Ecological Modelling 504 (2025) 111081

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel

Empirical dynamic modeling for prediction and control of pest populations

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ARTICLE INFO

Keywords:
Pest control
Empirical dynamic modeling
Stochastic dynamic programming
Integrated pest management

ABSTRACT

Insect pests pose a threat to humans by jeopardizing food security in agricultural systems, acting as vectors for infectious diseases, and damaging forests and other ecosystems. Despite decades of research, effective pest management remains challenging. Incomplete understanding of the mechanisms behind pest population dynamics limits our ability to anticipate outbreaks. Hence, pest management is often reactive, meaning control actions are taken once outbreaks have already begun, allowing for damage to occur. Here we show that a data-driven model can effectively predict outbreaks, allowing us to optimize control strategies, targeting pests before outbreaks occur. Specifically, we explore empirical dynamic modeling paired with stochastic dynamic programming to keep insect populations within acceptable bounds. We show that this framework reduces outbreaks in several simulated and empirical scenarios. Our study provides a promising framework to reduce losses from pests.

1. Introduction

Insect outbreaks have significant consequences, destroying approximately 18–20 % of several major crops worldwide (Sharma et al., 2017) and spreading diseases, which cause >700,000 deaths annually (WHO 2020). Invasive insects also disturb up to 85 million hectares of global forest area per year (van Lierop et al., 2015), threatening forest biomass and contributing to climate change, with total impacts, including those from native insects, being even higher (Fei et al., 2019). Together, the total estimated cost of pest outbreaks is at least $76 billion per year globally (Bradshaw et al., 2016), and these costs are expected to increase with climate change (Deutsch et al., 2018).

Given the impact of insect pests, it is increasingly important to reduce their damage and management costs. To this end, there have been increased efforts in integrated pest management (IPM) research, which aims to use information about the state of the environmental, economic, and social system to guide decisions regarding biological control (e.g. the use of a natural enemy of the pest), behavioral control (e.g. the use of pheromones to disrupt mating behavior and hinder reproduction), and chemical control (e.g. application of pesticides) to suppress pest populations (Stern et al., 1959). A successful IPM program involves carefully monitoring pests and their damage, using those observations to set control recommendations, and assessing the effect of the control techniques (Dara 2019; Kogan 1998).

In practice, some insect pests, including certain crop pests, must be managed whenever they occur and can cause potential damage at any level. Other pests, however, exhibit outbreaks or cyclical eruptions where populations rapidly go from low to high abundance at irregular intervals (Berryman and Stark, 1985; Berryman, 1990). In these cases, it is helpful to be able to take action in anticipation of a outbreak. Although early interventions have been applied successfully in some systems; e.g., spruce budworm management in North America (MacLean et al., 2019) and locusts in Africa (Belayneh, 2005) and Australia (Hunter, 2004); many outbreak management programs are reactive. In a reactive program, managers apply control once the population of a pest exceeds an unacceptable threshold (e.g., economic threshold (Stern, 1973)), so interventions often occur after damage has begun (Oliver and Roy, 2015). Although this is a reasonable method, there is likely room for improvement. However, since ecological systems are highly complex with numerous interacting variables, it is difficult to accurately predict when pests pose the highest risk of outbreaks that exceed damage thresholds and how each control technique impacts dynamics (Garrett et al., 2013; Tonnang et al., 2017). This - among other obstacles (Parsa et al., 2014) - has hindered adoption of predictive pest management in practice (Stenberg, 2017).

Theoretical ecologists have proposed to improve pest management

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https://doi.org/10.1016/j.ecolmodel.2025.111081
Received 1 December 2024; Received in revised form 3 March 2025; Accepted 4 March 2025
Available online 12 March 2025
0304-3800/

with control theory methods, such as Pontryagin's Maximum Principle (Bakhtiar et al., 2022; Fitri et al., 2021; Ghosh and Bhattacharya, 2010; Kar et al., 2012; Whittle et al., 2008), model predictive control (Zangina et al., 2021; Jesus et al., 2020), and dynamic programming (Hackett and Bonsall, 2019; Shoemaker, 1981; Yokomizo et al., 2009). While these studies are excellent examples of optimal control for pest management, many involve mechanistic models based on strong, simplifying assumptions, which unfortunately fall short of representing real-world dynamics with great accuracy. Since optimal control policies are sensitive to model structure, small changes in assumptions can lead to drastically different management advice (Boettiger, 2022; Essington, 2013; Wood and Thomas, 1999). Theoretical studies can lack empirical validation, making it challenging to apply their results to real-world scenarios.

At the other extreme, carefully parameterized mechanistic models for specific species (e.g., Dantzig, 1974; Zhang et al., 2010) have been developed and validated with empirical data in the past. While effective in their target applications, they were not easily transferable to other species (Hudgins et al., 2019). More recently, scientists have combatted this limitation by developing a general modeling framework that can be applied to any species (e.g. Rossini et al., 2025), however it requires general understanding of the species' biological lifecycle and population dynamics. This is a limitation for understudied species in which biological information is missing. For example, Yonow et al. (2023) identified numerous knowledge gaps in the biology of an invasive land snail, and had to make assumptions about density dependent mortality when developing a mechanistic model. To minimize assumptions, long experiments to estimate parameters are needed, and these challenges slow the adoption of mathematically optimized pest management (Deguine et al., 2021).

Although developing and validating mechanistic models (e.g. Rossini et al., 2025) should remain a long-term aspiration, a more immediate solution is needed for species with uncertain biological mechanisms. In line with recent discussions on good modeling practice (Jakeman et al., 2024), we recognize that ecological systems are complex and uncertain, and constructing detailed mechanistic models requires careful evaluation of assumptions. Here, we take advantage of the fact that model-free, data-driven models have been shown to improve predictive capabilities (SB Munch et al., 2018; Perretti et al., 2013), and develop a data-driven approach to pest control. Given time series of species' abundance and historical control actions, we use empirical dynamic modeling (EDM) (Sugihara and May 1990; Sugihara, 1994; Takens, 1980) based on Gaussian process regression (GP-EDM, Munch et al., 2017) to anticipate outbreaks (Material and Methods). This approach avoids strong assumptions about insect biology, copes with incomplete observations of the ecosystem, and has been used successfully to predict insect dynamics (Kollas et al., 2024). Leveraging GP-EDM forecasts and stochastic dynamic programming (SDP), we solve a multi-objective optimal control problem to generate control policies (Bellman, 1958; Clark and Mangel, 2000), a method known as empirical dynamic programming (EDP, Brias and Munch, 2021). While the idea of combining data-driven forecasts with optimal control methods has been used to identify management policies in fisheries applications (Boettiger et al., 2015; Brias and Munch, 2021), to the best of our knowledge, data-driven optimal control in insect pest management is not widely adopted and has minimal documentation in the literature (e.g. Meisner and Rosenheim, et al. 2016).

