# Spatially Explicit Agents And Landscape Models Coupled In A Single Framework? It All Depends On How You View It


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## Abstract

Many of the environmental, ecological, and social problems we wish to explore require a mixture of landscape-oriented models, individual-based models, and some level of interaction between these elements. Few simulation modeling frameworks are structured to handle both styles of model in an integrated fashion. ECO-COSM is a framework that is capable of handling complex integrated models with both landscape and agent components. It uses a Probe-based architecture to allow model components to have access to the state of other components. This common design pattern for promoting information-hiding in applications is the critical component of ECO-COSM's broad modeling capability. It allows agents to apply perceptual filters to their observations of the landscape, or apply decision-making strategies in the face of incomplete or uncertain observations. ECO-COSM is demonstrated with a landscape model of metapopulation dynamics, an agent model of squirrel dispersal, and a coupled landscape-agent model to evaluate field data acquisition strategies for identifying nutrient hotspots.


## 1. Introduction

There is a large body of research utilizing models of multiple interacting agents making land-use decisions, ultimately driving changes to the regional land cover (see Parker et al., 2002 for a review). In these models, a number of autonomous agents make decisions using information about the landscape, its relation to the agents, and interaction among the agents themselves. Their decisions in turn influence the evolution of the underlying landscape, which itself is represented by a cellular model. The agents themselves do not necessarily have a spatially explicit representation; as land-use managers, their decisions regarding land-cover change are of interest, not their locations on the landscape.

In other modeling domains, knowledge of the agents' locations upon the landscape is critical, for example in animal dispersal and human movement studies. These agents are typically not acting as primary drivers of landscape evolution; rather, the landscape drives the agents' future spatial arrangement and states. In this case the term 'individual-based models' (IBMs) is used more commonly than 'agent-based models'. Although the landscape is evolving under the influence of larger scale forces, the short modeled timeframe relative to the temporal scale of landscape change allows the landscape to be treated as a static pattern. Consequently the IBM is usually constructed as a collection of autonomous agents moving relative to a set of static grid layers representing the landscape. These models have generally been constructed using an agent-based modeling framework that can access GIS data (e.g. Westervelt, 2002).

However, there are domains for which the scale of landscape change may be similar to the scale of agent movement: for example, reaction and emergency response during a natural hazard such as a landslide or flood, or evolution of faunal populations under resource succession or depletion. In these cases independent, complex agent models and landscape models may operate simultaneously, with some degree of mutual influence on future state. There are examples of linked agent-landscape models in the literature (e.g. Holt et al., 1995) but they tend to be model-specific endeavours. It is rare to find a general-purpose modeling framework that allows construction of coupled, spatially explicit agent and landscape models. Swarm (Minar et al. 1996) is perhaps the best known example, however the landscape is technically a sub-swarm of 'landscape cell agents' and must be implemented with a structure that differs from the common CA-based approach to landscape modeling.

This paper shows how ECO-COSM, a simulation modeling framework used to build spatially explicit simulation models, can accommodate relaxed CA-style landscape models, spatially explicit agent-based models, and coupled agent-landscape models. We begin with an outline of the ECO-COSM structure. The focus of the outline is on the framework elements most relevant to model coupling, namely the Probe architecture. The framework is illustrated by an example landscape model and an agent-based model. It concludes with an example of a coupled agent-landscape model, and a discussion of how the models may operate simultaneously with distinctly different temporal structures (event-driven and uniform time step) at different temporal scales.

## 2. ECO-COSM

Extensible Component Objects for Constructing Observable Simulation Models (ECO-COSM) provides a library of modular software objects that manage the structure of space and time within a simulation, including mechanisms to handle concurrent activity among objects within the simulation (Figure 1). It goes beyond being a simple collection of objects, and acts as an application framework; that is, a reusable, 'semi-complete' application that can be extended or specialized to produce custom applications (Johnson and Foote, 1988).

There are many ways to build spatio-temporal structure in a simulation; the manner of specification within the software framework forces the modeler to make his or her assumptions about space and time explicit. Most modeling frameworks have a certain set of assumptions built into them, such as all spatial interactions taking place on a two-dimensional lattice. ECO-COSM packages objects with such embedded assumptions into replaceable modules so that they may be changed if desired. Following Martin's (1996) Dependency Inversion Principle, many of the classes in the framework are defined as abstract interfaces, with concrete implementations of the structure. From a basic model, additional complexity may be added by creating new, concrete implementations of the framework interfaces and replacing some components with more sophisticated alternatives. Once the basic model is developed, the entire body of work can be reused as the model evolves; only the new components of the model need to be constructed. This ensures that space and time are handled in an identical manner for all model variations, and the same assumptions apply in all cases. Any change in results may be directly attributed to the changes made in the replaced component.

