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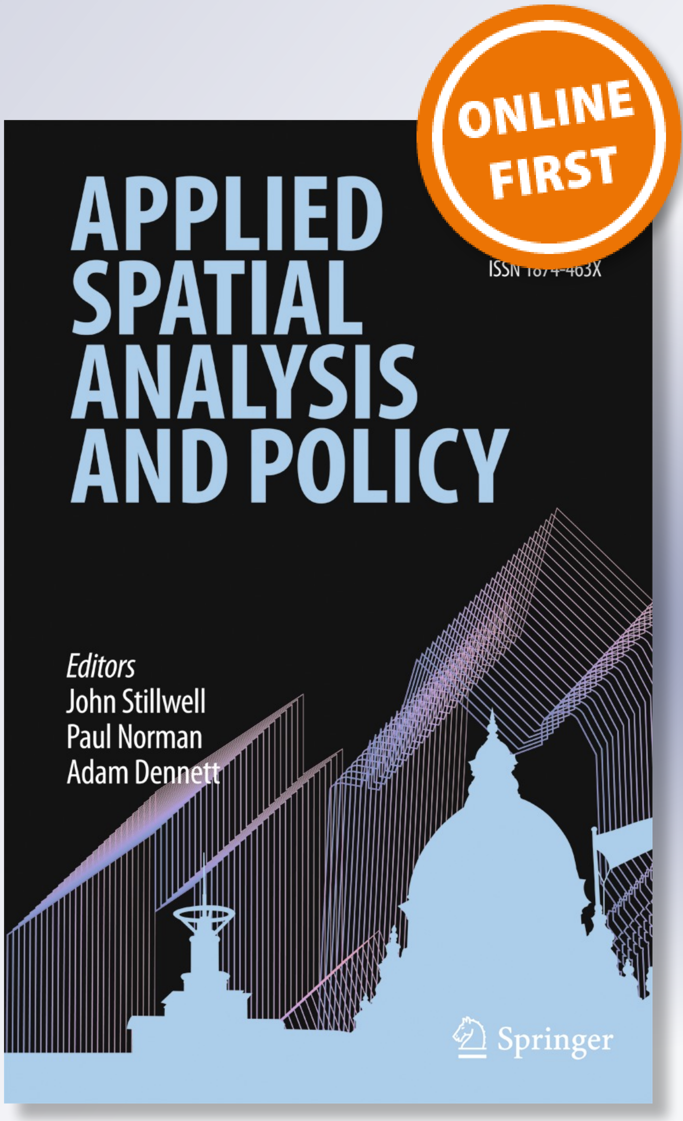

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Exploring the Added Value of Population Distribution Indicators for Studies of European Urban Form

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Abstract In Europe, landscape metrics dominate studies that apply quantitative analyses to urban form. Indicators describing population distribution in more detail than just population density, which in Europe are often neglected because of the difficulty in data acquisition, are likely to be more adequate for describing the socioeconomic perspective on urban form. This study aims to disclose the linkage between landscape metrics and population distribution metrics and to provide a better understanding of population distribution patterns. In our study, we quantified urban form in 35 European cities using the most common indicators from both groups of indicators, including measures for the gradient of population density with distance from the city center or (in-) equality of population distribution. We found that landscape metrics correlate only weakly with population distribution indicators by analyzing the correlation matrix. To obtain more insight into the largely neglected group of population distribution indicators, we also applied a regression analysis to understand their underlying information. The results show that population distribution indicators are related to other basic characteristics of

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cities, such as planning coordination and latitude. The indicated influence of national planning regime on urban form could stimulate further discussion on the effectiveness of urban planning measures. Our study demonstrates that population distribution indicators provide a different perspective than landscape metrics in describing urban form. We therefore stress that it is essential to include population distribution indicators also for describing European cities when aiming to comprehensively describe urban form.

Keywords Urban form · Population distribution indicator · Landscape metrics · European cities · Density gradient

Introduction

Urban form can be defined as the spatial pattern of human activities at a certain point in time (Anderson 1996). It is the result of a variety of influences, including site and topography, the economic and demographic development of a city and past planning efforts (Batty and Longley 1994; Schwarz et al. 2010). In turn, urban form can also affect socioeconomic conditions and environment of the city (Camagni et al. 2002). Given that more than half of the world's population now lives in cities, it is crucial to be clear about how to describe and compare urban form across cities.

There are two major groups of indicators for measuring urban form. One measures land use/land cover of a city (landscape metrics, section 1.1.1), while the other focuses more on the socioeconomic aspects of urban form (e.g. the density of the population or employment, section 1.1.2). While utilizing the concept of urban form, some studies use only landscape metrics to present the urban form (Aguilera et al. 2011; Ou et al. 2013; Weber et al. 2014), others for North America mainly use population distribution indicators (Edmonston et al. 1985; Tsai 2005). When combining population distribution indicators with landscape metrics while discussing urban form, the majority of authors focus on population density on various spatial levels (Ewing et al. 2002; Torrens 2008). Moreover, we noticed that likely due to limited data availability most socioeconomic indicators in urban form studies, especially for Europe (Antrop 2004), are describing only the situation of the city as a whole in continent-wide urban studies, for example the overall population density, but are not differentiating the distribution pattern within the city (Kasanko et al. 2006; Schwarz 2010). Studies making use of more detailed population distribution indicators such as density gradient are mostly focusing on US cities (Ewing et al. 2002; Torrens 2008). However, findings related to urban form of US cities are likely not transferable to European cities, as the latter often have preserved their historical city centers by restricting high-rise buildings there and rather focusing on commercial areas in the city center instead of office buildings. Moreover, the interrelationship between landscape metrics and population distribution pattern other than population density is rarely studied. To provide a more detailed understanding of population distribution patterns, specifically in European cities, and also of the relationship between landscape metrics and population distribution patterns, we (i) calculate the most commonly used indicators from both landscape and population distribution metrics for a set of European cities, we (ii) systematically examine the relationships within and between these two indicator families and (iii) we explore the relationship of various metrics of population distribution with other city characteristics, such as economic status or spatial planning regime.

Review of Urban Form Indicators

Landscape Metrics

Landscape metrics were developed in the late 1980s to quantitatively describe the physical structure of landscapes by analyzing maps of land use or land cover. The use of landscape metrics proved to be very useful for representing urban form (Galster et al. 2001; Holden and Norland 2005) because landscape metrics can identify and describe the spatial component of the entire urban area and also capture the dynamics of change and growth processes (Herold et al. 2003). Moreover, landscape metrics are often used to analyze urban environmental problems related to urban form, such as traffic-induced noise (Weber et al. 2014) or the urban heat island phenomenon (Schwarz et al. 2012).

The landscape metrics that are often used in urban form research fall mostly into the following categories: area and edge metrics, shape metrics, aggregation metrics, and diversity metrics.

Area and edge metrics such as total area provide the basic information for many indices. As the most straightforward and basic metrics, this group can be seen in most urban form studies and provide fundamental information about the urban structure.

Shape metrics represent a collection of unitless metrics that describe the geometric complexity and/or compactness of patches, for example area-weighted mean shape index describing shape complexity. Most of these shape metrics are based on perimeter-area relationships and deal with overall geometric complexity (Mcgarigal 2001). There are studies that provide evidence that shape metrics can have an influence to the cooling effect of urban green spaces (Jaganmohan et al. 2016).

