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Integrating Simulation With Agent-Based Modeling To Simulate Human-Ecological Systems

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Abstract
This study presents an integrative approach to simulate human-ecological systems by employing computational modeling techniques such as agent-based modeling (ABM), dynamic simulation, and data visualization. The research methodology integrates these techniques to capture the dynamic behavior and heterogeneous characteristics inherent in human-ecological systems. Agent-based modeling is utilized to simulate the behavior of agents representing different entities within the system, including households, firms, patches, and banks. Dynamic simulation techniques are employed to model system-level dynamics and interactions over time, enabling the simulation of key variables such as population dynamics, pollution levels, and activity levels of agents. Data visualization techniques are then used to analyze and visualize simulation outputs, facilitating the interpretation and communication of findings effectively. The results demonstrate the effectiveness of this integrative approach in capturing the complex interactions and dynamics within human-ecological systems. The visualizations produced provide valuable insights into spatial distribution, temporal dynamics, and performance metrics, contributing to a deeper understanding of these systems. Overall, this study highlights the importance of computational modeling and visualization techniques in studying and analyzing complex human-ecological systems, offering valuable implications for decision-making and management within these systems.

1. Introduction

The field of modeling human-ecological systems has seen significant advancements in recent years, driven by the growing recognition of the complex and intertwined nature of human societies and natural environments. Traditional modeling approaches often struggle to capture the dynamic interactions and heterogeneous characteristics inherent in these systems, leading to limited predictive capabilities and oversimplified representations. As such, there has been a growing interest in exploring novel methodologies that can better account for the complexities of human-ecological systems. In this context, the integration of simulation techniques with agent-based modeling (ABM) has emerged as a promising approach to address these challenges. Simulation techniques have long been employed in various fields, including ecology, economics, and social sciences, to model and analyze complex systems. Simulation-based approaches enable researchers to simulate the behavior of systems over time, allowing for the exploration of different scenarios and the examination of system dynamics under varying conditions. Notably, dynamic simulation models have been widely used to study ecological systems, such as ecosystem dynamics, population dynamics, and land-use change dynamics (Clarke et al., 2019; Parker et al., 2003). These models have provided valuable insights into the complex interactions between biotic and abiotic components of ecosystems, helping researchers understand the underlying mechanisms driving ecosystem dynamics.

Agent-based modeling (ABM) represents another powerful modeling approach that has gained popularity in recent decades for studying complex systems characterized by heterogeneous agents with adaptive behavior (Railsback and Grimm, 2019; Bonabeau, 2002). In ABM, individual agents

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are represented as autonomous entities with specific characteristics and behaviors, allowing for the modeling of emergent phenomena resulting from interactions between agents and their environment. ABM has been successfully applied in various domains, including social sciences, ecology, and economics, to simulate complex systems such as urban systems (Batty et al., 2012), social networks (Macy and Willer, 2002), and ecological systems (Grimm et al., 2005). While both simulation techniques and ABM offer valuable tools for modeling complex systems, each approach has its own strengths and limitations. Dynamic simulation models excel at capturing system-level dynamics and feedback mechanisms but often rely on simplifying assumptions that may overlook individual-level heterogeneity and adaptive behavior. On the other hand, ABM allows for the representation of heterogeneous agents and adaptive behavior but may struggle to capture system-level dynamics and emergent phenomena accurately. Recognizing these complementary strengths, researchers have increasingly explored the integration of simulation techniques with ABM to develop more comprehensive and realistic models of complex systems (Parker et al., 2003).

