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Geospatial simulation steering for adaptive management

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ABSTRACT

Spatio-temporal simulations are becoming essential tools for decision makers when forecasting future conditions and evaluating effectiveness of alternative decision scenarios. However, lack of interactive steering capabilities limits the value of advanced stochastic simulations for research and practice. To address this gap we identified conceptual challenges associated with steering stochastic, spatio-temporal simulations and developed solutions that better represent the realities of decision-making by allowing both reactive and proactive, spatially-explicit interventions. We present our approach, in a participatory modeling case study engaging stakeholders in developing strategies to contain the spread of a tree disease in Oregon, USA. Using intuitive interfaces, implemented through web-based and tangible platforms, stakeholders explored management options as the simulation progressed. Spatio-temporal steering allowed them to combine currently used management practices into novel adaptive management strategies, which were previously difficult to test and assess, demonstrating the utility of interactive simulations for decision-making.

1. Introduction

Spatio-temporal simulations provide a powerful way to study complex spatial phenomena, develop spatial theories, and even forecast the future, especially when traditional experimental methods to reveal patterns and processes are difficult or impossible to implement (Sullivan and Perry, 2013). Accordingly, substantial research efforts have been devoted to developing dynamic, spatio-temporal models of large-scale, socio-ecological phenomena, such as biological invasions (Meentemeyer et al., 2011; Miller et al., 2017) or sustainable urban growth (Meentemeyer et al., 2013). These models are particularly useful for simulating the efficacy of interventions—such as strategies to curb the spread of invasive species—which may have delayed impacts, cost too much, or become controversial (Garner and Hamilton, 2011).

Given the complexity of socio-environmental problems, researchers increasingly use participatory methods to incorporate diverse stakeholder perspectives into problem-solving. Participatory modeling has been shown to help researchers develop relevant questions, construct better models, and generate solutions that can be easily translated into decisions (Voinov and Bousquet, 2010). Spatio-temporal simulations have proven effective in participatory modeling studies dealing with land use (Lagabrielle et al., 2010), flood hazards (Becu et al., 2017), and disease spread (Hossard et al., 2013; Gaydos et al., 2019), but there is still a need to better integrate these models into the decision-making process (Vukomanovic et al., 2019; Gaydos et al., 2019). Decision support poses a new challenge to modelers, requiring them to make models more interactive and reflective of the realities of decision-making. Most spatio-temporal simulations are not interactive, i.e., they are initialized with a set of inputs that cannot be adjusted while the simulation is running. Such a non-interactive workflow pairs well with Monte Carlo techniques that allow researchers to capture uncertainties associated with stochastic models and model ensembles, and to run calibration or sensitivity analyses by simulating large numbers of model realizations (Yang, 2011; Rubinstein and Kroese, 2016). However, a non-interactive simulation can obscure cause-effect relationships and is impossible to adjust in response to new information or to its own intermediate results. Moreover, most spatio-temporal models do not have interactive, visual interfaces, which are known to facilitate communication of results and

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their uncertainties, as well as help elicit user input (Voinov et al., 2016). Given decision-makers' need to quickly explore interventions and their consequences across space and time, these model limitations can exacerbate the knowledge-practice gap, a common challenge in modeling wherein model insights do not directly inform actionable on-the-ground decisions (Voinov et al., 2016; Cunniffe et al., 2015).

Outside of a participatory modeling context, interactive modeling has been studied in computer science and related disciplines for several decades (McCormick et al., 1987). Computational steering refers to a mechanism for interactively controlling the variables of a simulation as the computation is in progress, and is often used to better understand parameter space and simulation behavior (Mulder et al., 1999; Matkovic et al., 2008). In addition to efficiency, computational steering also improves communication and discussion by providing immediate visual representation of the model and results (Van Wijk et al., 1997). Computational steering has been used to advance research in a variety of fields, including atmospheric and weather science, physics, and medical research dynamics (Jean et al., 1995; Walker et al., 2007; Johnson and Parker, 1995) and has proved especially important in computational fluid dynamics simulations (Marshall et al., 1990; Wright and Hargreaves, 2013). Additionally, certain agent-based modeling frameworks provide a form of computational steering for model exploration (Rossiter, 2015; Cordasco et al., 2013) or simulation coupling (Jaxa-Rozen et al., 2019).

