Improving Farm Yield through Agent Based Modeling

Anmol Bharadwaj[1], Dhanya Shaji[2]

[1,2]Student, Galgotias University

Abstract
This paper explores the potential of Agent-Based Modeling (ABM) using NetLogo to enhance farm yield. Traditional approaches to agricultural management often overlook the complexity and interdependencies within farming systems. ABM offers a dynamic and flexible framework to simulate the behaviours of individual agents within a farming ecosystem, enabling a more nuanced understanding of the factors influencing yield. By modeling the interactions between agents such as farmers, crops, pests, weather conditions, and market dynamics, this study aims to identify optimal strategies for improving farm yield while minimizing input costs and environmental impacts. Through experimentation and scenario analysis, various farming practices and policies can be simulated and evaluated in silico, providing valuable insights for real-world decision-making. This interdisciplinary approach integrates concepts from computer science, economics, ecology, and agronomy to develop a holistic understanding of agricultural systems. The findings of this research contribute to the development of sustainable farming practices and policy interventions to address food security challenges in a rapidly changing world.

Keywords: Agent-Based Modeling (ABM), NetLogo, Dynamic modelling, Simulation

1. Introduction
Agriculture plays a critical role in global food security, livelihoods, and environmental sustainability. With the world's population projected to reach 9.7 billion by 2050, the demand for food is expected to increase substantially, placing unprecedented pressure on agricultural systems to enhance productivity while minimizing environmental degradation. Traditional approaches to agricultural management often rely on simplistic models that fail to capture the complex interactions and feedback loops inherent in farming ecosystems. In recent years, however, there has been a growing recognition of the need for more sophisticated tools to understand and optimize farm yield.
Agent-Based Modeling (ABM) has emerged as a powerful approach to address this challenge by simulating the behaviours of individual agents within a system and capturing the emergent properties that arise from their interactions. NetLogo, a widely used platform for ABM, provides a flexible and intuitive framework for modeling complex systems, making it particularly well-suited for studying agricultural dynamics. By representing farmers, crops, pests, weather conditions, and market dynamics as autonomous agents with their own behaviours and decision-making processes, ABM offers a novel approach to understanding the complexities of agricultural systems.
This paper aims to explore the potential of ABM using NetLogo to improve farm yield. By simulating the interactions between agents in a farming ecosystem, we seek to identify optimal strategies for increasing productivity while minimizing input costs and environmental impacts. Through experimentation and

scenario analysis, we can evaluate the effectiveness of different farming practices and policy interventions in enhancing yield and sustainability.

This interdisciplinary approach integrates concepts from computer science, economics, ecology, and agronomy to develop a holistic understanding of agricultural systems. By bridging the gap between theory and practice, ABM has the potential to inform real-world decision-making and contribute to the development of sustainable farming practices and policies. In the following sections, we will discuss the theoretical foundations of ABM, describe the methodology for modeling agricultural systems using NetLogo, and present the results of our simulations, highlighting insights for improving farm yield and addressing food security challenges.

2. Literature Review

Agent-Based Modeling (ABM) has gained popularity in agricultural research due to its ability to capture the complexity of farming systems. This review by Janssen and Ostrom (2006) provides an overview of ABM applications in agriculture, highlighting its potential to simulate the behaviour of individual agents such as farmers, consumers, and policymakers, and its utility in understanding issues such as land use change, natural resource management, and agricultural policy.

NetLogo: A Tool for Modeling Complex Systems: NetLogo, a widely used platform for ABM, offers a user-friendly interface and extensive libraries for modeling complex systems. Wilensky (1999) describes the features and capabilities of NetLogo, emphasizing its suitability for simulating agricultural systems due to its flexibility, scalability, and support for spatial modeling.

Improving Farm Yield through Simulation Modeling: Simulation modeling has been employed to analyse the impact of different factors on farm yield. In their study, Antle and Stoorvogel (2006) use a simulation model to assess the effects of climate change and adaptation strategies on agricultural productivity, highlighting the importance of considering both biophysical and socioeconomic factors in agricultural modeling.

Agent-Based Modeling of Crop-Livestock Systems: Crop-livestock systems are characterized by complex interactions between crops and livestock, as well as between farmers and markets. In their research, Berger et al. (2012) use an ABM approach to simulate the dynamics of crop-livestock systems in developing countries, demonstrating the potential of ABM to inform policy interventions aimed at improving productivity and sustainability.