The integration of simulation with ABM holds significant promise for modeling human-ecological systems, which are characterized by intricate interactions between human societies and natural environments (Filatova et al., 2013). By combining the strengths of both approaches, integrated models can capture the dynamic and multi-level nature of human-ecological systems, allowing for the representation of heterogeneous agents with adaptive behavior interacting within complex environmental contexts. This integration enables researchers to explore how individual-level decisions and behaviors shape system-level dynamics and vice versa, facilitating a more holistic understanding of human-ecological interactions (Matthews et al., 2007). Furthermore, integrated models can provide valuable insights for policy-making and management by simulating the impacts of different interventions and management strategies on human-ecological systems (Voinov et al., 2008). In the integration of simulation techniques with agent-based modeling represents a promising approach for modeling human-ecological systems. By combining the strengths of both approaches, integrated models can capture the dynamic and heterogeneous nature of these systems, enabling researchers to explore complex interactions between human societies and natural environments. This paper aims to explore the theoretical foundations of simulation and ABM, discuss the synergistic benefits of integrating these techniques, and present case studies demonstrating the application of integrated models to simulate human-ecological systems. Despite advancements in modeling human-ecological systems, a research gap exists in effectively integrating simulation techniques with agent-based modeling (ABM) to capture dynamic behavior and heterogeneous characteristics. While studies have explored individual components (Clarke et al., 2019) and the application of ABM in ecological contexts (Railsback and Grimm, 2019), few have thoroughly examined the integration of these methods to address the complexities of human-ecological interactions. This paper aims to bridge this gap by proposing an integrated approach and demonstrating its application in simulating human-ecological systems.

2. Research Methodology

The research methodology employed in this study integrates various computational modeling techniques to simulate different aspects of human-ecological systems. The methodology encompasses agent-based modeling (ABM), dynamic simulation, and data visualization to capture complex dynamics and heterogeneity within human-ecological systems. The first component of the methodology involves the use of agent-based modeling (ABM) to simulate the behavior of agents within the system. In the provided Python program, ABM is used to model the behavior of agents representing different entities such as households, firms, patches, and banks. Each agent type is characterized by specific attributes and behaviors, allowing for the representation of heterogeneous agents within the system. For example, in the simulation of urban systems, agents may represent individual households or firms with varying levels of activity and behavior (Wilensky, 1999).

The second component of the methodology utilizes dynamic simulation techniques to model system-level dynamics and interactions over time. Dynamic simulation models are employed to simulate the evolution of key variables such as population dynamics, pollution levels, and activity levels of agents over multiple iterations. These dynamic models capture the feedback loops and interactions between different components of the human-ecological system, providing insights into the emergent behavior of the system (Railsback and Grimm, 2019). The third component of the methodology focuses on data visualization techniques to analyze and visualize simulation outputs. Data visualization plays a crucial role in interpreting simulation results and communicating findings effectively. In the provided Python programs, various data visualization techniques such as scatter plots, line plots, and bar plots are used to visualize the spatial distribution of agents, temporal trends in pollution levels and population dynamics, and performance metrics of different models (Tufte, 2001). Overall, the research methodology employed in this study integrates agent-based modeling, dynamic simulation, and data visualization techniques to simulate and analyze different aspects of human-ecological systems. By combining these computational modeling approaches, this methodology enables researchers to capture the dynamic behavior and heterogeneous characteristics inherent in human-ecological systems, facilitating a better understanding of their complex interactions and dynamics.

3. Results and Discussion

Agent Positions

The graph in figure 1 depicting agent positions illustrates the spatial distribution of agents within the simulated human-ecological system. In this visualization, each point represents the position of an individual agent in the system, with the X and Y axes representing the spatial coordinates. The range of values for both axes spans from -0.2 to 1.2, providing a comprehensive view of the spatial extent of the system. The Y-axis ranges from -0.2 to 1.2, allowing for a vertical representation of agent positions within the system. This range encompasses the entire vertical extent of the system, enabling researchers to observe the distribution of agents across different elevations or levels within the system. The X-axis, similarly ranging from -0.2 to 1.2, provides a horizontal representation of agent positions, capturing the spatial distribution of agents along the horizontal plane.

