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# Planning from a future vision: inverse modeling in spatial planning

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**Abstract.** Spatial planning seeks to regulate demand for land resources with a view to securing the well-being of urban and rural communities. It identifies the decisions that should be made in light of a preferred future development. Yet, preferences for future development change as demands for housing, recreation, food, and life styles are changing rapidly. In this study we aim to introduce a new approach for spatial planning, where the point of departure is not current data, but a future desired by stakeholders. To this end, we propose an inverse modeling approach where the result is a set of values for parameters identified as being key to reach a desired future. We apply the approach to a case study in a metropolitan area in Switzerland in order to illustrate its capabilities for sustainable planning. We invert a hedonic house-price model for identifying urban development options in the case-study area. We show how one can determine the relevant trade-offs between locational, structural, and socio-economic characteristics given a desired house-price level, and the possible locations and relevant trade-offs for areas where future noise-emitting factories are to be planned. We discuss advantages and shortcomings of the approach for planners and draw conclusions about the effectiveness of the approach as a means of encouraging lay people and stakeholders to become involved efficiently in sustainable development issues.

## 1 Introduction

There is bound to be conflict over land use. Available land resources are shrinking while demand is increasing. The pressure is especially high in cities where the world will have to make living space for three billion more people in the next fifty years— double what we have today. Spatial planning seeks to regulate such demand with a view to securing the well-being of urban and rural communities. It identifies the decisions that should be made in light of a preferred future development. It defines criteria and frameworks for realizing a desired future spatial development. Yet, preferences for future development change as demands for housing, recreation, food, and life styles are changing rapidly.

In the 1950s a plan was thought of as the choice of one single future and the way to implement it; however, the planning discipline rapidly realized that, without developing new approaches addressing uncertainties, problems of rapid urbanization would never be tackled correctly. Strategic planning entered the sphere of planning in the 1960s during the debate about structural planning in Britain, the Netherlands, France, and Germany (Sartorio, 2005). From this point on, spatial planning was not eliminating uncertainties but addressing them by including a set of desirable futures, a set of possible outcomes of actions, and a set of possible actions (Hopkins, 2001). Many forecasting methods were developed to predict dynamic spatial patterns, especially in the urban context, from cellular automata (eg, Batty and Xie, 1994; Couclelis, 1985; 1997; White and Engelen, 1997), logistic growth regression models (Allen and Lu, 2003; Hu and Lo, 2007; Landis and Zhang, 1998; Wu and Yeh, 1997), neural networks (Almeida et al, 2008; Tortosa et al, 2009), and gravity models (Tsekeris and Stathopoulos, 2006) to multiagent systems (Benenson and Torrens, 2004). All these approaches, however, only address the future through the mirror of the past. They use data from today's situation to predict future development. However, this can lead to a dead end, if drivers of the current problems become the main drivers of the planning process, thus transferring our problems to the future.

Planning from a future vision of a desirable outcome, followed by the question "what shall we do today to get there?" might be more effective in resolving problems than the ways in which spatial planning and modeling have operated in the past. Inferring information about the constituents of a system using knowledge about the behavior of the system and its structure is known in technical and business planning under the term 'backcasting'. Applications of backcasting approaches range back to when Lovins (1976) proposed backcasting as an alternative planning technique for electricity supply and demand. The 'backwards-looking analysis' of Lovins was replaced by energy backcasting (eg, Kuisma, 2000; Robinson, 1982) and expanded to strategic planning for sustainability (eg, Dreborg, 1996; Holmberg, 1998), participative backcasting tools involving stakeholders in local sustainability planning (eg, Carlsson-Kanyama et al, 2008), and transportation planning (eg, Geurs and van Wee, 2004; Schippl and Leiser, 2009). Common to these applications are that future desired conditions are envisioned and steps are defined to attain those conditions. Since the methods in backcasting are predominantly qualitative and constituted by principles, they are only useful for the overall structuring of relevant questions, thoughts, and measures, and not directly applicable to spatial planning.

Comparable problems in physical sciences are referred to as inverse problems and are solved using mathematical analyses. Scientists and engineers frequently wish to relate physical parameters characterizing a model to collected observations. The problems start with some procedure for predicting the response of a physical system with known parameters, such as the Newtonian gravitation equation relating the gravitational potential to the density. One would then not try to predict the gravity given the density (the forward problem), but would try to turn gravity measurements into direct information about the density of the earth. For spatial planners, the problem would start with some models for predicting spatial development (forward problem), and the planners would ask how spatial parameters measured at a time $t_0$ characterizing the current state of a spatial development should be set to reach a predicted or a desired spatial development at a future time $t$ (inverse problem). The framework of the forward problem for planners is illustrated in figure 1(a), where a set of $n$ given parameters at a time $t_0$, denoted by $\{\alpha_0, ..., \alpha_n\}_{t_0}$, are used to forecast the state of a spatial development at a time $t$ in the future, denoted by $S_t$. Figure 1(b) illustrates the case of the inverse problem for planners, where a set of desired parameters at a time $t$, denoted by $\{\alpha_0, ..., \alpha_n\}_t$ are derived from a desired future spatial development ($S_t^{\mathrm{d}}$).

