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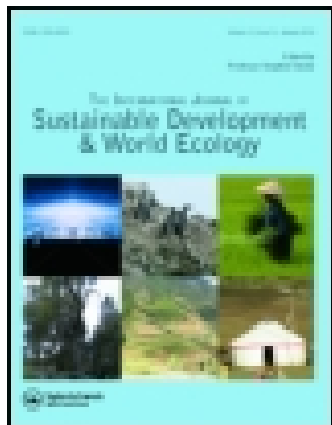
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The well-being of nations: an empirical assessment of sustainable urbanization for Europe

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The current integrity of the planet is being stressed beyond its biological capacity, and understanding urban landscapes is more important now than ever. A major landmark in human–planetary evolution was reached recently with a majority of people now living in cities, and rural-to-urban migration is predicted to continue into the next century. Landscape change associated with exponential population growth poses major challenges to coupled human and natural systems. Although some progress has been made, to date there exist no ‘ideal’ instrument for achieving sustainability on neither regional nor local scales. Because there is limited applied evidence investigating landscape form (e.g. configuration) and population dynamics (e.g. population density) with measures of sustainability, this research area requires further investigation. Using Human Wellbeing Index (HWI) and Ecosystem Wellbeing Index (EWI) from Robert Prescott-Allen’s *The Wellbeing of Nations: A Country-by-Country Index of Quality of Life and the Environment*, a macroscale empirical study was created to further understand sustainable urban development across 33 European countries. Exploratory spatial data analysis was utilized to illustrate Wellbeing clusters across the study area, and spatially enabled regression methods were employed to create regional sustainable urbanization models for explaining Wellbeing indices. With population density, two urban class configuration metrics (e.g. COHESION, PD) were found significant at explaining both HWI and EWI. Between 2000 and 2006, changes in urban morphology and population density were also assessed for 31 of the aforementioned 33 European countries. Findings suggest that conventional urbanization processes will continue to disconnect socioeconomic welfare from life-supporting ecosystem services.

Keywords: applied sustainability science; landscape change; landscape ecology; macroscale ecology; sustainable development planning; spatial autoregressive modeling; spatiotemporal analysis; urban configuration

1. Introduction

Anthropogenic stressors to Earth’s life-supporting ecosystems will continue to increase as global human population increases. During the 1987 World Commission on Environment and Development, the Brundtland Commission’s report, *Our Common Future*, confirmed that global population had surpassed its ecological carrying capacity. Carrying capacity is the largest number of any given species (e.g. *Homo sapiens*) that a habitat (e.g. Earth) can support indefinitely (Keiner 2005). Humankind’s resource demands, measured by ecological footprint (EF) at the global scale, now surpasses the planet’s natural biocapacity by roughly a 50% overshoot; furthermore, the consumption rate of sea and land resources has been projected to require two Earths by the 2030s (WWF 2014). Humanity’s population has grown exponentially since the Industrial Revolution of the late 1700s (Wu 2008), and some continents (e.g. Africa) will likely see this geometric growth into the next century. Recently, with an 80% probability, world population was projected to increase to between 9.6 and 12.3 billion by 2100 and likely continue growing thereafter (Gerland et al. 2014). These findings refute previous studies (i.e. Lutz et al. 2001; UN 2004) that total global

population growth would stabilize just over 9 billion by 2100.

The ecological integrity of the planet is stressed far beyond its limits (WWF 2014), thus understanding human-dominated landscapes is more important now than ever. Specifically, the transition from the natural/native landscapes to urban landscapes is having the greatest impact on Earth (Wu 2010). Metabolization of natural habitat for human need has resulted in fragmented landscapes that are increasingly vulnerable to anthropogenic disturbances (Leu et al. 2008). It has been commonly accepted that human impacts are not limited to a single area, as disturbances influence multiple ecosystems’ great distances from their initial establishment (Turner et al. 2001; Alberti 2008). The metabolization of healthy and ecologically intact landscapes to support human needs has been consistently recognized as one of the most unsettling of all human activity (Foley et al. 2005; Liu et al. 2007). Landscape change influences natural systems across spatial and temporal scales by fragmenting landscape patches, isolating habitats, abridging ecosystem dynamics, introducing exotic species, controlling and modifying disturbances, escalating climate change, reducing global biodiversity, altering hydrological cycling, and disrupting

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nutrient cycling and energy transfer (Alberti 2005, 2008; Foley et al. 2005; Hoegh-Guldberg et al. 2007; Liu et al. 2007; Grimm et al. 2008; Milly et al. 2008; Pickett et al. 2011).

Increasingly, sustainability scientists have focused on understanding the complex dynamics that result from coupled environmental and human systems (Clark 2007). Landscape ecology, a practice for understanding relationships between geographical patterns and ecological processes across temporal and spatial scales (Wu & Hobbs 2007), has become the focal discipline for operationalizing sustainable development (Wu 2008). Landscape ecology and sustainability science are both concerned with the complex interactions between society and nature (Clark & Dickson 2003; Reitan 2005). Further, they are both devoted to solution-driven and place-based research that integrates all three facets of sustainability (economic welfare, environmental quality, and social equity) across local, regional, and global scales (Wu 2008). Evaluation, or calibration, of landscapes can be provided through existing measures of sustainability, and are vital for assessing landscape functions for sustainable development purposes (Mander & Uemaa 2010). Evaluation indices convey a rapid single-number impression of site characteristics that are used widespread in ecological and landscape ecological studies (Spellerberg 1992). Indicator-based assessment of landscape function provides a fundamental method for modeling relationships during sustainable landscape planning (Leitão & Ahern 2002; Mander & Uemaa 2010). Although landscape ecology research has focused on sustainability goals, there remain limited modifications to sustainable development policy or to sustainable land use decision-making (Naveh 2007).

The existing challenges of sustainable development remain in its operationalization (Keiner 2006). Effort must be made for the application of initiatives that do not merely pay lip service to the words, but earnestly do justice to its conceptual roots (e.g. sustainable yield) (Campbell 2000). Modeling, assessment, and monitoring of coupled human–environmental systems can be accomplished through the use of landscape ecology metrics within various spatial science tools (e.g. GIS) (i.e. Shaker et al. 2010; Shaker & Ehlinger 2014). For applied environmental management and planning purposes, landscape pattern studies have revealed ecological associations to urbanization through use of evaluation indices (i.e. Shaker & Ehlinger 2014). Recently, several analyses have been successful at using landscape ecology metrics to assess the spatiotemporal dynamics of urbanization (i.e. Weng 2007; Shrestha et al. 2012; Su et al. 2012). Albeit, progress has been made at elucidating dynamic pattern on process, the age-old question of what the ‘optimal’ urban form remains as open as it has ever been (Batty 2008).

