What are landscape models and why use them?

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*Assigned Reading*: Turner et al. 2001 (Chapter 3); Mladenoff et al. (1999)

*Objective*: Describe the varied purposes and uses of landscape models to examine questions about pattern-process relationships, and provide a protocol for building and using landscape models. Highlight what landscape models can and cannot do for us in addressing current resource management topics.

*Topics covered:*
1. What are landscape models?
2. Purposes of landscape modeling
3. Types of landscape models
4. Steps in building and using landscape models
5. Caveats in the use of landscape models

*Comments*: Some material taken from Turner et al. (2001) and Dean Urban’s Landscape Ecology course notes, Duke University.
1. What are Landscape Models?

Models play an important and increasing role in landscape ecology, in large part because the sheer size of landscapes makes field studies logistically difficult. Similarly, landscape dynamics unfold over time scales that are difficult to embrace empirically. For both of these reasons, it is difficult to conduct experiments that would allow landscape ecologists to assess alternative management scenarios or to assess the potential impact of anthropogenic change scenarios (climate or land use change).

Models can take on many different forms, including both physical forms (e.g., miniature replicas of real systems, such as model cars) and abstract forms, including verbal models constructed from words, graphical models depicted as pictorial representations and mathematical models defined using symbolic notation to define relationships describing the system of interest. According to Turner et al. (2001), a model is any abstract representation of a system or process. Landscape models are typically of the mathematical kind, although we often construct and use abstract conceptual models to portray landscape relationships.

There are so many different types of mathematical models used to explore landscape ecological relationships, that a precise definition of a landscape model is difficult. Here, we will consider a landscape model to be any mathematical model designed to represent at least one landscape
pattern-process relationship of interest. This creates a pretty big umbrella, but one that is necessary to encompass the myriad types of landscape models in use today.

In this course, we will discuss and use a variety of landscape models. For example, we will discuss the use of *metapopulation models* to simulate the dynamics of populations inhabiting a mosaic of habitat patches. Most commonly, the habitats themselves are considered to be a constant background for the metapopulation; that is, the habitats do not themselves undergo any dynamics. A second important class of models we will consider in great detail will be models concerned with the dynamics of landscapes themselves, typically focusing on changes in land cover as driven by disturbance and succession. This class of landscape model is sometimes referred to as a *landscape disturbance-succession model* (LDSM).

Before delving into LDSMs in the next lecture, it will be useful to consider some issues that are pertinent to landscape models in general (and all ecological models for that matter). Much of the material included here was summarized by Dean Urban from Mankin et al. (1975) and Cale et al. (1983). For more in-depth treatment, Haefner's 1996 book is remarkably thorough and readable.
2. Purposes of Landscape Models

To begin, let’s first consider the purpose of a landscape model. As it turns out, landscape models (and all ecological models) are developed and used for many different purposes, including:

- To provide a formal organizing framework for ideas or data.
- To provide a framework for comparison across systems, providing the equivalent of experimental design and control that is so elusive in landscape-level field studies.
- To interpolate or extrapolate understanding, especially to extrapolate across scales.
- To explore real or hypothetical scenarios, especially in cases where experiments are not easy to conduct for ethical or logistical reasons.
- To make predictions about specific scenarios.
3. Types of Landscape Models

Landscape models may be described and classified in various ways, and there have been several such attempts to do so. None of the classifications are entirely satisfactory, however, due to the growing complexity and hybridization of models. Instead, it is probably more useful to consider the properties often used to describe landscape models.

- **Deterministic versus stochastic** – A model is deterministic if the outcome is always the same once inputs, parameters, and variables have been specified. In other words, deterministic models have no uncertainty or variability, producing identical results for repeated simulations of a particular set of conditions. A model is stochastic if there is an element of chance affecting the outcome given any set of input conditions. Thus, the same input conditions will result in different outcomes for every simulation. Most landscape models are stochastic.
• *Analytical versus simulation* – A model is analytical if it has a closed-form mathematical solution; that is, a solution can be obtained from a mathematical equation. Modeling population growth as an exponential function is an example of an analytical model. A model is a simulation if it lacks a close-form solution and therefore must rely on computer methods (a simulation model) to obtain model solutions. Simulation is the use of a model to mimic, step by step, the behavior of the system that we are studying. Thus, simulation models are often composed of a series of complex mathematical and logical operations (i.e., algorithms) that represent the structure (state) and behavior (change of state) of the system. Most landscape models involve simulation.
• Static versus Dynamic – A model is static if it describes relationships that are constant – they typically lack a temporal dimension. A model is dynamic, on the other hand, if it represents systems or phenomena that change through time. However, dynamic models often contain static components. For example, many LDSMs model disturbance and succession as dynamic processes (i.e., they change over time), but parts or all of the underlying biophysical template of the landscape is treated as static (i.e., unchanging over time). Increasingly, more and more landscape models are dynamic, as they include a temporal as well as spatial dimension.
Continuous versus discrete time – If the model is dynamic, then change with time may be represented in many different ways. If differential equations are used (and numerical methods are available for the solution), then change with time can be estimated at arbitrarily small time steps. More often, however, landscape models are written with discrete time steps or intervals, whereby the system transitions from step to step at discrete intervals. For example, most LDSM’s employ discrete timesteps of 1 year or 1 decade. In general, most landscape models employ discrete time.
**Types of Landscape Models**

