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(54) **MODEL-PREDICTIVE CONTROL OF PEST PRESENCE IN HOST ENVIRONMENTS**

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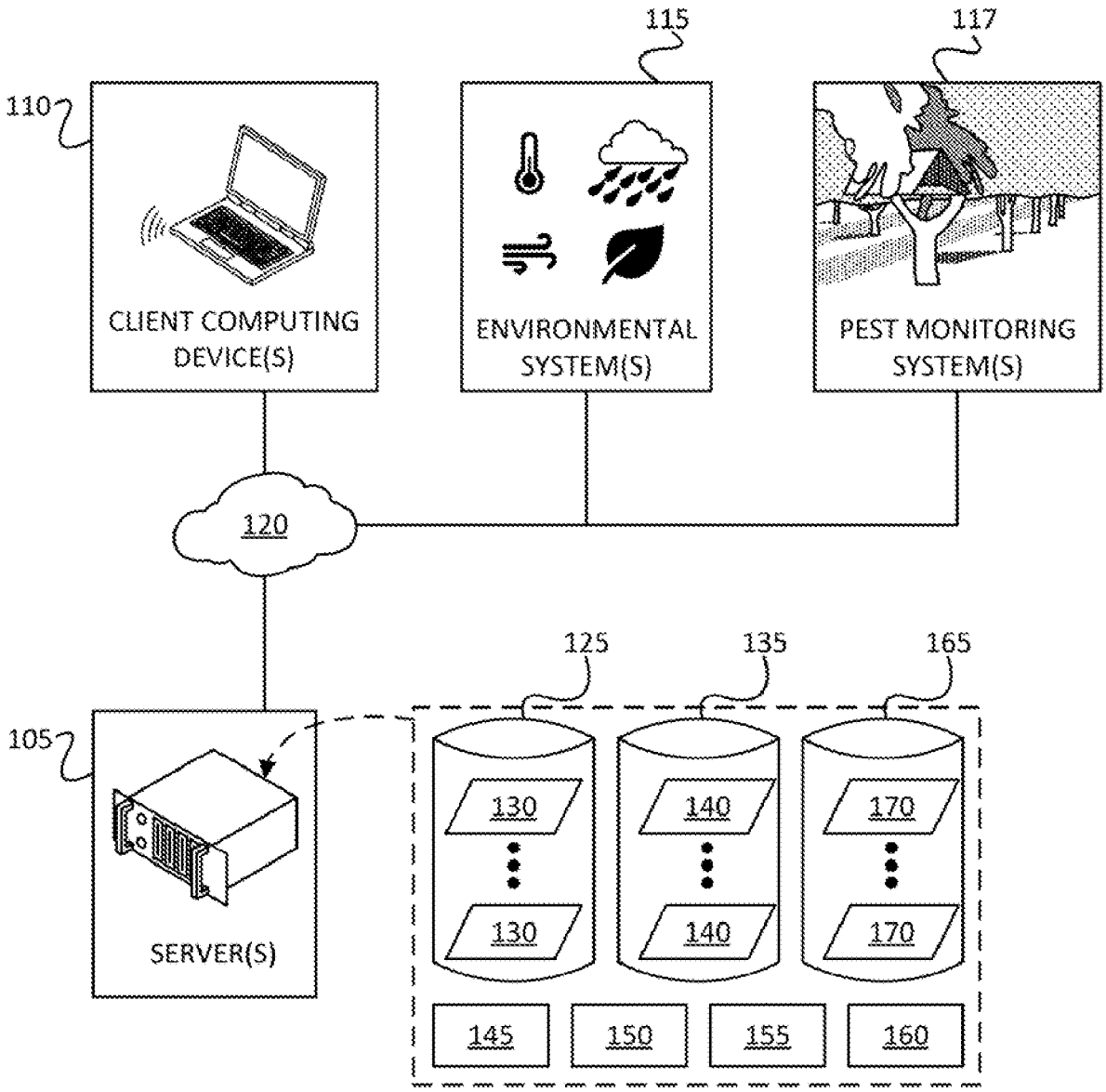
(57) **ABSTRACT**

Systems and methods for controlling a population of a pest are provided. A computer implemented method for controlling a population of a pest can include receiving population data describing a presence of a pest in a host environment at a first time. The method can include receiving environmental data describing the host environment over a prediction horizon including and temporally after the first time. The method can include generating an intervention action for the first time using the population data and the environmental data as inputs to a control model configured to output the intervention action as part of an optimization of the presence of the pest over the prediction horizon. The method can also include outputting the intervention action.



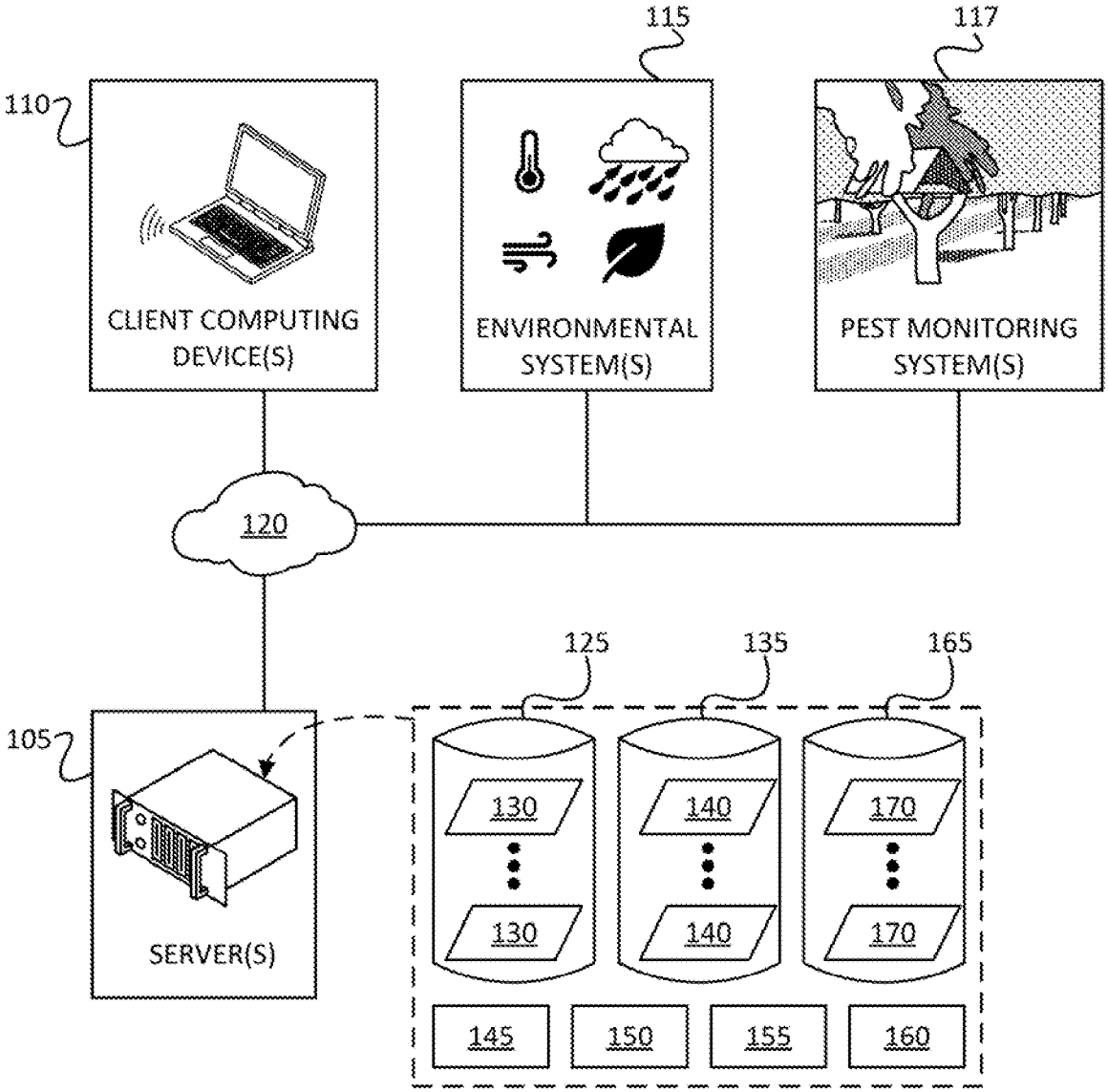

115
117
110
CLIENT COMPUTING DEVICE(S)
ENVIRONMENTAL SYSTEM(S)
PEST MONITORING SYSTEM(S)
120
125
135
165
105
SERVER(S)
130
130
140
140
170
170
145
150
155
160

FIG. 1

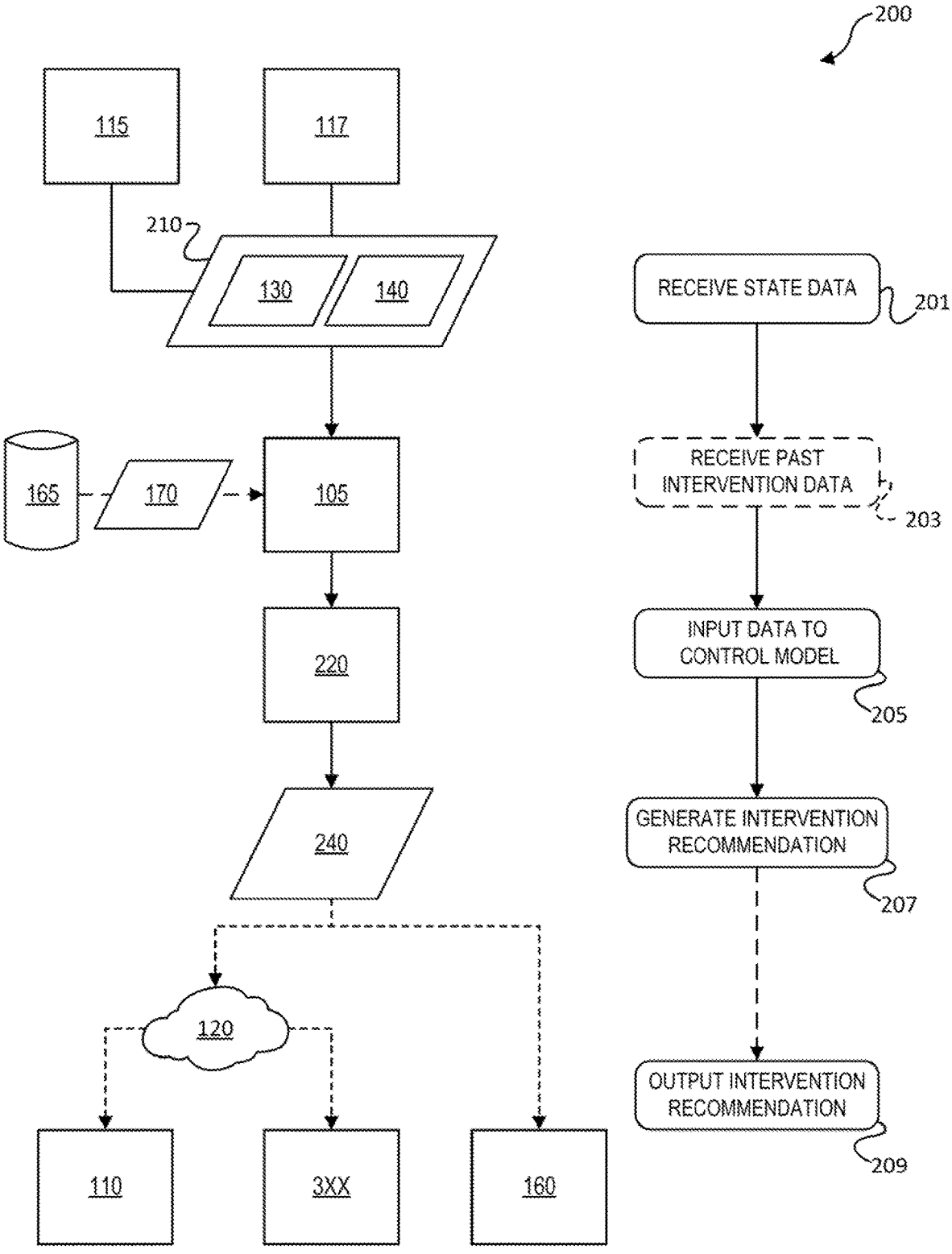

200
115
117
210
130
140
165
170
105
220
240
120
110
3XX
160
RECEIVE STATE DATA
201
RECEIVE PAST INTERVENTION DATA
203
INPUT DATA TO CONTROL MODEL
205
GENERATE INTERVENTION RECOMMENDATION
207
OUTPUT INTERVENTION RECOMMENDATION
209