An empirical study is presented hereafter to investigate if recent urbanization trends move us closer to, or farther away from, sustainability. Specifically asked: (a) how does the urban mosaic at the macroscale help to explain measures of sustainable development across 33 European

countries and (b) can those statistical associations be used to elucidate findings from an urban landscape change analysis for 31 of the aforementioned 33 European countries between 2000 and 2006. To address these questions, three null hypotheses are tested: (1) no significant relationship exists between urban landscape form and population characteristics and Human Wellbeing Index (HWI) across Europe; (2) no significant relationship exists between urban landscape form and population dynamics and Ecosystem Wellbeing Index (EWI) across Europe; and (3) recent European urbanization trends do not move us closer to global sustainability. This research aims to help operationalize sustainable development through expanding scientific understanding, and by providing methods for modeling and monitoring sustainable urbanization across macroscales.

2. Study area

This empirical analysis of sustainable urbanization focuses on 33 countries within Europe (Figure 1). Several attributes of this region make it an optimal location for this research. Europe, one of the world’s seven continents, is recognized as the birthplace of Western culture and urbanization. Urbanization is a fundamental characteristic of European civilization, and has progressively spread from the Southeast around 700 B.C. to the whole continent (Antrop 2004). Europe, the second smallest continent by surface area, is divided from Asia by the watershed divisions of the Caucasus and Ural Mountains, the Ural River, the Caspian and Black Seas, and the waters linking the Black and Aegean Seas (Ostergren & Le Bossé 2011). Countries, like ecoregions, are areal units defined by a combination of similar geographic characteristics (e.g. geology, vegetation, beliefs, language), which have a mature history spanning centuries for any of the study area nations. Encompassing roughly 6.8% of Earth’s land area, Europe has the highest country and population densities of all continents. Although some nations are in population decline, approximately 11% (2010) of the world’s population remains in Europe, where four out of five residents dwell in urbanized regions (EC 2006). Total population specific to the study area countries is above 560 million (2012).

The 33 independent nation-states were chosen from the approximate 50 encompassing the continent of Europe. Nation-states were included in this study if they were dually represented in Prescott-Allen’s (2001) *The Wellbeing of Nations: A Country-by-Country Index of Quality of Life and the Environment*, and the circa 2000 land cover data set put forth by the European Union’s coordination of information on the environment (CORINE). The 33 European countries are mostly contiguous, minus the Russian lands between Lithuania and Poland, the territories making up Kosovo, Montenegro, and Serbia, and Switzerland. Exclusive to the study area, the combined sovereign states or dependent territories cover about 5.8 million km². Lastly, European nations

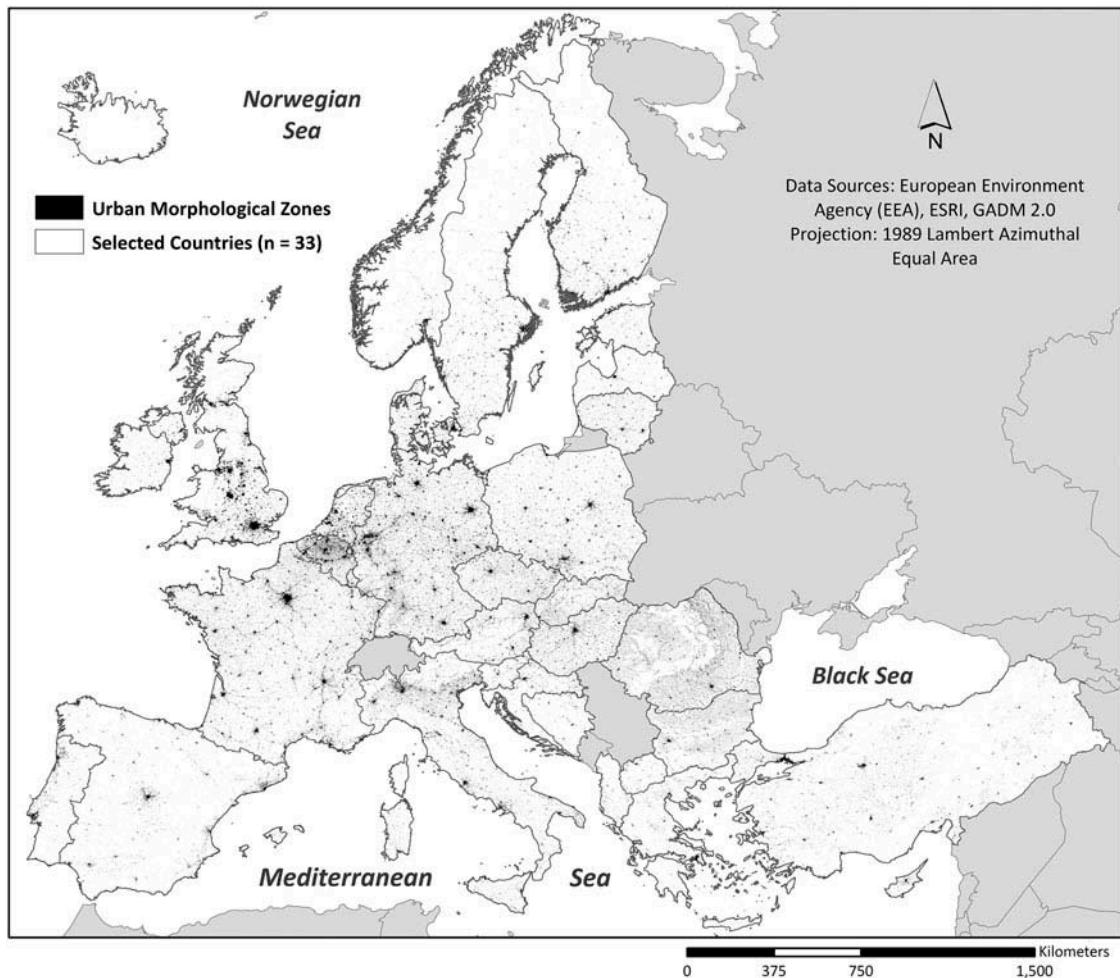


Figure 1. Study area countries displaying CORINE Urban Morphological Zones (UMZ) for 2000.

can be recognized for starting the modern sustainable development movement, and it can be contended that European nations continue to lead the endeavor.