Aggregation metrics, for instance the contagion index, refer to landscape texture that describes the tendency of patch types to be spatially aggregated. They could be employed to calculate the spatial configuration and structure of urbanization and activities (Torrens 2008).

Diversity metrics such as Shannon's Diversity Index, taking into account different types of patches and their extent, express critical information about the landscape composition without taking into account the uniqueness or potential ecological, social, or economic importance of individual patch types (McGarigal et al. 2012). Yeh and Huang (2009) related patterns of landscape diversity to urbanization processes and tested the theory of urban growth.

The quantification of all metrics used in this study to describe the physical form is given in "indicators for landscape patterns" section.

Population Distribution Indicators

Population distribution is another dimension of urban form that reveals its socioeconomic aspect. Studies that utilized fine-grained population data to describe urban form in transportation and smart growth studies are mostly available in US (Cervero and Kockelman 1997; Lewis et al. 2012), likely due to good data availability from the US census.

The employment distribution is another interesting pattern for urban form, focusing on place of work instead of residence. Many studies of this research strand aim at identifying centers and sub-centers of employment, in the context of urban sprawl (Hamidi and Ewing 2014; Small and Song 1994). Combining data on residence and employment could without doubt help to better describe urban form. However, we do not consider employment here, as the focus of our study is to compare indicators related to places of residence with indicators related to buildings and built-up areas. What is more, fine-grained employment data is even harder to come by for European cities than population data in the sense of residence.

In the following, we introduce the indicators that are applied in our study. Their quantification is explained in more detail in "indicators for population distribution" patterns section.

Gross and net Population Density All population distribution indicators considered here are based on population density. Two population densities are commonly used. While gross density is calculated as the population number divided by the whole area, net density is the population number divided by only the residential area. Since the spatial distribution of the population over the entire urban area is better reflected by gross density, while the net density is more suitable for comparing densities at a finer scale (Hammer et al. 2004; Lu and Guldmann 2012).

Density Gradient The density gradient describes the prevailing pattern in cities in which population density decreases from the city center to the outer city regions. The most commonly used model to describe the density gradient is the negative exponential function (Clark 1951). Gradient values are commonly calculated by fitting a linear model of the logarithm of density against distance using ordinary least-squares techniques (Mills and Tan 1980). Many different studies used the parameters of this equation to disclose different city structures and their developmental stages. For example, Mills and Tan (1980) found that cities in developed countries had flatter density gradients than those in developing countries. Ewing et al. (2002) showed that the higher the density gradient is, the more centered is the metropolitan area. The change in density gradient (becoming flatter) is also considered as one dimension when measuring city sprawl or compactness (Ewing et al. 2002; Torrens 2008).

After Clark (1951), many different formulas have been introduced to better reveal the relationship between the distance to the city center and population density. For example, the quadratic exponential function (the so-called Newling model, Newling 1969) compensates for the weakness of the exponential function by allowing for a fitted decline in population density at the city center, i.e., a crater – a commonly observed phenomenon due to a relative lack of residential land use in the center (Latham and Yeates 1970; McDonald 1989). Furthermore, Latham and Yeates (1970) and Newling (1969) proved that when the urban area grew and matured, the crest moved away from the city center (McDonald 1989). The power law is another frequently mentioned function for describing the density gradient. The inverse power law can embody the fractal property, i.e., the self-similarity, often observed in cities (Batty and Kim 1992).

The density gradient as such assumes a mono-centric city. However, some studies also extended the density gradient for the polycentric context and found that the polycentric assumption works better compared to the monocentric model in some metropolitan areas (Griffith 1981; Small and Song 1994). Hamidi and Ewing (2014) also discussed that in the US, around 1/3 of the cities are better described by a polycentric model compared to a monocentric model. However, in the European context, the monocentric model still dominates the majority of urban structures (Oueslati et al. 2013). Therefore, and because we focused only on the city administrative area instead of the larger region, we here keep the monocentric assumption for the density gradient and work with the comparatively simpler monocentric models for the population gradient.

Indicators for the Evenness of Population Distribution In addition to the density gradient, there are other indicators to measure population distribution patterns. The Gini coefficient is a measure of inequality of income and is frequently adapted in urban studies to measure the inequality of the population distribution among sub-city districts (Shim et al. 2006; Tsai 2005). The Moran's I, which is used to measure spatial autocorrelation, was adapted to estimate the level of clustering (Torrens 2008; Tsai 2005). For example, Moran's I reveals the spatial relationships of high-density sub-city districts, i.e., whether they are clustered or randomly distributed.

Aims and Organization of the Study

To provide comparative knowledge of spatially explicit population distribution patterns within European cities and their relationship to the more often used landscape metrics, we examine the relationship between landscape metrics and population distribution indicators in 35 European cities (for the list of cities see Fig. 1 and appendix). Specifically, we ask whether the large body of work on landscape metrics for Europe misses important aspects of urban form, namely, the distribution of population within the urban area. Moreover, to shed light on population distribution indicators as potentially important but for Europe often neglected measures of population distribution, we further characterize them by testing for their relationships with other basic city characteristics that are frequently used to describe cities, such as economic power, geographic location or urban planning scheme.

Data and Methods

Data Description

We used population numbers in sub-city districts from Urban Audit (Eurostat 2013) for population distribution indicators. A sub-city district is defined as a subdivision of the city according to criteria based on population size (5000–40,000 inhabitants). We evaluated data from the 1999–2002 period because data is incomplete for other periods. Furthermore, we only considered cities with more than 30 sub-city districts, to obtain a robust estimation of the density gradient. Therefore, we had to exclude several small- and mid-size cities within Europe. To increase the number of cities included in the study, we used additional data from other sources (Office for National Statistics for the

UK and data on the city of Leipzig provided by the city authority). In total, we were able to include 35 cities in this study (see Fig. 1, the list of cities and number of districts is in the appendix).

Data from Urban Atlas (EEA 2010) were used to analyze the landscape metrics of European cities. Urban Atlas provides pan-European land cover data for Large Urban Zones (LUZ) with more than 100,000 inhabitants as defined by Urban Audit. A LUZ is an approximation of the functional urban zone which contains the core city, i.e. the administrative boundary, and its surrounding area. Because population data for sub-city district is only available within core cities, we used only the land cover information within these boundaries. The land cover data set from the 2005–2007 was used for calculation of landscape metrics.

