Agent-based modelling and networks: Case study of the emerald ash borer

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Abstract

Geographic automata systems composed of agent-based models (ABM) are capable of representing complex, spatio-temporal phenomena such as insect infestation. However, ABMs are often difficult to understand and explain thus imposing limits of their usefulness. This study proposes the integration of spatial network theory and a geospatial ABM to help provide a more complete depiction of ABM behaviour. The approach simulates insect infestation using the emerald ash borer insect infestation as a case study. Network theory facilitates the mathematical characterization of agent behaviour and the underlying infestation processes as they emerge in the simulation and provides a more complete understanding of the processes from which large scale patterns of spread are generated.

Keywords: Geographic automata, agent-based modelling, network theory, insect infestation, emerald ash borer

1. Introduction

Complex systems theory seeks to understand how bottom-up dynamics generate non-linear, emergent patterns of real world spatio-temporal phenomena such as ecological systems. Ecological systems such as insect infestation can be conceptualised as a complex system and modelled using geographic automata such as agent-based models (ABM) by representing interacting, heterogeneous, adaptive individuals or "agents" and their varying spatial environments from which landscape-level patterns of spread emerge. ABMs have been developed to represent patterns of spread of important forest invasive insect species such as the mountain pine beetle (Perez & Dragicevic, 2010; Bone & Altaweel, 2014) and the emerald ash borer (Anderson & Dragicevic, 2015; 2016). Particularly, the emerald ash borer (EAB) is an invasive insect, native to Asia, first discovered in Detroit, Michigan, US, in 2002 (Straw et al, 2013) and is responsible for the wide-spread decline of ash across the US, south-western Ontario, and Quebec, Canada. ABMs can be used to simulate EAB dynamics and patterns of spread, to better aid in management and decision making leading to eradication.

Although useful, ABM's ability to capture the complexity in such phenomena comes at a cost. ABMs can be very difficult to understand (Grimm & Railsback, 2012). Specifically, heavily parameterized ABMs that include stochastic processes can be perceived as black boxes as the model's internal processes that give rise to emergent behaviour may be difficult to identify, even in well-developed ABMs (Topping et al., 2010). Approaches such as sensitivity analysis and robustness analysis seeks to overcome these challenges by linking changes in model input with changes in model output, however the complexity of ABMs limits the information that can lead to a complete picture of model behaviour from these classical methodologies (Broeke et al., 2016). Consequently, the development of a framework to generate measures that describe, characterize, and help understand the internal processes that give rise to emergent system behaviour in ABMs may be useful.

Network theory can be used to represent complex systems as a set of nodes and links and facilitates the mathematical characterization of the systems' structure and behaviour (Barabasi, 2014). Specifically, a set of measures can be generated from the network structure to quantify and explain the processes from which complex, system-level behaviour emerges. Networks are traditionally used to represent non-spatial phenomena, however, they have a potential to be integrated within geographic automata systems such as geospatial ABMs to better represent, quantify, and understand spatio-temporal phenomena, although this has been largely unexplored in the literature. Therefore, the main objective of this study is to develop an approach that integrates a network model and geospatial ABM to better understand and represent forest insect infestation processes, using the emerald ash borer (EAB) infestation as a case study.

2. Methodology

The developed network-ABM integrates two sub-models, the geospatial ABM as a baseline model and the network model (Figure 1). Specifically, the geospatial ABM provides the platform for which to represent the EAB phenomenon and the network model facilitates the storage, analysis, and visualization of the network structure and behaviour over space and time.

