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Multi-objective optimisation framework for calibration of Cellular Automata land-use models

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A B S T R A C T

Modelling of land-use change plays an important role in many areas of environmental planning. However, land-use change models remain challenging to calibrate, as they contain many sensitive parameters, making the calibration process time-consuming. We present a multi-objective optimisation framework for automatic calibration of Cellular Automata land-use models with multiple dynamic land-use classes. The framework considers objectives related to locational agreement and landscape pattern structure, as well as the inherent stochasticity of land-use models. The framework was tested on the Randstad region in the Netherlands, identifying 77 model parameter sets that generated a Pareto front of optimal trade-off solutions between the objectives. A selection of these parameter sets was assessed further based on heuristic knowledge, evaluating the simulated output maps and parameter values to determine a final calibrated model. This research demonstrates that heuristic knowledge complements the evaluation of land-use models calibrated using formal optimisation methods.

Software availability

Name of software: Parallel-NSGAII
Developer: Jeffrey Newman
Contact address: The University of Adelaide and BNHCRC North Terrace, ADELAIDE, SA 5005
Contact email: jeffrey.newman.au@gmail.com
Year first available: 2016
Hardware & software required: Cross-platform; compiles under clang, visual studio and the GNU compiler chain. Hardware requirements dependent on land-use model used
Program language: C++
Program size: 13 MB
Availability and cost: GPL-2.0 Open source software
Downloadable from: https://github.com/jeffrey-newman/parallel-nsgaII-backend

1. Introduction

Modelling of land-use change plays an important role in many areas of environmental planning, such as river basin management (Van Delden et al., 2007), natural area preservation (Hewitt et al., 2014), the development of sustainable agricultural practises (Murray-Rust et al., 2014a; 2014b), and the influence of urban dynamics on surrounding regions (Haase et al., 2012; Lauf et al., 2012). To better understand the influences of land-use changes, models are increasingly being used as part of decision support systems to evaluate policy that influences spatial planning (Van Delden et al., 2011) To represent land-use dynamics realistically, such models must incorporate complex socio-economic and biophysical drivers with human-environment interactions (Lambin et al., 2001). As a result, Land-Use Cellular Automata (LUCA) have become a popular modelling framework for evaluating land-use changes, as they are able to simulate the behaviour of complex systems with a high degree of realism (Hewitt et al., 2014).

Historically, Cellular Automata methods were proposed for application to geographic systems by Tobler (1979), with LUCA models first used to replicate observed fractal patterns of urban evolution (Couclelis, 1985, 1989; Batty and Longley, 1994), followed

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by their development into dynamic land-use models (White and Engelen, 1993c; Clarke et al., 1997). Much effort has been invested in developing LUCA models for different global regions, with applications reviewed by Santé et al. (2010). This includes the advent of generic spatial modelling platforms SLEUTH (Clarke et al., 1997) and Metronamica (Van Delden and Hurkens, 2011), which provide well tested models for a range of applications to different study regions. With such generic platforms simplifying model development requirements significantly, research focus on the calibration of LUCA models has increased in recent years (e.g. Blecic et al., 2015; Cao et al., 2014; García et al., 2013; Li et al., 2013; Van Vliet et al., 2013b; Van Vliet et al., 2016).

Calibration of a land-use change model is the process of determining a model parameter set, through the initial setting of model parameters, the iterative adjustment of these parameters based on comparison of the model output with observations, and the selection of a final parameter set, for application to a specific case for long term scenario analysis (adapted from Van Vliet et al. (2016)). The iterative adjustment stage of calibration of LUCA models is extremely complex, as land-use change is a path dependent process that is driven by multiple interdependent processes with uncertain outcomes (Brown et al., 2005). Conventionally this stage of calibration of LUCA models is manual (Van Delden et al., 2012), incorporating the modellers' process understanding to address this inherent uncertainty. However, implementation of such methods is time consuming, subjective (Jafarnezhad et al., 2016), and lacks transparency and repeatability (García et al., 2013). Consequently, in order to make parameter adjustment more efficient and repeatable, there has been an increasing focus on automating this process (Van Vliet et al., 2013a).