The solution set of desired parameters $\{\alpha_0, ..., \alpha_n\}_t$ contains relevant information on the properties and characteristics of the desired future spatial development. Therefore, the next step for planners is to use that information to drive the system from $S_{t_0}$ to $S_t^{\mathrm{d}}$, or equivalently from $\{\alpha_0, ..., \alpha_n\}_{t_0}$ to $\{\alpha_0, ..., \alpha_n\}_t$. In this regard, Engl et al (2000) argue that one of the motivations for using inverse modeling is to find out

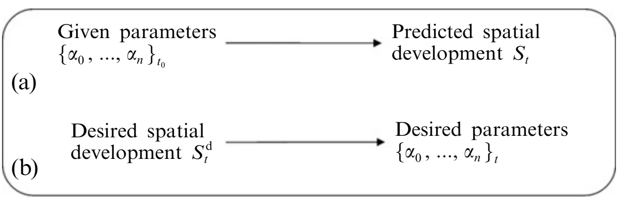


**Figure 1.** Illustration of the forward (a) and inverse (b) problem for spatial planners.

how to influence a system's present state via parameters in order to steer it into a different state in the future. The time span needed to reach such a future state will be given mainly by the spatiotemporal dynamics between parameters and the state of spatial developments. Thus, the problem begins with finding a mathematical model for forecasting the response of the spatial system. Such models generally incorporate both known and unknown parameters. In the latter case statistical methods can be used to estimate the unknown parameters.

While searching the solution for an inverse problem is a mathematical problem (Tenorio et al, 2008), there is a range of possible applications in different fields ranging from exploration geophysics (eg, Menke, 1989; Parker, 1994; Scales and Tenorio, 2001; Tarduno et al, 2009) to environmental modeling (Giudici, 2003; Henze et al, 2009; Kaminski et al, 2001), medical imaging (Arridge, 1999; Courdurier et al, 2008; Louis, 2004), engineering applications (Martinez-Luaces, 2009; Schneider et al, 2009; Soemarwoto et al, 2009), and nondestructive evaluation (Francini et al, 2006; Liu and Han, 2003; Udpa and Udpa, 1988). A comprehensive review of central topics from pure and applied mathematics and from several of the many areas of science and technology that give rise to inverse problems is given in the 25th anniversary issue of the journal *Inverse Problems* (Symes, 2009). A promising approach linking the concept of backcasting and inverse modeling is given by Osidele and Beck (2003). Their 'adaptive community learning' approach bases future endpoints on stakeholders visions and works backward using inverse methods to identify attributes of the model that are critical to attaining prescribed endpoints. In spite of the recognized use of such approaches for addressing complex planning problems to our best knowledge the application of inverse modeling in spatial planning has only been investigated by Rabino and Laghi (2002). They used an inverse approach to induce rules for modeling land-use dynamics based on cellular automata. Yet, the potential of such an approach for sustainable spatial planning might far exceed results of this study and merits more detailed exploration.

In this study we aim to introduce a new approach for sustainable spatial planning, where the point of departure is not current data, but a future desired by stakeholders. The result is a set of values for parameters identified as being key to reaching the desired future. After describing the inverse modeling approach, we apply it to a case study in a metropolitan area in Switzerland in order to illustrate its capabilities for sustainable spatial planning. The goal of the preliminary assessment is to show the type of planning questions can be answered using the approach, for example (i) given the current state-of-the-art of modeling future spatial states, are the spatial developments desired by the stakeholders reachable?; (ii) where should the desired development take place?, and (iii) what are the trade-offs between the different solutions? We discuss advantages and shortcomings of the approach for planners and draw conclusions about the effectiveness of the approach as a means of encouraging lay people and stakeholders to become involved efficiently in sustainable spatial development issues.

## 2 The inverse approach

Solving an inverse problem entails solving a problem coming from a scientific model. The phenomenon that relates the parameters to the observations can be represented by a mathematical linear or nonlinear operator G linking the space of observations $d$ with the space of parameters $\alpha$. While the set of parameters is usually called the model space, the set of observed data is called the data space ($d$). Aster et al (2005) describes an inverse problem as:

$$d = \mathrm{G}(\alpha_{\mathrm{true}}) + \varepsilon \,, \qquad (1)$$

where $d$ may be a function of time and/or space or may be a collection of discrete observations. The term $\alpha_{\text{true}}$ represents a set of parameters from a 'perfect' or 'noiseless' experiment, that is, an experiment where $\alpha_{\text{true}}$ satisfies $d = \mathrm{G}(\alpha_{\text{true}})$. Finally, $\varepsilon$ is a random noise component. The goal of inverse modeling is to search a solution for unknown $\alpha_{\text{true}}$ parameters such that $\mathrm{G}(\alpha_{\text{true}})$ becomes close to $d$. In other words, we make inferences about the parameters from the set of observed data by fitting the model to the data. For example, an investor might want to know what the locational or socioeconomic characteristics of a certain new neighborhood are given the prices of the planned dwellings. The data fitting can be achieved by minimizing the difference between the observed data and the estimated parameters as a function of the operator G. Snieder (1998) gives a comprehensive review of the approaches to estimate the models by data fitting.

However, in many inverse problems, the model that one aims to determine is a continuous function of the space parameters. Inverse problems are thus usually called 'ill-posed', a mathematical concept referring to problems in which the solution may not be unique or is not stable under perturbations on data. For this reason, inverse problems are often difficult to solve. Rabino and Laghi (2002) claim that in the case of unstable solutions, small changes in the observations (data) may correspond to big changes in the phenomenon being observed. In other words, algorithms to solve the problem are likely to produce very different solutions if inputs are changed just a little. Though sophisticated mathematical algorithms to tackle ill-posed problems have been proposed in the literature [widely detailed by Engl et al (2000)], Rabino and Laghi (2002) stress the importance of possessing prior information about the unknown system [ie, about the $\mathrm{G}(\alpha_{\text{true}})$ itself] derived from one's own experience. Prior information can be employed to delimit the space of possible solutions of the problem as well as to contribute to reducing the instability of solutions. Similarly, Scales and Snider (2000) point out that for practical inverse problems one is interested in patterns that can be used in a meaningful way for making decisions. In practice, these decisions are usually not based exclusively on the estimated model, but involve the integration of other data as well as human expertise.

