Integrated Environmental Planning
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CHAPTER 7

Environmental Modeling and Simulation

The use of models in planning has enjoyed a long tradition dating back well over four decades. Interest in the use of models is based largely on two familiar planning themes: (1) the need to consider the implications and consequences of decisions before actions are taken, and (2) the requirement to incorporate a large number of interacting variables into a process view of the planning area. Added to these general rationales for using models in planning is the recognition that environmental and regional planning have undergone significant changes that have had a profound impact on the value models enjoy as decision-support aids (Klosterman, 1998). One noteworthy change has been the widespread adoption of low-cost tools and data, such as geographic information systems. However, as these systems became more accessible, it soon became evident that an information system alone cannot meet all the needs of the planner (Harris & Batty, 1993). This realization has renewed interest in the art and science of computer modeling and has stimulated development of integrated tools to support planning and environmental decision-making (Holmberg, 1994; Lein, 1997). In this chapter the fundamental principles of modeling and simulation are introduced, and the role of models in environmental planning is examined with emphasis given to the issues of model design and application.

Models and modeling

The activity of modeling and the creation of models are neither new nor necessarily complex. Since the very early days of our existence, humankind has been urged to interact with our environment to fulfill essential needs. Through this interaction we developed ideas and concepts as to how our environment worked and how we could navigate our world to recover the resources we required to ensure our survival. Over time, these "models" of interaction have become more varied and sophisticated to define more "mature" forms of interaction with the "real world" (Spriet & Vansteenkiste, 1982). Within the realm of science, the interaction between humans and our environments can be approached using either formal or abstract representations. Such representations define models. However, models are only useful if they capture the essential features of the objects, events, or entities they have been designed to represent.

As a device for aiding human insight and comprehension, modeling describes a process that consists of two basic steps: (1) model-building and formalization and (2) model analysis and application. A simple representation of this relationship is given in Fig. 7.1. As suggested by Fig. 7.1, all models begin with the real world. This real world is then simplified to form a representation of key processes that influence the behavior of something we wish to learn more about (climate, land-use change, population growth, ecosystem functioning). Our representation may take several forms, yet regardless of form, a model is produced that stands as a formal characterization of something we are keenly interested in learning more about. This characterization is then examined with reference to the real-world system on which it is based and, if accepted, the model can be used to help understand how that real-world system behaves. The model produced through this process is simply an abstraction of the object, system, or idea in some form other than that of the entity itself, and has value because it can help us to explain, understand, or improve some facet of the real system it represents.

When placed into the context of environmental planning, a model may explain an exact replica of the object (system) at a reduced scale, or it may represent an abstraction of the object's salient properties. In either case models serve several important functions. For the planner perhaps the most useful are prediction and comparison, although there are many other equally relevant functions models fulfill:

- An aid to thought
- An aid to communication
- An aid to experimentation
- An aid to training and instruction.

Model-building, therefore, provides a systematic, explicit, and efficient way for experts and decision-makers to focus their judgment and intuition in a highly structured way. Because a model is a simplification of reality, it may be the only way to understand systems whose geographic scale or complexity might otherwise place them beyond our physical or mental grasp (Hardisty, Taylor, & Metcalfe, 1993). For example, if we wanted to understand an air pollution problem it would be infeasible and unpopular to burn large quantities of coal to see how air quality would change. Thus when we are confronted with a complex relationship, the model may be the only solution. Of course the model is a simplification. Therefore, to be credible the model must retain the significant features of the process in question so its behavior closely approximates what we might find in the real system. Using our air pollution analogy from above, this means that our model should incorporate as many of the properties of the atmosphere, its chemistry, and flow characteristics as possible, so that a change in emission levels can be traced through the model to an outcome that can be evaluated. This point has significant implications for those who use and develop models. Since models are approximations, there is a highly selective and subjective aspect to their design, structure, and purpose.

Several classification schemes have been devised to help understand the types of models that

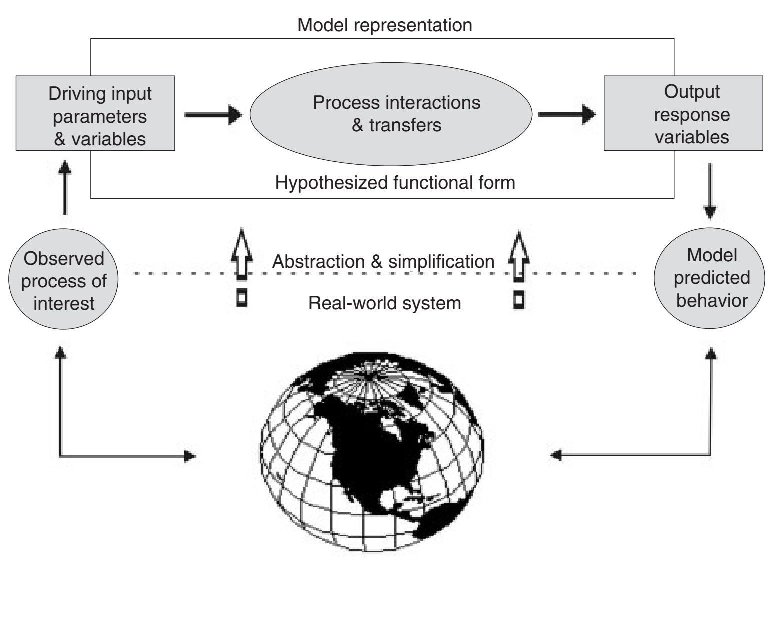

Fig. 7.1 Modeling the "real" world.

have been developed and the nature of the systems they represent. A very simple division separates models into two general groups: descriptive and normative. A descriptive model offers a stylized portrayal of reality with either an emphasis on equilibrium structural features (Static), or on changes in processes or functions over time (Dynamic). Normative models employ the use of analogues. Models may also be conceptual, theoretical, symbolic, mathematical, or statistical. Generally, three basic types of models can be identified (Table 7.1). Regardless of structure, it is the complexity of environmental systems that compels the development and use of models. Furthermore, because environmental planning problems are multivariate and dynamic, relying exclusively on professional judgment does not provide enough support for decision-making. As shown by Vlek and Wagenaar (1979), within any decision problem there is typically a discrepancy between the existing state and the desired state of a given system. While reducing this discrepancy is the goal, there is often more than one possible course of action. Such decision problems are common in planning, particularly when one is considering the environmental consequences of a decision, the pattern of change a decision may induce, or the irreversible commitment of resources that may follow from a decision. In each of these examples the potential number of variables involved is likely to be large, the interrelationships complex, and the uncertainty surrounding the problem high, and the role of models becomes obvious. We would like to explore a "future" before it arrives.

Table 7.1 Basic types of models.

Type	Description
Hardware model	Models that take the form of scaled analogue representations of some physical system
Conceptual model	Models that take the form of charts, pictures and diagrams depicting system arrangement and flow
Mathematical model	Models that take the form of numerical expressions that represent critical aspects of process, physical laws, and measured values and relationships
Digital model	Models that describe mathematical models that have been translated into a computer language and encoded for machine execution

Certain features of a planning problem will point to the appropriateness of a model-based solution. These conditions include:

- A large number of decision, exogenous, and state variables.
- A large number of components.
- Complex and nonlinear functional relationships.
- High degrees of risk and uncertainty.
- A hierarchical structure.
- Multiple and often conflicting objectives.
- Multiple decision-makers.