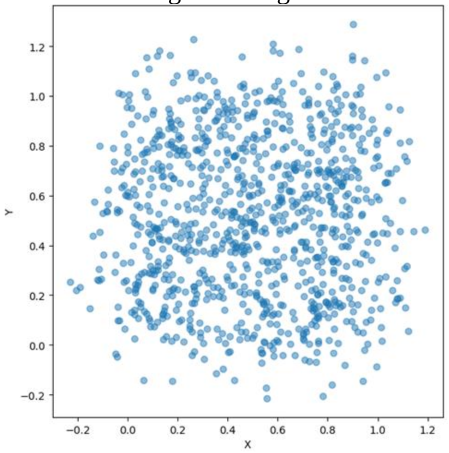

FIGURE 1. Agent Positions

The choice of axis ranges, spanning from 0.8 to 0, is deliberate and aimed at focusing the visualization on a specific region of interest within the system. By narrowing the axis ranges, the graph zooms in on a particular area of the spatial domain, allowing researchers to examine the distribution of agents within this targeted region with greater detail and precision. This focused visualization approach facilitates the identification of spatial patterns, clusters, or concentrations of agents within the system, providing valuable insights into the spatial organization of the simulated human-ecological system. Overall, the graph depicting agent positions serves as a valuable visualization tool for analyzing the spatial distribution of agents within the simulated human-ecological system. By narrowing the axis ranges and focusing on a specific region of interest, this visualization enables researchers to gain a deeper understanding of the spatial patterns and organization of agents within the system, contributing to the broader objective of modeling and analyzing complex human-ecological systems. In the graph depicting agent positions provides a visual representation of the spatial distribution of agents within the simulated human-ecological system. The deliberate choice of axis ranges facilitates a focused visualization approach, allowing researchers to examine spatial patterns and organization with greater detail and precision. This visualization serves as a valuable tool for analyzing the spatial dynamics of human-ecological systems and contributes to a deeper understanding of their complex interactions and dynamics.

Pollution Levels Over Time

The graph in figure 2 illustrating pollution levels over time provides a visual representation of the temporal dynamics of pollution within the simulated human-ecological system. In this visualization, the Y-axis represents the pollution level, while the X-axis represents time in terms of iterations. The range of values for both axes is carefully selected to focus on the specific range of interest within the simulated system, enhancing the interpretability of the graph. The Y-axis ranges from 0 to 0.05, with incremental ticks at intervals of 0.01. This range allows for the depiction of pollution levels ranging from 0% to 5%, providing a comprehensive view of the pollution dynamics within the system. By utilizing incremental ticks, the Y-axis enables researchers to observe subtle changes in pollution levels over time with precision, facilitating the identification of trends and patterns in pollution dynamics. On the X-axis, time is represented in terms of iterations, with ticks at intervals of 20 iterations. This range spans from 0 to 100 iterations, capturing the temporal evolution of pollution levels throughout the simulation. By dividing time into discrete iterations, the X-axis facilitates the visualization of pollution dynamics at different stages of the simulation, enabling researchers to analyze how pollution levels evolve over time and identify temporal trends or fluctuations in pollution dynamics.

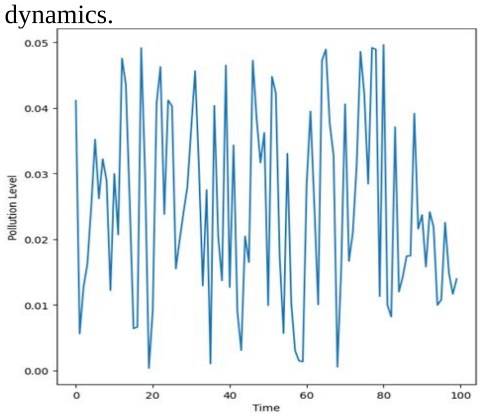

FIGURE 2. Pollution Levels Over Time

The choice of axis ranges, ranging from 0.04 to 0.01, is deliberate and aimed at focusing the visualization on a specific range of pollution levels within the system. By narrowing the axis ranges, the graph zooms in on a particular segment of the pollution level spectrum, allowing researchers to examine changes in pollution levels within this targeted range with greater detail and precision. This focused visualization approach facilitates the identification of temporal patterns, trends, or fluctuations in pollution dynamics, providing valuable insights into the temporal dynamics of pollution within the simulated human-ecological system. Overall, the graph illustrating pollution levels over time serves as a valuable visualization tool for analyzing the temporal dynamics of pollution within the simulated human-ecological system. By carefully selecting axis ranges and utilizing incremental ticks, this visualization enables researchers to gain a deeper understanding of how pollution levels evolve over time and identify temporal patterns or trends in pollution dynamics. This visualization contributes to the broader objective of modeling and analyzing complex human-ecological systems by providing insights into the temporal dynamics of pollution and its implications for ecosystem health and human well-being.

