Geographic Modeling: Approaching Reality in Land Use Simulation Pragmatically

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Abstract

Geographic research necessitates different types of models that aim at reducing the complexity of reality, enabling us to analyze its representations. Models allow us to infer exploratory and confirmatory findings about causal links between different geographic conditions, different social, political, and economic actors, their behaviors, and land use and its dynamics. However, the spatial, temporal, and attributive nature of data complicates the appropriate model choice for specific research purposes. This conceptual paper keeps track of model construction in the context of land use and land use change. It reveals different issues where particular caution is required, such as spatial and temporal dependency and heterogeneity, scale-dependency, and bidirectional causality. With geographic research being increasingly under the influence of econometric methods, we contend that it is necessary to provide intermediary qualitative layers of evidence between conceptual and, especially, empirical and simulative models of land use and land use change to ensure robust findings about causal relationships between observed variables.

1 Introduction

The rapid rise of Geographical Information Systems (GIS) over the last decades has created manifold opportunities for geographic research. The digitization of analogue land use plans as well as the development of ever finer-grained remote sensing data accompanied by interpreting algorithms has been promoted by researchers and policy-makers, adding to the utility of GIS. Scientists from various fields have developed increasingly broad and specialized spatially explicit econometric and simulative methods that enable us to explore questions of land use and land use change. Both ANSELIN (2010) and IRWIN (2010) provide comprehensive literature reviews on a multitude of currently available techniques.

The plethora of newly elaborated or refined statistical and quantitative methods confronts scientists in land use and land use change with a difficult challenge: How should a specific research question be correctly conceptualized and how should the appropriate methods be selected? And how can the applied models be ensured to usefully represent and measure objectives which we commonly phrase as the "real world"?

Reflecting on these questions is crucial in order to deliver reliable and valid research answers. Our paper discusses the conceptualization of research models focusing on land use and land use change, and highlights the main challenges in light of an ever increasing focus on quantitative geodata.

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We contend that the provision of intermediary qualitative layers of evidence linking the conceptual and empirical or simulative models of land use and its dynamics is a necessity to improve the explanatory quality and robustness of the proposed theoretical arguments and causal relationships and between the observed variables.

2 The Necessity of Modeling the "Real World"

The study of reality and its spatio-temporal conditions necessitates breaking down the "real world" into a scientific model. Reality can be understood as an extremely complex system that consists of different elements (see O'SULLIVAN & PERRY 2013, 3 ff.): (1) Components, which are "distinct parts or entities that make up the system", (2) state variables, which "describe the overall condition of the system at a particular point in space and time", (3) processes, which determine the transition mechanisms of the system and its components, and (4) "interactions between system components." The practically endless complexity of any real world system forces us to simplify it in order to be able to view it in a scientific manner. This is typically achieved through a model. Quoting BOX (1979a, 2), O'SULLIVAN & PERRY (2013, 4) explain that a model constitutes a simplification of reality, which can never be true, but, fortunately, only needs to be useful to be justified. Well chosen (and parsimonious) models can, according to BOX (1979b, 2 f.), often be useful approximations of reality. Following BOX (ibid. 2), "parsimony is desirable because

(i) when important aspects of the truth are simple, simplicity illuminates, and complication obscures;
(ii) parsimony is typically rewarded by increased precision (…); [and]
(iii) indiscriminate model elaboration is in any case not a practical option because this road is endless."

O'SULLIVAN & PERRY (2013, 23) point to LEVINS (1966, 422) who highlights the limitations that models have. He stresses the trade-offs between the realism, generality, and precision of a model. Only two of the three goals may be achieved in a scientific modeling endeavor. Models that would include all possible variables and may explain a specific pattern of land use at a certain location would be realistic and precise, but they could not be generalized. Land use models that are realistic and general, on the other hand, naturally have to be imprecise, as they cannot capture the spatial heterogeneity of specific locations. And finally, general and precise models cannot be realistic, as they would need to include an almost infinite number of relevant factors.