FIG. 2

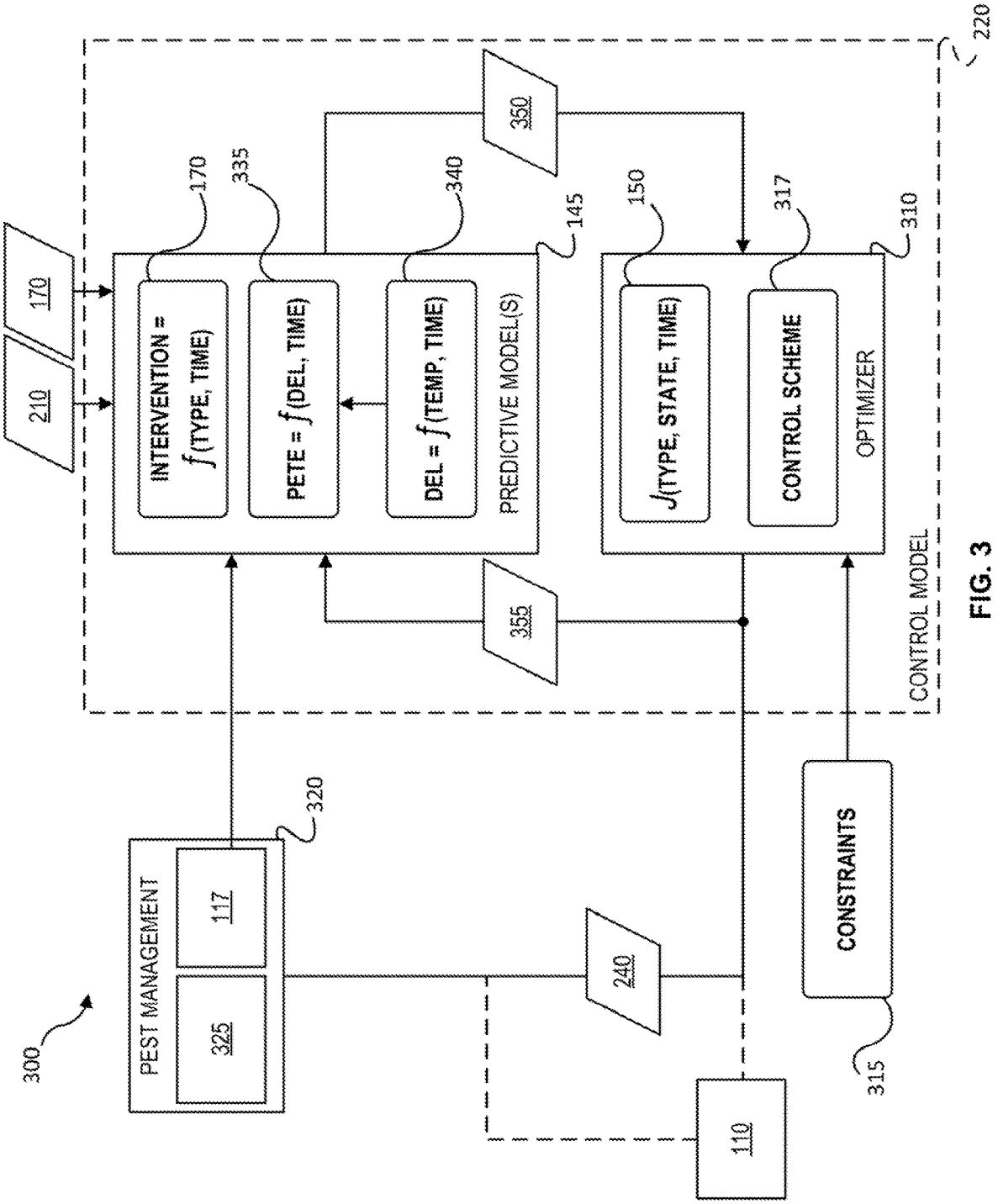

300
PEST MANAGEMENT
325
117
320
210
170
INTERVENTION = f(TYPE, TIME)
PETE = f(DEL, TIME)
DEL = f(TEMP, TIME)
PREDICTIVE MODEL(S)
145
170
335
340
350
355
J(TYPE, STATE, TIME)
CONTROL SCHEME
OPTIMIZER
150
317
310
CONTROL MODEL
220
240
110
CONSTRAINTS
315

