Land Use Policy 42 (2015) 194–209

Contents lists available at ScienceDirect

Land Use Policy

journal homepage: www.elsevier.com/locate/landusepol

Urban green and blue: Who values what and where?

Heather A. Sander*, Chang Zhao[1]

Department of Geographical and Sustainability Sciences, The University of Iowa, 316 Jessup Hall, Iowa City, IA 52241, United States

ARTICLE INFO

Article history:
Received 12 February 2014
Received in revised form 30 June 2014
Accepted 30 July 2014

Keywords:
Urban environmental amenities
Economic valuation
Urban planning
Urban sustainability

ABSTRACT

Urban water bodies (bluespace) and vegetated open spaces (greenspace) are key sites for building urban sustainability, promoting social, economic, and environmental objectives and influencing human well-being. Building sustainable cities requires an understanding of how urbanities value these amenities, how values vary within cities, and of the factors influencing these values. Hedonic pricing, an economic-valuation technique, is commonly used to estimate values for green and bluespaces based upon home sale prices, but typical applications fail to identify how these values vary within cities, leaving a gap in decision-makers' knowledge and limiting their ability to plan green and bluespaces that promote urban sustainability. The present study examines this issue by identifying spatial variation in the values of urban green and bluespace across the Twin Cities metropolitan area of Minnesota, USA using both global and local regression techniques. We find that the values of all blue and greenspace amenities examined vary significantly spatially and that values for these amenities can differ greatly from those estimated using global models. Importantly we find that that the influence of treecover on home sale price is always positive when this relationship is significant and that the landscape context in which an amenity occurs impacts its value with features such as trails, water bodies, and wetlands being more valuable in locations with protected natural areas than elsewhere. We also find evidence that wealth influences access to blue and greenspace, in many, but not all cases, leading to reduced access to these features among poorer groups. These finding suggest that, when used in planning and policy-making, global values may lead to the provision of urban green and bluespaces that fail to meet the needs and desires of local residents. Identifying variation in these values, as in this study, will facilitate more targeted planning of green and bluespace and thus more liveable, sustainable cities.

Introduction

Urban blue and greenspaces are key resources for building sustainable, resilient, and adaptive urban systems. These spaces promote numerous social and ecological objectives (Colding and Barthel, 2013), providing environments for ecological learning (Barthel et al., 2010a,b), congregating and building social ties (Levkoe, 2006; Saldivar-Tanaka and Krasny, 2004), interacting with nature (Krasny, 2009), and relaxation and exercise (White et al., 2013b). They also provide wildlife habitat (Sadler et al., 2010) and economic benefits (Sander et al., 2010; Sander and Haight, 2012); mitigate air pollution, heat islands, and flooding (Bowler et al., 2010; Depietri et al., 2012; Manes et al., 2012); and positively impact human health (Tzoulas et al., 2007; White et al., 2013a). These considerations influence how these spaces are cast in the minds of decision-makers in designing urban landscapes that meet social, economic, and environmental objectives.

Benefits provided by urban green and bluespace vary within and among cities, however, and are shaped by a variety of factors, including their composition, landscape position and context, use, governance, and socioeconomic conditions. These characteristics combined determine the benefits produced by urban green and bluespaces and, in turn, the stability, adaptability, and resilience of urban social-ecological systems. The location, design, and management of urban green and bluespaces thus influence urban sustainability. This creates a critical question in urban policy and planning: Where should green and bluespaces be located and how should they be structured to meet combined social-environmental objectives?

Answering this question requires an understanding of how urbanites value blue and greenspaces. Economic valuation techniques are commonly used to measure these values, among them hedonic pricing, a revealed-preference approach that estimates homebuyers' willingness-to-pay for environmental amenities

* Corresponding author. Tel.: +1 319 353 2964.
E-mail addresses: heather-a-sander@uiowa.edu (H.A. Sander), chang-zhao@uiowa.edu (C. Zhao).
[1] Tel.: +1 319 335 0151.

http://dx.doi.org/10.1016/j.landusepol.2014.07.021

based upon sale prices. This approach identifies value in a manner that is based on the actual choices of individuals, utilizes readily available data, and relates directly to local tax bases and is thus often favoured because it identifies how communities benefit from amenities. The use of values estimated using hedonic price models (HPMs) in setting urban green and bluespace policy, however, is problematic because these features benefit different residents in different ways, causing their values to vary. HPMs produce one value for an amenity to represent an entire urban population and ignore variation within urban areas, masking differences. Using HPM-generated values in policy-making thus has a levelling effect, treating all individuals and neighbourhoods as though they value and demand these amenities identically.