Depending on the specific use and purpose of a model, those trade-offs between realism, generality and precision have to be balanced by the constituting researcher according to the three main characteristics of models. STACHOWIAK (1973, 131 ff.) describes them as (1) representation, (2) reductionism, and (3) pragmatism. The first aspect stresses the role of models as "representations of natural or artificial originals which themselves can be models" (ibid. 131, authors' translation from German). To deal with questions on land use and its dynamics, researchers typically draw on artificial originals, may they be maps, plans, aerial or satellite images, which themselves are models. The reduction characteristic highlights the quality of a subjective and purposive simplification. According to STACHOWIAK (1973:132), models typically do not capture all the attributes of the original, but only those that seem to be relevant to the creator and the users of a specific model. The pragmatism characteristic, finally, specifies the functionality of a model, addressing the "why" and "what for". STACHOWIAK (1973, 132) argues that models are not assigned per se to a certain original. They fulfill their replacement function for specific discerning and/or acting model-using subjects, within certain time intervals and under the restriction of certain mental or actual procedures (ibid. 132 f.). This means that the purpose of a model is explicated through a contextual, temporal, and subjective problem oriented differentiation. Creating models, hence, depends heavily on which goals should be achieved through its specific design. Their concrete form is conditioned by the type of conducted research (either exploratory or confirmatory), the specific research questions, and the available data.

3 Model and Research Types

Researchers generally use different types of models over the course of a research project. Among these are conceptual models, mathematical models, empirical models, and simulation models (O'SULLIVAN & PERRY 2013, 4 ff.). Beyond this way of structuring models, other approaches such as pattern orientation (METCALF 2014, 42; GRIMM & RAILSBACK 2005), where simulated patterns were compared with empirical patterns over time, and model narratives, can be utilized.

The construction of a **conceptual model** is usually the beginning of any modeling exercise. This conceptual model can later be specified through one or more of the other three model types. One of the main purposes of a conceptual model is to lay out a model that is "expressible in words" (O'SULLIVAN & PERRY 2013, 4 f.; BOSSEL 1994 coined the term "word model"). A very simple example in connection with land use and land use change modeling may be the following description: "The more restrictive the land use plans for a certain locality, the lower its urban sprawl". However, the conceptual modeling of a certain system under investigation may often be more demanding and necessitate further modeling efforts through the description of the model purpose, its relevant components, state variables, processes and interactions. Moreover, a proper conceptual model typically presents and justifies the applied rules for its construction. Conceptual models are usually translatable into cause-and-effect diagrams. In such a diagram, relationships and interactions between the components under certain conditions can be illustrated.

The design of conceptual models also depends on the style of research, which can either be exploratory (inductive) or confirmatory (deductive). Both research styles usually complement each other, with exploratory research designs being the appropriate tool for comparatively uninvestigated phenomena and topics, and confirmatory research designs being beneficial for phenomena that have already been scientifically covered. Exploratory research does not have any hypotheses about the investigated phenomena beforehand, and aims at examining the potential relationships and interactions between its system components with the available data at hand. Hypotheses about such connections are usually made *a posteriori* at the end of the research process. A conceptual model that treats a real world phenomenon in an exploratory manner, hence, has to reflect its specific aims in its composition. Confirmatory research predicts or tests *a priori* hypotheses during the research process. These hypotheses may be derived from one's own reasoning or from work conducted by others. The advantage of confirmatory research is that it reduces the chances of committing so called "type I errors" in reasoning. This type of error relates to the confirmation of a hypothesis, which would need to be dismissed in fact due to statistical miscorrelation. Concerning land use and land use change analysis, such an error could occur if we observe specific land use patterns in urban agglomerations of a country above a certain threshold number of inhabitants. The assumption that the number of inhabitants serves as an explanation for certain land use patterns on a global scale would then be erroneous, because other factors, for instance the specific land use regulation for metropolitan areas in the investigated country, may account for the land use patterns under investigation. While confirmatory research may lower the chances of running into such a fallacy, the correct conceptual modeling of the phenomena at hand is equally important. O'SULLIVAN & PERRY (2013, 6) conclude that in many areas of research (especially in the social sciences, which partially touch the work on land use and land use change) "verbal descriptions remain the primary mode of representation, and extremely elaborate conceptual models are routinely presented in words alone (…)". They name the works of Adam Smith and Karl Marx as typical examples of such intricate conceptual models of the socio-economic/political reality whose complexity has caused them to be open to interpretation, and, thus, to be disputed. O'SULLIVAN & PERRY (2013, 6) add that the "subsequent mathematisation of economic theory through the twentieth century has not greatly reduced the interpretative difficulties: however we represent them, complicated models remain complicated and open to interpretation."