ECO-COSM was used to construct a spatially explicit, patch-occupancy style metapopulation model that extends the original model developed by Caswell and Cohen (1991), integrating resource heterogeneity into the system's colonization, extinction and competitive pressure processes. The framework's modular structure made an ideal environment for evolving from a globally parameterized model that solely focused on species interactions to one that incorporates system influences at multiple spatial and temporal scales (Graniero, in review). In the final model (Figure 2), the local resource availability depends upon a static substrate Layer $b$, a global climate signal time series $M(t)$, and possibly a regional disturbance Layer $d$. The value of each cell $n$ in the resource Layer $r$ at a given time $t$ is calculated over a range [0-1] as:

$$r_n = M(t) \times b_n - d_n \qquad (1)$$

The model includes two interacting species: a 'fugitive' species which can easily colonize new areas, and a 'superior' species which is not as resilient, but can eliminate the fugitive species via competitive exclusion. In species Layer $f$, each cell $n$ indicates which of the species, $s_1$, $s_2$, or both, occupy the cell. At a given time $t$, the probability $D_i$ that species $s_i$ will be disturbed out of an occupied cell $n$ is

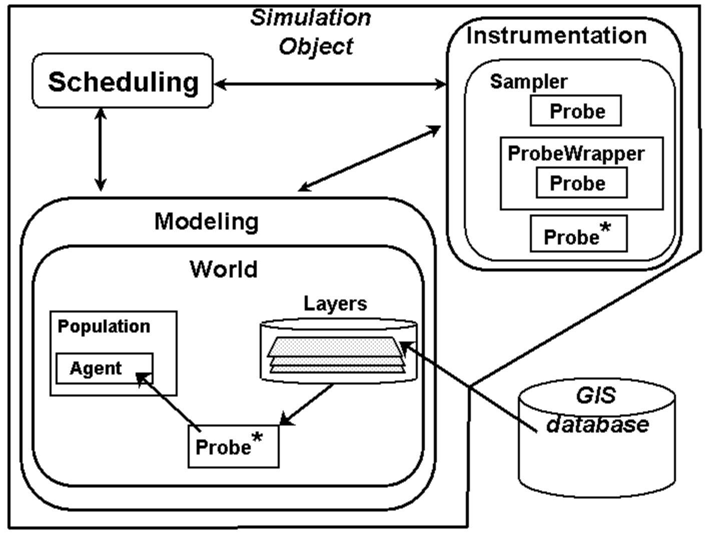


Figure 1. The main subsystems and objects of the ECO-COSM simulation framework. Note that in the World object, Agents and Layers cannot query each others' state except through a Probe in the Instrument interface, in the same way that the modeler accesses the state of the model. (From Robinson and Graniero, 2005a)

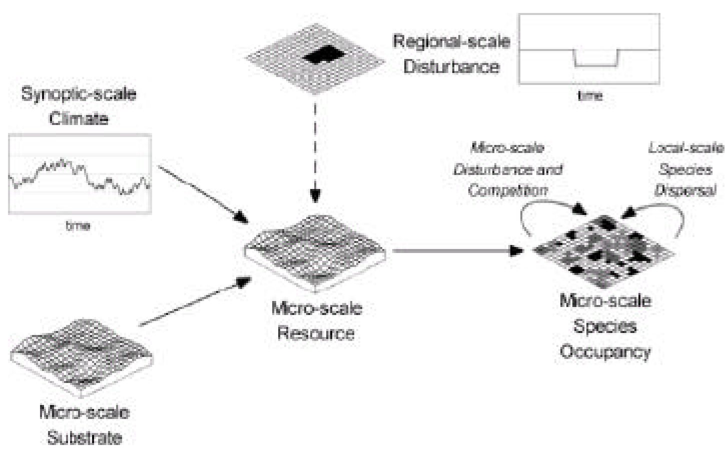


Figure 2. A spatially explicit patch occupancy model that incorporates stochastic CA-style species interactions. Local colonization, extinction and competition parameters depend upon local resource levels, which in turn are dependent upon a static substrate, a global climate signal, and regional disturbances. (From Graniero, 2001).