To evaluate EDP for pest management, we used a series of simulations representing common strategies: I) biological control, II) chemical control, III) behavioral control, and IV) IPM (i.e. the use of both chemical and biological controls) (Table S1). We compared the performance of our data-driven approach against two benchmarks: 1) the optimal policy using perfect knowledge of the data-generating model to produce management policies (as has been done in theoretical studies, e.g. Hackett and Bonsall, 2019; Yokomizo et al., 2009), and 2) a reactive policy, which only applies control after the pest has exceeded an unacceptable threshold. These benchmarks represent the best-case scenario and an approximate status quo, respectively. We evaluated the importance of stochasticity by simulating all scenarios with various levels of process noise. In addition, we compared trade-offs between two competing objectives of minimizing the costs associated with pest pressure and minimizing the cost of interventions.

For completeness, we followed the simulation analysis with an application to field data. We applied the method to a cotton pest, *Lygus hesperus*, and a vector of West Nile virus, *Culex pipiens*, in California. These empirical analyses demonstrate the predictive power of empirical dynamic modeling and allowed us to begin evaluating the utility of EDP in real management scenarios.

2. Materials and methods

To develop data-driven pest management decisions with EDP we followed two main steps. First, we used GP-EDM to forecast the future pest population from historical data. Second, we used these results to determine a control policy via SDP.

Fig. 1 shows an illustration of the EDP procedure on simulated data. We simulated a 2D scenario using a host parasitoid model (Table S1). Ecosystem dynamics (top box) include the population dynamics of a pest (x), an enemy of the pest (y), and the control history of human interventions in the form of insecticide sprays (u). To perform "full state" EDP, the first step was data-driven forecasting (second box) where we fit the function $x_{t+1} = f(\boldsymbol{x}_t, u_t)$ with GP regression (surface) to the available data (black dots), where $x_t^1 = x_t$ and $x_t^2 = y_t$. We then determined the EDP control policy with stochastic dynamic programming (third box) and approximated the optimal action (color) to take in any given state, $[x_t^1, x_t^2]$ (left). For comparison we determined the theoretical optimal policy based on the true data-generating model (right). Finally, we implemented each policy (bottom box) by determining the appropriate action for the current state (light blue), resulting in new dynamics for the pest (dark blue). We compared this to the economic threshold (grey dotted line) to evaluate cost (Eq. (2)).

Here we first describe GP-EDM then discuss details of the optimal control problem and its SDP solution. Finally, we provide details about our simulation experiments and empirical case studies.

2.1. Gaussian process regression

We used GP regression (Munch et al., 2017) to approximate the function, $x_t = f(\boldsymbol{x}_{t-1}, u_{t-1}) + \epsilon_{t-1}$ where $\epsilon_{t-1} \sim N(0, V)$ is process stochasticity, $u_{t-1}$is the control action at time $t-1$, and $\boldsymbol{x}_{t-1}$ are the inputs containing each state variable at time $t-1$, and $\boldsymbol{x}_{t-1}$ are the inputs containing each state variable at time $t-1$. In scenarios where we had data for the full system (e.g. multiple species/variables), $\boldsymbol{x}_{t-1}$ contained the data for all variables. When only pest abundance was available, lags were used to compensate, $\boldsymbol{x}_{t-1} = [x_{t-1}, x_{t-2}, \ldots, x_{t-E}]$ (see Empirical Dynamic Modeling).

The GP is specified by a mean function $m(\boldsymbol{x})$, and a covariance function $C(\boldsymbol{x}, \boldsymbol{x}')$. To remain consistent with previous applications of GP regression in ecology (e.g., Munch et al., 2017; Brias and Munch, 2021; SB Munch et al., 2018; Rogers and Munch, 2020), we rescaled the input data to have a mean of zero and a standard deviation of one. We set the prior mean function to $m(\boldsymbol{x}) = 0$ since we did not assume prior knowledge about the function characteristics. We used the squared-exponential covariance function, $C(\boldsymbol{x}, \boldsymbol{x}') = \sigma^2 exp\left(-\sum_{i=1}^{n} \phi_i (x_i - x'_i)^2\right)$, where $\sigma^2$is the pointwise variance, n is the dimension of each input (i.e. dimension of the system for the full-state case or number of lags for the partial-state case), and the $\phi_i{}'s$ are input-specific inverse length scale parameters which govern the flexibility of the function. Note that when $\phi_i = 0$, f is constant in the i_{th} input direction. To avoid overfitting, we used 'automatic relevance determination' (ARD, Neal, 1996). ARD encourages sparsity by assigning half normal

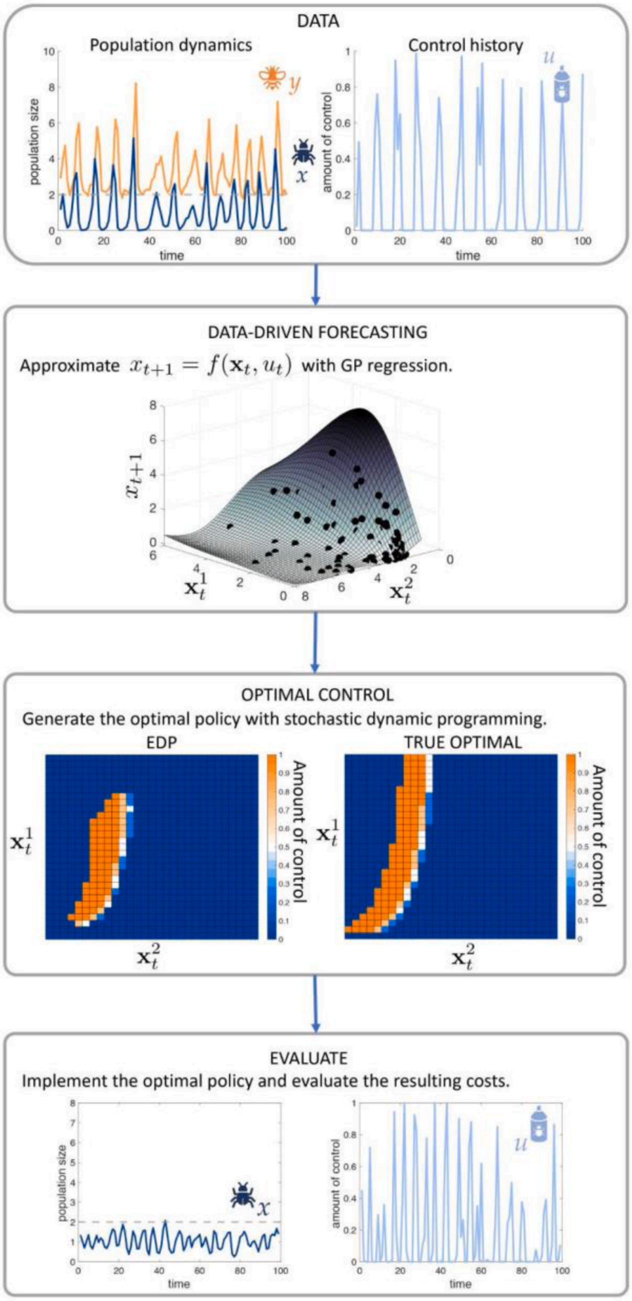

Fig. 1. A 2D example of EDP for pest management. Ecosystem dynamics (top box) include the population dynamics of a pest (x), a species that interacts with the pest (y), and the control history of human interventions (u). First (second box), we approximate the function $x_{t+1} = f(\boldsymbol{x}_t, u_t)$ with GP regression (surface) to the available data (black dots). Given the predictive model, we determine the optimal control policy with stochastic dynamic programming (third box). This generates the approximated optimal action u (color) that should be taken in any given state $[x^1{}_t, x^2{}_t]$ (left), which is like the theoretical optimal policy (right). Finally, we implement the optimal actions on new data (bottom box). That is, at each time step, we determine the current state, x_t, and apply the optimal action (light blue, right) to the ecosystem. This results in new dynamics for the pest (dark blue, left), which we compare to an economic threshold (gray dotted line) to evaluate cost. See Material and Methods for more details.