Depending on the type of conducted research (inductive or deductive, theoretical or empirical), but independent of their degree of realism, generality, and precision, conceptual models can lay the basis for other types of models. **Mathematical models** represent one of the additional model types "where component states are represented by variables and the relationships between them by mathematical equations" (O'SULLIVAN & PERRY 2013, 8). Mathematical models are typically deductive and important for the calibration and verification of the original or otherwise developed models. The degree of complexity of mathematical models varies depending on the model purpose and the degree of simplification (see BOSSEL 2004), as well as on the applied methods and techniques.

Complementary to mathematical models, so called **empirical models** aim at inferring general rules through observations, measurements and experiments. Empirical models substantiate the more abstract and generalized assumptions of conceptual and mathematical models by operationalizing the model variables and their relationships with "real world" data or artificial originals such as aggregated geospatial data. In the contemporary scientific literature, conceptual models, which are supposed to provide us with plausible models and hypotheses about the real world, are typically accompanied by empirical models, which aim to either prove or disprove the assumed relationships and interactions between the variables under investigation. Especially since the onset of the quantitative revolution in geography, empirical "models are generally statistical in nature, with regression models the most widely used technique" (see O'SULLIVAN & PERRY 2013, 8). Also the analysis of land use and land use change is now predominantly conducted with quantitative empirical models that accompany deductively conceived hypotheses of conceptual models. Both ANSELIN (2010) and IRWIN (2010) provide in-depth analyses and reviews of the history and the current spectrum of (econometric) empirical modeling approaches. While econometric techniques in empirical models have become state-of-the-art research design methods over the last years, the "meaningful interpretation of observed statistical relationship can be challenging" (ibid. 8 f.). Empirical models typically aim at showing statistically significant causal relationships between variables. Significance in this case means that a certain relationship has not, with high probability, occurred randomly. ANSELIN (2010, 17) points out, however, that significance has “little use in the analysis of massive data sets since everything tends to be significant.” The question of significant causal links is further complicated by “reversed or cyclical causality and interaction effects” (ibid. 17).

A fourth type of model is a so-called **simulation model.** As O’SULLIVAN & PERRY (2013, 11) put it, simulations “are implementations, usually in a computational setting, of an underlying conceptual or mathematical model.” They allow for an explicit rule-based implementation of spatial, temporal, and attributive features. Simulation models can represent deterministic as well as stochastic processes. Simulation might be an appropriate alternative to empirical models as it allows for very detailed analyses of a model that is otherwise impossible (ibid. 11). Simulation models are useful tools for the exploration of complex relationships and for the explicit inclusion of spatial and temporal interaction effects, and they are recurrently used for predicting the future. Similarly to empirical models, we see a continuous broadening and deepening of simulation model applications. HEPPENSTALL et al. (2012) and KOCH & MANDL (2011, 2013) can be consulted for an exemplary overview of simulation models in geography that either explicitly or implicitly include aspects of land use and its dynamics.

4 The Building Blocks of Models: Patterns, Processes & Scale

The goal of geographic research today is typically to reveal causal relationships between system components and processes. To look at this goal more closely in the context of constructing conceptual, mathematical, empirical, and simulation models, it is necessary to consider three different fundamental aspects: patterns, processes, and scales (O’SULLIVAN & PERRY 2013, 29). These elements define research processes and affect the interpretation of results in a significant manner.

