

# Spatial Modelling

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## 11.1. Introduction

Ecology is a spatial science (Tilman & Kareiva, 1997). Therefore, it is important to be able to model the distribution, movement, and dispersal of species and individuals across a varied and variable landscape. The methods and techniques introduced in Chapter 9 for individual-based models (IBMs) are similar to those used in spatial modelling. This chapter gives an overview, with examples from early methods, for spatial modelling in ecology leading to the state-of-the-art models with current applications.

Compartment models are zero-dimensional models, because all of the processes occur in one place without distinguishing any spatial relations between the compartments. This simplifies the system for ease of finding mathematical solutions, but also obscures the complex reality of ecological systems. The assumption is more reasonable in lake models where one can assume the system represents a continuously stirred tank reactor (CSTR), but even that has severe limitations, as lakes can have vertical (stratification) and horizontal (spatial) variation. Approaches have been developed to overcome this constraint by specifically adding spatial dimensions to the interactions of the ecological components. The rise of Geographical Information Systems (GIS) and remote sensing has

contributed greatly to the tools available for explicitly representing ecological space. Landscape ecology and spatial modelling are two of the most common tools to benefit from this contribution (Turner and Gardner, 1991). As a general rule, these models are more complex because they add the additional spatial dimensions and require additional knowledge about how movement occurs on the landscape.

As with all models, their application to ecology helps formalize our understanding and develop theory about how ecological processes interact across spatial patterns. According to Turner, Gardner, and O'Neill (2001), there are three general conditions for which spatial models are important:

1. When spatial pattern may be one of the independent variables in the analysis
2. When predicting spatial variation of an attribute through time
3. When the question involves biotic interactions that generate patterns

The first condition refers to questions such as: How do species forage differentially across a landscape of variable resources? How do nutrient inputs respond to vegetation variation across a watershed? The second condition deals specifically with the change in time of the landscape, such as questions of succession or following disturbance. The third often deals with homogeneous space and varying organism traits resulting in the emergence of heterogeneous distributions across the landscape and are generally modelled using cellular automata. Landscape models cover a broad diversity of types and applications; the most frequent subject includes single species metapopulation dynamics influenced by factors such as fragmentation, corridors, dispersal, and invasion. Models that represent disturbance and vegetation dynamics are also common. An area that has seen recent attention and is still in need of more is the integrated models of ecological and socioeconomic processes. The rapidly increasing availability of GIS tools and software has greatly aided the development of spatial models, but one must not let the technological advances outpace the ecological understanding or what is left will be a technically advanced, but unreliable model. One key for successful spatial models is that the model equations should include ecological processes, rather than just correlations, so that the individuals can change over time given different environmental conditions. In this manner, with

a dynamic spatial model, the interactions of the ecological species can lead to unexpected or emergent behavior as is often observed in nature. In the next section, we review the early contributions to spatial models in ecology.

### 11.1.1. Concepts and Terms

A key concept in the area of spatial modelling is *scale*, which refers to the spatial extent of the ecological processes. It is important to choose an appropriate scale related to the specific question at hand, because the processes that affect the different organisms may influence them differently depending on the scale. In fact, many processes operate at multiple scales.

The presence of spatial *patterns* is a key feature of organisms distributed on a landscape. The patterns arise as a result of the ecological processes and the behavioral response of the organisms. Patterns can be classified into three broad distribution categories: (1) *gradients*, which show a smooth directional change over space; (2) *patches*, which show clusters of homogeneous features separated by gaps; and (3) *noise*, which are the random fluctuations not explained by the model. Identification of the pattern can be accomplished with two methods, point pattern and surface pattern analyses. The first category describes the type of distribution and what processes may have caused the pattern. Nearest neighbor method is a common approach to implement this. The second category deals with spatially continuous data and statistical techniques such as correlograms or variograms, which can be used to quantify the magnitude and intensity of the spatial correlation in the data. *Spatial autocorrelation* is an important concept because it identifies the likelihood that samples taken close to each other are more similar than would have occurred by random chance. Positive spatial autocorrelation occurs when the values of samples are more similar than expected by chance and they are negatively spatially correlated otherwise. Most ecological data show some spatial autocorrelation. This tends to decrease with distance. Closer objects tend to have more positive autocorrelation than those further apart since the phenomena that shape species behavior — environmental factors, communication, or interactions — are more similar with proximity.

Acquisition and handling of spatial data are necessary when dealing with spatial models. The availability of spatial data has exploded, thanks to the development of advanced satellite *remote sensing*. The first Earth observation satellite, the Television and Infrared Observation Satellite (TIROS), was launched in 1960 and used mainly for television signal transmission and weather monitoring. Now, such satellites are used for identifying land cover, crop management, forest management, water management, ice cover analysis, national security, and so forth. Some of the most common satellites are from the United States (Landsat), France (SPOT), and India (IKONOS). Prior to the advent of this technology, aerial photographs served as the source for spatial data, and is still used today for gathering information about a specific time and place when a specific resolution is needed, such as for ground truthing satellite data.

In 1972, the U.S. government launched the first in a series of Landsat satellites. The program began at National Aeronautics Space Administration (NASA), but was transferred to the National Oceanic and Atmospheric Association (NOAA) and is now managed by the United States Geological Society (USGS). Since the first launch, there have been six additional satellites ([Table 11.1](#)), although the latest was over a decade ago and has had some technical problems. Only two remain active — Landsat 5 and 7. Landsat 5, intended for a 3-year mission, has been sending data for over 25 years at a maximum transmission bandwidth of 85 Mbit/s. It was developed as a backup to Landsat 4 and carries a Thematic Mapper (TM) and Multi-Spectral Scanner (MSS). It orbits at

**Table 11.1** Satellite Chronology of the U.S. Landsat Program

Satellite	Launch date	Status
Landsat 1	July 23, 1972	Terminated January 6, 1978
Landsat 2	January 22, 1975	Terminated January 22, 1981
Landsat 3	March 5, 1978	Terminated March 31, 1983
Landsat 4	July 16, 1982	Terminated 1993
Landsat 5	March 1, 1984	Still functioning
Landsat 6	October 5, 1993	Failed to reach orbit
Landsat 7	April 15, 1999	Still functioning, but with faulty scan line corrector