- **Mechanistic, Process-based, Empirical**

- **Mechanistic**...is commonly used to distinguish models that seek to explicitly represent relationships in a manner consistent with their real-world behavior, as opposed to “black box” approaches.

- **Process-based**...is commonly used to distinguish models with components specifically developed to represent specific ecological processes.

- **Empirical**...is commonly used to distinguish a model with formulations derived from real data, as opposed to models based solely on theoretical relationships or expert opinion.

- *Mechanistic, process-based, empirical* models – These three terms are used frequently to describe models and are often confusing.
  - In practice, the term “mechanistic” is commonly used to distinguish models that seek to explicitly represent relationships in a manner consistent with their real-world behavior, as opposed to models that grasp at any formulation that might satisfactorily represent the ultimate behavior of the system (i.e., the so-called “black box” approach).
  - In practice, the term “process-based” is commonly used to distinguish models with components specifically developed to represent specific ecological processes; for example, equations for disturbance spread in a LDSM.
  - In practice, the term “empirical” is commonly used to distinguish a model with formulations derived from real data, as opposed to models based solely on theoretical relationships or expert opinion.
Types of Landscape Models

- **Spatially Implicit vs Spatially Explicit**

  **Spatially Implicit**...spatial dimension is implied but not explicit in the model (e.g., island models).

  **Spatially Explicit**...the variables, inputs, or processes have explicit spatial locations and, moreover, location matters to the process being modeled.

- *Spatially implicit versus spatially explicit* – A model is spatially explicit when the variables, inputs, or processes have explicit spatial locations and, moreover, that location matters to the process being modeled. Nearly all landscape models are spatially explicit, since landscapes are fundamentally spatial entities. However, not all landscape-relevant questions require a spatial model to address. For example, many (earlier) metapopulation viability models are spatially implicit, not explicit. That is, the spatial subdivision and separation of habitat patches (i.e., local subpopulations) is implicit in the model, but the precise relative location of each patch is not specified or accounted for in the model.
4. Steps in Building and Using Landscape Models

Models evolve in interrelated stages:

- **Conceptualization**—How does the system work? What are the entities that define the structure of the system? What are the key processes? This stage might yield a narrative model, a concise statement of how (we think) the system works.
Formalization.--What are the state variables? What mechanisms and constraints will be included, and which will be excluded? What assumptions will be made about the system? At what spatial and temporal scales will the model operate? Often, this stage of model-building results in the construction of a schematic model, perhaps a Forrester diagram (a "box and arrow" model).
• Implementation.--What form will the model equations take? How will the model be solved? What language will be used (fortran? c++? java?), and what platform will it run on? (PC? UNIX workstation?). This stage involves writing code, translating words or diagrams into equations.
Steps in Landscape Modeling

- Parameterization

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- What data are needed to estimate all the parameters and set the initial conditions of the model?

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Verification.

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- Verification. Does the model do what you built it to do? Model verification refers to testing the model against the data used to construct and parameterize the model; that is, the data are not independent of the model-building process.
• Sensitivity/Uncertainty Analysis.—Sensitivity and Uncertainty analysis are closely related techniques aimed at understanding the relative importance of each input parameter in terms of its impact on the results. The methods for sensitivity and uncertainty analysis can vary somewhat, but essentially involve varying the input parameters (either one a time or simultaneously) by some amount (either by a small, fixed amount, e.g., 10% of the nominal value, or by the standard error in its estimate) and then regressing the output against the input parameters. The regression coefficients for each parameter indicate their relative sensitivities or importance in the model. A sensitive parameter, for example, is one that elicits a large change in model output for a small change in the input parameter. An uncertain parameter is one that is sensitive within the range of precision with which it can be estimated. A wide variety of model experiments might be devised to help understand the model's behavior. Some of these are less formal than sensitivity or uncertainty analysis. In particular, these formal analyses work best for certain kinds of models, especially those for which the input parameters assume independent, interval-scale values. For example, it is hard to vary categorical variables by +/- 10%, and it may be hard to interpret the regression results from parameters that covary. In these cases, less rigidly defined yet still systematic model analysis can meet the same goal: to understand why the model behaves the way it does. A better understanding of model behavior, especially parameter sensitivity and uncertainty, can lead directly to model improvements by identifying those parameters (and by extension, model processes or constraints) that most need refinement.
• **Analysis.**—Model analysis consists of formal or informal "model experiments" designed to determine what makes the model behave the way it does.
Validation