priors for each ARD encourages sparsity by assigning half normal priors for each ϕ_i such that the prior mode is at 0. V and σ^2 were assigned fairly flat beta distributions $\beta(1.1, 1.1)$ to facilitate identifiability (see Munch et al., 2017 for further details). We updated the hyperparameters using resilient back propagation (Rprop, Blum and Riedmiller, 2013) to maximize the log of the marginal posterior. Although it is possible to infer f in a fully Bayesian way (e.g., with MCMC), we fixed the hyperparameters at their posterior modes to save computation time and used the standard formulae for conditioning in a multivariate normal distribution to make predictions (Munch et al., 2017).

2.2. Empirical dynamic modeling

In cases where we do not have data for all the variables in a system, Takens's theorem of time delay embedding (Takens 1981) states that the attractor (i.e., the point, set of points, or orbit to which a dynamical system converges) can be reconstructed with lagged time series of a single state variable. This provides a theoretical foundation for a model of the form $x_t = f(x_{t-1}, x_{t-2}, \ldots, x_{t-E}) + \epsilon_{t-1}$ where x is the observed state variable, E is the 'embedding dimension', ϵ is the process error, and f is the 'delay-embedding map'. Many function approximation methods can be used (e.g., local linear regression (Farmer and Sidorowich, 1987) or neural networks (Bakker et al., 2000)). In this paper, we fit f via Gaussian process regression (Munch et al., 2017). Although methods based on Takens's theorem have been applied since the 1980′s in a wide range of disciplines, under several different names, recent applications in ecology have largely been published under the name EDM. More examples and overviews of EDM can be found (Ye et al., 2015; Chang et al., 2017; Munch et al., 2020), and extensions of EDM for stochastic systems are also available (Munch et al., 2020; Stark et al., 2003).

2.3. Using forecasts to inform decisions

EDM can be extended to include additional covariates such as interacting species, environmental drivers, and spatial replicates (Deyle and Sugihara, 2011; Ye and Sugihara, 2016; Rogers and Munch, 2020; Johnson et al., 2021). Using historical management actions as covariates (e.g., pesticide applications) opens the possibility of using EDM to evaluate management policies. Concretely, suppose we would like to control the dynamics of an insect population by applying insecticides, given time series for insect abundance (x_t) and pesticide applications (u_t), $t = 0, 1, \ldots, T$. In the simplest case, in which the insect does not interact with other species or drivers, we could fit a model $x_t = f(x_{t-1}, u_{t-1}) + \epsilon_{t-1}$. Applying optimal control theory to the inferred model allows us to generate management policies. In the more realistic case where the focal insect interacts with other – unobserved – species, the model is of the form, e.g., $x_t = f(x_{t-1}, u_{t-1}, \ldots, x_{t-E}, u_{t-E}) + \epsilon_{t-1}$.

2.4. The optimal control problem

The objective of our optimal control problem is to minimize the cumulative discounted cost of pest management from the current time to sometime in the distant future. We expressed this goal as

$$
\begin{aligned}
\min_u J(x, u) &= \sum_{t=1}^{\infty} \gamma^t c(x_t, u_t) \\
&\text{subject to} \\
x_t &= f(\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}) \\
x(0) &= x_0
\end{aligned}
\tag{1}
$$

where x is the state (e.g., pest abundance and enemy abundance), u is the control (e.g., amount of pesticide applied), γ is a discount factor, and c is the stepwise cost of being in state x_t and taking control action u_t.

One important step in setting up an applied optimal control problem is specifying the cost function. In this pest control context, we considered two primary objectives: (1) minimize the cost of pest pressure (e.g., through yield loss), and (2) minimize the cost of applying interventions. There is a trade-off between these two objectives, and their priority might vary in different scenarios. To capture these competing objectives, we defined a combined cost function given by

$$c(x_t, u_t) = \theta \frac{x_t}{1 + e^{-10(x_t - x_{thresh})}} + (1 - \theta) u_t. \tag{2}$$

The first term in Eq. (2) captures the cost associated with pest pressure, where the cost is negligible when the pest abundance (x_t) is below a threshold (x_{thresh}), and the cost increases linearly above the threshold. This is similar to the "economic threshold" concept (i.e., the pest abundance at which control should be applied to stop economic damage (Stern, 1973)) and is useful because effective management programs should maintain pests within acceptable bounds rather than eliminate them completely (Lewis et al., 1997). The second term in Eq. (2) captures the cost of applying control, assuming cost is linearly related to the amount of control applied. The parameter θ in [0,1] is a weight used to tune the priority of the competing objectives. For example, $\theta = 0.99$ prioritizes minimizing pest pressure. In applications, θ may be eliminated when both costs can be expressed in equivalent units (e.g., dollars).

The IPM strategy involved two control variables, so the cost was in the form,

$$c\left(x_t, u_t^c, u_t^b\right) = \theta_1 \frac{x_t}{1 + e^{-10(x_t - x_{thresh})}} + \theta_2 u_t^c + \theta_3 u_t^b \tag{3}$$

where u^c is the chemical control variable, u^b is the biological control variable, and θ_i places weight on the i^{th} term of the cost function.

2.5. Dynamic programming

Bellman's principle of optimality (Bellman, 1958) shows that the optimal control problem Eq. (1) can be solved via the dynamic programming equation,

$$V(\boldsymbol{x}) = \min_{\boldsymbol{u}} E[c(\widetilde{x}, \boldsymbol{u}) + \gamma V(\widetilde{x}) | \boldsymbol{x}, \boldsymbol{u}]$$

where $V(\boldsymbol{x})$ is the long-term discounted cost of being in state $\boldsymbol{x}$, $c(\widetilde{\boldsymbol{x}}, \boldsymbol{u})$ is the cost of applying $\boldsymbol{u}$ and ending up in state $\widetilde{\boldsymbol{x}}$, and E is the expectation over the next state given the previous state and control.

