INTRODUCTION TO MODELING LAB: CAUSAL LOOP & STOCK AND FLOW MODELS

Preparation for Lab

In preparation for this lab you should read this entire handout, review the Keen and Spain reading assigned for class on the role of models in ecology, review chapters 56 of Brooker et al. (specifically section 56.3), and complete the causal loop and stock and flow exercises in this handout and bring these to lab. You should arrive in lab being able to define or explain the following terms and concepts: mechanistic hypothesis, model, stock, flow, positive and negative feedback, steps of modeling (conceptualization, formalization, calibration, validation, sensitivity analysis), exponential growth, logistic growth, r-selected species, and k-selected species.

Learning objectives:

1. Understand basic modeling concepts and terminology and the role that model building plays in the scientific process.
2. Understand the role that positive and negative feedback play in regulating system dynamics. Gain experience using and causal loop diagram to identify feedback interactions.
3. Understand how stock and flow simulation models can be used to model system dynamics.
4. Gain experience building simple dynamic simulation models of populations growing with and without resource constraints.

Important Note on Meeting Locations*:

All lab sections will meet in computer laboratories and NOT in their normal locations. Please plan to arrive five minutes early and get settled at a computer (with a partner if necessary) so that we can start on time.

Day	Section & Instructor	Computer Lab	Modeling Assistants
Tues	1A Bennett	Kettering100	Xander & Lila
Tues	1B Laushman	King 135	Casey& Charles
Wed	2A Bennett	King135	KevinS &Jackie
Wed	2B Roles	King 201	Gaby& Charles
Thurs	3A Bennett	Kettering100	KevinS & Walta
Thurs	3B Roles	King 135	Xander & Lila
Fri	4A Bennett	Kettering100	Gaby & Erika
Fri	4B Roles	King 201	KevinD & Walta

- Kettering 100 is the computer lab located in the middle of the first floor hallway between the south entrance of the Science Center and the atrium.
- King 135is a Computer Science lab located on the first floor of King, it is the eastern most room on the north corridor (just *past* the social science computer lab).
- King 201 is the Computer Science Lab located on the second floor in the middle of the east hallway.

Background

Models and the scientific process:

Three broad goals of the systems sciences are understanding, prediction and management. Ecological scientists use a variety of methods to gain understanding of ecological patterns and processes. Observations made of the "real world" in the field and in the laboratory are an important source of new hypotheses. A *mechanistic hypothesis* provides an explanation of causal relations and predicts how pattern and process might change under different conditions. Manipulative and comparative experiments often follow observational studies because they provide a means of testing the validity of hypotheses. If data collected are consistent with the explanations embodied in our hypotheses, then we take this as support for the hypothesis. If experimental data are inconsistent with hypotheses then we revise our hypotheses accordingly. In the most general sense, a *model* can be defined as a simplified, abstract representation of reality that is designed to help explain and/or predict causal relationships. Mechanistic hypotheses are a fundamental type of model within the sciences. However, in all types of models, our goal is to abstract the complexity of the real world into a simpler modeling world. The modeling world contains only the essential components and interactions associated with the questions and problems we seek to resolve. We attempt to solve our question or problem in the modeling world. We then interpret the implications that our findings have on our understanding of the real world.

Types of models:

Mechanistic hypotheses are critical, but the process of model building extends into all realms of the human experience and sciences. Indeed, each of us is continuously engaged in a process of model building that involves using our five senses to translate our observational experiences with the natural world into *mental models* – symbolic constructs of reality – that make sense out of this input and inform our real-time decision making. Our ability to construct mental models has served the human species well through evolution. However, mental models are often poorly suited for explaining systems with many components, processes that operate over large time and space scales and interactions that involve complex feedback with time delays. Unfortunately, many of the most pressing biological and ecological challenges we face today possess these attributes. Fortunately, just as microscopes and telescopes have allowed us to see parts of reality that are outside the resolution of our eyes, various kinds of models extend the capacity of the human mind to interpret complex interactions that are beyond our native modeling capacities. *Conceptual models* are distinct from simple mental models in that assumed relationships are made explicit, often in the form of logical statements and diagrams that indicate relationships. Mechanistic hypotheses, theories, maps of relationships among ecological components (for example food webs) – these are all conceptual models. In preparation for this lab you will gain experience with a class of conceptual model called *causal loop diagrams*, which are used to identify and understand the ways in which positive and negative feedback influence system dynamics.

Another important class of models that you are already familiar with are *physical* and *biological models*. The lab rat (*Rattus norvegicus*) and the fruit fly (*Drosophila melanogaster*) are good examples of biological models of organisms. These species are often selected as model organisms for genetic, behavioral and physiological study because they are relatively easy to rear in the lab and they possess properties that are representative of many other species including humans. We conduct experiments on these organisms with the assumption that the hypotheses tested and mechanisms revealed apply to a much broader class or organism. In ecology, we often construct simplified model ecosystems in the field or lab, termed "microcosms" or "mesocosms", that are the ecological equivalent of the lab rat. As with other models, accurately translating findings from experiments conducted on biological models (the modeling world) to the real world is an important and sometimes challenging part of the process.