Market Dynamics and Agricultural Decision-Making: Farmers' decisions are influenced by market dynamics, including prices, demand, and access to inputs. In their study, Balmann et al. (2003) develop an ABM framework to analyse the impact of market uncertainty on farmers' decision-making processes, highlighting the importance of incorporating market dynamics into agricultural models to improve their predictive accuracy.

Policy Interventions for Sustainable Agriculture: ABM has been used to evaluate the effectiveness of different policy interventions in promoting sustainable agriculture. In their research, Cardenas et al. (2011) use an ABM approach to simulate the effects of payment for ecosystem services (PES) schemes on land use decisions and environmental outcomes, demonstrating the potential of ABM to inform policy design and implementation.

Overall, the literature reviewed highlights the potential of ABM, particularly using platforms like NetLogo, to improve our understanding of agricultural systems and inform decision-making aimed at enhancing farm yield, sustainability, and resilience to global challenges such as climate change and food security. However, further research is needed to refine ABM techniques, incorporate additional factors such as social dynamics and institutional arrangements, and validate model outputs against real-world data to enhance their predictive accuracy and utility for policy analysis and implementation.

2.1 Observations

Our agent-based model is informed by a comprehensive review of existing studies, providing a versatile platform for simulating various farming scenarios. Drawing insights from [1] for understanding diverse farming strategies, [2] for incorporating smart farming techniques, and [3] for optimizing irrigation management, our model enables farmers to anticipate risks and refine strategies using data from these sources. This holistic approach enhances crop management, facilitates risk assessment, streamlines decision-making processes, and fosters optimization, ultimately leading to enhanced farm yield and sustainability.

3 Methodology

This section delineates the research methodology utilized in constructing the model, elucidating the process of data collection, development of the agent-based model, and its calibration. Furthermore, it acknowledges the limitations and ethical considerations inherent in the study, laying a robust groundwork for future research endeavours aimed at enhancing farming yield through the utilization of agent-based modeling.

3.1 Agent Based-Model Development

The core of our methodology revolves around constructing an agent-based model tailored to simulate farming practices and their impact on yield. This model captures the intricate interactions among agents such as plants, insects, and farmers, incorporating attributes like disease resistance. Refinement of the code included considerations for factors such as soil fertility, water availability, disease rates, and labour costs. By integrating real-world parameters and user inputs, we ensured that the model reflects authentic farming conditions, calibrated meticulously to align with historical data for accuracy.

3.2 Netlogo

Utilizing NetLogo, a versatile multi-agent simulation software, the project simulates intricate systems comprising multiple agents. NetLogo provides a user-friendly interface, robust modeling capabilities, and flexibility in defining agent behaviours, generating visual representations, and analysing outcomes. The simulation code encompasses agent behaviours, variables, and control flow logic, facilitating comprehensive modeling of the farming ecosystem.

3.3 The Simulation Stages:

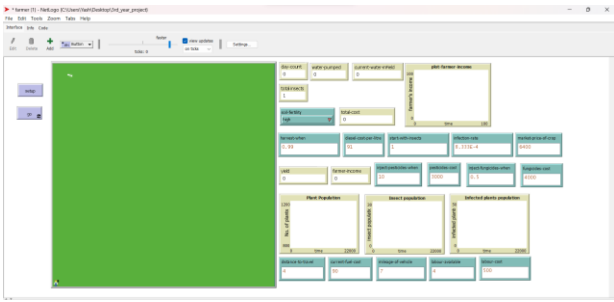


Figure 3.1: Setup of the model

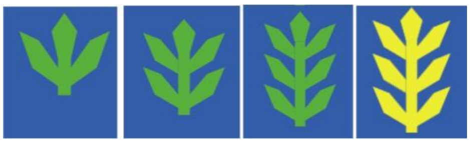
The simulation begins with the setup phase, which initializes various elements to establish the simulation environment. This includes clearing the space and resetting the tick counter. Global variables such as crop growth, disease, and income are initialized, alongside flags and counters that control the simulation. Initial conditions are set to ensure the simulation commences with the desired parameters for agents and environmental settings.

The main loop of the simulation, known as the Go Procedure, advances the simulation by one tick in each iteration. This stage comprises several sub-functions that execute different tasks during each tick.