We solved the dynamic programming equation with value iteration. Specifically, we followed the procedure: (1) Create an evenly spaced grid of possible states; we used 30 evenly spaced points between 0 and $1.25^{*}max(x)$ in the training data. (2) Create an evenly spaced grid of possible actions u; we used 5 evenly spaced points between 0 and 1. 3) To solve the DP equation, we approximated the expectation as

$$E\left\{c(\widetilde{x}, u_l) + V(\widetilde{x}) \middle| x_j, u_l\right\} \approx \sum_{i}^{size(state\_grid)} P_{jl}(x_i)\{c(x_i, u_l) + \gamma V(x_i)\}$$

where we estimated $P_{jl}(x_i)$ with GP regression. 4) From the dynamic programming equation, update the value function as $V(x_j) = min_u E\left\{c(\widetilde{x}, u_l) + V(\widetilde{x}) \middle| x_j, u_l\right\}$ and extract the policy as $u^*(x_j) = argmin_u E\left\{c(\widetilde{x}, u_l) + \gamma V(\widetilde{x}) \middle| x_j, u_l\right\}$. 5) Iterate steps 3 and 4 until the value function and the optimal policy converge (i.e. the absolute change in the value function and policy between successive iterations was <0.001).

2.6. Simulations

To evaluate EDP, we simulated data with a host-parasitoid model, which in the absence of control, is given by

$$\begin{aligned} H_{t+1} &= H_t e^{r(1 - H_t/K) - \alpha P_t} \\ P_{t+1} &= \beta H_t\left(1 - e^{-\alpha P_t}\right) + \gamma \end{aligned} \tag{4}$$

Hare [r is the growth rate of the host, K is the carrying capacity of host, β is the searching efficiency of the parasitoid, α is the number of parasitoids that emerge from each parasitized host, and γ is a migration coefficient for the parasitoid (Hassell, 2000; Jang and Yu, 2012 H represents the pest population that we aim to control and P is a natural enemy of the pest. Importantly, this model serves as a data generation tool rather than a true representation of insect population dynamics. It omits biological complexities such as developmental stages, host plant interactions, and other ecological factors, because its purpose is solely to produce synthetic data for EDP analysis. The model equations are not used in the EDP process. Validation using real insect data is addressed in subsequent sections.

There are various ways in which a manager might try to control an insect pest population. To evaluate generalizability of EDP, we simulated multiple control strategies. See Table S1 for functional forms and parameters of each scenario. A description of each is given below.

I. *Biological control*

There has been substantial effort to develop control techniques that suppress pests naturally while causing minimal untargeted damage. One option is to use natural enemies of the pest to reduce its densities. Biological control was modeled by adding parasitoids to the system (Table S1). This is most appropriate for modeling augmentative biological control as it increases the density of a natural enemy that is already present in the system, though we can conjecture this effect is present in a conservation or manipulative biological control scenario in which managers manipulate the environment to increase natural enemy counts.

I. *Chemical control*

We simulated the effects of chemical control (i.e., insecticide applications) as a direct reduction in the pest population. Since it is rare for insecticide applications to remove all pests, we assumed that a fraction of the population was removed after a pesticide application. We set this "pesticide efficiency" parameter (i.e., the maximum proportion of the population that can be reduced by spraying pesticides) to 0.6 (Table S1).

I. *Behavioral control*

Behavioral control, in the form of mating disruption, MD, aims to decrease pest population growth by releasing pheromones into the environment to hinder mating. Alternatively, in sterile insect technique (SIT), sterile insects are released. While this is not strictly behavioral control, both methods aim to reduce pests' reproduction and we modeled them as a fixed reduction in pest growth (Table S1).

I. *Integrated pest management*

Although less harmful forms of control are desirable for sustainable pest management, experimental work needs to be done to determine the reliability of these methods. The development of non-chemical pest control is still an active area of research, and as a result, many managers are unlikely to completely abandon the use of pesticides. Some combination of chemicals and natural approaches is one approach to IPM. We simulated IPM by using a combination of chemical and biological controls. Thus, instead of approximating $x_t = f(x_{t-1}, u_{t-1}) + \epsilon_{t-1}$ with GP regression, we approximated $x_t = f\left(x_{t-1}, u_{t-1}^c, u_{t-1}^b\right) + \epsilon_{t-1}$, where u^c is chemical control, and u_b is biological control. The objective was to find the optimal combination of chemical and biological control to minimize the cost function (Eq. (3)).

We simulated strategies I-IV with three levels (low, moderate, and high) of process noise (Table S1). In all scenarios, we simulated 600 data points. After removing 300 transient points, the remaining points were split into 100 points for training, 100 points for testing to evaluate the R^2 forecast accuracy, and 100 points of secondary testing data to evaluate the control methods (which we call the "control" set). To generate initial time series, we applied a random amount of control periodically in the training and testing sets. We applied no control in the control set, which allowed us to compare our controlled results to the natural dynamics of the pest. For strategies I-III, we evaluated the methods at eleven evenly spaced values of θ between 0.001 and 0.999. For strategy IV, we evaluated methods at 21 different values of $(\theta_1, \theta_2, \theta_3)$ where $\theta_1 + \theta_2 + \theta_3 = 1$.

Our ability to effectively manage the pest population depends on the quality and type of data that is available. Thus, we explored two cases of available data.

Case 1: Data for both species - "full-state" EDP

In the first case, we assumed that the training data included abundance of both the pest and its natural enemy, as well as the control. We fit a GP to approximate $[H_{t+1}, P_{t+1}] = f(H_t, P_t, u_t)$ with the training data and evaluated the forecast accuracy on the subsequent testing data. Given the fitted model, we used EDP to produce an optimal policy for all possible combinations of H and P. To evaluate the EDP policy, we continued the simulations in the control set by using the same parameters from the original simulation. Since EDP determines the optimal policy on a grid, we interpolated linearly to approximate the optimal control for each simulated state. We iterated this procedure in the simulation model for the 100 steps in the control set.

Case 2: Data for only the pest - "partial-state" EDP

Next, we assumed that we only had abundance data for the pest and control. That is, the natural enemy was unmonitored. To model the dynamics, we fit $H_{t+1} = f(H_t, H_{t-1}, u_t)$. The remainder of the procedure including forecasting in the test set and policy evaluation in the control set was identical to Case 1. Assuming that integrated pest managers would be unlikely to neglect monitoring the natural enemy, we did not evaluate this method for IPM.

EDP policies were compared against two benchmarks. The first was the optimal dynamic programming policy derived from the data-generating model. This represents an unrealistic best-case scenario in which managers have perfect information on how the system works. The second benchmark was a reactive policy in which control was applied when the current state of the pest was above a specified threshold. The amount of control was proportional to θ.

We acknowledge that, in reality, many pest managers do try to preempt damage and make informed judgments about when suppression is necessary. However, this is not always done formally and consistently. We suggest that while the reactive program is a simplification of the real world, it is nevertheless a reasonable benchmark.