Mathematical, numerical and/or computational models are extensions of conceptual models in which hypotheses and relationships between system components are expressed in numbers, formulas and often analyzed using computers. As with other classes of models, there is a great diversity of overlapping categories of numerical models. For example, you may be familiar with (or at least have heard of): analytical models, simulation models, statistical models, box models, stochastic versus deterministic models, empirical versus theoretical models, static vs. dynamic models, etc. The world is full of different kinds of models involving numerical analysis! Each is designed to address different kinds of questions, to solve different types of management problems, and to contribute to different parts of the scientific process.

In this week's lab you will gain hands-on experience working with *dynamic simulation models*, a class of models that are used to explore how system components change over time. We are typically interested in understanding how internal components of a system interact with each other and with the outside world in ways that generate the behavior or the "system dynamics" that we observe. The mechanisms associated with our hypotheses are built into the equations governing interactions in these models. Just as with other types of hypotheses, discrepancies between the output of a simulation model and the behavior of the real world reveal gaps or inaccuracies in our understanding. A simulation model that has been tested under a variety of conditions and accurately reproduces patterns observed in nature can, with great caution, be used to predict what might happen under new sets of conditions that have not yet been experienced. In many cases, dynamic simulation models provide the only means available for predicting the behavior of complex systems. For example, simulation models are essential tools for predicting the consequences of current human activities on the future climate.

<u>What is a "good" model? What are models good for?</u>

Natural scientists, including biologists and ecologists, use a diversity of models to help ask and answer important research questions and solve management problems. A "good" model is one that addresses the specific question or problem that it was designed to address. The modeling process should always start with a well-defined question or problem. However, modeling is iterative in the sense that all steps of the modeling building process (see the eight steps below) force the research to reconsider assumptions and to revise hypotheses. Often times the process of model building raises new questions and stimulates revision of existing questions. Computational modeling can be thought of as a kind of experimentation.

Three key goals of experimental science (including modeling) are to achieve high degrees of control, realism and generality. *Control* is the ability to manipulate an experimental system and to quantitatively and precisely relate cause and effect. *Realism* is the extent to which the knowledge we gain from our experiment or model world is directly translatable to the patterns and processes we are seeking to understand or manage in the real world. *Generality* is the range of different types of systems to which our experiment or model findings apply. The different tools we use to understand the real world strike different balances between control, generality and realism. For example, experiments conducted in whole natural ecosystems generally have a low degree of control, a high degree of realism and an intermediate level of generality. Computational models, on the other hand, provide a very high degree of control and often a high degree of generality. However, the realism of a computer model is constrained by the assumptions that go into that model. As some say, "garbage in, garbage out". In this light, computational models are particularly useful for identifying gaps in our knowledge and deficiencies in our assumptions, thereby forcing us to revise our hypotheses.

<u>Eight steps of building dynamic simulation models:</u>

There is variation in in how people conceptualize the modeling process, but the steps enumerated below capture many common features.

1. *Identification of a question or problem*: This is always the right starting place because the value of a model can only be assessed relative to whether it helps answer a question or solve a problem.
2. *Conceptualization*: This is the process by which ideas about the way the real world works are translated into clear mechanistic hypotheses. The model world created in this process is a simplified and abstracted version of reality. In dynamic simulation models this reality is often defined by stocks, flows and feedback (more on this later). System boundaries are identified. Internal processes and external forces acting on the system are identified and distinguished. Revisions seek to identify and include the minimum degree of complexity necessary to address the question or solve the problem.
3. *Formalization*: This is the process by which a conceptual model is translated into mathematical formulas and developed as computer code. This entails identifying appropriate equations or logic algorithms that accurately reflect hypothesized relationships among variables within the system. This part of the process also involves identifying numerical values for coefficients (for example growth rates, contact rates, maximum values, initial values, etc.)
4. *Calibration*: When first completed a model rarely exhibits dynamics that are consistent with those that characterize the real world system being modeled. Calibration is the process by which the model structure and coefficient values are altered within a range of observed values so that model output conforms to data observed in real systems. Often times the conceptual model, including underlying hypotheses, needs to be revised to achieve calibration.
5. *Validation* (verification): After a model is calibrated the modeler uses an independent dataset (not the one used for calibration) to test the models ability to predict dynamics under a different set of conditions. Model output can disagree with data collected on real systems for a range of reasons: the theoretical basis may be incorrect, conversion of theory to equations (formalization) may be wrong, there may be errors in the computer code, the numerical techniques may fail, and the experimental data collected on the "real world" may be inaccurate.
6. *Sensitivity analysis*: This is the process by which the values of model coefficients and initial conditions are systematically varied in order to determine which ones the model output is most sensitive to. This is a particularly important step when models are being used to assist in experimental design. Variables that a model is sensitive to may be important ones to measure carefully in experiments that take place in nature.
7. *Experimentation/prediction*: Computer simulation models create an excellent environment for asking and answering what-if questions. Of course the output and predictive value of a model is only as good as the assumptions that are built into it.
8. *Translation*: This is the process by which we take findings from the modeling world and interpret what they mean for the real world. The realism of our model is constrained by all of the assumptions that are made in developing the model.