3. Materials and methods

3.1. Wellbeing of nations' indices

Indicators are progressively acknowledged as useful tools for planning and policy-making because they deliver evidence on a nation's progress toward their individual targets within the three subareas of sustainability (Shaker & Zubalsky 2015). Over two decades have passed since Agenda 21 petitioned for sustainable development indicators; however, there remains no agreement concerning the best approach to their use or design. For this study, it is believed that sustainable urban development is best assessed if the three facets of sustainability (economic welfare, environmental quality, and social equity) are organized independently into either socioeconomic or environmental conditions. In doing so, the ensuing analysis uses HWI and EWI from Robert Prescott-Allen's (2001) *The Wellbeing of Nations: A Country-by-Country Index of*

Quality of Life and the Environment, as landscape evaluation metrics.

The 33 study area countries were selected partially by *Wellbeing of Nations* representation; furthermore scores range from 24 to 82 and 20 to 49 for HWI and EWI, respectively (Figure 2). Both multi-metric sustainable development indices scale between 0 and 100, with increasing values corresponding to improved sustainability condition. Additionally, index scores have been divided into five equal groups to provide a narrative scale of well-being: good (100–81), fair (80–61), medium (60–41), poor (40–21), and bad (20–1) (Prescott-Allen 2001). Across the 180 nations, only Denmark, Finland, and Norway have a 'good' HWI. Of the 180 countries surveyed, 48% had a 'poor' or 'bad' EWI; 9% were 'fair,' and none scored 'good.' Source data for Wellbeing indices were collected between 1997 and 1999. HWI includes more socioeconomic input variables than many other popular human-focused sustainability measures (e.g. Human Development Index). HWI is the equally weighted average of 36 metrics across the following five categories: health and population [2 indicators]; wealth [14 indicators]; knowledge and culture [6 indicators]; community [10 indicators]; and equity [4 indicators] (Prescott-

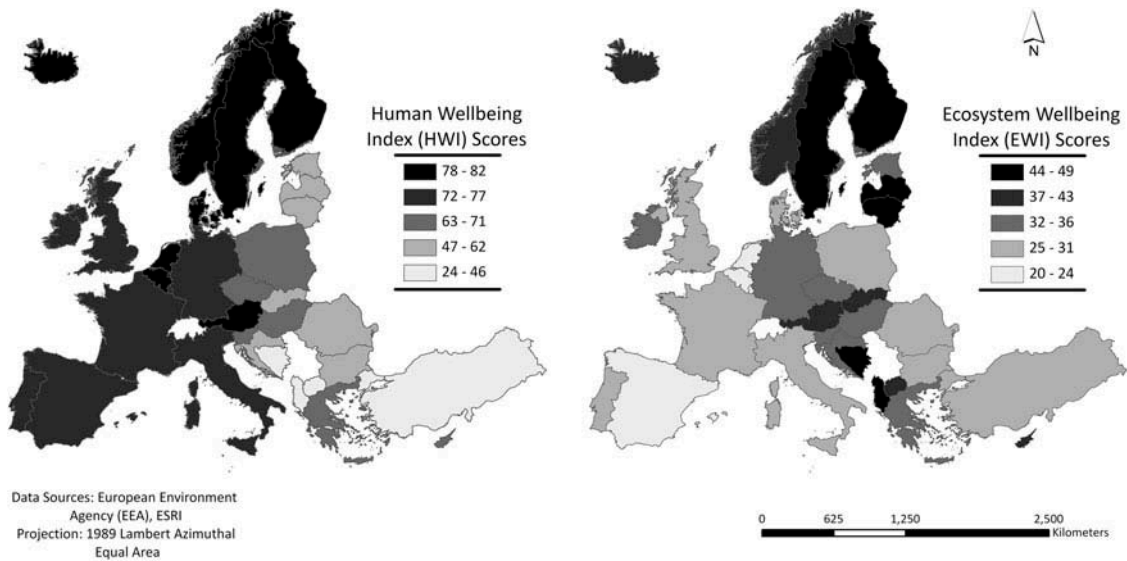


Figure 2. Relative distribution of Human Wellbeing Index (HWI) and Ecosystem Wellbeing Index (EWI) scores for the 33 study area nations.

Allen 2001). EWI is a comprehensive measure of environmental condition, and is more holistic in its evaluation than many other popular environmentally focused sustainability measures (e.g. EF). EWI is the equally weighted average of 51 metrics across the following five categories: land [5 indicators]; water [20 indicators]; air [11 indicators]; species and genes [4 indicators]; and resource use [11 indicators] (Prescott-Allen 2001). For the 33 study area countries, a Pearson product-moment correlation coefficient test (two-tailed) rendered HWI and EWI statistically independent ($r = -0.24$, $P = 0.170$). Although the single number scores of HWI and EWI effectively describe socioeconomic or environmental condition of sustainability, and could be used for temporal monitoring and management, the Wellbeing Assessment has only been calculated once.

3.2. Landscape data

Patterns of urbanization were quantified at the country scale using key population and land cover data sets across Europe. *Population dynamics data* for 2000 and 2006 were obtained from the European Union's Eurostat, the United States Central Intelligence Agency World Factbook, or a country's unique census program. *Territorial boundary data* for each nation were sourced from the GADM (ver. 2) database of Global Administrative Areas (www.gadm.org). Each country should be considered as its own landscape for this study. From these data, the following seven population dynamics variables were derived for each country: area, perimeter, total population, population density, number of cities with population greater than 250,000, and number of cities with population greater than 500,000. Ideally, urban population density would have been included within this analysis but those data were not readily available for all study area countries.

Urban form data came from 2000 (ver. 15) and 2006 (ver. 15) CORINE land cover (CLC) data administered through the European Environmental Agency (EEA). The EEA, beginning operations in 1994, is an organization of the European Union for providing robust, objective information on the environment. The EEA's mandate is to help the European Community and its collaborating territories make educated decisions about improving environmental integrity, integrating environmental needs into economic policies, and moving towards sustainability. 2000 CLC data were interpreted from Landsat-7 ETM imagery for 32 participating nations circa 2000 (± 1 year), and 2006 CLC data were construed from IRS LISS III and/or SPOT-4 for 38 nations circa 2006 (± 1 year) (EEA 2007). The following basic parameters are the same for both CLC2000 and CLC2006: choice of scale of 1:100,000, a minimum mapping unit of 25 hectares, and minimum width of linear elements of 100 m. CLC data are provided through either a 100-m or 250-m seamless raster database. The standardized CLC nomenclature includes 44 land cover classes grouped into three hierarchical levels; furthermore, both CLC2000 and CLC2006 data sets have a geometric accuracy better than 100 m and thematic accuracy greater than 85% (Büttner & Maucha 2006; EEA- European Environment Agency 2007).