The comparison with both benchmarks was done by calculating average "excess cost" of EDP and the reactive control. To do so, we subtracted the total cost (Eq. (2) or 3) accumulated over the control interval by following the optimal policy (i.e., the best-case benchmark) from the totals under the EDP and reactive policies.

2.7. Empirical case studies

Although simulations allow us to evaluate the success of EDP across various hypothetical scenarios, there are many other potential factors that were not explicitly modeled. Since these other factors can influence forecast accuracy and control performance, we further tested our methods on empirical data. The goals were two-fold: First, to evaluate whether the EDM algorithm could accurately predict the dynamics of real-world insect data and the impact of interventions. Second, to compare historical control efforts in real systems to the policy generated with EDP. It is important to note, however, a control performance cannot be validated on historical data since it is impossible to alter the historical controls.

We tested our methods on one agricultural pest and one disease vector. The agricultural pest was *Lygus hesperus* from commercial cotton fields in central California. *Lygus* threatens cotton yields by damaging the cotton plants early in the growing season (Godfrey et al., 2013). The data included samples collected between 1997 and 2008 from 567 cotton fields. Together, there were samples from 1500 field-year combinations. Approximately every week during the growing season (∼June-August), pest control advisors (PCAs) or growers took sweep net samples. The mean number of *Lygus* caught in the net per 50 sweeps was used as the density estimate for *Lygus*. Active ingredients, targets, and timing of various management interventions were also tracked in every field.

We treated each field-year as an independent time series. Since EDM requires long time series, we filtered out time series with <15 *Lygus* samples, leaving 142 series. To model control efforts, we included insecticide sprays as a binary variable. That is, when *Lygus* was listed as a target in an insecticide application, the control variable was assigned a value of 1 and 0 otherwise. Note that this is a simplification because insecticides targeting other species could also influence *Lygus* dynamics. We randomly selected 80% of the 142 field-year time series to training the GP EDM model. The other 20% were held out for testing forecast accuracy and evaluating control policies. After square root transforming the data, we fit a EDM model with $E = 2$ to the training data and evaluated the R^2 for one-step-ahead forecasts in the testing data.

To evaluate EDP, we defined a cost function based on the University of California Agriculture and Natural Resources Statewide Integrated Pest Management program (UC IPM) for *Lygus* (Godfrey et al., 2013), which suggests sliding thresholds because cotton becomes more resilient to *Lygus* later in the season. In light of this, we defined different cost functions for distinct periods of the growing season. All cost functions were given by Eq. (2), where we set $x_{thresh} = 1$ for the early squaring period of the season (∼ early June), $x_{thresh} = 2$ starting in mid-June, and $x_{thresh} = 8$ during mid-squaring (∼ early July). We varied θ from 0.4 to 0.999 and used EDP to determine policy for each state and each period of the growing season. For each field-year, we initialized the start-of-season input at the true data point. We used the GP to determine the next state given the current state and control policy. Using the result as the next state, we repeated this for the whole time series and all field-years in the test set. We tracked the total number of sprays and the total number of *Lygus* predicted to emerge above the sliding threshold to evaluate costs. We obtained separate costs for each value of θ, which were used to construct a Pareto front. To evaluate the historical control efforts, we initialized the input as we did for EDP. Then we input historical control actions into the GP to get the next state and iterated this procedure for all the time series in the testing data. As a result, we were able to compare the total number of sprays and emerging *Lygus* with the EDP output.

The second case study involved the mosquito *Culex pipiens* in California. The species is a vector of West Nile virus (WNV), which is an endemic in California and can cause long term physical and mental disabilities (Holcomb et al., 2021). Because of its harmful impacts on humans, aerial applications of pesticides are used to target adult populations of mosquitoes to slow or prevent transmission of WNV (Carney et al., 2005).

We used mosquito trap count data from California's Sacramento County provided by the CalSurv data management system. Historical pesticide application records were obtained from the Sacramento-Yolo Mosquito and Vector Control District (SYMVCD) from 2006 - 2017. We split the data into six spatial regions (Figure S5) and analyzed the time series of monthly average mosquitoes per trap in each region. We supplemented this with control data in the form of a binary variable (i.e., 1 when insecticides were sprayed in that region/month, zero otherwise). We used a hierarchical GP regression (Munch et al., 2017) to approximate the future growth rate of the mosquito as a function of the previous abundance. To allow for seasonality, we included explicit time dependence in the model via $log\left(\frac{x_{t+1}}{x_t}\right) = f\left(x_t, sin\left(\frac{2\pi}{12}n + c\right), u_t\right)$, where n is the month of the year. We evaluated the R^2 for sequential one-step-ahead forecasts for the full time series from 2006 to 2017, where we initialized the input at each site with the true data and then computed one-step-ahead forecasts. We constructed a Pareto front for the EDP policy and compared it to the historical policy.

3. Results

We compared EDP to the optimal and reactive benchmarks by evaluating the excess cost of the control policies (see Material and Methods). We considered two cases for EDP, (1) full-state EDP (trained on data for all state variables) and (2) partial-state EDP (trained on lags of the pest data). We also explored trade-offs between competing objectives by evaluating the cost (Eq. (2)) at various values of $0 < \theta < 1$ Doing so produces a Pareto front which shows the set of solutions for which it is impossible to decrease one cost without increasing the other (Williams and Kendall, 2017).

3.1. Policy generation based on data alone outperforms reactive control

Under all the scenarios tested in the simulated data, EDP outperformed the reactive approach and had relatively low excess costs compared to the best-case scenario benchmark, even with moderate levels of noise (Table S1) (Fig. 2 and 3). On average, for the time series lengths tested, EDP produced a policy closer to the optimal policy when data for the full state was available. In general, EDP produced nearly optimal results at extreme values of θ (i.e. θ close to 0 or 1), and its excess costs increased at intermediate θ (Fig. 2a,c,e). Pareto fronts for each method (Fig. 2b,d,f), showed that the policies strike a balance between the competing objectives at intermediate θ values as demonstrated by the black outlined points in Fig. 2b,d,f.

The results were generally similar for the more complex IPM scenario (Fig. 3), and EDP outperformed the reactive policy. At the extremes (i.e., when one $\theta_i = 0$), EDP performs nearly optimally, and excess cost increases at intermediate values. The reactive approach performs optimally at one extreme (i.e., when no weight is placed on the cost of pest pressure). An example of the optimal control rules and resulting dynamics of each method shows that EDP and the optimal policy effectively keep the pest population within acceptable bounds, while the reactive approach does not (Fig. 4a,c,e). All three methods, however, use a combination of biological control and chemical control (Fig. 4b,d,f).

Overall, the level of noise in the dynamics influenced the performance of EDP, but the reactive approach was relatively consistent for the full range of noise levels we tested (Fig. 5). Across all scenarios, both cases of EDP reduced excess costs compared to the reactive approach by a substantial amount (Table S3). Even in the worst cases, EDP reduced excess costs relative to the reactive policy by at least 33% in the partial-state case, and it reduced costs by at least 48% in the full-state case. Both cases appeared to work best under low noise and behavioral control.

