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A fuzzy-constrained cellular automata model of forest insect infestations

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Abstract

Geographical and ecological processes are complex systems where individual elements interact to create complex behaviour. These systems can be examined with spatially explicit models such as cellular automata (CA) that explain how interactions at the local level lead to global patterns. Tree mortality patterns caused by forest insects provide a good case for CA as local interactions lead to changes at the landscape level. However, problems exist with defining aspects of insect–host relationships that explain the susceptibility of a tree to insect attack. The main objective of this study is to develop a GIS-based CA model of forest insect infestations that incorporates fuzzy set theory in order to obtain information from high resolution remote sensing (RS) images. The model is based on tree mortality patterns caused by outbreaks of mountain pine beetle (MPB), *Dendroctonus ponderosae* Hopkins, in the central interior of British Columbia, Canada. Fuzzy sets are used in order to represent the susceptibility of trees to MPB attack and to acknowledge the uncertainty inherent in dealing with geospatial data. Fuzzy values provide the input for the CA Sub-Model where MPB attack behaviour is constrained by the susceptibility level of trees. The results from the model reflect the process of MPB infestations as described in the literature and exhibit non-linear dynamics expected in ecological processes. This study reveals that fuzzy-constrained CA modelling can provide useful information for forest management in the presence of insect outbreaks.

Keywords: Cellular automata; Fuzzy sets; GIS; Insect infestations; Remote sensing

1. Introduction

Geographical and ecological processes are complex dynamic systems with an inherently spatial nature. The complexity is manifest in the numerous elements that interact locally to produce global patterns that are difficult to predict, while the spatial nature is apparent in the significance of scale, distance and spatial arrangement of the interacting elements. Complex systems theory is suitable for incorporating both the complexity and spatial significance in ecological processes, and can provide results that enhance ecological knowledge for decision support systems. One class of complex system

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models that has recently gained recognition in ecology is cellular automata (CA) (Cannas et al., 1999; Grist, 1999).

CA are dynamic models that are discrete in time, space, and state (Baltzer et al., 1998). CA models typically consist of five main components: (1) a grid of cells, (2) cell states, (3) the neighbourhood, (4) transition rules that determine how cells change from one state to another at each time step, and (5) the number of time steps for which the model is run (White and Engelen, 2000). The grid is composed of a number of cells that are typically identical in size and shape. Cells at initial time T_i can take on an infinite number of states that are traditionally represented as discrete. The neighbourhood refers to the cells in a defined area surrounding each individual cell that will have an influence on the state of that cell at the next moment in time (i.e. T_{i+1}). The transition rules express how the state of each cell in the neighbourhood influences the future state of a cell from one time step to another. A CA model can be formulated as

$$s_{xy}^{T_{i+1}} = f(s_{xy}^{T_i}, N_{xy}^{T_i}), \tag{1}$$

where $s_{xy}^{T_i}$ and $s_{xy}^{T_{i+1}}$ are the states of cell at a location described with x and y coordinates at time T_i and T_{i+1}, respectively; $N_{xy}^{T_i}$ represents the neighbourhood surrounding cell xy; f represents the transition rules that explain how the initial state will change in the next time step. The number of time steps refers to the temporal extent of the model.

The discrete nature of cell states makes CA attractive for spatial-temporal modelling in a geographic information system (GIS) raster-based environment, which describes the world as a static representation based on a discrete array of cells. GIS and CA are complementary with regards to spatio-temporal modelling as the former provides the spatial framework for geographic data while the latter contributes the temporal dimension for describing change. Furthermore, the ability to develop realistic spatial models within a GIS environment has progressed due to the increasing availability of remote sensing (RS) data. In geography, GIS-based CA have proven especially successful in simulations of urban dynamics (White and Engelen, 1993; Batty and Xie, 1994; Couclelis, 1997; Clarke and Gaydos, 1998), rural residential settlement patterns (Deadman et al., 1993), and socio-environmental systems (Engelen et al., 1995) among others. CA models have also gained popularity in the field of ecology as discrete cell states can represent the presence of organisms at a given location which can change over time due to competition and resource allocation (Cannas et al., 1999; Grist, 1999). Baltzer et al. (1998) explain that discrete cell states are advantageous for modelling ecological processes because discrete state transition can be governed by a probability distribution based on the initial state of each cell.

While CA are applicable for modelling numerous ecological scenarios, problems exist when examining complex processes where cell states cannot be readily defined as discrete. A good example is representing a tree in a forest by its susceptibility to attack by an insect, whereby susceptibility is defined by numerous variables of the insect–host relationship. In such cases, two main problems exist with providing a binary definition (i.e. susceptible or not susceptible to attack by an insect).

The first problem concerns the issue of uncertainty in defining susceptibility. It is difficult to use traditional approaches to this problem such as defining a tree with binary values like susceptible or not susceptible, or deriving the probability of a tree becoming attacked when lacking sufficient data on insect attacks. This is due to the fact that insect disturbances are driven by numerous components of the insect–host relationship that are difficult to understand. Appreciating this relationship is further complicated by the presence of numerous climatic variables such as temperature, wind, humidity and precipitation, which, coupled with the geographic variation of a species' life cycle, produce varying results and incomplete knowledge on insect behaviour. Therefore, considering a raster-based representation of a forest landscape, significant uncertainty is present when attempting to assign a discrete binary or probability value to a cell describing a tree's susceptibility to attack. Furthermore, deriving probabilities requires sufficient data that illustrate the types of trees that are most likely to be attacked. However, the spatial and temporal resolutions of commonly used geospatial data (Fall et al., 2004; Nelson et al., 2004; Riel et al., 2004) hamper the ability to study and understand the forest infestation process at the individual tree level. This is because it is difficult to determine attack patterns at the tree level with large-scale images collected over a short or inappropriate time period.