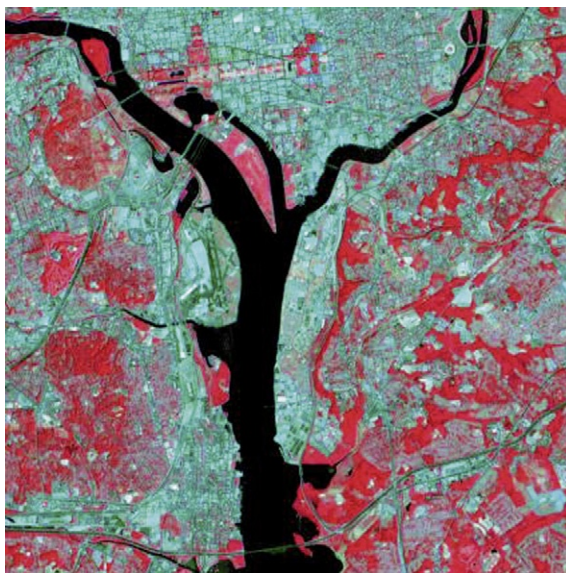
**Table 11.2** Spectral Bands of the MSS Sensor

Band	Wavelength ( $\mu\text{m}$ )
1	0.45–0.52
2	0.52–0.60
3	0.63–0.69
4	0.76–0.90

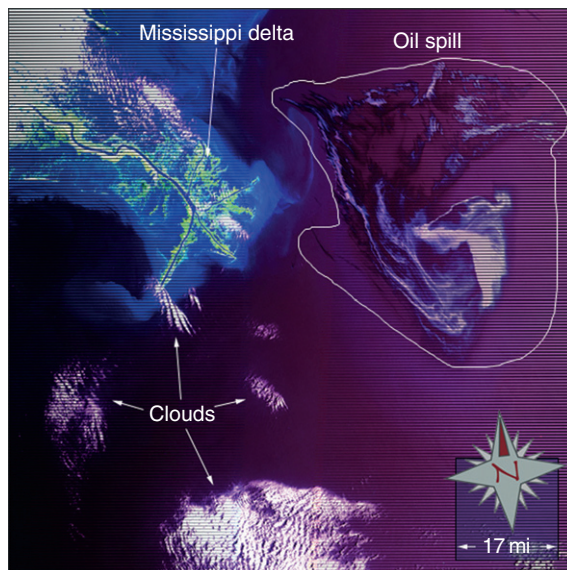
an altitude of 705 km and takes 16 days to scan the entire Earth. The MSS has four bands (Table 11.2) and scans at a resolution of about 76 m. This scanner was placed on the first four Landsat satellites, but has been phased out due to the improved TM sensor. TM sensors have seven bands of image data (Table 11.3) with resolution of about 30 m. It is a useful tool for identifying ground cover types as well as albedo and its relation to global climate change. In Landsat 7, the TM was upgraded to what was called an Enhanced Thematic Mapper Plus (ETM+). Landsat 7 also orbits at 705 km and takes 16 days to scan the entire Earth's surface. Resolution of the ETM+ is 15 m in the panchromatic band and 60 m in one thermal infrared channel. Images from the Landsat satellites are in false color (e.g., Figures 11.1 and 11.2) and must be managed and classified according to the user's interest. Data from these satellites are available from the USGS at <http://landsat.gsfc.nasa.gov/data/where.html>. Much of the archived ETM+, TM, and MSS data are available for free. These data are used in applications such as Google Earth and NASA World Wind.

**Table 11.3** Thematic Mapper Bands

Band	Wavelength ( $\mu\text{m}$ )	Resolution (m)
1	0.45–0.52	30
2	0.52–0.60	30
3	0.63–0.69	30
4	0.76–0.90	30
5	1.55–1.75	30
6	10.4–12.5	120
7	2.08–2.35	30



**FIGURE 11.1** False infrared color image of Washington DC (15 m resolution) taken from Landsat 7. (As a work of the United States Government, the image is in the public domain.)



**FIGURE 11.2** False infrared color image from Landsat 7 of the Mississippi Delta showing the oil spill following the explosion of the Deepwater Horizon Offshore drilling rigs taken on May 1, 2010. (As a work of the United States Government, the image is in the public domain.)

With such abundant data, it is necessary to have platforms in which to import, store, manipulate, and present them. As stated previously, the rise of GIS has met this challenge. Essentially, it is the computational merging of cartography and database technology. A GIS is any tool that allows the user to integrate, store, edit, analyze, share, and display spatial data. The boundaries and specifics depend on the application, but in all cases it provides for the analysis of the spatial information. There are many types of image processing software, such as IDRISI, EASI/PACE, ENVI, LCCS, ER Mapper, ERDAS Imagine, and GRASS GIS. One purpose of this software is to convert the “raw” data from satellite images into specific land use classifications. There has been a number of different land cover classification systems used, such as the “Global Land Cover Classification Collection 1988.” This classification system distinguishes 14 land cover classes: 0) water, 1) evergreen needleleaf forest, 2) evergreen broadleaf forest, 3) deciduous needleleaf forest, 4) deciduous broadleaf forest, 5) mixed forest, 6) woodland, 7) wooded grassland, 8) closed shrubland, 9) open shrubland, 10) grassland, 11) cropland, 12) bare ground, and 13) urban and built. An unsupervised or supervised process can be used to classify data. The unsupervised process group’s structure is based on similar signals and is useful when previous knowledge of the area is not available and it minimizes the opportunity for human error. The disadvantage is the lack of control over the classification process, which may result in groups that do not correspond to physical real-world data. A supervised process uses known samples to “train” the identification process of unknown pixels. This approach is more time-consuming and assumes a good working knowledge of the area, but gives greater control over the classification process.

The combination of remote sense data and GIS has greatly contributed to the development and implementation of spatial models in ecology. Next we discuss some of the early pioneer applications, as well as the current state-of-the art technology.