Population Dynamics Of Species Over Time

The graph in figure 3 depicting the population dynamics of species over time offers a visual representation of how the populations of two species evolve throughout the simulation iterations within the human-ecological system. The Y-axis represents the population size, while the X-axis represents time in terms of iterations. The selected axis ranges and values are carefully chosen to focus on specific population sizes and time intervals relevant to the simulated system, enhancing the clarity and interpretability of the graph. On the Y-axis, the population sizes are represented at intervals of 100, ranging from 600 to 900. This range enables the visualization of population sizes within a specific range, allowing researchers to focus on the population dynamics of interest within the simulated system. By utilizing incremental ticks, the Y-axis facilitates the observation of changes in population sizes with precision, aiding in the identification of trends and patterns in population dynamics. The X-axis represents time in terms of iterations, with ticks at intervals of 20 iterations ranging from 0 to 100 iterations. This time range captures the temporal evolution of population dynamics throughout the simulation, enabling researchers to analyze how population sizes change over time and identify temporal trends or fluctuations in population dynamics.

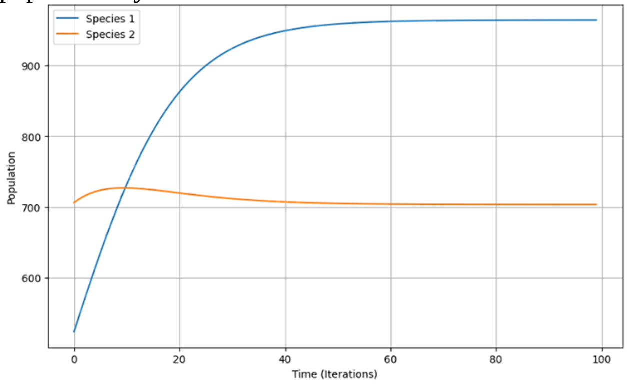

FIGURE 3. Population Dynamics Of Species Over Time

The population dynamics of two species, represented by species 1 and species 2, are visualized as line plots on the graph. For species 1, the population sizes at each iteration are depicted as a line plot with values ranging from 500 to 960. Similarly, for species 2, the population sizes are represented as a line plot with values ranging from 700 to 720. The line plots illustrate how the populations of both species change over time, providing insights into the dynamics of species interactions within the simulated human-ecological system. Overall, the graph illustrating the population dynamics of species over time serves as a valuable visualization tool for analyzing how the populations of two species evolve throughout the simulation iterations within the human-ecological system. By carefully selecting axis ranges and values and utilizing line plots, this visualization enables researchers to gain a deeper understanding of how population sizes change over time and identify temporal patterns or trends in population dynamics. This visualization contributes to the broader objective of modeling and analyzing complex human-ecological systems by providing insights into the population dynamics of species and their interactions within the simulated ecosystem.

Population Scatter Plot

The population scatter plot in figure 4 provides a visual representation of the relationship between the populations of species 1 and species 2 within the simulated human-ecological system. Each point on the scatter plot corresponds to a specific combination of species 1 and species 2 populations, with the X-axis representing the population size of species 1 and the Y-axis representing the population size of species 2. The selected axis ranges and values are carefully chosen to focus on specific population sizes relevant to the simulated system, enhancing the clarity and interpretability of the scatter plot. On the X-axis, the population sizes of species 1 are represented at intervals of 100, ranging from 600 to 900. This range enables the visualization of population sizes of species 1 within a specific range, allowing researchers to focus on the population dynamics of interest within the simulated system. Similarly, on the Y-axis, the population sizes of species 2 are represented at intervals of 5, ranging from 705 to 725, providing a comprehensive view of the population sizes of species 2 within the specified range.