HPMs also fail to recognize processes that influence the values of amenities. Firstly, HPMs estimate what individuals actually pay for green and bluespace. Estimated values are therefore a function of wealth and likely represent what individuals can afford; not what they desire. HPM also assumes that, given income, home purchasers select homes with the combination of attributes they desire. The decisions of planners and developers regarding the locations and attributes of different urban developments and amenities, however, lead to differentiation in neighbourhood attributes. Thus, homes with the desired combination of attributes may not exist or may be unaffordable to a given home purchaser. The ability of the wealthy to pay for open space and the bundling of open space with other high-value amenities may also lead to the clustering of high-quality, high-value homes with high amenity levels. This may exclude the poor from certain locations and amenities, for example by resulting in high-end homes in neighbourhoods near parks which are thus unaffordable to the less-wealthy. HPM also assumes that purchasers are aware of amenities and their benefits. This awareness may be limited for certain groups (e.g., recent immigrants) whose values HPM thus cannot capture.

These limitations mean that HPM estimates of environmental value may present incomplete or inaccurate estimates of green and bluespace values. HPMs may, however, be generated using alternative methods such as locally weighted regression, an implementation of HPM that allows for the estimation of willingness-to-pay for green and bluespace amenities for individual homes, thus allowing for identification of spatial variation in willingness-to-pay for urban green and bluespace. While these models still suffer from many of the limitations detailed above, they provide fuller indicators of environmental value for exploration using additional methods (e.g., surveys) to facilitate a more comprehensive understanding of the value of greenspace and bluespace. This, in turn, can help to better target the design of urban green and bluespace networks that meet the needs of urbanites based upon importance of these amenities as indicated by estimated willingness-to-pay for them in concert with additional data, for example the results of surveys and stakeholder meetings.

The present study begins to address this issue by identifying spatial variation in the values of urban greenspaces (vegetation, parks, and trails) and bluespaces (recreational lakes) across the Twin Cities metropolitan area (TCMA) of Minnesota, USA using both global and locally weighted regression techniques. We first use a global HPM to estimate economic values associated with these amenities as they accrue to single-family homeowners, thereby identifying average willingness-to-pay for green and bluespace. We then estimate a local HPM, allowing us to estimate willingness-to-pay for green and bluespace for individual homes and to explore spatial variation and patterns in these values. This research thus begins to answer questions of where to locate and how to design urban green and bluespace to meet combined social-environmental objectives by addressing the central questions of where, by whom, and for what these spaces desired. This use of locally estimated HPM represents an appropriate starting point for answering these questions by identifying locations of positive, negative, and non-significant value for these amenities. It also enables us to identify the basic characteristics of these locations with respect to housing stock and green and bluespace and differences among them. This adds to our understanding of the value of green and bluespace and will inform a comprehensive analysis of urban green and bluespace value by targeting future analyses aimed at identifying factors that influence green and bluespace values using additional approaches. This will enable us to identify where green and bluespace is of highest and least value and under what conditions and will enhance our understanding of the equitable allocation of urban green and bluespace facilitating the design and management of more liveable, sustainable urban environments that better meets the needs of urbanites.

Literature review

Hedonic price modelling

Hedonic price modelling is a statistical modelling technique in which the price, P, of a marketed good (e.g., a single-family residential home), i is viewed as a composite of its structural (S_i), neighbourhood (N_i), and environmental characteristics (Q_i) such that:

$$P_i = \beta_0 + \beta_1 S_i + \beta_2 N_i + \beta_3 Q_i + \varepsilon_i \quad (1)$$

Under assumptions of a single market at equilibrium with perfect competitiveness and of informed buyers, the first partial derivative of an estimated HPM with respect to a specific characteristic may be used to estimate that characteristic's marginal implicit price (MIP), marginal willingness-to-pay for changes in it (Freeman, 2003).

HPMs are typically estimated using ordinary least squares (OLS) regression. Residual spatial autocorrelation, the tendency of residuals of similar value to occur together in space, may complicate such models, violating basic assumptions of independent and evenly distributed errors. Spatial autocorrelation may occur in the error term (e.g., when spatially structured predictor variables are omitted from a model), in the lag term (e.g., spatial autocorrelation in a dependent variable), or may be present in both terms. Spatial econometric modelling techniques can address this issue. One such technique, simultaneous autoregressive (SAR) modelling adds a term to an OLS model to account for spatial dependence (Cressie, 1993; Haining, 2003). Implementing this term requires a user-defined spatial weight matrix, W, to identify the degree of influence of each neighbour on a given observation. Definition of weights may follow many methods (Anselin and Bera, 1998; Fortin and Dale, 2005), but typically is based on distances between neighbours such that nearer neighbours receive higher weight values and exert greater influences than farther neighbours.

Three corresponding types of SAR models, error, lag, and mixed, address the three forms of spatial autocorrelation (Anselin and Bera, 1998; Haining, 2003). SAR error models add a term to represent the spatial structure of the spatially dependent error term, $\lambda W \mu$, such that:

$$Y = X\beta + \varepsilon_i + \lambda W u \quad (2)$$

Y represents the response variable, X is a matrix, β represents a vector of the slopes associated with predictor variables in the original matrix, and u is the spatially dependent error term. SAR lag models add a term to account for spatial autocorrelation in the lag term, ρWY:

$$Y_i = X\beta + \varepsilon_i + \rho WY \quad (3)$$