$$D_i = p_{di}^{\ r_n} \tag{2}$$

where $p_{di}$ is a resiliency coefficient for species *i*. The probability $C_i$ that species $s_i$ will colonize an unoccupied cell *n* is

$$C_i = 1 - e^{-f_i d_i r_n} \tag{3}$$

where $d_i$ is the dispersal coefficient and $f_i$ is the frequency or proportion of local cells (examined over a specified kernel) occupied by species $s_i$. The probability of competitive exclusion of species 2 by species 1 is $p_{c.}$ These equations were embedded into StepRules which are associated with their respective Layers; at each time step, each Layer's StepRule is invoked to calculate the next state for each cell.

As the model is being set up, a Command object that invokes a target Layer's StepRule is placed on the Schedule for each Layer. The Scheduling subsystem is structured for discrete-event modeling (Banks and Carson II, 1984). In order to create a regular, uniformly stepped temporal scheme, the Command objects for each StepRule automatically reschedule themselves for the next time unit.

## 2.1 The Probe architecture

The instrumentation subsystem is conceptually the most complex and most versatile in the entire framework (Figure 3). It allows the modeler to create very sophisticated data collection tools, connecting them to a working simulation model with no impacts or side effects on the model calculations. A model, as constructed using the framework components, will execute successfully from start to finish and terminate with none of the results observed or captured. Probes and associated ProbeWrappers are used to observe, record, and analyze the states and behaviors of objects that make up the model proper as it runs. Probes are obtained from Probeable model components, providing access to component state but keeping the mechanics opaque. This is a common object design pattern called the *Observer* (Gamma *et al*., 1995). The model, representing the formalized behavior of some ecological system, remains completely separate from any result data gathered for later analysis. This insulates the model results from potential programming side effects due to changes in monitoring or data collection code.

The primary power of the subsystem lies in the ProbeWrapper, a specialization of the Probe interface. Every ProbeWrapper instance has another Probe (possibly a ProbeWrapper itself) embedded within it. When the ProbeWrapper is queried, it in turn queries the embedded Probe. When it receives the embedded Probe's result, the ProbeWrapper may perform any kind of operation on it before passing it on as its own result (Figure 4). This is known as the *Decorator*

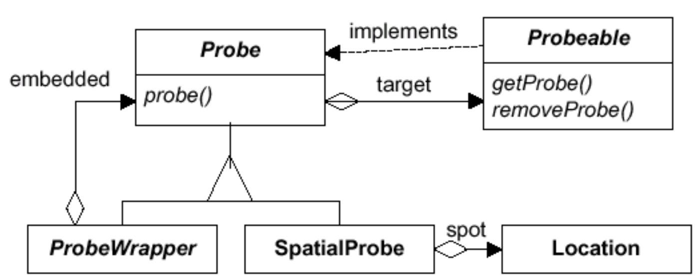


Figure 3. Structure of the **Probe**, **Probeable**, **ProbeWrapper** relationship (from Robinson and Graniero, 2005a).

design pattern (Gamma *et al*., 1995). In this manner, the 'pure' state returned by a Probe may be modified: the modeler may work with data that are derived from the model's current state, but do not necessarily match the exact state. For example, a Gaussian error term may be added to the value of a grid cell before being recorded in the output, simulating instrument error. This mechanism has been used to investigate the influence of spatial sampling strategies on our ability to accurately characterize an ecosystem (Graniero, in prep).