Daily activities drive the simulation's progression, with procedures triggered as the day count increases. These activities include:

A. **Tracking the day count**: The "day-count" variable records the number of days elapsed in the simulation, incrementing by 1 with each new day. In the simulation, each day corresponds to 132 ticks.
B. **Watering the field:** Patches representing the field are colored blue to symbolize irrigation.
C. **Managing plant growth**: The growth rate influences the appearance and stage of plants. When the growth rate exceeds 0.9, plants turn yellow, indicating they are ready for harvest. Between 0.9 and 0.75, they take on the shape of a mature plant, while between 0.75 and 0.5, they appear as medium-sized plants.

Figure 3.2: Stages of crop growth



D. **Disease Management**: Plants are susceptible to infections determined by the disease rate and their resistance levels. Infected plants exhibit a red hue and experience a decrease in health.
E. **Harvest Verification**: The simulation verifies if the conditions for harvesting have been met. Once the proportion of mature plants exceeds a predefined threshold, indicating readiness for harvest, the plants are harvested. Subsequently, the farmer's income is adjusted based on transportation and labor costs.

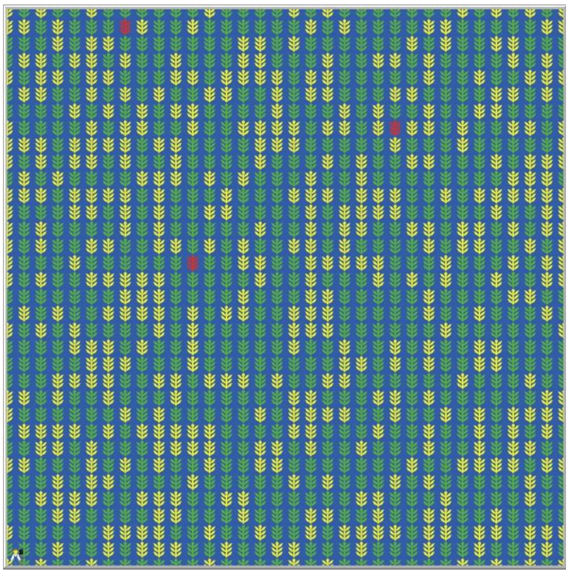


Figure 3.3: Yellow plants representing crops ready for harvest.

3.4 Experiment and Analysis

After model development, experiments were conducted, manipulating variables such as fertilizer applica tion and labor costs to evaluate their impact on crop yield. Various scenarios were devised to analyze the combined effects, focusing on crop productivity, disease occurrence, and farmer income as primary indicators. Results highlighted the positive correlation between fertilizer usage and productivity, as well as the direct impact of labor costs on income.

The flowchart in Figure 3.4 outlines the crop lifecycle within the model. The simulation begins by initializing farmers, patch colors, and insect populations. Plowing is initiated, followed by daily tasks. Watering occurs daily for plowed fields. Transplanting and growth phases are influenced by factors such as disease resistance and soil fertility. Pesticide and fungicide injections are triggered in response to excessive insect presence. Harvesting is contingent upon surviving plants meeting a specified threshold, with failed crops being discarded. Harvested crops undergo transportation, labor, pesticide, and fungicide expenses before being sold.

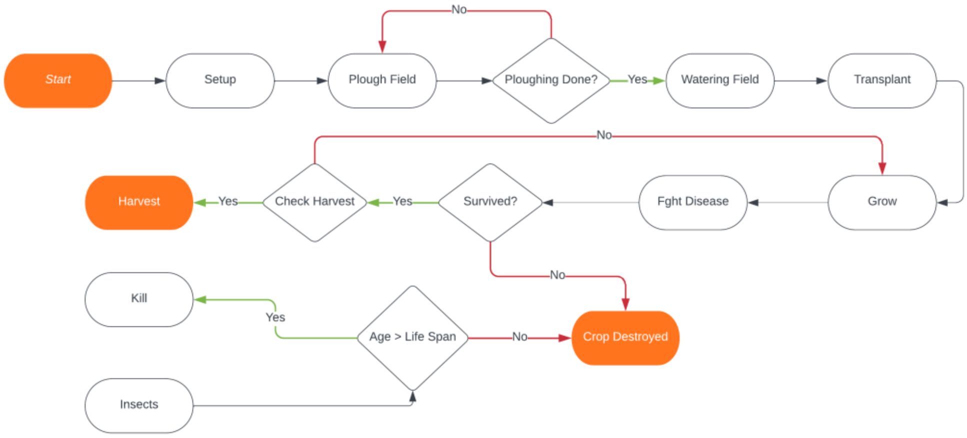


Figure 3.4: Flowchart

3.5 Limitations

The agent-based model simplifies the intricacies of real-world farming systems and may overlook certain complexities inherent in agricultural practices. These simplifications could potentially lead to a lack of fidelity in representing the dynamics of farming operations accurately. Moreover, biases present in the data sources used to inform the model may introduce inaccuracies and limitations in its predictive capabilities.