FIG. 3

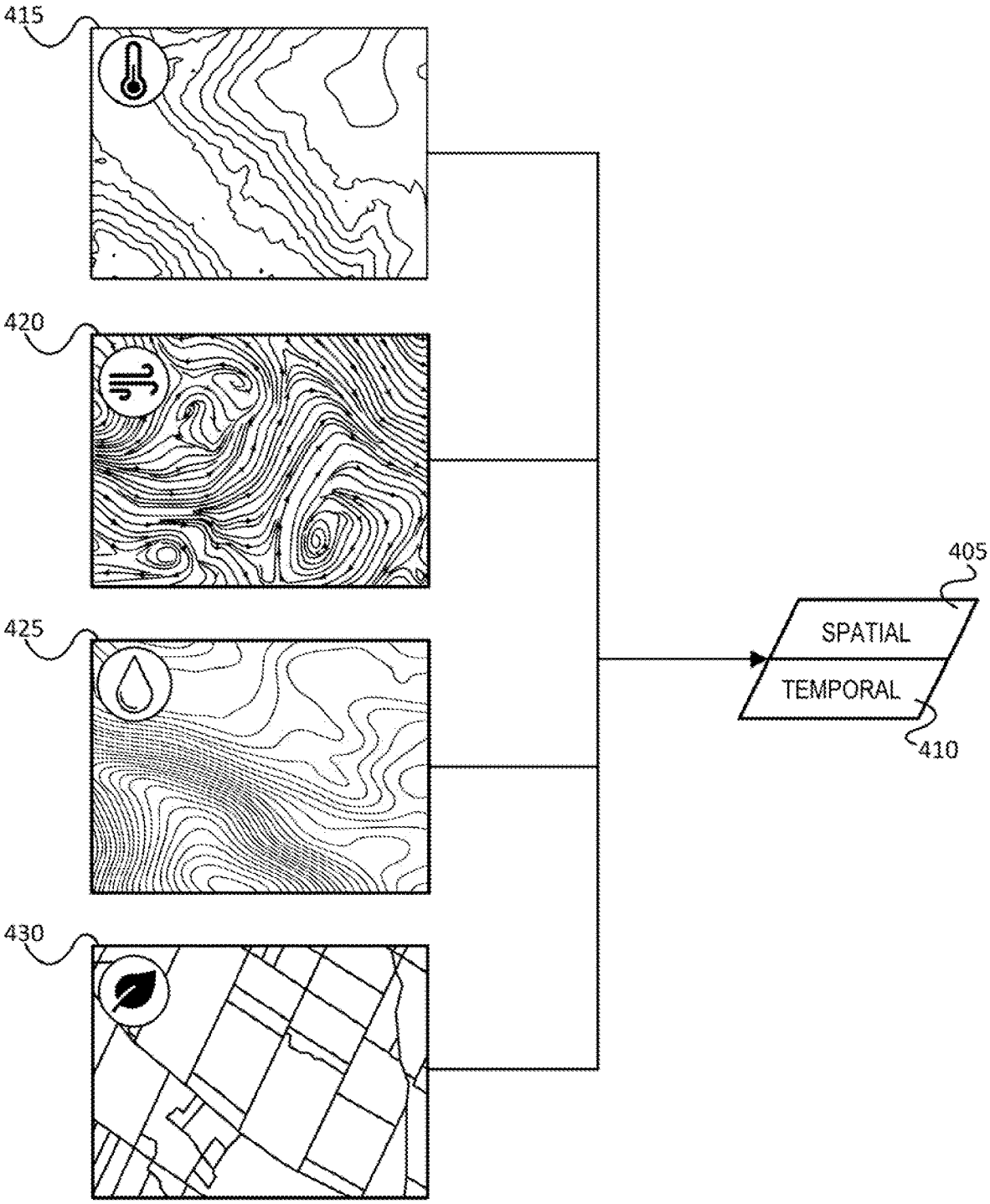


FIG. 4

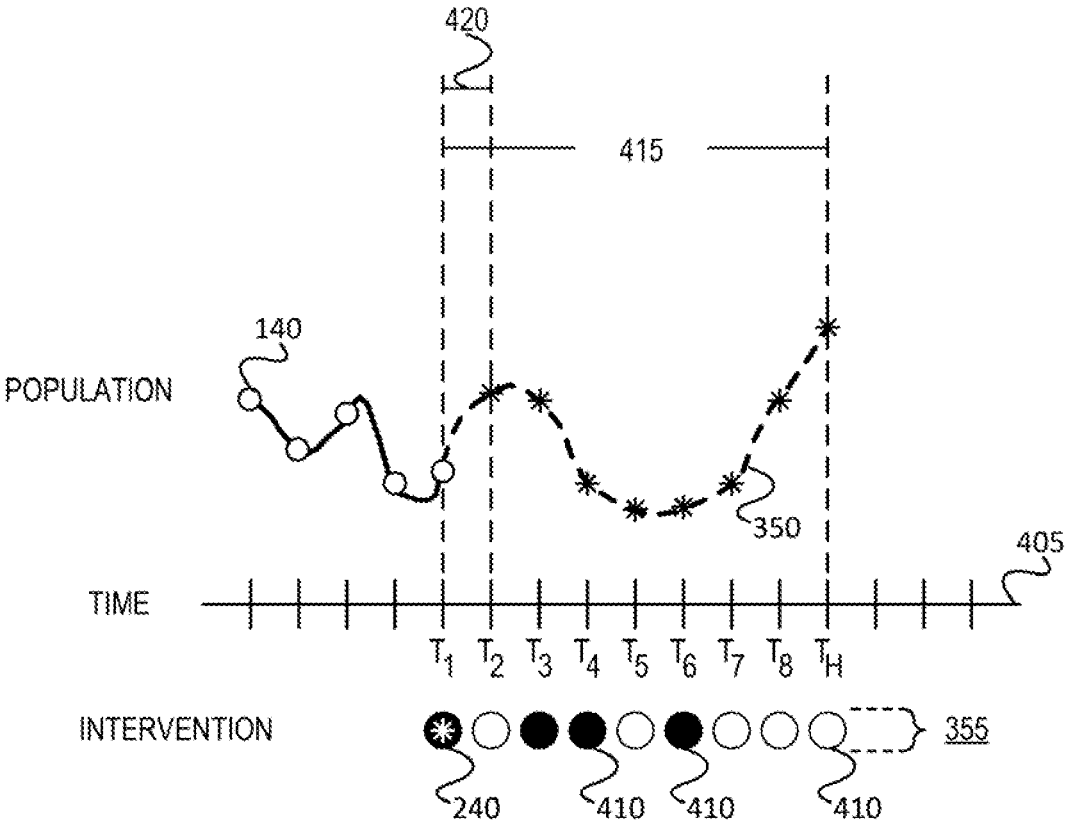

420
415
140
POPULATION
350
405
TIME
T1 T2 T3 T4 T5 T6 T7 T8 TH
INTERVENTION
355
240
410
410
410

FIG. 4B

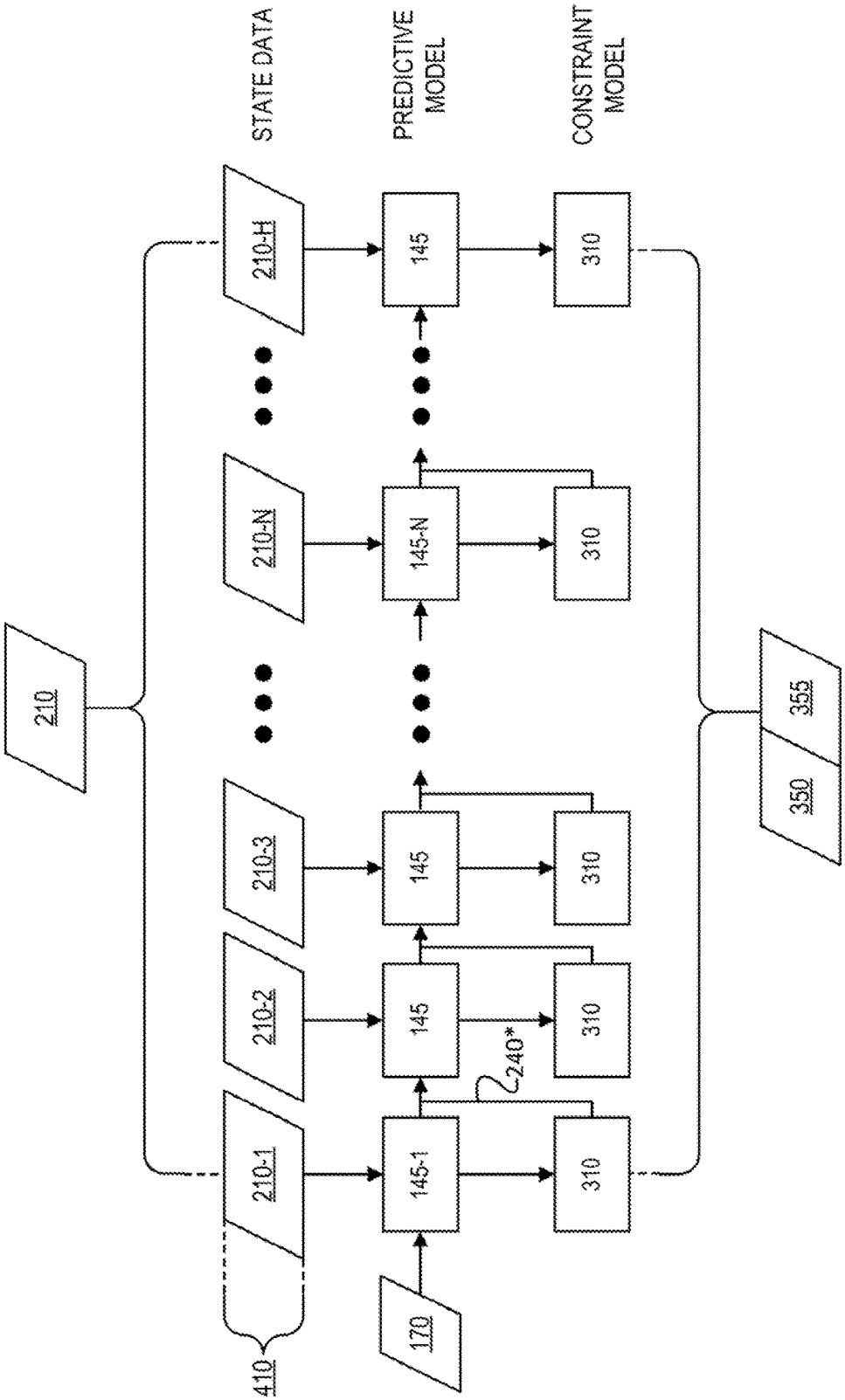

STATE DATA
PREDICTIVE MODEL
CONSTRAINT MODEL
210
210-1
210-2
210-3
210-N
210-H
145-1
145
145-N
310
240*
170
410
350
355

FIG. 5

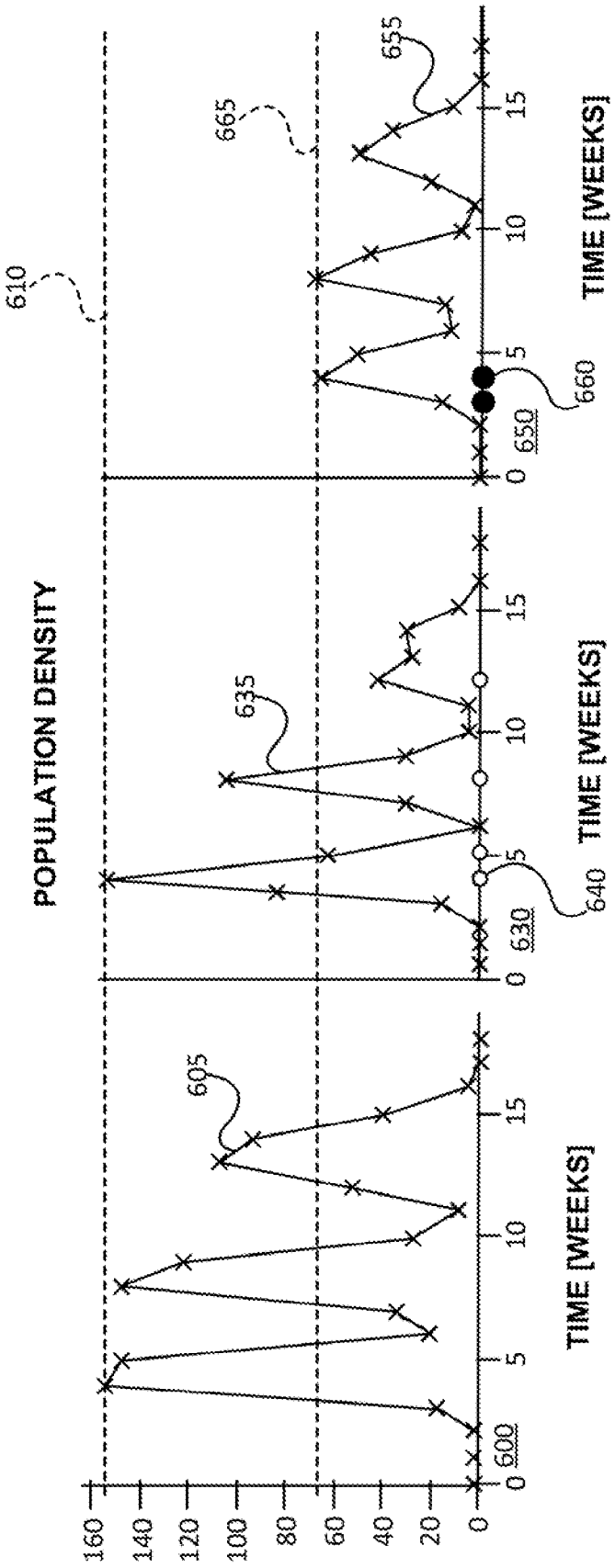


FIG. 6A

FIG. 6B

FIG. 6C

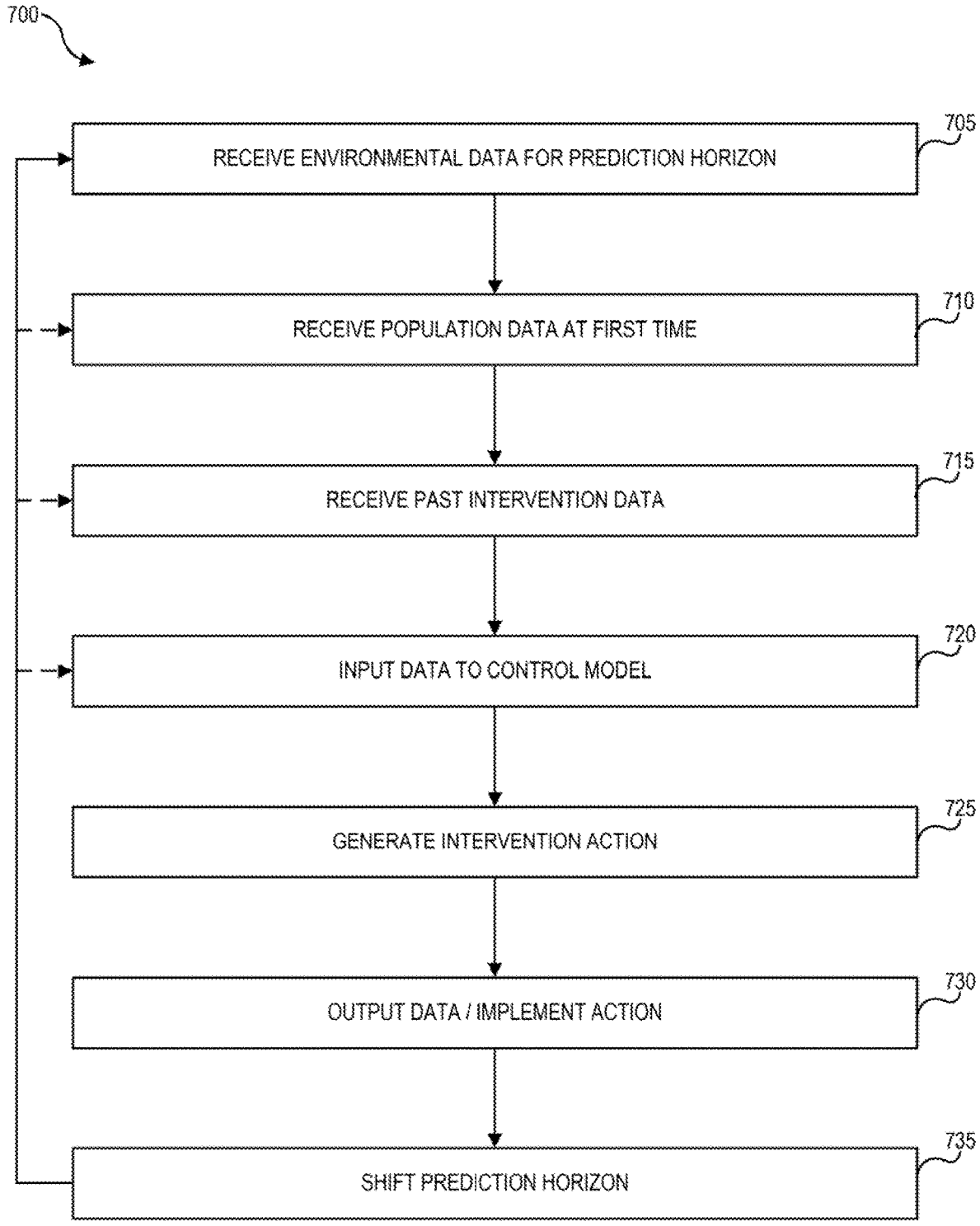

700
RECEIVE ENVIRONMENTAL DATA FOR PREDICTION HORIZON
705
RECEIVE POPULATION DATA AT FIRST TIME
710
RECEIVE PAST INTERVENTION DATA
715
INPUT DATA TO CONTROL MODEL
720
GENERATE INTERVENTION ACTION
725
OUTPUT DATA / IMPLEMENT ACTION
730
SHIFT PREDICTION HORIZON
735

FIG. 7

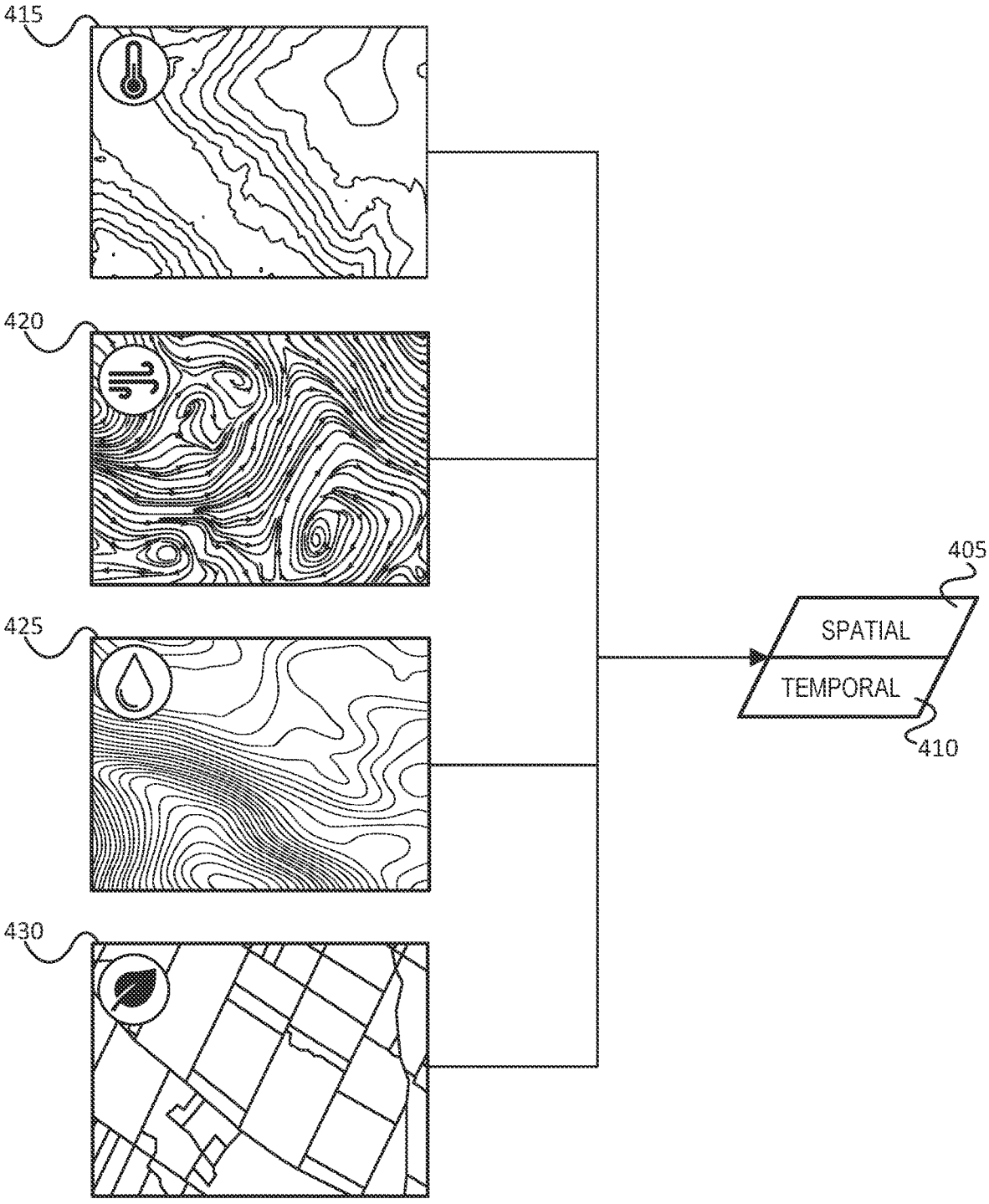


FIG. 4A

MODEL-PREDICTIVE CONTROL OF PEST PRESENCE IN HOST ENVIRONMENTS

TECHNICAL FIELD

[0001] This disclosure relates generally to sensor systems, and in particular but not exclusively, relates to systems and techniques for monitoring and predictive control of pest populations.

BACKGROUND INFORMATION

[0002] Many important agricultural pests are insects. The study of biological life cycles, such as the developmental cycles of insects, is known as phenology, and many phenological models exist for different pest insect species. The overall goal of pest modeling is to predict aspects of insect population dynamics within a season to inform management decisions, such as the timing of pesticide applications or other interventions. Accurate prediction of interventions is crucial for pest management, can help reduce pesticide use, and can reduce crop damage by enabling more precise application.

[0003] Insect pests pose a major threat to agricultural systems and food security. Despite widespread effort to mitigate the impacts of insects, pest management remains challenging. In practice, management typically involves corrective actions that are too late to avert damage. For example, insect pests destroy approximately 20% of global grain crops every year through a combination of direct damage (e.g., consumption) and indirect damage (e.g., spreading disease and parasites). Typically, interventions such as spraying or trapping are implemented in response to a threshold change in population or emergence of a pest, or by following a set schedule.

[0004] Pest intervention remains a labor intensive and challenging process. For example, typical techniques for pest intervention, such as reactive methods or intervention scheduling, do not account for effects of interventions on pest populations, the host environment, or competing objectives including resource allocation and regulatory compliance. There remains a need, therefore, for a predictive approach that integrates physical constraints and competing objectives to significantly reduce insect pest emergence with fewer interventions than the conventional reactive and/or scheduled approaches.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] Non-limiting and non-exhaustive embodiments of the invention are described with reference to the following figures, wherein like reference numerals refer to like parts throughout the various views unless otherwise specified. Not all instances of an element are necessarily labeled so as not to clutter the drawings where appropriate. The drawings are not necessarily to scale, emphasis instead being placed upon illustrating the principles being described.

[0006] FIG. **1** is a schematic diagram illustrating components of an example system for controlling a population of a pest, in accordance with embodiments of the disclosure.

[0007] FIG. **2** is a process flow diagram illustrating an example process for controlling a population of a pest, in accordance with embodiments of the disclosure.

[0008] FIG. **3** is a data flow diagram illustrating an example control system for generating intervention actions, in accordance with embodiments of the disclosure.

[0009] FIG. **4**A is a schematic diagram illustrating example environmental data, in accordance with embodiments the disclosure.

[0010] FIG. **4**B is a schematic diagram illustrating example state data and intervention data, in accordance with embodiments the disclosure.

[0011] FIG. **5** is a schematic diagram illustrating example data flows of an open loop optimization of predicted state data and intervention actions to generate an intervention action, in accordance with embodiments of the disclosure.

[0012] FIG. **6**A is an example population graph illustrating example population data as a function of time in a system without intervention, in accordance with embodiments of the disclosure.

[0013] FIG. **6**B is an example population graph illustrating example population data as a function of time in a system with reactive intervention, in accordance with embodiments of the disclosure.

[0014] FIG. **6**C is an example population graph illustrating example population data as a function of time in a system with predictive intervention described in reference to FIGS. **1-5** and FIG. **7**, in accordance with embodiments of the disclosure.

