Chapter 1. Simulation Models: Why? Who? When?

Simulation models have become important tools in Botanical Epidemiology. There are many reasons for this, but we emphasize three of the more important: (1) they enable exploration of hypotheses, and as such, have become invaluable means to guide research; (2) they are unique approaches to integrate (in the literal term of the word) epidemiological knowledge, in the form of experimental results; and (3) they enable connecting epidemiology with other fields of study ranging from agrophysiology to ecology, and from social sciences to natural resource management, for example. This module, and this introductory chapter, is intended to guide the potential user of simulation models. It is not, in any way, meant to be comprehensive on the very diverse simulation tools that already exist, but focuses on mechanistic, dynamic models. Similarly, it is not meant to provide any coverage of the breadth of applications; however, for interested readers, we provide references to use as a possible starting point.

Why use simulation models?

Simulation models are meant to answer questions which scientists have in a dynamic, quantitative, and often, a pictorial way. Much of the epidemiological research and its applications, in particular, involve a large number of components, actors, and factors. Assembling these in a coherent framework may seem a daunting task, especially for beginners, and can lead to confusion, even for experienced scientists, especially if the objectives of such an exercise are not well defined. This has often resulted in modeling activities becoming an end in themselves, instead of being one of the many tools plant disease epidemiologists may use to analyze and provide answers to crop health problems.

Thus, simulation models have to address specific questions (Zadoks and Rabbinge, 1985), lest becoming self-centered and often unable to bring forward new insights. The insights can be of many kinds. They may be limited to the (very important) objective of better delineating the limits and components of the problem at hand, of identifying key factors that determine the behavior of pathosystems, of deriving disease management options and quantifying their potential efficacy, or of providing a framework for future research, such as, e.g., the quantification of the effects of components of resistance in partial resistance.

Another worthwhile use of simulation modeling is that it still represents today the sole way to numerically integrate the available information often derived from experiments on processes

underpinning plant disease epidemics. This type of application has the important value of enabling a numerical visualization of knowledge gaps.

Simulation models enable mobilizing available (primarily quantitative) knowledge of a system, and exploration of a system's behavior. This property of simulation modeling is derived from the link between integration levels in biological systems (Rabbinge and De Wit, 1989), that is, the fact that simulation models are based on the principle that the behavior of a system at one level of integration (say, a field) is a reflection of processes operating at the next-lower level of biological integration (e.g., plants, diseased or healthy), that form the population that is present in the field. In other words, simulation enables upscaling, that is, the integration of processes occurring at a given level of hierarchy within a system (e.g., 'a site on a leaf is infected') to a higher scale of hierarchy of that system (e.g., 'an epidemic takes place'). As a result, simulation modeling is unique as a scientific approach, because it enables one to explore possible futures. Of course, simulation modeling is a key approach currently used to study the effects of climate change on earth's systems, including plant disease epidemics. There is however a large number of other applications of the extrapolation power of simulation modeling. This was already recognized by pioneers in the field, who actually conducted simulation-based experiments in botanical epidemiology a long time ago (Teng, 1985).

Critical to the approach, however, is to specify the purpose of modeling prior to engaging into the modeling work. This implies that one has to choose among the many applications of modeling. Defining the purpose of modeling, in many ways, entails the underpinning question of model evaluation – will the anticipated model be evaluated? In which way? Do data exist that are appropriate for model evaluation available? Model evaluation is a scientific field of its own (Teng, 1981), but is first a philosophical scientific issue: models, including simulation models, only consist of carefully chosen components of a system; and a system is a simplification of (modeled) reality.

Thus, (simulation) models can only be proven wrong, to some degree. The notion of 'validation' applied to models (as well as to theories in general, Popper, 1963) might imply that a model is 'true', while the only truth is the reality, of which models are only simplifications. In many ways, therefore, scientists might be more interested in developing simple, parameter-sparse models, that can easily be evaluated, whether in terms of their inherent consistency (the model operates as the investigator intends it to), or in terms of their outcomes (the model's outputs reasonably match the available observation). Teng (1981) provides an important discussion on the philosophical background of model evaluation.

Another reason for investigators to favor parameter-sparse models emerges when models are intended for applied purposes: in such a case, one will often choose a model that requires little

information to operate, so as to be accessible to the largest number of users, in the broadest range of contexts.