Steering can open up new possibilities to explore geospatial "what if?" questions collaboratively with stakeholders. Although the term "steering" can be used in participatory modeling literature to mean interactive adjustments of key input model variables (Niño-Ruiz et al., 2013; Voinov et al., 2016), we are specifically concerned here with spatio-temporal steering, i.e., allowing users to spatially intervene at any step of the simulation. This type of steering can be critical for strategizing the management of dynamic systems. Computational steering is one of several possible implementations of spatio-temporal steering. Some researchers have demonstrated how, with the help of interactive environments, computational steering can help explore complex spatio-temporal decision-space; the prime example is World Lines (Waser et al., 2010; Ribičić et al., 2013), which combines computational steering of a flooding simulation with versatile, interactive scenario visualization. Waser et al. (2010) demonstrated the approach with a levee-breach scenario, exploring possible methods for closing the breach by simulating the strategic positioning of sandbags in different spatial configurations. Another example of what-if scenario modeling was presented by Afzal et al. (2011) in the context of infectious disease modeling. These authors developed a decision-support environment on top of a mathematical, epidemiological spread model to interactively evaluate scenarios with different mitigating measures Afzal et al. (2011).

Despite general agreement about the advantages of computationally steering simulations, this methodology is still the exception rather than the rule, especially outside of computer science (Pickles et al., 2005), because there are several barriers to its broader usage. One is the increased technological complexity of model implementation, leading to high code maintenance costs and possibly more error-prone code. Another is a lack of user-friendly interfaces that facilitate steering for users with different technical backgrounds. Furthermore, high-performance computing platforms typically associated with computational steering often lack the necessary visualization capabilities and interactivity. Technological advances, such as GPU computing, allowed researchers to make many simulations more interactive and accessible through desktop interfaces (Linxweiler et al., 2010; Afzal et al., 2011; Ko et al., 2014). However, the increased need to provide simulation steering capabilities to analysts and stakeholders has necessitated the use of web-based solutions (Deodhar et al., 2014; Shashidharan et al., 2017) and alternative interfaces offering more natural user interactions (e.g., virtual reality environments (Mulder et al., 1998; Wenisch et al., 2005) or touch-table and tangible interfaces (Mittelstädt et al., 2013; Tonini et al., 2017)).

Spatio-temporal steering also poses conceptual challenges when dealing with stochastic models. Given that there are multiple realizations of a simulation running at the same time for a stochastic model, it is not obvious which realization to use to make steering decisions. Visualizing several stochastic runs using an aggregate representation—such as a probability or an average of model results (Ribičić et al., 2013)—can inform users about the potential range of outcomes. However, real-world decisions are based on observations best represented as a single stochastic run. Applying steering to stochastic spatio-temporal simulations is therefore challenging to inform strategies used in adaptive management, which bases decisions on evaluation of past actions, current observations, and future forecasting.

We encountered these challenges when designing a participatory modeling workshop focused on the spread of an invasive forest disease, sudden oak death (SOD), in Oregon. SOD spread poses serious environmental and economic risks, but because treatments are costly at large scales, decision-makers must strategically target treatments across time and space (Cunniffe et al., 2016). During a prior participatory modeling workshop we conducted (Gaydos et al., 2019), stakeholders expressed the need to explore yearly treatment interventions, which led us to incorporate spatio-temporal steering into our modeling framework. In this paper, we detail how we overcame several challenges associated with steering a stochastic simulation and identify three conceptual approaches to spatio-temporal steering in a participatory modeling context. We present a novel adaptive management approach that better represents the realities of decision-making by allowing both reactive and proactive spatially-explicit interventions. We also suggest simpler, alternative ways to design steerable simulations that do not require the implementation of computational steering, to reduce associated technological complexity.

The paper is structured as follows: Section 2 identifies several conceptual and implementation challenges associated with steering of spatio-temporal simulations and develops methods to address them. In Section 3 we apply the methods in an epidemiological simulation and describe our steering implementation and interfaces developed for our participatory modeling case study. Using this case study, Section 4 demonstrates how workshop participants applied the novel adaptive management approach to interact with the simulation and develop relevant management scenarios. Sections 5 and 6 highlight the importance of using the adaptive management approach during the workshop and discuss the limitations and future work.

2. Methods

2.1. Steering stochastic simulations

Representational and conceptual challenges accompany any attempt to steer many stochastic model realizations or a model ensemble. To condense the spatial information from all independent runs, aggregate renderings are typically used (Ribičić et al., 2013). Spatial results are aggregated using an aggregation operator, returning a single value for each spatial unit, such as mean, minimum, maximum, standard deviation, or count. In this way, modelers can obtain, for example, a probability map of infection or maximum height of flooding. Such aggregate views, however, are not always suitable, as they tend to hide the patterns and behavior of an individual simulation run. For example, an infection or fire can jump over the unaffected areas of a landscape, but such rare events may not be captured in the aggregate. Similarly, an urban growth simulation can create patches of new development with distinct sizes and shapes that are not represented in the aggregate. In these cases, the aggregate view can confound understanding of results and even distort expectations of future events (Fig. 1).