## 3 A case study—planning for new dwellings in a metropolitan area

### 3.1 Preliminaries: modeling spatiotemporal dynamics in hedonic house-price models

Hedonic analysis of housing markets is an important part of the toolbox of applied urban economics (Sheppard, 1999). A number of examples in urban and also land-use studies can be found in the literature (eg, Geoghegan et al, 1997; Irwin, 2002; Kim et al, 2003). Though hedonic models can be fitted using ordinary least square (OLS), more sophisticated techniques have been developed in order to account for the spatial dynamics of the model's components. Two approaches are particularly popular in the literature: (1) the spatial autoregressive regression, developed by Anselin (1988), and geographically weighted regression (GWR), developed by Fotheringham et al (2002). While the former accounts for the spatial autocorrelation of the data, the latter uses spatially varying parameter estimates to deal with spatial heterogeneity (also known as spatial nonstationarity of parameter estimates). When data is collected across space and time, more advanced parametric methods have been proposed in the literature to describe and explain how spatial processes evolve over time, such as spatial panel data models (Anselin, 1988), spatiotemporal autoregressive models (Pace et al, 1998), and more recently, a spatiotemporal version of GWR, in which local parameter estimates are allowed to vary over space and time (Crespo et al, 2007; Huang et al, 2010).

In a simple way, a temporal hedonic house-price model can be expressed as follows:

$$\boldsymbol{P}_t = \mathbf{X}_t \boldsymbol{\beta}_t + \varepsilon_t , \tag{2}$$

where $\boldsymbol{P}$ is a vector of house prices, $\mathbf{X}$ is a matrix of house determinants, $\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated, $\varepsilon$ is a random component, and the subindex $t$ corresponds to the time at which variables are observed. Of particular interest is the estimation of $\boldsymbol{\beta}_t$ which provides valuable spatiotemporal information on relationships between house prices and their determinants. However, if more emphasis is to be placed on forecasting, contributions from other techniques such as time-varying coefficients can bring more insight on how time-series processes evolve over time. For example, Brown et al (1997) and Tucci (1995) suggest the use of an autoregressive specification of first order for the time series $\boldsymbol{\beta}_t$ in order to account for the memory of the process. Broadly speaking $\boldsymbol{\beta}_t$ can be written as a stationary autoregressive temporal process of first order as:

$$(\boldsymbol{\beta}_t - m_{\boldsymbol{\beta}_t}) = \varphi(\boldsymbol{\beta}_{t-1} - m_{\boldsymbol{\beta}_t}) + \varepsilon_t , \tag{3}$$

where $m_{\boldsymbol{\beta}_t}$ is the mean of the corresponding time series, $\varphi$ is a coefficient ranging between $-1$ and 1, and $\varepsilon_t$ is a random time series with zero mean. It is worth noting that the memory of the process is captured by both the mean of the process ($m_{\boldsymbol{\beta}_t}$) and the autoregressive ($\boldsymbol{\beta}_{t-1}$). Autoregressive models are particularly useful for short-term forecast because future values are highly influenced by past observations. In the long term though, the forecast of future values will tend to approach the mean of the process.

**3.2 Our forward model**

The metropolitan area of Zürich (Switzerland) is one of Europe's economically strongest areas and Switzerland's economic centre. The canton comprises 171 municipalities with almost 1.3 million inhabitants. As a hotspot of living, working, and commuting, the metropolitan area of Zürich is characterized by high density and a high development dynamic. Empty dwellings are rare, and the pressure to build new neighbourhoods is very high.

The following two examples illustrate how inverse modeling can support decision makers to identify urban development options in the canton of Zürich. Given a desired house-price level, firstly we show how one can determine what the relevant trade-offs between locational, structural, and socioeconomic characteristics of existing dwellings are in order to reach the desired price level. Secondly, we address the questions of what are possible locations and what are the relevant trade-offs for areas where future noise-emitting factories are to be planned.

As depicted in figure 2, the *forward model* is based on a hedonic house-price model employed by Loechl and Axhausen (2010). The underlying data for the model were taken from a webpage including rent offers from various Swiss real-estate online platforms between December 2004 and October 2005. The addresses for all dwelling units in the dataset were geocoded at building level and matched with a wide set of spatial variables. Overall, the dataset links rent prices with (1) *locational variables*: average time to the city center (CARTT_CBD), regional public transport accessibility to employment (PTACC), distance to the next rail station (RAILSTATION), presence of a highway in the proximity (HIGHWAY), presence of noise level above 52dB (AIRNOISE), terrain slope (SLOPE), visibility of the lake (VIEW_LAKE), and evening solar exposure (SOLAR_EVE), (2) *structural variables*: floor area (SQM), type of property (ISHOUSE), and date of construction (BUILT..TO..), and (3) *socioeconomic variables*: number of jobs in hotels and restaurants in the proximity (HOTREST_JOBS), population density (POP_DENS),

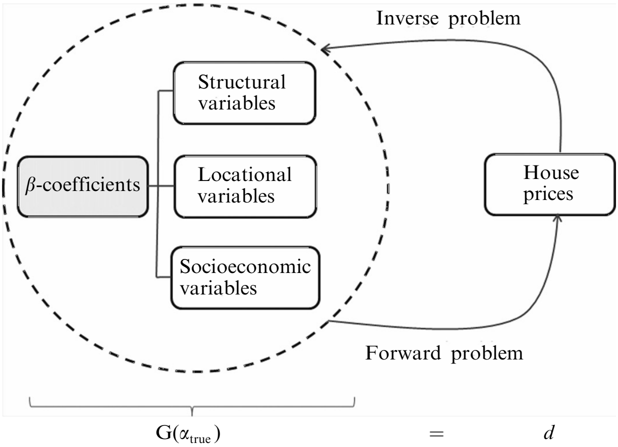


**Figure 2.** Case-study framework illustrating the link between the forward and the inverse modeling approach.

percentage of foreigners (FOREIGNERS), and tax level of the zone (TAXLEVEL) of 8592 dwelling units in the canton of Zürich. A more detailed description of all variables with the coefficient values of the global regression model is given in appendix A.

