Computers, Environment and Urban Systems 39 (2013) 121–135

Contents lists available at SciVerse ScienceDirect

Computers, Environment and Urban Systems

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

Model testing and assessment: Perspectives from a swarm intelligence, agent-based model of forest insect infestations

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ARTICLE INFO

Article history:
Received 27 October 2011
Received in revised form 15 October 2012
Accepted 16 October 2012
Available online 8 November 2012

Keywords:
Agent-based models
Verification
Calibration
Validation
Swarm intelligence

ABSTRACT

Model testing procedures represent a major challenge in the development of agent-based models (ABMs). However, they are required stages for a model to be accepted and to serve as a forecasting, management or decision-making tool. This study presents a comprehensive approach for testing ForestSimMPB, an agent-based model (ABM) designed to simulate mountain pine beetle (MPB), Dendroctonus ponderosae Hopkins, outbreaks at the scale of individual trees. ForestSimMPB is a complex system model that is using swarming intelligence, capable to represent individuals' behaviours and spatial interactions that influence their surrounding environment. Swarm Intelligence (SI) methods are integrated into the ABM in order to reproduce the collective reasoning and indirect communication of autonomous agents representing MPB behaviour within the forest environment. Model testing approach consist of verification, calibration, sensitivity analysis, validation and qualification stages. Model testing is accomplished by simulating MPB infestations using both the ForestSimMPB model and a Random–ABM model that serves as a null model. Outcomes comparison and assessment are performed using raster-based techniques as well as spatial metrics. Aerial photographs of the British Columbia, Canada study sites are used in this model testing approach. Results indicate that ForestSimMPB model representations of MPB outbreaks are more similar than Random model representations to the spatial distribution of MPB-dead trees.

1. Introduction

The study of the spatio-temporal dynamics of forest ecosystems, as a result of natural disturbances such as insect infestations, requires theoretical and practical approaches to provide insights for understanding and controlling the impacts of such disturbances. Interactions taking place between host trees and insects within the forest, at a tree level, form part of a complex geographic process. Geographical systems have been recognized as complex (Batty & Torrens, 2005), but they can be simplified enough to build robust theory and models that can be applied to different scenarios. The use of agent-based models (ABMs) and associated tools is becoming mainstream research in a variety of disciplines such as land use planning (Li & Liu, 2009; Ligmann-Zielinska & Jankowski, 2007; Martens, Benenson, & Levy, 2010), resource management (Bone & Dragićević, 2010; McDonald et al., 2008), criminology (Malleson, Heppenstall, & See, 2010), ecology (Anwar, Jeanneret, Parrott, & Marceau, 2007; Li, Mynett, Penning, & Qi, 2010) and landscape ecology (Entwisle, Malanson, Rindfuss, & Walsh, 2008; Jepsen et al., 2006; Parker et al., 2008) amongst others.

The majority of agent-based (AB) simulation models are built to meet practical management needs; however, following on model testing, these can also be used to represent and analyze complex dynamics, provide indicators of potential impacts and to learn about the original system (Aumann, 2007). ABMs constitute an excellent tool to represent and analyze the complex dynamics of ecological systems (DeAngelis & Mooij, 2005). Ecological models are built for scientific research purposes, but increasingly for forecasting and management objectives (Rykiel, 1996). These models are constituted by theoretical assumptions to represent one or many processes that occur in the real-world which transform some aspects of the geographic space through time (Batty & Torrens, 2005). With the goal of using ABMs for environmental policy-making and spatial knowledge discovery, model testing procedures are essential to the model development process if models are to be accepted and used to support decision making (Refsgaard & Henriksen, 2004). Model verification, sensitivity analysis, calibration, validation and qualification are important components of the modelling process (Crooks, Castle, & Batty, 2008; Kocabas & Dragićević, 2007; Refsgaard & Henriksen, 2004; Rykiel, 1996). Verification concerns the correctness of a model construction, making

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http://dx.doi.org/10.1016/j.compenvurbsys.2012.10.004

sure that model implementation matches its design (Crooks et al., 2008). Calibration involves the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set (Manson, 2007). Sensitivity analysis quantifies how changes in the values of the parameters alter the value of the outcome (Kocabas & Dragićević, 2006). Validation has to do with the truthfulness of a model with respect to its problem domain, both in a structural sense and in a "goodness of fit" sense (Manson, 2003). Finally, a model is valid only over the domain for which it has been validated; therefore, qualification aims at discovering this domain by revalidating the model for new cases (e.g. study sites) (Rykiel, 1996). All five of these steps are closely interconnected with each other; indeed the terms really refer to five aspects of a single problem. While some steps can be omitted without making it impossible to carry out the others, other steps are central to model testing. For example, verification and qualification are frequently ignored, at the cost of a greater uncertainty about the reliability and usefulness of the model, but it is still possible to calibrate and validate the model. On the other hand, without calibration, it is impossible to validate or qualify the model; and while generalized verification and sensitivity analyses can be carried out; their implications for the model are limited.