3.2. Policy generation based on empirical data outperforms historical policies

In the empirical case studies for *Lygus* and *Culex pipiens*, it was not possible to develop best case scenario benchmarks. However, we used

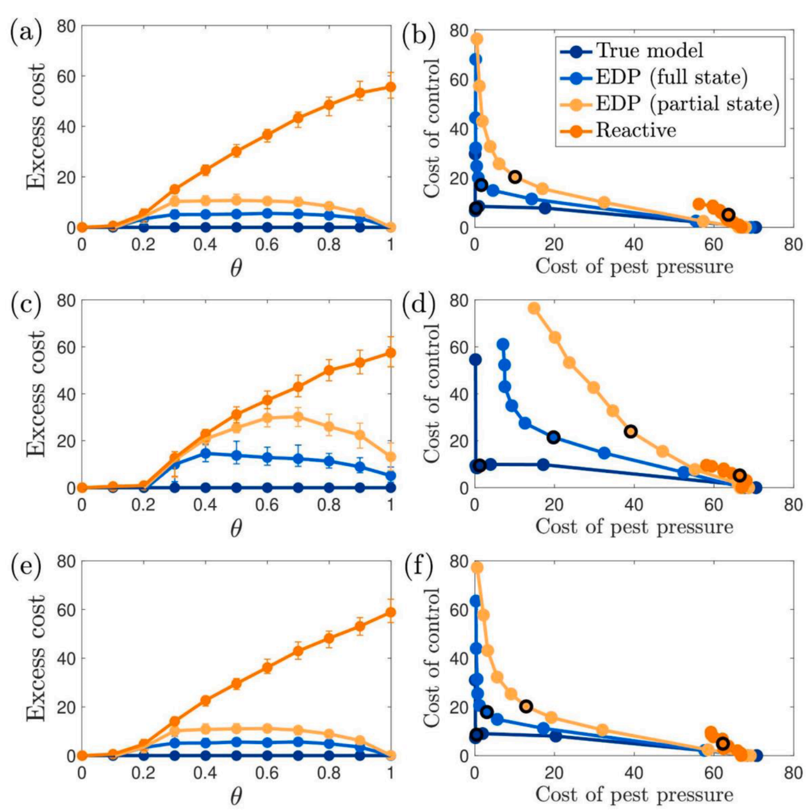

Fig. 2. Results over 100 simulations of biological control (a,b), chemical control (c,d), and behavioral control (e,f) with a moderate level of noise in the data (Table S1). Left panels show the median (dots) and lower and upper quartiles (error bars) for the excess cost of each method compared to the optimal policy (a,c,e). Pareto fronts show the trade-off between the cost of pest pressure and the cost of control (b,d,f). Each point in the Pareto fronts corresponds to a value of, ordered such that $\theta = 0.\ 001$ in the lower right $\theta = 0.\ 999$ in the upper left. Points outlined in black correspond to $\theta = 0.\ 5$.

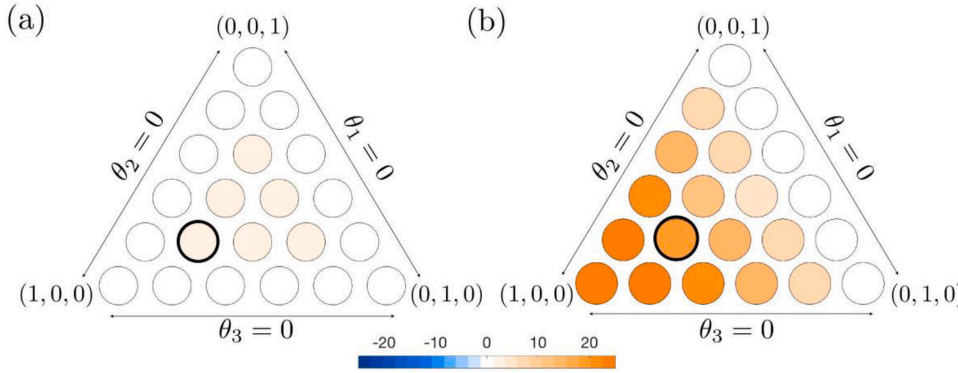

Fig. 3. Results over 100 simulations of IPM control using EDP (a) and a reactive control (b) with a moderate level of noise in the data. The color in each circle is the average excess cost for a specific $(\theta_1, \theta_2, \theta_3)$ triplet. Light circles indicate low excess cost and darker circles indicate high excess cost. The circle outlined in black corresponds to $(\theta_1, \theta_2, \theta_3) = (0.6, 0.2, 0.2)$, and an example of the output dynamics for this triplet is shown in Fig. 4.