As we intend to explore how compensation schemes between the different variables differ across space, we used a local regression approach to fit the forward model. As described in section 3.1, GWR is a simple but very powerful statistical technique allowing $\beta$-coefficient estimates to vary own space. Thus, instead of deriving one global $\beta$-coefficient estimate for each explanatory variable as done by OLS, GWR produces a set of local $\beta$-coefficient estimates for each point from the dataset. Local $\beta$-coefficient estimates derived from GWR thus account for local variability of the explanatory variables. It may, however, occur that some explanatory variables do not exhibit sufficient local variability, yielding misleading local estimates associated with such variables. In such cases, a mixed GWR model is most likely to perform more accurately than a pure GWR model. Mixed GWR allows some $\beta$-coefficients to vary over space while others remain fixed. The selection of which variable will be globally or locally considered in the model can be done simply by analyzing the variability of the explanatory variables over space as well as the sign and $t$-values of the local estimates from GWR.

The functional form of the model is represented as:

$$\boldsymbol{P} = \mathbf{X}_a \boldsymbol{\beta}_a + \mathbf{X}_b \boldsymbol{\beta}_b + \varepsilon \,, \tag{4}$$

where $\boldsymbol{P}$ is a vector of the rents of the property (measured as the net monthly rent, $\mathbf{X}_a$ and $\mathbf{X}_b$ are the matrices of explanatory variables associated with global and local coefficients, respectively, $\boldsymbol{\beta}_a$ are the global coefficients (excluding the intercept term), $\boldsymbol{\beta}_b$ is a matrix of location-specific coefficients (including the intercept term), and $\varepsilon$ is a vector of residuals assumed to be random and spatially uncorrelated. The global variables include PTACC, ln(RAILSTATION), HIGHWAY, AIRNOISE, SLOPE, VIEW_LAKE, TAXLEVEL, SOLAR_EVE. The local variables include SQM, ISHOUSE, BUILT...TO..., ln(CARTT_CBD), HOTREST_JOBS, POP_DENS, and FOREIGNERS. It is worth pointing out, that according to the notation used in figures 1 and 2, the set of $\alpha$ parameters of our forward model comprises both the $\beta$-coefficients ($\boldsymbol{\beta}_a$ and $\boldsymbol{\beta}_b$) and the explanatory variables ($\mathbf{X}_a$ and $\mathbf{X}_b$) defined in the hedonic modeling specification [equation (4)]. As our motivation is to solve the inverse model for a set of chosen explanatory variables, we first fit the forward model by mixed GWR to derive the $\beta$-coefficient estimates, and next, we proceed to solve the inverse model for the chosen explanatory variables given a desired level of house rent.

The model fitting showed a higher goodness of fit compared with the global model or the pure GWR. Root mean square error (RMSE) for the mixed GWR equals 301.5, while the global model has a RMSE of 433.5 and the pure GWR a RSME of 324.6. A Moran's test was performed to check the spatial autocorrelation of residuals. The test showed a statistically significant but low spatial autocorrelation among residuals, with a Moran's *I*-index based on the inverse of the distance between the locations equal to 0.061.

To solve the inverse problem, we follow the approximation method suggested by Pajonk (2009) for which the difference $|\hat{P} - P^{\mathrm{d}}|$ must be small in some norm for all possible input/output combinations of the model, where $\hat{P}$ is a mixed-GWR estimate of house rents and $P^{\mathrm{d}}$ is a desire level of house rents. That is, different combinations of chosen explanatory variables are replaced in equation (4) until $\hat{P}$ approaches $P^{\mathrm{d}}$.

Finally, it must be noted that we are using cross-sectional data for fitting the hedonic house-price model and for inferring future spatial development from the inverse model. As stated in section 3.1, inverse modeling inference is associated with long-term temporal analysis so that data covering a long period of time is ideally desired for the analysis. For instance, the mean of the temporal process will more accurately capture the memory of the process as the number of observations increases over time. However, for illustrative purposes in this study, we assume that the values of the $\beta$-coefficients derived from the mixed-GRW model approximate the mean of the corresponding time series.

### 3.3 The air noise problem

It is generally argued that the locational variable air noise is negatively correlated to house prices (Feitelson et al, 1996), which in our case is corroborated by the negative sign of the AIRNOISE coefficient (see appendix B). Using the model from equation (2), we proceed using the inverse approach to analyze how the economic compensation scheme may vary across space for locations in which the average daily air noise exceeds 52db (which we will refer on to as *noisy locations*). This level lies between the maximum permissible planning level for noise from road traffic of zone I (recreational zones) and zone II (residential and official building zones) in Switzerland (LSV, 2008). Figure 3 shows the noisy locations together with the rest of the sampled data for the canton of Zürich. Noisy locations are located mostly near the airport, major roads, and highways. In order to obtain spatially explicitly results in a statistically meaningful way, we selected six clusters for analysis, three of which include noisy areas. Our motivation in selecting three clusters located outside noisy areas is to provide insights on possible locations where new factories could be planned. Appendix C provides a description of the averaged variables for each cluster.