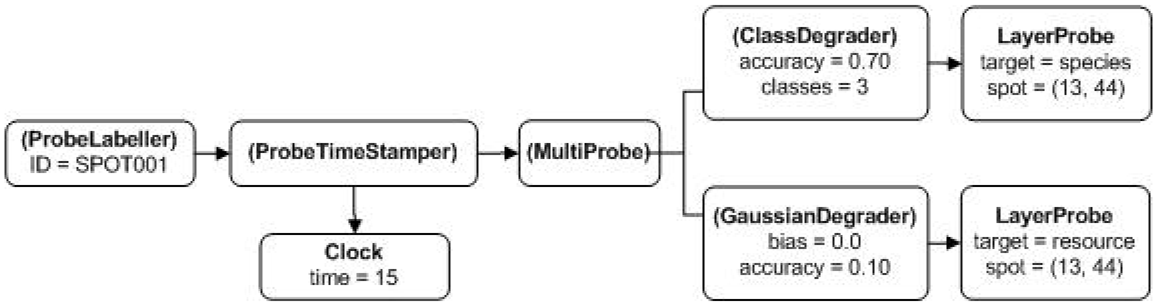


Figure 4. An example nested Probe composition used by an Instrument. Names in parentheses indicate ProbeWrappers. The state of two Layers, namely *species* and *resource*, are probed for their current state at location (13,44). The values are degraded to simulate instrument and classification error, and the results are combined together into a single time stamped record. (Adapted from Graniero, 2001).

## 2.2 The role of probes in an agent-based model

Any computing environment designed to support development of spatially explicit individual-based models must allow the agent to evaluate and interact with other individuals as well as to acquire and maintain knowledge about the surrounding landscape (Westervelt, 2002). From a GIS perspective, an animal agent must be able to query the state of relevant GIS layers within its local perceptual range and use that information to make decisions regarding its mobility, behavior, and change of internal state (Figure 5) Within the ECO-COSM framework, this requirement is directly handled by the Probe mechanism. By obtaining Probes from relevant Probeable landscape layers (and possibly from other Agents as well) on initializing the model, an Agent acquires a perceptual inventory of its world.

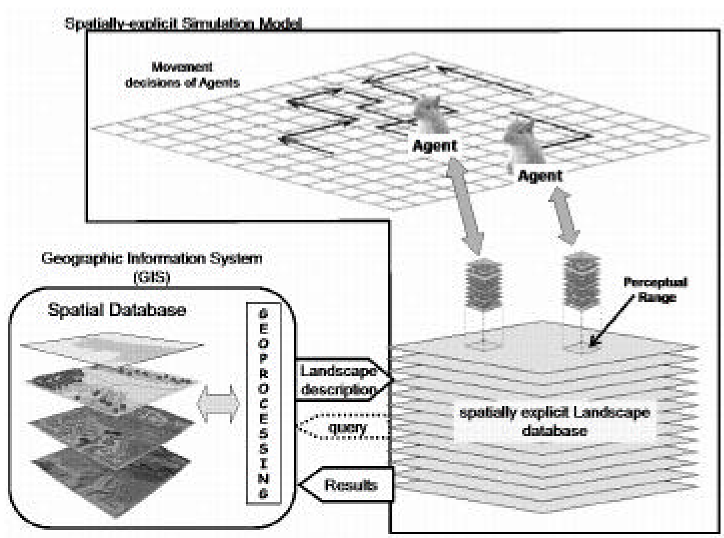


Figure 5. A conceptual illustration of the major components of a spatially explicit ecological model that focuses on movement behavior of individual animals, e.g. natal dispersal. Note the loosely coupled relationship with the geographic information system. (From Robinson and Graniero, 2005b)

An important principle in individual-based modeling is that each Agent may view and respond to the world in a different manner, whether by differences in the archetypical characteristics of one species over another, or by small variations among individuals within a population. This is easily achieved by using ProbeWrappers, which in essence are used to modify the 'pure' result retrieved from a Probeable object in some way. For example, the land cover type observed at a distance may be subject to random misclassification due to limits of perceptual range. Alternatively, the state's description scheme may be modified to suit the purpose of the observer: the grid cell may be described as 'mature oak' in the land cover Layer, but the observing Agent may perceive it as 'suitable location for inhabiting'. By wrapping Probes in slightly different ways for different individual Agents of a certain type, it is possible for the modeler to introduce variation in an individual's ability to perceive the world while using the same basic decision-making process. ECO-COSM was used in this manner to the explore the use of different fuzzy logic-based decision-making approaches to model the natal dispersal behavior of eastern gray squirrels (*Sciurus carolinensis*) on a GIS representation of an area near the Land Between the Lakes National Recreation Area (Robinson and Graniero, 2005a).

