Complex Adaptive Systems, Systems Thinking, and Agent-Based Modeling

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Abstract Systems thinking and complex adaptive systems theories share a number of components, namely emergence, self-organization, and hierarchies of interacting systems. We seek to integrate these schools of thought and discuss the similarities and differences of these two models, to introduce systems dynamics and agent-based modeling as methods for modeling complex systems, and how causal-loop diagrams can be used as a means to clarify the complex interactions among components (agents). We then apply a mixture of these different but similar techniques to a fly ecosystem modeling problem to demonstrate their effectiveness.

1 Complex Adaptive Systems

Complex adaptive systems (CAS) are all around us. Common examples given are ecosystems, financial markets, the brain, ant colonies, economies, and many other examples where large numbers of constituents independently interact on a local level that yield some unanticipated nonlinear outcome at scale. Despite the ubiquity of these systems, it is generally conceded that there is no one standard definition of CAS. For our purpose, we shall define a CAS as:

> a system composed of a large number of independent simple components that locally interact in an independent and nonlinear fashion, exhibit self-organization through interactions that are neither completely random nor completely regular and are not influenced by some central or global mechanism, and yield emergent behavior at large scales that is not predictable from observation of the behavior of the components [1, 2].

The smallest component elements of a CAS are commonly referred to as *agents* [3]. Agents are the smallest unit of organization in the system capable of producing

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a given response for a specific stimulus. This stimulus/response behavior of an agent is governed by a few very simple rules. In CAS, we see local interactions of groups of agents, both homogenous and heterogeneous, in a variety of different configurations. In small quantities these interactions can be anticipated, as there are usually a limited set of interactions that each agent can perform. These random local interactions generally yield outcomes approximate to the sum of the potential of each interaction; in some cases, however, as we see larger combinations of agents in varying proportions acting in different ways, we see complex and potentially novel behaviors from these combinations of agents that yield significantly greater outcomes than we would expect. When agents combine in such a way as to produce these emergent behaviors, we refer to this as aggregation and to the specific collection of agents required to produce the effects as *aggregate agents* [3]. These aggregate agents group together with other aggregate agents to form increasingly larger CAS with richer sets of emergent behaviors and interactions.

2 Systems Thinking

Another mechanism used to describe complex systems is *systems thinking* [4]. In systems thinking, we look at the combination of interdependent component systems that make up the whole and study how the state of the global system changes as a result of the interactions of the component systems [5]. This concept is referred to as a *system of systems* [6]. How a system component reacts to information from its environment, as well as the range of interaction options available to the component, identifies the type of behavior exhibited by the component. These behaviors are generally classified as either *goal-seeking* or *purposeful* [6]. With goal-seeking behaviors, a component system is capable of producing a single fixed response using a range of methods in a single environment; these are sometimes referred to as *responsive* [6] or *uni-minded* [5] systems. Purposeful behaviors, alternately, are exhibited by a component system that is capable of producing multiple varied responses to multiple stimuli under many different conditions. Systems that operate with purposeful behaviors produce a much greater variety of potential outcomes and, therefore, provide the greatest potential for novel emergent behaviors. These systems are sometimes referred to as *multi-minded systems* [5]. Four concepts are necessary to describe a purposeful system: a hierarchy of systems; processes of communication among the systems; the stimulus/response combinations that can be activated to produce change among component systems; and definable emergent properties that arise from the interdependent systems [4].

Analytical approaches to system modeling work well with goal-seeking systems, since it is possible to deconstruct these systems into their component parts, study the function of those parts, and then attempt to explain the behavior of the aggregate system in terms of those interactions [5]. In many cases, these interactions can be described using systems of equations and a mathematical model of the system produced. For purposeful systems, however, it is either impractical to capture all of the possible stimulus-response cases to produce an exhaustive system of equations or the sheer quantity of these equations produces an intractable or unsolvable system. Because of the vast number and variety of combinations of interactions among agents in these systems, many times it is either impossible or impractical to use analytical methods to determine systems of equations capable of exhaustively describing the dynamics of these systems.