[0015] FIG. **7** is a block flow diagram illustrating an example method for controlling a population of a pest, in accordance with embodiments of the disclosure.

[0016] In the above-referenced drawings, like reference numerals refer to like parts throughout the various views unless otherwise specified. Not all instances of an element are necessarily labeled to simplify the drawings where appropriate. The drawings are not necessarily to scale, emphasis instead being placed upon illustrating the principles being described.

DETAILED DESCRIPTION

[0017] Embodiments of a system, a method, and computer executable instructions for model-predictive control of a population of a pest in a host environment are described herein. In the following description, numerous specific details are set forth to provide a thorough understanding of the embodiments. One skilled in the relevant art will recognize, however, that the techniques described herein can be practiced without one or more of the specific details, or with other methods, components, materials, etc. In other instances, well-known structures, materials, or operations are not shown or described in detail to avoid obscuring certain aspects.

[0018] Reference throughout this specification to "one embodiment" or "an embodiment" means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment of the present invention. Thus, the appearances of the phrases "in one embodiment" or "in an embodiment" in various places throughout this specification are not necessarily all referring to the same embodiment. Furthermore, the particular features, structures, or characteristics can be combined in any suitable manner in one or more embodiments.

[0019] Insect pests pose a major threat to agricultural systems and food security. Despite widespread effort to mitigate the impacts of insects, pest management remains challenging. In practice, management typically involves corrective actions that are too late to avert damage. For example, insect pests destroy approximately 20% of global

grain crops every year through a combination of direct damage (e.g., consumption) and indirect damage (e.g., spreading disease and parasites). Typically, intervention includes implementing an intervention in response to a threshold change in population or emergence of a pest, or by following a set schedule.

[0020] The study of biological life cycles, such as the developmental cycles of insects is known as phenology, and there are many existing phenological models for various pest insect species. The overall goal of pest modeling is to predict various aspects of insect population dynamics within a season to inform management decisions, such as the timing of pesticide applications or other interventions. Since most insects cannot reliably maintain constant body temperature, insect life cycle and population dynamics are strongly dependent on environmental conditions, such as ambient temperature. A widely used method of quantifying the relationship between temperature and insect biology makes use of a parameter referred to as growing degree days (GDDs). GDDs describe a measure of time and temperature for which the ambient temperature exceeds the lower developmental temperature threshold.

[0021] Models based on GDD estimates rely on heuristics developed in laboratory conditions that, while simple and easy to implement, incorporate simplifying assumptions to reduce the number of parameters and cross-coupling of environmental factors. Such simplifications introduce error and significantly limit the flexibility of the GDD models to adapt to in situ growing conditions. For at least this reason, pest intervention prediction and timing remain a labor intensive and challenging process. As a result, pest management systems typically rely on reactive intervention, based on pest population measurements rising above a threshold value or rate, or by scheduled interventions that do not adapt to in situ conditions.

[0022] GDD models can be calibrated using field measurements, requiring multiple pest trap measurements over multiple days, but only a limited set of models are available for each pest/host combination, and empirical models cannot be adapted for events that are not simulated in laboratory conditions. For example, empirical models used to predict pest populations do not account for effects of interventions on pest populations, the host environment, or competing objectives including allocation of limited intervention resources or regulatory compliance. There remains a need, therefore, for a predictive approach that integrates physical constraints and competing objectives to significantly reduce insect pest abundance with fewer interventions than the conventional reactive and/or scheduled approaches.

[0023] In an illustrative example, many insect pests have distinct generations within one season, referred to as multivoltinism. Different generations manifest as distinct population peaks in observations from a particular season or year. Knowledge about the emergence of each generation is important when managing many pests, as the generations can have distinct biology and interactions with crops. Timing, type, and extent of interventions can be optimized to reduce the overall impact of a pest on the environment (e.g., crop damage) as well as to balance competing objectives (e.g., intervention equipment usage, cost of materials, environmental impact of interventions).

[0024] In the context of almond cultivation, the first generation of navel orangeworm typically lays eggs on old fruits left over from the previous year and does not directly damage future harvests. Subsequent generations in the same orchard, however, tend to be synchronized with the development of new fruit and cause significant crop damage. In this example, interventions can differ between pest generations. For example, the first generation can be treated to trap adult insects (e.g., using pheromone traps), while a second generation can be treated to reduce egg or larval numbers (e.g., by spraying), before the pest is established or proliferates in an orchard. In some embodiments, interventions include targeted chemical interventions, such as mating disruption, that do not kill insects directly, but rather prevent/reduce reproduction as an approach to limit the proliferation of the targeted pest.

[0025] In reference to the forthcoming paragraphs, description of embodiments focuses on navel orangeworm (*Amyelois transitella*, a type of moth) infestation of almond orchards as an example pest/host combination, but alternative applications are contemplated where model predictive control can be applied to control pest population through optimization of intervention timings in line with competing objectives. In general, the techniques described can be applied to pest/host systems for which some ground-truth data is available, for example, through regular albeit infrequent visits by human inspectors, that can be supplemented with rich environmental datasets including historical data, current data, and/or predicted data.

[0026] Examples of alternative pest/host systems can include, but are not limited to, flying insects (e.g. *Lepidoptera, Cynipidae, Diptera*) and/or non-flying insects (e.g. *Aphidae, Lygus*). In some embodiments, non-animal pests can also be modeled in addition to or in place of insect pests. For example, non-insect pests include but are not limited to weeds (e.g., invasive, parasitic, competitor, or otherwise undesirable plants) and plant diseases (e.g., fungal, bacterial, protozoan, viral, etc.). In some embodiments, different models apply to different pest types, corresponding to characteristic growth and proliferation dynamics.

[0027] As such, the techniques described herein (e.g., predictive model control incorporating machine-learning and/or mechanistic models), can be adapted to a given pest/host system. In situ environmental conditions and the complex interactions between the measured and/or predicted environmental parameters can serve as inputs to predictive models paired with optimizer models to converge a constraint model to a target value (e.g., as part of a minimization algorithm). The constraint model can be used to introduce one or more competing objectives. Through optimization of predicted pest population in tandem with the competing objective(s) over a moving prediction horizon, an intervention action at a current time can be generated that both reduces the overall impact of the pest on the host environment and reduces the equipment/resource demand of intervention strategies and the environmental impact of interventions, among other competing objectives.

[0028] In this way, environmental data and pest population data can be leveraged to predict future population inputs for optimizer control models. The optimizer models, in turn, can be configured to generate intervention actions as part of an optimization of pest population and competing objectives over a prediction horizon. Intervention data, such as the economic, resource, and time demands of diverse types of interventions can be included as part of constraint models. Such diverse inputs permit model predictive control techniques to be used to determine which intervention action to

take and/or whether to take an intervention action at a given time period during a growing season. In the context of this disclosure, the term "intervention action" describes one or more operations undertaken by a pest management system including planning, scheduling, and executing an intervention, which can include spraying, deploying natural predators, deploying traps, etc.

[0029] In an illustrative example, a pest monitoring system of pheromone traps can be used to estimate the population density of navel orangeworm in an almond orchard. A control model can include a predictive model configured to predict future pest populations using intervention data, population data, and environmental data, and an optimizer model configured to generate a set of intervention actions over the prediction horizon. An intervention action can be generated based at least in part on optimizing the set of predicted invention actions using a constraint model (e.g., minimizing a "cost" function, where cost refers to non-economic costs). The process of generating and/or receiving pest population data, environmental data, and prior intervention data can be repeated iteratively as part of a control scheme to actively manage predictive interventions, rather than applying a reactive or pre-scheduled intervention process. Advantageously, the techniques and systems described herein improve the performance of pest management systems at least in part by reducing the number of interventions and the emergence of pests.

[0030] FIG. **1** is a schematic diagram illustrating components of an example system **100** for controlling the population of a pest, in accordance with embodiments of the disclosure. Example system **100** includes: one or more servers **105**, one or more client computing devices **110**, one or more sources of environmental data **115**, one or more pest monitoring systems **117**, and a network **120**. The server(s) **105** include: a first database **125** of environmental data **130**, a second database **135** of pest population data **140**, one or more constraint models **145** and one or more predictive models **150** encoded in software **155**. As part of software **155**, server(s) **105** include instructions by which models **145-150** are configured and/or deployed using computer circuitry **160**. In some embodiments, server(s) **105** further include a third database **165** storing intervention data **170** that describes intervention actions that have been implemented corresponding to one or more agricultural regions (e.g., as part of a spatially localized pest management system).

[0031] The following description focuses on embodiments implementing a networked system for configuring and/or deploying models **145-150** for generating predicted population density and intervention predictions for a given pest/host combination over a prediction horizon, and for optimizing the intervention predictions using one or more optimization criteria to determine an intervention action to be taken. It is contemplated, however, that some embodiments of the present disclosure include some or all of the processes being implemented on client computing device(s) **110**, such as a laptop, smartphone, or personal computer. For example, configuration and development of models **145-150** can be implemented using server(s) **105**, while completed models **145-150** can be transferred to client computing device **110** via network **120** and can be deployed directly on client computing device **110**. Similarly, the constituent elements of example system **100** can be hosted and/or stored on a distributed computing system (e.g., a cloud system) rather than in a unitary system. For example, first database **125**, second database **135**, third database **165**, and/or computer circuitry **160** can be implemented across a distributed system, such that portions of environmental data **130**, population data **140**, software **155**, and/or intervention data **170** can be stored or executed by a distributed computing system in one or more physical locations.

[0032] In an illustrative example of the operation of example system **100**, server(s) **105** and/or client computing device(s) **110** receive state data **210** (in reference to FIG. **2**) including environmental data **130** describing conditions and physical characteristics of a host environment that are measured and/or predicted by sources **115** and/or pest population data **140** describing the presence and/or abundance of a pest in the host environment that is measured by pest monitoring system **117**. The presence of the pest can include whether the pest is present at all (e.g., a "true" or "false" value) as well as an estimate of pest population density in the host environment. Environmental data **130** can be or include meteorological data, hyperspectral data, topographic data, segmented and/or classified image data, or the like, as described in more detail in reference to FIG. **4**A. Environmental data **130** can be accessed, received, and/or stored locally on client computing device **110**. Additionally or alternatively, environmental data **130** can be accessed, received, and/or stored on server(s) **105** via network **120**.

[0033] Control models include predictive models **145** that are configured, trained, and/or prepared to input environmental data **130** and to output predicted population data, which can be pushed to user devices, such as client computing device **110**. In some embodiments, example system **100** is configured to implement automated procedures, such as scheduling interventions, implementing interventions, generating notifications to be presented to users of client computing devices **110**, through direct control communication with automated or pseudo-automated pest management systems **320** (in reference to FIG. **3**). In this context, automated refers to operation without human involvement (e.g., as an autonomous vehicle configured to implement an intervention, such as spraying), and pseudo automated refers to a system that implements one or more automatic actions and also includes some human involvement (e.g., a system that prepares for an intervention and includes a human user to implement the intervention, such as a human driver of a spraying system).

[0034] In the context of example system **100**, sources of environmental data **115** are represented by a collection of visual symbols (e.g., a thermometer), to simplify visual explanation. Sources of environmental data **115** include, but are not limited to, in situ sensors, orbital imaging/spectroscopy platforms, meteorological models or data collection systems, and/or user-labeled data. As an illustrative example, sources of environmental data **115** can include in situ sensors for ambient temperature, humidity, carbon dioxide, chemical pollution, GPS location, wind speed, atmospheric pressure, or the like (e.g., as in a meteorological sensor station). In some embodiments, sources of environmental data **115** also include meteorological predictions for the host environment generated by a weather model. Environmental data **130** can be localized to a physical area by correlating physical locations of sensors (e.g., GPS data) with extent information describing the physical space where host vegetation is grown (e.g., the metes and bounds of an almond orchard within a polyculture agricultural region).

[0035] Extent information can be generated by manual labeling of map data and/or satellite images (e.g., hyperspectral images indicating spatial variation in water content), automated (e.g., without human intervention) classification/segmentation of satellite images, or through communication of planting data with agricultural systems, such as planting systems that include internet-connected systems. In an example, a planter can include a GPS sensor and an interne connected computer system that can generate planting data describing locations and seed identifier information for planting operations. In turn, the planting data can be shared with example system **100** as part of environmental data **130**.

[0036] Pest population data **140** can be collected as part of the operation of pest monitoring system **117** by various sampling methods used by growers. For example, pheromone traps, egg traps (for flying insects, e.g. *Lepidoptera*), suction traps (for aphidae) or bucket sampling and/or sweep sampling (e.g., for non-flying insects, e.g. *Lygus*). Inspection rates can vary within a season but for pheromone and egg traps, traps are checked typically at least once per week. Different sampling methods have different degrees of reliability, but typically the data can include noise. For example, a pheromone trap for navel orangeworm captures only adult male moths, relying on an estimate of the proportion of male insects in the overall population to estimate the total population including both male and female insects. Data analysis and entry into example system **100** can include manual counting, automated assessment using computer vision models (e.g., machine counting), weight-based counting, or other techniques.

[0037] In some embodiments, intervention data **170** describe prior interventions taken in the host environment. Intervention data **170** can be received from client computing device(s) **110**, including but not limited to planting systems, by manual user input, and/or as part of outputting operations as described in more detail in reference to FIG. **2**. In this way, it is contemplated that example system **100** will support iteration of models **145-150** using intervention actions to improve future performance of pest management actions with respect to one or more competing objectives.

[0038] As described in more detail in the forthcoming paragraphs, predictive model **145** generates predicted population data **350** (in reference to FIG. **3**) for an optimizer model **310** by processing state data **210** and generating a predicted population dataset based at least in part on kinetic aspects of pest population development, such as a DEL parameter **340**, as described in more detail in reference to FIG. **3**. Predicted population data **350** are used to generate predicted intervention data **355** using an optimization routine for constraint model **150**, for example, through one or more control schemes **317**. Environmental data **130**, population data **140**, predicted population data **350**, intervention data **170**, and predicted intervention data **355** can be used as part of an optimization of constraint model **150** over one or more iterations, as described in more detail in reference to FIGS. **3-8**.

