2) by calculating the intra-class correlation coefficient (ICC, see below) between each pair of 'urbanization scores'. We also tested the repeatability between these scores and the original urbanization scores of Bókony et al. (2012) which were compiled by 3 observers.

Thirdly, we evaluated the agreement between the manual scores and the semi-automated scores in multiple ways. We measured the performance of the classification model by the % of correctly classified cells during both the training (i.e. the first half of the images) and the testing (i.e. the other half of the images) phase, and by calculating the area under the ROC (receiver operator characteristic) curve. The ROC curve plots the proportion of true positive classifications in relation to the proportion of false positive classifications; the area under this curve is 1 for perfect models and 0.5 when classification is random (Hanley & McNeil, 1982). Then we tested the agreement between the semi-automated scores and the manual scores on which the classification model was built on (GS3) both at the level of cells for the Veszprém campus site (Cohen's kappa) and at the level of images of all sites (ICC). We also tested the repeatability between the semi-automated scores and the other sets manual scores (GS1, GS2, VB1, and VB2).

Finally, we compared the 'urbanization scores' generated by the manual method (i.e. the original manual scorings of Bókony et al. (2012), GS1, GS2, GS3, VB1, and VB2) and the newly developed semi-automated scoring method to those extracted from the ArcGIS measurements, at the level of sites, using ICC. We did not assess the error of the ArcGIS method as we treated this as a 'yardstick' for relatively accurate quantification of landscape cover.

To investigate the ecological applicability of the scoring methods we repeated the analyses of Bókony et al. (2012) that tested the effects of landscape urbanization on birds' body condition, and then we compared the results. In short, we used linear mixed-effect (LME) models that contained each of the 11 measures of environmental stress as dependent variable, 'urbanization score' and various confounding variables as predictors, and capture site as random factor to control for the non-independence of individuals captured at the same site. Then we reduced the initial models by backwards stepwise selection, omitting the effect with the highest *P*-value step by step until only significant ($P < 0.05$) effects remained, but never excluded our predictor of interest, i.e. urbanization and the random factor (for more details on data analysis see Bókony et al., 2012). We ran the models with 'urbanization scores' provided either by the semi-automated scoring method or by ArcGIS measurements, and compared the results with those

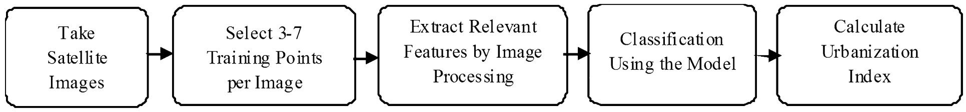

Fig. 2. Process of calculating 'urbanization score' in semi-automated scoring method.

published by Bókony et al. (2012) based on their manual scores. We took the parameter estimate for 'urbanization score' from each of the 11 models and tested the repeatability (ICC) over the three approaches pair-wise.

Statistical analyses were run in R 3.0.1 (R Development Core Team, 2014), using the 'icc' function of the 'irr' package for calculating the ICC, with 95% confidence intervals. The ICC approach tests for repeatability by expressing the proportion of variance in a character (e.g. 'urbanization score') that occurs among rather than within groups (e.g. different methods or different observers); for further details see Lessells & Boag (1987).

3. Results

3.1. Agreement at the image cell level

By investigating within-observer repeatability, we found that the manual scores for image cells of the Veszprém campus site showed high agreement between the first and second scorings of the 10 observers, including 8 observers who had no previous experience with the manual scoring method (Table 1a; $p < 0.012$ for all kappa tests). As for between-observer repeatability, the percentage of 12 observers assigning the modal value (i.e. the most frequently assigned score) for a cell averaged 70–90% for the 100 cells, showing that most observers agreed significantly on the scores of most cells (Table 1b; $p < 0.001$ for all kappa tests). Between-observer repeatability for each land-cover type varied with the amount of cover, as measured in ArcGIS, in each cell (Fig. A2). For buildings we found the highest uncertainty of manual scoring (i.e. the lowest % of agreement with the modal value) for cells with intermediate cover (ca. 20–30% of buildings per cell), whereas for vegetation and paved surfaces the observers agreed the least when cell cover was close to zero (Fig. A2).