Applying models in environmental planning, however, is not without its limitations. Critics of model-based approaches to problem-solving focus on the argument that models are often overly simplistic representations of very complex real systems. Due to their simplicity they are prone to inaccuracies and tend to distort decisions involving important planning resources (Gordon, 1985). Compounding the issue of accuracy is the general observation that far too often the wrong model is selected or the selected model is applied inappropriately. When this happens the results obtained via the model can lead to intractable errors in analysis or inaccurate conclusions. The appropriate use of models in planning depends on whether the model simulates the consequence of realistic decisions, has been validated as an accurate representation of the real world, is reliable, and expresses reliability according to its defined limitations. If these conditions are met, then the model can provide valuable support in making a decision.

When considering the use or development of a model, application typically begins with a problem that involves prediction or comparison as part of the answer. Although there are no formal rules to direct the design of a model, the approach to successful implementation follows the general principle of elaboration and enrichment. According to this simple strategy the model evolves from a simple representation of the processes involved toward a more detailed representation that reflects the complexities of the process more clearly (Lein, 1997; Shannon, 1975). Therefore, modeling involves constant interaction and feedback between the real-world system and its representation. As this model evolves, it is tested, refined, and validated until a useful approximation of the system of interest emerges.

The iterative nature of model development suggests that regardless of sophistication all models are approximations that contain critical assumptions pertaining to the system they represent, the pattern of cause and effect used to capture how the system behaves, and the functional relationships depicted by the elements contained in the model. As an analytic procedure, modeling consists of four key activities (Shannon, 1975): the ability to (1) analyze a problem, (2) abstract from the problem its essential features, (3) select and modify basic assumptions, and (4) enrich and elaborate the initial design. At the completion of these phases, the resulting model can be applied to simulate a real system, and through simulation insight can be gained that helps us understand how the real system responds to change.

The simulation process

An integral feature of the modeling process is the representation of some aspect of the real world using the constructs of systems theory and the placement of the resulting model into an experimental design targeted toward an understanding of that system's future state. These two qualities of modeling connect us back to the systems view of planning introduced in Chapter 1, and move us forward into the realm of computer simulation. Thinking back to Chapter 1, the attraction of systems thinking was its facility for structuring and understanding the behavior of complex interrelationships. When applied to a problem, systems thinking led to the design of a systems model where the variables to include in the system were specified, the hypothetical relationships among variables comprising the system were explained, the structure of the system was described, and the design of a functional form was tested and refined. Using the representation's tools of systems analysis, this initial design can be translated into a "working" model that can be applied toward the solution of a problem.

Designing a model of a real system and conducting experiments using this model describes the general process of simulation. As an experimental and applied methodology, simulation modeling seeks to: (1) describe the behavior of systems, (2) construct theories or hypotheses that account for an observed behavior, (3) use these theories to predict future behavior. Because this is an applied methodology, simulation involves both the construction of the model and the analytical use of the model for studying a problem. Analysis and experimentation are central themes in this process as the problem, filtered through the model, is examined in a controlled and systematic way to reveal new insights and test present assumptions (Fig. 7.2). These central concepts also connect simulation to the goals of planning by providing an analytic device that can test alternatives, evaluate allocation strategies, and examine critical trends within the planning area.

To successfully apply computer simulation methods in environmental planning, three interrelated activities must be understood:

1 Model Design – the initial stage in the simulation process that includes a detailed formulation of the problem, a clear definition of the system, and the specification and testing of a model.
2 Model Application – the second stage in the process that includes calibrating the model, selecting the scenario to examine, and executing the model.
3 Analysis and Implementation – the final stage in the simulation process that concerns the interpretation of the results obtained from the model and the implementation of those results

Given the methodology imposed by these activities, a simulation experiment can be looked at as a procedure for acquiring information. This means that through the experimental run of the model, it will produce results that can provide insight into the problem, and these results can be data in the form of numerical approximations of some change in a variable, or it can be a graphic representation of how something may look given the

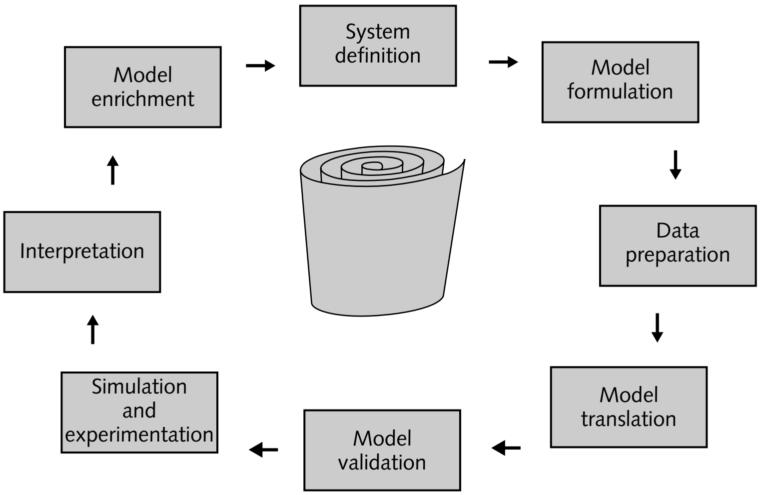

Fig. 7.2 The process of simulation modeling.

inputs that were selected to drive the model. Making certain that this information is useful and its limitations understood introduces several important considerations that guide the simulation experiment:

- Validation and Verification – describes a series of tests applied to the model in order to establish a level of confidence in the model and the inferences drawn from the simulation. Because a model is essentially a theory describing the structure and interrelationships of an observable phenomenon, validation is not concerned with whether the model is a "true" representation of the actual system, but rather whether the insights gained from the simulation experiment are reasonable. Through validation it is possible to explain the operational utility of the model. This may involve several specific tests to build confidence, such as face validity to determine if the model results appear correct and assumption testing to ascertain whether critical assumptions in the model can be supported.
- Sensitivity Analysis – because a model receives input data and processes that data to generate an output, how the model responds to the variables and parameters used in a simulation greatly influences its useful application. As a test, sensitivity analysis consists of systematically varying the values of the parameters and input variables over a range of known extreme cases. The analyst can then observe the effect of these extreme values on the model performance and the results it provides. Through sensitivity testing: (1) limitations in the model due to the values used to parameterize and conduct a simulation can be identified; (2) effects produced by extreme conditions on the stability of the model can be noted; and (3) clues to guide future enhancements and modifications of the model can be located.
- Experimental Design and Execution – running a simulation experiment is the process of applying the model to observe and analyze the information it provides. The experimental design selects a specific approach for gathering the information needed to enable the environmental planner to draw valid inferences. Three essential steps direct this process (Shannon, 1975):
  1. Determination of the experimental design criteria.
  2. Synthesis of the experimental model.
  3. Comparison of the model to standard experimental designs to select the appropriate methodology.

Typically, the simulation experiment concerns resolving an answer to the question, "How does a change in *x* affect *y*?" In an environmental planning context we may ask how a change in land use might affect surface run-off, or how an increase in vehicle trips will affect air quality. Thus, the final design of the simulation tends to be strongly influenced by the criteria deemed pertinent to that question. Among the criteria to consider when finalizing the design are:

1 The number of factors to be varied.
2 The number of values or levels to use for each factor.
3 Whether the various levels are quantitative or qualitative.
4 Whether the levels of the various factors are constant of random.
5 Whether nonlinear effects will be measured.
6 The number of measurements that will be taken for the response variable.
7 How interactions between factors will be measured.
8 What level of precision is required for an effective analysis?

These eight points remind us that a simulation experiment is only as sound as the techniques used in its construction. This suggests that the validity of the results gained through simulation can be affected by the techniques used in data collection and the methods employed when summarizing the data. Therefore, to be useful, simulation must fit within the context of a clearly defined problem. The problem focus takes the form of a forecast, where the planner seeks insight into the future state of the planning area and the forces of change that will drive the planning area toward this new state. Expressing the problem in the form of a forecast directs attention to the question of prediction and its connection to the modeling and simulation process.