It follows from the above remarks that, as in experimental research, the simplest model enabling the investigator to (1) better understand the behavior of a system, and (2) clearly answers specified questions is often to be preferred to complicated structures. The latter are difficult to evaluate, complex in their inherent behavior, and often very difficult to use for practical plant protection purposes. Therefore, a simple, clear, and easily shared model reflects that the question addressed has been clearly expressed.

Who are the users of simulation models?

Development of simulation models does not require mathematical and programming expertise. But it does require (1) a good understanding of the system under consideration, (2) some basic knowledge of calculus, and, again, (3) a good articulation of the scientific question at hand.

For botanical epidemiologists, critical steps thus are to (1) clearly specify the objectives of simulation modeling, (2) have a good outline of the system to address (this will be addressed in the next chapter) with numerical information of the next-lower level of integration (e.g., the monocyclic processes of epidemics), and (3) match the above two points with independent available data that pertain to the level of integration to be modeled (e.g., an epidemic), in order to enable the evaluation of the model that has been developed.

When to use simulation models?

The use of simulation becomes apparent as soon as a number of factors are considered to influence the behavior of a system. Many approaches, especially statistical ones, are available to analyze interactions in (biological) systems. Simulation modeling constitutes a unique approach in that it enables the simultaneous handling of a range of such factors and 'see' their influence on the behavior of a system, such as the course of an epidemic. In addition to the "Why" reasons listed above, one key outcome of simulation modeling is a better understanding of which components of a (plant-pathogen) system are truly important in its behavior, and which are presumably less so.

In plant pathology, especially in botanical epidemiology, as well as in the analysis of the translation of epidemics into crop losses, one is always dealing with dynamic processes. Simulation modeling is a powerful approach to address such processes. Over the course of time, some components

of a system will have an increasing, or decreasing, effect on the behavior of the considered system (e.g., the dynamics of an epidemic, or the build-up of yield - and thus of yield losses - over time). Anticipating such switches, especially when combined with factors that are considered important in the properties of the considered system (e.g., environmental or man-made factors) is extraordinarily difficult. Simulation modeling provides a unique way to visualize, understand, and quantify such dynamics.

Lastly, simulation models can also represent good educational tools: they can provide an intuitive hands-on analysis of (plant-disease) systems.

Summary

- Simulation models have a number of applications. In particular, simulation models:
  - allow exploration of the behavior of plant-pathogen systems;
  - in doing so, they enable mobilizing experimental data;
  - enable exploring the sensitivity of plant-pathogen systems to some of their (specified) components;
  - allow exploration of "futures", i.e., analyze how the considered system might behave under yet-undocumented conditions.
- Development of simulation models *does not require* mathematical and programming expertise. But it *does require* (1) a good understanding of the considered system, (2) some basic knowledge of calculus, and (3) a good articulation of the scientific question at hand.
- Simulation modeling is a powerful approach to address dynamic processes. Over time, some components of a system may have stronger, or weaker, effects on the behavior of a system (e.g., the dynamics of an epidemic, or the build-up of yield - and thus of yield losses). Such questions can powerfully be addressed through simulation modeling.
- Simulation models are good educational tools: they can provide an intuitive hands-on on analyzing (plant-pathogen) systems.

References

Popper, K. R. 1963. Conjectures and Refutations: The Growth of Scientific Knowledge. Routledge, London.

Rabbinge, R., and De Wit, C.T. 1989. Systems, models and simulation. Pages 3-15 in: Simulation and Systems Management in Crop Protection. Rabbinge, R., Ward, S.A. and Van Laar, H.H., Eds. Pudoc, Wageningen, 420 p.

Teng, P.S. 1981. Validation of computer models of plant disease epidemics: a review of philosophy and methodology. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz 88:49-63.

Teng, P.S. 1985. A comparison of simulation approaches to epidemic modeling. Annual Review of Phytopathology 23:351-379.

Zadoks, J.C., and Rabbinge, R. 1985. Modelling to a purpose. Pages 231-244 in: Advances in Plant Pathology, Vol. 3. Mathematical Modelling of Crop Diseases. C.A. Gilligan, ed. Academic Press, London.