Four decision models were used to simulate dispersal behavior. Three decision models were based on fuzzy set theory and varied according to the logical connectives used. The fourth model was a crisp (nonfuzzy) model. Hence there were four populations of agents with each population using a different decision model. Figure 6 shows a dispersal example of each type of agent. The agents were programmed with no Probe awareness of each other, and the agents do not modify the landscape in any way. Therefore, the agent simulations were executed simultaneously on the same landscape with no interference. In general, the fuzzy agents' pattern of behavior was more plausibly realistic than that of the agents using crisp logic. This means that by using the ECO-COSM approach, a range of behaviors within a single species can be modeled. This is more realistic than assuming all agents have a single, identical decision model. In addition, the results shown in Figure 6 illustrate how this approach has yielded plausible results that do not rely upon stochasticity, thus providing a more satisfying framework for understanding how movement behavior may be influenced by landscape and ecological factors as well as the decision model.

Since squirrels tend to set up home ranges in areas not contested by conspecifics we ran the simulations for landscapes with different levels of conspecific coverage. The base line situation was the case of social fencing where there were no 'holes' in the conspecific landscape. Variations in the base line were implemented by randomly allowing for 20, 40, and 60 percent of the landscape to be composed of unoccupied 'holes.' A conspecific 'hole' was therefore a spatially explicit goal for a disperser. Figure 7 illustrates that variations in landscape perception, implemented via the ProbeWrapper, and consequent use of the information in the decision model, did have an effect on the agents' ability to find a suitable location for establishing a home range. It is clear that in all situations the agents using the fuzzy decision model were more successful at finding a home range.

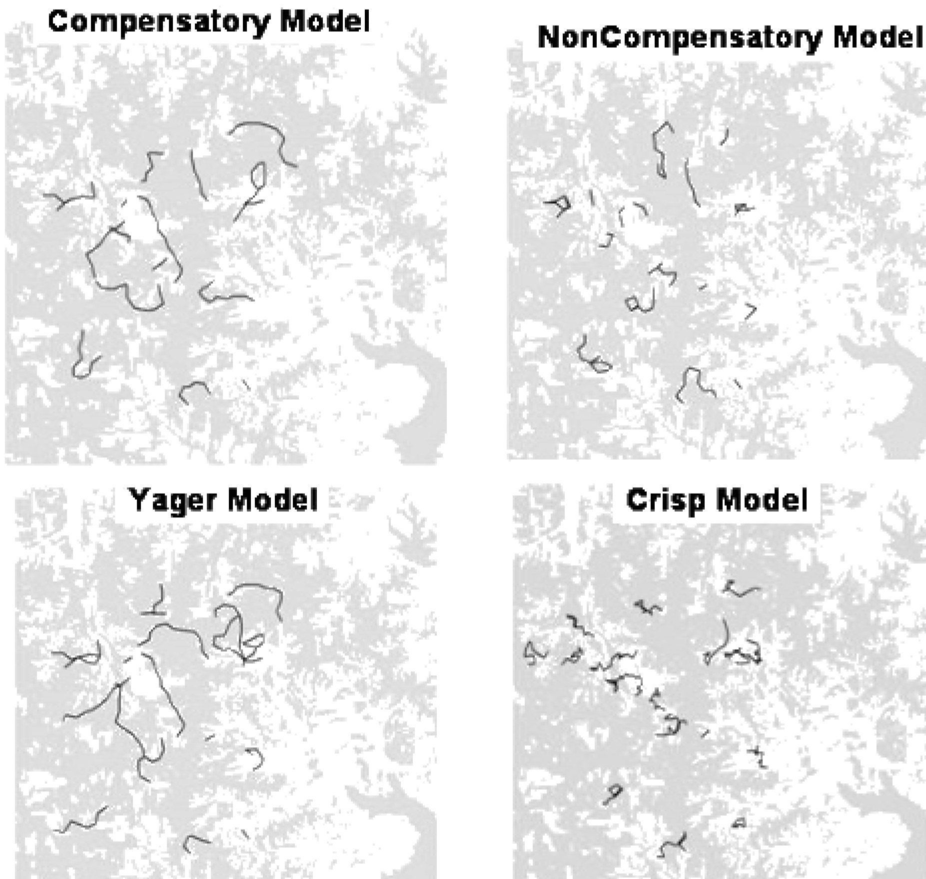


Figure 6. Example movement patterns for each agent decision model. The grey areas are least suitable as home range locations. The lines show dispersal paths for each squirrel agent. The same starting points were used for each decision model. (From Robinson and Graniero, 2005a.)