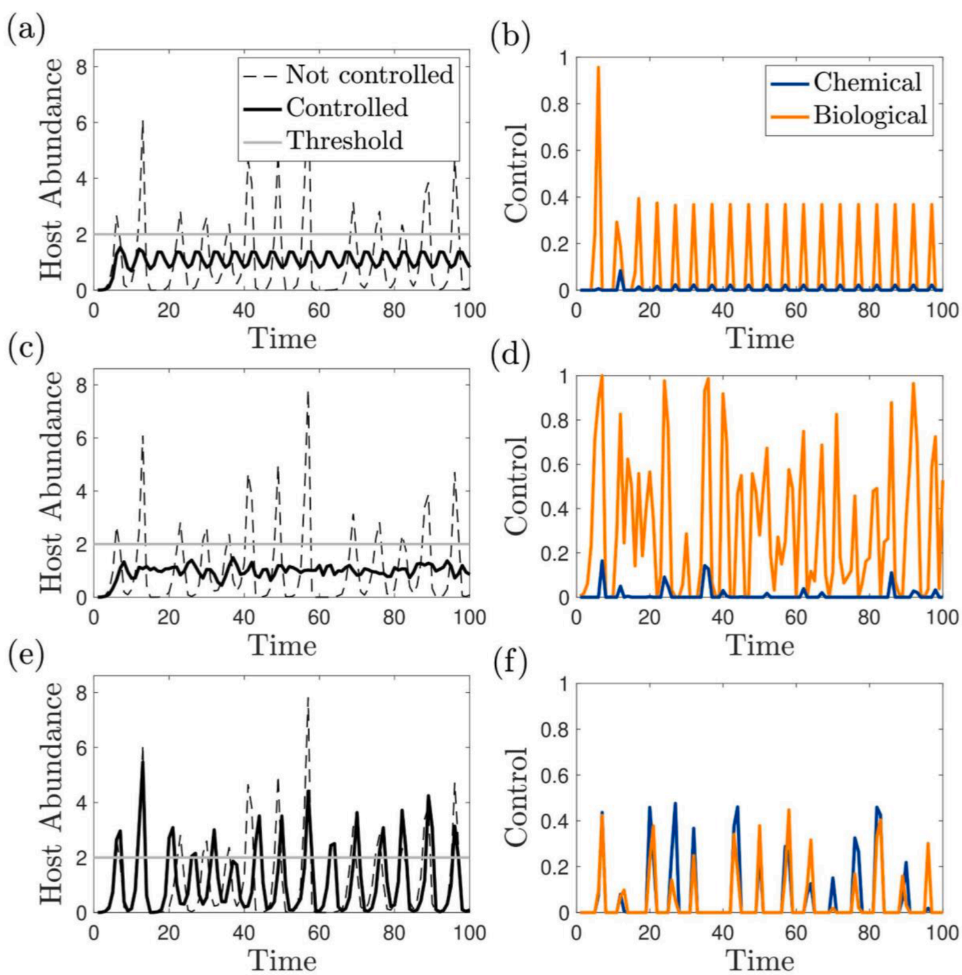

Fig. 4. Results of a single simulation of IPM control based on the true model (a,b), EDP (c,d), and the reactive method (e,f). Comparisons between uncontrolled dynamics of the pest (dotted black lines) and controlled dynamics of the pest (solid black lines) (a,c,e). The amount of chemical (blue) and biological (orange) applied (b,d,f) to achieve the controlled dynamics.

the historical control actions from the data as realistic status quo benchmarks and compared them to the EDP policies. In both cases, the EDP policy outperformed the historical policy. For *Lygus*, the forecast accuracy was $R^2 = 0.54$, and the historical policy fell above the EDP Pareto front (Fig. 6a), indicating that it may have been possible to achieve nearly 45% less pest pressure with the same number of sprays used historically. Alternatively, it may have been possible to achieve the same amount of pest pressure with ~ 60% fewer sprays. Similarly, the out of sample forecast accuracy was $R^2 = 0.58$ for *C. pipiens*, and the historical control actions fell above the EDP Pareto front (Fig. 6b). This suggests that ~ 8% reduction in mosquito pressure or ~ 60% reduction in pesticides could have been achieved. While we cannot truly evaluate the EDP policies on the historical data, these results suggest that policy improvement might be possible.

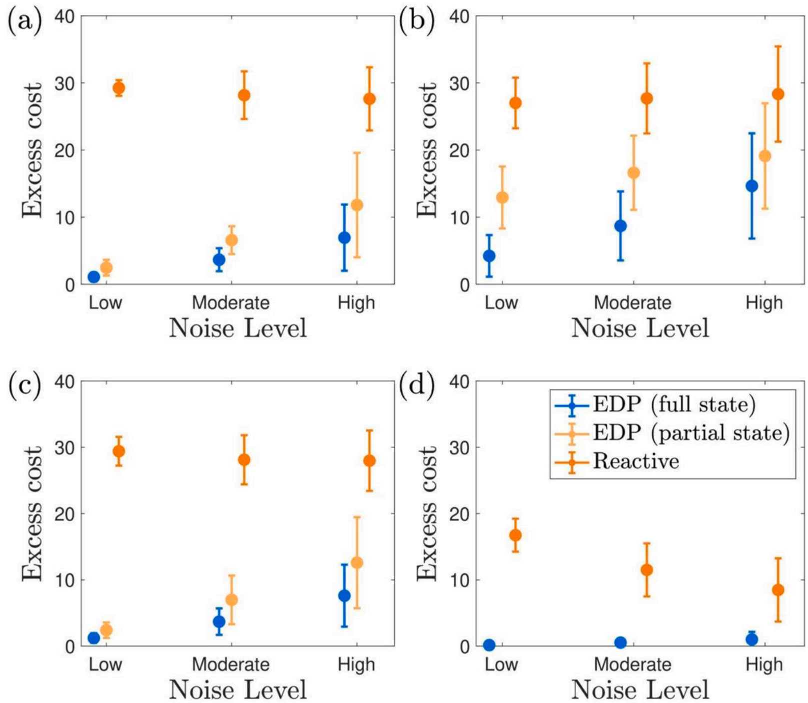

Fig. 5. Mean (dots) and average standard deviation (error bars) of excess cost over 100 simulations of all θ for biological control (a), chemical control (b), behavioral control (c), and IPM (d). Note that there is no partial state EDP for the IPM control.

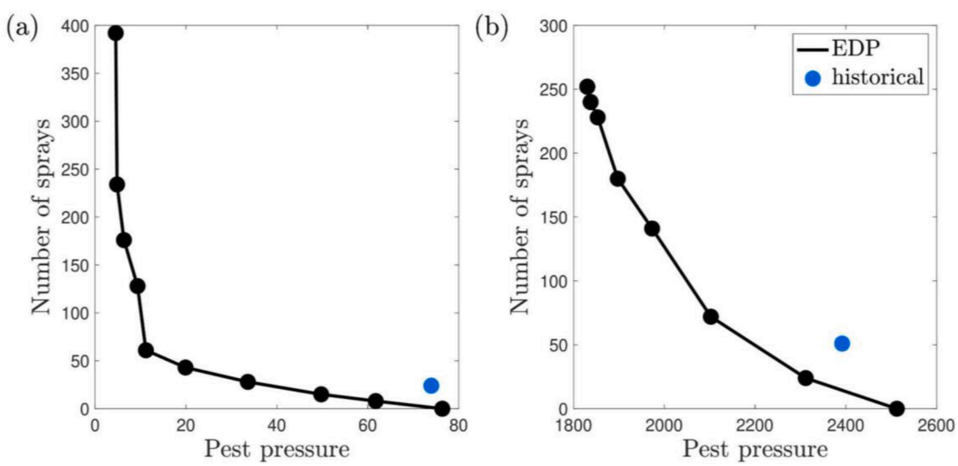

Fig. 6. Pareto fronts of EDP and the historical policy for *Lygus* (a) and C. pipiens (b). Each point in the Pareto front corresponds to a value of θ, ordered such that θ is low in the lower right θ is high in the upper left.

4. Discussion

Our analysis suggests that, under the conditions we tested, EDP can mitigate the impacts of pests. With complete or incomplete data, EDP produces nearly optimal management policies and outperforms reactive and historical approaches to pest management. Even in the worst cases, the method achieved a reduction in excess cost that could save millions of dollars (Bradshaw et al., 2016). EDP's flexibility allows it to handle a variety of control types, including IPM strategies, and cope with data complications such as incomplete observations and high noise with minimal modifications.

This work indicates that reactive programs, which intervene when pests exceed some threshold are sub-optimal. However, this raises a natural question of what is the alternative. For example, it is reasonable to wonder if it is always be more effective to intervene when pest densities are low. Although it was not feasible to visualize the optimal policy for the thousands of simulations tested, the third box in Fig. 1 clarifies this question to some degree. The optimal policy given by the true model indicates that applying control is optimal at a wide range of pest densities, but the amount and necessity of control depends on the state of another species. This highlights that management advice cannot rely solely on current pest abundance. Effective methods must consider the impacts of other ecosystem components either directly or through time delay embedding. Therefore, proper monitoring and data sharing should remain a strong priority.