Specifically, this study uses only the predefined 100-m data sets known as urban morphological zones (UMZs) for 2000 and 2006 created from CLC2000 and CLC2006, respectively. UMZ describe the urban tissue of an area by reclassifying several urban impacted land cover classes, which are less than 200 m apart, into a single class data set (Simon et al. 2010). *Urban proportions* (composition) and *patterns* (configuration) were quantified from CORINE UMZ data sets with landscape ecology metrics established for quantifying

the heterogeneous mosaic of land use and land cover (Turner et al. 2001; Leitão et al. 2006; McGarigal et al. 2012). FRAGSTATS version 4.1 (McGarigal et al. 2012), free and publicly available software, was used for calculating land cover compositions and configuration for each country landscape. During landscape processing, UMZ data were preserved at 100 m resolution, and queen contiguity was selected for class-level metric calculation. As there remains no minimum set of landscape ecology metrics for capturing the majority of landscape structure (Wagner & Fortin 2005), 50 UMZ class metrics were calculated for multivariate reduction into a highly relevant subset.

3.3. Data analysis

This study emphasized the importance of investigating coupled human–environmental systems at macroscales. ‘Macroscales,’ extents larger than landscapes, can be defined as regional or continental scales with distances spanning hundreds to thousands of kilometers (Urban et al. 1987). At these extents, the biological (e.g., species, population, communities), geophysical (e.g. climate, physiography, hydrology, geochemistry), socioeconomic (e.g., cultures, economics, political systems) components of Earth synergize into ‘macrosystems,’ and many environmental problems have their causes and consequences at these geographic scales (Heffernan et al. 2014). A spatially enabled method was constructed to systematically analyze, model, and monitor sustainable urbanization through space and time using a five-step process. To meet the normality requirement for parametric tests, non-Gaussian distributed variables were transformed using common methods. The Shapiro–Wilk normality test was used to

determine if transformation was needed, and which mathematical operation was most effective per variable.

First, the multivariate statistical methods, principal components analysis and correlation coefficient (r) analysis, were used to reduce UMZ landscape measures. UMZ class metrics with strongest loadings on orthogonal axes were kept. The seven previously established population characteristic and 24 remaining landscape metrics were then reduced further using Pearson’s correlation analysis, to remove metrics that exhibited a high degree of collinearity ($r > 0.75$). When statistical redundancy occurred between two predictor variables, the metric with natural Gaussian distribution, literary justification, and statistical relevance to both HWI and EWI was chosen.

Second, a priori regression models were developed to test the first two hypotheses. The remaining urban landscape variables were modeled against HWI and EWI through standard ordinary least squares (OLS) multiple regressions, refined within a multimodel selection framework (Burnham & Anderson 2002; Diniz-Filho et al. 2008). All conceivable models that could be acquired by combining five predictors (Table 1) were produced (i.e. 31 for both HWI and EWI), and the Akaike weight (w_i) of each model was calculated; w_i is an Akaike Information Criterion (AIC)-derived index that reflects the probability that model i is actually the best explanatory model among all possible models (Terribile et al. 2009). Finally, a priori OLS models were compared and ranked based on their coefficient of determination (R^2) and corrected Akaike Information Criterion (AICc). As a preferred measure of model fit, the lower the AICc values the closer the approximation of the model is to reality; however, a ‘serious’ difference between two models is when the difference in AICc differs by at least three (Fotheringham et al. 2004). To measure the impact of multicollinearity, the variance

Table 1. Selected independent population and urban landscape variables.

Abbreviation	Name	Description	Justification
Pop. Density*	Population density	Number of people in the country, divided by total country area	A measure of human abundance
PLAND*	Percent urban morphological zone	Total urban morphological area in the country, divided by total country area	Composition measure
PD*	Patch density	Total number of urban patches in the country, divided by 100 hectares (#/100 ha)	Fragmentation index
COHESION*	Patch cohesion index	$0 \leq \text{COHESION} < 100$. Approaches 0 as the proportion of the country comprised of the urban class decreases, and becomes increasingly subdivided and less physically connected	A measure of physical connectedness
PROX_CV -- †	Proximity index coefficient of variation	The area sum of all urban patches whose edges are within a specific search radius of the focal urban patch, divided by the square of its distance from the focal patch	A measure of isolation/proximity

Notes: All landscape measures computed based on CORINE raster data with 100 m cells, and using 8-neighbor rule.

See Leitão et al. (2006) and McGarigal et al. (2012) for metric details and equations.

†Calculated using a search radius of 1 km.

--Denotes random spatial pattern.

*Denotes < 1% chance spatial pattern is random.

inflation factor (*VIF*) was assessed. *VIF* > 10 indicates definite problems of multicollinearity; *VIF* > 2.5 indicates potential areas of concern.

Third, for all remaining variables, the level of spatial autocorrelation was assessed using the common exploratory spatial data analysis (ESDA), global Moran's *I*-test. Spatial autocorrelation, the lack of numerical independence of an attribute across space, is frequently found in geographically managed and distributed data (Legendre & Legendre 1998). Spatial autocorrelation poses difficulties when using classical parametric statistical tests (e.g. ANOVA), because it violates the necessity of distributed error independence (Legendre & Legendre 1998; Haining 2003). Additionally, standard errors are likely underestimated when positive autocorrelation is present and Type I errors (incorrect rejection of a true null hypothesis) could be strongly inflated (Legendre & Legendre 1998; Dormann et al. 2007). Furthermore, spatial autocorrelation can cause a shift in regression coefficients depending on whether a global or local autoregressive approach is used (Bini et al. 2009). The existence of spatial autocorrelation is seen as a significant limitation for hypothesis testing and prediction (Lennon 2000; Dormann et al. 2007). Lennon (2000) called spatial autocorrelation in ecological studies 'red herrings' and contended that practically all analyses over space need to be reconsidered. Wagner and Fortin (2005) also suggested using analysis techniques that allow for scrutinizing residuals spatially. Further, Boots (2002) suggested when species (e.g. *Homo sapiens*) are impacted by numerous processes over their range, inference should be performed using locally enabled statistics. One benefit of spatial autocorrelation is that it can provide useful for assessing pattern relationships to process. To illustrate spatial clustering of HWI and EWI, the local index of spatial association (LISA) Anselin Moran's *I*-test was conducted using queen contiguity.