Automatic parameter adjustment methods generally make use of formal optimisation methods that maximise model performance metrics (Blecic et al., 2015; Cao et al., 2014; García et al., 2013; Li et al., 2013). Consequently, the success of these methods relies heavily on the ability to assess performance in a quantitative fashion. This assessment has to consider two separate properties of LUCA model performance: (i) locational agreement, alternatively termed cell-by-cell agreement (Hagen-Zanker, 2009), which is the match of pixels between simulated outputs and the corresponding observed data (Van Vliet et al., 2013a; Hagen-Zanker, 2009), and (ii) landscape pattern structure, which is the inferred realism of land-use change processes captured by the difference between observed and simulated landscape patterns (Engelen and White, 2008). Consequently, automatic parameter adjustment of LUCA models can be considered a multi-objective optimisation problem (Hagen-Zanker, 2008).

At present, multi-objective optimisation has only been applied to the parameter adjustment stage of calibration of LUCA urban growth models that are implemented with two land-use classes, despite the capacity of these models to consider a broader range of land-use classes, using the SLEUTH metrics (Trunfio, 2006) or logit regression model fitness functions (Cao et al., 2014). Whilst this work has merit in characterising urban and non-urban interactions, it represents a less complex calibration problem than LUCA models that consider multiple dynamic land-use classes, as these are more complex models that possess a significantly larger number of parameters for calibration. In contrast, studies that have used optimisation approaches for the calibration of LUCA models with multiple dynamic land-use classes have only considered a single objective. For example, Blecic et al. (2015) considered only the locational agreement element of performance for parameter tuning, and while García et al. (2013) used both locational agreement and landscape pattern structure metrics, these were combined into a single objective during the optimisation process, where as a result, important trade-offs between locational agreement and landscape pattern structure could not be examined. Both studies also generated only one possible model parameterisation for future scenario analysis, limiting the ability to understand how calibrated parameters are potentially influenced by the metrics used for optimisation.

To address these shortcomings, the objectives of this paper are (i) to present a multi-objective optimisation framework that automates the parameter adjustment stage of calibration of LUCA models with multiple dynamic land-use classes, enabling the identification of multiple model parameter sets that could be suitable for long-term scenario analysis; and (ii) to demonstrate the application of the framework on the case study comprising the Randstad region in the Netherlands. The remainder of this paper is organised as follows: The proposed multi-objective optimisation-based calibration framework is introduced in Section 2, followed by a description of an application to a case-study of Randstad in Section 3. The results for the case study are presented and discussed in Sections 4 and 5. The conclusions and recommendations of this work are presented in Section 6.

2. Proposed multi-objective optimisation-based calibration framework

The proposed multi-objective optimisation framework for calibration of LUCA models with multiple dynamic land-use classes is presented in Fig. 1. As shown, the framework is comprised of four stages. First, in the selection stage, the components required for optimisation are chosen. Next, in the specification stage, to ensure an efficient and robust output, certain aspects prevalent to the previously selected components are specified. Following this, the multi-objective optimisation parameter adjustment is implemented and run to completion. Finally, the resulting model outputs are assessed, quantitatively evaluated using a neutral model, followed by heuristic interpretation of the outputs to decide on a final model parameter set.

2.1. Selection stage

In the selection stage, the four main components for optimisation are chosen, as shown in Fig. 1: the LUCA model to be used and the parameters to be adjusted, the optimisation algorithm used for the parameter adjustment process, and the map comparison metrics used to assess model performance.

2.1.1. Model and parameters

The LUCA model determines the number and type of parameters that require adjustment. The parameters within LUCA models are used to capture the processes that influence land-use changes, such as the physical suitability of the landscape and the influence different land-use classes exert on each other. The consideration of multiple dynamic land-use classes, as is the case for transition potential models derived from White and Engelen (1993c), introduces a large number of parameters that must be adjusted, to capture the respective influences of each process on different land-use classes (García et al., 2013). The most notable example of parameters for transition potential models are neighbourhood rules, which characterise the influence different land-use classes exert on each other at different distances (Riks, 2015). For example, considering a neighbourhood size of eight cells introduces 30 parameters for each neighbourhood rule. As the number of neighbourhood rules is the product of the total number of land-use classes and the number of actively allocated land-use classes, the resulting number of parameters that could be adjusted is large. Consequently, it is desirable to be judicious about which parameters to include in the automatic adjustment process.