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Biological reinforcement learning simulation for natural enemy -host behavior: Exploring deep learning algorithms for population dynamics

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A R T I C L E I N F O

Method name:
Artificial intelligence for biological control

Keywords:
Artificial intelligence
Biological control
Pest-natural enemies
Interaction

A B S T R A C T

This study introduces a simulation of biological reinforcement learning to explore the behavior of natural enemies in the presence of host pests, aiming to analyze the population dynamics between natural enemies and insect pests within an ecological context. The simulation leverages on Q-learning, a reinforcement learning algorithm, to model the decision-making processes of both parasitoids/predators and pests, thereby assessing the impact of varying parasitism and predation rates on pest population growth. Simulation parameters, such as episode count, duration in months, steps, learning rate, and discount factor, were set arbitrarily. Environmental and reward matrices, representing climatic conditions, crop availability, and the rewards for different actions, were established for each month. Initial Q-tables for parasitoids/predators and pests, along with population arrays, were used to track population dynamics.

- The simulation, illustrated through the Aphid-Ladybird beetle interaction case study over multiple episodes, includes a sensitivity analysis to evaluate the effects of different predation rates.
- Findings reveal detailed population dynamics, phase relationships between predator and pest populations, and the significant influence of predation rates.
- These insights contribute to a deeper understanding of ecological systems and inform potential pest management strategies.

Specifications table
This table provides general information on your method.

Subject area:	Environmental Sciences
More specific subject area:	Biological control of pest using natural enemies
Name of your method:	Artificial intelligence for biological control
Name and reference of original method:	Minsky, M. 1954, Theory of Neural-Analog Reinforcement Systems and Its Application to the Brain-Model Problem, PhD thesis, Princeton University
Resource availability:	https://github.com/komimensah/Komi_RL

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Background

Deep learning algorithms are subset of machine learning algorithms that utilize neural networks with multiple layers [1]. The field of deep learning has revolutionized various domains, ranging from computer vision to processing and synthesis of natural language [2]. Reinforcement learning (RL) is one of the deep learning algorithms, primarily been employed for tasks involving pattern recognition and decision-making in complex data-driven environments [3]. However, there is a growing interest in exploring the applicability of these algorithms beyond traditional data-centric scenarios. The study of Frankenhuis et al. [4] affirmed the benefits of RL in the field of behavioural ecology and how RL methods using biological mechanisms are applicable to solve problems associated with development and learning processes in organisms. These algorithms have the capability to capture complex patterns and relationships from large datasets, making them well-suited for modelling the dynamics of ecological systems and they have shown great promise in simulating and studying population dynamics [5]. Reinforcement Learning algorithms are adept at identifying and learning from complex patterns within large datasets, which is essential for modeling the intricate and dynamic interactions between pests and their natural enemies in ecological systems. RL excels in environments where decision-making processes must adapt to changing conditions, making it suitable for simulating the adaptive strategies of natural enemies and pests in response to environmental changes and interventions. Its ability to model population fluctuations and interactions within ecological systems makes RL an ideal tool for developing more accurate and effective pest management strategies, thus enhancing our understanding and control of these complex biological processes.

This paper aims to investigate the potential of deep learning algorithms, specifically RL, in studying population dynamics of organisms, focusing on the behaviour of natural enemy (parasitoids, predators, etc.), a class of insects that exhibit unique biological interactions with their hosts, making them a subject of interest for ecological research and pest management strategies [6]. Adult females parasitoid usually oviposit inside or on the immature stage (either egg or larvae) of the host organism, and the developed larvae feed and annihilate the host over time [7]. Herbivore densities and parasitoid parasitism rates have a major impact on the dynamics of interaction between a pest and its natural enemy [8]. Parasitoids influence population dynamics of pest herbivores and have the potential to control pest populations effectively [9]. In other hand, insect predators primarily feeds on other insects or arthropods as their main source of food. Their behaviors encompass a wide range of actions and strategies employed by these creatures to locate, capture, subdue, and consume their prey [10]. These behaviors are shaped by the predator's evolutionary adaptations and the specific ecological niches they occupy. Understanding the behavioural patterns and decision-making processes of natural enemies is essential for predicting their interactions with hosts, identifying factors influencing their population dynamics, and developing effective pest management strategies. Studying these aspects can help in devising sustainable and targeted approaches to control or manage pest populations while minimizing ecological impact.