Fourth, to address errors associated with spatial autocorrelation in regression analysis, a local conditional autoregressive (CAR) technique was used. CAR is a spatial auto-Gaussian technique that corrects for errors in regression models (Wall 2004). CAR addresses spatial autocorrelation by estimating how much the response variable at any one site reflects response values at surrounding sites, which is achieved by adding a distance-weighted function of neighboring response values to the model's explanatory variables (Dormann et al. 2007). As in most multiple regression interpretation, the dominant autoregressive practice is to rank the standard partial regression coefficients (Sokal & Rohlf 1995) or associated *t*-values of coefficients of explanatory variables (Tognelli & Kelt 2004) under the assumption that higher coefficients represent stronger 'effects' on the dependent variable (Bini et al. 2009). Finally, CAR model residuals were assessed by global Moran's *I* statistic, histogram and spatial correlogram. Analyses were performed using ESRI's ArcMap 10.2 Spatial Statistics toolbox, JMP (ver. 11) (SAS 2013), and Spatial Analysis in Macroecology (ver. 4) (Rangel et al. 2010).

Fifth, to test the third and final hypothesis, a landscape change analysis was conducted on 31 of the aforementioned 33 study area countries. The United Kingdom and Greece were not assessed in the landscape change analysis because they were excluded from the CLC2006 data set. Urban landscape variables found statistically associated to both HWI and EWI during regression analyses were computed for 2006. Next, the average rate of change for each urban and population metric was calculated using the following equation (Su et al. 2011):

$$R = \sqrt{[n - 1] \frac{R_2}{R_1}} - 1$$

where *R* is the rate of urban expansion; *R*₁ is the capacity of urban landscape metric at the date *t*₁; *R*₂ is the capacity of urban landscape metric at the date *t*₂; and *n* is the difference of years between the two dates (in this case, six years between 2000 and 2006).

4. Results

4.1. Exploratory spatial data analysis

Taking all 33 countries' landscapes into account, Global Moran's *I* revealed varying levels of spatial autocorrelation for both the dependent variables and independent variables. Four out of the five independent variables recorded less than 1% chance of having a random spatial pattern (Table 1). ESDA reported HWI and EWI to be spatially dependent on their neighbors. The Global Moran's *I* score for HWI was 0.31, *z*-score = 6.15, and for EWI it was 0.20, *z*-score = 4.15. Thus, both dependent measures of sustainability urbanization had less than 1% likelihood, and their spatial distributions were the result of random chance. The LISA index, Anselin Moran's *I*-test, displayed clustering of HWI and EWI across the 33 European countries (Figure 3). Improved human welfare was centered around Denmark, and decreased levels clump Albania, Bosnia and Herzegovina, Bulgaria, Macedonia, Romania, and Turkey together. Improved ecosystem integrity bundled Norway, Finland, and Sweden together, while diminished condition bunched Belgium, France, Luxembourg, Netherlands, and Spain.

4.2. Global and local regression

The multimodel selection framework produced seven a priori models: three urban landscape models for predicting HWI across 33 European country landscapes, and four models for EWI (Table 2). Four variables were used in three OLS regression models to explain between 43% and 59% of HWI variation. Four variables were used in four OLS regression models to explain between 13% and 46% of EWI variation. *VIF* magnitudes ranged between 1.00 and 2.30 for all multiple regression models, thus the multicollinearity problem among independent variables was virtually nonexistent. The seven distinct models allow for

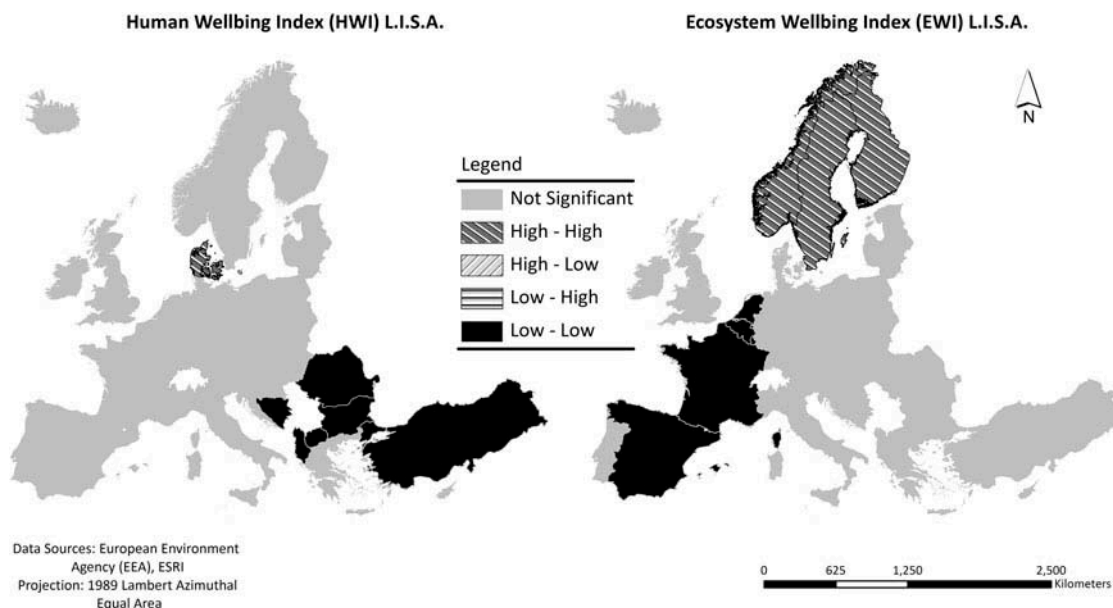


Figure 3. Local Anselin Moran's *I*-test index of spatial association illustrating clustering of Human Wellbeing Index (HWI) and Ecosystem Wellbeing Index (EWI) across the study area. Spatial autocorrelation determined using queen contiguity.

Table 2. Relationships between urbanization predictors and Wellbeing indices explored by OLS regression.

No	Dependent	OLS			OLS R^2	AICc value	OLS model sig.
		Std. beta coefficients regression					
1	HWI	+0.78 × (COHESION***)	-0.56 × (Pop. Density**)	+0.56 × (PD**)	0.59	248.37	***
2	HWI	+0.63 × (COHESION***)	+0.25 × (PROX_CV*)		0.47	254.84	***
3	HWI	+0.65 × (COHESION***)			0.43	254.15	***
4	EWI	-0.56 × (Pop. Density***)	-0.28 × (COHESION*)		0.46	216.17	***
5	EWI	-0.50 × (PD**)	-0.42 × (COHESION**)		0.38	220.62	***
6	EWI	-0.57 × (Percent Urban***)			0.32	220.93	***
7	EWI	-0.36 × (COHESION*)			0.13	229.26	*

Notes: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

Symbols enclosed in parentheses designate individual P -values.