Prediction and scenario projection

Modeling and simulation facilitate one of the main goals of planning, that of prediction. Because a plan is essentially an attempt to explain how the landscape will evolve through the implementation of specific goals and policies, the ability to predict what might happen if a clearly defined policy choice is selected serves an essential analytical need. Prediction, of course, does not necessarily imply that future conditions will be forecast exactly. Rather, prediction implies that certain assumptions about the future can be explored and evaluated. Modeling and simulation support this type of evaluation by creating an environment where a range of alternatives can be examined and a range of potential future arrangements of the built environment can be explored.

According to Rescher (1998), any prediction worth considering must rest on an evidential basis. This suggests that some rational substantiation must exist, because serious cognitive interest attaches to rational prediction, and for those that are credible there is good reason to accept them as correct. When predicting, there must be an actual commitment to a future-oriented claim. Consequently, the predictive character of those future-oriented declarations depends on the user of those declarations. However, not every future-oriented thesis represents a prediction. Thus, for a claim to constitute an actual prediction, there must be someone who makes or accepts it. Consequently, prediction differs in its objectives and purpose from scenario projection.

Based on these observations, the concept of a scenario can be defined in several different ways. Koplik et al. (1982) define a scenario as a possible sequence of processes and events that are describable by equations involving specified physical parameters. Other, less technical definitions characterize the concept as

- A hypothetical sequence of events constructed for the purpose of focusing attention on causal processes and decision points.
- An exploration of an alternative future.
- An outline of one conceivable sequence of events and states given certain assumptions.

A scenario, therefore, is a tool for ordering one's perceptions about alternative future environments in which today's decisions might play out. In practice, scenarios resemble a set of stories, written or spoken, built around carefully constructed plots. Stories are an old way of organizing knowledge, and when used as planning tools, they defy denial by encouraging – in fact, requiring – the willing suspension of disbelief. Stories can express multiple perspectives on complex events, and scenarios give meaning to these events. Yet, despite its story-like qualities, scenario planning follows systematic and recognizable phases. The process is highly interactive, intense, and imaginative. It begins by isolating the decision to be made, rigorously challenging the mental maps that shape one's perceptions, and hunting and gathering information, often from unorthodox sources. The next steps are more analytical: identifying the driving forces (social, technological, environmental, economic, and political); the predetermined elements (i.e., what is inevitable, like many demographic factors that are already in the pipeline); and the critical uncertainties (i.e., what is unpredictable or a matter of choice, such as public opinion). These factors are then prioritized according to importance and uncertainty. These exercises culminate in a small set of carefully constructed scenario "plots" (Schwartz, 1991; Mason, 1994; Wack, 1984).

If scenarios are to function as learning tools, the lessons they teach must be based on issues critical to the success of the decision. Since only a few scenarios can be fully developed and remembered, each should represent a plausible alternative future, not a best-case, worst-case, and "most likely" continuum. Once the scenarios have been fleshed out and woven into a narrative, the planner identifies their implications and the leading indicators to be monitored on an ongoing basis. A scenario, therefore, has several distinguishing characteristics that guide its creation and application in modeling. First, and perhaps most importantly, scenarios are hypothetical simply because the future is unknowable. The best one can hope for is to explore alternative possible futures. Therefore a scenario will never materialize exactly as described due to the impact of unforeseen events and responses (Fowles, 1978). Secondly, a scenario professes to be only an outline of a possible future. For that reason, a scenario only seeks to identify the key branching points of a possible future to highlight the major determinants that might cause the future to evolve from one branch rather than another. Thus, the scenario serves to sketch in the primary consequences of a causal chain of events in a highly selective manner (Fowles, 1978). Finally, a scenario should be multifaceted and holistic in its approach to the future.

The test of a good scenario is not whether it portrays the future accurately but whether it enables an organization to learn and adapt. When applied to problems in environmental planning, scenarios are a means to integrate individual analyses of trends and potential events into a holistic picture of a possible future. In this context, scenarios become powerful planning tools precisely because the future is unpredictable. Hence, unlike traditional forecasting methods, scenarios present alternative images instead of extrapolating current trends from the present. Scenarios also embrace qualitative perspectives and the potential for sharp discontinuities that econometric models exclude. Consequently, creating scenarios requires planners to question their broadest assumptions about the way the world works so they can anticipate decisions that might be missed or denied. Thus, the planner creates a scenario to describe the interaction of trends and events and to explore the possible course of alternative decisions on the future state of the planning area. To be effective, a prerequisite for scenario use in planning must be a sensing of incipient societal change, whether those changes are demographic, environmental, economic, technological, or some combination of the above. Given this, the scenario serves as a synoptic view of the total future environmental possibilities and is designed to meet five analytic objectives (Wilson, 1978):

1 To combine alternative environmental development into a framework that is consistent and relevant to the planning area.
2 To identify "branching points," potential discontinuities and contingencies that can serve as valuable early warnings.
3 To formulate strategies that can translate alternative environmental developments into policy recommendations.
4 To provide a basis for analyzing the range of possible outcomes.
5 To test the outcomes of various planning strategies under alternative environmental conditions.

An important consideration when applying scenarios in planning is the fact that there is no inevitability to the future. For this reason, it is critical to present as many varying views of the future as practical in order to define

- Trends that are probable but "shapeable."
- Trends that are probable but not amenable to policy influences.
- Trends that are possible and "shapeable."
- Trends that are possible but not amenable to policy influences.

While there is no single best method to follow when developing a scenario, a prototypical pattern can be offered. In general, developing a scenario requires compiling a detailed listing of all phenomena potentially relevant to the problem. Added to this list are the processes and events that influence change. Armed with this basic information, specific effects and consequences can be identified. Next, the scenario can be explained in written form and reviewed to assess the credibility of the pathways and connections that shape alternative futures. Once expressed in this form, a reasonable number of possible futures can be selected for further analysis.

Because more than one description of the future is possible, a major issue in the use of scenarios in planning relates to the problem of selection. Several methods have been introduced to guide scenario selection: simulation, event-tree analysis, and expert judgment. The relative merits of each have been summarized by Ross (1989). Although specifics differ, selection methods address two distinct functions: (1) ensuring completeness of the list mechanisms that are considered, and (2) screening out irrelevant and incredible mechanisms to produce a list of reasonable scenarios. Of the selection methods introduced, the most useful to the environmental planner is the event tree. An event tree is a scenario constructed in the form of a diagram (Fig. 7.3). These diagrams describe events and processes that explain specific chains of cause–effect–effect–consequence relationships. Using an event tree the logical sequence of cause and effect leading to a specific outcome can be traced. This feature has the advantage of allowing scenario developers to follow the causal sequence and critically review the plausibility of each step, examine the logic and assumptions inherent to an event chain, and evaluate in probabilistic terms the likelihood of the relationship depicted.