## 11.2. Spatial Ecological Models: The Early Days

One of the main questions addressed through spatial models is the distribution and movement of material or energy across the landscape. To model this movement, there must be a spatial grid over which the

movement occurs, as well as a set of rules for the movement to follow. In the absence of such rules, it is assumed that the movement is random across the landscape. This approach is used to generate neutral models for comparison (Caswell, 1976). The neutral model generates random patterns, assuming that species do not interact or react differently to differences in abiotic factors. In reality, the movement is constrained by physical and biological processes as described in the following section. Therefore, the utility of a neutral model is to compare how far from this unrealistic situation is the actual system at hand. The further from this baseline, the more articulated or organized the system, which can then be used as a measure of distance from “equilibrium.”

One alternative to the zero-dimensional model was to apply reaction diffusion theory to the distribution of movement along a spatial gradient. This approach uses mathematical models to explain how species disperse across a landscape based on the concentration gradient, which causes the organisms to spread out across the landscape from areas of high population to areas of low population. This provided a mechanism for spatial distribution, but did not capture relevant ecological processes in which organisms more actively make choices about moving across the landscape. Therefore, it was unable to explain observed patchiness and adequately represent the behavior of discrete individuals.

One of the first attempts to combine process-based compartmental modelling with spatial considerations was by Sklar, Costanza, and Day (1985), when they studied the habitat succession of the Atchafalaya delta/Terrebonne marsh area in Louisiana. They divided the area in fixed, equal-sized, square cells (today hexagonal grids are common). The choice to use a finite element method with a fixed grid is appropriate for systems with fixed hydrologic structure. Variable sized mesh grid is used in some hydrodynamic modelling, whereas the grid approach is used in global atmospheric circulation models. Within each cell was a two-compartment, dynamic, nonlinear simulation model representing suspended sediment and bottom sediments with exchanges between them. Furthermore, to make it spatially dynamic, each cell was connected to each adjacent cell by exchange of water and materials. In this first version of the model, there was allowable exchange of salt, sediment, and water across the grids, but not movement of organisms. The spatial extent includes 1,162,641 grid cells representing 50 m<sup>2</sup> each. Initial conditions and parameter values were taken from data and high



**Table 11.4** Range of Values for Variable to Classify Habitat Types

Habitat Type	Variable	Range
Upland	Water	0 –8000 m <sup>3</sup>
	Salt	0– 30‰
	Bottom sediments	<510 cm <sup>3</sup>
Fresh marsh	Water	20–10000 m <sup>3</sup>
	Salt	0–5‰
	Bottom sediments	<480– 510 cm <sup>3</sup>
Brackish marsh	Water	20–10000 m <sup>3</sup>
	Salt	5–15‰
	Bottom sediments	<480–510 cm <sup>3</sup>
Salt marsh	Water	20–10000 m <sup>3</sup>
	Salt	10–30‰
	Bottom sediments	<480–510 cm <sup>3</sup>
Open water	Water	<1000 m <sup>3</sup>
	Salt	0–30‰
	Bottom sediments	<480 cm <sup>3</sup>

altitude photographs from 1956. They classified the habitat types into five categories: upland, fresh marsh, brackish marsh, salt marsh, or open water depending on the values of the three main variables (Table 11.4). The model simulation was run until the model condition was stable. Constant inputs and a series of IF-THEN statements were used to determine if the cell had switched to a new habitat type based on the water level, salinity, and depth of bottom sediments. The model was validated using photographic data from 1978 (later 1983).

Building on this simple water exchange model, the authors added ecological processes of primary production and decomposition (Costanza et al., 1990). The improved model, called CELSS (short for Coastal Ecological Landscape Spatial Simulation), consisted of seven state variables: water volume, salt, sussed, nitrogen, biomass, detritus, and elevation. The cell size was adjusted to 1 km<sup>2</sup> and the model consisted of 2479 interconnected cells. Simulation results showed a strong similarity to photographic data. The model was then used to consider five different climate scenarios modelled out to the year 2033. All runs showed a marked decrease in all classification types except “open water,” which dominated the future landscape due to the sea level rise as a result of increasing climate. This example provided a powerful new approach to combining process-based ecological models linked together across a landscape.

## 11.3. Spatial Ecological Models: State-of-the-Art

The generalized grid approach introduced by Sklar and Costanza has been adopted and modified for many other studies. The journal *Ecological Modelling* recently published a special issue titled: *Spatially Explicit Landscape Modelling: Current Practices and Challenges* (Volume 220, Issue 24, 2009). It contained a review article and 17 research papers describing the current state-of-the-art methodologies, models, and applications. Three examples from that issue, plus one additional one, are provided in the following sections — forest succession, savanna succession, agricultural succession, and fish habitat suitability along a river corridor.

### 11.3.1. Example 1: Forest Succession After Blowdown

Rammig, Fahse, Bugmann, and Bebi (2006) developed a spatially explicit model to simulate forest succession of Norway spruce in the Swiss Alps following a windstorm blowdown that occurred in 1990. Significant damage was done to the spruce, flattening an area of approximately 128 ha. Following the blowdown, a monitoring program went into place to track the changes in vegetation within the affected area. The spatially explicit model was developed according to the ODD protocol (see Chapter 9). The area within the model was divided into  $100 \times 100$  grid cells each with a cell size of  $1 \text{ m}^2$ . Within each cell was an individual based tree-regeneration model. Cells were classified according to 1 of 12 micro-site types, depending on the site characteristics at time  $t = 0$ . The sites were defined by factors such as disturbed soil, fallen logs, decaying wood, and different herbaceous vegetation layers. The condition of the micro-site influences the ability for spruce establishment and growth. The model state variables are the number and height of Norway spruce in each cell. The model process overview and scheduling is given in [Table 11.5](#). The first step is to assess the change in the micro-site condition. This is followed by the dispersal of seeds to new sites, and then the germination and establishment of spruce on the new sites. Lastly, the growth and mortality of the spruce is modelled using a vegetation growth model for individual trees. The model parameters were taken from the literature and from a 10-year observation record at the blowdown site. The model time step was one year. The model was run for 50 years and repeated 100