For geographic research, and especially for investigations about land use and land use change, **patterns** are often the starting point to discover processes and relationships of a given system (see MEENTEMEYER 1989, 168 in ibid. 29 f.). LAWTON (1999, 178 in O’SULLIVAN & PERRY 2013:30) describes patterns “as regularities in what we observe in nature; that is, they are ‘widely observable tendencies’.” And IRWIN (2010, 69) sees “patterns, either static or evolving over time (…) [as] the outcome of processes. Patterns, in his view, “are revealed by spatial land use/land cover data, but processes are not.” Patterns, hence, in a geographic context, are spatially discernable properties of underlying components that may be closely related to the idea of spatial heterogeneity, which, in a most basic sense, describes the uneven distribution of components in a spatial landscape.

Processes are closely related to patterns. O’SULLIVAN & PERRY (2013, 30) define a process as “any mechanism that causes a system to change its state, and so potentially to produce characteristic patterns.” While research has the tendency to investigate the effects of processes on patterns, the authors stress that there may be causal links in both directions, especially in the social world. Similarly to the relational likeness of patterns and spatial heterogeneity, processes may closely reflect spatial dependence. According to ANSELIN (2010, 5), spatial dependence represents “a special case of cross-sectional dependence, in the sense that the structure of the correlation or covariance between random variables at different location is derived from a specific ordering, determined by the relative position (distance, spatial arrangement) of the observations in geographic space (or, in general, in network space)." More simply, it can be summed up by TOBLER's (1970) approach who contends that "nearby things are more similar than distant things".

Especially in cross-sectional analyses it may be very challenging to unravel the links between patterns and processes. While this kind of data may be useful to identify specific patterns, additional temporal data is needed to shed more light on the direction of the relationships (see ANSELIN 2010, 5). To consider the question of causality more closely, let us imagine a specific land use pattern such as urban sprawl around the metropolitan areas of a country, assuming that suburbanization processes have led to these patterns. Urban sprawl, however, may in turn have an influence on any subsequent processes, possibly causing increased traffic congestion, for example, which is followed by a relocation of people back to the city center later. Such lines of argument can continue over even longer time frames, making it difficult to draw a clear distinction between what is causing what. It is equally difficult to separate spatial heterogeneity from spatial dependence (ibid. 5), especially while using cross-sectional data. ANSELIN (2010, 5) relates this to the problem of differentiating "between true and apparent contagion. (…) As a result, it is impossible to distinguish between the case where the cluster is due to structural change (apparent contagion) or follows from a true contagious process." Hence, it is a great advantage to follow the links between spatial patterns and the connected processes and its changes over time in order to achieve better insights into the causal mechanisms of a model (see also O'SULLIVAN & PERRY (2013, 29).

Linked to the question of patterns and processes, the issue of **scale** is very important for the composition of appropriate model types. Scale can be relevant for the units of components, state variables, relationships, and interactions (depending on the degree of its aggregation), and for the spatial and temporal scope of an analysis. All variable values used in models are constructed and artificial units. Temporal, spatial, and thematic attributes are not "naturally" given, but are derived from conscious decisions, that are later (at least temporarily) accepted by others as conventions, metaphors, or theories, even if they are related to "natural" phenomena (such as time). The problem of choosing the adequate scale for the spatial and temporal units in a model is inseparably linked to the scale-dependent variability of the represented phenomena and the dependent outcomes of model analyses.

There is no such thing as a "natural" **spatial unit**. Different spatial units are themselves already artificial originals of the real world. This equally applies to the choice of the smallest adequate spatial unit from which one begins to aggregate data used in scientific analysis, e.g. administrative-territorial or functional polygons, or uniform raster cells (see SIDHARTHAN & BHAT, 331). Spatial dependence (spatial autocorrelation) as well as spatial heterogeneity (spatial non-stationarity) add even more complexity to the analysis of spatial data. Spatial dependence is a particular concern for raster data, as, according to IRWIN (2010, 76), they "are delineated by equal-area cells rather than the boundaries of the decision making unit (in this case, parcels) and thus massive problems of spatial dependence arise in using these data to estimate a land use change model." If we choose raster cells with a high resolution (e.g., 20m x 20m) it is likely that several bordering cells belong to the same land parcel and are thus owned and used by the same land owner. But, as the boundaries of ownership are not observed in such a model, "any transition in land use that is modeled using cells as the unit of observation will falsely treat cells that correspond to the same parcel as independent observations. For the same reasons these models will generate biased estimates of local interactions, e.g. they will estimate a positive land use interaction among neighboring cells when in fact none may exist. In such cases, parameter estimates reveal correlations, but not causal relationships" (ibid. 76). In addition to the definition of spatial units, the definition of their borders also possibly influences the outcomes of model analyses. (see ANSELIN 1995, 93 ff., LEUANGTHONG et al. 2008, 59 ff., MILLER & HAN 2009, 11).