Other basic city characteristics, which we term the 'city profile', and which we use for further analysis to understand the meaning of the population distribution indicators in more detail are summarized in Table 1: GDP of cities were acquired from Urban Audit. We extracted location information, i.e., longitude, latitude and whether it is a coastal city, from the EuroBoundary Maps (EuroGeographics 2013). To indicate the presence of physical barriers to city development, we calculated the maximum difference in elevation in a buffer area around the city (radius 20 km) from the European elevation map (EEA 2004). Moreover, we characterized a city using an urban planning schema, which refers to the coordination of spatial planning from European Spatial Planning

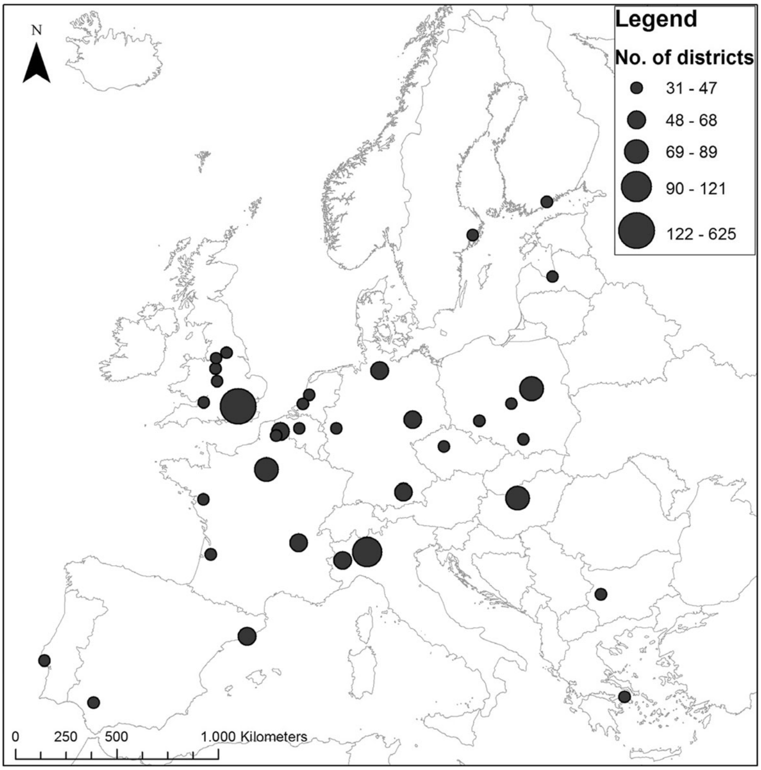


Fig. 1 Distribution of cities included in this study. Circle size indicates the number of sub-city districts (see legend)

Table 1 City profile variables

City profile variables	Variable type
If the city is located at the coast	Boolean, 0 as not coastal city, 1 as coastal city
GDP	Continuous variable
Planning scheme	Categorical variable, detailed explanation in section 2.1
Longitude	Continuous variable
Latitude	Continuous variable
Elevation difference in the buffer area	Continuous variable

Observation Network (ESPON) project "Governance of Territorial and Urban Policies from EU to Local Level" (Joaquín Farinós Dasí 2007). There are two main directions of spatial planning coordination: vertical (i.e., communication and cooperation between different hierarchical levels of the planning organization) and horizontal (communication and cooperation across the same level). The level of comprehensiveness in both coordination directions reflects their current spatial planning scheme that is influenced by history and tradition as well as the openness for the change in the future. All of the European countries are sorted into one of five categories: A, Strong in both directions (e.g. Germany, France); B, Mainly vertical coordination (e.g. Austria, Hungary); C, Mainly horizontal coordination (e.g. Sweden, UK); D, Weak in both directions (e.g. Norway); and N, Strong urbanism tradition (e.g. Spain, Portugal). The strong urbanism tradition is only concerning the built environment through binding plans in contrast to land use plans that are more flexible for the built and non-built environment.

Calculating Indicators

Indicators for Landscape Patterns

The landscape metrics we applied here are listed in Table 2. We used Fragstats (McGarigal et al. 2012) to calculate landscape metrics using rasterized data from Urban Atlas. Of the 20 land use categories provided by Urban Atlas, we regrouped all continuous and discontinuous urban fabric categories in Urban Atlas into one 'Build-up area' category. To consider the scale effect of landscape metrics, we tested the 30 m and 100 m raster conversions. As landscape metrics for these two resolutions were highly correlated, we used the finer scale resolution for our analysis.

In this study, we selected and calculated metrics that are frequently used in urban form studies. Their quantification and interpretation is summarized in Table 2. For *area and edge metrics*, we include total urban area, percentage of urban area, percentage of green space, largest patch index for urban area, mean patch area as well as number of patches (both for urban area). Total edge and edge density from this category of landscape metrics are also considered. From the category *shape metrics,* we use area-weighted mean shape index, area-weighted mean fractal dimension index and perimeter-area fractal dimension, which reflect shape complexity across a range of spatial scales. For *aggregation metrics*, the Interspersion and Juxtaposition Index (IJI) and contagion index are included. From the group of *diversity metrics* Shannon's Diversity Index and Simpson's Evenness Index are calculated.

Table 2 Urban form indicators used in this study (definitions based on FRAGSTAT (McGarigal et al. 2012), Clark 1951, Tsai 2005)

	Indicator	Abbreviation	Formula	Note	
Population distribution indicators	Gross density	POPDEN	$density = \frac{population}{area}$		The basic of other population distribution indicators.
	Negative exponential function	DENGRA	$density = Ae^{-bx}$	x: distance to city center b: density gradient A: density at the center	The density gradient indicates the trend of density decrease from the city center. The low value often indicates a sprawled city.
	Gini coefficient	Gini	$Gini = \frac{\sum_i^N \sum_j^N \lvert y_i - y_j \rvert}{2N^2 \overline{y}}$	N: number of districts in the city $y_{i,j}$: population density of a district i or j $\overline{y}$:mean population density	Gini coefficient measures distribution evenness. When it is high, the population is distributed unevenly among districts.
	Moran's I	Moran	$Moran = N\sum_{i=1}^N \sum_{j=1}^N W_{ij}(X_i - X) \frac{(X_j - X)}{\left(\sum_{i=1}^N \sum_{j=1}^N W_{ij}\right)(X_i - X)}^2$	N: number of sub-city districts $X_{i,j}$: population in sub-city district i or j W_{ij}: inverse distance between sub-city districts i and j	A high positive Moran's I indicates that high-density sub-city districts are closely clustered, and a value close to 0 indicates random scattering and a value close to −1 representing a 'chessboard' development pattern.
	Can Newling model be fitted?	FIT	$density = e^{ax^2 + bx}$	x: distance to city center a, b: parameters of the equation FIT is a binary indicator of whether a is positive (model cannot be fitted) or negative (model can be fitted).	When the model fits, the city follows the density structure with a crater in the middle.
Landscape metrics - Area and edge metrics	Urban Area	CA	Size of residential urban area		It provides basic information of city size.
	Percentage of residential area	PLAND	Percentage of residential area		Basic information of land use structure.
	Green share	green.share	Percentage of green area in LUZ		
	Largest patch index for urban area	LPI	$LPI = \frac{MAXa_j}{AREA}(100)$	a_j: area of urban patch j AREA: total landscape area (m^2)	LPI is a simple measure of dominance by quantifying the percentage of total landscape area comprised by the largest patch.
	Mean patch area	AREA_MN	$AREA_MN = \frac{\sum_{j=1}^n x_j}{n}$	x_j: area of the urban patches n: number of urban patches	Average size of urban patch.