**Table 11.5** Process Overview and Scheduling of Spatial Model Following the ODD Protocol

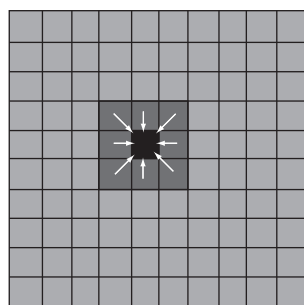
Processes (in Order)	
1) Changes in micro-sites	New micro-sites assigned according to transition probabilities and neighborhood rules
2) Seed dispersal	Random seed distribution, number depends on occurrence of mast years
3) Germination	Norway spruce may establish in each cell depending on micro-site specific germination probabilities
4) Growth	Modified Bertalanffy growth equation
5) Mortality	Intraspecific competition within spruce and interspecific competition between spruce and herb layer

times to gain estimates for mean outputs values. This model was able to adequately simulate the regeneration dynamics of the spruce forest. Of particular interest were the management implications regarding actions such as the clearing of fallen logs and the expectation for the length of duration for recovery of the forest stands.

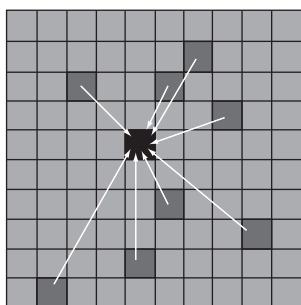
In a subsequent study, Rammig and Fahse (2009) modified the original model to construct a nonspatial point model from the original one in order to test and compare the predictions made by the spatial and nonspatial models. The goal was to determine the added value of using a spatial model compared to a nonspatial model. Is the extra complexity worth the effort, or can a nonspatial model give comparable results? Therefore, this second model can be considered an extended sensitivity analysis to the first model. The model was derived from the original model, allowing the use of the same parameter values, thus providing a more direct comparison. The main modification to the model involved using a random draw for determining the nearest neighbors. In the original model, the influence of each cell was felt from the eight nearest neighbors. In the revised model, those eight neighbors are drawn randomly from the landscape, eliminating a direct role for spatial proximity (Figure 11.3).

Figure 11.3 illustrates that the selection of cells influencing the local micro-site conditions are spatially selected in the original model and randomly selected in the follow-up model. This allows the investigation of the role of space without changing the overall model structure (Rammig & Fahse, 2009).

The new model produced results that generally overestimated the number of trees for all of the different height classes (Figure 11.4), in

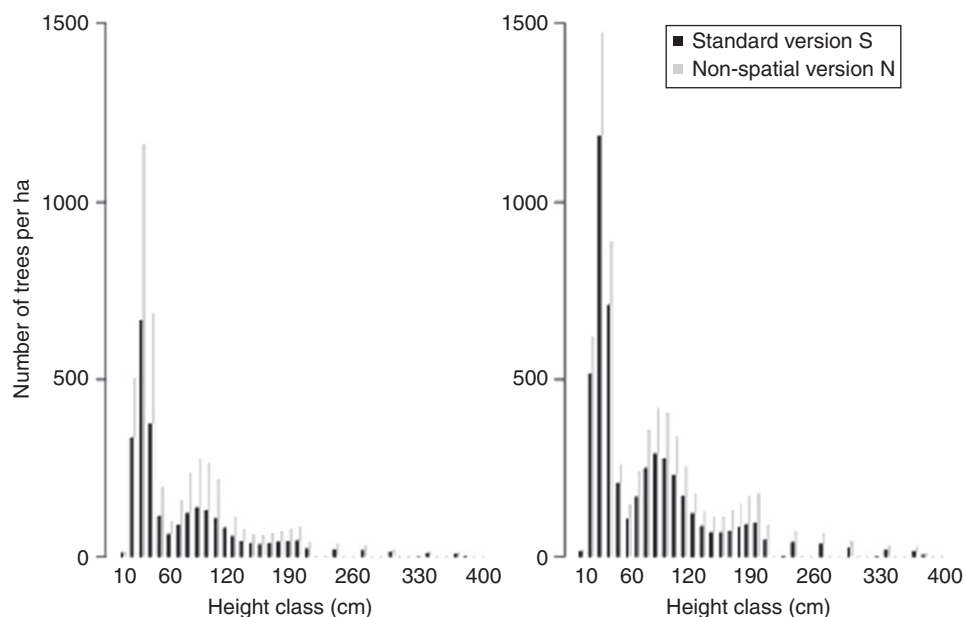


The state of the center cell is determined by the 8 next neighbours



The state of the center cell is determined by 8 randomly drawn cells

**FIGURE 11.3** Selection of cells that influence the local micro-site conditions are spatially selected in the original model and randomly selected in the follow-up model. This allows for the investigation of the role of space without changing the overall model structure. (From Rammig & Fahse, 2009.)



**FIGURE 11.4** Results from the nonspatial model overestimate the number of trees in each height class. (From Rammig & Fahse, 2009.)

which the total number of trees changed from just over 2600 stems in the spatial model to almost 5000 stems of height 1 to 400 cm in the non-spatial model. This difference is attributed to the role that favorable regeneration sites have on the model; spruce recruitment takes place on favorable sites, such as those dominated by rowan, that tended to