Solutions for $\mathbf{X}_a$ or $\mathbf{X}_b$ are obtained following the approximation method proposed by Pajonk (2009). Thus, different values of either $\mathbf{X}_a$ or $\mathbf{X}_b$ are substituted in equation (3) in order to reach a desired level of rent accounting for the economic compensation as follows:

$$P^{\mathrm{d}} = \bar{\mathbf{X}}_a \hat{\boldsymbol{\beta}}_a + \bar{\mathbf{X}}_b \bar{\hat{\boldsymbol{\beta}}}_b \,, \qquad (5)$$

where $\bar{\mathbf{X}}_a$ and $\bar{\mathbf{X}}_b$ are matrices of averaged explanatory variables associated with global and local variables, respectively, for each cluster, $\hat{\boldsymbol{\beta}}_a$ is the vector of global $\beta$-coefficient estimates derived from the OLS regression (see appendix A), and $\bar{\hat{\boldsymbol{\beta}}}_b$ is the vector of averaged mixed GWR local $\beta$-coefficient estimates for each cluster.

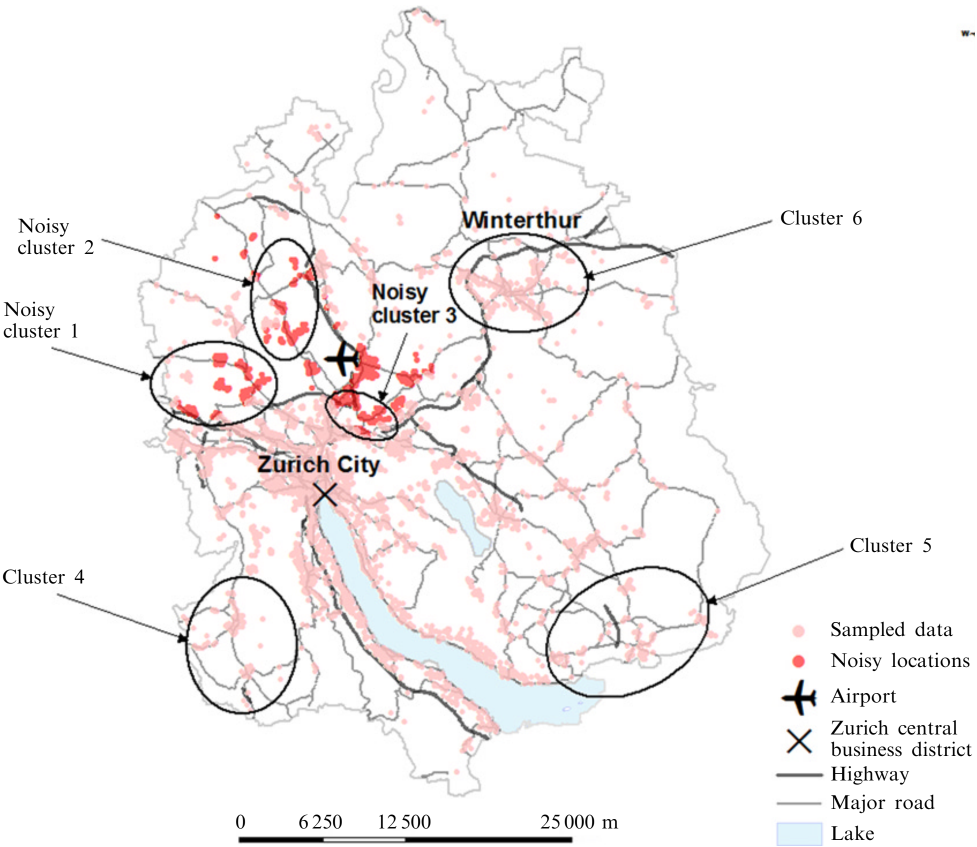


**Figure 3.** [In color online.] Locations of the sampled data for the hedonic house-price model (noisy locations exceed an average daily air noise of 52 db).

$P^{\mathrm{d}}$ denotes a 'desired rent' for which $\bar{\mathbf{X}}_a$ or $\bar{\mathbf{X}}_b$ is to be solved. From appendix A, we derive that 85 [CHF] is the economic compensation that residents from noisy locations should receive due to the exposure to high level of air noise. The 'desired rent' can thus be estimated as $P^{\mathrm{d}} = \hat{P}_{\mathrm{avg}} + 85$ for each cluster, where $\hat{P}_{\mathrm{avg}}$ is the average mixed GWR estimated house rent of the corresponding cluster.

Table 1 shows the average of local $\beta$ estimates from the mixed-GWR model coupled with the average estimated house rents ($\hat{P}_{\mathrm{avg}}$) and the 'desired rent' ($P^{\mathrm{d}}$) for each cluster. As can be observed, average local estimates exhibit significant variability over the six clusters. The only exception is the SQM estimate which shows a low variability. However, it must be noted that the local SQM estimates exhibit a significant spatial variability over the whole canton of Zurich, ranging from a minimum of 9 [CHF/m$^2$] to a maximum of 34 [CHF/m$^2$].

Economic compensation for excessive noise can be achieved in different ways. For example, from a local perspective, compensation can be made by improving accessibility to Zurich Central Business District (CBD). Figure 4(a) depicts by how much the average travel time to Zurich CBD by car has to be decreased to compensate for the economic losses caused by excessive noise for the three noisy clusters. The results indicate that the optimal value of the ln(CARTT_CBD) local estimate are 11.5, 4.3, and 1.8 mins for noisy clusters 1, 2, and 3, respectively. Such differences among clusters may be explained by the difference in the current accessibility of the different clusters. Residents from the noisy cluster 1 respond more rapidly to reductions in the travel time

