

## Remote sensing data assimilation in modeling urban dynamics: objectives and methodology

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### Abstract

The problem analysis, planning and monitoring phases of sustainable urban management policies require reliable information on the urban environment and its dynamics. Geospatial and socio-economic data supplemented with knowledge on dynamic urban processes are incorporated in the land-use change models currently available to planners and policy makers. They enable them to assess the impacts of decisions on the spatial systems that they are to manage. To be usefully applicable the models need extensive calibration. Current calibration methods, however, do not take into account uncertainties in reference land-use data and uncertainties in the parameterization of land-use change models. As a result, uncertainty in land-use change predictions are mostly unknown. The ASIMUD project aims to provide a solution to this issue by applying a particle filter data-assimilation framework to the calibration of land-use change models. The framework will use remote sensing derived land-use data at time steps that they are available in order to optimize the parameters in the model. The proposed calibration framework will be based on the comparison of spatial metrics derived from historic remote sensing images and land-use change simulation results. Parameters used in the simulation model will be tuned so that the simulated urban growth patterns, as described by the metrics, match the patterns observed in the remote sensing imagery. It is expected that the approach will result in a quantification and reduction of the uncertainty in simulations of future land use.

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## 1. Introduction

In recent years a number of powerful high-resolution land-use change models have progressed beyond purely conceptual and theoretical considerations and aim at realistically representing geographical systems in terms of the processes modeled, the geographical detail attained, and the calibration and validation of the modeling outcomes [1]. This is certainly the case for cellular automata (CA) based land-use change models [2]. These models are gradually becoming important instruments for the assessment of policies aimed at improved spatial planning and sustainable development [2] as well as scenario-analysis [3]. Clearly, neither good science nor practical planning and policy making can be based on tools which produce questionable output; rather the tools must be robust and reliable, based on the best available scientific knowledge and data. This raises to the highest level of importance the issue of the calibration and validation of the models [4].

A proper historic calibration of land-use change models typically relies on the availability of time series of land-use maps [4]. Since the production of the detailed land-use maps needed for land-use change modeling is still a costly and time-intensive manual process, time series are often lacking or contain inconsistencies in mapping methodologies, legends and scales [5]. This will result in measured land-use changes caused by mismatches in the mapping procedures rather than an indication of real changes in the land-use patterns of interest.

Long time series of archived earth observation images from medium resolution (MR) sensors, like Landsat TM/ETM+ and SPOT HRV, are a potentially interesting additional data source for the historic calibration of land-use change models. Spaceborne remote sensing images have many advantages over the use of land-use maps for a historic calibration [5]: data acquired by a remote sensing sensor is more consistent in time and the temporal coverage is much larger than the update frequency of land-use maps. The spatial resolution of MR imagery, 20-60 m, is sufficient for modeling urban dynamics, typically done at 50 to 500 m resolution.

A major disadvantage of remote sensing data, however, is that the relation between the observed surface reflection and land use is indirect and complex, because land use refers to human activities taking place at the earth's surface as opposed to land cover that can be more easily detected by remote sensing analysis [6]. Nevertheless, typical land-cover arrangements found in urban areas (e.g. built-up versus non built-up area) can to some extent be linked to urban function. As such, spatial metrics describing the composition and spatial configuration of land cover reveal information about urban land use. Originally developed for landscape ecological research, spatial metrics have recently been shown to have considerable potential for the analysis of urban environments [7].

In spite of all the research efforts on the development of remote sensing based land-use classification algorithms, the accurate classification of all land-use classes required by sophisticated land-use change models remains a challenge [8]. This hampers a direct comparison between land-use maps produced by remote sensing and simulated land-use maps using goodness of fit measures, such as fuzzy kappa [9], that are commonly used in the historic calibration procedure. In the STEREO II MAMUD project (Measuring and Modeling Urban Dynamics) [10] a method has been developed for comparing land-use patterns and urban morphology derived from classified images, with those derived from model simulations, based on spatial metrics [11]. Although land-use maps directly obtained from remote sensing data do not have the same level of thematic detail as the land-use maps conventionally used for historic calibration of land-use change models, results of the MAMUD project show that spatial metrics derived from frequently available and temporarily consistent remote sensing data are able to capture characteristic urban development patterns and thus can be used for calibration [12].

A major shortcoming of current calibration methods, however, is that uncertainties in parameters, in input data, and in reference data required for calibration are neglected. This leads to uncertainties in the prediction of future land use, which need to be quantified and reduced.