1. **Simplified Representation**: The agent-based model employed in this study offers a simplified depiction of farming systems, condensing multifaceted processes into discrete actions and variables. This simplification might not fully capture the nuanced interactions and dependencies present in real-world agricultural settings. For instance, the model may overlook factors such as soil heterogeneity, local climate variations, and socio-economic factors that can significantly influence farming outcomes.
2. **Omission of Complexities**: In striving for computational efficiency and model tractability, certain complexities inherent in farming practices might be omitted or oversimplified. For instance, the model may not fully account for the diverse range of crop varieties, pest species, and agronomic practices adopted by farmers in different regions. Such oversights could limit the model's ability to accurately simulate the outcomes of diverse farming scenarios.
3. **Biases in Data Sources**: The accuracy and reliability of the model outputs are contingent upon the quality and representativeness of the data used for calibration and validation. Biases inherent in the data sources, such as sampling biases, measurement errors, or outdated information, could introduce uncertainties and limitations in the model's predictions. For example, if the data used to parameterize

the model predominantly originate from a specific geographical region or farming context, the model's generalizability to other settings may be compromised.

Overall, while agent-based modeling offers valuable insights into the dynamics of farming systems, it is essential to acknowledge and critically evaluate the limitations stemming from model simplifications and data biases. Future research efforts should aim to refine model structures, incorporate additional complexities, and utilize diverse datasets to enhance the robustness and applicability of agricultural simulation models.

4 Implementation and Results

This section delves into the implementation of a project aimed at enhancing farming yield through agent-based modeling, focusing on setup, agent behaviors, labor, labor costs, and crop growth. Additionally, it discusses simulation parameters and the software tools utilized.

4.1 Identifying Variables

Table 4.1 provides a comprehensive overview of the variables and parameters within the agricultural simulation model, encompassing critical aspects such as crop harvesting, yield, water management, disease spread, insect characteristics, and financial considerations including farmer income and fertilizer subsidies.

Variable	Description
harvest-at	Denotes threshold for plants, indicating the stage at which plants are considered ready for harvest. It plays a crucial role in determining the timing of crop harvesting.
yield	It represents the accumulated yield of harvested crops throughout the simulation period. Serves as a key metric for assessing the productivity and efficiency of agricultural practices.
day-count	It tracks the number of days passed within the simulation. It provides temporal context and enables the modeling of time-dependent processes and events.
fertility-factor	It quantifies the fertility level of the soil, categorized into low, medium, and high fertility states. It influences crop growth and productivity, with higher fertility soils typically yielding better results.
water-pumped	It reflects the total amount of water pumped into the field for irrigation purposes. Effective water management is essential for ensuring optimal crop growth and yield.
farmer-income	It represents the financial earnings accrued by farmers through agricultural activities. It

	is influenced by various factors such as crop yield, market prices, and input costs.
current-water-in-Field	It denotes the current amount of water present in the field, providing insight into soil moisture levels and irrigation requirements.
disease-rate-per-day	It signifies the rate at which diseases spread within the crop population. It is a critical factor in assessing disease management strategies and their impact on crop health.
days-since-pesticide and days-since-fungicide	It tracks the number of days elapsed since the last application of pesticide and fungicide, respectively. They help in implementing proper pest and disease control measures while adhering to recommended application intervals.
pesticide-used	It indicates whether a pesticide has been applied in the field, providing information on pest management practices.
ploughing-time and labour-time	It represents the time required for plowing the field and the time allocated to labor for various agricultural tasks, respectively. Efficient labor management is essential for optimizing farm operations.
labour-cost	It denotes the financial expense associated with employing labor for agricultural activities, influencing overall production costs and profitability.
disease-resistance	It quantifies the resistance levels of plants against diseases, informing crop breeding and selection strategies for disease-resistant varieties.
health	This indicates the overall health condition of plants, with higher values representing healthier plants. It is influenced by various factors such as pest and disease pressure, nutrient availability, and environmental conditions.
energy and lifespan	It characterize the energy levels and lifespan of insects, influencing their behavior, population dynamics, and impact on crop health.

government-subsidy	It denotes the subsidy provided by the government on fertilizers, affecting input costs and farmer profitability.