3 Agent-Based Modeling

Returning to our definition in 1.1, a CAS is a system composed of a large number of agents that interact with each other in a nontrivial manner and yield emergent behaviors. Each of these agents operate using a set of simple rules as their *internal model* of the global system and produce outcomes using simple rules that are part of this model [3, 7, 8]. Internal model refers to the mechanisms used by an agent to issue a response to a given stimulus and to "learn" new rules through interaction with its surroundings. An *agent-based model* (ABM) is a representation of the constituent agents that make up a system along with a mechanism to allow agents to interact through information exchange with the environment as well as other agents. These agents operate according to rules that attempt to approximately replicate the properties and behaviors of the actual components in the real world.

ABMs are computational models that enable us to understand how different combinations of large numbers of agents produce global outcomes through their discrete local interactions. The outcomes of these models are sensitive to initial conditions and may produce different outcomes according to the inherent randomness of nature that they attempt to reproduce. Mathematical or statistical analysis may be used to verify output of ABMs to determine how accurately they represent the corresponding real-world system; it is very difficult in many cases, however, generate mathematical models to represent the same varied nonlinear emergent outcomes possible as these systems are NP-Hard or NP-Complete [9, 10]. Because of this feature of complex systems, ABMs are one of a handful of tools useful for exploring the emergent behavior of such systems.

4 Systems Dynamics

Just as ABM is a modeling method couched in the language of CAS, systems dynamics (SD) is a modeling method traditionally applied to problems in the social sciences and similar disciplines. Similar to ABMs, SD models are solved computationally through iteration over time. SD models differ from ABMs, however, in that the interactions among components of the system are defined in terms of state variables which are controlled through systems of difference equations. This requires a much more mathematically-rigorous definition of a complex system than is required by ABM; however, the resulting model can be directly-analyzed using mathematical methods, unlike the output of ABMs that requires additional statistical analyses after the fact [8].

Since SD models are described in terms of systems of difference equations, such descriptions do not always provide an intuitive guide to the interactions of system components. To remedy this, a mechanism known as *causal loop diagramming* (CLD) was developed to provide a visual description of system components and their interactions. A good discussion of CLDs is found in [11]. A CLD provides a mechanism to illustrate the interaction among the state variables (i.e., systems) through the use of positive and negative feedback loops. While this method does not necessarily capture the relative magnitude of information flows among the various components, it does make it very easy to understand which relationships are responsible for system expansion (*reinforcing loops*) and which relationships help to keep the system in control (*balancing loops*). We believe that CLDs can also be a good mechanism to describe the interactions among agents in an ABM.

5 Application

An example case that we shall use for this study is the interactions among fly populations, climate, and the environment and how they can lead to large-scale fly infestations. We shall begin by describing the general problem in terms of fly biology and environmental interactions. Next, we will present a systems thinking approach to the problem describing it as a systems of systems. Then we present our implementation of the ABM used to represent the CAS. Finally, we provide a discussion of our work.

The biology of common species of flies documents the relationships between temperature and humidity and fly development and reproduction. Using this information, we have been able to develop and validate an ABM that generates outcomes compatible with historical data over a five-year period. We have also sought to extend the composition of these systems with other systems such as dumpster placement, sanitation methods and schedules, insect control programs, and the effects of customer interactions with the environment can be modeled as a purposeful system of systems.