Even though there are simulation models exploring the effects of forest disturbances such as insect outbreaks in forest cover changes, the scientific literature does not report many studies based on complex systems theory and their application in decision making by government agencies and forestry managers. This is probably due to the fact that no attempts to calibrate, verify or validate such models have been reported. Given that the ABM approach describes non-linear spatial systems, it becomes difficult to use a unique approach in the model testing procedure (Manson, 2007). Hence, the challenge faced in model verification, calibration, validation and qualification is to find the appropriate methods that serve to identify and minimize the errors in ABM outputs, as well as to communicate an appropriate level of trust that the simulation results deserve.

The objective of this study is to bring perspectives and establish a series of approaches for model testing stages such as verification, calibration, sensitivity, validation and qualification, and implement them within an ABM. More particularly the ForestSimMPB (Pérez & Dragićević, 2011) model is used for the purpose of the comprehensive model testing. This model simulates forest insect infestation caused by MPB, offering a novel approach for representing MPBs' aggregation behaviour. For the purpose of testing the Random–ABM model was developed, specifically for this study, to serve as a null model. The testing procedures are implemented on a study area located in North-Central Interior of British Columbia (BC), Canada. In the following sections, the ForestSimMPB model testing steps – verification, calibration, validation and qualification – and approaches used are reported, using case-study analysis to assess the model performance.

The rest of the paper is organized as follows. Section 2 summarizes the theoretical foundations of model testing. Section 3 outlines the ABM models used in this study and the model testing steps. In Section 4, data and methodology are presented; detailed description of the experiments that were developed and implemented is provided. Section 5 presents the results and discusses the findings. Finally, conclusions and implications are drawn in Section 6.

2. ABM testing theory

AB simulation models built to forecast and offer indicators of potential impacts can serve their purpose only if they stand in a certain relation of similarity or analogy to the systems represented. The trustworthiness of an AB model depends on both its ability to predict the possible behaviours of a complex system and its capacity to stimulate new insights about it. To achieve consistency when modelling, it is essential to evaluate the degree to which the model resembles the real geographic phenomena that the model is designed to simulate. Model testing and assessment allow us to demonstrate the adequacy and strengths of these abstractions of reality; the goal is to put the model and the knowledge underlying the model under evaluation (Aumann, 2007; Manson, 2003, 2007; Musiani, Anwar, McDermid, Hebblewhite, & Marceau, 2010). Verification, calibration, sensitivity, validation and qualification are considered essential parts of the model testing procedure, and simultaneously important steps of the model development process (Crooks et al., 2008; Oreskes, Shrader-Frechette, & Belitz, 1994; Rykiel, 1996).

2.1. Verification

Once developed, the ABM must be verified by checking whether the model behaves as expected; often referred to as *internal validation* (or *inner validity*). The process of verification can be also interpreted as a technical affair that relates to how faithfully and accurately modelling ideas are translated into computer code or mathematical morphism (Manson, 2003, 2007; Rykiel, 1996). Verification lies mostly in driving the model's underlying mathematical and computational components to fail by varying model configurations according to some anticipated model inputs. Cracking open the model for verification purposes is similar to sensitivity analysis, in which parameters are varied across repeated model runs in order to observe changes in simulation performance (Brown et al., 2008; Grimm et al., 2005; Kocabas & Dragićević, 2006; Ligmann-Zielinska & Sun, 2010; Topping, Høye, & Olesen, 2010). Difficulties of verification are further complicated by the fact that most simulations rely on random numbers to generate the effects of unmeasured variables and random choices. Therefore, repeated runs can be expected to generate different outcomes (Smith, Goodchild, & Longley, 2009). Thus, very detailed ABM verification processes have not been reported in the literature.

2.2. Calibration

Calibration is an essential part of model testing, and it seeks to find the values of the parameters that permit the model to best characterize the emergent spatiotemporal dynamics and the individuals' behaviour within the system being modelled. Different definitions of calibration can be found in literature. Refsgaard and Henriksen (2004) define it as the procedure of adjustment of parameter values of a model to reproduce the response of reality within the range of accuracy specified in the performance criteria. In ABM, calibration is regarded as the process of improving the agreement of a programmed calculation or set of calculations with respect to a chosen set of benchmarks – choice of information that is believed to be accurate or true for use in calibration – through the adjustment of parameters implemented in the model (Manson, 2003; Trucano, Swiler, Igusa, Oberkampf, & Pilch, 2006). Some examples of calibration have been documented in the development of ecological AB models (Grimm et al., 2005; Pitt, Box, & Knowlton, 2003; Railsback & Harvey, 2002).

2.3. Validation

Validation is related to building the right model (Aumann, 2007); it involves demonstrating that the behaviour of the model represents the behaviour of the system with sufficient accuracy as well as determining the degree of agreement between the model and the real-world system (Fall, Sachs, Shore, Safranyik, & Riel,