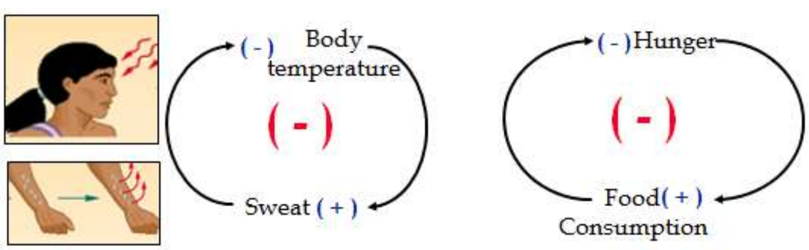
I. Conceptual Modeling with Causal Loop Diagrams

Importance of Feedback in Dynamic Systems:

Feedback can be defined as a condition in which output or effects of one system component either directly or indirectly return to affect that component. Feedback regulation is ubiquitous in dynamic systems and ranges in scale from sub-cellular to biosphere levels. Causal loop diagrams are a type of conceptual model that helps us to understand and communicate underlying causality associated with feedback. *Causal* means cause and effect, *loop* refers to a closed chain of relationships. This type of conceptual modeling is widely used in all of the fields associated with system dynamics. *Positive feedback* means that change in one direction causes further change in that same direction. Positive feedback provides a system with the capacity to grow (or shrink). *Negative feedback* means that change in one direction is counteracted. Negative feedback provides a system with the ability to resist change and maintain stability, often in the face of changing external conditions. The interplay among feedback loops within a complex system often provides that system with its unique dynamic properties. Your objective in the exercise below is to gain familiarity with causal loop diagrams.

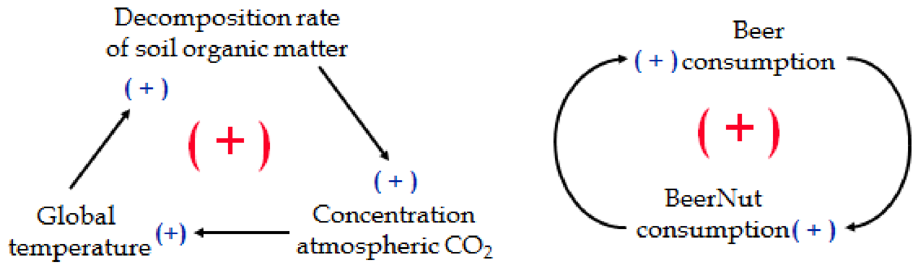
Examples:

<u>Negative feedback</u>

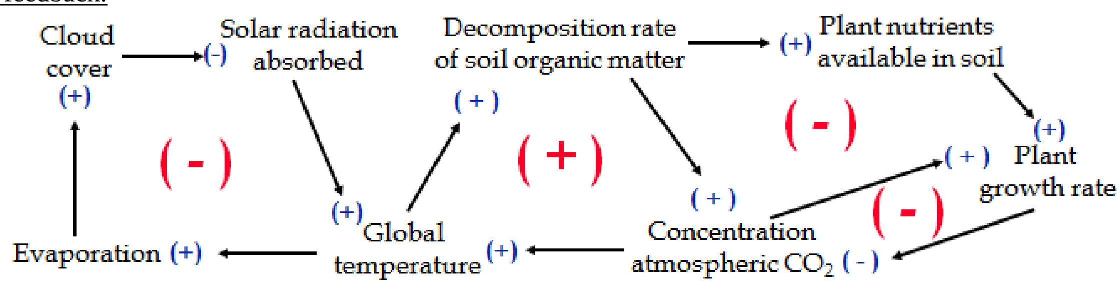


The relationship between sweat and body temperature is an example of negative feedback because change is counteracted: an increase in body temperature causes an increase in sweat which causes a decrease in body temperature which then elicits a decrease in sweating and so forth. The (+) sign at the tip of the arrow from body temperature to sweat means that a change in body temperature leads to the same direction of change in sweat (i.e. increase leads to increase, decrease leads to decrease). The (-) sign implies that change in opposite directions. The sign in the middle of the loop indicates whether the loop as a whole is positive or negative feedback.

Positive feedback:



Compound feedback:



Note that a given positive feedback loop can often operate in either expanding or contracting directions. For example in the compound feedback model immediately above, a pessimist might note that increasing CO_2 leads to increasing temperature which leads to increasing decomposition of soil organic matter, which increases CO_2 (positive feedback). Many climate scientists are concerned about the possibility that we may be reaching a tipping point in which this positive feedback loop kicks into high gear. At the same time, it is also true that successful efforts to increase plant growth (perhaps through planting or fertilization) can potentially lead to decreased CO_2, decreased temperature and decreased decomposition, thereby reducing other sources of feedback (positive feedback, but in the direction of minimization). In most living systems positive feedback is ultimately constrained by negative feedback. Feedback loops are almost always embedded in larger feedback loops. The dynamics we observe are, to some extent, controlled by the boundaries that exist in reality and in our models.