The main objective of the STEREO II ASIMUD (Remote Sensing Data Assimilation in Modeling of Urban Dynamics) project is to incorporate the metric-based calibration method developed in the MAMUD project [11] in a probabilistic framework in order to quantify and reduce the uncertainty in simulating future land use through the use of data-assimilation techniques, and to test the applicability of the approach both at the urban and at the regional level. The probabilistic framework will use a particle filter data-assimilation algorithm to calibrate model parameters by taking into account 1) uncertainties in input parameters that propagate through a land-use change model, and 2) uncertainties in reference data derived from remote sensing images. It is expected that the framework enables a quantification and reduction of the uncertainty in simulated future land use. The model used to develop and test the framework is the MOLAND model developed by the EU-JRC-IES [13]. This is one of the most elaborate and widely used cellular automata based land-use models currently available.

## 2. Methods

First, the historic calibration procedure commonly used to calibrate the MOLAND model will be explained. Next, details will be given on the calibration framework, developed in the MAMUD project, which uses spatial metrics derived from simulated land use and remote sensing data. The sources of uncertainty in the land-use change model and the remote sensing interpretation chain will be discussed. Finally, the use of this uncertainty information in the probabilistic framework will be explained.

### 2.1. Historic calibration of the MOLAND model

The calibration framework used in this study has been developed for the MOLAND model [13]. It has been applied to the city of Dublin (Ireland) [14], in the context of MAMUD and will be applied to the region of Flanders (Belgium) as well within ASIMUD. The model explores the likely development of land use for periods of some thirty-fourty years into the future, given alternative planning and policy scenarios and socio-economic trends. It progresses through time in yearly time steps and computes state changes for every cell in a regular grid measuring some 50-500 m on the side. Thus, every model grid cell represents at least one state variable in the model, meaning that the calibration of any model with the level of complexity of the MOLAND model is not trivial, rather requires time and effort. The task of the calibration is to ensure that the model behaves in a realistic manner and is able of generating observed spatial patterns. The calibration of the MOLAND model is a heuristic procedure based on trial-and-error [14]. It requires a reference land-use map, from which the actual map (i.e. the most recent available map) is reconstructed. The comparison between the reconstructed and the actual map is performed by means of dedicated goodness-of-fit measures. These consist of a number of statistical indicators and spatial metrics such as mean patch area, shape index and proximity index, Simpson's diversity index, and different Kappa statistics. The calibration consists of four steps: (1) an initial set of parameters describing the neighbor influence functions (attraction-repulsion parameters) is fixed. Generally, parameters are selected from previous applications of the model; (2) the stochastic parameter  $\alpha$  is then fixed.  $\alpha$  determines largely the scatterness of the land-use patterns and the size of clusters; (3) information with respect to the heterogeneous nature of the cellular space proper, amassed in suitability, accessibility and zoning maps, is next introduced; (4) then the fine tuning of the model starts (repeating of loop 1-2-3 with dedicated statistical analysis). Step 4 is repeated until the reconstructed map satisfactorily matches with the actual map. For a successful calibration, the time interval should be sufficiently long, typically 10 years, in order

to give the underlying processes in the system enough time to manifest themselves in a representative way. The poor availability of high quality and temporally consistent land-use maps often constrains the choice of the calibration period. The remote sensing based calibration framework, explained next, can increase the amount of data for the historic calibration, resulting in better predictions of the land-use change model.

## 2.2. Calibration framework using remote sensing

Fig.1a shows the concept of using spatial metrics for the calibration of land-use change models. Remote sensing derived land-use maps can be compared with simulated land-use maps of the same year using spatial metrics. Calibration of the land-use change model is done by tuning parameters, aiming at a minimization of the difference between spatial metrics produced by model simulations and those calculated from the remote sensing-based maps. This procedure can be applied each time a remote sensing image is available within the model calibration period. In the MAMUD project, the method has been tested for the MOLAND model of Dublin. Fig.1b shows an example for a class-level metric. A reference scenario, using a calibrated stochastic parameter  $\alpha = 0.4$ , is compared with an extreme scenario using  $\alpha = 50$ . The remote sensing derived metric corresponds better with the reference scenario than with the extreme scenario.