## 3. Coupled Agent-Landscape Models

ECO-COSM uses keyword-based identification of and access to World components, so an Agent only needs to specify which particular landscape layer is of interest at the conceptual level and does not need to be concerned about lower level details such as the layer's spatial structure (e.g. vector vs. raster) or how the layer changes state as the model executes. The landscape layers could be statically stored in a GIS database as in the squirrel dispersal model, or they could be dynamically simulated as in the patch occupancy model. In both cases, the Agent's method of accessing, filtering, and using the landscape information is identical. It is possible to develop and test an agent-based model on a static landscape and then replace the static landscape layers with dynamically evolving landscape layers with no change to the Agent code, as long as the same keywords are used to name the layers. Probes provide a means to view the model state but not to change it; therefore, a Probeable Layer in a landscape model sees no difference in passing state information to a simple output file or to an active Agent. As such, an agent-based model and a landscape model may be independently developed and tested in ECO-COSM as stand-alone entities, and subsequently coupled by combining their initialization descriptions into a single setup routine. Further model refinement can allow Agents to register changes to local states in the landscape model's Layers, more closely coupling the models' interaction.

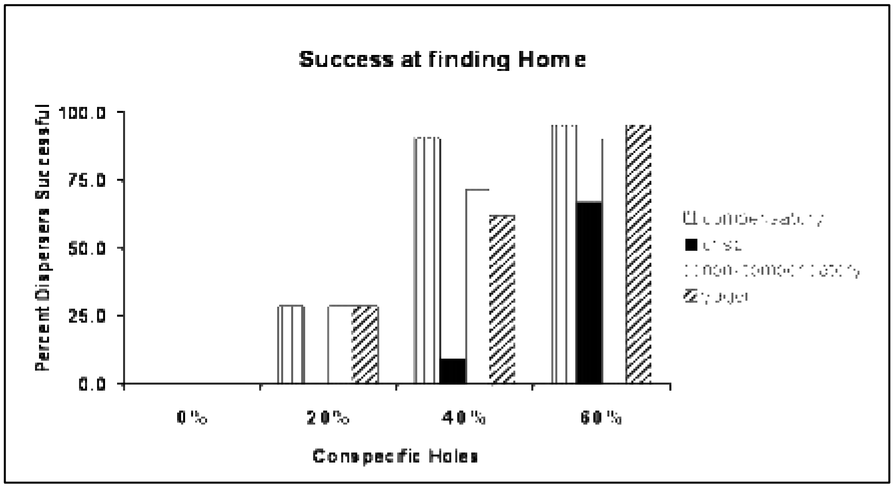


Figure 7. Percentage of squirrel dispersers in each decision model that found a location suitable as a home range.

For example, consider a highly simplified system where some nutrient diffuses according to Fick's Law:

$$\frac{\partial u}{\partial t} = D\left[\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right] \tag{4}$$

The Laplacian operator acts as a discrete, first-order approximation of Fick's Law on a grid with spacing $h$, and $i$, $j$ representing row and column coordinates on the grid:

$$\nabla^2 u\Big|_{i,j} = \frac{D}{h^2}\left(u_{i+1,j} + u_{i-1,j} + u_{i,j+1} + u_{i,j-1} - 4u_{i,j} +\right) + O\left(h^2\right) \tag{5}$$

The finite difference equation to estimate u at grid cell $i,j$ at time $t + k$ is then

$$u_{i,j}^{t+k} = u_{i,j}^{t} + k\nabla^2 u\Big|_{i,j} \tag{6}$$

where $k$ is small enough to effectively ignore the truncation error $O(h^2)$. This finite difference equation is easily implemented as a StepRule operating on a nutrient Layer.

In most natural environments the diffusion matrix is heterogeneous, often in a patchy pattern. Rather than applying a global diffusion coefficient $D$, the model uses a diffusion coefficient Layer, which is generated from Thiessen polygons surrounding random seed points $i$ with a randomly generated coefficient $D_i$. A spatially variable depletion rate is applied to the region, with the edge cells having a rate ten times higher than interior cells. The model is constructed with a reflecting BoundaryTopology to minimize edge effects in the diffusion model when identifying neighbour cells. Once a source Layer defining the local nutrient input rate is added, the result is a complete landscape model. At each time interval, the local state of the nutrient Layer is determined by neighbouring states and the local state at the corresponding location in the depletion and input Layers. Although the model is no longer strictly a CA-style model, it does fall under the more general coupled-map lattice model or interacting particle system (Czárán 1998).