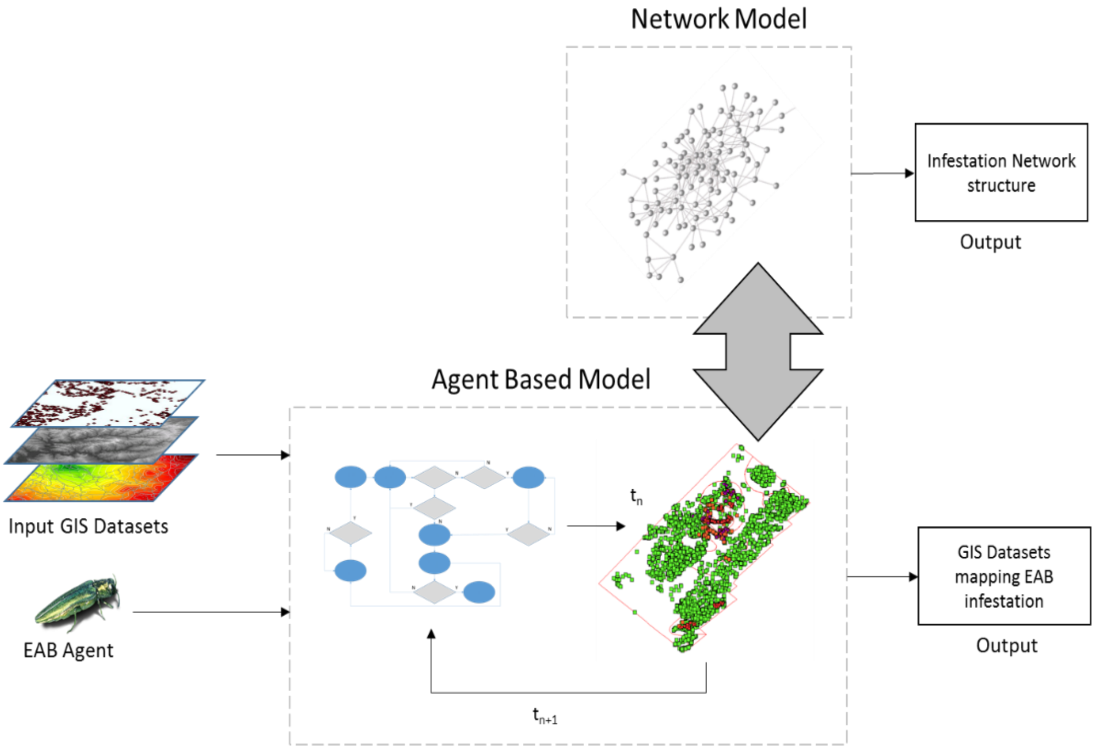

Figure 1. Conceptual representation of proposed network-ABM.

In this study, the already developed ABM of EAB (Anderson & Dragicevic 2015; 2016) has been used as a base model capable to simulate EAB spread at a regional scale in Oakville, Ontario, Canada. EAB adult, EAB larvae, and ash tree agents are designed to behave as they would in the real world using biological information documented in the literature. For example, agents are programmed to execute a variety of life cycle stages and are designed with a set of *state variables* and *parameters* that maintain the state of the agent at each iteration in the model (age, location) and limit the behaviour of the agent (maximum flight distance/day, chance of fertility, maximum number of offspring), respectively. Complex regional patterns of EAB spread emerge from EAB-host tree dynamics that are influenced by spatial and temporal variations at the local level. Host selection is influenced by the spatial location of the host, the level of host tree stress, the size of the host, and the tree type of the host. Model validation determined the spatial agreement between the model output and real world data with respect to location of infestation in 2009 with an overall accuracy of 72% and the spatial agreement between model output and the real world data with respect to severity of infestation with an overall accuracy of 64%.

The network model has been developed to abstract the representation of the EAB dynamics and spread into a set of nodes and links, embedded in geographic space. In the network, nodes represent the location of infested trees and the links represent the movement of an adult EAB between infests trees. The network model is integrated into the ABM, meaning once an ash tree in the ABM geospatial environment gets infested, it gets added to the network model. The nodes and links in the network model store information regarding the topology of the network i.e. which infested trees are connected to which.