Another challenge of steering stochastic simulations involves selecting the run(s) to use when exploring scenarios for real-world decision-making. Although each steering decision acts on all of the parallel

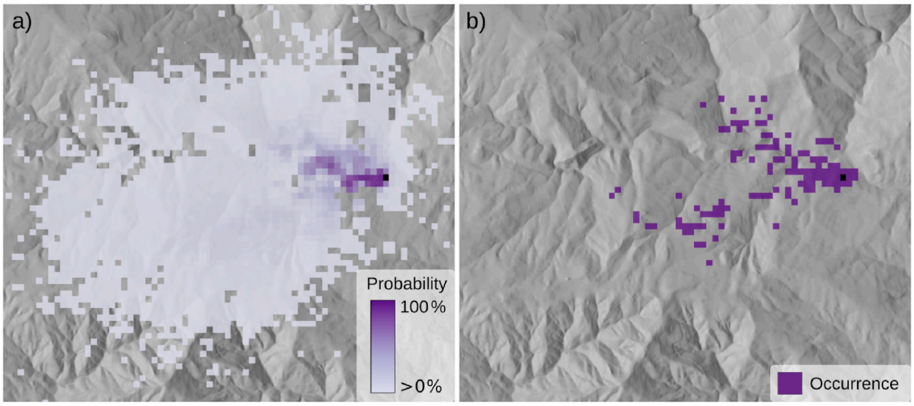

Fig. 1. Comparison of an aggregate representation (a) and an individual stochastic realization (b) of disease occurrence: (a) shows the modeled probability of disease occurrence based on 1000 stochastic runs. Although a large area has non-zero probability of disease occurrence, the probability is very low (90% of the area has a probability lower than 10%) and could lead to overestimation of risk based on visual inspection. Moreover, the probability does not reveal the pattern of the disease spread as simulated in (b) using a single stochastic run.

stochastic runs in the same way, it can result in vastly different consequences, depending on the run. For example, in the case of a spread simulation (disease, fire, etc.), performing a spatial intervention on a landscape (e.g., treating infected areas or creating firebreaks) might be effective only for certain stochastic runs and not have any effect on the rest of the runs.