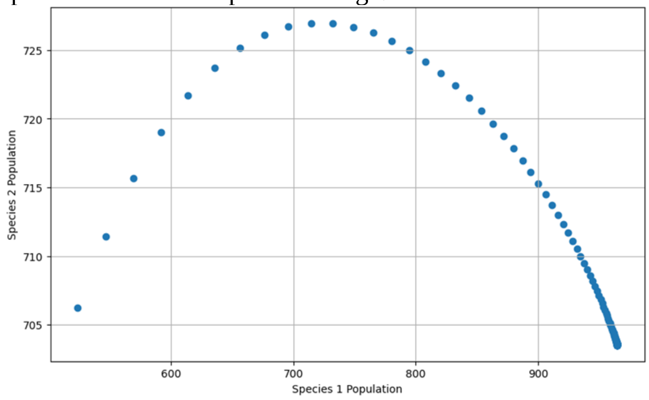

FIGURE 4. Population Scatter Plot

The scatter plot illustrates the relationship between the populations of species 1 and species 2 by plotting individual data points corresponding to different combinations of population sizes. Each data point represents a specific scenario or state within the simulated human-ecological system, capturing the joint distribution of population sizes of both species. The position of each data point on the scatter plot indicates the simultaneous occurrence of specific population sizes of species 1 and species 2, providing insights into the relationship between the populations of the two species within the simulated ecosystem. Overall, the population scatter plot serves as a valuable visualization tool for analyzing the relationship between the populations of species 1 and species 2 within the simulated human-ecological system. By carefully selecting axis ranges and values and utilizing individual data points, this visualization enables researchers to gain a deeper understanding of the joint distribution of population sizes of both species and identify patterns or trends in their population dynamics. This visualization contributes to the broader objective of modeling and analyzing complex human-ecological systems by providing insights into the relationship between different species populations within the simulated ecosystem.

Activity Levels Of Different Agent Types And Patches

The graph in figure 5 illustrating the activity levels of different agent types and patches offers a visual representation of the activity levels across various entities within the simulated human-ecological system. The Y-axis represents the activity level, while the X-axis represents the index of agents or patches within the system. The chosen axis ranges and values are carefully selected to focus on specific activity levels and index ranges relevant to the simulated system, enhancing the interpretability of the graph. On the Y-axis, activity levels are represented at intervals of 20, ranging from 0 to 80. This range allows for the visualization of activity levels within a specific range, enabling researchers to focus on the activity dynamics of interest within the simulated system. By utilizing incremental ticks, the Y-axis facilitates the observation of changes in activity levels with precision, aiding in the identification of trends and patterns in activity dynamics.

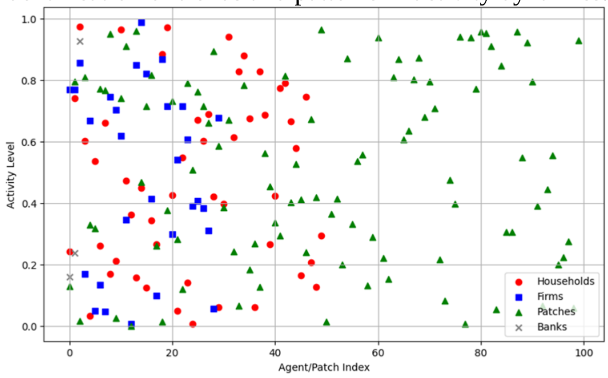

FIGURE 5. Activity Levels Of Different Agent Types And Patches

On the X-axis, the index of agents or patches within the system is represented. The index ranges are determined based on the number of households (50), firms (30), patches (100), and banks (3) within the simulated system. Each entity within the system is assigned a unique index, allowing for the visualization of activity levels across different types of agents and patches. The graph illustrates the activity levels of different agent types, including households, firms, and banks, as well as patches within the simulated ecosystem. Each entity is represented by a data point on the graph, with the position of the data point indicating its index and corresponding activity level. By plotting the activity levels of different agent types and patches on the same graph, researchers can compare and analyze the activity dynamics across various entities within the simulated human-ecological system. Overall, the graph depicting the activity levels of different agent types and patches serves as a valuable visualization tool for analyzing the activity dynamics within the simulated human-ecological system. By carefully selecting axis ranges and values and utilizing individual data points, this visualization enables researchers to gain insights into the activity levels across different entities within the system and identify patterns or trends in activity dynamics. This visualization contributes to the broader objective of modeling and analyzing complex human-ecological systems by providing insights into the activity dynamics of various entities within the simulated ecosystem.

