Agent-Based Simulations

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Agent-Based Models (ABMs) involve populations of interacting agents, with each agent being a distinct entity. An important quality of AMBs is the ability to simulate complex systems (i.e., those that contain complicated agent behavior mechanics). For example, it is via simulation that emergent properties of systems can be observed, properties that may not be apparent when behavior mechanics (i.e., rules guiding agents behavior) alone are inspected.

Probabilistic Agent-Based Models (PRAMs; [2]) is a novel modeling and simulation framework. PRAMs extend ABMs leading to a more compact representation of the agent population (lending itself to better runtime performance), better expressiveness, automatic lifted inference support [4] (which can thought of as a combination of efficient population- and subpopulation-level inference available at every step of an agent-based simulation), and sound probabilistic foundation. It is that last property, i.e., the fact that PRAMs are based on probabilistic agent behavior mechanics, that makes them amenable to conversion from and into probabilistic graphical model (PGMs), e.g., Bayesian networks and Markov chains, and their simulator derivatives (e.g., time-variant Bayesian networks [5]). Despite the benefits of PRAMs over ABMs listed above, they belong to the same class of models and it is possible to convert between the two.

While ABMs have been applied in many areas [?], they have begun to be used in agriculture only fairly recently. Moreover, most research involving ABMs focused on modeling populations of farms. Notably, ABM-based crop modeling has not been tapped into [3] [has it not actually?]. This study will help to change that by developing AI fluency in conversion and manipulation of crop models based on ABMs, PRAMs, PGMs, and ordinary differential equations (ODEs), all or some of which will be part of DSSAT [is there a better way of weaving this in?]. As we have described in Sec Modeling.Process, the ability to convert between model types is an elementary modeling operation; the ability to simulate a model like PRAM being another. As such, the synthetic modeler assistant, MAIA, will be versed in using them whenever the human modeler sees fit to ask for help.

Much like studies described thus far, this study will enable large-scale simulations involving one type of a crop. However, it will also enable large-scale simulations of multiple plant types nested within farms (i.e., both plants and farms are agents; being relational, PRAMs lend themselves naturally to expressing nesting relationships). This is desirable because plant populations are not homogeneous due to slight variations in genetics among plants in a field. Also, at landscape scale, farmers do not all behave in the same way. Management practices vary, such as selection of crop and variety, planting date, fertilizer types and amounts, and so on. Also, on a temporal scale, any given farmer may decide to change these same variables from year to year based on past experience, ENSO phase (El Niño or La Niña), or what they saw their neighbor doing last season.

To that end, ABMs and PRAMs will be automatically instantiated with agent behavior mechanics based on causal relationships (and entire models) that INDRA, BICL, and MODX extract from scientific literature, existing agricultural models, and data. For individual agents which correspond to plants, populations of ABMs and PRAMs will be generated based on recorded population sizes (i.e., data) as well as numbers extracted from published research by ModX (e.g., tables). For individual agents which correspond to farmers, populations will be generated according to the most current farm surveys or, if not available, data from the local government involved. In later stages, computer vision ML algorithms will be used to seed the plant and farmer populations based on high-resolution aerial images.

This approach to multi-scale individual-based modeling will allow policy-level "what if" questions pertaining to the food system and social factors be answered via simulation by changing the behavior mechanics of plants, farmers, and their population (e.g., spacial distrubution). That is, a human modeler will customize an Abm or a Pram prepared by Maia via guided semi-automatic process, before handing it off to the AI again for simulation.

Being computationally intensive, large-scale agent-based simulations will run on top of Occam [1], a parallel workflow scheduling and management system [extend this description or refer to another section/study after consulting with Bruce].

References

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