HWI, Human Wellbeing Index; EWI, Ecosystem Wellbeing Index; OLS, ordinary least squares; COHESION, patch cohesion index; PD, patch density; PROX_CV, proximity index coefficient of variation.

a separation of independent variables that are correlated to socioeconomic or environmental conditions of sustainability.

The regression models clearly indicate that population density and configuration of UMZs are good predictors of sustainability at a macroscale. When combined with urban configuration metrics, population density was found negatively associated with both human and ecological systems (Table 2). The regression results also revealed that urban landscape measures influence socioeconomic welfare and environmental quality oppositely. The strongest individual predictor for describing HWI was *patch cohesion index* (COHESION, $R^2 = 0.43$, $P < 0.001$), and for EWI it was *percent UMZ of country* (Percent Urban, $R^2 = 0.32$, $P < 0.001$, Figure 4). A statistically significant linear relationship was also found between EWI and COHESION at the country scale ($R^2 = 0.13$, $P = 0.039$).

Akin to other urban-ecological integrity studies at more local scales (i.e. Shaker & Ehlinger 2014), the bivariate relationship between percent UMZ and EWI was negative logarithmic. These regression relationships allow for threshold of effect interpretation of landscape patterning, which remains largely absent from the sustainability science and landscape planning literature. Using a two-sided inverse prediction (0.95 confidence level), COHESION scores greater than 90.7 (86.9–92.3) provide Human Wellbeing conditions of 'medium' or better. Ecological Wellbeing approaches 'poor' status as a country's percentage of UMZs surpasses 1.9 (upper 95%). Further, conditions of Ecological Wellbeing decrease to the rank of 'medium' or worse as COHESION values exceed 87.7 (upper 95%).

The seven statistical models varied in their indication concerning which urban landscape variable most affected

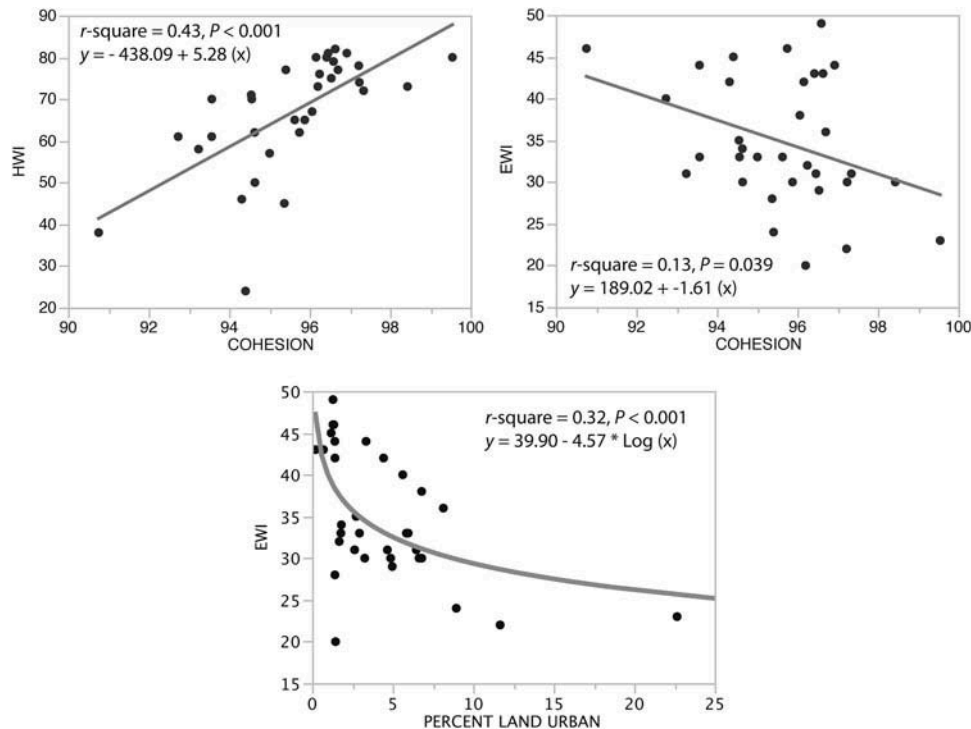


Figure 4. Bivariate scatter plot between Human Wellbeing Index (HWI) and patch cohesion index (COHESION). Bivariate scatter plots between Ecosystem Wellbeing Index (EWI) and COHESION, and percent urban morphological zone (Percent Urban).

sustainability conditions (Table 2). Of the three models used to predict HWI, COHESION remained the strongest influencing urban landscape metric individually or when combined; EWI had no predictor that was consistently the strongest across four models used. COHESION, however, was present in three of the four regression models predicting EWI. Specifically, the three independent variables, *Population density* (Pop. Density), COHESION, and *patch density* (PD), were used to predict both HWI and EWI across 33 European country landscapes. The three urban predictors combined to make one OLS multiple regression model to explain HWI. Defining that model, COHESION (std. coeff. = 0.78, $P < 0.001$) and PD (std. coeff. = 0.56, $P = 0.005$) positively impacted HWI, while Pop. Density (std. coeff. = -0.56 , $P = 0.004$) had a negative effect (Table 2). The three independent variables were used in two OLS multiple regression models to explain EWI. The first model integrated Pop. Density (std. coeff. = -0.56 , $P < 0.001$) and COHESION (std. coeff. = -0.28 , $P = 0.034$), and both were negatively associated to EWI. The second model incorporated PD (std. coeff. = -0.48 , $P = 0.002$) and COHESION (std. coeff. = -0.40 , $P = 0.009$), and both again negatively influenced EWI (Table 2).

The CAR analysis corroborated statistical directionality established using OLS regression for predicting Wellbeing condition across the 33 European country landscapes. That said, CAR analysis did reveal small statistical changes across the seven distinct models for predicting HWI and EWI. Three CAR models explained between 42% and 54% of HWI variation, and four CAR models

explained between 13% and 43% of the variation of EWI (Table 3). The strongest individual CAR predictor for understanding HWI and EWI remained COHESION ($R^2 = 0.42$, $P < 0.001$) and Percent Urban ($R^2 = 0.30$, $P < 0.001$), respectively. A statistically significant bivariate CAR relationship was also found between EWI and COHESION at the country scale ($R^2 = 0.13$, $P = 0.044$). Of the three CAR models used to predict HWI, COHESION remained the strongest influencing urban landscape metric individually or when combined, and EWI had no CAR predictor that was consistently the strongest across the four models (Table 3).