Although EDP shows promise, a few caveats exist. First, real systems are subject to economic complexities that could make optimization challenging. Dynamic programming policies are sensitive to model predictions. This is evident in our results, which showed that increasing noise in the dynamics decreases forecast accuracy (Table S2), thereby reducing the performance of EDP (Fig. 5). High levels of observation error may be present in insect data. Although the forecast accuracy suggests that observation error did not prevent us from making reasonable predictions in the empirical case studies, it is important to carefully consider forecast accuracy before generating management advice.

Second, the historical control strategy and data quality can affect EDP performance. For example, if control has only been applied in a limited region of the state space in historical data, the GP might inaccurately estimate population dynamics reactions to control in other regions. In addition, if data are imprecise, the method could produce suboptimal policies. Managers adopting this method should be aware of which historical control strategies offer the highest probability of success (Supporting Information S2, Table S4) and should carefully record intervention actions. Generally, it is best to have reliable data on the effect of treating both low and high densities of pests.

Finally, in cases with higher dimensions (e.g., number of species or number of EDM lags is greater than 3), EDP - as implemented here - is not computationally feasible. Similarly flexible, but more scalable methods such as approximate dynamic programming (Powell, 2011; Sutton, 1988), reinforcement learning (Sutton, 2018), or model predictive control (Morari and Lee, 1999) could be used instead, but future studies should evaluate the trade-offs of these methods in pest management.

Additional next steps should also be considered. First, insect development depends on environmental conditions, especially temperature, so future studies should explicitly account for temperature or growing degree days (Naves and Sousa, 2009) by using multivariate embedding (Deyle and Sugihara, 2011) or multiview embedding (Ye and Sugihara, 2016) to improve predictions and policies. Similarly, many crops are only vulnerable to pests during specific times in the season. We addressed seasonality by generating separate policies for distinct growing season stages (*Lygus*) or by incorporating a seasonal term into the EDM model (*C. pipiens*). Future work should explore more explicit and scalable ways to incorporate crop phenology and seasonal variability. Models incorporating these factors could begin bridging the gap between this strictly data-driven approach and highly parameterized mechanistic models. Similarly, real pests face complexities that were not directly incorporated into our simulation tests, such as overwintering survival, which significantly impacts pest pressure in the following season and is sensitive to weather conditions (Lawton et al., 2022). For some pests, mating disruption and SIT are only effective when pest populations are at low densities (Louis and Schirra, 2001; Witzgall et al., 2008), which might justify a state-dependent reduction in pest growth rate (e.g. Ben et al., 2020) rather than the constant reduction used in our simulations. To achieve a more thorough understanding of the benefits and limitations of the EDP approach, future studies should expand the simulation analyses to study the effects of alternative underlying dynamics such as climate-driven dynamics, host plant interactions, stage division, spatial dynamics, and overlapping generations (Barclay, 1982; Li et al., 2019; Nestel et al., 2004; Yonow et al., 2004, 2023).

Future work needs to evaluate various cost functions. Our cost function formulation included pest pressure and the cost of control with an emphasis on suppressing pests below an economic threshold while minimizing control actions. However, this is just one possible cost function which served as an initial proof-of-concept. Practical management must avoid risks from numerous evolutionary, environmental, and ecological factors that we have not yet considered. For example, it has been shown that low doses of pesticides can increase risk of resistance (Muniz-Junior et al., 2023), and IPM approaches should account for these evolutionary risks (Namias et al., 2021). Similarly, minimizing pesticide runoff risk (van der Werf, 1996) and harmful impacts on non-targeted organisms, such as pollinators and birds, are important objectives for real-world pest management. In cases where we have data for both pests and non-target species, we can extend the multi-objective framework to identify policies that simultaneously suppress pests and protect non-target species. This approach has been used in fisheries contexts (Brias and Munch, 2021) to balance harvesting and conservation goals in multi-species settings, and a similar approach could be relevant for pests.

Although the applications to *Lygus* and *Culex* are promising, it is not possible for us to empirically validate alternative control policies *post hoc*. The ultimate test of this method should involve collaboration among empiricists, growers, or vector control agencies, and should set up controlled experiments to compare EDP and alternatives in a real system.

Overall, our results reveal valuable insights about monitoring and managing insect pests. Under the conditions we studied, having complete observations for the system had a strong advantage over partial observations (i.e., data only for the pest) (Fig. 5). This is consistent with other recent developments in EDM – multiple series can often be leveraged to significant advantage (Ye and Sugihara, 2016) In addition, having complete and precise data for historical control actions is important (Table S4). Although ecological sampling is costly, our study provides a clear incentive to invest in comprehensive monitoring programs. Recent developments of automated insect trapping methods (Pegoraro et al. 2020; Rydhmer et al., 2022) and user-friendly tools to help managers track and store data (Chambers et al., 2015; Lagos-Ortiz et al., 2018) make this increasingly feasible and would likely yield profitable results in the long term. Our method could be useful in conjunction with these modern systems to aid in real-time decision making.

Although there is clearly more work to be done and real-world validation is needed, the proposed method is a step toward efficient pest management and could provide a meaningful advancement to the field. Our approach aligns with several elements of good modeling practice outlined by Jakeman et al. (2024), particularly in demonstrating strengths and weaknesses in the model performance through both simulated and empirical tests. Through benchmarking, we conclude that EDP generates nearly optimal management advice without the need for strong assumptions or long experimental parameterization, and it allows us to work directly with limited noisy data. While well-validated mechanistic models should certainly be utilized when they are available, this work offers an immediate advantage in understudied systems by providing an alternative approach when predictive mechanistic models have not been developed. The flexibility of the method makes EDP a viable solution for ecological management outside of pest control (e.g. fisheries). Importantly, EDP requires minimal fine-tuning for each new application and thus can produce useful management guidance in a wide variety of scenarios.

Funding

This study was supported by funding from the Lenfest Oceans Program, NOAA's HPCC Program, and NOAA Grant NA19OAR4170353 through the Fisheries-Sea Grant Joint Graduate Fellowship Program in Population and Ecosystem Dynamics. The statements, findings, conclusions, and recommendations are those of the authors and do not necessarily reflect the views of Sea Grant or NOAA.

CRediT authorship contribution statement

Bethany J. Johnson: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marcella M. Gomez:** Writing – review & editing, Supervision, Methodology. **Stephan B. Munch:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bethany Johnson reports financial support was provided by National Oceanic and Atmospheric Administration Population and Ecosystem Dynamics Fellowship. Stephan B. Munch reports financial support was provided by Lenfest Oceans Program. Bethany Johnson reports a relationship with X, The Moonshot Factory that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors sincerely thank J. Rosenheim for providing access to the *Lygus* data and guidance on the *Lygus* biology and management practices in central California cotton. C.M. Barker and E. Lonstrup with CalSurv for providing access to mosquito trap data. K.M. Holcomb and C.M. Barker, and G. Goodman from Sacramento-Yolo Mosquito & Vector Control District for providing access to mosquito intervention data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2025.111081.

Data availability

Data will be made available on request.

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