Table 2 (continued)

	Indicator	Abbreviation	Formula	Note	
	Number of patches	NP	Number of sealed urban patches in city		A low NP indicates compactness.
	Total edge	TE	Sum of perimeters of all sealed urban patches		Total edge is an absolute measure of total edge length of urban patches.
	Edge density	ED	$ED = \frac{\sum_{k=1}^{m} e_k}{A}(10000)$	e_{ik}: Total length (m) of edge in landscape involving urban patches; A Total landscape area (m^2)	Edge density reports urban edge length on a per unit area basis and reflects the complexity of shapes.
Shape metrics	Area-weighted mean shape index	SHAPE_AM	$SHAPE_AM = \frac{\sum_{i=1}^{N} p_i/4\sqrt{s_i}}{N} \times \frac{s_i}{\sum_{i=1}^{N} s_i}$	s_i , p_i: area and perimeter of patch i N: number of patches	It indicates the regularity of the patches. It equals 1 for rasterized circular features or square cells and increases with irregularity.
	Area-weighted mean fractal dimension index	FRAC_AM	$FRAC_AM = \frac{\sum_{i=1}^{N} 2\ln(0.25 \times p_i)}{\ln s_i} \times \frac{s_i}{\sum_{i=1}^{N} s_i}$	s_i , p_i: area and perimeter of patch i	It indicates an increase in shape complexity. It approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.
	Perimeter-Area Fractal Dimension	PAFRAC	$PAFRAC = \frac{2}{\frac{\left(N\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij} \ln a_{ij}\right) - \left[\left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}\right)\left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln a_{ij}\right)\right]}{\left(N\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}^2\right) - \left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}\right)}}$	s_i , p_i: area and perimeter of patch i N: number of patches	It reflects shape complexity with approaching 1 for shapes with very simple perimeters such as squares, and approaching 2 for shapes with highly convoluted, plane-filling perimeters.
Aggregation metrics	Interspersion and juxtaposition index	IJI	$IJI = \frac{-\sum_{i=1}^{m'}\sum_{k=i+1}^{m'}\left[\left(\frac{e_{ik}}{E}\right)\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left[\frac{1}{2}m'\left(m'-1\right)\right]} \cdot 100$	e_{ik}: total length (m) of edge in landscape between patch types (classes) i and k. E total length (m) of edge in landscape, excluding background. m: number of patch types (classes) present in the landscape, including the landscape border, if present	IJI equals the observed interspersion over the maximum possible interspersion for the given number of patch types. IJI approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI = 100 when all patch types are equally adjacent to all other patch types.
	Contagion	CONTAG	$CONTAG = 1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]\left[\ln P_i\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2\ln m} \cdot 100$		

Table 2 (continued)

	Indicator	Abbreviation	Formula	Note	
				P_i: proportion of the landscape occupied by patch type (class) i g_{ik}: number of adjacencies (joins) between pixels of patch types (classes) i and k based on the double-count method m: number of patch types (classes) present in the landscape, including the landscape border, if present	CONTAG approaches 0 when the patch types are maximally disaggregated (i.e., every cell is a different patch type) and interspersed (equal proportions of all pairwise adjacencies). CONTAG = 100 when all patch types are maximally aggregated.
Diversity metrics	Shannon's Diversity Index	SHDI	$SHDI = -\sum_{i=1}^{m}(P_i \cdot \ln P_i)$	P_i:proportion of the landscape occupied by patch type (class) i	SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity). SHDI increases as the number of different patch types increases and/or the proportional distribution of area among patch types becomes more equitable.
	Simpson's evenness index	SIEI	$SIEI = \frac{1-\sum_{i=1}^{m} P_i^2}{1-\left(\frac{1}{m}\right)}$	P_i:proportion of the landscape occupied by patch type (class) i m: number of patch types (classes) present in the landscape, excluding the landscape border, if present	SIEI = 0 if the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types becomes increasingly uneven (i.e., dominated by 1 type). SIEI = 1 if the distribution of area among patch types is perfect.

Indicators for Population Distribution Patterns

The two most common models of the relationship between population density and distance from the city center were considered in this study: the negative exponential function and the Newling model (see equations for all indicators in Table 2). The alternative power-law model was also tested but not applied here, because it did not provide much additional information and R^2 was lower than for the negative exponential function (data not shown). For all density gradients, we used gross population density, because it better reflects the spatial distribution of population over the whole area (Lu and Guldmann 2012). Both the negative exponential and the Newling model were fitted with a linear model at the semi-log scale (McDonald 1989). Instead of using the most dense district as the city center, we determined city centers by the 'best fitting method' developed by Alperovich (1983): For each city, all center points of sub-city districts were considered as candidates of the city center and the negative exponential function was fitted for every candidate point. The point with maximum R^2 for the negative exponential function was then labeled as the city center. Visual quality control using maps of all cities confirmed that this method provides a robust and reliable estimation of the center of a city. The distance between the geometric center of each sub-city district and the city center are considered as their distances to the city center.

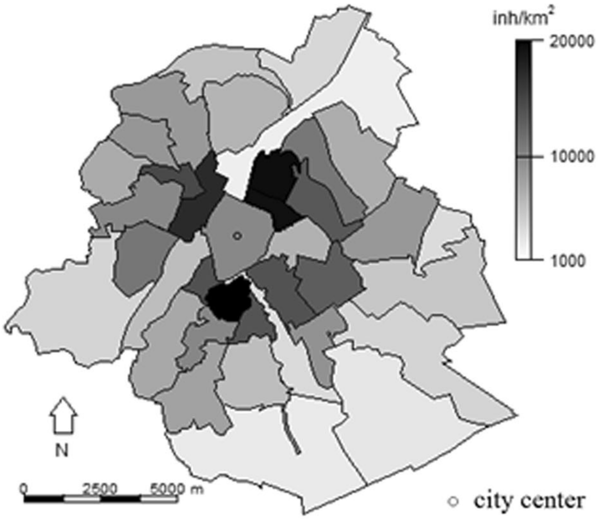
In Table 2, the coefficient b in the negative exponential function, which is the slope of the linear function in the semi-log space, is the density gradient of the city. In the Newling model, we are interested in the quadratic coefficient a. If the density gradient fits the "bump" shape (i.e., the fitting leads to a negative a), this indicates a decay of the population density in the city center. Figure 2b) presents an example with the negative exponential model and the Newling model fitted to data (Brussels). Fitting the Newling model for European cities revealed that it does not fit data of all cities. There are examples with positive quadratic coefficients a in the semi-log space, which contradicts Newling's original assumption. To make use of this valuable information (if a city follows Newling's assumptions), we used whether the fitting yielded a negative a, i.e. the city population shows a "bump" shape, as a binary indicator in our study.

Furthermore, we applied the Gini coefficient to measure population distribution inequality. The Gini coefficient ranges from 0 to 1. A higher Gini coefficient means that urban population concentrates in a few sub-city districts. A low value indicates that population is evenly distributed. Moran's I coefficient ranges from −1 to 1, with a high positive value indicating that high-density sub-city districts are closely clustered, a value close to 0 indicating random scattering and a value close to −1 representing a 'chessboard' development pattern. Both indicators were calculated following Tsai (2005); the equations are given in Table 2.