The three independent variables (Pop. Density, COHESION, PD) combined to make one CAR multiple regression model to predict HWI. The strongest urban landscape model predicting HWI was COHESION (std. coeff. = 0.71, $P < 0.001$) and PD (std. coeff. = 0.66, $P < 0.001$) positively associated, and Pop. Density (std. coeff. = -0.57 , $P = 0.008$) negatively (Table 3). The three aforementioned independent variables were used in two CAR multiple regression models to explain EWI. The first model integrated Pop. Density (std. coeff. = -0.60 , $P < 0.001$) and marginally significant COHESION (std. coeff. = -0.27 , $P = 0.052$), and both negatively influenced EWI. The second model incorporated PD (std. coeff. = -0.51 , $P = 0.001$) and COHESION (std. coeff. = -0.41 , $P = 0.004$), and both again negatively impacted EWI (Table 3). Testing residual spatial dependence of each CAR model, using global Moran's I statistic, revealed no spatial errors. Although residual

Table 3. Relationships between urbanization predictors and Wellbeing indices explored by CAR regression.

No.	Dependent	CAR			
		Std. beta coefficients regression	CAR R ²	AICc value	CAR model sig.
1	HWI	+0.71 × (COHESION ^{***}) +0.66 × (PD ^{***}) -0.57 × (Pop. Density ^{**})	0.54	256.89	***
2	HWI	+0.51 × (COHESION ^{***}) +0.24 × (PROX_CV)	0.43	260.73	***
3	HWI	+0.56 × (COHESION ^{***})	0.42	258.39	***
4	EWI	-0.60 × (Pop. Density ^{***}) -0.27 × (COHESION)	0.43	221.94	***
5	EWI	-0.51 × (PD ^{**}) -0.41 × (COHESION ^{**})	0.36	226.74	***
6	EWI	-0.56 × (Percent Urban ^{***})	0.30	225.72	***
7	EWI	-0.36 × (COHESION [*])	0.13	232.85	*

Notes: *P < 0.05; **P < 0.01; ***P < 0.001.

Symbols enclosed in parentheses designate individual P-values.

CAR R²: represents total explained variance (predictor + space).

HWI, Human Wellbeing Index; EWI, Ecosystem Wellbeing Index; CAR, conditional autoregression; COHESION, patch cohesion index; PD, patch density; PROX_CV, proximity index coefficient of variation.

distributions varied from normal to skewed, spatial correlograms of the seven distinct CAR models suggest a reduction of errors across space. Finally, when comparing OLS and CAR results model, one had a shift in covariate rank based on standardized beta coefficients; all other models remained consistent.

4.3. Urban landscape change

The 31 countries represent a gradient of urbanization ranging from 0.22% to 22.9% UMZ in 2006. The European nations included in the change analysis have fluctuating levels of urbanization, however collectively the region continued to see noteworthy population growth and a considerable amount of UMZ expansion between 2000 and 2006. For the entire study area, more than 14 million people were added during the six years. Population density increased from 112.19 in 2000 to 114.65 in 2006 at an average rate of 0.4% per year (Table 4). Land cover also transformed substantially for the study area during the time period. Specifically, over one million new hectares (11,023 Km²) of urban land was generated during the period, with percent UMZ increasing from 4.4% in 2000 to 4.8% in 2006 at an average rate of 1.2% per year.

Table 4. Changes in urbanization measures between 2000 and 2006 for 31 European countries.

Parameters	Study region (n = 31 countries)		Annual rate (%)*
	2000	2006	
PLAND (%)	4.430	4.760	1.242
PD	0.026	0.028	1.014
COHESION	95.596	95.844	0.043
Population density (persons/km ²)	112.192	114.646	0.365

Note: *Equation for calculation: $R = \sqrt[n]{R_2/R_1} - 1$, where R is the change rate; R₁ is the value at start year; R₂ is the value at end year; n represents the difference of years between the two dates.

The spatial and temporal patterns of population and landscape composition at the country scale allowed for identification of fast and slow urbanizing nations that could not be detected at the continental level. Germany had the greatest population in 2006, followed by Turkey, and then France; however greatest population density was observed in Netherlands (465 persons/Km²), then Belgium (341), and Germany (231). Iceland had the fewest people in 2006, preceded by Luxembourg and Cyprus; however lowest population density was observed in Iceland (3 persons/Km²), preceded by Norway (15), and Finland (16). Twenty-two of the 31 countries had positive population growth, with the greatest increase in population density observed in Albania (2.4%), preceded by Turkey (1.8%), and then Iceland (1.7%). Nine of the 31 countries had negative population growth, with the greatest decrease in population density observed in Bulgaria (-1.2%), preceded by Latvia (-1%), and then Romania (-1%). For both dates, Germany maintained the greatest total area of UMZ with over 30,300 Km² in 2006, while Iceland preserved the least amount with less than 230 Km². Belgium had the greatest percent of UMZ in 2006 with 22.9%, followed by the Netherlands (12.9%) and Luxembourg (9.7%). Iceland recorded the lowest percent of UMZ in 2006 with 0.22%, preceded by Norway (0.7%) and Sweden (1.3%). All but one country had positive growth of percent UMZ, with the greatest increase observed in Albania (19.9%), then Portugal (5%) and Poland (3.8%). Slovakia was the only country with negative UMZ land cover change with -0.4%, while Slovenia (0.1%) and Latvia (0.1%) had the lowest amount of positive growth.

Landscape pattern metrics helped to highlight trends in urbanization over the six-year period, which could not be assessed with composition measures. The irregularity of development across Europe is reflected in patch configuration metrics as measured by PD and COHESION for UMZ which ranged between 0.001 and 0.074 and 92.91 and 99.44, respectively, in 2006. Results from the change analysis revealed that the number of new urban areas was the more important fragmentation characteristic of

European urbanization, with PD increasing at an annual rate of 1% (Table 4). Additionally, the results reveal a small but rising trend in COHESION with an average rate of 0.04% per year. The overall increasing level of COHESION suggests that urban areas across Europe have become more physically connected in recent years.