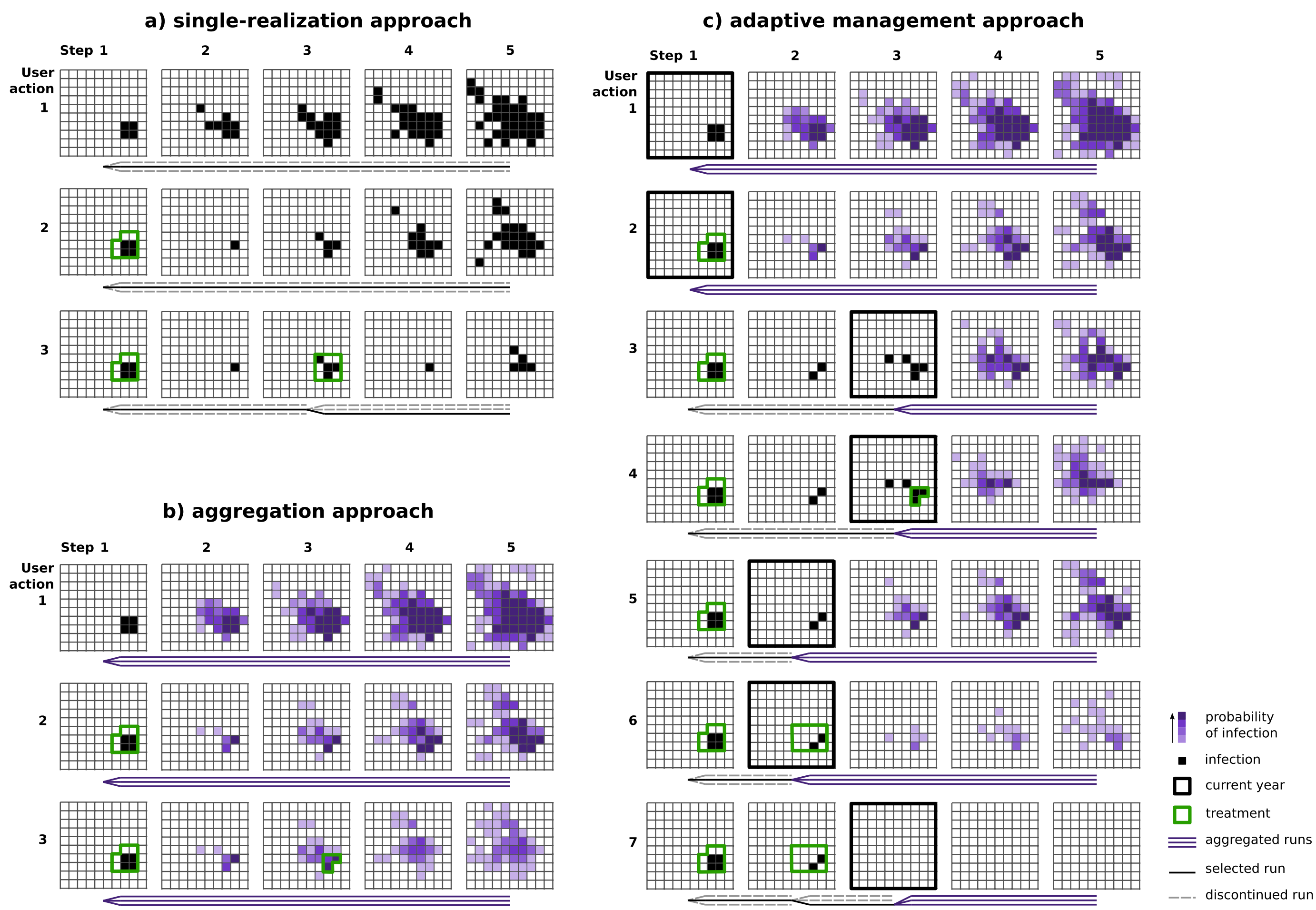

Fig. 2. Schema of different approaches to steering a stochastic simulation, with managing a plant disease as an example: a) In the single-realization approach, we compute the disease spread for five steps without any interventions and then decide to treat with 50% efficacy in simulation step 1. A selected run shows there is still one infection in the following step. We therefore decide to treat in step 3, at which point a new set of stochastic runs is launched, and the run with the most average characteristics from the set is selected. Alternatively, we can simply compute only a single stochastic run. b) In the aggregation approach, we can see the initial infection in simulation step 1 and the probability of infection in subsequent steps. We apply a treatment in the first simulation step and then another treatment focused on the areas with highest probability of infection in step 3. This treatment did not affect certain runs, resulting in low probability of wide-spread infection in step 5. c) In the adaptive management approach, we can see initial infection in step 1 and the probability of infection in the future if untreated. We then apply treatment with a certain level of efficacy, leading to a reduced probability of infection (action 2). In action 3, we move two simulation steps forward to find out that 5 cells were infected, then we decide to treat part of the infection in action 4. However, it results in limited success. In actions 5 and 6, we decide a better strategy would be to go back one step to treat earlier and apply a larger treatment to prevent he spread; this choice indeed results in a low spread probability in action 6. In action 7, we move one year forward to find out that we completely eradicated the disease.

Based on the different questions one can answer by steering stochastic spatio-temporal simulations, we distinguish three different approaches to steering: a) the single-realization approach, b) the aggregation approach, and c) the adaptive management approach (Fig. 2).

2.1.1. Single-realization approach

The single-realization approach is very similar to steering a deterministic model with no uncertainty in initial conditions, as the user interacts with only one stochastic run. The run can be selected from a pool of stochastic runs based on certain criteria, e.g., average characteristics of the modeled phenomena. Once an intervention is made, a new set of stochastic runs branches out of the current state, while the runs that were not selected do not continue (Fig. 2a). This approach enables examination of model behavior and patterns without obscuring them by aggregation (Fig. 1a). At the same time, it allows users to avoid runs with extreme or atypical characteristics that could confuse and hinder understanding of cause-and-effect relationships. Conversely, it allows a user to purposefully select an extreme run, to better understand worst case scenarios. The limitation of run selection is that it needs to be done early during the simulation, when all runs are very similar. Alternatively, one stochastic run can be selected randomly, while the rest of the runs are still computed and aggregated to provide statistical summaries of all the runs.

2.1.2. Aggregation approach

With the aggregation approach, the simulation starts from initial conditions, and steering is performed based on aggregated views of simulation steps. Typically, a probability map would be used to show the frequency of the modeled phenomenon across multiple stochastic runs, but other statistically derived values could be used as well. An intervention is applied at a selected simulation step to all stochastic runs. This approach helps to identify how a set of interventions impacts the probabilistic distribution of a modeled phenomenon (Fig. 2b).