Model validation refers to tests against independent data, that is, data not used in building the model; difficult to validate predictions made over large areas and long time scales

- Verify that behavior is within empirically known bounds
- Verify that modeled behavior is consistent with known ecological system behavior
- Validate process components

Validation -- Model validation refers to tests against independent data, that is, data not used in building the model. In general, the farther removed from the initial model-building domain, the stronger the validation test. Validation establishes how robust the model is, in a way analogous to extending the domain of a regression. Typically, model validation accrues as a model is used in more applications that are increasingly far removed from the application that originally motivated its construction.

True validation of many landscape models, in particular landscape change models, is often impractical or impossible due to the long temporal scale of the model. For example, it is impossible to truly validate the predictions of a landscape disturbance-succession model designed to simulate landscape behavior over several hundred years because it would take several centuries to confirm and dispute the model predictions. In such cases, the alternative is to: 1) verify that model behavior is within empirically known bounds (e.g., by hindcasting or running the model forward in time to today from an historical starting point to determine whether the current landscape condition is within the range of variability of the model predictions), 2) verify that modeled behavior is consistent with known ecological system behavior, and/or 3) validate the individual process components.
4.1. Model Evaluation

Model evaluation has several purposes. Most commonly, evaluation connotes the degree to which the model can reproduce empirical observations, that is, how well it matches data. But other criteria might also be of interest. Because models are, by definition, simplifications of real systems, we might wish to consider the extent to which the model "overlaps" with the real system. Finally, if our goal in model building was heuristic, we might be more interested in how useful the model is in marshaling our understanding of the system.
Models are typically evaluated in terms of how well their output matches data, that is, in terms of model accuracy. A model can match data in several ways:

- **Precision** Absolute "closeness" of fit between model predictions and data.
- **Bias** Systematic under- or overprediction, regardless of precision.
- **Timing** The model matches the data pattern, but is out of sync; for example, a hydrologic model might match the peak runoff values but do this a day late.
- **Damping** The model reproduces the mean, but misses the range (either over- or underdamped); for example, a hydrologic model might get the timing of runoff correct but consistently predict values that are too low (or high).
- **Scale** The grain size at which model-data comparisons match most closely; for example, the model might miss the fine details but capture the gross patterns (see Costanza 1989 for multiple-resolution tests designed for spatial models).

All of these are components of model accuracy in the general sense of the term, but the relative importance of each component might vary according to the goal of the modeling application.
Model Goodness

Other criteria for model evaluation, beyond accuracy, might be considered. Mankin et al. (1975) used Venn diagrams to represent the degree to which a model reproduces (overlaps) the real system. They defined three domains:

- **U** = the universe of all possible observations of the system;
- **S** = the system as known (those things actually observed of the system);
- **M** = the domain of behaviors of the model.

This framework defines a domain **Q**, which is the intersection of **M** and **S**, or the domain of behaviors shared by the model and the system. Within this framework, Mankin et al. defined two additional criteria for model evaluation:

1. **Model adequacy** increases as **Q** increases relative to **S**. That is, adequacy focuses on the range of behaviors that the model can realistically reproduce of the system.

2. **Model reliability** increases as **Q** increases relative to **M**. Thus, reliability focuses on the behaviors of the model that are unrealistic; that is, as reliability decreases, the model behavior becomes increasingly unrealistic.
The relative importance of these two aspects of model evaluation depend on the goals of the application:

- If predictions are the goal, then the model's adequacy must be established and predictions confined to the domain $Q$, rather in the same sense that regressions are valid within the domain of $x$ values used to fit the regression. And as with regression, the predictions may be completely valid within this domain even if there is a large domain wherein the model is unreliable ($M$ not in $Q$). Establishing the domain $Q$ determines the model's domain of applicability, its "safe zone" for applications.

- Although the domain $M$ not in $Q$ contributes to the model's unreliability, pushing a model into this domain is the only way by which we can increase our understanding of the system. That is, we can use a model to make predictions that have not been observed of the system, and if these predictions are subsequently validated we expand $S$, our knowledge of the system. We learn new things only when we push a model beyond the domain things we already agree on, which is $Q$.