Procedure for Building Causal Loop Diagrams:

1. Start by brainstorming a list of variables associated with the phenomenon under consideration. Then, begin your causal loop diagram by selecting only those key system elements that are important and causally related to each other.
2. Arrows between variables are used to indicate the direction of causality. For instance, if you have two variables, “amount of coal burned” and “amount of acid rain generated” an arrow would be directed from the coal to the acid rain (i.e. the burning of coal affects the generation of acid rain). A causal loop is a set of variables that are connected with a complete circle of causality; tracing arrows in a forward direction leads from one variable back to that same variable.
3. Points of arrows are labeled with (+) or (-) sign to indicate positive or negative effect between the connected variables. The (+) symbol means that change in the variable at the tail of the arrow causes the variable at the point of the arrow to change in the same direction (i.e., if the one at the tail increases, then this necessarily causes the one at the point to increase). Since an increase in coal leads to an increase in acid rain (and a decrease in coal leads to a decrease in acid rain) you would label the end of this arrow with a (+). *Important*: when labeling, consider each pair of variables connected by an individual arrow in isolation from all others (completely ignore all other variables and arrow connectors while you are labeling each pair).
4. Determine the overall sign of a feedback loop by counting the total number of (-) signs at the end of the arrows within a complete loop of arrows. The loop is a *positive feedback* if there is an even number of (-) signs (or no - signs). The loop is a *negative feedback* if there is an odd number of (-) signs. Place a large (+) or (-) sign in the center of each loop to indicate the overall direction. “Compound” causal loops contain several interacting feedback loops, some of which may be positive and some of which may be negative.

General advice for causal loops:

1. Define and name your variables carefully. In particular, avoid variable names that already imply directionality (e.g. “amount of acid rain” is an appropriate variable, “increase in acid rain” is ***not*** appropriate). Generally your variables should be nouns rather than verbs.
2. Confusion will inevitably result if you attempt to think about multiple arrows simultaneously when you are labeling variable pairs. Focus only on the **direction** and **sign** of causality in each pair of connected variables in isolation from all other variables. Then, when you are done labeling each individual arrow, determine the sign of the loop as a whole.

3. Unlike stock and flow models, which you will use in the next exercise, in causal loop diagrams connections between variables do not necessarily represent flows of material or energy. Instead they represent a chain of causal relationships.
4. If it helps to clarify dynamics, it is fine to include external ("forcing") variables that are cause, but are not themselves affected by the dynamics depicted (i.e. though they influence dynamics, they are not actually part of a closed loop within the system represented by your model).
5. As with all models, you should strive to use the minimum number of variables necessary to capture the dynamics of interest. The first draft of your causal loop diagram generally can and should be reorganized and simplified in order to increase clarity of interpretation. There is never one, single correct visual presentation of a causal loop diagram (but there are certainly diagrams that are logically incorrect and/or confusing to look at).

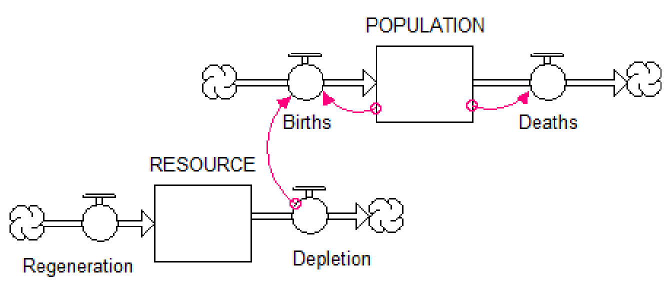
Build these practice causal loop models in preparation for lab:
Draw causal loops between the underlined variables in each scenario below. Use the procedures described above to label the whole loop as either (+) or (-):
1. Money in a bank account (bank balance) and how much money comes in each month as interest.
2. A colonizing group of termites have just invaded a downed tree in a forest. For now, assume that the supply of cellulose in the fallen tree biomass is unlimited (at least over the period being modeled). Consider only the termite population (i.e. number of termites) and the birth of new termites.
3. Consider the scenario above, but now over a longer period in which cellulose in the fallen tree is continuously depleted by several generations of the voracious termites. For this causal loop diagram consider the termite population and available tree biomass in the fallen tree.
4. Consider a predator and prey population composed of number of foxes and number of hares.

II. Box Models: Learning to Think in Stocks and Flows

Stocks and Flows:

Box or budget models are a widely used type of model that conceptualize a system as being composed of stocks, flows and additional variables and feedback connections that control flows. A *stock* (also known as a "state variable") is any system component that stores stuff. The "stuff" can be energy, materials, number of organisms, widgets, information or anything that can accumulate or be depleted over time. Flows (also known as rate equations or differential equations) function as the valves that control the movement of stuff into and out of stocks. With box models, a key aspect of the conceptualization process (step 2 in model building) involves translating your understanding of causal relationships into a system of stocks and flows.