Traditionally, studies on population dynamics of insects have relied on mathematical models, and statistical approaches that capture the interactions between different life stages and environmental factors [11,12]. Although these approaches provide valuable insights into the ecological processes governing the interactions between natural enemies and their hosts, they often fall short in capturing the complexity and adaptability of these organisms within dynamic environments. For instance, in contrary to traditional models, RL could be employed to model interactions between insect populations and their environment, taking into account the influence of environmental factors, such as temperature, humidity, and resource availability, on population dynamics [13] and guide the optimization of resource allocation decisions, such as allocating monitoring efforts between different pest populations or determining the allocation of limited resources for pest control [14]. Population dynamics play a pivotal role in the stability and functioning of ecosystems. The fluctuations in population size and composition over time are influenced by various factors, including environmental conditions, resource availability, and the interactions between species [15]. Studying and predicting population dynamics in natural enemy-host systems is a complex task due to the inherent complexity of ecological interactions and the nonlinear nature of population dynamics.

On the other hand, while RL presents a promising approach due to its data-driven nature, noise elimination is fundamental. Datasets derived from natural environments can contain significant noise due to measurement errors, environmental variability, and other factors. Therefore, before applying the developed RL methodology, it is crucial to implement noise elimination techniques to ensure the accuracy and reliability of the predictions in real-world applications. This step is essential to fully harness the potential of RL in modeling insect population dynamics and optimizing pest management strategies.

To explore the potential of deep learning algorithms for population dynamics of natural enemies, this study proposes a biological reinforcement learning simulation. The simulation incorporates reward, climatic, and crop availability matrices, creating a dynamic environment that mimics real-world conditions. By employing RL techniques, the simulation enables the predators to learn and adapt their actions based on observed rewards, leading to population-level consequences.

The research question addressed in this study is whether deep learning algorithms, such as RL, can be effectively applied to model and analyze the population dynamics of parasitoids. Specifically, the investigation focuses on how RL algorithms can learn and optimize natural enemy-pest behaviour based on feedback from the environment, which includes rewards, climatic conditions, and crop availability.

Method details

The study presents one of the first attempts to apply a biological reinforcement learning model to simulate the interactions between a pest and its natural enemy. The methodology involves artificially creating a simulated environment with generated environmental variables where both organisms live and interact for resource competition. The methodology is broadly divided into three main stages:

Table 1
Stages of biological reinforcement learning model to simulate the interactions between a pest and a natural enemy.

Stage 1: Initialization of the Environment	Stage 2: Simulation Execution	Data Collection and Analysis
• The simulation runs for n episodes or iterations (numEpisodes). Each episode simulates n months (numMonths), and each month contains a maximum of n days (numSteps). • Two Q-tables are initialized for the natural enemy and pest respectively, each with n states (numStates) and n actions (numActions). • Reward and environmental matrices for each month are created. These matrices include climatic conditions and crop availability, which are randomly generated for the purpose of this study. • Population arrays for the parasitoid and pest are initialized to zeros. They will be updated as the simulation runs. • A sensitivity analysis parameter, the parasitism rate, is defined as values between the minimum and maximum predation rate of the natural enemies.	• **Stage 2: Simulation Execution** • **Initialize Simulation Parameters:** • Set the number of episodes E, the number of months M per year (12), and the number of days D per month (30 or 31). • Initialize Q-tables for both the natural enemy (parasitoid) and the pest. • **Episode Loop:** • For each episode e (from 1 to E): • **Monthly Loop:** • For each month mm (from 1 to M): • **Daily Loop:** • For each day dd (from 1 to D): • **Action Selection:** • The parasitoid and pest independently choose actions Ap and Ae respectively, using the epsilon-greedy policy. • **Time Complexity:** O(1) for each agent per day. • **State Transition:** • Determine the next state based on the chosen actions and the current state. • **Time Complexity: O(1).** • **Reward Calculation:** • Calculate rewards based on current climatic and crop conditions. • **Time Complexity:** O(1). • **Q-Table Update:** • Update the Q-tables for the natural enemy and pest using the observed rewards and the predicted future rewards from the new state. • **Time Complexity:** O(1) for each Q-table update. • **Population Update:** • Update the populations of the natural enemy and pest based on the parasitism rate, and the defined growth and death rates. • **Time Complexity:** O(1). • **Simulation Output:** • After all episodes are completed, aggregate and analyze the results to evaluate the performance and dynamics observed in the simulation. • Generate visualizations and summaries of the population dynamics and other key metrics. • **Overall Time Complexity for Each Episode:** O(M·D·(Ap+Ae)) • **Total Time Complexity for All Episodes:** O(E·M·D·(Ap+Ae)) • Since M and D are constants (12 and 30/31 respectively), the time complexity simplifies to: O(E·(Ap+Ae))	• The population results for each episode are stored for the sensitivity analysis. • After all episodes, the average population results for each parasitism rate are calculated. • The population dynamics of the parasitoid and pest over time are plotted. • A phase plot is created to visualize the relationship between the natural enemy's population and the pest population. • Sensitivity analysis results are presented as surface plots to show how the natural enemy and pest populations change over time with different parasitism rates.