The agreement between the semi-automated scores and the manual scores used for training classifier (GS3) was also significant for the Veszprém campus site (Table 1c; $p < 0.001$ for all kappa tests) and was comparable to the agreement between manual scores of different observers (see Table 1b). Overall, the performance of the classification models for the three land-cover categories for all sites was around 80% during both the training and the testing phase of the semi-automated method (Table 2). The area under the ROC curve was higher than 0.7 in each case, showing that the expected performance of the SVM classifiers was appropriate for our purposes (Table 2).

3.2. Agreement at the 'urbanization gradient' level

The 'urbanization scores' for the full set of 21 sites gained by the repeated manual scorings of two observers (GS1–GS2 and VB1–VB2) showed very high within-observer repeatability (Table 3) as can be seen from the remarkable overlap of points along the y axis on Fig. 3a. For vegetation, both observers attained the highest repeatability for the least urbanized sites with high vegetation cover (Fig. A3), whereas for buildings and paved surfaces they were the least consistent when scoring sites with intermediate urbanization (Fig. A3).

The between-observer repeatability amongst the manual 'urbanization scores' by G.S, V.B. and Bókony et al. (2012) was high and significant in all comparisons (Table 3 and Fig. 3a). Repeatability was also high and significant between the 'urbanization scores' yielded by the semi-automated method and the various manual scorings (Table 3 and Fig. 3b), and between the ArcGIS measurements and all manual and semi-automated scorings (Table 3 and Fig. 3c). The agreement between the manual scores of Bókony et al. (2012) and our scores calculated from ArcGIS measurements was highest when vegetation cover was high and the cover of buildings and paved surfaces was either very small or very large (Fig. A4).

3.3. Agreement of ecological results

Models of avian body condition containing different urbanization scores yielded qualitatively identical results for each of the body condition indices investigated (Fig. 4; see the details of the final models in Table A2). Parameter estimates for the effect of urbanization were highly repeatable between the manual scores of Bókony et al. (2012) and both our semi-automated scores (ICC = 0.838, $p < 0.001$, $N = 21$) and the ArcGIS scores (ICC = 0.938, $p < 0.001$, $N = 21$). There was a somewhat lower but still highly significant repeatability between the semi-automated scores and ArcGIS scores (ICC = 0.73, $p = 0.003$, $N = 21$; Fig. 4).

4. Discussion

The study of urbanization gradients has been quite a popular research area in the latest decade, and such studies use a great variety of methods to quantify the intensity of urbanization. Here we compared three broad approaches within the framework of an ecological problem to assess the reliability and applicability of two scoring methods against well-accepted geoinformatics measurements. Although several similar approaches and global maps have been applied to quantify differences across urban–rural gradients using remote-sensing data (e.g. Arino et al., 2007; Bartholome & Belward, 2005; Elvidge et al., 2007; Imhoff, Lawrence, Stutzer, & Elvidge, 1997; Pap et al., 2013; Schneider et al., 2010; Sexton et al., 2013), finding a globally applicable way of measuring land-cover features on a relatively fine scale remains a challenge. Global maps usually have coarse spatial resolution (mostly 1–2 km) and their applicability varies across differently developed regions (reviewed by Schneider et al., 2010), whereas databases with finer spatial resolution (e.g. 30–300 m) are typically specific to certain regions or time intervals or study systems (e.g. Arino et al., 2007; Prins, Petersen, Aunins, & Priednieks, 2005; Sexton et al., 2013). Within each of these frameworks, urbanized areas are represented as a function of different features such as population numbers, night-time lights, and satellite-derived land-cover classes; resulting in inconsistencies in how they depict the urban landscape (Schneider et al., 2010). The approach we propose here offers a simple alternative for quantifying relative levels of urbanization in a standardized way in whatever region of the Earth at fine spatial scale, and allows researchers to flexibly choose the type of landscape features without depending on national land-cover datasets and regionally specified parameters. As a starting step, here we examined the performance of this approach using a particular setup of ca. 1.6 m resolution and 3 major land-cover types within one 'urban ecoregion' (Schneider et al., 2010).