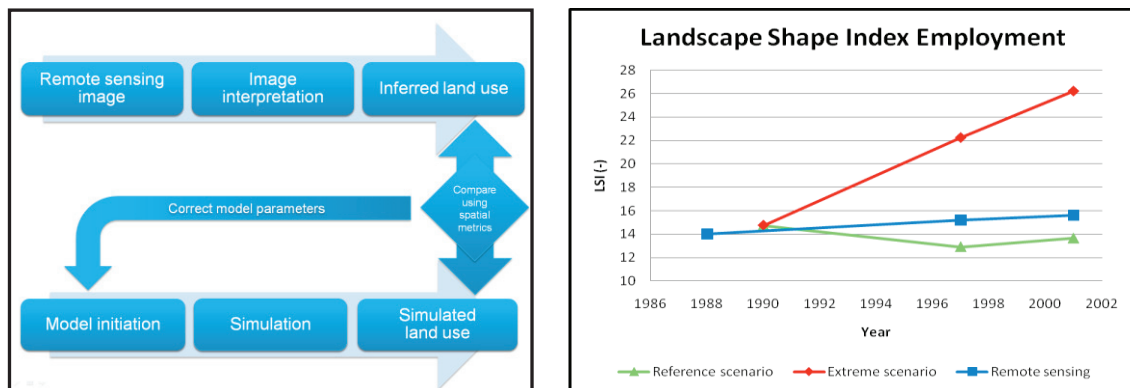


Fig.1. (a) concept of using spatial metrics for calibrating land-use change models; (b) example of the Landscape Shape Index calculated for the employment class for two scenarios of MOLAND simulations for Dublin and three remote sensing images.

## 2.3. Uncertainty in the MOLAND land-use change model

Spatially-dynamic modeling of land-use change involves uncertainty caused by attribute errors, positional errors, logical inconsistencies, incompleteness and temporal errors in the model and in the reference land-use maps used for initiation and calibration. It is assumed that positional errors of the geo-referenced input maps are smaller than the resolution used in the model (200 m for Dublin, 300 m for Flanders). Logical consistency and completeness have been tested in previous applications of the model. Temporal accuracy is determined by the synchronization of temporal input data and the model time step. These uncertainties are assumed to be small and are ignored. Uncertainties in the reference land-use maps, however, can be important, but are difficult to quantify objectively. Therefore, the only uncertainties that will be considered here are uncertainties in input parameters. First, the uncertain input parameters of the land-use change models need to be identified and quantified. Next, the deterministic land-use change models are run as stochastic models using Monte Carlo techniques in order to propagate

different scenarios of uncertainties in input parameters through the model. This part of the project will provide predictions of future land-use accompanied by probability maps.

#### *2.4. Uncertainty in the remote sensing interpretation chain*

Remote sensing data analysis involves uncertainty caused by limitations of the data and the image interpretation methods used. Since uncertainties propagate through the processing chain, they will affect land-use maps inferred from remote sensing images and the derived land-use patterns, quantified by means of spatial metrics. An important part of the project is to characterize error and uncertainty in the different steps of the land-use interpretation process, using ground-truth data and process-related uncertainty models based on classification approaches. This analysis will be carried out for metric-based classification approaches developed in the MAMUD project. Furthermore, sensitivity analysis will be carried out to estimate the relative contribution of different steps in the processing chain on land-use uncertainty. This will provide information on the process components that contribute most to uncertainty in observed land-use patterns and derived spatial metrics, and may indicate which measures could be taken to reduce overall uncertainty in the land-use interpretation process and, consequently, in the calibration of the land-use change model. It will also give information on the sensitivity of different spatial metrics to uncertainty in land-use pattern, which might be one of the criteria for selecting a particular spatial metric for calibration purposes.

#### *2.5. Probabilistic framework for land-use change models*

For error propagation modeling and particle filtering use will be made of a Python framework for spatio-temporal modeling [15] [16]. The framework offers a combined interface for the task of model construction and optimization. Modeling options are Monte Carlo simulation and data-assimilation methods such as the Particle Filter and the Ensemble Kalman filter. Data assimilation is a method for estimating an unknown probability density function recursively over time using incoming data, e.g. from measurements or remote sensing, and a process-based model. In the ASIMUD project a particle filter data-assimilation algorithm will be used. Its advantage is that no assumptions are made on the probability distribution of the model states. Moreover, state augmentation techniques required in the Ensemble Kalman filter to reconstruct probability distributions of state variables at update moments are not needed, because the complete model state is propagated over time [16]. This is considered a large advantage in land-use change modeling because state augmentation for these models is difficult if not impossible. The particle filter calculates state predictions and their confidence intervals. This requires that the uncertainties of the model input variables and parameters are known. Particle filters are widely used in various research fields, including environmental sciences (e.g. [17]). To our knowledge, the particle filter has not been used in land-use change modeling.

### **3. Conclusions**

Current calibration methods of land-use change models do not take into account uncertainties in the parameterization of these models and in the land-use data used as a reference. This leads to uncertainties in the prediction of future land use, which need to be quantified and reduced. The ASIMUD project aims to provide a solution to this issue by applying a data-assimilation framework to the calibration of land-use change models. The particle filter algorithm optimizes parameters of the land-use change model by taking into account the uncertainties in input parameters that propagate through the model and uncertainties in reference data derived from remote sensing images, which are expressed by the probability density

function of spatial metrics derived from both sources. This approach should result in quantified and reduced uncertainties in predicted future land use.

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