**Table 1.** Averaged values of rents and local estimates for each cluster.

| | Noisy Cluster 1 | Noisy Cluster 2 | Noisy Cluster 3 | Cluster 4 | Cluster 5 | Cluster 6 |
|---|---|---|---|---|---|---|
| *Rents* | | | | | | |
| $\hat{P}_{avg}$ [CHF] | 1754 | 1566 | 1604 | 1855 | 1576 | 1395 |
| $P^{d}$ [CHF} | 1 839 | 1 651 | 1 689 | 1 940 | 1 661 | 1 480 |
| *Averaged local coefficient estimates* | | | | | | |
| SQM | 14.2 | 13.8 | 12.7 | 14.0 | 14.0 | 13.8 |
| ISHOUSE | 392.5 | 240.0 | 222.4 | 382.3 | 381.7 | 491.3 |
| BUILBEF20 | 166.7 | 413.9 | 240.0 | 166.7 | 107.6 | 53.0 |
| BUIL21TO30 | 95.1 | 361.7 | 97.2 | 256.6 | 38.5 | 113.5 |
| BUIL81TO90 | 30.4 | −50.7 | 66.0 | 100.0 | −69.8 | −17.9 |
| BUIL91TO06 | 157.0 | 61.9 | 146.1 | 179.3 | 39.1 | 124.3 |
| ln(CARTT_CBD) | −202.4 | −659.3 | −953.1 | −239.5 | −331.8 | −87.9 |
| HOTREST_JOBS | 0.12 | 0.95 | −0.03 | 0.95 | 0.69 | 0.25 |
| POP_DENS | −0.80 | −0.28 | −0.44 | −2.20 | −1.16 | −0.12 |
| FOREIGNERS | −1123.0 | −857.4 | −417.9 | −1560.0 | −939.8 | −1211.7 |

to the Zurich CBD than residents from the noisy clusters 2 and 3. Additionally, it might occur that the workplace of most of the residents from the noisy cluster 3 is not located in the Zurich CBD, as it may be in the case of cluster 1 for example, so that the rent of properties in cluster 1 would respond more rapidly to reductions in the ln(CARTT_CBD) variable than the rent of properties in clusters 2 and 3. Figure 4(b) shows the results on a map, where points are drawn proportionally to the extent to which the accessibility to the Zurich CBD must be improved in order to compensate for the 85 CHF loss caused by the air noise.

Another way to compensate for the noise is to increase the floor area of properties. However, as the average of the SQM local estimates exhibits low spatial variability across the clusters (see table 1), the compensation scheme will also exhibit low

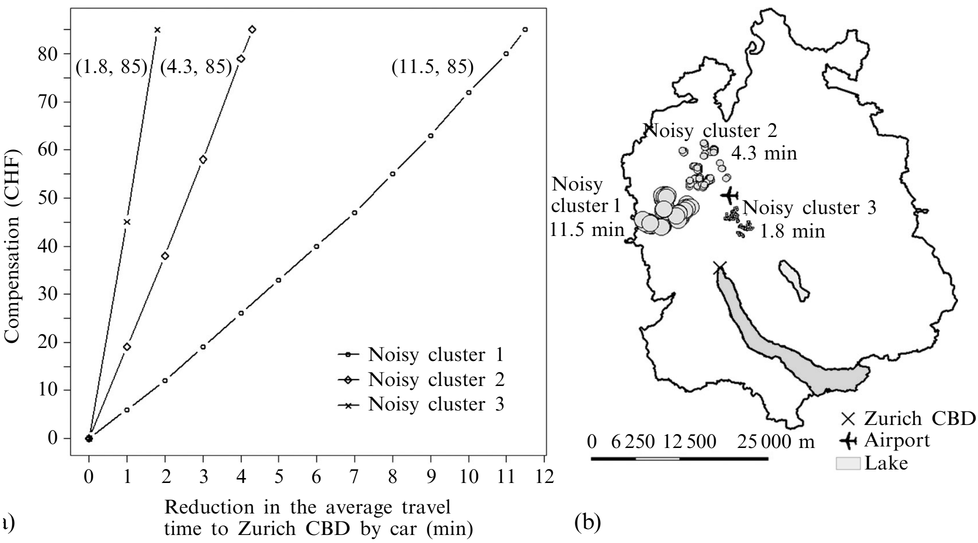


**Figure 4.** Compensation level for excessive noise level by change in accessibility to the Zurich Central Business District (CBD) for the three noisy clusters: (a) optimal value of the CARTT_CBD variable for each noisy cluster; (b) representation of the optimal vlaue of the CARTT_CBD for each noisy clustrer on the Canton of Zurich map.

spatial variability. An economic compensation of 85 [CHF] for residents living in the noisy areas can be achieved by an increment in property size of the approximately 6.2 $m^2$. From a global perspective, the economic compensation can also be achieved by reducing the income-tax level for residents living in each noisy cluster. The value of the TAXLEVEL global parameter is $-2.7$ which means that house rents drop by 2.7 CHF as the tax level decreases by 1%. In this case, the economic compensation of 85 [CHF] can be achieved by a 36% reduction in the current income-tax level.

### 3.4 Future noise-emitting factories

In order to identify locations for new noise-emitting factories, we evaluated the compensation scheme at locations where the noise level is below 52dB. Results for the three clusters indicate that economic compensation for potential high levels of air noise can be achieved by reducing the average travel time to the Zurich CBD by car by 9.7, 11.4, and 26.8 mins for clusters 4, 5, and 6, respectively. From an urban planning perspective, a reduction in these travel times is unfeasible. More practicable values can be obtained by simultaneously reducing the income-tax variable. Figure 5 shows the trade-off between the reduction in the tax-level variable and the accessibility to the Zurich CBD by car. As expected, the larger the reduction in the tax level, the smaller the reduction in the accessibility to the Zurich CBD. For example, with a reduction of approximately 20% in the tax level for cluster 5, the average travel time to the Zurich CBD by car is reduced by 4 min instead of the original 9.7 min. Similarly, for cluster 6, the tax level must drop by approximately 27.5% in order to have a reduction in the average travel time to the Zurich CBD by car of approximately 4 min instead of the original 26.8 mins.