The first stage consists of the initialization of the environment. This stage involves defining the basic parameters and structures that will guide the interactions of the organisms. The second stage consists of executing the simulation. The stage involves running several iterations of the simulation and automatically updating the behaviors of the system *i.e.*, the populations of the pest vis a vis of the parasitoid based on predefined rules. The third stage consists of data collection and analysis that involves collecting and analyzing the resulting data, including population dynamics and sensitivity analysis. The details methodology is presented in Table 1.

The directed graph presented in Fig. 1 shows the comprehensive methodology used in the study. The node represents every stage in the methodology, while each edge shows the transition from one stage to another. The graph begins with 'Parameter Initialization' and ends with 'Sensitivity Analysis', highlighting the iterative nature of the methodology and the feedback loops that it contained. Each node is colored for ease of identification and a better understanding of the process.

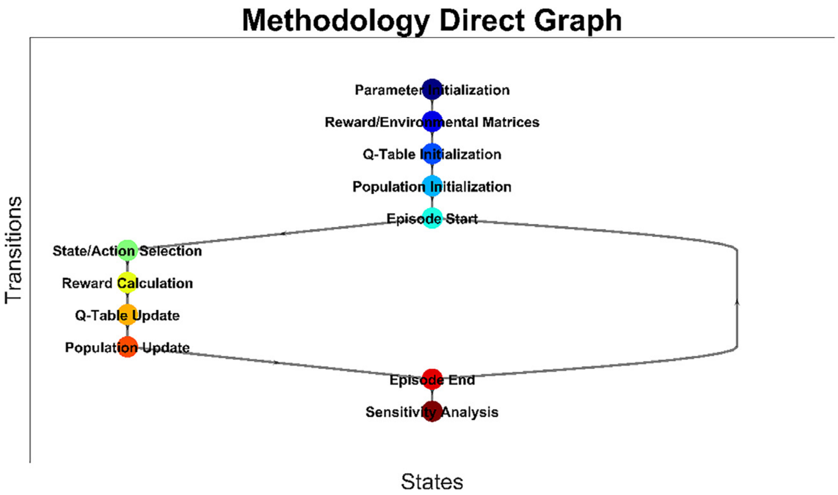

Fig. 1. Methodology direct graph.

Method validation

In this simulation, we use a simplified environment with assumed parameters where aphids and ladybird beetles interact over a year, with monthly time steps. The goal is to train the predator (representing the ladybird beetles) to learn optimal actions that lead to effective aphid population control. In the Biological RL simulation for a natural enemy-pest behavior, we analyzed the dynamics of populations for both the predator and the pest, as well as their sensitivity to changes in predation rate. These results provide a detailed understanding of the population dynamics and sensitivity of parasitoids and pests under varying environmental conditions. The graphical results are presented in Fig. 2 with details in Table 2.

Limitations

The outcome of this research has significant implications for pest management strategies and ecological studies. By gaining insights into the decision-making processes of predators, researchers and practitioners can develop targeted interventions to control pest