Although scenarios are useful tools in planning, they are not without limitations (Godet & Roubelat, 1996). Discussing the use and misuse of scenarios in long range planning, Godet and Roubelat (1996) remind us that a scenario is not a future reality, but a way of foreseeing the future. In a scenario we are using the present to suggest all possible or desirable futures. The future is not being predicted, which implies that our scenarios are only useful if they are relevant, coherent, likely, and transparent. This places tremendous responsibility on the planner, who must ask the

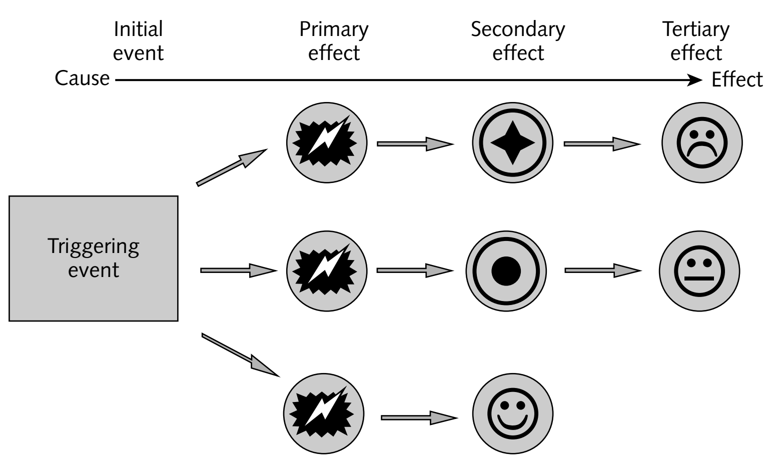

Fig. 7.3 A stylized event tree diagram.

right questions and clearly formulate the hypotheses that are the keys to the future.

Computer modeling methods

Developing scenarios can be a valuable way to gain insight regarding the causal processes that influence the future state of the planning area. However, to make a scenario useful as a predictive device, the facts, decision points, and causal mechanisms must be operationalized to permit the consequence of outcomes to emerge for a set of selected endpoints. Operationalizing a scenario means putting it into motion, letting it run, and observing what its products might look like. Placing a scenario in motion requires developing a simulation experiment to model critical features of the hypothetical sequence of events and using simulation as a means of exploring the output generated by the model. There are various approaches available to model the causal processes implied by a scenario, and numerous methodologies used to capture and characterize causality. Thus, when the focus in planning shifts to the question of modeling, the issue of which method best explains the process of interest must be resolved.

Causal relationships can be defined in either of two contrasting ways: (1) continuous versus discrete processes or (2) stochastic versus deterministic processes. When used to explain process, the terms "continuous" and "discrete" refer to the nature or behavior of the system as evidenced by a change in its state with respect to time. A system (process) whose changes occur continuously over time are termed continuous, whereas systems whose changes in state occur in finite quanta or jumps are referred to as discrete. The terms "stochastic" and "deterministic" refine the nature of how those changes occur. A deterministic process is one in which each new state is completely determined by its previous state of defining conditions. Thus, a deterministic system evolves in a completely fixed and conclusive way from one state to another in response to a given stimulus (Lein, 1997). Stochastic processes contain an element of randomness that influences the transition from state to state. Stochastic systems suggest a behavior that may be probabilistic in nature and explained in terms of a probability function. Based on an understanding of the problem and the causal mechanisms involved, the decision must be made regarding which of the above definitions can be used to represent process in a model. This decision must also take into consideration the geographic scale and the level of spatial resolution needed to adequately represent the process of interest as an active feature of the landscape. Finally, the controlling variables and parameters that drive the system need to be identified, and values for these entities must be obtained and evaluated.

The range of modeling methodologies and their technical specifications are well beyond the scope of this chapter. Excellent treatments of modeling with reference to planning and environmental management can be found in Gordon (1985), Klosterman et al. (1993), and Hardisty et al. (1993). In place of an exhaustive review of modeling methods, this section will examine a selection of modeling "recipes" that can be employed when theorizing about causality and developing the kernel of a simulation study. The selected recipes define fundamental representational schemes for expressing causal processes and approximating the behavior of a system, and include the methods of:

1. Monte Carlo sampling
2. Markov processes
3. Optimization
4. Systems dynamics
5. Cellular automata.

Before embarking on this review, it is helpful to explain the basic process of converting knowledge of a system into a numerical model and to describe how these techniques fit into that process. For the purposes of our discussion, a model is constructed in four phases, each with a specific objective.

1. **Specifying the purpose of the model** – every model is designed to meet a specific need for information. Whether calculating river flow, population changes, or the spatial interaction between land-use zones, execution of the model will give valuable insight into the behavior of the process under investigation.

2 **Specifying the components to be included in the model** – because a model is an abstraction or simplification of reality, the elements that drive the behavior of the system must be identified. These components determine the functional form of the model and explain key interactions that describe process.
3 **Specifying the parameters and variables associated with the components** – the descriptive elements that are used to explain the system must be measurable qualities and quantities for numerical simulation to work. Thus, each element has to be expressed in terms of a value that reflects its present status as well as its dynamic nature.
4 **Specifying the functional relationships among components, parameters, and variables** – this final phase concerns the explicit treatment of process and how the model will capture the behavior of the system. The functional relationships defined here establish flows of information, matter, or energy as directed by the rules used to govern model behavior. The basic functional forms can include any of the following:
   a. **Deterministic relationships** – explaining the conditions where behavior is completely determined by the state equations used in the model to calculate the state of selected components.
   b. **Probabilistic relationships** – defining the condition where underlying processes expressed in the model can be represented by governing rules of probability.
   c. **Stochastic relationships** – characterizing behavior or processes where uncertainty is high and random elements of chance influence behavior. Such relationships are not rigidly controlled by probability, but rather follow a more heuristic pattern with greater potential variability.

The problems encountered in environmental planning typically involve some aspect of all three relationships expressed above. In many situations selecting the correct modeling strategy is not easy and may be influenced by data availability, lack of underlying theory, and the degree of uncertainty inherent to the problem.

To understand how process can be represented and to decipher the "black-box" view of models as analytical tools, their underlying structure and mathematical foundations can be examined. Because many models used in environmental planning share these fundamentals, the techniques demonstrated reveal the elegance and simplicity of the modeling process and illustrate how root ideas can be easily adapted to new situations and problems.

Monte Carlo sampling

Monte Carlo sampling is rooted in the concept of simulating systems containing stochastic or probabilistic elements (Shannon, 1975; Evans & Olson, 1998). Simulation models based in this technique trace their origins to the work of von Neumann and Ulan during the development of the atomic bomb. Although the technique had been known for many years prior to that period, its success at Los Alamos quickly encouraged its application to problems in a range of disciplines. Although the primary use of Monte Carlo sampling is its utility for simulating probabilistic situations, it can also be applied to completely deterministic problems that cannot be solved analytically.

Using the analogy of a Roulette wheel on a gaming table, Monte Carlo sampling employs artificial experience or data generated by the use of a random number generator and the cumulative probability distribution of interest to produce a pattern of numbers that represents the behavior of "real-world" objects, events, or entities. The procedures used to generate random numbers rest at the core of this modeling technique. Typically, random numbers can be acquired from a computer program or subroutine that can provide uniformly random digits. However, in most simulation models we often wish to generate random numbers whose distributions are other than uniform. In these instances the uniformly distributed pseudorandom numbers generated by our program are used to "draw" or sample values from a known frequency (probability) distribution (Harbaugh & Bonham-Carter, 1981). The probability distribution to be sampled can originate from a variety of sources, including:

- Empirical data derived from past records of the event or process (i.e., stream flow, traffic counts, wind speeds).
- A recent experiment or field test that generated measurement values of the event or process.
- A known theoretical probability distribution (i.e., Gausian, gamma, poison).

The random numbers generated based on one of the above methods are used to produce a randomized stream of variates that will duplicate the expected experience (behavior) as a function of the probability distribution being sampled.