A variety of measures can be generated from the topological information stored in the network model as the network structure begins to form and large scale patterns of spread emerge. Node degree k is one of the basic measures of network science, defined as the sum of links that connect to a node (Barthelemy, 2011). For example, degree k for infested tree node i is the sum of links from i to other infested tree nodes. The degree distribution of the entire network can be plotted on a histogram by calculating $P(k)$ or the fraction of nodes in the network with degree k. The degree k of the nodes and the degree distribution of the network can provide information on network behaviour and structure.

3. Results and Conclusions

The simulation results generated by the network-ABM maps the location of trees infested with EAB after one year and are presented in Figure 2. Specifically, the ABM-only generated output (Figure 2A) can be compared with the underlying network structure generated by the integrated network-ABM model (Figure 2B). From the network structure, the degree distribution can be calculated and plotted as a histogram, presenting distribution of the fraction of nodes in the EAB infestation network with degree k (Figure 3). For example, for a large fraction of nodes, $k = 1$ and for a very small fraction of nodes in the network, $k = 63$.

The integration of networks within the geographic automata system has the capability to quantify and give transparency to model processes that give rise to emergent patterns and help to provide a more complete representation of the model behaviour. The node degree k and the degree distribution (Figure 3) generated in preliminary network-ABM results suggest that in regional scale EAB insect infestation, a few trees become highly connected and many trees do not become very connected. This distribution suggests the presence of hubs in the network i.e. trees which are very commonly infested in the network across time. Hubs may be evidence of a highly centralized network structure and removing hubs in a network may lead to system collapse (Barabasi, 2014). Understanding why and where these hubs are generated may help to understand EAB dispersal and resilience to eradication. Continuing to explore infestation network structure and behaviour and quantify how changes in structure may impact network development and behaviour is useful to aid in pest management and decision making.