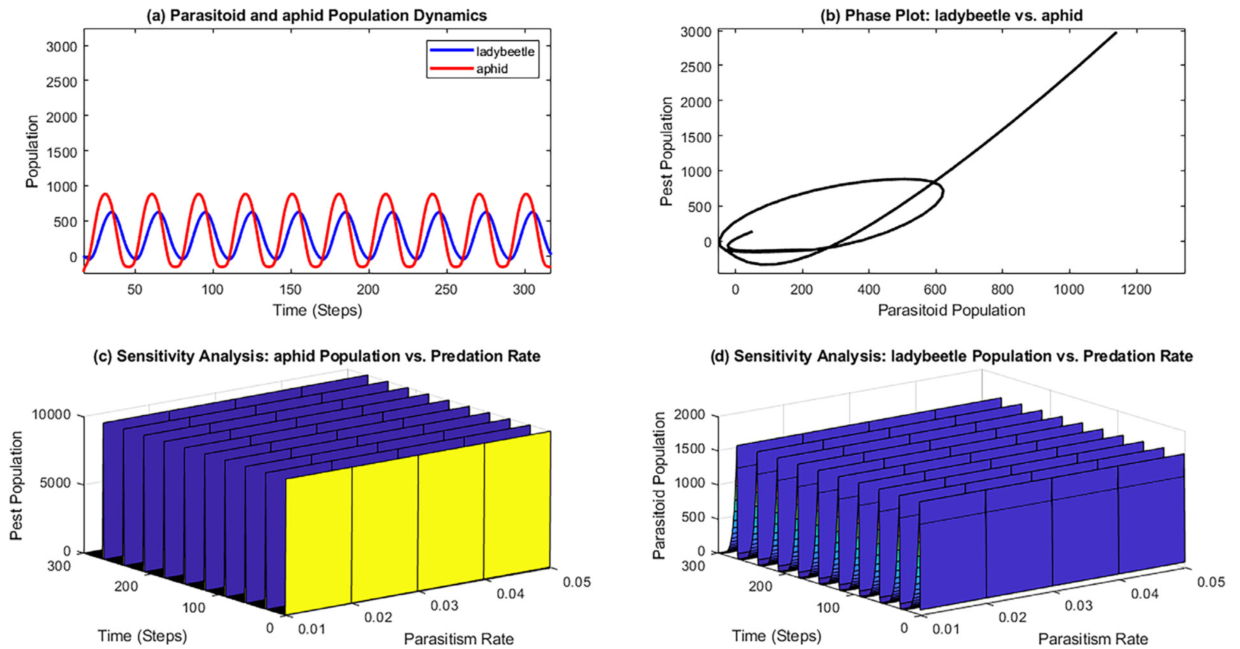

Fig. 2. Biological reinforcement learning simulation for natural enemy -host behavior: the dynamics of populations and phase plot for both the parasitoid and the pest (a) and (b) respectively, as well as their sensitivity to changes in parasitism rate (c), and (d).

Table 2
Results of the simulation.

Natural enemy and pest population dynamics	Phase plot: natural enemy vs. pest	Sensitivity analysis: pest population vs. predation rate	Sensitivity analysis: natural enemy population vs. parasitism Rate
Fig. 2a illustrates the coexistence of the parasitoid and pest populations over a period of 300 steps. The blue curve corresponds to the parasitoid population while the red curve corresponds to the pest population. These curves show an equilibrium observed trend in the populations of natural enemy and pest over time.	Fig. 2b is a phase plot that shows the relationship between the natural enemy population and the pest population. It demonstrates a coexistence relationship between parasitoid and pest populations.	Fig. 2c is a 3D surface plot that presents a sensitivity analysis for the pest population, concerning the natural enemy rate and time. The x-axis represents the varying predation rate, the y-axis represents the time in steps, and the z-axis represents the pest population. The surface plot shows that the proposed approach can be used to describe the observed sensitivity of the pest population to variations in the predation rate.	Fig. 2d, similar to Fig. 2c, represents a 3D surface plot for the sensitivity analysis, but for the natural enemy population. The plot demonstrates that can be used to describe the observed sensitivity of the natural enemy population to variations in the parasitism rate.

populations while minimizing the use of harmful pesticides. Additionally, this study contributes to the growing body of knowledge on the applicability of deep learning algorithms beyond traditional data-centric tasks. However, further research is needed to refine the simulation model, incorporate real-world data, and validate the findings in field experiments. By pursuing these directions, we can advance our understanding of population dynamics, ecological interactions, and decision-making processes in parasitoids, ultimately leading to more effective and sustainable approaches for pest management and ecosystem conservation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Komi Mensah Agboka: Conceptualization, Methodology, Validation, Data curation, Writing – original draft, Writing – review & editing. **Emmanuel Peter:** Writing – original draft, Writing – review & editing. **Erion Bwambale:** Writing – original draft, Writing – review & editing. **Bonoukpoè Mawuko Sokame:** Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

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