Stocks are typically represented as boxes and flows are represented as pipe-like arrows extending into and out of stocks. Thin arrows are used to represent relationships among variables that control flows. In the conceptual model immediately below, the growth in the size of the POPULATION stock occurs via a Births flow that is dependent on both the size of the POPULATION and the Depletion flow out of a RESOURCE stock. The Death flow out of the POPULATION is dependent only on the current size of POPULATION. The RESOURCE itself grows through a Regeneration flow and is consumed through a Depletion flow. This stock and flow conceptual model tells us a good deal about dependencies and relationships among variables, but the specific equations controlling flow into and out of stocks would be specified in the associated dynamic simulation model.



Many phenomena can be understood in terms of stocks and flows. For example the ecology of a wetland ecosystem is strongly influence by hydrology. So if we were creating a model to answer questions about wetland processes, we would likely want to model factors controlling water levels. Inflows might include: direct precipitation, streamflow from its drainage basin and groundwater inputs. Outflows might include evaporation from the water surface, transpiration from the leaves of plants, overflow to downstream ecosystems and groundwater discharge. Different processes control each of these flows and are likely to change seasonally and as the ecosystem matures. For example, evaporation is controlled by air temperature, wind speed, exposed water area, etc. Transpiration (loss of water through the leaves) is influenced by these same factors but is also controlled by the total leaf area which, in turn, is a function of season, plant type, age of wetland, etc.

Consider the causal loop diagrams you created in the previous exercise. Draw a rectangle around each of the variables below that is a stock and circle those that are flows.

1. Bank Balance, Interest	2. Termite population, Births
2. Termite Population, Tree biomass	3. Foxes, Hares

III. Simulation Modeling with Stocks and Flows using STELLA

Approach:

Let's assume that you have identified a question or problem and have developed a conceptual model that attempts to define and explain the interactions between relevant system components. The best way to begin building a simulation model is to start with the minimum degree of complexity necessary to answer your question or problem. Ask yourself, "what are the fewest possible stocks and flows necessary to begin to capture the relationships needed". After this simplest model is operable, complexity can be sequentially added if it proves necessary. The exercises below models this approach; we will start with a simple model and add additional features to represent a greater degree of ecological complexity.

<u>How to maximize learning while building models:</u>
In this brief exercise modeling assistants who are current enrolled in *Systems Modeling* class (ENVS340) will introduce you to STELLA and then guide you through the development of the models below. In order to maximize learning it is critical that you mentally simulate the model dynamics *before* you let the computer do the work. This means actually sketching out on paper the pattern that you expect your model to produce, and it means talking through the rational for your expectations with a colleague (i.e. a student at an adjacent computer). This is important because the process of evaluating discrepancies between your expectations and the actual model output is what allows you to test your mechanistic understanding of the relationships in the model and thereby build new thinking skills. If you run the model before you have completely thought through potential behavior you end up developing post-hoc (after-the-fact) explanations that do not meaningfully test or challenge your understanding.

<u>Introduction to the STELLA modeling environment:</u>
From the program menu within the Windows Start menu, open STELLA and lick on the "Model" tab on the left hand side of the page. Your modeling assistants will introduce key tools in the modeling interface and guide you through model development. The final two pages of this handout are a reference that explains the essential features of the STELLA modeling environment. You may not have time to build all four of the models in the scenarios below. Depending on pacing, your modeling assistant may ask you to examine premade versions of these same models which can be downloaded from www.oberlin.edu/faculty/petersen/Bio102LabModels.stm

Modeling Scenarios:

<u>1. Growth based on a constant rate of inflow:</u>
Question: What pattern of stock growth occurs when the flow into a stock is constant?

Background/scenario: It is sometimes the case that the flow into a stock is not dependent on the amount of stuff stored in that stock. An example is flow of water from a stream into a wetland; the existing volume of water does not affect the rate at which stream water flows into the wetland.

What to do: Together with your modeling assistant, you will build the conceptual model pictured below and then insert initial stock value and an equation for stream flow. You will predict the pattern you expect to see over time in volume water in wetland BEFORE you actually run the model and then try to understand and explain discrepancies.

Initial condition and flow equation:[1]

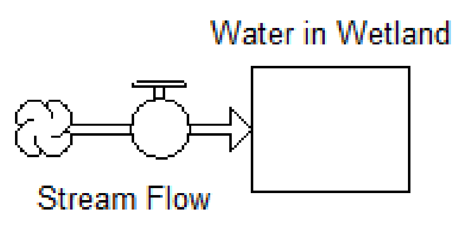
- Water_ in_Wetland = 10 {thousands of gallons}
- Stream_Flow = 0.1 {thousands of gallons per day}

Run → "Run Specs"

- Simulation length 0-100 days
- DT = 0.1
- Sim speed = 0.05 real seconds

Graph

- Water_in_Wetland
- Scale: 0 → 20
- Click "Sketchable"



[1] Flow equations are also referred to as rate equations or differential equations. They describe the rate of inflow or outflow and are always expressed in the same units as the stock but per unit time. So, in this case, since the wetland water storage stock is defined as having in units of thousands of gallons and we are looking at flows in units of days, Stream_Flow must be in units of thousands of gallons per day. A rate is the change in stuff per time. If our Water_in_Wetland stock were named W, we would write the complete inflow equation as $\Delta W/\Delta t$ or dW/dt = Stream_Flow.