Monte Carlo sampling is relatively simple in concept. Shannon (1975) provides an excellent discussion of the major steps involved by means of an example that can be worked by hand (Table 7.2). To draw an artificial sample at random from a population that can be summarized by a probability function, let's consider a hypothetical simulation model dealing with the deposition of solid waste in a municipal landfill. The model in our example is constructed so that the quantity of solid waste deposited per increment of time (years) is an exogenous input to the model. The quantity of solid waste can be defined as the volume (thickness) deposited uniformly over the area of the landfill per increment of time. In designing the model an initial step would be to gather actual data about the frequency distribution of solid waste quantities at a sample of existing landfills. In practice this might prove to be difficult, but we might have volume data of annual deposition for 500 landfills throughout the United States. The data can be displayed as a series of discrete intervals in a histogram based on the frequency with which measurements fall into each class of the histogram. This empirical distribution can be converted to a cumulative distribution to enable the draw of random variates. Using this cumulative distribution, artificial experience for our landfill can be generated to characterize its life expectancy. Thus to simulate solid waste deposition in a computer model we can sample the cumulative frequency distribution represented by the histogram through the use of a random number generator. This can be accomplished in either of two ways:

1 Random samples can be drawn from the observed empirical distribution itself.
2 If the frequency distribution can be approximated by known theoretical distributions, samples can be drawn from that distribution provided that we can write its function and estimate its parameters (such as the mean, and standard deviation for a normal distribution).

For the present example, let's assume we have drawn our samples from the cumulative distribution. With these samples we would like to evaluate the life expectancy of a candidate landfill site over a 50-year time horizon. Using a random number generator a series of variates can be drawn to represent annual solid waste deposited at the site. If the numbers 09, 57, 43, 61, 20 are drawn for the first five years of operation, then resulting patterns of solid waste can be derived as shown in Table 7.3. Running this hypothetical model for all 50 years in our example, a synthetic process can be generated to simulate landfill performance. The values representing the 50-year sequence can then be used to evaluate landfill capacity. If the random numbers used are in fact uniformly distributed and random, then each number from the data of interest will occur with the same relative frequency as we might expect in the "real world." In this example the artificial experience is typical of what we have been experiencing with the real system.

Table 7.2 Basic steps in Monte Carlo sampling.

Step 1	Plot or tabulate the data of interest as a cumulative probability distribution function with the values of the variate on the *x*-axis and the probabilities from 0.0 to 1.0 plotted on the *y*-axis.
Step 2	Choose a random decimal number between 0.0 and 1.0 by means of a random number generator.
Step 3	Project horizontally the point on the *y*-axis corresponding to the random number until the projection line intersects the cumulative curve.
Step 4	Project down from this point of intersection on the curve to the *x*-axis.
Step 5	Write down the value of *x* corresponding to the point of intersection. This value is then taken as the sample value.

Based on Shannon (1975).

Table 7.3 Simulated landfill deposition in millions of tons.

Random number	Simulated range
0.09	0.0–1.00
0.57	4.0–5.0
0.45	2.0–3.0
0.61	4.0–5.0
0.20	1.0–2.0

When one is creating a model that defines stochastic or probabilistic elements, an important consideration in the application of the Monte Carlo method relates to the issue of whether to use empirical data or a theoretical distribution. This question is significant for three reasons (Shannon, 1975). First, the use of empirical data carries the implication that the model is simply simulating the past. Therefore historic data replicates the performance of the system based on patterns that have already occurred. Assuming that the basic form of the distribution will not change over time does not presuppose that the patterns evidenced over a given time period will be repeated. Secondly, it is generally considered more computationally efficient to use a theoretical distribution. Lastly, it is much easier to change the defining parameters of a random number generator based on a theoretical distribution, perform sensitivity tests, and ask "what if" questions. Therefore, a more useful model can be produced using theoretical distributions (Shannon, 1975).

Markov processes

It has been observed that many environmental processes that are random in their occurrence also exhibit an effect in which previous events influence, but do not rigidly control, subsequent events. Such processes are referred to as Markov processes. In simple terms, a Markov process characterizes the condition in which the probability of the process under investigation being in a given state at a particular time can be deduced from knowledge of the immediately preceding state (Harbaugh & Bonham-Carter, 1981). This general characteristic of system behavior is referred to as a Markov chain. A Markov chain can be conceptualized as a sequence or chain of discrete states in time or space where the probability of the transition from one state to a given state in the sequence depends on the previous state. Thus, the general form of a Markov chain explains a series of transitions between different states or conditions of a system such that the probabilities associated with each transition depend only on the immediately preceding state, and not on how the process arrived at that state (Harbaugh & Bonham-Carter, 1981). Based on this premise, a Markov chain will typically contain a finite number of states and the probabilities associated with the transitions between states do not change with time. Consequently, a Markov chain in its general form defines a short "memory" of process that extends only for a single step at a time and stops after that single step. A chain that exhibits this characteristic is termed a first-order Markov chain. This fundamental definition can be extended to describe the condition where the probabilities associated with each transition are based on earlier events of multiple dependence relationships. Perhaps the most important characteristic of Markov chains is that they exhibit a dependence on the probabilities associated with each transition of the immediately preceding state. This quality is called the Markov property, and to apply this modeling technique effectively, the phenomena under investigation should exhibit this fundamental behavior. Fortunately many processes encountered in environmental planning share this trait. Therefore, the planner can make effective use of Markov chains as components in probabilistic dynamic models.

To illustrate how Markov models can be applied in environmental planning we can explore the problem of land-use change and use the Markov property to help forecast the likelihood of future land-use transitions. As demonstrated in previous work, land use and land cover change can be characterized as stochastic (Lein, 1990). This assumption is based on the observation that the physical use of land, while often described using an economic rationale, is ultimately determined by the locational decisions of governments, corporations, and private individuals. Such locational decisions introduce behavioral influences into the land development process, creating the situation where the use of a parcel of land becomes a function of policy decisions, the physical suitability of land, and an intangible set of personal motivations that may or may not be guided by economic incentives. The consequence of this complex series of operations is a pattern of land occupance that when viewed collectively represents a series of random elements acting in space. Thus in a stylized way the pattern of land-use change can be explained as stochastic where past trends can influence the future state of the system (Bourne, 1971; Bell, 1974).

With the process of land-use change now characterized as Markovian, a parcel of land (*L*) will define a specific condition or form of use. That condition describes a particular state (s_1) at that instant in time (t). Associated with that parcel (*L*) is a set of probabilities ($p_1, p_2, \ldots, p_n$) that express the likelihood of parcel (*L*) occupying the same or a different state ($s_1, s_2, \ldots, s_n$) at time ($t + 1$). In this example there is a given set of states, each representing a category of land use, and the implicit requirement that parcel (*L*) can be in one and only one state at time (t). However, based on the probability of change, parcel (*L*) can move successively from one state to another. Consequently, the probability of change projects parcel (*L*)'s position in the system and defines the condition it may assume.

According to the Markov chain model, the set of probabilities characterizing the land-cover system is expressed in the form of a transition probability matrix [**Z**]. This matrix describes the basic behavior evidenced by the system as expressed by the Markov chain and defines the principal pattern of movement as elements in the system change from state to state. Each element in the matrix, therefore, reflects the probability of a transition from a particular state (that state pertaining to a given row in the matrix) to the next state (that state pertaining to the particular column) (Harbaugh & Bonham-Carter, 1981).

For a simple three-state system the transition probability matrix may be written as:

$$\begin{array}{cc} & \begin{array}{ccc} s_1 & s_2 & s_3 \end{array} \\ \mathbf{Z} = \begin{array}{c} s_1 \\ s_2 \\ s_3 \end{array} & \begin{bmatrix} Z_{11} & Z_{12} & Z_{13} \\ Z_{21} & Z_{22} & Z_{23} \\ Z_{31} & Z_{32} & Z_{33} \end{bmatrix} \end{array}$$

where each element in the matrix explains the probability of movement from one state to another. In our land-use example, that might look something like this hypothetical case:

	Urban	Agric.	Forest
Urban	0.9	0.1	0.0
Agriculture	0.6	0.3	0.1
Forest	0.4	0.4	0.2

In this simple example, the matrix suggest that if the land cover system is in state s_1 (urban) its most probable next state is urban (s_1). However, if the system is in state s_2 (agriculture), a transition to urban is probable, as is the transition to forest (0.1). Finally, if the land-use system is in state s_3 (forest), a transition to either urban or agriculture is equally probable. Here we can see that the simulation of process involves use of the transition probability matrix to select the state of the system. In this example, to simulate change in the land-cover system the matrix of transition probabilities must be computed and the resulting values used to produce a representation of the system at time ($t+1$).