For 2006, Luxemburg logged the greatest PD value with 0.074, followed by Czech Republic (0.066) and Germany (0.053). Iceland recorded the lowest PD score with 0.001, preceded by Norway (0.004) and Sweden (0.005). Twenty-three of the 31 countries had positive PD growth, with the greatest increase observed in Albania (6.6%), then Portugal (4.1%) and Poland (3.7%). Eight of the 31 countries had negative PD scores, with the greatest decrease observed in Latvia (−1%), preceded by Slovakia (−0.8%), and then Cyprus (−0.6%). In 2006, Belgium recorded the greatest COHESION score with 99.44, followed by Netherlands (97.69) and Italy (97.31). Slovakia logged the lowest COHESION score with 92.91, preceded by Bulgaria (93.27) and Czech Republic (93.68). Twenty-six of the 31 countries had positive COHESION growth, with the greatest increase observed in the Netherlands (0.08%), then Spain (0.06%) and Lithuania (0.05%). Five of the 31 countries had negative COHESION scores, with the greatest decrease observed in Belgium (−0.017%), preceded by Portugal (−0.017%), then Slovenia (−0.010%).

5. Discussion

5.1. Corridors or fragmentation

Macroscale sustainable development is likely best assessed using country landscapes, as progress can be directly linked to a government's policies and its inhabitants' practice. This study provided specific thresholds of urbanization effect on sustainability condition, which remains an unrepresented area of research and a topic needing further support in policy and planning. Understanding the effects of landscape change on ecosystems is critical for preserving or restoring healthy, functional, and intact ecosystems. Human population growth, and migration to urban areas, has led to fragmentation and overall losses of habitat due to conversion of natural landscapes for anthropogenic purposes (Riitters et al. 2000; FAO 2006). The first null hypothesis stated that no significant relationship exists between urban landscape form and population characteristics and HWI across Europe. Across the three regression techniques used, the urban connectively measure *patch cohesion index* (COHESION) remained the strongest predictor for explaining the variability of HWI. This relationship signifies the importance of anthropogenic corridors for improving conditions of human well-being. Since statistical relationships were found between UMZ configuration metrics and population density with HWI, the first null hypothesis is rejected.

The second null hypothesis stated that no significant relationship exists between urban landscape form and

population dynamics and EWI across Europe. Across the three regression techniques used, the urban composition measure *percent urban* and the connectively measure *patch cohesion index* (COHESION) were strongest at explaining the variability of EWI. Most analyses of coupled urban-ecological systems connect changes in the ecological systems with meek aggregated metrics of urbanization (e.g., percent urban land cover, population density); however, these measures only offer crude predictions of conditions and a limited suite of planning or management responses (Alberti 2008). However, the COHESION is a configuration measurement of physical connectedness, and provides to a knowledge base for sustainable urban form. A key finding from this study is that urban patterns are simultaneously improving socioeconomic systems while degrading our life-supporting ecosystems. Rands et al. (2010) called attention to this global phenomenon, and said that numerous thriving nations have metabolized natural resources in the past to advance their present status, and developing countries are in the process of exploiting ecological well-being to improve their socioeconomic circumstance. Since statistical relationships were found between UMZ configuration metrics and population density with EWI, the second null hypothesis is also rejected.

5.2. An urbanizing global paradox

'A finite world can support only a finite population; therefore, population growth must eventually equal zero' (Harding 1968, 1243). Across habitable continents, it is likely that Europe will be the first to reach this milestone. Unfortunately, it should be realized that the impacts of urbanization will be faced by the next few generations (under foreseeable technology), even after population growth has stabilized. Harding's (1968) tragedy of the commons focused on both human overpopulation and pollution, and his main thesis was that common resources would always be overexploited when utilized by selfish individuals. Some researchers now argue that environmental degradation is not due to overpopulation as much as it is direct and indirect overconsumption of resources and pollution by the rich (Weinzettel et al. 2013). Specifically, an increased demand for food, fiber, fuels, and construction materials have metabolized Earth's natural resources causing a projected 70% increase in global footprint when projecting from 2004 to 2050 (Weinzettel et al. 2013). The results of the regression analyses within this article consistently showed that population density was negatively associated to both HWI and EWI, thus confirming the importance of stabilizing population growth. However, once population growth approaches zero, it can be presumed that humanity's addiction to material goods and consumption standards will remain a problem into the next century.

The third and final null hypothesis stated that recent European urbanization trends do not move us closer to global sustainability. The urban landscape change analysis

provided results that UMZ composition and configuration increased from 2000 to 2006 for the study region. The urban landscape change analysis also revealed that population density intensified during that same time period, but at a much lower rate. Landscape metrics helped to highlight trends in European urbanization over the six-year transition. The low population growth, in comparison to increases in urban land cover composition and configuration, suggests that the built density of urban areas may be decreasing. Implying that urban growth and sprawl legislation between 2000 and 2006 was ineffective across most of the countries in this study. Although a positive relationship was found between landscape configuration measures and HWI, the inverse was established between those metrics and EWI. The overall findings of this study uncover that urban patterns across Europe have disconnected socioeconomic welfare from life-supporting ecosystem services; furthermore, the urbanization trend between 2000 and 2006 suggests these findings will continue into the future. Thus, the third and final hypothesis is accepted because the recent European urbanization trends assessed in this article do not move us closer to global sustainability.

The global urbanization trend is closely related to ecological well-being and to profound fluctuations of socioeconomic conditions (UNMP 2004; Crane & Kinzig 2005). Besides the environmental ramifications of urbanization, questions remain concerning how changes to socioeconomic well-being will impact future relationships between humans and their environment (NRC 1999; Kates 2001; Clark & Dickson 2003). There remains an obligation to stabilize human population growth while providing an increase in living standards, simultaneously doing so within the constraints of Earth's environmental limits (NRC 1999; Kates 2001; Parris & Kates 2003). Close to one billion people currently live in 'extreme economic poverty' (less than 1 US dollar/day), and lack access to life-supporting ecosystem services to meet essential needs (World Bank 2008). Although resolving social injustices should remain a focal point for sustainability policy-makers, this analysis suggests that life-supporting ecosystems across Europe are significantly more compromised than socioeconomic welfare. Within sustainability science, policy-making, and applied practice, this dilemma is often viewed as a 'chicken or egg' scenario, which it is definitely not. Although a few countries have registered environmental management and policy successes, the rate of biodiversity loss at the global scale does not seem to be decelerating (Butchart et al. 2010). Shaker and Zubalsky (2015, 10) signified the importance of this problem by asking: 'at what point does the metabolization and destruction of life-supporting ecosystems start to hinder humanity's social equity and economic welfare?' Indeed, this question should remain central to sustainable development research, as human behaviors should eventually match Earth's environmental limits and available ecosystem services (Ehrlich & Ehrlich 1996; Wackernagel & Rees 1996) to avoid social chaos (Ruckelshaus 1989). In conclusion,

results from studies like this one help to improve management of Earth's coupled human–environmental systems and humanity's quest towards sustainability.

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