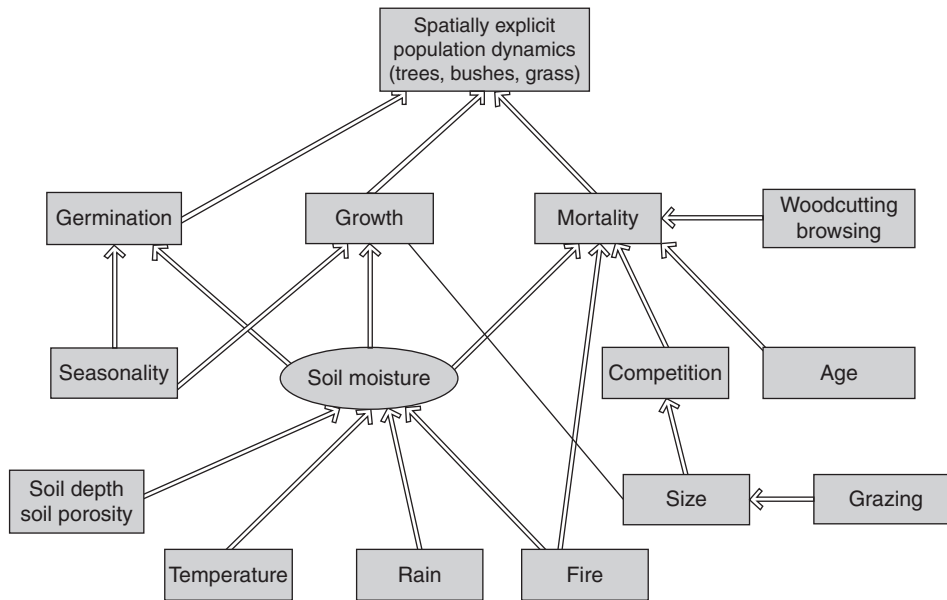
be clustered together on the landscape and, hence, in the spatial model. Thus, the spruce regeneration was clustered in these regions in the spatial model, but not constrained by this distribution in the nonspatial model since the rowan sites could be randomly influencing any cells in the nonspatial model. The overall chance of selecting a rowan cell as a neighbor increased and the Norway spruce establishment and growth benefited from this unrealistic circumstance.

This approach shows the sensitivity of the model to the spatial considerations and has important management implications, because the non-forested areas in the high mountain regions pose a risk for increased rockfalls and avalanches. Therefore, it is important to understand the impact of clearing fallen vegetation from the blowdown zone to maximize the regeneration and the ability of the forest to protect the surrounding villages from natural disasters.

### 11.3.2. Example 2: Long-Term Savanna Succession

Savanna ecosystems are heterogeneous environments characterized by the presence of trees, bushes, and grasses. Nutrient and soil moisture availability are usually the limiting factors affecting the biomass growth in savannas, and overall biomass is impacted by competition, fire, grazing, and harvesting. There is a hypothesis that savannas are naturally patchy environments due to these constraints. Moustakas et al. (2009) developed a spatially explicit savanna succession model to better understand long-term savanna dynamics as well as test the patchy landscape hypothesis. This model is described in detail in the following section.

Similar to the previous example, the grid lattice is  $100 \times 100$  cells, but here each cell represents approximately  $3 \text{ km}^2$  for an overall coverage of about  $90,000 \text{ km}^2$ . The state variables of the model are the number of individual trees, bushes, and grass biomass. The vegetation model on each grid cell includes biotic and abiotic factors. The latter factors include temperature and soil moisture characteristics. The former covers the wide range of ecological processes controlling the vegetation biomass dynamics, such as growth and germination factors, and competition terms as well as mortality and grazing/harvesting values (Figure 11.5). Overall, the model has more than 50 parameters initialized from the literature and from field observations. The authors selected a model with

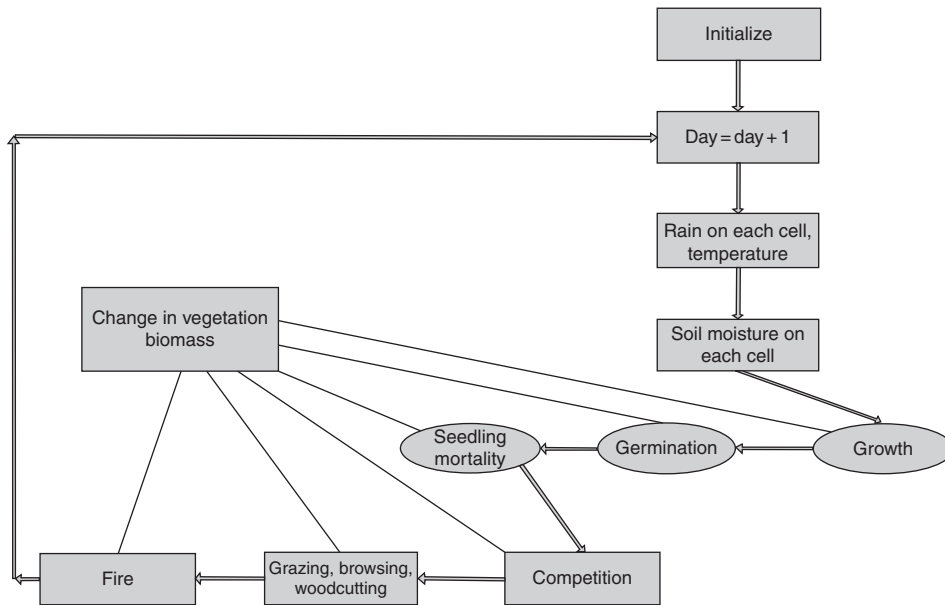


**FIGURE 11.5** Conceptual diagram of the vegetation dynamics model. Arrows show the influence of the starting process to the one connected. (From Moustakas et al., 2009.)

high complexity, but the well-known processes of the plant dynamics make it possible to have high confidence in the model results. The initialization of state variable values, such as size and age of each tree, was randomly chosen from within reasonable ecological ranges. Because of this random initialization, the model took some time to pass through a transient phase and reach stable conditions. Therefore, while the model is run for 2100 years, the first 100 years of the simulation were excluded from the model results as this time period was used to bring the model to stable conditions. The cells are updated on a daily time step and vegetation growth depends on the soil moisture and season.

The authors considered application of the model to two different regions: an arid savanna (122 mm/year average precipitation and thin soils) in western Namibia and a mesic savanna (780 mm/year average precipitation and brown calcareous soils) located on the Serengeti Plains of Tanzania. They were interested in improving savanna succession to help with management of the ecosystem.