Transition probabilities are derived from the frequency distribution of the objects that comprise the various states of the system. Producing this distribution of state transitions involves nothing more than the tabulation of the number of transitions (moves) from each state to every other state in the system. Computationally the process involves filling a tally matrix, counting the movement of objects from state to state, then converting that matrix to transition probabilities by dividing by the sum of the rows. The calculation of a transition probability matrix, however, explains only a single step in a Markov chain. For a multiple-step transition defining the transition over more than one time step, the series of probabilities is determined by "powering" the transition probability matrix [**Z**]. The term "powering" simple means to raise the matrix [**Z**] to some power. The product of powering the matrix reflects the transition to the next time step in the simulation. The general form of the succession of matrix powering can be written as:

$$Z_{(n)} = Z_{(n-1)} \cdot Z.$$

In the present example we can use a one-step process to produce a distribution of lands uses for $(t+1)$ from the patterns that explain the system at time (t) (the present state of the land-use system) and time $(t-1)$ (the land-use pattern one step back in time). As used in our example, the condition explained above assumes that the process of land-use change is a discrete-time phenomenon. Therefore, while the surface is dynamic, change is observed by using discrete slices of time.

We can extend this idea to long time sequences. For instance, if we chose to examine the case where the system beginning in state (i) would be in state (j) after n steps, the Markov chain could be expressed as:

$$\boldsymbol{Z}_{(n)} = \begin{bmatrix} Z_{11}^{(n)} & Z_{12}^{(n)} & Z_{13}^{(n)} \\ Z_{21}^{(n)} & Z_{22}^{(n)} & Z_{23}^{(n)} \\ Z_{31}^{(n)} & Z_{32}^{(n)} & Z_{33}^{(n)} \end{bmatrix}$$

The solution to this problem is easily derived by use of matrix algebra. The matrix notation demonstrating the solution to our problem is shown in Table 7.4.

Optimization

Optimization is one of several methodologies that fall within the general subject matter of operations research. Operations research is a name given to the procedures used to study and analyze problems concerned with the control or operation of systems. Within this broad definition, operations research explains the systematic application of quantitative methods, techniques, and tools with the goal of evaluating probable consequences of decision choices. The decisions considered using optimization typically involve the allocation of resources with the objective to improve the effectiveness of the system. Therefore, most operations research problems center around the optimization of a specific feature or flow in the system, such as goods, information, technical properties, capacities, or any tangible characteristics that lends themselves to strategies where "costs" are to be minimized and benefits maximized given a set of constraints.

The essential characteristics of operations research include:

- Examining function relationships in a system.
- Adopting a planned approach to problem-solving.
- Uncovering new problems for study.

With respect to the problems encountered in environmental planning, operations research can be thought of as a form of applied decision theory where the collection of mathematical techniques and tools is used in conjunction with a systems perspective to address decision problems. Certain attributes of a problem may lend themselves to treatment using optimization, particularly those involving complex relationships that can be abstracted into the form of mathematical or statistical models.

Any operation research application draws on five common phases of analysis:

1 Formulating the problem.
2 Constructing a mathematical model to represent the operation under consideration.
3 Deriving a solution to the model.
4 Testing the model and evaluating the solution.
5 Implementing and maintaining the solution.

Because environmental planning is concerned with the problem of maintaining an optimal balance between social needs and environmental process, methods that can provide insight regarding the "optimal" allocation of resources can greatly assist the decision process. Viewing optimization at its most fundamental level, most methods are applied to human-designed or controlled systems where some optimal situation is the goal. Although determination of what precisely defines the "optimal" relies exclusively on human judgment, the majority of techniques direct efforts toward the maximization of benefits. Analytical optimization techniques, therefore, are

Table 7.4 Markov analysis matrix notation.

1. Initial step:
   Z
2. Raising to the second power:
   $Z^{(2)} = Z \times Z$
3. Raising to the third power:
   $Z^{(3)} = Z^{(2)} \times Z$

applied in a problem-solving context where the need exists to either maximize or minimize a clear and narrowly defined objective (the objective function).

Satisfying this objective function recognizes that any system encountered by the planner operates with constraints that limit options. Such constraints may identify design limitations, carrying-capacity measures, safety considerations, or criteria that influence biological functioning. For example, a planner may desire a subdivision plan that utilizes land as efficiently as possible at the lowest environmental cost. Here, cost can be expressed in relation to habitat fragmentation and "efficiency" becomes the objective function given the constraint that the plan cannot increase fragmentation beyond a threshold. From this simple example it can be seen that the theory of optimization shares several similarities to the concepts embedded in the idea of system control. However, there are significant differences that should be understood. Perhaps the most important distinction is that system control is primarily concerned with the response of a system under conditions of fluctuating inputs. Optimization considers the definition and properties of an objective function that may be applied as the criterion for control. While subtle, this distinction suggest that optimization methods are applied in a more prescriptive manner.

A wide array of optimization methods are available to select from, and most are variations of the mathematical programming model. Mathematical programming is rich in its facility for resolving objective functions. In our discussion here we will limit our scope to those programming methods that are linear in nature. The methods of linear programming form two broad categories: (1) direct search and (2) indirect search. Each of these classes can be further divided into more specific algorithms. Regardless of the algorithm applied, the focus remains fixed on the concept of an objective function. This term defines a dependent variable (Y) whose value depends on one or more independent variables ($x_1, x_2 \dots, x_n$). The goal of optimization is to either maximize or minimize the objective function by finding the values of the independent variables such that:

$$Y_{(\max)} = f(X_1, X_2, \dots, X_n).$$

Or

$$Y_{(\min)} = f(X_1, X_2, \dots, X_n).$$

For optimization problems where the objective function is a linear combination of the decision (independent) variables and subject to linear inequality constraints, its solution can be by obtaining values of ($x_1, x_2, \dots, x_n$), so that the linear function

$$Z = c_1x_1 + c_2x_2 + \dots + c_nx_n$$

is either maximized or minimized subject to the constraints:

$$a_{11}X_1 + a_{12}X_2 + \dots + a_{1n}X_n <= b_1$$

$$a_{21}X_1 = a_{22}X_2 + \dots + a_{2n}X_n <= b_2$$

$$\vdots$$

$$a_{m1}X_1 + a_{m2}X_2 + \dots + a_{mn}X_n <= b_m$$

where:

$$x_1 >= 0, x_2 >= 0, \dots, x_n >= 0$$

and a_{ij}, b_i are given as constants.

One widely used approach for solving linear programming problems is the application of the Simplex method (Hillier & Lieberman, 1967). An excellent example illustrating the basic principles of the Simplex method can be found in Harbaugh and Bonham-Carter (1981). According to this technique, given two decision variables, a relation can be expressed where

$$Z = 4x_1 + 3x_2 = 24,$$

and the variable Z is to be maximized subject to the constraints that

$$x_1 \leq 5, \text{and } x_2 \leq 4$$

and

$$4x_1 + 3x_2 \leq 24: x_1 \geq \phi; x_2 \geq \phi.$$

Representing the problem graphically, the constraints x_1 plotted against x_2 for an area that defines the feasible solution space (the area shaded on Fig. 7.4). By plotting the values of the objective function across the solution space the optimum solution can be defined as the point (x_1, x_2) at which Z is maximized and falls within the area of the feasible solution. Careful interpretation of the figure identifies the point as the apex of the shaded region where $x_1 = 3$ and $x_2 = 4$.