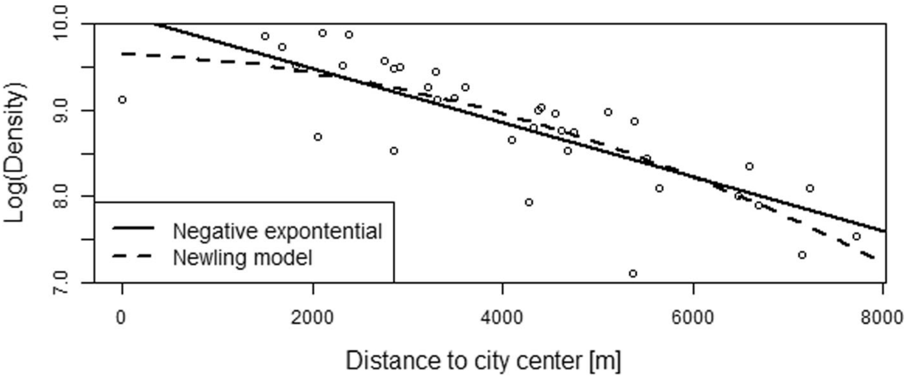
Statistical Analysis

Indicator Distances and Correlation Analysis

We used pairwise indicator distance comparison and correlations to analyze the relationship between and among landscape metrics and population distribution



(a)



(b)

Fig. 2 Population distribution in Brussels. (**a**) Population density of each district, (**b**) density gradient of the negative exponential function and the Newling model. Although the curve of the Newling model does not have a clear "bump" shape in the graph, the flatter curve compared to the negative exponential function in the central area still better captures the relatively low density in the city center. The Gini coefficient is 0.34 and Moran's I is 0.06

indicators. For computing indicator distances, we first standardized the values for all landscape metrics and population distribution metrics. Second, for any pair of cities, we computed the sum of Euclidian distances (R package 'hopach', van der Laan and Pollard 2014) between a) the standardized landscape metrics and b) the population distribution metrics. Thus, for instance, a low value for distances between standardized landscape metrics means that the standardized values for all landscape metrics under consideration are similar for this specific pair of cities, while a high value shows that the standardized values for the landscape metrics vary for this case. Third, we plotted the distance between standardized landscape metrics against the distance between standardized population-related for every pair of cities. A "stars in the sky" pattern indicates that high differences in one indicator set (e.g., landscape metrics) do not necessarily lead to high differences in the other (population distribution indicators). The second method calculates the correlation between two indicator sets. Correlation is often applied in urban form indicator studies (Schwarz 2010; Tsai 2005). We applied Spearman's rank correlation coefficient and only considered significant correlations ($p < 0.05$).

Hierarchical Partitioning

For a further understanding of population distribution indicators, we applied the hierarchal partitioning method to link population distribution indicators and other city characteristics (city profile variables, Table 1) using the R package 'hier.part' (Walsh and Nally 2015) with R^2 as a goodness-of-fit measure. The hierarchical partitioning method is an analytical multiple regression method that identifies the most likely causal factors while alleviating multicollinearity problems; i.e., it can calculate the effect of predictor variables independently of other collinear predictors (Olea et al. 2010). In a nutshell, hierarchical partitioning tries out all possible linear regression models and provides an overview of the variance explained by a single variable. This method is well suited for our study because different variables of the city profile are correlated. The independent effect of every city profile variable provided by the method can be understood as the share of explained variance explained solely by this factor, and a high effect indicates a strong relationship between indicator and city profile variable. However, due to the large number of individual regressions underlying the analysis on the one hand and the correlations among the city profile variables on the other hand, interpreting all single regression coefficients is not proper. Relationships between the most influential city profile variables and the population distribution indicators will instead be visualized and discussed using scatterplots or boxplots.

Results

Descriptive Statistics for All Indicators

The descriptive statistics for all indicators and maps of population distribution indicators are provided in the appendix. The coefficients of variation for indicators are high, which demonstrate the diversity of cities included in the study. The population distribution indicators show that no spatial pattern is visible for density gradient, Moran's I and Gini coefficient. The eastern cities in our data set have lower gross density values. In northern cities, the Newling model was more likely to not be fitted, i.e., these cities tend not to have a bump in the density profile.

Pairwise Comparison of Indicators' Value Distances

The "stars in the sky" pattern (Fig. 3) demonstrates that cities can be similar in terms of landscape metrics but very different regarding population-related indicators, and vice versa. The differences between the standardized values for the two indicator sets

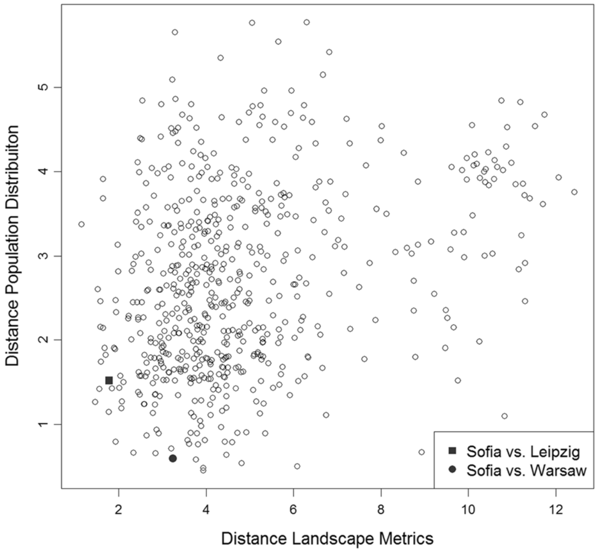


Fig. 3 Pairwise Euclidian distances for all city pairs, indicating their similarity in terms of landscape metrics and population distribution. All indicators were standardized. One dot represents one city pair and the summed Euclidian distance for each indicator group, respectively. The scale of landscape metrics distances is larger than that of population indicator distances because more landscape metrics than population-related indicators were calculated

become clearer when focusing on two exemplary pairs of cities: Sofia and Leipzig are more alike with respect to landscape metrics, while Warsaw is more similar to Sofia in terms of population distribution. The assertion that differences in landscape metrics are not related to differences in population distribution indicators can be further supported by visually comparing these three cities (Fig. 4, Table 3). Sofia and Leipzig look more alike with respect to large parks in the center, while Warsaw is characterized by many small parks and, subsequently, by rather scattered patches of urban area (second row of maps in Fig. 4). In contrast, population distribution is more similar between Sofia and Warsaw: both have a very high density in some of the central districts (Fig. 4, top row of maps) and a similar Gini and Moran's I coefficient.

Correlation between Indicators

Correlations were analyzed to more thoroughly examine the different relationships between all indicators. The correlation matrix (Fig. 5) shows strong correlations (59 significant correlations out of 105 pairs, 53%) among the landscape metrics, in agreement with other indicator studies (Bhatta et al. 2010; Schwarz 2010). At the same time, correlations among population distribution indicators are relatively weak (3 significant correlations out of 10 pairs: 30%). One remarkable observation is that population density has a negative correlation with the Gini coefficient. This means that when population density is high, the population is more likely to be unevenly distributed.

With the exception of the Gini coefficient and population density, all other population distribution indicators have very weak correlations with most landscape metrics (With Gini coefficient and population density: 30 significant correlations out of 75