Table 1
Agreement of scores across 100 cells for the Veszprém campus site.

	Buildings (B)	Vegetation (V)	Paved surfaces (R)
(a) Repeatability within observer (% of agreement)			
Observer KD	99	99	97
Observer GS	95	93	96
Observer CL	96	93	82
Observer LA	80	83	100
Observer VPZ	90	74	91
Observer NGA	80	84	88
Observer AGY	76	75	92
Observer GM	70	73	95
Observer SZG	70	73	95
Observer VB	64	68	86
Average of 10 observers	**83**	**82**	**93**
(b) Repeatability between 12 observers (% assigning the modal value)	**70**	**74**	**91**
(c) Repeatability between semi-automatic and manual cell scores (GS3)	**67**	**69**	**91**

Kappa statistics marked bold are significant at $p \leq 0.001$.

Table 2
Overall accuracy of the *B*, *V* and *R* classification models in the semi-automated scoring method.

	Training	Testing	Area under the ROC curve (±SE)
Buildings (B)	82.09%	80.1%	0.734 ± 0.050
Vegetation (V)	86.09%	76.7%	0.746 ± 0.062
Paved surfaces (R)	84.45%	86.3%	0.708 ± 0.090

First, we evaluated the manual scoring method introduced by Liker et al. (2008). Although this method has been applied in a handful of studies (Bókony et al., 2010, 2012; Liker et al., 2008; Zhang & Zheng, 2010; Zhang et al., 2011), its validity had not been addressed empirically. The main advantages of the manual scoring method are its very simple classification rules with large tolerance ranges and its easy applicability to any kind of aerial image of study areas, including freely accessible GoogleMaps images. However, its results are inevitably prone to the subjective evaluating decisions made by different observers during the process of classifying the land-cover contents of each image cell. Here we have shown that there is indeed considerable variation both within and between observers when assigning the values of 0, 1 or 2 to the same set of image cells, especially when the amount of land-cover to be evaluated in a given cell is intermediate (for buildings) or small (for vegetation and paved surfaces). This variation well reflects the different and sometimes inconsistent cognitive classification rules applied by the observers; for example, small and/or scattered patches of vegetation or paved surfaces covered by canopy can be easily missed from consideration. Similarly to this, estimating whether total building cover is below or above 50% in an image cell (resulting in classification value of 1 or 2) proved to be the hardest task for observers when scoring cells with intermediate amounts of building cover.

Despite these uncertainties at the image-cell level, however, we have found that the manual scoring method is still a robust way of assessing the degree of urbanization of sites across different landscapes. First, at image cell level, the degree of agreement both within and between observers was often high, indicating that despite the above mentioned uncertainties, even completely inexperienced people agree more than they differ when scoring the same image cells. With some practice, one can reach >90% repeatability as shown by the re-scorings of G.S. in this study, but similar accuracy can also be achieved by inexperienced observers (see Table 1a). Second, and more importantly, the repeatability between the 'urbanization scores' generated for the same set of 21 sites by different observers was very high, demonstrating that they ranked the sites similarly with respect to urbanization. Since the goal of the scoring method is to provide a relative measure of urbanization, its validity ultimately depends on its performance at the level of sites. Different observers, or even the same person at different times, can differ in their cognitive rules by which they assign cell scores, but as long as they are consistent in these rules across sites, they will still produce consistent scores for placing the sites along the gradient, as shown by the >98% repeatabilities of manual 'urbanization scores'. Finally, the various manual scores of urbanization were also highly repeatable with the scores generated from the more objective and accurate measurements taken with ArcGIS, suggesting that the human eye is fairly effective in assessing the amount of cover by vegetation, buildings and roads overall across images.