Systems dynamics

Systems dynamics, or its more recent incarnation as dynamic modeling, refers to a family of models and an integrated modeling environment designed to approach the general problem of representing continuous systems and processes. Based on the ground-breaking work of Forester (1966) and the contributions of Richardson and Pugh (1983) and Hannon and Ruth (1994), systems dynamics is a methodology for understanding problems that are (1) dynamic in that they involve quantities that change over time, and (2) characterized by active feedback effects. Thus, this modeling approach to problem-solving applies to dynamic (continuous) problems that develop within systems characterized by feedback: a quality that has been shown to apply to both human systems and a broad spectrum of environmental processes (Hannon & Ruth, 1994; Ford, 1999).

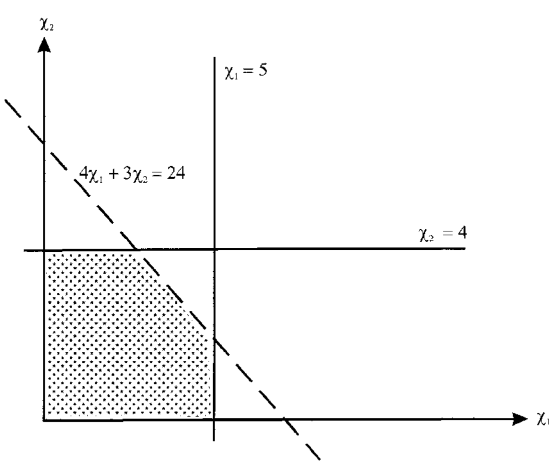

Fig. 7.4 Defining decision regions using the simplex method.

Successful application of dynamic modeling hinges on an understanding of feedback concepts and their role in defining dynamic systems. Perhaps the most basic definition of feedback explains the concept as the transmission and return of information to a system. This simple definition is central to developing the causal thinking needed in order to organize ideas in a system dynamics study (Roberts et al., 1983). Using feedback as a structuring concept, causal thinking requires the model builder to isolate key factors that direct the processes involved and explain their relationship to the system of interest. Through this type of mental experimentation the logic and connections that explain some observed behavior could be diagnosed. Illustrating these elements and connections in a simple systems diagram helps to reveal the causal influences that form the system and the possible feedback effects that may be at work (Fig. 7.5).

To demonstrate the general approach to dynamic modeling we can explore the farmland conversion process as an example. In this simple model we are interested in understanding the mechanisms that contribute to the change in land use from farmland to urban. At the rural–urban fringe of our hypothetical planning area, land market forces and the personal motivations of private landholders coupled with local government growth strategies have contributed to the gradual but steady conversion of land from agricultural uses to urban. While this example cannot approach the level of sophistication needed to

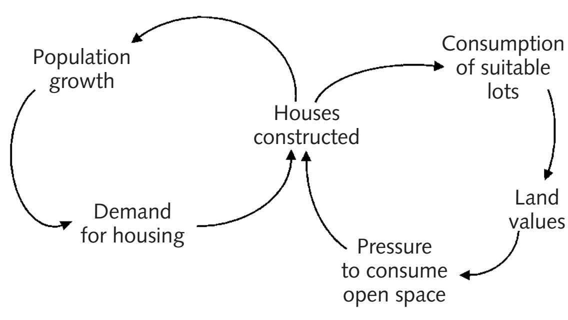

Fig. 7.5 Causal loop diagram of the urban development process.

explain the process completely, we can create a model that allows us to explore a set of plausible relationships that can be used to draft a more comprehensive farmland preservation program. Given the observed pattern indicative of the decline in farms in the region, we can create a scenario that can be evaluated by the model.

1 Unmarried young adults migrate to regional centers for better job opportunities.
2 Population decreases and births fall below replacement.
3 Reduction in business services due to declining demand.
4 Reduction in key social services.
5 Loss of services induces out-migration of young families and ensures in-migration is minimal.
6 Aging population contributes to disintegration of balance in the community.
7 Farmholdings passing to next generation are offered for sale instead.
8 Farmland parcels are purchased by land speculators and held out of production.
9 Land costs within the urban center encourage decentralization of population and commercial activities.
10 Land held in speculation is sold for development.
11 Development increases market value of existing agricultural lands.
12 Increasing prices and taxes encourage marginal producers to sell land.

In this example, 12 causal forces were identified that contributed to the general process of rural to urban land conversion and the decline of farmland. Each of the relationships expressed can be reviewed to determine how well they explain the observed behavior. Once a reasonable sequence of cause and effect is achieved, the relationship can be specified and diagrammed. Diagramming causal relationships enables the chains and loops that connect elements of the process to be visualized. In addition, diagramming facilitates development of the model's initial structure and assists with the representation of feedback effects. The causal-loop diagram representing the farmland conversion process is shown in Fig. 7.6. Following the looping arrows illustrated in the figure gives the impression of causality, suggests how this system may behave over time, and defines the nature of feedback in the system. While this form of open-loop thinking is a central feature of dynamic modeling, understanding the behavior of feedback is the ultimate goal of the systems dynamic approach.

Feedback can assume several forms in a dynamic system, including:

- Single-loop positive feedback
- Single-loop negative feedback
- Multiple-loop feedback.

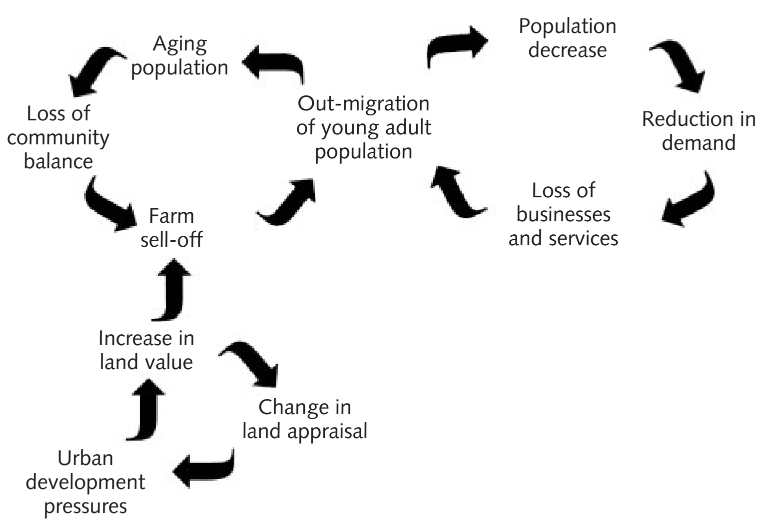

Fig. 7.6 The farmland conversion model.

With a focus on these feedback processes, dynamic modeling proceeds on the assumption that feedback structures are responsible for the changes a system undergoes over time, the premise here being that dynamic behavior is a consequence of system structure. Therefore, as both a cause and consequence of feedback, dynamic modeling looks within the system for the sources responsible for its behavior.

As suggested by Richardson and Pugh (1983), any problem viewed from this perspective is likely to be seen initially as a graph of one or more variables changing over time. Such graphs assist the modeling processes by

1 Focusing attention on the problem.
2 Helping to identify key variables in the system.
3 Helping to define the problem dynamically.

Graphing important variables and inferring graphs of other significantly related variables produces the problem focus of undertaking this type of study. In essence, displaying graphs over time is the reference mode of behavior for the model and gives limited indication of the patterns that will develop and that should be incorporated into the modeling effort.