[0039] FIG. **2** is a process flow diagram illustrating an example process **200** for modeling population dynamics of a pest, in accordance with embodiments of the disclosure. Example process **200** may be implemented by one or more constituent elements of example system **100** of FIG. **1**, including but not limited to server(s) **105** and/or client computing device(s) **110**. Example process **200** includes operations **201-209** for receiving environmental data **130** and generating pest intervention recommendations **240** using control model(s) **220** including predictive models **145** and constraint models **150** as part of an optimization of competing objectives including the presence of a pest in the environment and the resource demand and/or environmental impact of interventions over a prediction horizon **415** (in reference to FIG. **4**B), also referred to as "H." In the context of the present disclosure, prediction horizon "H" describes a period of time over which state data **210** is available from which population data **140** can be predicted for use in iterative optimization of control model(s) **220**.

[0040] Example process **200** is illustrated as a series of operations **201-209** implemented by a computer system using models encoded in software. For example, the operations of example process **200** can include implementation of models **145** and **150**, stored as computer-readable instructions in software **155** that are executed by computing circuitry **160** of server(s) **105**. In some embodiments, the operations of example process **200** are divided between multiple systems. For example, at least a subset of the operations of example process **200** can be executed locally on client computing device **110**, while a different subset of the operations of example process **200** can be executed on a distributed system of server(s) **105**. For example, outputting operations can be executed on client computing device **110** as part of an interactive pest monitoring and/or management platform that solicits user feedback and provides notifications of pest population dynamics in advance and/or in near-real time, as part of scheduling and implementing intervention actions.

[0041] In this context, the term "near-real time" is used to refer to a delay in delivering pest population data within a time frame during which an intervention can be effectively staged. For example, an intervention recommendation can be characterized by a timing window on the order of days and a spraying operation can occupy a period of time of hours, such that a delay in receiving pest population data and/or intervention recommendations on the order of minutes or hours does not impair the effectiveness of the prediction. Similarly, where an intervention is time-sensitive on the order of hours, population data that is delayed by hours can still be effective if the data accurately describe future conditions more than one day in advance.

[0042] The order in which some or all of the process blocks appear in example process **200** should not be deemed limiting. Rather, one of ordinary skill in the art having the benefit of the present disclosure will understand that some of the operations can be executed in a variety of orders not illustrated, or even in parallel, with some operations omitted or with some optional operations included. Advantageously, operations **201-209** of example process **200** can be prioritized, parallelized, distributed, or otherwise coordinated to provide population and/or intervention data within a timeframe where it can be effective for the user, being informed, for example, by the temporal sensitivity of the data being generated. In this way, the performance of pest management systems, including automated systems, can be improved over that of fixed-schedule or reactive pest management systems, as described in more detail in reference to FIG. **7**.

[0043] At operation **201**, example process **200** includes receiving state data **210**, including environmental data **130** and/or population data **140**. Environmental data **130** can be received directly and/or indirectly from sources **115**, for

example, through operation of a data retrieval system configured to request environmental data **115** and/or to receive environmental data **115** according to a refresh cadence or other timing. For example, an application hosted on client computing device **110** can receive environmental data **130** from sources **115** via network **120**. Pest population data **140** can be received from pest monitoring system(s) **117** directly (e.g., where pest monitoring includes sensor bearing systems that can communicate with server(s) **105** over network **120**) and/or indirectly from client computing device(s) **110** (e.g., via a user-initiated upload). Client computing device(s) **110** and/or server(s) **105** can then process environmental data **130** locally to generate state data **210**. In some embodiments, operation **201** can include communication of environmental data **130** between sources **115** and server(s) **105**, where generation of state data **210** occurs at least in part on server(s) **105**.

[0044] In some embodiments, environmental data **130** includes data for a plurality of physical locations as part of a spatiotemporal dataset, as described in more detail in reference to FIG. **4**A. For example, environmental data **130** can include two-dimensional projection data (e.g., iso-contour maps) for atmospheric pressure, precipitation, wind speed, or the like, that can be developed by meteorological or other models using point-data measured by in situ sensors. As such, environmental data **130** can be received from sources **115** that are in situ (e.g., local sensors) and/or from computer systems that communicate with in situ sensors to generate estimated and/or predicted environmental data **130**. Example system **100** can receive environmental data **130** through intermediary systems (e.g., publicly available weather data), rather than communicating directly with a network of sensors specific to the pest/host system. To address limitations in sensor networks and/or prediction systems, in some embodiments, operation **201** includes accessing multiple redundant data sources. Advantageously, accessing redundant environmental data **130** addresses delays in availability of environmental data **130** from any given source and further corrects for error by aggregating environmental data **130**.

[0045] At operation **203**, example process **200** can include receiving past intervention data **170**. In the context of generating an intervention action **240** for the current time, prior intervention data can be propagated into future predictions as part of optimizing a constraint function over one or more growing seasons as well as over a prediction horizon. In an illustrative example, state data **210** can be received at operation **201** corresponding to a prediction horizon of four weeks. Optimizing for competing objectives of controlling the presence of a pest in the host environment by applying spray pesticide and reducing the impact of spraying on agricultural output can include imposing a constraint on the total quantity of pesticide applied per unit area. In this way, spray timings can be optimized to reduce predicted pest emergence over the prediction horizon while also minimizing the quantity of pesticide applied over the prediction horizon, as well as over the entire growing season, by propagating intervention data **170** from prior iterations of example process **200** and/or from other sources of intervention data **170**.

[0046] At operation **205**, example process **200** includes inputting data, including state data **210** and/or intervention data **170**, to control model **220** configured generate intervention action **240** as part of optimizing a set of predicted intervention actions **355** over the prediction horizon **415** "H" (in reference to FIG. **4**B). As described in more detail in reference to FIGS. **3-5**, predictive models **145** can take in multiple inputs, including but not limited to environmental data **130**, pest population data **140**, and/or intervention data **170** corresponding to a period of time preceding prediction horizon "H."

[0047] State data **210** can include fewer points of population data **140** than environmental data **130**. As such, predictive model(s) **145** can be configured to generate predicted population data **350** (e.g., population density, pest emergence, etc.) that can be used to estimate pest population dynamics at a future time, temporally after the time for which intervention action **240** is generated. In an illustrative example, predictive model(s) **145** can be used to describe population density, cumulative population density, and emergence information at a second time point, temporally after a first time point of intervention action **240**, for which population data **140** is unavailable. The first time point and the second time point can be separated by a time-step **420** (in reference to FIG. **4**B) that can be a parameter of pest management system **320**. The time-step can be on the order of minutes, hours, days, weeks, or longer, based at least in part on the time scale of a given intervention method and/or a sampling period of population data **140**.

[0048] Pest population data **140** can be collected using pest monitoring system(s) **117** that are sampled and/or replaced according to a sampling period of about one week. To that end, the frequency of intervention actions can correspond with the sampling period (e.g., one recommendation per week) or can be more frequent or less frequent, depending on the time used to implement an intervention (e.g., where a spray intervention can be completed in less than one week and population data is based on weekly trap catches, intervention actions **240** can be generated more frequently than the sampling period). In some embodiments, the intervention period can be constrained by environmental restrictions, system limits, or other constraints. For example, the frequency of intervention actions of a given type (e.g., spraying, mite dispersal, or the like) can be limited by environmental constraints or logistical factors, where application is limited not only by total dose, but also by dose over time to impose a minimum period between intervention actions.

[0049] At operation **207**, example process **200** includes generating intervention action **240** as the output of control model **220**. As described in more detail in reference to FIG. **3**, intervention action **240** corresponds to an entry in a set of predicted intervention data generated via an optimization of an intervention schedule over prediction horizon "H," based at least in part on optimizing a value of constraint model **150**. As described in more detail in reference to FIG. **1**, constraint model can include terms to balances multiple competing objectives including but not limited to presence of the pest in the host environment, resource demands and logistical demands of intervention systems, impacts of interventions on the host environment, and/or impacts of inventions on the surrounding environment.

[0050] Control model **220** can include diverse model architectures and a number of different optimization paradigms implemented as an optimizer **310**. As an illustrative example, optimization can include one or more approaches for model predictive control including but not limited to genetic algorithms, nonlinear constrained optimization tech-

niques (e.g. trust region methods, active-set algorithms, sequential quadratic programming, or interior point algorithms), or graph-based searches of intervention data including a cost-optimized search algorithm. Nonlinear constrained optimization techniques (e.g., Pontryagin's principal or Hamilton-Jacobi-Bellman non-linear optimization), linear-quadratic regulator optimization, and/or reinforcement learning approaches (e.g., machine learning models) can be used to solve an optimal control problem over multiple prediction horizons for a period of time for which environmental data, state data, and/or intervention data are available. Additional and/or alternative approaches include graph-based searches of intervention data **170** using a cost-optimized search algorithm. Optimized search algorithms can include classic tree search algorithms, local search algorithms, or Monte Carlo search algorithms.

[0051] In the context of linear-quadratic regulator-based model-predictive control, control model **220** can implement predictive model(s) **335** as a set of linear differential equations (e.g., as PETE model described in reference to FIG. **3**) and can implement constraint model **150** as a quadratic function. Optimization of a linear quadratic regulator involves minimizing constraint model **150**, which can be defined as a sum of individual contributors to an overall impact of intervention actions over prediction horizon "H." Iteratively modifying predicted intervention actions **355** and revising predicted population data **355** toward convergence permits control model **220** to determine intervention action **240** (e.g., immediately or as part of a scheduled pest management system).

[0052] For genetic algorithm approaches, optimizer model **310** can generate two or more parent sets of predicted intervention actions **355** (e.g., by random generation), from which a number of child sets can be propagated by various techniques (e.g., random combination, pseudo-random combination, etc.) and the child sets can be evaluated using constraint model **150**. Optimizer **310** can iterate over multiple generations to converge one or more candidate sets of predicted intervention data **355** toward an optimized value of an objective function (e.g., a loss function, cost function, or the like), to evolve one or more elite candidates most likely to correspond to a presence of the pest in the host environment that is balanced with competing objectives, such as a reduced resource demand and/or logistical cost of interventions.

[0053] In the context of Hamilton-Jacobi-Bellman non-linear optimization, control model **220** implements a "value function" that represents the minimum value of a temporal integral of the constraint model **150** and a residual value at time T=H.

$$V_T(x(0), 0) = \min_u \left\{ \int_0^T C[x(t), u(t)]dt + D[x(T)] \right\}$$

Where V_T is the value function, C is the constraint model, and D is the residual value as a function of predicted population data **350**. In the context of pest management, the constraint model (accounting for competing objectives) can represent a population model with intervention effect and the residual value can be based on the pest information. As a discrete-time counterpart, the value function can be replaced by Bellman's equation, which can be solved with value iteration or policy iteration. In some cases, the residual value can represent a projected impact of the pest in the environment as a result of the remaining pest presence that can result in future damage to agriculture and/or the environment. Inclusion of the integral permits that minimization of the value function over the prediction horizon to represent the optimum solution for a control vector "u(t)" that represents the set of predicted intervention actions **355**.

[0054] In the context of optimization in line with Pontryagin's principal, control model **220** can implement a minimization of an objective functional, J, defined for the system of pest population management as a function of state data **210** and intervention data **170** over time from a first time point, corresponding to the time of intervention action **240** to a time T=H.

$$J=\Psi(x(T))+\int_0^T L(x(t),u(t))dt$$

Where $\Psi(x(T))$ is defined as a partial derivative of the state function, evaluated at the endpoint of prediction horizon H, representing a residual state of the system. L represents a Lagrangian formulation of constraint model **150** that is integrated over time from the first time point to time T=H. The optimization is implemented by control model **220** at least in part by satisfying the four optimality conditions of Pontryagin's principal, as would be understood by a person skilled in the art of computer control. In some embodiments, the objective functional includes a discrete summation, rather than an integral, where state and intervention data are discrete time variables:

$$J(x, u) = \sum_{t=0}^{H-1} \ell(x_t, u_t) + \phi(x_t)$$

There the term u(t) represents control inputs to pest management system **320** as a function of time, with values being generated as a function of predicted pest population data **355** in accordance with one or more control schemes **317**. In the function above, Φ refers to additional terms not directly dependent on interventions and/or populations.

[0055] Additional terms "Φ" can include but are not limited to environmental and health related factors included as part of model predictive control. As an illustrative example, pesticides include harmful chemicals that can damage surrounding ecosystems when they make their way into rivers, lakes, and groundwater. This process is known as "pesticide leaching," and heavy rainfall and irrigation increase the risk of leaching. To that end, Φ can include rainfall predictions from environmental data as an input to quantify runoff risk associated with spraying pesticides. In another example, the time prior to harvest can be an additional term that modifies weather pesticide application is permissible. For example, shortly before crop harvest, pesticide application can leave residue on the crop that can be harmful when consumed by humans. Similarly, the non-economic "cost" of pesticide application can increase during a window of time preceding a harvest to reflect that pesticide application is disfavored, but not impermissible.

[0056] Control model **220** can incorporate machine learning models that are trained to predict intervention action **240**. In an illustrative example, a machine learning model can be trained to input state data **210** and intervention data **170** and to output a predicted set of intervention actions **355** (e.g., a sequence-to-sequence model such as an RNN,

LSTM, or GRU model). Training can be based at least in part on a set of labeled training data from prior executed pest management operations and/or using synthesized data produced from model-predictive control simulations using other methods described herein. Advantageously, machine learning techniques can capture latent interactions between different constraints that can be less apparent and therefore excluded from analytical formulations of predictive model(s) **145** and constraint model(s) **150**. In some embodiments, machine learning models can be trained to input a set of predicted intervention actions **355** and state data **210** and to output an optimized set of predicted intervention actions **355**. As such, it is understood that such machine learning techniques can include training a model to approximate the behavior of the pest-host system in response to intervention actions.

[0057] In some embodiments, example process **200** includes outputting intervention action **240** at operation **209**. Outputting operations can include electronic communication of intervention action **240** in a computer system, such as server(s) **105** and/or client computing device(s) **110** or between different systems, as in distributed networked systems and/or between server(s) **105** and client computing device(s) **110**. In some embodiments, outputting operations include storing intervention action **240** and/or intervention data **170** in a data store, such as a memory device of server(s) **105** and/or client computing device(s) **110**.