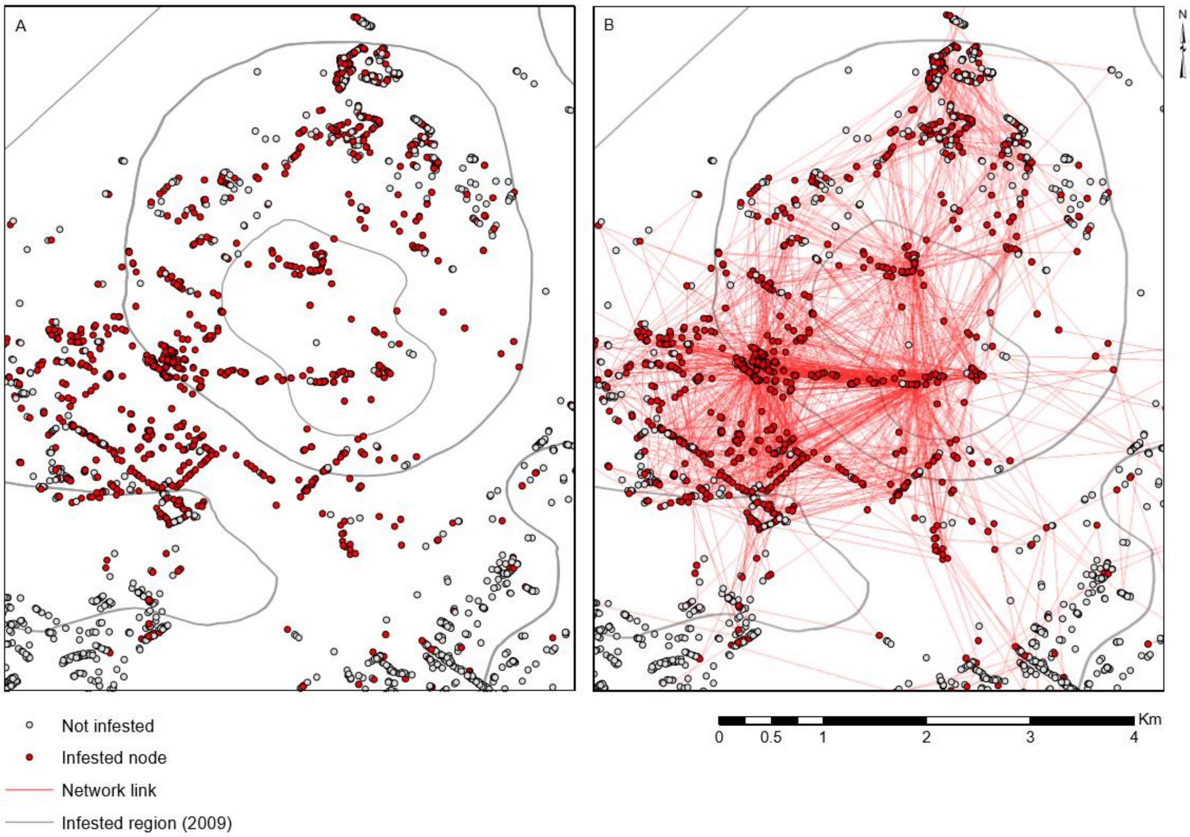

Figure 2. Simulation results presenting the location of trees infested after one season of EAB infestation in 2008 generated using (A) ABM only and (B) network model integrated with ABM.

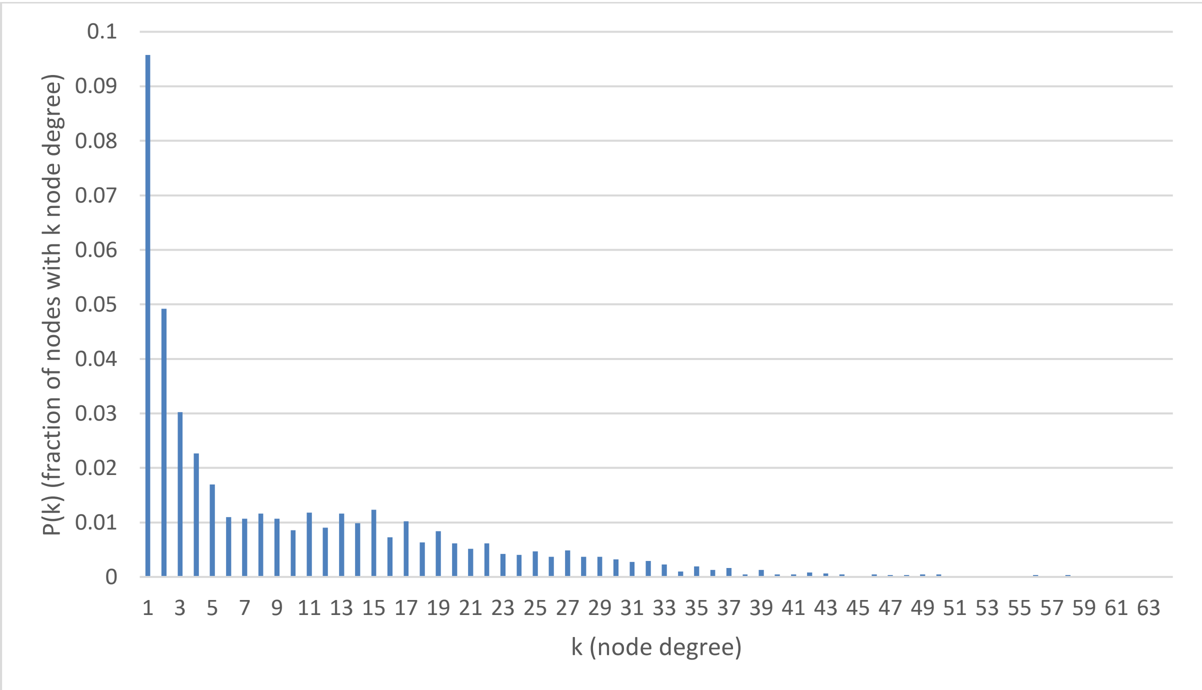

Figure 3. Degree distribution generated by developed network-ABM.

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