In analyses of geodata covering specific **time** periods that aim at discovering or confirming causal relationships, it is usually implicitly assumed that time has only a one-dimensional direction (from the past to the future), setting certain conscious or pragmatic constraints on its models, even if time reversibility and time plurality de facto exist (see KLEIN 1995, 32 ff.). Every time-sensitive scientific investigation sets certain conscious or pragmatic constraints on its models. The availability of and ability to process data, the model's purpose, the specific research questions and the desired degree of precision predetermines the choice of points and intervals in time. These choices also urge a definition of the time units applied in a certain model. Even for cross-sectional analyses the fixing of a point in time can be critical as different moments during a year may predetermine the outcome of an analysis. Land use change, for example, may depend on seasonal characteristics, which makes it crucial to review the operationalized variables. Similarly, for longitudinal analyses, the choice of time intervals can be decisive for the results of a study. Often, the initial and end point of a time period in an inquiry are associated with some kind of naturalism, as if the process under investigation would start at point t_0 and end at point t_n. There is, however, the need to equally consider the processes that have led to the specific arrangement of components and the processes at point t_0, and to discuss the implications that may go beyond the point t_n. To concretize this argument, let us imagine an example in the context of land use and land use change. A scientific longitudinal investigation about the influences of land use regulations on urban sprawl with $[t_0 - t_n]$ will likely arrive at very different conclusions if such a regulation is introduced at the point t_{0-1} rather than at the point t_{0+1}. The same issue applies to variations, fluctuations or interdependencies within the interval of $[t_0 - t_n]$. Seasonal changes or spatial compensations of intraregional disparities that may occur (aggregated) during the given time interval need to be taken into consideration in order to understand the internal processes. Moreover, the complexity of longitudinal analyses is increased by the assumption of temporal dependency (or temporal autocorrelation), which means that temporally adjacent units may possess similar or strongly different values in comparison to a temporally random array (see BAHRENBERG et al. 2003, 362). This temporal preservation tendency implies the need for a model-adequate fixing of temporal steps to be able to interpret auto-correlative patterns as such (see BACKHAUS et al. 2008, 114 ff.).

In a spatial context, the issue of scale-dependency can, according to MEENTEMEYER (1989, 168 in O'SULLIVAN & PERRY 2013, 37), lead to three well-known fallacies that potentially invalidate the results of geographic research: (1) "individualistic fallacy is the inappropriate use of finer grain data to make macro-level inferences (problems of interpolation or upscaling); (2) cross-level fallacy is the inappropriate use of data from one part of a population to make inferences about another (problems to do with transferring information between systems at the same scale); (3) ecological fallacy is the inappropriate use of macro-level data to make inferences about finer grains (problems of extrapolation or downscaling)."

The main reason for these fallacies lies in the inherent dependency of model outcomes on the varying composition of the chosen spatial units which is well known in geography as the "modifiable areal unit problem" (MAUP) (see OPENSHAW 1984). The aggregation or disaggregation of data across spatial units is not only a problem of a spatial scale but includes temporal and thematic variability. As shown above, the choice of certain temporal scales might produce very different analysis outcomes. This means that one should add a "modifiable temporal unit problem" (MTUP) (see ÇÖLTEKIN et al. 2011). BOSSEL (2004, 46; 1994, 24), for example, differentiates the MTUP into different categories, depending on their reaction time, such as process (immediate), feedback (short-term), adjustment (mid-term), self-organization (long-term), and evolution (very long-term). For inquiries on land use and land use change, it would be equally important to consider social components and units, and depending on the aggregation of the variable scale, one must expect different outcomes of analyses as well. Hence, we can additionally speak of a "modifiable social unit problem" (MSUP) (see KOCH & CARSON 2012). In comparison, social units can be aggregated even more diversely and heterogeneously as spatial or temporal units. A possible aggregation chain could be person – family – neighborhood – work colleagues – association – political party – trade union – social network (another socio-spatial aggregation chain can be found in MCMASTER & SHEPPARD 2004, 4 f.).