[0058] Similarly, outputting operations can include generating visualization and/or notification data and communicating the data to a user device or other associated device, such as a smartphone or an internet-connected piece of agricultural equipment. Agricultural equipment can incorporate many of the same types of electronic devices as client computing device **110** or smart phones. As such, operation **209** can include communicating with agricultural equipment, for example, over network **120**, such that notifications and/or visualizations can be presented to a user of the agricultural equipment through display devices, acoustic speakers, or the like, that are incorporated into the equipment. In the example of a smartphone, the visualization and/or notification data can be formatted using standardized communication protocols, such that outputting can include sending a digital message including population data **240**, intervention timing data, or other types of notifications, without a specialized application.

[0059] Outputting operations can also include communicating intervention action **240** with a pest management system **320** (in reference to FIG. **3**). In some embodiments, outputting to pest management system **320** includes autonomous or semiautonomous initiation of an intervention actions **240**. For example, intervention action **240** can be initiated through modifying a logistics system managing pest intervention equipment. Where the logistics system manages resource allocation, such as spray trucks, mite dispersal, trap teams, or other automated, pseudo-automated, or manual interventions, outputting intervention action **240** can include engaging an intervention resource **325** within a window of time corresponding to the first time point for effecting intervention action **240**.

[0060] Following operations **207** and/or **209**, example process **200** can be repeated over one or more iterations with updated state data **210** and/or intervention data **170** for an updated prediction horizon. For example, prediction horizon H can be shifted by one or more timesteps T to permit control model **220** to generate a second intervention action **240** corresponding to a second time temporally after the first time of a first intervention action **240**.

[0061] FIG. **3** is a data flow diagram illustrating an example control system **300** for generating and implementing intervention actions, in accordance with embodiments of the disclosure. Example control system **300** can be implemented by one or more constituent elements of example system **100** of FIG. **1**, including but not limited to server(s) **105** and/or client computing device(s) **110**. Example control system **300** can include one or more algorithms encoded in software **155** including one or more iteration loops used to implement optimization of intervention action **240**. Example control system **300** includes control model **220** implementing predictive model(s) **145** and an optimizer **310** configured to minimize constraint model **150** over prediction horizon H. Example control system **300** can include one or more pest management systems **320** deployed to monitor the presence of a pest in a host environment (e.g., pest monitoring system **117** of FIG. **1**) and/or to effect intervention action(s) **240**.

[0062] As described in more detail in reference to FIG. **2**, control model **220** is configured to implement an optimization of a set of predicted intervention actions **355** over prediction horizon H, based at least in part on set of predicted population data **350** and constraints **315** included as part of constraint model **150**. Over one or more iterations, competing objectives encoded in constraint model **150** can be balanced by modifying predicted intervention actions **355** and iteratively regenerating predicted population data **350**. As described in more detail in reference to FIG. **7**, generating intervention action **240** can form a part of a model-predictive control algorithm for managing the presence of a pest in the host environment, where updated state data **210** and intervention data **170** are provided to control model **220** for a new prediction horizon H following operation **207** of example process **200**.

[0063] Selection of predictive model(s) **145** can be informed by details of the pest/host system. As an illustrative example, for insect pests, predictive model(s) **145** can include mechanistic models such as the Predictive Extension Timing Estimator (PETE) model **335**. Other predictive models **145** for insect-pests include, but are not limited to, the Ricker model, the Lotka-Volterra model, and the spruce budworm model. Advantageously, predictive models **145** can be selected to account for particular pest population dynamics, which can be specific to a genus, species, or pest/host system. For example, the Lotka-Volterra model includes predator-prey interaction terms, and the spruce budworm model includes terms to account for outbreak dynamics. In this context, the term "outbreak dynamics" refers to a mechanism of pest proliferation that is infrequent and significant in extent. For example, an outbreak of spruce budworm in the Canadian province of Quebec in 2006 resulted in defoliation of approximately 3,000 hectares of forest after several decades of inactivity by the pest.

[0064] PETE model **335** implements a simplifying assumption that insect population development rate is determined primarily by ambient temperature. PETE model **335** assumes that the rate of development is directly proportional to the temperature in excess of some species-specific lower developmental threshold (just like degree days) and that the dynamics of emergence are governed by a delay differential equation (DDE). The PETE DDE takes the form of a system of k equations:

$$\frac{dr_1}{dt} = \frac{k}{DEL(t)}\left(I(t) - r_1(t)\left(1 + \frac{1}{k}\frac{DEL(t)}{dt}\right)\right)$$

$$\frac{dr_2}{dt} = \frac{k}{DEL(t)}\left(r_1(t) - r_2(t)\left(1 + \frac{1}{k}\frac{DEL(t)}{dt}\right)\right)$$

$$\frac{dy}{dt} = \frac{k}{DEL(t)}\left(r_{k-1}(t) - y(t)\left(1 + \frac{1}{k}\frac{DEL(t)}{dt}\right)\right)$$

[0065] where I(t) represents the input population at time "t," y represents the predicted emergence at a later time temporally after t, DEL **340** represents a delay parameter that is the reciprocal of the rate of development, r_i represents intermediate rates, and k represents the number of equations in the system.

[0066] The delay DEL(t) at each timepoint can be described by:

$$DEL(t) = DEL_{PETE}(t) \times DEL_{NN}(t)$$

$$= \frac{TDD}{\max(0,\ T(t) - T_0)} \times f_\theta(x(t))$$

where f_{74} represents ML model **145** and x(t) represents Environmental data **130** at time "t." In some embodiments, DEL(t) is used to solve PETE model **335** above using a Euler solver with timestep dt=0.25 days to obtain the predicted emergence y(t).

[0067] In an illustrative example, PETE model **355** can be applied to model population dynamics of an individual life stage of an insect, for example the emergence of an adult insect from the pupal stage. In this context, the term "emergence" describes a change in population density of the adult insect over time. Since adult insects develop from pupae, "emergence" indicates a positive rate of change of the population density. In some embodiments, it is assumed that the total population of insects is conserved, such that the sum of the number of pupae and the number of adult insects remains constant over time. In some embodiments, additional dynamics are introduced into mechanistic model(s) **150** to account for parasitism, natural death of pupae and/or adult insects, and other factors. Such dynamics can include, but are not limited to, additional terms added to population equations to reduce the population of insects in either life stage.

[0068] For PETE model **335**, the total emergence of insects is equal to the total number of input insects. In this way, solving the above system for y and dividing by the input population will return a population density that integrates to 1. In PETE model **335**, the number of insects in the pupal stage serves as the initial population I(t). Insects emerge into the adult life stage after spending time in the pupal stage, the duration of which depends on the ambient temperature. Emergence as adult insects occurs after a time delay, reflected as a change in the adult population y(t).

[0069] It is assumed that the pupation stage can be described by "k" latent 'micro-states' that each insect must pass through before emergence, where "k" is an integer. The "r" variables in the above equations represent the population in each of the k latent micro-states as a function of time. It should be noted that the latent 'micro-states' do not correspond to instars or other physiological stages of insect development. Instead, each system of k equations describes a single life stage or generation (e.g. a model with k=6 does not represent six generations) that is accurately described by the simplifying assumptions of PETE model **335**. In the context of example control system **300**, latent micro-state emergence parameter r_i can be considered as a latent variable internal to the mechanistic model(s) **150**.

[0070] As DEL(t) **340** is a term in each of the k rate equations, the rate of emergence of the adult stage depends on the rate of growth and on the number of intermediate stages. Timing of emergence and the shape of a population emergence curve are accurately described by an Erlang distribution with shape parameter k and time-dependent mean and variance:

$$\mu_\tau(t) = DEL(t)$$

$$\sigma_\tau^2(t) = \frac{\mu_\tau(t)^2}{k}$$

where $\mu_\tau(t)$ represents the mean value of the Erlang distribution for population density and $\sigma_\tau(t)$ represents the variance of the Erlang distribution. As such, DEL determines the location and width of the emergence curve and k its shape. In an illustrative example, k=1 produces an exponential distribution where population is proportional to e^r, while for larger values of k the population density distribution approaches a Gaussian distribution.

[0071] Ambient temperature information is incorporated into PETE model **335** through DEL term **340**, defined as:

$$DEL(t) = \frac{TDD}{\max(0,\ T(t) - T_0)}$$

[0072] where TDD represents the mean number of accumulated degree-days to go through the stage of growth, T(t) is the temperature and To is the lower temperature threshold for growth. It is apparent that DEL(t) is undefined in circumstances where T(t) is below T_0. It is important to note that DEL is defined as the reciprocal of the rate of growth, defined as proportional to the temperature above the lower threshold temperature. In this way, where ambient temperature is less than the lower threshold temperature, the rate of growth is zero.

[0073] A limitation of PETE models **335** is that selecting the values for parameters used in TDD and k can be challenging. Where the mean and variance of emergence time for a population of insects are known, for example, from lab experiments, the Erlang mean and variance equations can be used to determine parameters. In some cases, heuristic-based techniques involve estimating a time to half-emergence of an insect from multiple in situ collections in different host environments over multiple growth seasons of the insect. From collection data, the time to half-emergence can be used to compute Erlang mean and variances, as the Erlang distribution is symmetrical about a central mean. It is noted, however, that both techniques present significant drawbacks. Using laboratory determined growth parameters can ignore the influence of Environmental data **130** other than ambient temperature. Similarly, collection data, based on samples taken from traps, can be labor intensive and produce inconsistent results that are also

affected by environmental factors not accounted for in PETE models **335** (e.g., insect activity).

[0074] As a further limitation, fitting TDD and k parameters using gradient-descent from in situ trap data is difficult, as "k" is an integer, making the latent microstate equations not differentiable with respect to k. To address this limitation, in some embodiments, a value for "k" can be estimated using coordinate descent to alternately optimize TDD and k, where TDD is updated with standard gradient update with fixed k and k is then selected by exhaustive search on the training loss with fixed TDD.

[0075] In some embodiments, example control system **300** implements ML model(s) as part of predictive models **145** to generate input data for mechanistic model(s) such as PETE model **335**. For example, input data can include values for the DEL function generated by inputting environmental data **130** including temperature data and other data, as described in more detail in reference to FIG. **4**. Advantageously, ML model(s) can learn the nonlinear dependencies of DEL **340** on temperature and other weather and environmental factors. The system of "k" latent microstate equations can then be solved with the predicted value of DEL **340** to obtain predicted population density over time.

[0076] In some embodiments, PETE models **335** can include terms to account for one or more effects of interventions and other factors on the predicted emergence "y." As an example, an attrition rate, AR(t) can be included as a function of time. Additionally or alternatively, an intervention effect term (1−u(t)) can be included, where u(t) represents the intervention condition at time "t" from first time t_o to t=H. The expression for a PETE model **335** including the additional term is provided below:

$$\frac{dy}{dt} = (1-u(t))\frac{k}{DEL(t)}\left(r_{k-1}(t) - y(t)\left(1 + \frac{AR(t)\cdot DEL(t)}{k} + \frac{1}{k}\frac{dDEL(t)}{dt}\right)\right)$$

[0077] Attrition, in the context of pest population dynamics, represents a sink term in the predicted emergence that does not correspond to transition from the current life stage or generation to the subsequent life stage or generation. For example, attrition can describe reduction of an emergence attributable to disease, predation, or other causes of reduction in emergence. As an illustrative example, models described herein can include predation dynamics, pest-disease dynamics, or the like. A predation rate can be expressed as:

$$h(w) = \frac{w^2}{1+w^2}$$

where "h(w)" represents the predation rate as a direct modifier of the population growth rate that is dependent on the population "w," a function of time and environmental factors.

[0078] Predicted population data **350**, such as y(t) from PETE model **335**, can serve as an input to optimizer **310**, to be used as part of an optimization of the presence of the pest in the host environment against one or more constraints **315** as represented in constraint model **150**. A general form of constraint model **150** for discrete-time data can include:

$$J(x_t) = \sum_{k=t}^{t+H-1} [\theta x_k + (1-\theta)u_k]$$

where x(k) is a function of predicted population data **350**, such as pest population density, at time k that represents the impact of the pest on crop yields, u(k) represents the "cost" of predicted intervention action **355** at time k, and Θ represents a tuning parameter between zero and one by which optimizer **310** can modify the relative emphasis placed on reducing pest populations as opposed to conserving intervention resources. For example, a larger value of Θ emphasizes the impact of the presence of the pest in the host environment relative to the importance of constraints **315**. Where Θ is relatively small, the importance of resource demand, logistical factors, and/or environmental factors included as constraints **315** into constraint model **150** is emphasized by optimizer **310**.

[0079] The nominal value of Θ can be tuned as part of optimizer **310** operations, as part of an optimization process over a longer timeframe than prediction horizon H. In an illustrative example, a season-long upper limit on spraying can be imposed by regulation, as part of environmental protections to reduce runoff into watercourses. As such, optimizer **310** can modify Θ toward smaller values as a growing season progresses, and/or as a function of the number of intervention actions **240** that contributed to the upper limit. Similarly, the type of intervention action **240** being determined for the timepoint can affect the value of Θ.

[0080] Predicted intervention actions **355** can be generated in accordance with one or more control schemes **317**, based at least in part on predicted population data **355**. For example, a Heaviside feedback control scheme **317** can be configured to return a false value for predicted pest population density or predicted pest emergence at time t=k that is below a threshold value and to return a true value for a density or emergence value above the threshold value. In this way, predicted intervention actions **355** can represent a sequence of Boolean values representing a schedule of intervention actions.

[0081] In some embodiments, multiple control schemes **317** can be implemented by optimizer **310** to account for system dynamics (e.g., pest emergence) indicated by predictive model(s) **145**. For example, a feedback control scheme can include derivative terms indicative of rate of change, such that intervention action predictions are informed by pest emergence as well as nominal population density. In some embodiments, control schemes **317** inform the generation of an initial set of predicted intervention actions **355**, after which optimizer **310** uses the optimization schemes described in reference to FIG. **2** to minimize constraint model **150**.