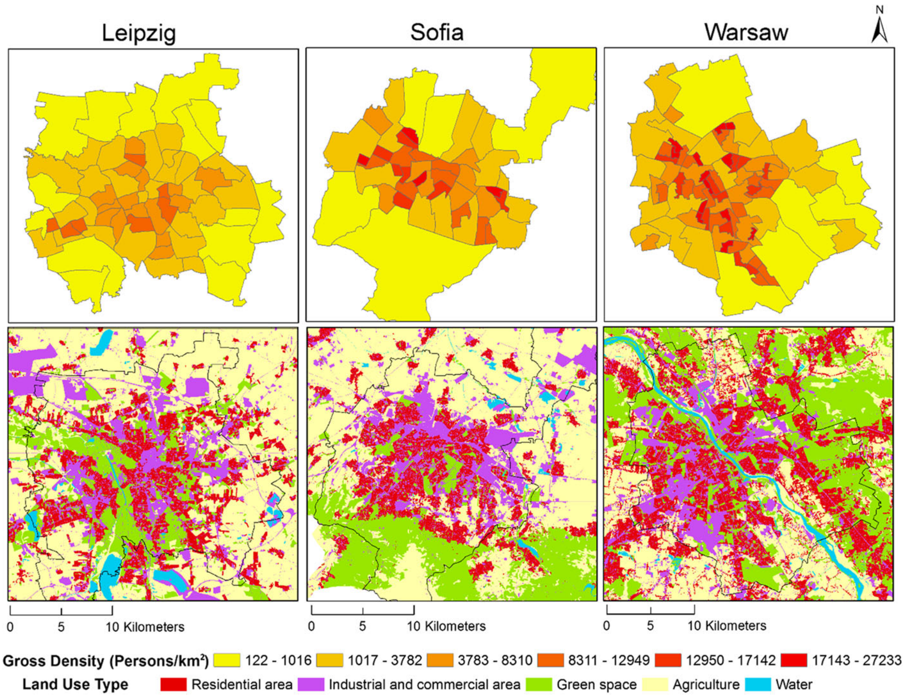


Fig. 4 Population distribution maps (*above*) and land use maps (*below*) of Leipzig, Sofia and Warsaw

pairs: 40%; without Gini coefficient and population density: 7 out of 42 pairs: 16%). The negative correlation between the Gini coefficient and population density accompanies the fact that their correlations with landscape metrics are similar, but in opposite directions. This result indicates that landscape metrics alone might not cover all important aspects of urban form.

Regression Results

Regression analysis was conducted using hierarchical partitioning to study the relationships between selected city profile variables and the population distribution indicators, with the aim of further characterizing this group of indicators. Table 4 gives the explained variance for all indicators and the independent effects of the city profile

Table 3 Population distribution indicators for Leipzig, Sofia and Warsaw (standardized data in parentheses, i.e. mean of all cities' values = 0 and S.D. = 1). Abbreviations are given in Table 2

	Leipzig	Sofia	Warsaw
DENGRA ($*10^{-4}$)	3.48 (1.34)	2.35 (0.14)	2.02 (−0.22)
MORAN	0.05 (−0.54)	0.01 (−1.37)	0.02 (−1.03)
GINI	0.48 (1.14)	0.44 (0.79)	0.42 (0.48)
POPDEN (person/km^2)	1223 (−0.69)	2426 (−0.47)	3266 (−0.32)
FIT	1	1	1

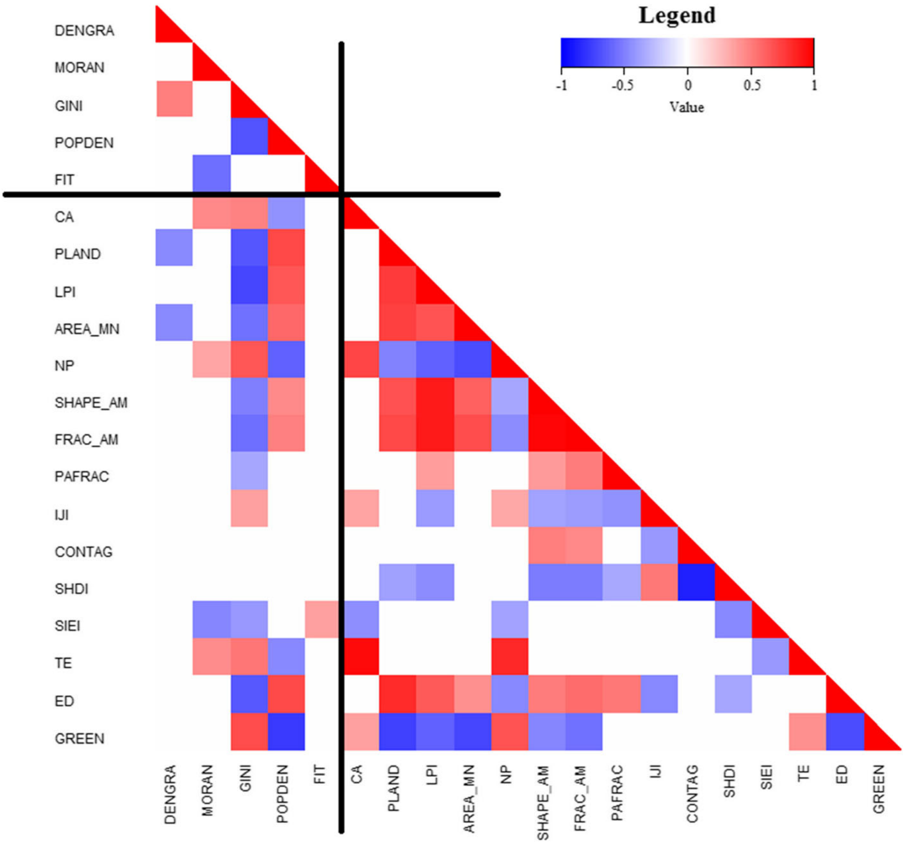


Fig. 5 Correlation matrix for population distribution indicators and landscape metrics. Red indicates positive correlations, while blue indicates negative correlations. Intensity of color represents the degree of the correlation. Correlation values with $p > 0.05$ are excluded (white). Abbreviations are given in Table 2

variables. Figure 6 visualizes the relationships between population distribution indicators and those city profile variables with independent effects greater than 0.1.

A considerable amount of variance (between 24% and 65%) in population distribution indicators can be explained using the city profile variables. If we look at the independent effects of each city profile variable, there are several interesting findings:

Table 4 Independent effects of city profile variables on population distribution indicators

Independent effects of city profile variables							
Population distribution indicator	Coast	GDP	Planning	Longitude	Latitude	Elevation difference in the buffer area	Total R^2
Density gradient	0.2	0.04	0.17	0.03	0.11	0.03	0.38
Moran I	0.02	0.07	0.09	0.003	0.05	0.01	0.24
Gini	0.03	0.04	0.19	0.11	0.03	0.05	0.45
Density	0.13	0.10	0.22	0.01	0.15	0.05	0.65
fit	0.16	0.01	0.06	0.004	0.01	0.04	0.28