The dynamic model takes form as the variables defined by the causal loop diagrams are translated into the structural components that will become the formal model. Translation requires representing each component of the system according to the role it plays in the process. According to the language of dynamic modeling there are four critical components used to construct a model:

- Stocks or levels – defining the value or accumulated value of a variable.
- Flows or rates – explaining process equations that act on the stock or level.
- Connectors – describing links that transfer information about the stock or level to control.
- Time step – defining the period of time over which the values of stock should be updated during a run of the model.

Typically, translation involves transferring the model from its representation as a causal diagram to a computer model using a special-purpose simulation language. Presently the commercially available simulation program developed by High Performance Systems called STELLA II typifies the characteristic dynamic modeling environment. Programs such as STELLA II provide a range of functionality for quickly prototyping computer simulation models. The main advantage of this type of modeling environment is that it does not require the designer of the model to possess knowledge of a conventional programming language such as C, Pascal, or Fortran. Modeling tools like STELLA II are a type of graphical programming language that employ graphic objects which can be assembled on a "white board" to construct a functioning system model. Placed into this design construct the form of the model can be easily understood and the processes acting on the problems can be more quickly identified. However, the greatest advantage of this approach is the relative ease by which changes can be made to the values given to variables in the model. Since the values assigned to variables and constants can be modified, exploring contrasting scenarios, adjusting time horizons, and altering functional relationships can be done without altering the general structure of the model. This feature greatly enhances the role of dynamic modeling as a decision support tool.

Cellular automata

Cellular Automata were introduced in the late 1940s by John von Neumann (von Neumann, 1966; Toffoli, 1987) and popularized in the late 1960s with the development of the "Game of Life" (Gardner, 1970; Dewdney, 1990). Cellular automata are often described as the counterpart to partial differential equations, which have the capacity to describe continuous dynamic systems. A cellular automaton is essentially a model that can be used to show how the elements of a system interact with each other. The basic element of a cellular automaton is the cell. A cell is a type of memory element and stores states that represent characteristics of the system under investigation. These cells can be two-dimensional squares, three-dimensional blocks, or they may take some other geometric form such as a hexagon. Each element comprising the system is assigned a cell and cells are arranged in a configuration. For example, cells joined together to form a single line comprise a one-dimensional cellular automaton, whereas cells arranged on a grid form a two-dimensional cellular automaton. In either instance, cells arranged according to a one-dimensional or two-dimensional lattice represent a static state. To introduce change (or dynamics) into the system, rules must be added to the model. The purpose of these rules is to define the state of the cells for the next time step. In cellular automata, dynamics occur within neighborhoods, and different definitions of neighborhoods are possible. For the two-dimensional lattice four neighborhood definitions are common: (1) the von Neumann neighborhood, (2) the Moore neighborhood, (3) the extended Moore neighborhood, and (4) the Margolus neighborhood (Fig. 7.7).

In the initial configuration of the cellular automata, each cell is assigned a "starting" value from the range of possible values typical of the system under study. For instance, if the range of possible values (states) were 0 to 1, then each cell would be assigned a 0 or 1 in the initial configuration. A transition function and a transition rule are also associated with each cell. Working in concert, the transition rule and function take as input the present states (values) of all the cells in a given cell's neighborhood and generate the next state of the given cell. When applied to all of the cells individually in a cellular automaton, the next state of the whole cellular automaton is generated from the present state. Then the next state of the cellular automaton is copied to the present state and the process is repeated for as many clock cycles as desired.

Cellular automata are rapidly gaining favor as a tool for modeling dynamic spatial systems (Batty & Xie, 1994; Cecchini & Viola, 1992; Engelen et al, 1996; White & Engelen, 1997). When compared to traditional approaches based on differential or difference equations, cellular automata have notable advantages: they are inherently spatial with rule-based dynamics; computationally efficient; can model systems with very high spatial resolutions; and provide and intuitive link to geographic information systems data formats (White & Engelen, 1997). For these reasons cellular automata show great promise as a basis for regional and environmental modeling (Clarke et al., 1994; White & Engelen, 1997). For example, in a recent study undertaken by Clarke, Hoppen, and Gaydos (1997), a cellular automaton simulation model was developed to predict urban growth as part of a project for estimating the regional impact of urbanization on climate. In this study the rules of the model were more complex than for the typical application, and allowed specific growth scenarios to be performed by the model using historic land-use/land-cover data sets. A similar study conducted by White and Engelen (1997), an integrated model of regional spatial dynamics, consisted of a cellular automaton-based model of land use linked to a geographic information system, to nonspatial regional economic and demographic models, and to a simple model of environmental change. Based on their initial testing of this integrated package, the cellular automata

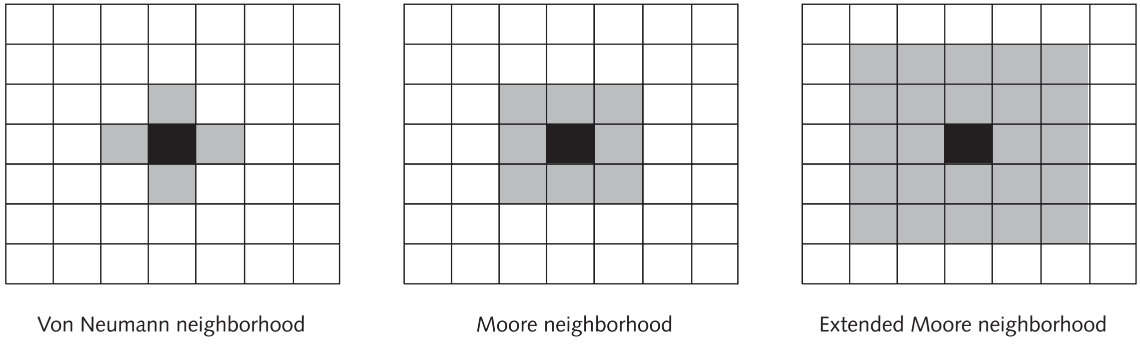

Fig. 7.7 Cellular neighborhoods.

enabled detailed modeling and realistic prediction of land-use patterns and provided a way to introduce environmental factors into the simulation. Although the authors caution that it may not be possible to predict the state of any land-use system far into the future, reasonable forecasts of land-use patterns over a period of 10 to 15 years can be made with measured confidence if the growth rate of the region is known. What this model does is support "what if" experiments, allowing the user to explore various possible futures and develop insights that may be of use in strategic planning.

Summary

As a future-oriented activity, environmental planning relies on the application and development of models to explore "what if" situations and test the outcome of various policy decisions and alternatives. The issues related to the use of models in environmental planning and the design of simulation experiments were examined in this chapter. Introduced in this discussion were the foundation techniques that rest at the core of many of the models used in environmental planning. The techniques selected for this discussion included Monte Carlo sampling, Markov chain analysis, dynamic modeling, and cellular automata. With a solid understanding of these techniques the advantages and disadvantages of using models in planning can be understood. In addition, the methods of modeling outlined in this chapter help the environmental planner decide what to model, how to design a simulation experiment to acquire information, and how to interpret the results of modeling studies. Taken together these topics support the intelligent use of models and stress their value in the formulation of environmental plans.

Focusing questions

What is a model and how do models contribute to the simulation process?

Develop a simple scenario: outline the causal chain of events that might unfold following a decision to relocate and expand a highway through a rural area.

Compare and contrast dynamic, probabilistic, and stochastic models; how do these forms influence the representation of a system?

What considerations guide the use of models in general, and how do they influence the interpretation of results obtained from a simulation experiment?