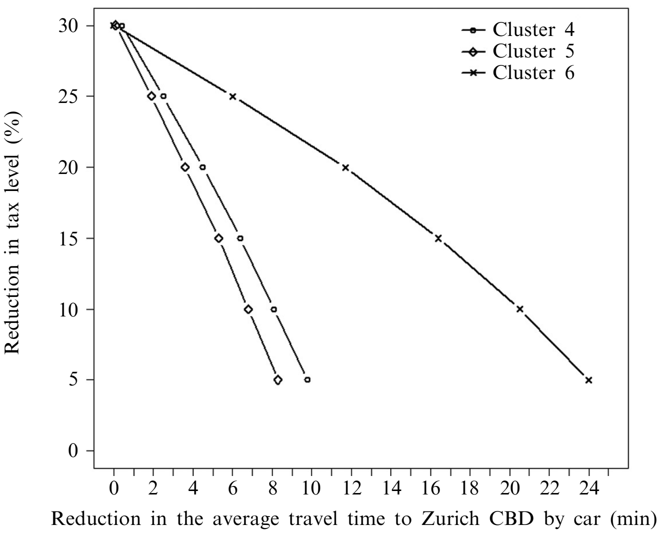


**Figure 5.** Trade-off between tax level and accessibility to the Zurich Central Business District (CBD) for new noise-emitting factories for clusters 4, 5, and 6.

## 4 Discussion

Making plans requires defining a contingent path through a sequence of decisions. Put another way, planning relates to conscious envisioning of desirable outcomes followed by a study of conditions and actions to reach such outcomes. Analogously, we show in this study how inverse modeling facilities answering the *how* to reach a specified outcome using a desirable future value as the starting point. By applying inverse modeling to spatial econometric modeling, we show how one can identify local trade-offs between relevant attributes for rent prices in a spatially explicit manner, thus testing the attractiveness of locations for new spatial development.

Especially in cities, where environmental constraints are usually much more stringent in the center than in the periphery, the challenge is to find ways to break the present urban sprawl and to test the feasibility of new paths along which a desired densification could take place. In this study, we quantify how much an investor might have to compensate residents for new noisy facilities in order to maintain a certain living standard. The selected case-study applications are in good agreement with criteria formulated by Dreborg (1996) to decide when a method of backcasting (as opposed to forecasting) is useful: (1) the problem studied is complex, affecting many sectors and levels of society; (2) there is a need for major changes; (3) dominant trends are part of the problem; (4) one of the reasons for the problem is externalities; and (5) the time perspective is long enough to allow for deliberate choices. Results show that considering externalities such as noise in the planning of new facilities may support a densification of urban development. In the canton of Zurich, favorable locations for new noisy facilities are situated close to the city center, where noise is already considerable. This, of course, does not correspond with current development practice, where building on 'green areas' is cheaper than building in the city.

Using hedonic modeling to evaluate feasible trade-offs in the inverse modeling framework is a way to obtain insight into locational, structural, and social preferences of living. Other trade-off analysis may include socioeconomic variables such as population density, proportion of foreigners, professional level of residents, as well as locational variables such as visibility of a lake surface or accessibility to public transport. Further research may include additional explanatory variables commonly used in hedonic house-price modeling, such as accessibility to schools, shopping centers, or hospitals. This would broaden the trade-off alternatives for economic compensation arising not only from high levels of air noise, but also from any other type of negative externality affecting the living standard of inhabitants.

However, it is important to note here that results from inverse modeling rely on the selection of the appropriate model specification as well as on the goodness of fit of the statistical method employed to calibrate such a model. In order to minimize the effects of the inherent uncertainly associated with local and global estimates on the inverse model analysis, we performed the analysis at cluster level rather than at single-building level. In the latter case, extreme values are likely to yield biased estimates and so misleading conclusions may be drawn. However, it is also worth noting that the accuracy of results is also subject to the size of clusters. The value and accuracy of local estimates will likely be affected by the size of the cluster. In general, the bigger the cluster, the higher the bias of the averaged local estimates employed in the analysis.

The issue of using cross-sectional data for solving inverse modeling must of course be studied and considered more carefully. Though the method we propose in this study will not vary in essence, clearly its statistical robustness would be augmented by the use of spatiotemporal data. However, spatiotemporal data is not always easy to collect, especially when the model comprises a number of explanatory variables of different classes. In such cases, the use of complementary econometric approaches to deal with long-term inference on parameters may play an important role in finding a more accurate solution for the inverse model. For instance, long-term values of the $\beta$-coefficients can be derived using other models such as Bayesian inference from the information provided by the cross-sectional data.

In conclusion, despite the current limitations of the presented approach, the two case studies demonstrate that inverse modeling can be a powerful tool for developing alternative spatial plans utilizing future visions. Because of its potential to answer the question "what shall we do today to get there?" our approach might be especially supportive in political efforts (eg, Science Advisory Board, 1995) to establish early-warning systems for identifying undesirable spatial developments. The next steps will be to demonstrate the use of such an approach to increase political effectiveness of strategic spatial-development goals and visions. While participative backcasting has already been applied successfully in strategic planning (Carlsson-Kanyama et al, 2008; Dreborg, 1996; Höjer and Mattsson, 2000; Robinson, 1982; 1990), the use of quantitative spatially explicit inverse modeling might support the efforts of planners to achieve long-terms goals of sustainability.