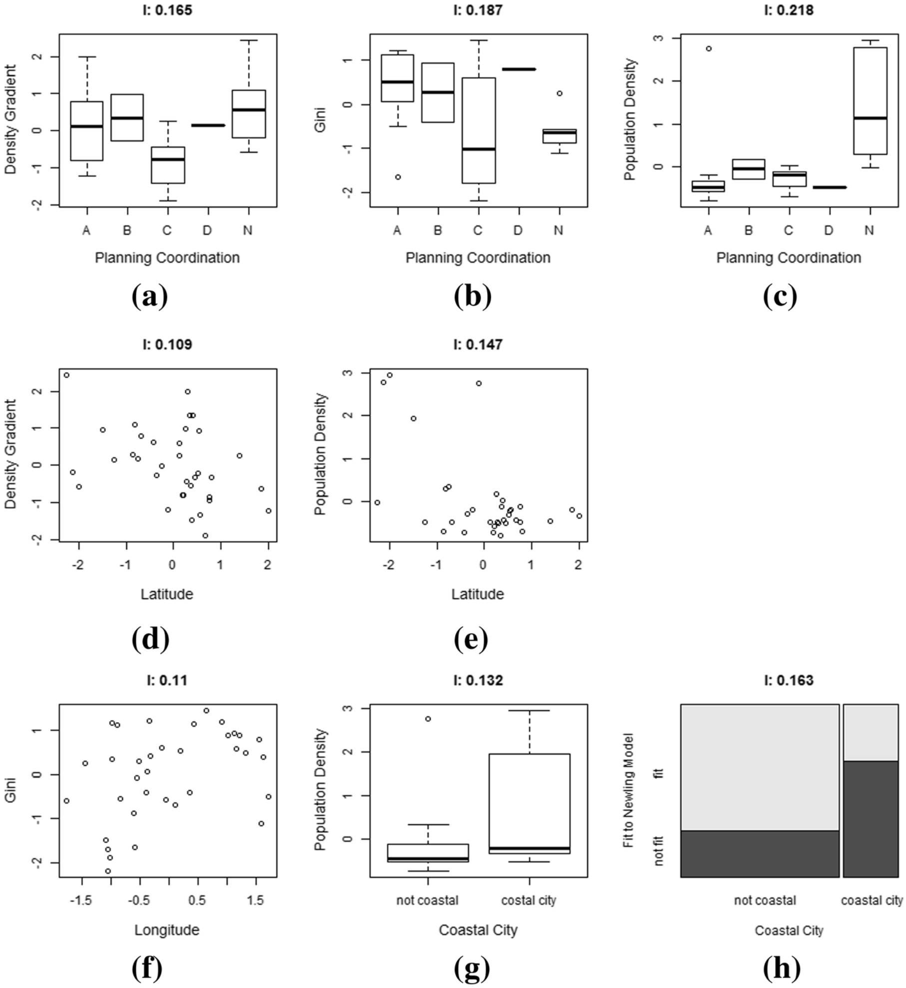


Fig. 6 Visualization of the relationship between city profile variables and population distribution indicators for those with independent effects larger than 0.1. I values are the independent effect of the respective variable. Values of metric variables are standardized for comparability

1. The planning structure has the highest explanatory power of all city profile variables for all population distribution indicators. The density gradient, the Gini coefficient and gross density are the three indicators with the highest independent contributions from planning (Fig. 6a–c, respectively). The density model (Fig. 6c) is remarkable because cities within class N ("Not classified in the comprehensive integrated approach," i.e., with an urbanism tradition) are characterized by much higher density than the other cities.
2. Latitude plays an important role for population distribution indicators. In our samples, we could see an increasing trend in the density gradient and a decreasing trend in the population density with increasing latitude. This means that high-latitude cities in our sample have a steeper density gradient (indicating more compact cities) and a lower gross density than low-latitude cities.
3. The Gini coefficient has a positive correlation with longitude.

4. Coastal cities have a higher gross density than non-coastal cities.
5. A larger share of coastal cities does not show a population distribution pattern that follows Newling's assumptions.
6. GDP does not have a high independent contribution to population distribution indicators.
7. The indicator that could be explained best by these city profile variables is gross density; Moran's I, in contrast, has the lowest R^2 in all regressions.

Discussion

We analyzed the relationship between landscape metrics and population distribution indicators to describe urban form. As one of two strands of urban form indicators, landscape metrics have received more attention in European urban studies than have population distribution indicators. Considering the potentially important role of population distribution (Linard et al. 2012), we hypothesized that the population distribution indicators could potentially show other additional aspects of urban form. By calculating landscape metrics and population distribution indicators for 35 European cities, we could confirm our assumption that landscape metrics and population distribution indicators do not reveal the same information on urban form. A subsequent regression analysis of the relationship between population distribution indicators and other basic city properties (the 'city profile') yielded interesting relationships and helps to further characterize and better understand the family of population distribution indicators.

Added Value of Population Distribution Indicators

The "stars in the sky" pattern in the pairwise distance comparison plot for the two indicator sets shows that two cities which are similar to each other in landscape metrics are not necessarily similar in population-related indicators and vice versa. An example using the urban form of three cities (Leipzig, Sofia, and Warsaw) intuitively illustrates the difference between landscape metrics and population distribution indicators. The three cities were chosen because they are similar to each other in one indicator set: Sofia is similar to Leipzig in terms of landscape metrics and Sofia and Warsaw are similar with respect to population distribution indicators. To explain the similarities within these three cities, we checked the locations and maps of these cities. Sofia and Warsaw are more similar to each other in terms of their location (Eastern Europe) and are both capital cities, which could relate to their similarity in terms of population-distribution indicators. Leipzig and Sofia are similar to each other in landscape metrics compared to Warsaw because of the large green space in the middle of the city. Moreover, there is a major river (Vistula) passing through Warsaw, which is not the case for Leipzig (which has only small rivers) or Sofia.

Relationships among Separate Indicator Sets

Our correlation results confirm previous findings that landscape metrics are correlated among themselves (Bhatta et al. 2010; Schwarz 2010). Correlations are generally weaker among population distribution indicators. However, we find a negative correlation between population density and the Gini coefficient. Our results for European cities are in line with Tsai's (2005) results, which showed negative correlations for 219 US metropolitan areas. However, the correlation is much stronger in European cities (−0.67) than in US cities (−0.097). The stronger correlation indicates that in Europe, denser cities tend to have a higher likelihood that the population is distributed unevenly among the districts. The Gini coefficient is also positively correlated with the density gradient. This indicates that the less even the distribution of people in a city, the more likely that city is to have a high density gradient. This phenomenon is likely be caused by a concentration of population in the central districts of these cities.

There are few correlations between landscape metrics and population distribution indicators, which are mostly found between the Gini coefficient and population density. Although the correlations cannot be ignored, there are more indicator pairs between the two indicator sets without any significant correlation. This finding suggests that the two indicator sets quantitatively capture different aspects of urban form. This is in line with the study by Schwarz (2010), which, in a procedure to reduce the number of indicators and find a minimum set of indicators to quantitatively describe urban form, excluded only two indicators because of correlations between landscape metrics and population distribution indicators. Like our study, the Schwarz (2010) study found a weak relationship between the two indicator sets, although there are some different indicators applied in the two studies and the study purposes are not exactly the same. In Kasanko et al. (2006), European cities clearly showed different rankings when ordered by compact or loose urban structure versus high or low population density, which also indicates the weak correlation of land use and population density. Torrens (2008) does not have a direct comparison of population distribution indicators and landscape metrics, but the suggestions of using multidimensional character of cities hints the fact that the two indicator sets describe different aspects of cities.

The population density gradient correlates very little with all other indicators in our study, including landscape metrics and other population distribution indicators, and thus is likely to provide a unique perspective in terms of urban sprawl/compactness, which all other indicators cannot offer. Moreover, the low correlation between the ability to fit the Newling model and landscape metrics means that established landscape metrics cannot capture patterns such as a bump shape in population density, with low population density in the city center. This finding clearly demonstrates the unique value of this new indicator.

In summary, many of population distribution indicators are not strongly related to landscape metrics and thus measure an additional aspect of urban form. A quantitative description of population distribution within a city cannot be captured when evaluating landscape metrics alone. Landscape metrics capture the spatial, two-dimensional layout of built structures in a city. Therefore, information on population distribution clearly provides additional value to studies on urban form.