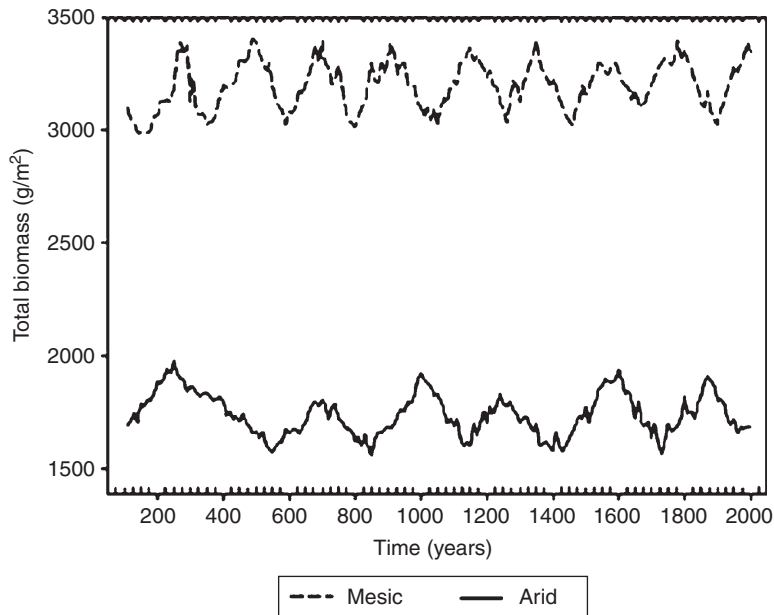
After the model is initialized, during each daily time step the cell site characteristics are updated based on temperature and precipitation



**FIGURE 11.6** Flow chart showing the process for the spatially explicit model. (From Moustakas et al., 2009.)

which in turn affects the soil moisture. The vegetation dynamics (growth, germination, and mortality) then respond to these environmental conditions. Competition, grazing, and fire further influence the overall change in vegetation biomass (Figure 11.6).

Model results show that total biomass followed a cyclic behavior with grass for about 3 years, bushes for about 50 years, and trees for about 200 years. Tree biomass was similar under both precipitation conditions, but bush biomass doubled in the mesic environment and grass biomass increased sevenfold due to the greater precipitation and soil moisture. Over time, the open savannas were encroached by woody vegetation, which then eventually gave way to a transition back to open areas again. The long-term period for this dynamic was  $\sim 230$  years for the mesic environment and  $\sim 300$  years for the arid environment (Figure 11.7). The patchiness of the landscape is affected by fire, grazing, and harvesting, yet these actions did not prevent the observed vegetation cycles. Typical management practice is to remove the woody material through controlled burns or grazing that encroaches on the open savannas, but these results show that this transition to a



**FIGURE 11.7** Model results covering 2000 years showing the long-term cyclical trend in woody biomass structure. (From Moustakas *et al.*, 2009.)

woody dominated ecosystem is a naturally cyclic process and that total eradication of the woody material should be avoided unless the aim is to convert the savanna ecosystem solely into grasslands for pastoral reasons.

A model of this type, which incorporates general ecological knowledge with site-specific parameterization, is useful in projecting the landscape changes over time. The model could be applied to other savannas, but would need to be reparameterized to local conditions. More interestingly, this model could be applied to the current locations, but under the conditions of climate change. In other words, human changes to the concentration of greenhouse gases result in new temperature and precipitation patterns. While this model was only looking at the long-term dynamic under current conditions, it would be easy enough to extend the analysis over a long time period for a changing climatic regime. Better understanding of these important ecosystems under the changed climate conditions is important information as the global community grapples with the issue of reducing greenhouse gas

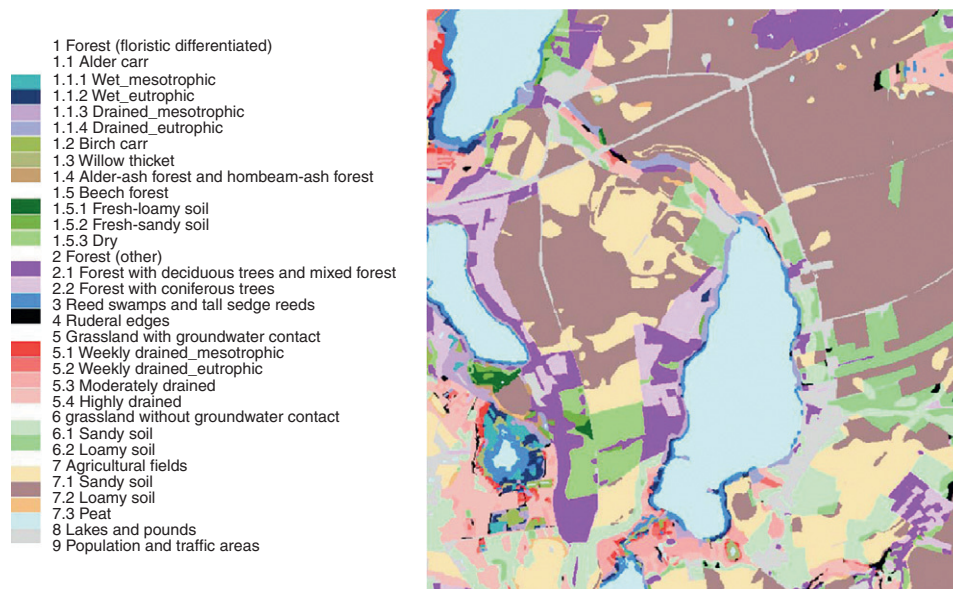


emissions. In fact, these models will be called upon to simulate the new climatic conditions and assess the impacts of these changes on the global biosphere.

### 11.3.3. Example 3: Ecosystem Indicators to Assess Agricultural Landscape Succession

Müller, Schrautzer, Reiche, and Rinker (2006) introduced an ecosystem-oriented indicator set and applied it to a landscape level to assess retrogressive succession in a wetland ecosystem. The model combines field-based measurements linked with GIS for the Bornhöved Lakes District of Northern Germany. It runs 30 years to derive the indicator levels and results of carbon and nitrogen compounds, which demonstrate a shift of the landscape from a sink function to a source. Overall, the indicator set is derived to assess ecosystem structure, such as biodiversity and number of specialized species, as well as ecosystem function measured in terms of energy balance, water balance, and matter balance. For the classification, ecosystem types were characterized according to their soil and vegetation structures. Model results were validated by measurements in the main research area. The classification focused on ecosystems of Histosols and mineral soils. The most common ecosystem type was cultivated fields on mineral soils (64.4%) followed by grasslands and beech forests on mineral soils (13.6 and 4.1%). Wet and drained alder carrs and other alder carrs on Histosol accounted for 1.7% and 2.9% of the study area, respectively, and weakly drained wet grasslands on Histosol made up the remaining 1.2% of cover (Figure 11.8).