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## Appendix A

**Table A1.** Descriptive statistics of the model's variables.

| Variable | Type[a] | Description | Min | Max | Mean |
|---|---|---|---|---|---|
| *Response variable* | | | | | |
| RENT | C | Monthly net asking rent in CHF | 476 | 15 000 | 1 841 |
| *Explanatory variables: 1 Structural* | | | | | |
| SQM | C | Floor area in $m^2$ | 20 | 400 | 91.3 |
| ISHOUSE | B | 1 if the property is a single family house, 0 otherwise | 0 | 1 | |
| BUILBEF20 | B | 1 if the property was built prior to 1920, 0 otherwise | 0 | 1 | |
| BUIL21TO30 | B | 1 if the property was built between 1921 and 1930 | 0 | 1 | |
| BUIL31TO80[b] | B | 1 if the property was built between 1931 and 1980 | 0 | 1 | |
| BUIL81TO90 | B | 1 if the property was built between 1981 and 1990 | 0 | 1 | |
| BUIL91TO06 | B | 1 if the property was built between 1991 and 2006 | 0 | 1 | |
| *Explanatory variables: 2 Locational* | | | | | |
| CARTT_CBD | C | Average travel time to the Zurich Central Business District by car in mins | 8 | 58.4 | 29.9 |
| PTACC | C | Regional public transport accessibility to employment | −19.4 | 12.4 | 10.7 |
| RAILSTATION | C | Euclidean distance to next rail station in km | 0.013 | 5.732 | 0.911 |
| AUTOBAHN | B | 1 if autoban located within 100 m, 0 otherwise | 0 | 1 | |
| AIRNOISE | B | 1 if daily average air noise is above 52dB, 0 otherwise | 0 | 1 | |
| SLOPE | C | Slope by 25 m raster | 0.00 | 0.26 | 0.036 |
| VIEW_LAKE | C | Visibility[c] of lake surface (>1 sqkm) in ha | 0.0 | 441.8 | 8 887.8 |
| SOLAR_EVE | C | Evening solar exposure index | 0.0 | 607.1 | 238.2 |
| *Explanatory variables: 3 Socioeconomic* | | | | | |
| HOTREST_JOBS | C | Number of jobs in hotel and restaurant industry within 1 km | 1.2 | 7 083.8 | 314.0 |
| POP_DENS | C | Number of inhabitants in hectare | 1.0 | 2 004.0 | 93.5 |
| FOREIGNERS | C | Percentage of foreigners[d] in hectare | 0.00 | 0.50 | 0.05 |
| TAXLEVEL | C | Local income-tax level as percentage of the basic cantonal tax | 69.0 | 122.0 | 110.3 |

Note: Min = minimum; Max = maximum.
[a] C = continuous; B = binary.
[b] Reference case, therefore this variable is not included in the calibration of the hedonic house price model.
[c] Visiblity of VIEW_LAKE variable is calculated based on 25 m DEM, not considering objects such as buildings or trees.
[d] Foreigners are defined as inhabitants with nationalities outside of North-Western Europe, North America, and Australia.

## Appendix B

**Table B1.** Ordinary leasts squares parameter estimates.

| Variable | Parameter estimate | $t$-value |
|---|---|---|
| Intercept | 2 212 | 23.7 |
| SQM | 18.9 | 128.4 |
| ISHOUSE | 290 | 8.5 |
| BUILBEF20 | 106.6 | 6.1 |
| BUIL21TO30 | 166.7 | 5.6 |
| BUIL81TO90 | −36.4 | −2.7 |
| BUIL91TO06 | 50.8 | 3.8 |
| Ln(CARTT_CBD) | −697.4 | −36.3 |
| PTACC | 20.5 | 5.8 |
| Ln(RAILSTATION) | −48.5 | −7.4 |
| AUTOBAHN | −128.7 | −3.7 |
| AIRNOISE | −85.2 | −5.9 |
| SLOPE | 1052 | 6.32 |
| VIEW_LAKE | 0.077 | 15.3 |
| SOLAR_EVE | 1 073 | 17.7 |
| HOTREST_JOBS | 0.059 | 7.5 |
| POP_DENS | −0.708 | −9.9 |
| FOREIGNERS | −628.9 | −4.6 |
| TAXLEVEL | −2.37 | −6.3 |

$R^2 = 0.77$
Moran's $I = 0.061$

## Appendix C

**Table C1.** Summary of some variables of each cluster.

| | Noisy clusters | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Number of properties selected | 195 | 222 | 303 | 201 | 170 | 428 |
| Average house price (monthly net rent in CHF) | 1765 | 1645 | 1583 | 1866 | 1558 | 1459 |
| Average floor area (SQM) | 99.5 | 92.8 | 83.7 | 106.8 | 95.5 | 82.4 |
| Number of flats (ISHOUSE = 0) | 195 | 222 | 303 | 201 | 170 | 428 |
| Number of properties built prior to 1920 (BUILBEF20) | 10 | 11 | 13 | 20 | 20 | 41 |
| Number of properties built between: | | | | | | |
| 1921 and 1930 (BUIL21TO30) | 0 | 3 | 2 | 0 | 0 | 13 |
| 1931 and 1980 (BUIL31TO80) | 78 | 124 | 171 | 36 | 22 | 288 |
| 1981 and 1990 (BUIL81TO90) | 62 | 26 | 42 | 63 | 46 | 51 |
| 1991 and 2006 (BUIL91TO06) | 45 | 58 | 75 | 82 | 82 | 35 |
| Average travel time to the Zurich CBD by car (mins) (CARTT_CBD) | 33.5 | 35.5 | 254 | 37.9 | 43.0 | 43.1 |
| Visibility of lake surface (VIEW_LAKE) | 0.00 | 0.00 | 35.7 | 181.2 | 302.4 | 0 |
| Average tax level (TAXLEVEL) | 106.2 | 113.2 | 95.2 | 116.9 | 118.2 | 121.9 |
| Average number of jobs in hotel and restaurant industry within 1 km (HOTREST_JOBS) | 98.6 | 40.6 | 440.2 | 46.7 | 56.9 | 247.3 |
| Average population density (POP_DENS) | 77.6 | 71.4 | 99.2 | 67.5 | 75.0 | 111.0 |
| Average proportion of foreigners (FOREIGNERS) | 0.047 | 0.057 | 0.080 | 0.036 | 0.049 | 0.051 |