Having found that the manual scoring method is suitable for quantifying the urban–rural gradient, our next goal was to find and validate a less labor-intensive alternative. The manual scoring requires at least one order of magnitude less time than the precise measurements with ArcGIS (for example, measuring

Table 3
The intra-class correlation coefficients (ICC) between 'urbanization scores' obtained by various methods (below the diagonal). Values in Italics (above the diagonal) show the results of ICC analyses when urbanization scores of the 21 sites were rank-transformed. In each case, $p < 0.001$.

	ArcGIS	Bókony et al. (2012)	GS1	GS2	VB1	VB2	Semi-automated
ArcGIS	–	*0.993*	*0.965*	*0.957*	*0.979*	*0.985*	*0.964*
Bókony et al. (2012)	0.97	–	*0.974*	*0.965*	*0.983*	*0.989*	*0.979*
GS1	0.958	0.994	–	*0.98*	*0.979*	*0.965*	*0.984*
GS2	0.955	0.991	0.997	–	*0.962*	*0.963*	*0.965*
VB1	0.972	0.986	0.988	0.987	–	*0.991*	*0.96*
VB2	0.977	0.988	0.988	0.989	0.998	–	*0.952*
Semi-automated	0.925	0.979	0.985	0.976	0.96	0.958	–

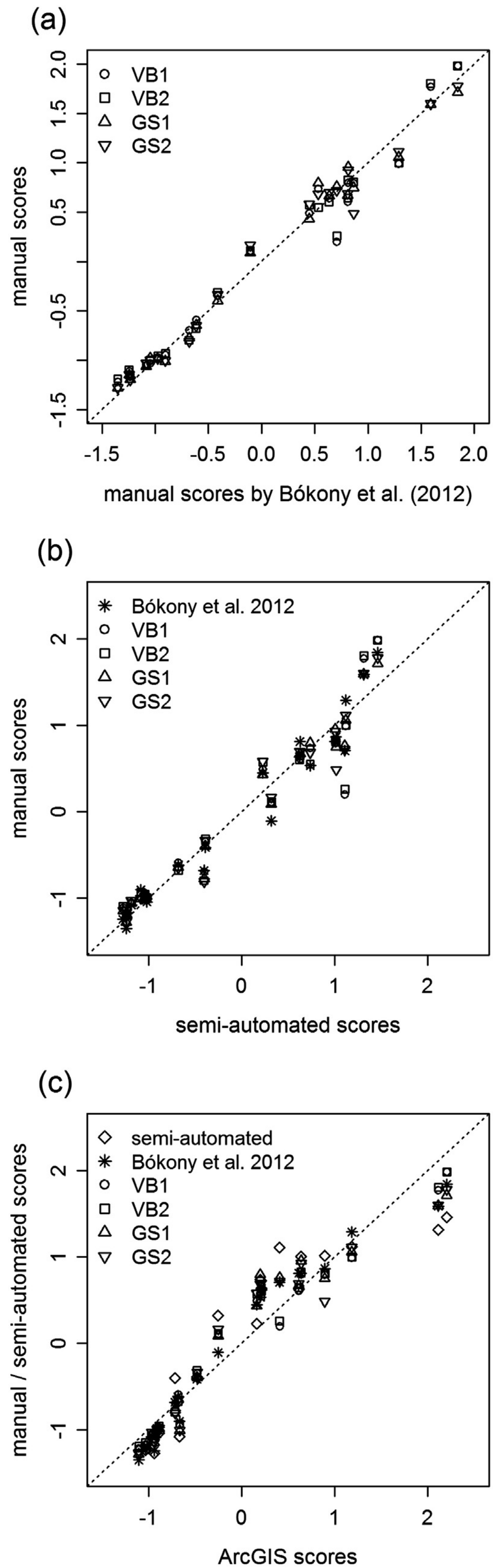

Fig. 3. Agreement of 'urbanization scores' for 21 sites (a) between various manual scores, (b) between the semi-automated and manual scores, and (c) between ArcGIS, semi-automated, and manual scores. The line stands for perfect agreement (i.e. $y = x$).