The functional variables were calculated using the Water and Substance Simulation Model (WAMOD). It describes processes of water nitrogen and carbon at each location and for lateral transfers of water and nutrients. Results indicate a decrease in species richness both in the wetland ecosystems and on the mineral soils. The overall changes represent a retrogressive succession in loss of specialization. The functional characteristics also show signs of retrogressive succession by a shift toward greater net primary production but less carbon storage. Therefore, the system has switched from a carbon sink to a carbon source as drainage and land use intensity increase (Müller et al., 2006). Nitrogen leaking is also observed to be higher in the mineral soils

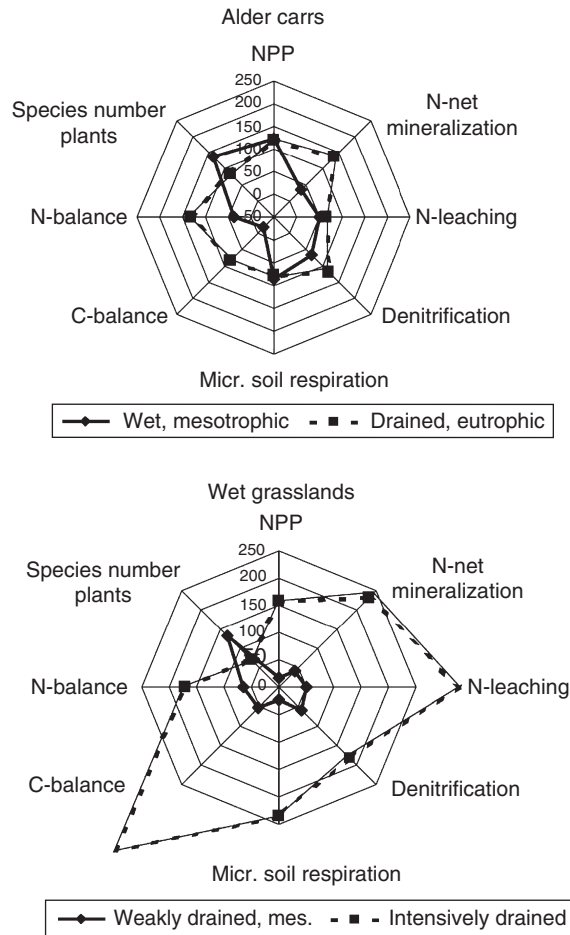


**FIGURE 11.8** Spatial distribution of the classified ecosystem types in the watershed of Lake Belau. (From Müller *et al.*, 2006.)

than in the Histosol, which contributes to eutrophication of the aquatic systems. Along the retrogressive successional gradient, the water budget tendency of decreasing biotic water use with increasing land use intensity is due to lower proportion of transpiration in evapotranspiration. Results from the study are presented in the amoeba-shaped diagram showing the differences in indicator values for four wetland types of ecosystems (Figure 11.9). In the alder carrs, the consequences of eutrophication are greater than that of draining. In the wet grasslands, the differences are higher, because the extensively drained area for agricultural purposes shows the greater deviation.

#### 11.3.4. Example 4: Fish Habitat Along a River Corridor

A final example in this chapter uses an aquatic model of fish habitat suitability. The spatial scale of a river could be collapsed to one linear dimension following the flow along the river, but here the river is wide compared to cell size in order to better track the fish movement and habitat preference. Therefore, it is quite common for such aquatic spatial models to be three-dimensional to account for the water depth as



**FIGURE 11.9** An amoeba diagram to compare four different stages of wetland retrogression. On the top, alder carrs are depicted; the bottom shows two wet grassland ecosystems. The selected ecosystem types represent the starting points of the retrogressions as well their end points. 100 (%) refers to the average values of the whole data set. (From Müller et al., 2006).

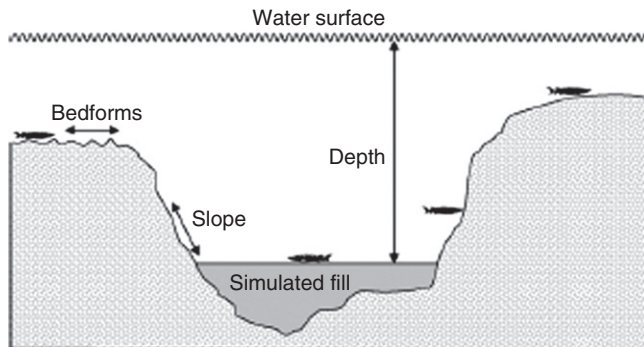
well. Hatten and Parsley (2009) developed a spatial model for white sturgeon habitat in the Columbia River. The river ecosystem is impacted by heavy volumes of commerce shipping and the subsequent dredging necessary to maintain open channels. In particular, there is concern that white sturgeon — an important ecological, sport, and commercial fish — mortality is impacted from the material deposition on the sturgeon habitat. The authors developed a spatial model to test the impact

of dredging material on sturgeon rearing habitat. They (1) used GIS and survey data to compile a river bathymetry database; (2) developed a habitat model for sturgeon using fish location data from 2002; (3) constructed a habitat suitability map, verified with fish location data from 2003; and (4) simulated the effects of in-water dredge deposition on sturgeon habitat by reducing water depths.