In Fig. 1, we model the individual systems and their interactions using a CLD. In our model, we are primarily concerned with the density of our local fly population, as this is the leading indicator of whether a fly infestation of the adjoining facility will reach a problematic level. In an unregulated environment, populations are affected by two means: reproduction and migration [12]. As food availability increases, population density increases as flies from surrounding communities immigrate into the local community. As population density increases, the chance of mating increases accordingly, which leads to increased egg-laying activity. If egg laying increases and the ambient air temperature is within an acceptable range, egg

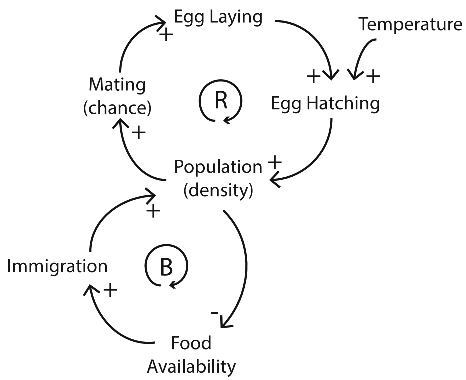

Fig. 1 Causal loop model of a fly ecosystem (Abbott, R. and Bacaksizlar, N.)

hatching increases proportionally, leading to additional increases in population density.

This allows us to expose the exchange of information among the individual systems and the corresponding interdependencies and increased complexity that emerges from these exchanges. This diagram allows us to explain the known relationships among system components; however, it does not allow us to identify novel behaviors that may emerge over time as the system scales along various dimensions.

In an attempt to model the complex system that represents this ecosystem, we created an ABM that emulates the interaction of the most common fly species with their environment to determine conditions under which fly populations will emerge to a significant enough level to threaten a business establishment and what configurations and barriers are most effective at mitigating this health risk. This model was constructed using NetLogo, a powerful tool for developing ABMs [13]. We also included seven years of climate data [14] for the area to drive the behavior of the agents, and we used data [15] derived from the inspection system of a local pest control management company to assist in validating the outcomes produced by the model.

Using information on the biology of common flies [12], we produced a model agent using a small number of rules. These rules governed the migration and life cycle behaviors of the individual fly agents as they interacted with their environment. For each iteration of the model, we began with different random initial conditions for the number of fly agents at various stages of their life cycle. We also varied the placement of food to simulate the placement of waste receptacles (e.g., trash cans, dumpsters, etc.) as well as incidental food-bearing waste dropped around the facility, such as next to cars in the parking lot as well as along high-traffic foot routes.

When running our base model, we learned some interesting behaviors about the randomness of a fly bloom occurring. With no external controls on the population (e.g., pest control and sanitization protocols or non-natural food sources), even with a thorough seeding of random insect populations, it is not likely that a long-lived fly

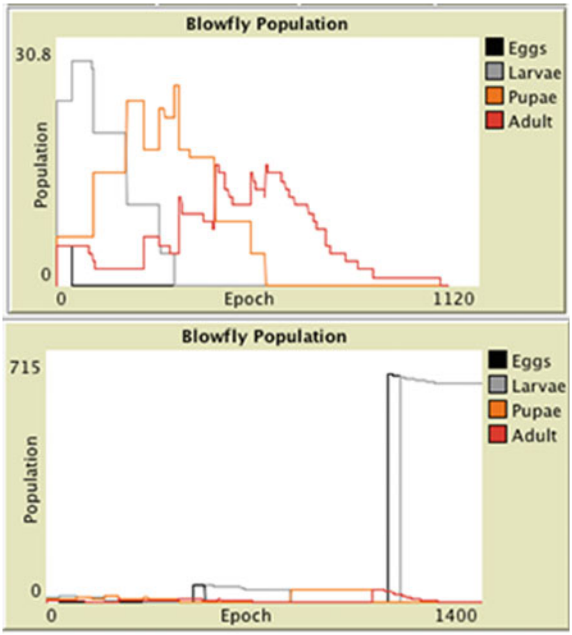

Fig. 2 The *top graph* indicates a model run that did not yield a continuing generation, while the *bottom graph* indicates a continuing generation

plague will occur, as represented by the top graph in Fig. 2. In most iterations of the model, the local fly population will leave the area in favor of other more food-rich environments. With just the right combination of flies at the proper life-cycle stage and placement of food sources, a continuing generation can be produced by the population, as shown in the bottom graph in Fig. 2.