4.2 Results

Fertilizer Quantity Influence: The simulation underscores the significant impact of fertilizer quantity on plant yield. When fertilizer quantity falls below 300kg per hectare, the yield adjustment formula remains at 1, whereas surpassing 300kg triggers a formula adjustment to 2 [5]. While fertilizer cost directly impacts farmer income but not yield, government subsidies positively contribute to farmer income. These economic variables introduce complexity to the agricultural simulation, enriching its predictive capacity.

The formulated adjustments based on fertilizer quantity are as follows:
- For quantities less than 300kg per hectare:
$15.2 \times (\text{fertilizer quantity} - 165)$
- For quantities greater than 300kg per hectare:
$590 \times (\text{fertilizer quantity} - 300)$

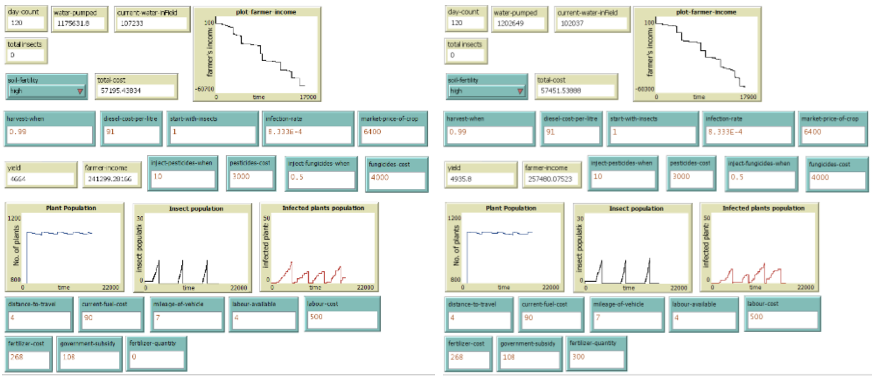


Figure 4.1: (a) Fertilizer boosts yield (b) its absence reduces it.

Soil Fertility Dynamics: Soil fertility emerges as a crucial determinant of crop production. The model incorporates three fertility levels: high, medium, and low. Through Figure 4.2, it becomes apparent that, with all other factors held constant, yield varies and diminishes as fertility transitions from high to low.

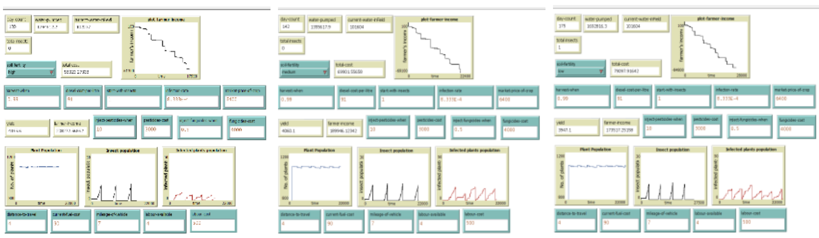


Figure 4.2: Effect of high, medium, low fertility

Insect Population Impact: The population of insects on the farm emerges as a pivotal factor influencing crop production. Figure 4.3 illustrates the discernible difference in yield corresponding to insect population levels. Specifically, higher initial insect counts, as depicted in Figure 4.3(a), correspond to reduced yield, whereas lower initial insect counts, as shown in Figure 4.3(b), align with higher yield outcomes.

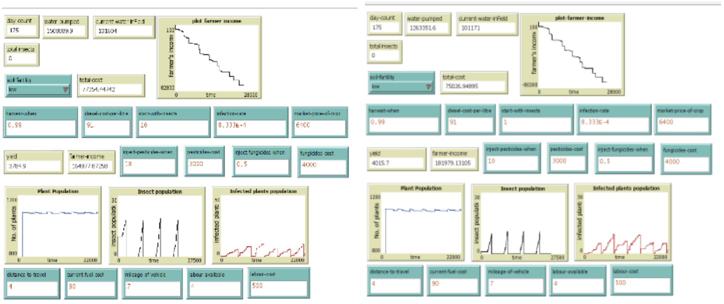


Figure 4.3: (a) High Initial Insect Count; (b) Low Initial Insect Count.