2. Unconstrained growth:
Question: What pattern of stock growth occurs when the flow into a stock is directly proportional the current size of the stock?

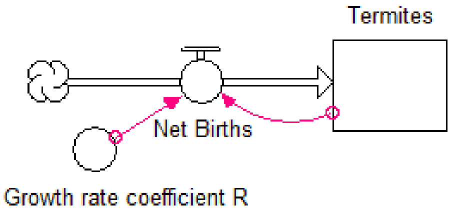
Background/scenario: Imagine that a colonizing group of termites have just invaded a downed tree in a forest (i.e. your second causal loop scenario). Assume that the supply of cellulose is unlimited (at least over the period being modeled). Build a model, sketch and discuss your predictions and then run the model.

Initial conditions and flow equation:

- Termites = 10 {termites}
- Net Births = R*Termites {termites/day}

Coefficients:

- Growth_rate_coefficient_R = 0.2 {1/day}
- Death rate coefficient, D = 0.15 {1/day}



3. Growth on a finite non-renewable resource:
Question: What patterns are evident when a population grows on a finite resource that can be depleted but not replenished?

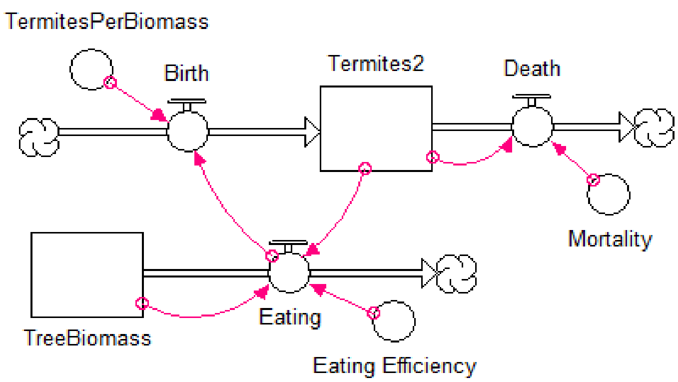
Background: Consider the same scenario as above, but now over a longer period in in which the cellulose in the tree trunk is depleted by several generations of the voracious termites.

Initial conditions and flow equations:

- Termites = 10 {termites}
- TreeBiomass = 1000 {kg C}
- Eating: Termites2*TreeBiomass*Eating_Efficiency {kg C/day}
- Birth: Eating*TermitesPerBiomass {termites/day}
- Death: Termites2*Mortality

Coefficient values:

- Eating Efficiency = 0.00024 {1/termites /day}
- Mortality = 0.15 {1/days}
- TermitesPerBiomass = 1.2 {termites/kg C}



4. Growth on a renewable resource (logistic growth):
Question: How might a population respond to situation in which there is a continuous but limited food supply?

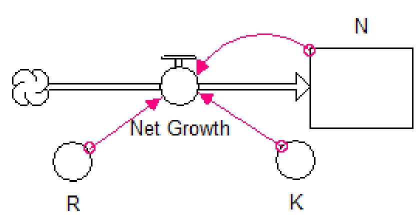
Background: Now imagine our termite population invades a mature forest that is in what ecologists term a "mosaic steady state". This means that old trees are falling down and creating patches in which young trees mature. As a whole, the forest has a stable tree populations of different ages and let's assume that the activity of our termites does not disrupt this stability. Further assume that the rate at which trees fall creates a stable food supply that can support a specific forest-wide population of termites. In this model we *parameterize* the effect of termites food supply itself, meaning that we model its effect without directly modeling the fallen tree biomass itself. The coefficient "K" represents the "carrying capacity", or the maximum number of termites that can be continuously supported by the supply of falling trees within the forest. For simplicity in the equation, N refers to the termite stock and R refers to the growth rate coefficient. Create the conceptual model pictured below and enter the equation for growth into Net_Growth.

Initial conditions and flow equation:

- N = 10 {termites}
- Net growth = R*N*(1 - (N/K))

Coefficient values

- R = 0.2 {per year}
- K = 1000 {what units make sense here?}



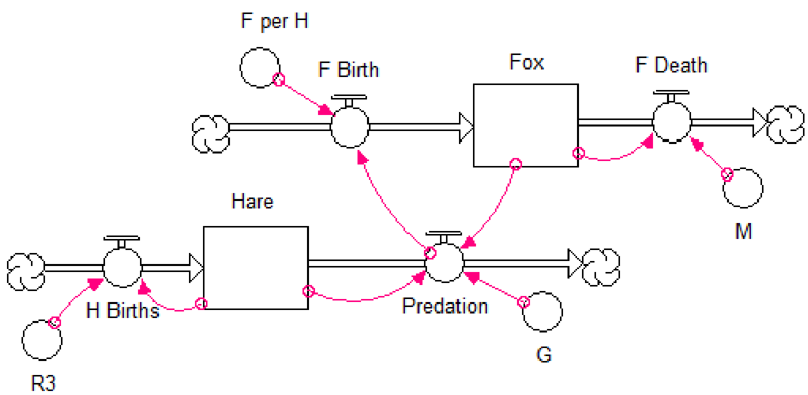
Discussion: The model you have just constructed is one version of "logistic equation", a commonly used formulation for modeling populations growing on a renewable but limited resource. It is instructive to consider the growth equation in two pieces. Considered by itself, how would the stock N respond to an inflow of R*N? What value does the term (1 - (N/K)) approach when K>>N (i.e. when the population is far below carrying capacity)? What value does it approach when K<<N (when the population is close to carrying capacity)? How does this transition affect the dynamics you observe? When ecologists discuss "R-selected" and "K-selected" species, the R and K terms come from this equation. Can you explain how these two life history strategies relate to the logistic growth equation?