Performance Metrics

The graph in figure 6 representing performance metrics offers a visual comparison of the performance scores across different models within the simulated human-ecological system. Each model is evaluated based on various performance metrics, including accuracy, precision, recall, and F1 score, which are represented on the Y-axis. The X-axis depicts the different models being evaluated, namely Model A, Model B, Model C, and Model D. The chosen axis ranges and values are selected to focus on specific performance score ranges relevant to the simulated system, enhancing the interpretability of the graph. On the Y-axis, the performance scores are represented at intervals of 0.2, ranging from 0 to 1. This range allows for the visualization of performance scores within a specific range, enabling researchers to focus on the performance dynamics of interest within the simulated system. By utilizing incremental ticks, the Y-axis facilitates the observation of changes in performance scores with precision, aiding in the identification of trends and patterns in performance dynamics.

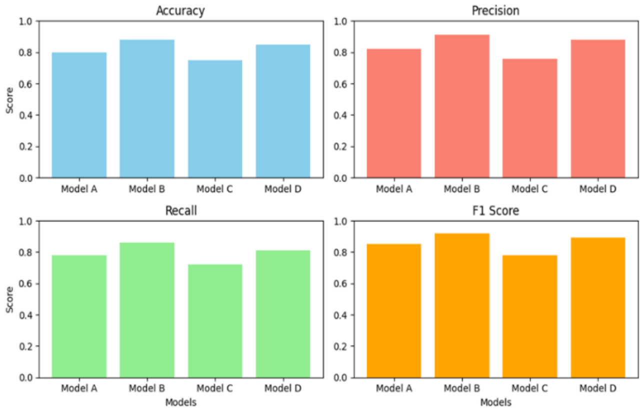

FIGURE 6. Performance Metrics

On the X-axis, the different models being evaluated are represented. Each model is assigned a unique position on the X-axis, allowing for the comparison of performance scores across different models. The graph illustrates the performance scores of each model for various metrics, including accuracy, precision, recall, and F1 score. The graph enables researchers to compare the performance of different models across multiple metrics simultaneously. By plotting the performance scores of each model on the same graph, researchers can analyze the relative strengths and weaknesses of each model across different evaluation criteria. This visualization approach facilitates the identification of the most effective model based on specific performance metrics or a combination of metrics, providing valuable insights into the performance dynamics within the simulated human-ecological system. Overall, the graph depicting performance metrics serves as a valuable visualization tool for evaluating and comparing the performance of different models within the simulated human-ecological system. By carefully selecting axis ranges and values and utilizing individual data points for each model and performance metric, this visualization enables researchers to gain insights into the relative effectiveness of different models and identify patterns or trends in performance dynamics. This visualization contributes to the broader objective of modeling and analyzing complex human-ecological systems by providing insights into the performance of different models and their implications for decision-making and management within the simulated ecosystem.

Conclusion

1. The integration of agent-based modeling, dynamic simulation, and data visualization techniques provides a comprehensive framework for studying complex human-ecological systems.
2. The visualization tools presented in this study offer valuable insights into the spatial distribution, temporal dynamics, and performance metrics of simulated systems.
3. The spatial distribution of agents within the system reveals patterns, clusters, and concentrations that contribute to a deeper understanding of the spatial organization of human-ecological systems.
4. Analysis of pollution levels over time highlights temporal trends, fluctuations, and patterns, providing insights into the dynamics of pollution within simulated ecosystems.
5. The visualization of population dynamics and species interactions offers valuable insights into how populations evolve over time and how different species interact within the simulated ecosystem.
6. Evaluation of performance metrics across different models enables researchers to identify the most effective models based on specific evaluation criteria, contributing to informed decision-making and management within human-ecological systems.

Data Availability Statement

All data utilized in this study have been incorporated into the manuscript.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

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