Applied Geography 34 (2012) 47–56

Contents lists available at SciVerse ScienceDirect

Applied Geography

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

Spatially explicit inverse modeling for urban planning

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Keywords:
Inverse modeling
Urban systems
Mixed-GWR
Hedonic modeling

A B S T R A C T

Urban modeling methods have traditionally followed a forward modeling approach. That is, they use data from today's situation to forecast or simulate future states of an urban system. In this paper, we propose an inverse modeling approach by which we shift our attention from solely forecasting or simulating future states of an urban system to steering it to a desired state in the future via key variables characterizing the system in the present. We first present a theoretical framework for the use of the inverse approach in urban planning. We test the power of the proposed method using a hedonic house price model in a metropolitan area in Switzerland to investigate the negative effects of densification on house prices. The model is calibrated by mixed geographically weighted regression in order to account for spatial variability of both key variables and model outputs. We show how devaluation of house prices caused by densification can be compensated by different levels of socioeconomic, locational as well as structural variables. We illustrate and discuss how trade-offs between variables may lead to more feasible results from an urban planning perspective. We conclude that the proposed method might be valuable for urban planners for developing implementable spatial plans based on future visions. In particular, the fact that other model specifications than hedonic house price model can also be employed to formulate an inverse model application, allows planners to address other type of problems or externalities from urbanization processes such as urban sprawls, environmental pollution or land uses change.

Introduction

Urban systems are complex systems made of a number of individual components that interact with one another through an intricate network (Baynes, 2009; Bretagnolle, Daudé, & Pumain, 2003; Liu, 2008) As Liu (2008) argues, urban systems consist of a set of elements or subsystems, such as population, land, employment, services and transport, to mention a few. All components of the system are interacting with each other through social, economic, and spatial mechanisms while they are also interacting with components of the environment. Some components such as urban population are expected to increase extensively over the upcoming decades. According to United Nations (2009), more than 50% of the population lives now in urban areas and this is expected to rise to 70% in 2050. Such rapid increase in the urban population will most likely cause people's welfare to decrease even long before 2050. Higher levels of population density in cities are generally associated with negative externalities such as pollution, traffic congestion and crime, among others, as well as with economic disequilibrium in the land and housing market. Yet, while planners are aware of these rapid changes, adaptation strategies and approaches tackling these growing challenges are still lacking.

A number of mathematical methods in the literature deal with urban development. The most popular are urban-growth logistic regressions which attempt to examine and forecast urban-growth using an econometric formulation (e.g. Allen & Lu, 2003; Hu & Lo, 2007; Landis & Zhang, 1998), neural-networks modeling by which the interaction between the different elements of an urban system is studied based on the way biological neural systems develop (e.g. Maithani, Jain, & Arora, 2007; Ou, Zhang, Ren, & Yao, 2003; Pijanowski, Brown, Shellito, & Manik, 2002), and gravity models which address the interaction between the elements of urban systems by using a similar formulation to the Newton's law of gravity (e.g. Tsekeris & Stathopoulos, 2006). Also, Agent-Based Models (ABM) and Cellular Automata (CA) have become popular for representing the actions, behavior and interactions of individual agents in space and time (Batty, 2009). In recent years, ABM and CA techniques have been particularly useful in modeling urban expansion (He, Okada, Zhang, Shi, & Zhang, 2006; Zhang, Zeng, Bian, & Yu, 2010).

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0143-6228/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.apgeog.2011.10.009

The advantage of hedonic house price model is that it allows exploring characteristics of urban systems. The market value of tradable goods, such as house prices, is linked to measurable attributes of the good being valued, thus providing a description of the urban system. The model can be estimated by means of econometric techniques such as ordinary least squares (OLS). In the case of housing market, price of properties are regressed on a set of socioeconomic, locational, and structural attributes which are generally measured at small areas such as districts or municipalities. The relationship between such attributes (explanatory variables) and house prices (response variable) correspond to the model's parameter estimates and can be interpreted as the consumer's willingness to pay for one additional unit of the corresponding house's attribute. Most of the explanatory variables generally employed in modeling house prices correspond to what Wegener (1994) and Liu (2008) have classified as urban subsystems, such as: housing (structural characteristic of properties), land use, employment, population density and location of workplaces among others. Accordingly, hedonic house price modeling can provide valuable information on the dynamics and complexity of urban systems by quantifying and relating a set of urban subsystems to a response variable. Numerous applications of house price models can be found in the literature. In particular, examples of how hedonic house price models can be used to analyze key variables in urban modeling are given by Nelson (1978), Bender and Hwang (1985), Ottensmann, Payton, and Man (2008).