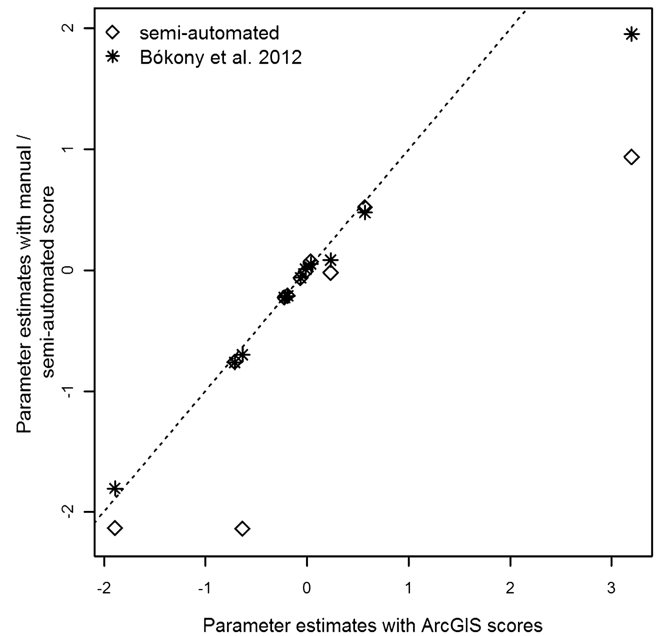

Fig. 4. Agreement of parameter estimates for the effect of urbanization on various measures of bird health from LME models including 'urbanization scores' generated by manual or semi-automated scoring or ArcGIS measurements (see Appendix: Table A2). The line stands for perfect agreement (i.e. $y = x$).

a complex urban site takes ca. 10–12 h with ArcGIS and ca. 1 h with the manual scoring); however, the manual method still gets quite time-consuming as the number of study sites increases. Also, more scoring probably leads to decreasing performance due to its monotony and the accumulation of human errors such as overlooking small details or mistyping the assigned values. Therefore we took the approach of Czúni et al. (2012) who developed the semi-automation of the manual scoring method, with fewer subjective errors and significantly less time required. Finding an appropriate approach to quantify urbanization based on automatic visual processing is challenging, since pixel-based algorithms are not effective enough due to the high variability in the visual appearance of an object type, depending on image resolution, season of the year, time of the day, prevailing weather, type of vegetation and building structure, etc. (Czúni et al., 2012). Thus, the semi-automated scoring method classifies image cells instead of pixels, following the logic of the manual scoring, based on 52 visual features. Here, we have shown that this method replicates the manually assigned cell scores similarly well as non-trained humans' scores agree with each other, and the 'urbanization scores' for the study sites are highly repeatable between the semi-automated method and 5 different sets of manual scoring. Furthermore, the semi-automated scores of urbanization were also highly repeatable with the scores from the more precise, polygon-based ArcGIS measurements. For both manual and semi-automated scores, we found that the agreement with ArcGIS scores was the highest for roads (Fig. A2 & A4), probably because determining the presence or absence of paved surfaces is the easiest task during the land-cover classification process. We found the poorest agreement at sites with intermediate urbanization, probably due to the difficulties in scoring image cells containing several buildings interspersed with patches of vegetation and other land-cover objects, as detailed above. The slightly sigmoid-like relationship on Fig. 3c is likely a reflection of the difference between the scoring methods and ArcGIS, i.e. intermediate cover may be overestimated and very large cover may be underestimated by the simplifying rules of image-cell scoring; however, these differences had little impact as the repeatability of 'urbanization scores' was >90% between ArcGIS and both scoring methods.