A single continuing generation, however, is not enough to indicate that a fly population will infest adjoining facilities. As seen in the bottom graph of Fig. 2, a continuing generation has only produced on the order of 700 eggs, total. Problems encountered at the degree necessary to produce infestations typically are the result of multiple generations of offspring, which can be produced within two weeks during warmer seasons [12]. From our model results, once a third generation of offspring are produced in an area with a continuing food source, the fly population will continue to grow unless active steps are taken to remove the food or to kill the population. A successful third-generation fly bloom is shown in Fig. 3.

When comparing the CLD and the output of the ABM, it is easy to recognize the strengths and limitations of each method. In CLD nomenclature, it is possible to clearly document the interactions between an agent and its environment, as both reinforcing and balancing forces [11]. The CLD, however, does not make it easy to measure the degree of these interactions or to identify emergent behavior such as explosive nonlinear growth that can occur under certain conditions. ABMs, in contrast, are able to surface these emergent behaviors as they are run under differing initial conditions; however, they do not provide a means for directly identifying the

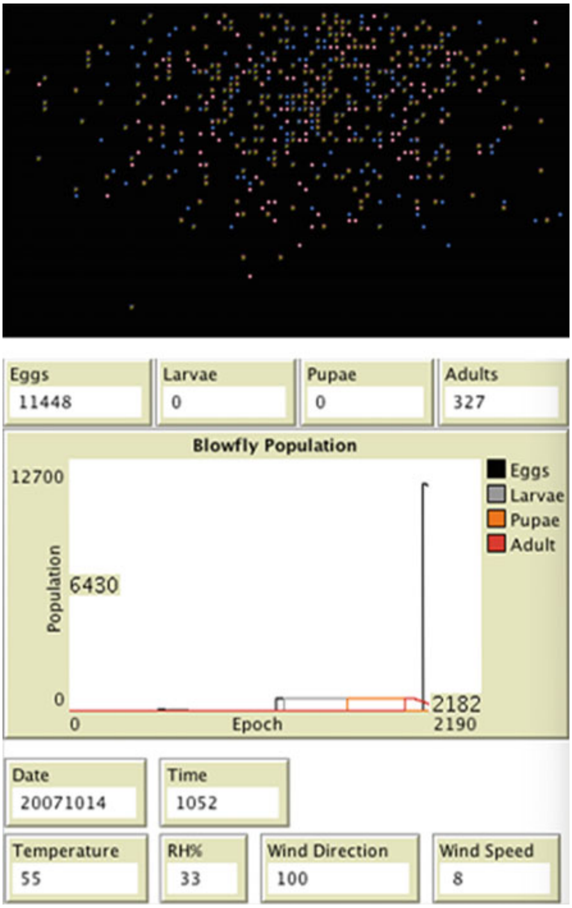

Fig. 3 A successful multi-generation fly colony achieved during epoch 1911 of our model

specific interactions that lead to such emergent behavior. These interactions usually identified during detailed analysis of model results.

We have described two different schools of thought, systems thinking and complex adaptive systems, both of which seek to describe the complexity of systems in terms of interacting components that share information and are capable of evolving or displaying novel behaviors through interaction. We have also described two different but similar modeling methods, systems dynamics and agent-based modeling, both used to simulate complex systems so that we can better understand and predict outcomes of complex systems. We have also described causal-loop diagrams, a method of illustrating the interactions among system components and how those interactions affect the overall organization of the system. We then applied some of these methods to the description of a biological system to demonstrate how the different systems can be effectively integrated to explore complex systems.

6 Summary

Systems thinking is an important way of approaching complex phenomena today. Complex Adaptive Systems and Agent-Based Modeling proved to be a potent combination of paradigms to address simulation and modeling of practical issues that challenge the society of today. In this paper we demonstrated the utility of combining Systems thinking and ABM on the example of pest control and management. Future work will focus on turning this type of thinking into a general-purpose tool for simulation and modeling.

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