5 Linking Different Approximations of Reality

So what conclusions can we draw in light of the manifold complications inherent to scientific modeling that we have explored above? First and foremost it is crucial to select the most appropriate model representing reality to fit a specific scientific purpose. As we have seen, models cannot be absolutely true, but they can be useful (see BOX 1979a, 2). To accomplish usefulness, however, it is of utmost importance to clearly lay down the relevant research questions and to check how they can be answered properly. In some cases it may not be possible to go beyond a conceptual model, especially in fields where there is little available data or where simulation modeling cannot at all be calibrated with real world data. While simulation models might still allow for interesting theoretical insights about complex phenomena such as emergence (see GREVE & SCHNABEL 2011), its complete decoupling from other types of models that build on "real world" data might possibly put the usefulness of this kind of model choice at risk, as it might not tell us a lot about what is happening in our empirical reality. This is an issue for not only geographic research but also for many other social sciences such as economics. Considering this thinking as appropriate would also give rise to a different understanding of the relationship between "reality" and "model representation" that recognizes both a limited access to the real and an independent explanatory status of the model, as MORRISON (2015, 209) recently claims: "As we can see, it was largely the model that came to define and constrain reality, and not vice versa".

The growing use of and dependence on quantitative data in geography leads to another problem. Statistical significance of observed relationships becomes hard to grasp when analyzing extensive data sets (see ANSELIN 2010, 17), its meaningfulness decreases and research results become increasingly hard to interpret. Additionally, there are often little means to exclude concerns about reversed or cyclical causality between the analyzed variables or possible interaction effects. On the one hand, the progressively complex nature of econometric techniques to include influencing factors such as spatial and temporal dependency and heterogeneity provides powerful tools to explore questions related to land use and its dynamics. On the other hand, such empirical models become increasingly difficult to understand and how to interpret the results. The openness to interpretation does not only apply to complex conceptual models but also to empirical models as O'SULLIVAN & PERRY (2013, 6) have stated. The researcher's decision on a method to explore a research question with statistical tools can, maybe too often, be questioned.

The consequence, from our point of view, is that the links between different model types in a research endeavor need to be improved. Too often, conceptual and, especially, empirical models are too far apart to ensure valid and reliable results. Conceptual models often propose plausible causal chains that subsequently get tested with geo-statistical quantitative methods. Unfortunately, there is frequently a substantial lack of intermediary evidence that supports the understanding that the empirically discovered link actually represents the link proposed in the conceptual model. Moreover, additional empirical evidence supporting the premises established in the conceptual model construction should be included in order to strengthen the validity of the theoretical assertions. In this context we think that the complementary use of qualitative data, e.g. data acquired through interviews, could help to fortify the proposed arguments, especially in the context of land use and land use change where we expect strong interactions between geographical conditions and social actors and behavior. Too often there has been a neglect of the cyclical causality between the emergence of specific land patterns, subsequent adaptation by social, political and economic actors and the emergence of new specific land patterns, etc… Qualitative data might equally help to circumvent erroneous conclusions as it may enable researchers to unravel complex and systemic spatial, temporal, or attributive influence factors that otherwise would go unnoticed. Even if remarkable improvements have been made over the last decades, quantitative empirical models often still suffer from a lack of data availability, especially for continuous longitudinal data that would allow for extensive panel data analyses. This will gradually change over time. Complementary qualitative data, however, can now help in enabling researchers to better link different model types in the research process to achieve more robust and reliable results.

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