As a final step of validating both the manual and the semi-automated scoring methods, we used the 'urbanization scores' generated by each method for the 21 study sites of Bókony et al. (2012) and repeated their analyses to investigate the effects of landscape urbanization on the body condition of adult house sparrows. We found that, in all 11 analyses of body condition indices, both the semi-automated method and the ArcGIS measurements yielded qualitatively the same results as the manual method, i.e. the predictor variables retained in the final models and whether or not they had significant effects were identical to the results of Bókony et al. (2012). Furthermore, the three different scores of urbanization received very similar parameter estimate values in most cases, as demonstrated by the high and significant repeatabilities among them. There were only two cases in which the three methods yielded relatively different parameter estimates; however, there was no bias between the three methods as the semi-automated scoring under-estimated the effect of urbanization in one case and over-estimated it in the other compared to the other two methods. We do not know the reason for this difference, but since both dependent variables were plumage coloration traits (bib size and wing bar size) we might speculate that measurement error might have been higher for these traits than for the rest of the body condition indices. Nevertheless, due to the higher uncertainty of these estimates the result was qualitatively unaffected, suggesting that the power of these two analyses might have been limited anyway. In analyses with obviously high power (i.e. scaled mass index, body mass, tarsus length), the three methods resulted in almost exactly the same parameter estimate values for urbanization.

Thus, we propose that the semi-automated scoring method is a reliable tool for standardized and time-efficient quantification of urban gradients, and it is open for further development to test and improve its applicability to a greater variability of landscape types. Firstly, since all the areas studied to develop (see Czúni et al., 2012) and ecologically validate our semi-automated method are located in Hungary, Europe, it remains to be seen how well the method can be applied to other geographical regions. Although our study sites represent a very wide range of the urbanization gradient from almost 100% vegetation to almost 100% building cover (see Fig. A1), there are very different landscape compositions in other parts of the world, with diverse city structures and types of buildings and vegetation. The classification models we built here are likely to work well for landscapes similar to ours and can be applied to score such new sites with our software, however, they might not be suitable for study sites looking very differently from ours; for such sites the semi-automated method should be trained and tested with manual scores obtained for those sites. Secondly, although we tested our method's applicability in the context of avian ecology, we propose it to be useful in other study systems. As different types of landscape features could be relevant for different organisms (e.g. Croci, Butet, Georges, Aguejdad, & Clergeau, 2008), incorporating further types of landscape cover into the classification process may be necessary, e.g. separating woods from other types of vegetation, or including water bodies, railways, construction areas, golf courses, rubbish-shoots, etc. Furthermore, while our method works well with study areas of 500 m × 500 m (Czúni et al., 2012) and 1 km × 1 km (this study) and images with pixel size of 164 cm, this spatial scale and resolution may be inappropriate for some study systems such as organisms with very small size and/or limited home range. Validating the method for much smaller or larger areas and study sites of variable size may further extend the method's applicability. With these future improvements our method could be useful for investigating a wide spectrum of animal taxa and research questions related to landscape urbanization.

5. Conclusions

To sum up, we have demonstrated that both the manual scoring method of Liker et al. (2008) and the semi-automated scoring method of Czúni et al. (2012) can be used to reliably quantify the intensity of urbanization along the urban–rural gradient. Both methods generated scores of urbanization that ranked the study sites along the gradient in a way that is consistent with more objective and precise geoinformatics measurements, and all three methods allowed for the same biological conclusions in a study of bird health indices. Thus, we propose that the semi-automated scoring method is a powerful tool for broad studies of urbanization, because it provides reasonable accuracy while it does not require expensive imagery and software, it is easy to use and, perhaps most importantly, allows researchers around the world to apply a standardized method for quantifying urbanization. This could be used in any study that does not aim to investigate or predict the effect of the exact amount of various land-cover types within habitats, such as basic ecological research and even certain areas of conservation biology and landscape planning. With further development, the semi-automated method can be expanded to include other types of land-cover features and apply to other spatial scales than those studied here. Therefore this methodology has the potential to provide a common context and greater integrity between urbanization studies conducted at different locations of the Earth, thereby helping us to draw better general conclusions about the impacts of urbanization on the world around us.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landurbplan.2014.07.010.These data include Google maps of the 21 sites described in this article.

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