Now, rather than using a static input layer, consider that the nutrient appears in the system via asynchronous pulses at specific point locations. Such a pattern may develop anthropogenically via outflow flushes, or naturally via hot spot/hot moment biogeochemical processes in elemental cycling (*cf.* McClain *et al.* 2003). Nutrient inputs are modeled as Agents, parameterized with a location, input rate, time period over which the input source is 'on', and time period over which the input source is 'off'. Although this simple behavior does not require the Agents to probe their environment, the Agent structure is convenient for having a number of discrete point objects with independent and similar, but not identical, behavior and managing them as a Population.

Now consider the following question: if such hotspot locations are not known *a priori* in the real world, what is the best search strategy to find them quickly in the field, especially if they can 'wink out'? Is it better to proceed with slow but complete local searching, or move faster with only a sub-sample of the adjacent region?

A Population of seeker Agents are added to the model, each simulating a field worker with its own search strategy. On model initiation, each Agent obtains a Probe targeted at the nutrient Layer, analogous to the instrument the field worker would use in the field to measure the nutrient concentration. In this example the Probe produces perfect measurement results, though it would be easy to simulate instrument error as described in Section 2.1. The Agents are all placed at the same random location, and after a delay period to let the landscape model reach stable conditions, the Agents begin to search for hotspots. Following some measure-and-compare search strategy, each Agent moves over the landscape until it determines that it must be at a hotspot, at which time it moves to a 'finished' Population. The simulation terminates once all Agents are in the 'finished' Population, or a specified period of time has passed.

To demonstrate, two variants of a simple brute force method were employed. To begin, the Agent measures the concentration at its current cell, then travels to each neighbouring cell (either the four cardinal cells of the von Neumann neighbourhood or all eight cells of the Moore neighbourhood, depending on the Agent) to take a measurement. If the original cell was the highest value it is determined to be a hotspot; the Agent moves back and decides it is finished. If it finds a neighbouring cell with a higher value, it moves to the neighbouring cell with the highest value, then starts the process again. The Agent acts with no memory; even if it just measured a cell, it still travels to it and re-measures. Once the Agent has a destination planned it schedules its next action to occur after the travel time it needs to reach the destination, where the travel time is simply the Euclidean distance between the source and destination cells. For example, if the Agent plans to move one cell to the east, it schedules its next action 1 time unit from now; if it plans to move to the south-east, it schedules its next action 1.414 time units from now. In the meantime, the landscape model independently follows its own scheduled activity, stepping through its calculations every $k$ time units.

As a simple experiment, the model was executed 50 times with diffusion patterns and hotspot locations and behaviors established randomly: ten diffusion patches varying between 0.35 and 0.65; and 40 point sources, with on- and off-intervals varying between 10 and 100 time steps.

One 'von Neumann Seeker' and one 'Moore Seeker' were placed at a common random location, and they began seeking a hotspot after time 1000.

Figure 8 shows the result of an example model trial. The von Neumann Seeker found a hotspot in 40.11 steps, whereas the Moore Seeker found a hotspot in 50.89 steps. This was one of only two trials in which the Seekers found different hotspots. In general, the von Neumann Seeker found a hotspot faster than the Moore Seeker (Table 1). However, the von Neumann Seeker only found a hotspot in 58% of the trials. In the other trials the first exploration produced all zero values (i.e. no concentrations above background levels), giving no evidence of a hotspot. In contrast, the Moore Seeker found a hotspot in 82% of the trials. Thus, if it is important to find a hotspot if it exists, this experiment suggests that it is better to opt for more careful, complete searching even though it will usually (but not always) take longer to find a hotspot.

The model is quite simplistic compared to the complex processes operative in the natural world, but it clearly demonstrates the interaction among model types. A landscape model operates with three interacting grids. Two different types of modeled agents are operative: one type uses Probes to examine state in the landscape model and therefore view its surroundings, make a movement decision, and carry out the motion; the other type changes the local nutrient concentration state through a controlled programming mechanism. Furthermore, the model components are operating in three different modes. The landscape model, structured as an explicit finite difference model, calculates its steps on a regular, sub-unit time scale. Outputs of current model state are dumped via probes on a regular, unit time scale. Each Agent works on its own discrete event schedule, with intervals between scheduled activities determined by the time to traverse the landscape to the Agent's target destination.