5. Lotka-Volterra predator-prey interactions:

Background and question: Dynamic simulation modelers are particularly interested in understanding and being able to distinguish between the behavior of stocks and flows that result from internal interactions and those that result from external forces acting on a system. For some time modelers have been particularly interested in internal interactions that result in stable oscillations in the absence of any external forces acting on a system. The model in this last scenario was independently developed by Alfred Lotka (1924) and Vito Volterra (1926). Lotka was interested in understanding internal dynamics that might explain oscillations in moth and butterfly populations and the parasitoids that attack them. Volterra was interested in explaining an increase in coastal populations of predatory fish and a decrease in their prey that was observed during World War I when human fishing pressures on the predator species declined. Both discovered that a relatively simple model is capable of producing the cyclical behaviors they observed. Since that time, several researchers have been able to reproduce the modeling dynamics in simple experimental systems consisting of only predators and prey. It is now generally recognized that the model world that Lotka and Volterra produced is too simple to explain the complexity of most and predator-prey dynamics in nature. And yet, the model significantly advanced our understanding of the critical role of feedback in predator-prey interactions and in feeding relationships that result in community dynamics.s

Consider a modeling world consisting solely of populations of one predator and one prey species (e.g. Fox F and Hare H). This model is structurally similar to the second termite model above except that termites become Foxes, TreeBiomass becomes Hare population and the birth inflow is inserted into the Hare population to allow it a means of growth in proportion to its population size. So in this simple modeling world, the prey population is unconstrained by food resources. Indeed, the only constraint preventing exponential growth of the Hare population is the existence of a Fox predator that consumes the Hare. In contrast to the Hare population, the Fox population has only one way of growing, and this is by consuming Hare. As in the second termite model Fox population growth is limited by a natural mortality loss term (exponential decay). The rate of Predation is a function of the size of both the predator and prey populations – the higher the number of each the more they come into contact and the more Hare that get consumed.

What to do: If you don't have time to build this model, download Bio102LabModels.stm and drag and drop the file into an open version of STELLA. If you DO have time to build, you can start by copying and pasting your second termite model, adding a birth inflow to the Hare population and then changing the names and coefficient values (the equations are otherwise identical!).



Flow equations:

- H_Birth = R3*Hare {Hare/area/month}
- Predation = G*Hare*Fox {Hare/area/month}
- F_Birth = F_per_H *Predation {Fox/area/month}
- F_Death = M*Fox {Fox/area/month}