[0082] For many pests, impact on crop yield is proportional to pest population, such that x(k) will be a linear function of pest population, where higher pest population will result in a greater damage extent. For example, x_k can represent a constant slope linear function of pest population "P." Direct correlation between pest population and reduction in crop yield can be expected in pest/host systems where the pest directly consumes or damages plants (e.g., herbivorous pests that consume leaf matter or fruits or lay eggs in fruits). An example of a direct pest is the Colorado potato beetle (*Leptinotarsa decemlineata*).

[0083] In some embodiments, x_k can include an exponential term to account for nonlinear dependency of pest impact (e.g., crop damage) on pest population (e.g., pest density). The exponential term can include a power ('p'), "x_k^p" such that impact increases exponentially with pest population, which can be characteristic of secondary pests that are typically held in check by predation (e.g., spider mites) or that exhibit a transition from a solitary to gregarious behavior above a given threshold density (e.g., locusts).

[0084] In some embodiments, x_k can include an inverse power

$$"x_k^{\frac{1}{p}}"$$

that can be characteristic of a pest that is a vector of a crop pathogen. In such cases, a relatively low presence of the pest in the host environment can introduce a potentially catastrophic effect on crop yield. The dynamics of crop yield impact can be governed by other models more specific to the pathogen and its spread through the host environment, which can be pest agnostic. An example of a vector-pest is the pea aphid (*Acyrthosiphon pisum*).

[0085] The term u_k can include one or more terms that represent the non-economic "cost" of implementing predicted intervention actions **355**. For example, a continuous and differentiable factor between zero and one can be defined to reflect the progress toward a total permissible dose for a pesticide on a given area of land over a growing season (e.g., read into constraint model **150** as constraints **315**), so that x_k and u_k can each be continuous and differentiable variables between zero and one. In some embodiments, the term u_k can also include one or more terms that represent the economic "cost" of implementing predicted intervention actions **355**. For example, a price-per-gallon of a pesticide product can be used to approximate an economic "cost" of a predicted intervention.

[0086] In some embodiments, u_k represents an opportunity cost associated with allocating intervention resources **325** to one region rather than another. Pest management system **320** can include limited intervention resources **325** with relatively little redundancy or excess capacity, as an approach to reduce capital expenditure and maintenance/labor costs. As such, the "cost" of implementing predicted intervention actions **355** can include equipment prioritization and other logistical considerations. In an illustrative example, pest management system **320** can coordinate intervention resources **325** for multiple agricultural environments susceptible to infestation by different pests, each managed by application of respective chemical pesticides. In this way, constraints **315** can include information about existing allocations of intervention resources **325** as a function of time. In some cases, a portion of the environment can be treated, such that u_k can reflect the portion of a constraint **315** representing the resource **325** allocation for the entire environment.

[0087] Embodiments of the present disclosure focus on spraying, but can also include other discrete and/or continuous interventions. In this context, the term "discrete" refers to an intervention that is applied at a specific time, such that intervention action **240** can be represented as a Boolean "true-false" for a given intervention type and a given time. The term "continuous" can refer to an intervention type that includes a proportion or other extent or magnitude factor or over a period of time including multiple time steps (e.g., continuously). For example, an intervention in a fruit orchard can be applied to a fraction of trees, in proportion to a population of a pest, such that u_k can be a continuous value between zero and one. In some embodiments, categorical control variables representing different control types can be included as part of model predictive control operations of example process **200**. For example, an exemplary intervention scheme can include multiple different pesticide types with different active ingredients.

[0088] Predictive model **145** can include a learned component implemented as a machine learning (ML) model. ML model(s) can be or include a fully-connected neural network model, a recurrent neural network model, a Long-Short Term Memory model, a gated recurrent unit model, or other model architectures capable of using state data **210** and intervention data **170** to estimate of DEL(t) (e.g., using environmental data **130** and intervention data **170** as an input). PETE model **335** can then generate predicted population data **355** that accounts for latent interactions between pest emergence and multiple environmental factors reflected in environmental data **130** in addition to ambient temperature effect.

[0089] As an example of nonlinear dependencies introduced by environmental factors, the presence of a pest can be described by activity and population density. Population describes the number of living pests, while activity describes a proportion of the population that is physiologically active in the environment at a given time. Activity may influence measurements of population and can introduce error in model predictions. For example, rain, wind and pesticide use can all reduce the number of flying moths captured in traps but might not impact the actual rate of development. Current sampling methods typically ignore environmental influence on activity, which can be accounted for through model corrections using environmental data **130**. Advantageously, learned models can account for activity changes in response to environmental factors other than ambient temperature.

[0090] FIG. **4**A is a schematic diagram illustrating example environmental data **130**, in accordance with embodiments the disclosure. Environmental data **130** includes spatial data **405** and temporal data **410**, allowing environmental data **130** to describe the state of a host environment in one or more spatial dimensions and in time. Environmental data **130**, as described in more detail in reference to FIG. **1-3**, can include data from multiple different sources, including temperature data **415**, wind data **420**, humidity data **425**, land-use data **430**, or the like.

[0091] Environmental data **130** can include temporal data **410** mapped to a geographic location of the host environment through spatial data **405**. In some embodiments, environmental data includes values for temperature **415**, wind **420**, humidity, and land-use **430**, but also can include precipitation, smoke, atmospheric pressure, or the like. In this way, introduction of ML elements into predictive model (s) **145** can model covariance between different spatial predictions at a given timepoint. Advantageously, such an approach can permit predictive models **145** to account for the influence of environmental conditions on intervention action **240** both spatially and temporally. In some embodiments, environmental data **130** include data for multiple physical locations, of which control model **220** generates intervention actions **240** for a subset of the physical loca-

tions. For example, a precipitation map can include data at a resolution higher than the predictive model(s) **145** can predict, based at least in part on limited resolution of other environmental data **130** or population data **140**. In this way, intervention action **240** can be generated at a lower spatial resolution than environmental data **130**.

[0092] Each data type can be expressed as a probability (e.g., a fraction or percentage), as a coded value, as a numerical value, or in other forms as may be received from the source(s) of environmental data **130**. Each environmental data point can be associated with a timepoint and geographical coordinates, for example, through a GPS reference. As such, environmental data **130** can describe a multi-modal dataset in space and time for the host environment. In some embodiments, environmental data **130** is represented numerically by a tuple including a timepoint, spatial coordinates, and a value for each environmental data type being measured (e.g., an n-tuple where n is the number of entries in the datum).

[0093] With respect to land-use data **430**, it is understood that some vegetation and/or land conditions can serve as direct hosts of pest organisms, some can serve as reservoirs of pest organisms, and some can serve as attractants or repellants for pest organisms. For example, wild land abutting a cultivated plot can serve as a reservoir of pest insects, where the wild land is not managed to limit the population of the pest. Similarly, crop rotation and other agricultural techniques can leave land fallow near a host environment, which can serve as a source of pest population. Land-use data **430** can encode one or more uses of land in the geographic area in and around the host environment. For example, land-use can be expressed numerically as a binary Boolean value, where true indicates host land and false indicates non-host land. In another example, land-use can be expressed numerically as a coded integer value, with each integer value corresponding to a different use. In some embodiments, land-use is classified from images by trained ML models, such that land-use can be expressed numerically as a probability that a given geographical position corresponds to cultivated land and/or as a host or reservoir environment. A probability value can provide a continuous and differentiable input to control model **220**, for example, as an input to predictive model(s) **145** to reflect a source term from a pest reservoir.

[0094] FIG. **4**B is a schematic diagram illustrating example state data **210** and example intervention data **170** as a function of time, in accordance with embodiments of the disclosure. For a series of timepoints **405**, set of predicted intervention actions **355** are represented as discrete Boolean actions **410**, respectively corresponding to a timepoint T_i where "i" is an integer between 1 and "H," with each value of "i" corresponding to a sampling frequency of pest population data **140** (e.g., using pest monitoring system **117**). "H" represents the length of time of a prediction horizon **415** over which predicted pest population data **350** can be predicted using state data **210**. Timepoints T are separated by timesteps **420**, the duration of which can be based at least in part on a sampling frequency of pest monitoring system **117** and/or a minimum separation between intervention actions **410**.

[0095] Prediction horizon **415** is illustrated as being the same length of time for population prediction and intervention prediction. In some embodiments, prediction horizon **415** for population prediction differs from prediction horizon **415** for intervention prediction. Some forms of intervention (e.g., spraying, mite dispersal, pheromone trapping, or the like) involve a prescribed course of intervention actions **410** including one or more periods of application/action and one or more periods of inaction. As such, intervention actions **410** can represent implementing an intervention (e.g., "taking an action") or not implementing an intervention (e.g., "not taking an action").

[0096] In an illustrative example, a set of predicted intervention actions **355** for spraying an orchard to reduce orange navelworm egg density can include multiple separate sprayings separated by a minimum period of time, such that prediction horizon **415** for interventions can include one or more timepoints T with actions and one or more timepoints T without actions, such that the total number of timesteps **420** exceeds the length of time for which environmental data **130** is available. Similarly, predicted intervention actions **355** can correspond to a shorter prediction horizon **415** than the length of time described by environmental data **130**, for example, where timeframes for scheduling and/or implementing intervention actions **410** are limited, but environmental data **130** is available for longer terms.

[0097] FIG. **5** is a schematic diagram illustrating example data flows for generation of predicted population data **350** and predicted intervention actions **355** for a prediction horizon **415**, in accordance with embodiments of the disclosure. Data flows illustrated herein represent interactions between predictive model(s) **145** and constraint model(s) **150**, as described in more detail in reference to FIGS. **1-3**, which can include operations executed by server(s) **105** and/or client computing device(s) **110** and using state data **210** and intervention data **170** as inputs.

[0098] Model predictive control includes generating a set of predicted control inputs that converge constraint model **150** to an optimum (e.g., minimum, maximum, or target) value over prediction horizon H, for which intervention action **240** represents a control input for a first time point that is typically the next control action to be taken. As such, generating predicted intervention actions **355** for multiple timesteps ("T") over prediction horizon **210** can include iteratively evaluating predictive model(s) **145** to generate a set of predicted population data **350** for timepoints T_1 to T_H. Similarly, predicted population data **350** can be used to generate predicted intervention actions **355** for timepoints T**1** to TH in line with control schemes **317**.

[0099] As illustrated, each iteration of predictive model(s) **145** includes inputting time-series state data **210**, as well as the preceding value corresponding to intervention data **170** and population data **140**. For example, a first iteration of predictive model(s) **145-1** receives as inputs a first timepoint of state data **210-1** and intervention data **170** (e.g., from third database **165**). The output of first iteration of predictive model(s) **145-1** can be used by optimizer **310** to generate a predicted intervention action corresponding to the first timepoint. In line with the model-predictive control approach, of example control system **300**, the predicted intervention action **355** corresponding to the first timepoint represents intervention action **240** when optimizer **310** has converged (FIG. **5** represents this conditional status with an asterisk "*"). For an "N^{th}" iteration of predictive model(s) **145**-N, the output of a preceding iteration "N-**1**" of predictive model(s) **145**-N-**1** and the corresponding output of optimizer

310 are used, along with the Nth timepoint for state data **210**-N, to populate the corresponding entry in predicted pest population data **350**.

[0100] FIG. **6**A is a graph **600** illustrating example population data as a function of time in a system without intervention, in accordance with embodiments of the disclosure. Graph **600** represents typical pest population data **140** for a host environment produced by an example embodiment of pest monitoring system **117**. In the example of FIG. **6**A, the pest host system is infestation of almond orchards by navel orangeworm (*Amyelois transitella*) in California, USA. In graph **600**, population data includes multiple generations over a period of about 20 weeks, with a peak population density **610** corresponding to the first generation of approximately 155 insects per trap on average.

[0101] FIG. **6**B is a graph **630** illustrating example population data as a function of time in a system with reactive intervention, in accordance with embodiments of the disclosure. Graph **630** demonstrates the impact of so-called "reactive" control that is typically implemented as a feedback control scheme using pest population data as an input to a model without a predictive component. Population data **635** of graph **630** is simulated using a simple feedback control model, with predictive model(s) **145** described in reference to FIG. **3** for the specific pest-host system of *Lygus* in strawberries. In contrast to graph **600** of FIG. **6**A, population data **635** for graph **630** reflects the impact of four simulated intervention actions **640** taken approximately at 4 weeks, 5 weeks, 8 weeks, and 12 weeks over the same 20 week growing period. In the simulation, interventions **640** correspond to spraying pesticide. The reactive control scheme indicates an improvement in pest population over multiple generations, with the duration of each generation being shortened and the peak populations in second and third generations being reduced relative to population data **605** of graph **600**. Peak population **610** remains approximately **155** insects per trap, however, revealing a relative weakness of reactive control schemes. Pest management systems can include sources of latency in control systems, such that a control input based on current population data **140** can be implemented after populations have continued to rise. This effect is demonstrated in graph **330**, in that initial growth in population data **635** is not reduced relative to the corresponding untreated dataset **605** of graph **600**. Population data **635** for the second and third generations reveal the progressive effect of the four interventions **640**, with a reduction in peak populations in contrast to corresponding data in graph **600**. By integrating the population curve over the growing season, reactive control reduces the total emergence relative to unmanaged crops by 47%.

[0102] FIG. **6**C is a graph **650** illustrating example population data **655** as a function of time in a system with predictive intervention described in reference to FIGS. **1**-**5**, in accordance with embodiments of the disclosure. In contrast to the simulated data in graph **630**, population data **655** reflects the improvements to pest management system **320** provided by model predictive control of pest populations in line with the embodiments of example process **200** and example control system **300**. With fewer interventions **660**, at 3 weeks and 4 weeks into the roughly 20 week growing season, peak managed pest population **665** is reduced significantly, from approximately 155 insects per trap to approximately 65 insects per trap. While *Lygus* is a direct consumer of fruit seeds, the early-stage of development of fruit affected by *Lygus* can also reduce pollination of flowers, which introduces higher order and other non-linear dynamics into the pest-host system between population **665** and reduction in crop yield.