- Finally, model utility requires only that $Q$ be nonempty-- that the model does something that the system does (something interesting, we hope).
Two final opinions on model evaluation:

- Conceptualization, formalization, and parameterization are three levels at which a model can be accepted or rejected -- each independently of how you judge the other levels (Botkin 1993). For example, having a "correct" conceptual model, with appropriate equations but inadequate parameterization would seem a less serious model failure than having an inappropriate conceptual model from the start. The former case might merely require more or better data, while the latter failure requires a major rethinking of the model. Unfortunately, most evaluation protocols do not allow us to separate these levels of model evaluation.

- Model validation is ongoing; continued success broadens a model's domain of applicability, but a model can never be completely validated. Indeed, referring to models in earth science, Oreskes et al. (1994) argue that models cannot be validated in principle. This is a formally logical consequence of the fact that models are simplifications of real systems, and so successful tests of the model still cannot "prove" that the model is correct. Thus, they argue, the primary utility of models is heuristic.
5. Caveats in the Use of Landscape Models

5.1 Modeling Pitfalls

There are many potential pitfalls in the use of landscape models, including:

- Risk that models are nothing more than ‘black boxes’ to users, where data goes in and data comes out but without any understanding of what goes on inside the model.
- Lack of model transparency (i.e., the inability of the user to see how the model actually works) can promote mistrust in the results.
- Implicit assumptions may be overlooked when applying models and interpreting results, which can lead to erroneous conclusions if the assumptions have not been met.
- Modeling tradeoffs may not be explicit, which can lead to universal dissatisfaction in the model results because the model is never viewed for what it was intended to do.
- Algorithms may be misunderstood by users, despite transparency, which can lead to distrust in the model and misapplication of the model.
5.2 Model Evolution

The modeling process can be phrased in terms of these stages of model evolution:

1. The early stages of model building (conceptualization, formalization) are often the most useful and informative stages of the process. This is often because the process of rigorously formalizing a conceptual appreciation of the system forces us to confront how many processes or interactions we are not quite sure about. Discovering what you don't know can be a powerful guide to further studies. Models are often especially informative when they fail, and sometimes when they fail quite early in the construction process.
2. This leads to what might be posed as two philosophies on modeling (actually, two endpoints of a spectrum). At one extreme, model-building is the last task one performs in a study: when we completely understand the system and have measured what we feel are its important features, we might build a model. At the other extreme, model-building is the first task in initiating a new study. In this, the process of building a model marshals field studies to gather the observations most critical to the model (these being identified via formalization, parameterization, and preliminary model analysis).

These two extreme approaches underscore the fact that the goals of the study often dictate which stages of model-building will receive the most emphasis. If the goal is to integrate information and generate a deeper understanding of the system, then the early stages of model-building are crucial (conceptualizing, formalizing) and model analysis is critical. Model tests might focus on evaluating alternative conceptual models or formalisms. If the goal is accurate predictions, then verification and validation against data are of paramount importance, and a variety of equally plausible (or even implausible!) model formalisms might provide accurate predictions in at least some cases.
3. Models tend to begin simply and then evolve toward increasing complexity and "realism" (often at the expense of tractability or interpretability). In part, this evolution occurs because as we test a model in new applications we often discover its inadequacies, and add new things to the model to "fix" it. This evolution toward increasing complexity comes at a price, however. As models become more complex they also suffer more from the uncertainty of specifying the nature of additional processes and estimating parameters for these features. Thus, model design becomes a trade-off between sins of omission and sins of commission. The "art" of modeling lies in finding a useful balance.
Lastly, it is important to recognize that while models play a vital role in landscape ecology, they are tools that provide a means to end; they are not the end itself, and are always only as good the data and understanding that goes it to them. Remember:

“Garbage in, garbage out”
Caveats in the Use of Landscape Models

With this in mind, landscape models allow us to:

- Handle complex multivariate relationships too complicated for the human mind
- Project into the future
- Identify the most influential driving factors
- Identify critical empirical information needs
- Identify interesting threshold or system behavior
- Identify the limits of our understanding
- Allow us to virtually explore “what if” scenarios

With all this in mind, remember that landscape models allow us to:

- Handle complex multivariate relationships too complicated for the human mind – most landscape modeling problems are simply too difficult for the human mind to track and require models.
- Project into the future – which is something we cannot do without landscape models.
- Identify the most influential driving factors – which allows us to focus attention on the few things that really matter the most.
- Identify critical empirical information needs – which allows us to focus future research on where it will do us the most good.
- Identify interesting threshold or system behavior – which can inform management of where, when, and how to avoid major impacts to the system.
- Identify the limits of our understanding – which can help frame the results in terms of uncertainty and provide direction for future research.
- Allow us to virtually explore “what if” scenarios – which is something we simply cannot do or cannot afford to do in the real world in most situations.