Explaining Population Distribution with the City Profile

To gain better insight into population distribution indicators that are omitted in the majority of European urban form studies, we conducted a regression analysis between city profile variables and population distribution indicators. The results reveal that information in city profile variables is associated with population distribution indicators. At least 24% of the variance in all population indicators could be explained by the chosen city profile variables. Among all of the population distribution indicators, population density is the one that can be best explained by city profile variables. In contrast, the elevation difference of surrounding areas is most weakly related to the population distribution indicators.

Among all of the city profile variables, planning coordination has the highest independent effect, indicating a strong influence on the population-related urban form. Cities in countries with an urbanism tradition (see below) clearly have much higher population densities than do other cities. In Fig. 6d, we saw that southern cities also have higher densities than other cities. This result confirms findings by Kasanko et al., (2006), who also noticed the more compact structure in southern European cities. We think that the higher density of southern European cities is at least partially due to their urbanism tradition (Category N in the ESPON categorization), with its focus on building regulations. Our results did not identify cities in the South with low population densities, in contrast to findings by Schwarz (2010), who also found many cities with low population density in the south. The limited data in our study set is the reason for this difference. Another notable finding is that cities with mainly horizontal coordination (category C) tend to have a flatter population density gradient and lower Gini coefficient, which could be an indication of stronger urban sprawl. However, confirming this assumption would require observing these patterns over time. The predominant horizontal coordination in spatial planning may lead to less effective planning from higher authorities and probably even competition between authorities at the same level. All of these effects could potentially lead to urban sprawl or at least a less effective control of sprawl. From these two examples, we can see clearly that planning coordination structure has an effect on population-related urban form. However, the directions of single effects and the detailed mechanisms behind them could not be fully resolved here and should therefore be subject to further study.

The independent effects of other city profile variables demonstrated that these variables have important effects on population-related urban form. First, Kasanko et al. (2006) believed that coastal or mountainous locations create very different development options than locations on a plain or along a river. We tested this statement by using the indicators of 'coastal location' and elevation difference as a proxy for the presence of physical barriers to city growth, such as mountainous regions in the surrounding area. The results show that coastal location has an impact on population density and the ability to fit the Newling model. Specifically, population density curves of non-coastal cities are more likely to exhibit the bump shape than those of coastal cities. This is likely because a non-coastal city can develop in all directions, which is closer to the assumption of the monocentric model. Therefore, one should be careful when applying a monocentric model to coastal cities. The same logic could apply to cities located at a lake shore or an international border. Second, and rather surprisingly, the mountainous location has a very small impact on the density model. This somewhat contradicts our findings regarding coastal cities, as both coast and mountains can be seen as physical barriers. The different result for mountainous locations could hint at an inappropriate quantification of physical barriers using the elevation difference which does not differentiate between continuous gradients and distinct cut-offs, or from advanced engineering that decreases the difficulty of physical obstacles like hill slopes. Third, Huang et al. (2007) found a moderate negative correlation between the GDP per capita and population density. On the contrary, Schwarz (2010) found a positive relationship between density and GDP per capita. Here, we cannot see any significant effect of GDP on urban form.

Limitations of the Study and Future Research

We are aware of several limitations of our study. First, the sample of cities is biased, on the one hand towards large cities because we excluded cities with less than 30 sub-city districts in the Urban Audit dataset so that we could calculate the density gradient and the Newling model in a robust way. On the other hand, most of the cities in the study are still experiencing population growth, even though there is a considerable number of shrinking mid-sized and small cities in Europe that would be worth taking into account. Second, we used administrative boundaries for cities in our study because population data were only available within these areas. However, the LUZ boundary is a delineation of cities which could better reflect the functional areas (Vliegen 2007). Third, the sub-city districts differentiated in the Urban Audit database are relative large (5000–40,000 inhabitants), so that depending on the city, considerable within-district variation might be present in terms of population distribution. Fourth, current data constraints imply around 3 years' time difference between population data and land use maps.

Considering these limitations, the access to fine-grained data is still one of the major problems for comparative urban form analysis in Europe, as data availability and data quality are crucial to this type of comparative analysis. Thus, improving the database would be a major step forward for future studies. Providing population data at a finer scale (i.e., more districts in cities so that small and mid-sized cities would not be left out) and LUZ data could offer a better chance to study population distribution indicators for Europe in depth and improve the credibility of our study. This holds even more for fine-grained data on employment to further increase the comparability with US studies. Moreover, the calculation of urban form indicators over time could reveal the dynamic of urban form, which could help us to obtain more insight into urban form indicators and their (inter-) relations. Such studies could, for example, check whether they can confirm the correlation of landscape metrics and population distribution evenness (Gini coefficient). Finally, repeating this analysis for other parts of the world except Europe and the US could further strengthen the findings regarding the influence of city profile variables, such as spatial planning, on population distribution.

Urban Atlas provides a great data source for urban land use study and the calculation of landscape metrics. Data in Urban Audit, as its counterpart for population data, is not as detailed or complete as Urban Atlas. GEOSTAT (Eurostat 2006), as a grid-based, pan-European population database, will ease the calculation of population distribution indicators. However, in GEOSTAT, population data in some countries do not stem from original surveys but is instead derived from land use maps (hybrid data). Because we learned from our results that land use maps and population distribution are not strongly correlated one should, however, be very cautious when using population data derived from hybrid data. Moreover, landscape metrics can only capture a two-dimensional view of built structures within a city. The third dimension, building height, is not accessible with classical remote sensing products for land cover and land use. Emerging data sets offer the possibility of also investigating building heights in cities (Wurm et al. 2014), which would offer promising possibilities for further studies. Thus, future research should also analyze the third dimension of urban form in comparison with population distribution indicators and ask whether building height more efficiently captures information about population density gradients and population distribution than 2D land cover and land use data.

Conclusions

Urban form, as a reflection of activities in the urban area, plays an important role in urban studies, and there has been a trend of quantifying urban form in the last two decades (Clifton et al. 2008). Between two major sets of urban indicators, landscape metrics describing the physical structure of a city and population distribution indicators describing the distribution of the population, the latter are often neglected in European studies of urban form because of difficulty in data acquisition. In our study, we quantified urban form in 35 European cities using the most common indicators from both groups. By comparing the indicators' correlations, we found that landscape metrics correlate only weakly with some of population distribution indicators. A regression analysis that aimed at understanding the information underlying population distribution indicators showed that these indicators are related to some other characteristics of cities, such as planning coordination and their location (city profile). These findings emphasize the importance and potential of including population distribution indicators in studies on urban form, also in Europe. Our comparative study between two major sets of urban form indicators clearly shows that population distribution indicators provide information complementary to landscape metrics. Therefore, they should not be ignored in the application of urban form indicators. We could also see that population distribution indicators depict the diversity of urban form in Europe. For example, for the gradient we find a large range of values (the highest population density gradient is 10 times as the smallest); the ability to fit the Newling model indicates different population distribution patterns around the central city area. Finally, the regression study shows that city profile information can explain population distribution indicators to some extent. For example, types of national planning regime have a strong influence on urban form as quantified with population distribution indicators. This implies that urban form, as described by population distribution indicators, is diverse, but also accords well with important city characteristics. In summary, using landscape metrics alone does not provide a complete picture of urban form. In future studies, we recommend also using population distribution indicators more frequently in Europe, especially for studies related to places of residence and resultant mobility of people, for example focusing on transportation or residential mobility. To allow for the consideration of population distribution indicators in future studies, better spatially explicit population data must be provided in Europe, and thus, enable an easy and comprehensive urban form measurement.

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