[0103] As shown, model predictive control results in reduced peak and total populations, corresponding to a 59% reduction in pest emergence, with half as many interventions **660** that take place earlier in the growing season and are not repeated. Advantageously, the model predictive control scheme illustrated in graph **660** also represents an improvement in management system **320** performance by facilitating more efficient use of intervention resources **325**. For example, with spraying for the host environment concluded within the first five weeks of the growing season, spray equipment can be reallocated to other locations and/or repurposed for other pests. Similarly, with advanced prediction of pest emergence, resources **325** can be provisionally allocated in anticipation of interventions. In this way, fleet distribution and material supply issues can be addressed in advance, reducing latency introduced by logistical systems and/or labor shortages. Furthermore, optimization of competing objectives that is handled by control model **220** balances the environmental impact, material and resource costs, and labor and equipment time of interventions **660** against the reduction in yield of fruit harvests in a way that is absent from reactive control shown in graph **630**.

[0104] FIG. **7** is a block flow diagram illustrating an example method **700** for controlling the presence of a pest in a host environment, in accordance with embodiments of the disclosure. Example process **700** describes an example of operations implemented by a computer system (e.g., server(s) **105** of FIG. **1**) as part of deploying example process **200** of FIG. **2**. The order in which some or all of the process blocks appear in process **700** should not be deemed limiting. Rather, one of ordinary skill in the art having the benefit of the present disclosure will understand that some of the process blocks can be executed in a variety of orders not illustrated or in parallel and can be repeated, omitted, or assigned to other systems.

[0105] At block **705**, the computer system receives environmental data **130** for a prediction horizon H (e.g., prediction horizon **415** of FIG. **4**B). As described in more detail in reference to FIG. **1**-**5**, environmental data **130** can be or include measured and/or predicted data describing a host environment for a pest/host system. Environmental data **130** can be received from one or more sources including weather systems (e.g., weather forecast data), in situ sensors (e.g., meteorological sensor stations), internet connected sensor-bearing devices (e.g., agricultural vehicles, mobile electronic devices, etc.), by manual entry by human users. In some embodiments, data are received separately from multiple sources, such that the computer system, as part of operations at block **705**, synthesizes environmental data **130** from the disparate source data. For example, each data source can be configured for a different sampling period, such that preparation operations can include sub-sampling at least some of the source data such that each entry of environmental data **130** includes a complete set of environmental measurements for each timepoint.

[0106] Environmental data **130** can be processed into other forms to be suitable for use as inputs to predictive model(s) **145**. For example, predictive model(s) **145** can be configured to input derived parameters (e.g., DEL parameter **340** of FIG. **3**) that can be determined using one or more

models (e.g., trained ML models, heuristic models, estimations derived from pest monitoring system **117** data) configured to generate predicted DEL parameters using environment data **130**. Advantageously, using environmental data **130** as part of state data **210** can improve the performance of pest management system **320** and control model **220**, at least in part due to a relative infrequency of samples from pest monitoring system **117** and the possibility of noisy data caused by sparse sampling.

[0107] At block **710**, the computer system receives population data **140** generated by pest monitoring system(s) **117** for a first time point. As described in more detail in reference to FIG. **1**, pest monitoring system(s) **117** can include manual, automated, or pseudo-automated systems, devices, or techniques for assessing the presence of a pest in the host environment. In an illustrative example, pest monitoring system **117** can include multiple pheromone traps distributed through an almond orchard and periodically replaced to gather time-series data for the emergence of a navel orangeworm pest. Population data **140** received at block **710** can include timepoints preceding the first time, such that predictive model(s) **145** can include prediction based on environmental data **140** and on emergence dynamics (e.g., derivative terms).

[0108] At block **715**, the computer system receives past intervention data. As illustrated in FIG. **6**C, intervention actions can have lasting effects on pest emergence, which can be accounted for in predictive model(s) **145**. As such, past intervention data **170** can be used as part of generating predicted intervention data **355**, as described in more detail in reference to FIG. **3** and FIG. **5**. Where no interventions have been implemented, or are otherwise not considered for predictive model(s) **145**, block **715** can be omitted from example method **700**.

[0109] At blocks **720-725**, the computer system inputs data received at blocks **705-715** to control model **220** and generated intervention action **240**. as described in more detail in reference to FIGS. **2-3**, control model **220** is configured to implement model-predictive control-based optimization of a set of predicted intervention actions **355** over prediction horizon H, of which the predicted intervention action **355** corresponding to a first time point is outputted as intervention action **240**. Optimization includes balancing competing objectives, such as crop damage due to pest presence, resource allocation constraints, equipment allocation constraints, labor allocation constraints, environmental restrictions on timing and extent of intervention, or the like. As such, through iterative optimization of the set of predicted intervention actions **355**, intervention action **240** can be determined that guides the pest-host system toward an optimum state at timepoint T_H. It is understood that the optimum state may not correspond to the absolute minimum possible pest emergence over the prediction horizon, as pest emergence is balanced against other constraints that may limit the number and magnitude of interventions indicated.

[0110] In some embodiments, the computer system outputs intervention action **240** or other data (e.g., input data **220**, environmental data **130**) at block **730**. Outputting operations, as described in more detail in reference to FIG. **2**, can include storing data, including data for intervention action **240** and/or predicted data **350-355** on one or more storage systems. Outputting operations can also include communicating data to associated systems (e.g., client computing device(s) **110**, pest management system **320**, etc.), as through notifications and audio-visual information for presentation to a user. Additionally or alternatively, outputting operations can include implementing interventions directly, as when pest management system **320** includes automated (e.g., without human involvement) or pseudo-automated (e.g., with human oversight or control) intervention systems, such as sprayer systems or automated deployment systems, as when an unmanned aerial vehicle deploys pest predator organisms to control pest populations (e.g., *Persimilis* to attack spider mites) or autonomous spraying systems can at least partially prepare intervention resources **325** for implementing intervention action **240** (e.g., scheduling a spray event, allocating spray equipment, initiating a spray action, configuring spray equipment, or the like).

[0111] At block **735**, the computer system iterates example method **700** by shifting prediction horizon H by one or more timepoints and repeating at least a subset of blocks **705-730**. In some embodiments, data are available for more timepoints than what are included in prediction horizon H. As such, block **735** can shift the prediction horizon H by selecting a new set of data already stored in databases of server(s) **105** or client computing device(s) **110**. In line with the principals of model-predictive control, implementing intervention action **240** at a first timepoint can be followed by shifting prediction horizon H forward (e.g., to exclude first timepoint and to cover timepoints T_2 to T_{H+1}) and repeating prediction and optimization operations using constituent models of control model **220** to generate a second intervention action **240**.

[0112] The processes explained above are described in terms of computer software and hardware. The techniques described can constitute machine-executable instructions embodied within a tangible or non-transitory machine (e.g., computer) readable storage medium, that when executed by a machine will cause the machine to perform the operations described. Additionally, the processes can be embodied within hardware, such as an application specific integrated circuit ("ASIC") or otherwise.

[0113] A tangible machine-readable storage medium includes any mechanism that provides (i.e., stores) information in a non-transitory form accessible by a machine (e.g., a computer, network device, personal digital assistant, manufacturing tool, any device with a set of one or more processors, etc.). For example, a machine-readable storage medium includes recordable/non-recordable media (e.g., read only memory (ROM), random access memory (RAM), magnetic disk storage media, optical storage media, flash memory devices, etc.).

[0114] The above description of illustrated embodiments of the invention, including what is described in the Abstract, is not intended to be exhaustive or to limit the invention to the precise forms disclosed. While specific embodiments of, and examples for, the invention are described herein for illustrative purposes, various modifications are possible within the scope of the invention, as those skilled in the relevant art will recognize.

[0115] These modifications can be made to the invention in light of the above detailed description. The terms used in the following claims should not be construed to limit the invention to the specific embodiments disclosed in the specification. Rather, the scope of the invention is to be determined entirely by the following claims, which are to be construed in accordance with established doctrines of claim interpretation.

What is claimed is:

1. A computer implemented method for controlling a population of a pest, the method comprising:

receiving population data describing a presence of a pest in a host environment at a first time;

receiving environmental data describing the host environment over a prediction horizon including and temporally after the first time;

generating an intervention action for the first time using the population data and the environmental data as inputs to a control model configured to output the intervention action as part of an optimization of the presence of the pest over the prediction horizon; and

outputting the intervention action.

2. The computer implemented model of claim **1**, wherein the control model comprises:

a predictive model configured to input the population data, the environmental data, and intervention data, and to output a predicted population density for the pest in the host environment at a timepoint of the prediction horizon temporally after the first time; and

an optimizer model, configured to input the predicted population density and to output an intervention recommendation by optimizing a constraint model.

3. The computer implemented method of claim **2**, wherein the predictive model comprises a Predictive Extension Timing Estimator (PETE) model with an intervention term, the intervention term modifying the PETE model to account for the effect of the intervention action on a pest emergence as a function of time.

4. The computer implemented method of claim **2**, wherein generating the intervention action comprises:

generating a set of predicted population density data for the pest over the prediction horizon using the environmental data, the population data, and the intervention data;

generating a set of predicted intervention actions for the prediction horizon using the set of predicted population density data as inputs to the optimizer model;

determining a value of the constraint model for the set of predicted intervention actions, wherein the constraint incorporates information for the presence of the pest in the host environment and the set of predicted intervention actions; and

iteratively updating the set of predicted population density and the set of predicted intervention actions until a convergence criterion is satisfied for the value.

5. The computer implemented method of claim **4**, wherein the constraint model includes:

a first term for the damage caused to the host environment by the pest; and

a second term for the resource demand attributed to the predicted intervention actions.

6. The computer implemented model of claim **4**, wherein generating the set of predicted intervention actions comprises a cost-optimized search of a database of intervention data.

7. The computer implemented model of claim **4**, wherein generating the set of predicted intervention actions comprises:

randomly generating two parent sets of predicted intervention recommendations over the prediction horizon;

initializing a genetic algorithm using the two parent sets, wherein the genetic algorithm is configured to populate an initial generation of child sets using the parent sets, to determine respective optimization factors for the child sets, and to select two or more retained child sets by comparison of the respective optimization factors;

re-initializing the genetic algorithm using the retained child sets; and

iterating the genetic algorithm over one or more subsequent generations until a marginal improvement threshold is satisfied.

8. The computer implemented model of claim **4**, wherein generating the set of predicted intervention actions comprises a non-linear constrained optimization of the set of predicted intervention actions and the set of predicted pest population data for the prediction horizon.

9. The computer implemented model of claim **4**, wherein the convergence criterion comprises a comparison of a marginal reduction of the value of the constraint model with a threshold value.

10. The computer implemented model of claim **1**, wherein the population data is first population data, the environmental data is first environmental data, the prediction horizon is a first prediction horizon, the intervention action is a first intervention action, and wherein the method further comprises:

receiving second population data describing the presence of the pest in the host environment at a second time temporally after the first time;

receiving second environmental data describing the host environment over a second prediction horizon temporally after the second time; and

generating a second intervention action for the second time using the second population data, the second environmental data, and the first intervention recommendation as inputs to the control model.

11. The computer implemented method of claim **1**, wherein the intervention action indicates no action at the first time.

12. The computer implemented method of claim **1**, wherein outputting the intervention action comprises outputting data for the intervention action to a pest management system.

13. At least one machine-accessible storage medium that provides instructions that, when executed by a machine, will cause the machine to perform operations comprising:

receiving population data describing a presence of a pest in a host environment at a first time;

receiving environmental data describing the host environment over a prediction horizon including and temporally after the first time;

generating an intervention action for the first time using the population data and the environmental data as inputs to a control model configured to output the intervention action as part of an optimization of the presence of the pest over the prediction horizon; and

outputting the intervention action.

14. The at least one machine-accessible storage medium of claim **13**, wherein the control model comprises:

a predictive model configured to input the population data, the environmental data, and intervention data, and to output a predicted population density for the pest in the host environment at a timepoint of the prediction horizon temporally after the first time; and

an optimizer model, configured to input the predicted population density and to output an intervention recommendation by optimizing a constraint model.

15. The at least one machine-accessible storage medium of claim **14**, wherein the predictive model comprises a Predictive Extension Timing Estimator (PETE) model with an intervention term, and wherein the intervention term modifies the PETE model to account for the effect of the intervention action on a pest emergence as a function of time.

16. The at least one machine-accessible storage medium of claim **14**, wherein generating the intervention recommendation comprises:

generating a set of predicted population density data for the pest over the prediction horizon using the environmental data, the population data, and the intervention data;

generating a set of predicted intervention actions for the prediction horizon using the set of predicted population density data as inputs to the optimizer model;

determining a value of the constraint model for the set of predicted intervention actions, wherein the constraint incorporates information for the presence of the pest in the host environment and the set of predicted intervention actions; and

iteratively updating the set of predicted population density and the set of predicted intervention actions until a convergence criterion is satisfied for the value.

17. The at least one machine-accessible storage medium of claim **16**, wherein the constraint model includes:

a first term for the damage caused to the host environment by the pest; and

a second term for the resource demand attributed to the predicted intervention actions.

18. The at least one machine-accessible storage medium of claim **16**, wherein generating the set of predicted intervention actions comprises a non-linear constrained optimization of the set of predicted intervention actions and the set of predicted pest population data for the prediction horizon.

19. The at least one machine-accessible storage medium of claim **16**, wherein the convergence criterion comprises a comparison of a marginal reduction of the value of the constraint model with a threshold value.

20. The at least one machine-accessible storage medium of claim **13**, wherein the population data is first population data, the environmental data is first environmental data, the prediction horizon is a first prediction horizon, the intervention action is a first intervention action, and wherein the instructions, when executed by the machine, cause the machine to implement further operations comprising:

receiving second population data describing the presence of the pest in the host environment at a second time temporally after the first time;

receiving second environmental data describing the host environment over a second prediction horizon temporally after the second time; and

generating a second intervention action for the second time using the second population data, the second environmental data, and the first intervention recommendation as inputs to the control model.

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