Yield Calculation:

The yield is determined as a function of the plant's health to account for damage inflicted by insects and diseases. In our simulation, each crop represents approximately 20-25 crops in a real farm, with the optimal transplanting distance set at around 22.5cm.

The yield (Y) is calculated using the formula:

$$Y = \frac{\text{health}}{100} \times 4.5$$

If the plant is in optimal health, the yield reaches its maximum potential. The yield is expressed in kilograms, with an average yield of 20 grams per crop. The constant 4.5 is derived from the formula:

$$\text{Yield Constant} = \frac{number\ of\ crops \times yield\ of\ one\ crop \times number\ of\ square\ meters\ in\ one\ patch\ /}{1000\ kg}$$

Substituting the given values:

$$Yield\ Constant\ = \frac{22.5 \times 20\ grams \times 10\ sq.m}{1000\ kg}$$

Thus, the Yield Constant is 4.5.

Total Cost Calculation:

To ensure profitability, it is essential to keep the total cost below the revenue generated. The total cost (TC) is calculated as the sum of various expenses:

$$Total\ cost\ = labour - available\ \times\ labour - cost + \ fungicides - cost\ +\ pesticides - cost + transportation - cost\ +\ water - expenses\ + ploughing - cost$$

The ploughing cost (PC) is determined by the formula:

$$Ploughing - cost\ =\ labour - time\ \times labour - cost \times labour - available$$

These formulas enable us to calculate the yield and total cost accurately, aiding in decision-making processes for optimizing agricultural practices and maximizing profitability.

5. Conclusion

The implementation of a farming yield improvement simulation, integrating various factors such as agent behaviours, labour availability, and labour costs, has provided valuable insights into the dynamics of agricultural systems. By simulating different scenarios and exploring strategies to enhance productivity, this simulation serves as a powerful tool for understanding the complexities of farming, optimizing resource utilization, and maximizing farmer income.

The flexibility of the generic model allows farmers to set or adjust parameter values, enabling tailored solutions to specific agricultural contexts. This empowers farmers to make informed decisions, leading to improved productivity, resource efficiency, and environmental sustainability. Moreover, by incorporating factors such as rainfall patterns in future iterations, the simulation can provide even more accurate and precise results, enhancing its utility for real-world applications.

Overall, the farming yield improvement simulation represents a significant step forward in agricultural modeling, offering practical insights and solutions to address the challenges of feeding a growing global population while minimizing environmental impact. As technology continues to advance and our understanding of agricultural systems deepens, simulations like these will play an increasingly important role in shaping the future of farming, ensuring food security, economic viability, and environmental stewardship for generations to come.

References

1. Antle, J. M., & Stoorvogel, J. J. (2006). Agricultural carbon sequestration, poverty, and sustainability. Environment and Development Economics, 11(4), 435-449.
2. Balmann, A., Happe, K., & Kellermann, K. (2003). Agent-based analysis of agricultural policies: An illustration of the agricultural policy simulator AgriPoliS, its adaptation and behavior. In Agricultural Sector Modeling and Policy Information Systems (pp. 229-247). Springer, Boston, MA.
3. Berger, T., Troost, C., & Bakker, M. (2012). Agent-based modeling of climate adaptation and mitigation options in agriculture. Journal of Agricultural Economics, 63(2), 312-332.
4. Cardenas, J. C., Janssen, M. A., Bousquet, F., Castillo, D., Worrapimphong, K., & An, L. (2011). Participation and commitment in voluntary programs: A multi-level analysis of the Mexican PSA-H Program. Journal of Policy Modeling, 33(2), 187-206.
5. DeAngelis, D. L., & Gross, L. J. (1992). Individual-based models and approaches in ecology: populations, communities and ecosystems. Chapman and Hall.
6. Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., ... & DeAngelis, D. L. (2005). Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science, 310(5750), 987-991.
7. Wilensky, U. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
8. Zeigler, B. P., Praehofer, H., & Kim, T. G. (2000). Theory of modeling and simulation: integrating discrete event and continuous complex dynamic systems. Academic Press.