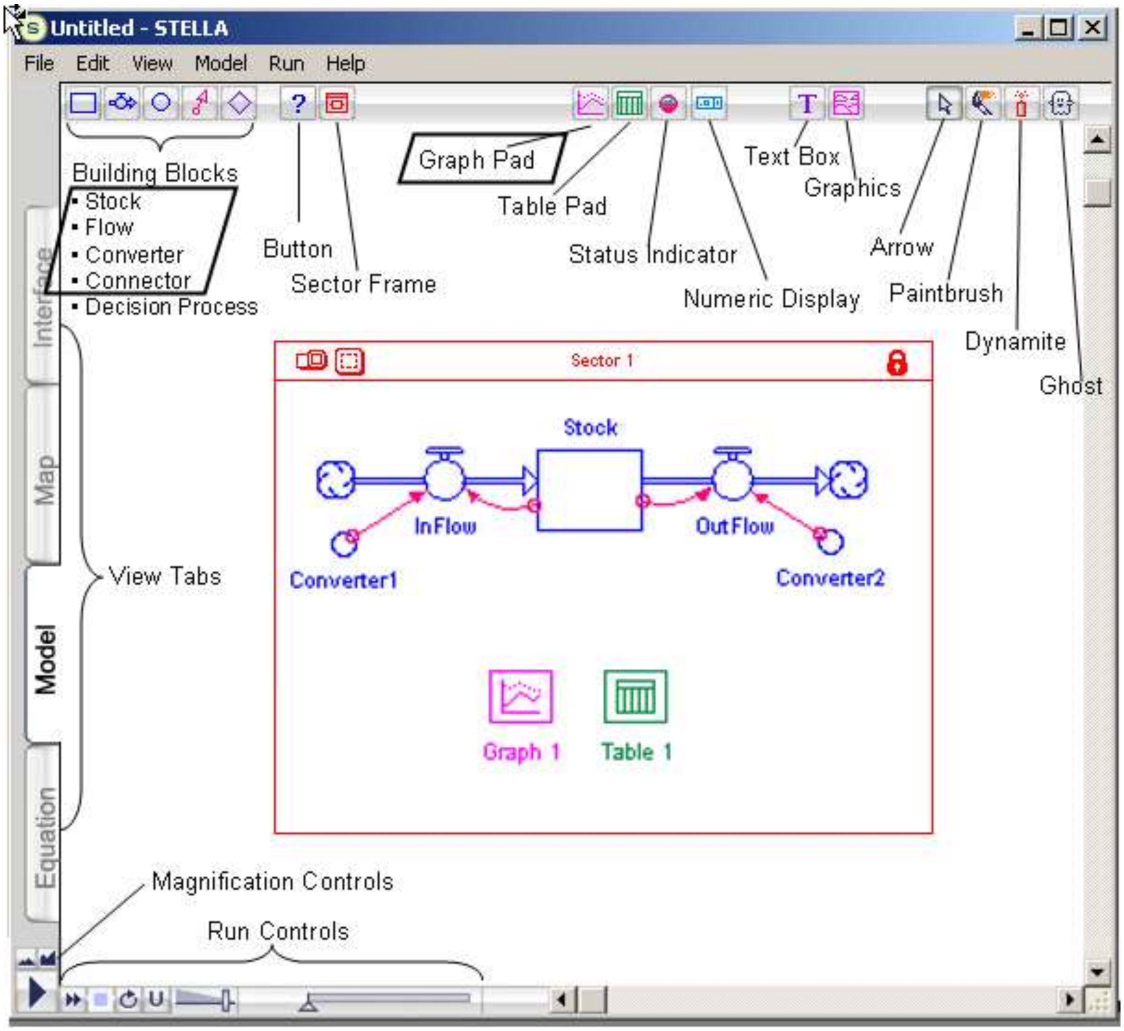
Initial conditions and coefficient values:

- Hare = 1500 {Hare per unit area}
- Fox = 50 {Fox per unit area}
- Hare birth rate coefficient = R3 = 0.1 {1 /month}
- Predation rate coefficient = G = 0.002 {1/Fox/month}
- Conversion of Hare to Fox = F_per_H = 0.1 {Fox/Hare}
- Fox mortality coefficient M = 0.2 {Fox/month}

Run → "Run Specs"

- Simulation length 0-100 months
- DT = 0.01 s(Important! This model is sensitive to the size of DT. You must change it to this smaller value for this model to work properly)

Appendix: STELLA 101 – Building Blocks and Tools



Anatomy of STELLA in the "model layer". The most important building blocks and tools that you will used in these exercises are outlined in parallelograms within the diagram above

Essential Building Blocks:

1. <u>Stocks</u> (= State Variables)
   - Represent anything that accumulates or is depleted over time
   - Describe the state of a system
2. <u>Flows</u> (= differential equations)
   - Contain equation describing rate of growth or loss (always have units of flow/time)
   - Can be "uniflow" (one directional) or "biflow" (two directional) depending on what is logical
   - The "cloud" symbol indicates unspecified source or sink for flow; clouds indicate bounds of your model -- what's included, what's not
3. <u>Converters</u>
   - Forcing functions (= external factors or conditions that influence internal dynamics)
   - Data for comparison ("calibration", "validation")
   - Numerical constants, coefficients, parameters
   - Equations (used for a, b or c)
   - Graphical relationships between variables (e.g. stimulus-response)
   - Various other odds and ends
4. <u>Connectors</u>
   - Indicate dependence
   - Indicate required inputs to equation for a flow or converter (but not to a stock)

Other Useful Tools:

1. Dynamite
   - Used to eliminate unwanted parts of model
   - Be careful! Don't release the mouse until you are sure you are blowing up the correct building block!
2. Graphs
   - Used to display the value of variables over time (time series)
   - Used to display relationships among variables (e.g. x-y scatterplots)

View Tabs:

1. Model: This is where you will spend all of your time. Here you build your conceptual model and fill it in with flow equations and coefficient values.
2. Equation: This allows you to see all of your flow equations and coefficient values.
3. Interface: This is where you can create fun control panels that you or others can use to experiment with different scenarios and/or use different coefficient values or forcing and boundary conditions
4. Map: You can use this to build your conceptual models without having to look at (?). This is pretty much redundant to the Model tab and can largely be ignored.

Menus:

1. FILE: Contains typical options. You can only have one STELLA model open at a time within a window, but you can open new copies of the STELLA model from the start menu.
2. EDIT: Contains the usual options.
3. MODEL: Most of this is not needed for beginning modeling. The "Model prefs…", however, allows you to "Animate" stocks, flows and converters in ways that can help you visualize that is occurring.
4. RUN:
   - Run: Used to run models
   - Time Specs: Where you set time units, duration, numerical methods, simulation speed
   - Sensi Specs: Used for "sensitivity analysis"
5. HELP
   - An incredible wealth of useful information!
   - e.g. See section, "Controls on model construction layer"