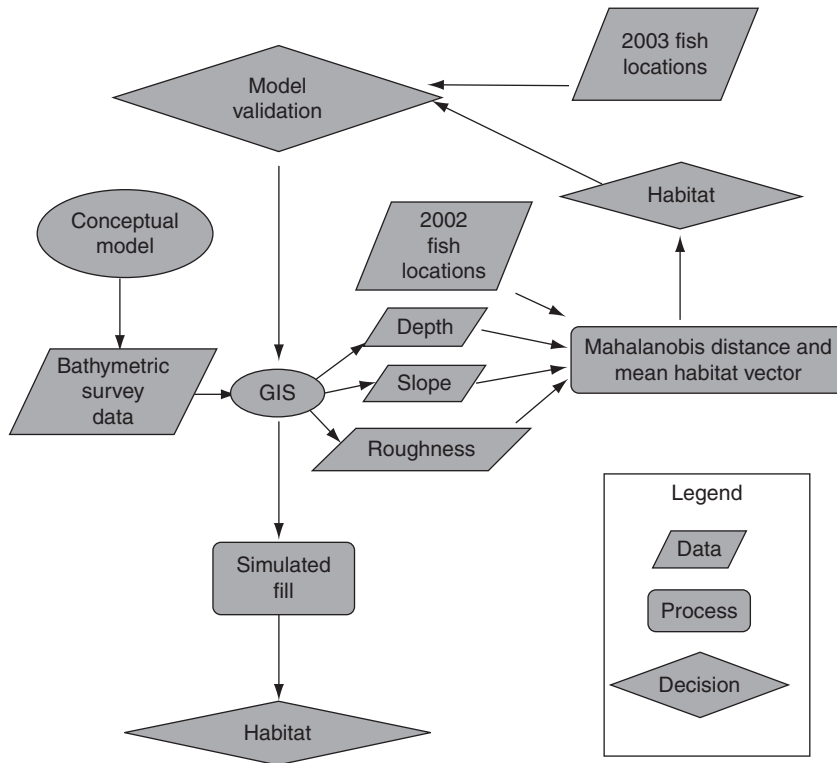
Knowledge about sturgeon ecology was taken from earlier studies showing that the fish are constantly moving with diel migrations preferring deeper zones in the daytime and shallower during night. They are benthic foragers and occupy a broad range of conditions as habitat generalists. However, they are impacted by water depth, bottom slope, and roughness; all of which are affected by the presence of the dredge fill material (Figure 11.10).

A 10 m resolution digital elevation map of the riverbed was created based on a bathymetric survey of the region in 2003. Fish population numbers were obtained from acoustic telemetry data gathered in 2002 and 2003. They tracked between 19 and 33 sturgeon, recording 74,000 locations in 2002 and 88,000 in 2003. From this, 5000 random values from 2002 were used to develop the model and 5000 random locations from 2003 were used to validate the model. The information was compiled in a GIS framework to determine the overall habitat suitability for sturgeon populations under existing conditions and then scenarios in which the fill increased by levels of 3 m increments (Figure 11.11).

The changes due to the increased fill measurements can be beneficial or harmful to the habitat rating resulting in four change classes: (1) low suitability, no change; (2) high suitability becomes low; (3) low suitability



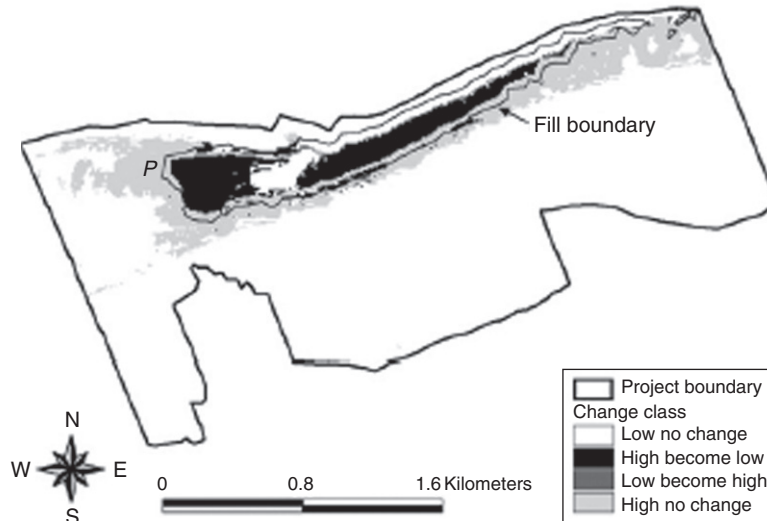
**FIGURE 11.10** Fill from dredging affects the water depth, bedform roughness, and bottom slope, all of which impact sturgeon habitat. (From Hatten & Parsley, 2009.)



**FIGURE 11.11** Conceptual model of steps and processes for the white sturgeon spatial model and the impact of fill on sturgeon habitat. (From Hatten & Parsley, 2009.)

becomes high; and (4) high suitability, no change. [Figure 11.12](#) shows that many regions experienced no change, but the central channel transitioned mostly from high suitability to low suitability. The model results showed that there was little change in the area (<1%) of suitable sturgeon habitat for fill levels up to 9 m. When this was increased to 12 m, there was a 12% decrease in suitable area and for 15 m fill, sturgeon habitat decreased by 44%.

This example provides another use for ecological models. Using this model, researchers were able to get a good estimation of the impact of fill without having to conduct a full-scale field trial to assess the changes. This has clear management implications, because the model indicates that the river has some absorptive buffer capacity to mitigate against low amounts of fill material (<9 m), but as this value increases,



**FIGURE 11.12** Estimated changes in sturgeon habitat under different dredge fill scenarios. The largest change is seen in the habitat that transitions high suitability to low suitability. (From Hatten & Parsley, 2009.)

the impact on sturgeon habitat increases noticeably, so a good policy recommendation is to keep fill levels below the critical threshold.

## Problems

1. Explain some ecological processes that make it necessary to use spatially explicit models.
2. When would it be appropriate to use (a) 0-D model, (b) 1-D model (c) 2-D model, and (d) 3-D model?
3. Management questions often drive the construction of the ecological models. What are some pros and cons of this approach?
4. Explain how a nearest neighbor grid cell approach represents spatial distribution on the landscape. What grid cell shape is most appropriate and why?
5. Explain the difference between gradients, patches, and noise.
6. Does spatial autocorrelation typically increase or decrease with distance? Why?
7. How are image data from Thematic Mapper Plus converted to ecological classifications?