All of the above mentioned methods have been exclusively used in urban studies to either characterize a current situation by modeling, or to predict or simulate future scenarios based on data from today's situation. This is what in the literature has been denoted as the *forward problem* (Scales & Snieder, 2000), that is, current data is used to fit a model from which predictions or simulations are derived. In a more recent study, Grêt-Regamey and Crespo (2011) propose the use of an *inverse problem* approach (Ashter, Borchers, & Thurber, 2005; Scales & Snieder, 2000; Tarantola, 2005) for planning sustainable urban systems. As opposed to the forward problem, in the inverse problem approach, a set of model's parameters characterizing a system are derived from a *given value* for the model's response. In urban planning, such *given value* can be defined by stakeholders as a desire future state for an urban system. Thus, inverse problem approach is intended to shift the focus in urban planning from mostly forecasting future states to planning from a future vision.

The paper is divided into two main sections: Firstly, we provide a theoretical framework to the inverse problem approach for urban planning proposed by Grêt-Regamey and Crespo (2011). We focus on system identification's tools to formulate and solve inverse models for urban systems. Secondly, we illustrate the systematic approach in a metropolitan area in Switzerland using a hedonic house price model showing how to deal with increasing population density.

The inverse approach

In inverse modeling, one deals with concepts and definitions frequently used in mathematical and econometric analysis. Yet, same expressions used by the different communities often refer to different concepts. For example, for mathematicians the term *parameter* refers to any type of quantity that defines certain characteristics of a system such as variables, constants or parameter estimates. While for econometricians *parameters* refer exclusively to linear quantities relating a dependent with the independents variables. Since we perform an econometric analysis in this study, and in order to avoid any confusion throughout the text, we will use the notation β to refer to the classical model parameters defined by econometricians, while θ will be used to denote the rest of parameters defining the model whether they are linear or not.

System identification

System identification is concerned with the formulation and estimation of mathematical models from observed input and output data. In the context of the inverse problem, we present a system identification procedure based on Pajaonk's (2009) contribution (Fig. 1). The system is defined as follows:

where the *input* (X) corresponds to quantities that influence other entities in the system through their relations to them and by this influence the system as a whole. These types of quantities are regarded as *independent variables*. The *output* (d) corresponds to measurable variables that are determined by both the *input* and the system itself. These *output* variables are also denoted as *dependent variables*. Similarly, *disturbances* (ε) are a type of input variable whose values cannot be chosen freely and follow a random probabilistic distribution. Finally, the *process* (**G**) corresponds to the transformation of input quantities to output variables. In econometrics, the process is given by the functional form relating the observed value of the dependent variable to the observed values of the independent variables through unknown parameters which can be estimated by statistical methods.

Pajonk (2009) and Tarantola (2005) argue that the scientific procedure for the identification of a system can be divided into the following three steps:

i) *Parameterization of the system*: Find a minimal set of model parameters and variables whose values completely characterize the system.
ii) *Forward modeling*: Use of a mathematical formulation to simulate the system output given values for the model parameters and the input.
iii) *Inverse modeling*: Obtain actual values of the model parameters given some values for the output of the *real* system.

If the system is well-quantified and system parameters are given based on either prior knowledge or statistical estimation, the forward model can be used for a physical system to simulate a new system output for a new set of system inputs. In contrast, the inverse model requires more sophisticated mathematical techniques to be solved as most of the inverse problems are typically ill-posed, that is, the solution of the problem is unstable or not unique.

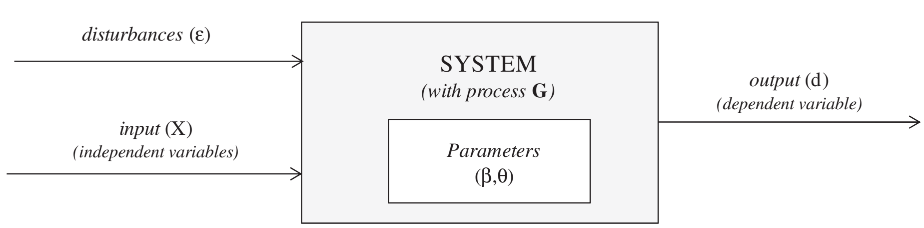

Fig. 1. Framework for describing a system defined as processes with input, disturbances, and output.