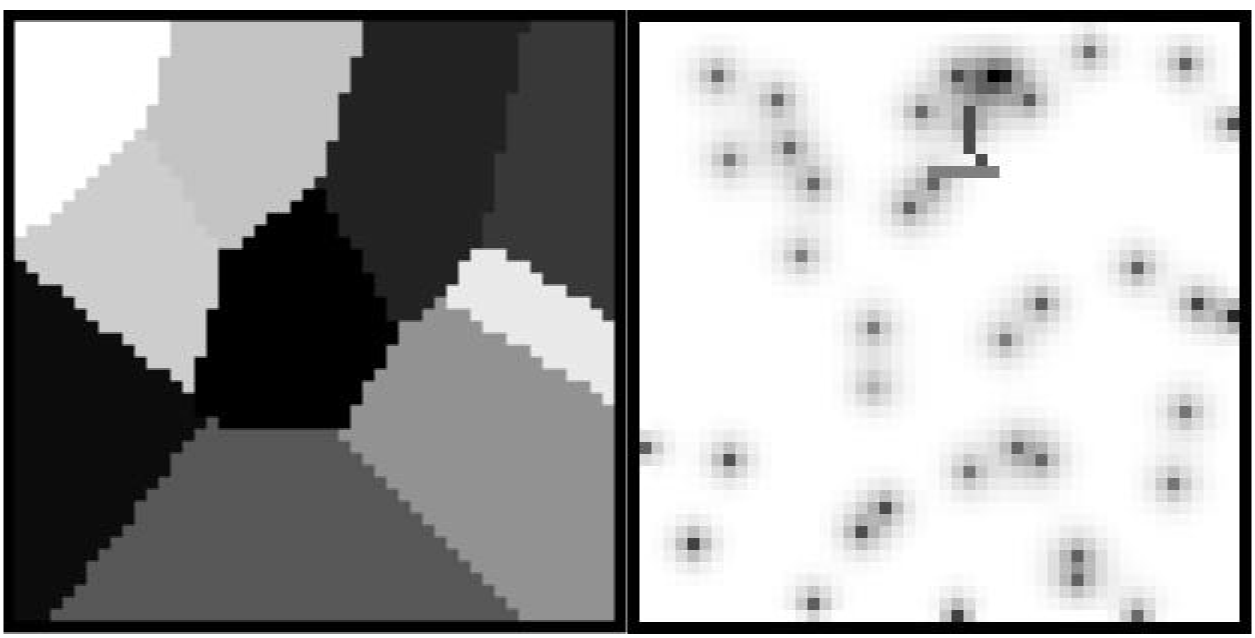

Figure 8. An example seeker model result. Left: patch pattern of the diffusion coefficient. Right: concentration map during final step, with seeker paths superimposed. Dark spots are the hotspots. Dark grey path seeks in the Moore (eight-cell) neighbourhood; light grey path seeks in the von Neumann (four-cell) neighbourhood.

Table 1. General seeker performance statistics for 50 simulation trials.

| | von Neumann Seeker | Moore Seeker |
|---|---|---|
| Success rate | 58% | 82% |
| Average seek time | 40.33 | 48.09 |
| Fastest seeker (when both find the same hotspot) | 74.1% of trials, faster on average by 25.7% | 25.9% of trials, faster on average by 5.1% |

## 4. Conclusions

ECO-COSM provides a powerful modeling framework for complex spatial simulations. Its design guards against code degradation by explicitly enforcing the object-oriented design principle of information hiding via the Probe mechanism. This not only improves upon the confidence one has in the simulation results as the model goes through many stages of evolution, it provides the fundamental structure to couple agent-based models to a landscape model. By using ProbeWrappers to modify the exact state returned from some location in a landscape Layer (or another Agent), sophisticated Agents can be constructed that:

1) use perceptual filters to modify their view of the landscape, or
2) make their decisions on incomplete or uncertain observations.

A discrete-event scheduling mechanism allows simple, uniformly stepped models to be executed simultaneously with complex, trigger-oriented agent collections. ECO-COSM also opens up the possibility for new explorations in coupled landscape-agent models. The Probe mechanism makes it straightforward to independently develop landscape models and individual-based models, then merge them as each model matures.


## 5. Acknowledgements

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