However, as mentioned earlier, certain, typically spatial, interventions might not affect some of the individual simulation runs, and therefore do not reflect real-world decisions. For example, in the case of forecasting disease spread several years in the future, a treatment applied in a later year of the simulation, and selected based on the probability surface, would not spatially overlap with the infected areas simulated by a portion of the stochastic runs. Real management decisions always take into account the latest available information about the observed infections, and so the aggregate approach may not be helpful. On the other hand, this approach is suitable for making more immediate decisions about future interventions, because it allows exploring which spatio-temporal configurations of interventions are likely to be most effective given current data and known uncertainties. For example, in the context of urban planning, one can ask questions such as: Which land should a rapidly growing city prioritize purchasing in order to build future park infrastructure, given projected development patterns and a limited annual budget? Ultimately, one needs to recognize the limitations of this approach for adaptive management and be cautious when applying it and interpreting the results.

2.1.3. Adaptive management approach

The adaptive management approach combines the previous two approaches to make simulation steering more closely model real-world decision-making, Adaptive management iteratively takes into account past actions and future probabilities, introducing the concept of past observations and future estimates to the modeling. In an adaptive management approach, we can pause the simulation at any time step and go back to a previous step, representing our "past" visualized as a single stochastic realization, or go forward into our "future" visualized as an aggregate of multiple runs based on the "present" conditions. As we move forward in the simulation, a single run representing the current reality is selected from the multiple runs representing the future. The single run can be selected randomly or specifically chosen to represent average characteristics among the set of all runs. Going back to add or change an intervention makes a previous step become the current reality, and subsequent steps represent future estimates that take the new interventions into account (Fig. 2c).

Rather than pinpoint the best time and location of future interventions, the adaptive management approach allows testing different strategies. For example, in the context of plant disease spread, one can answer questions such as: Are we able to eradicate or slow down a disease with a given yearly budget? Would front-loading our budget (i.e., spending a majority of the budget in the first year) lead to eradication? Is it better to focus on disease hotspots or isolated outbreaks? Do we need to treat the same places every year? What type of interventions would be most effective?

2.2. Steering implementation approaches

Instrumenting a simulation to enable computational steering can be a challenging task, often leading to separate implementations of that simulation for batch processing and for steering. Typically, the structure of the code needs to be adjusted to allow stopping and starting the simulation at any step. Additionally, the simulation needs to understand a certain communication protocol that controls the progress and has to maintain consistency in internal data structures throughout the simulation. As simulations are rarely developed with those needs in mind, the necessary restructuring of the simulation code can be difficult and can introduce errors to previously well-tested code. Moreover, the technological complexity can increase when simulations need to be deployed into cloud environments. Due to these challenges, we suggest considering alternative approaches to computational steering (Fig. 3a). These approaches are less complex to implement but come at a cost of reduced computational efficiency.

One such alternative to computational steering is an approach in which the simulation can save its complete state, terminate, and restart from the same step initialized with the saved state. An intervention is then incorporated by terminating the simulation, modifying the saved state, and restarting the simulation from the same step using the modified state (Fig. 3b). In this way, already computed steps are not repeated, but the user can still step back providing all of the simulations states are kept. The advantage of this approach is that reading and writing data are usually already part of a simulation and are possible to implement for any additional variables. Moreover, the structure of the code can remain intact. The downside is that the simulation needs to repeatedly read data, possibly large spatial data, allocate resources, and write outputs, which can take significant time. It can be particularly relevant for this approach to require a steering step be longer than a simulation step, i.e., the simulation can be steered only every n simulation steps. Practically, that reduces the necessary read and write operations, and it can simplify the user interaction as long as the steering step is carefully selected to reflect user's needs for intervention.

In cases when the simulation state is defined by many variables or complex structures but still runs fast enough, another alternative approach is to provide as input to the starting simulation a time-series of interventions and the corresponding time steps (Fig. 3c). When a steering intervention happens, the simulation is restarted from the beginning with different input, while acting as if the simulation just continued from the intervention. The obvious drawback is the need to recompute everything from the start. Despite the inefficient use of computational resources, this approach can be practical when the number of steering steps is small.

2.2.1. Steering manager

To accommodate the variability in models' steering implementations and interfaces, we employed a generalized steering architecture based on a client-server model, in which a steering interface communicates with the simulation indirectly, through a steering manager. The purpose

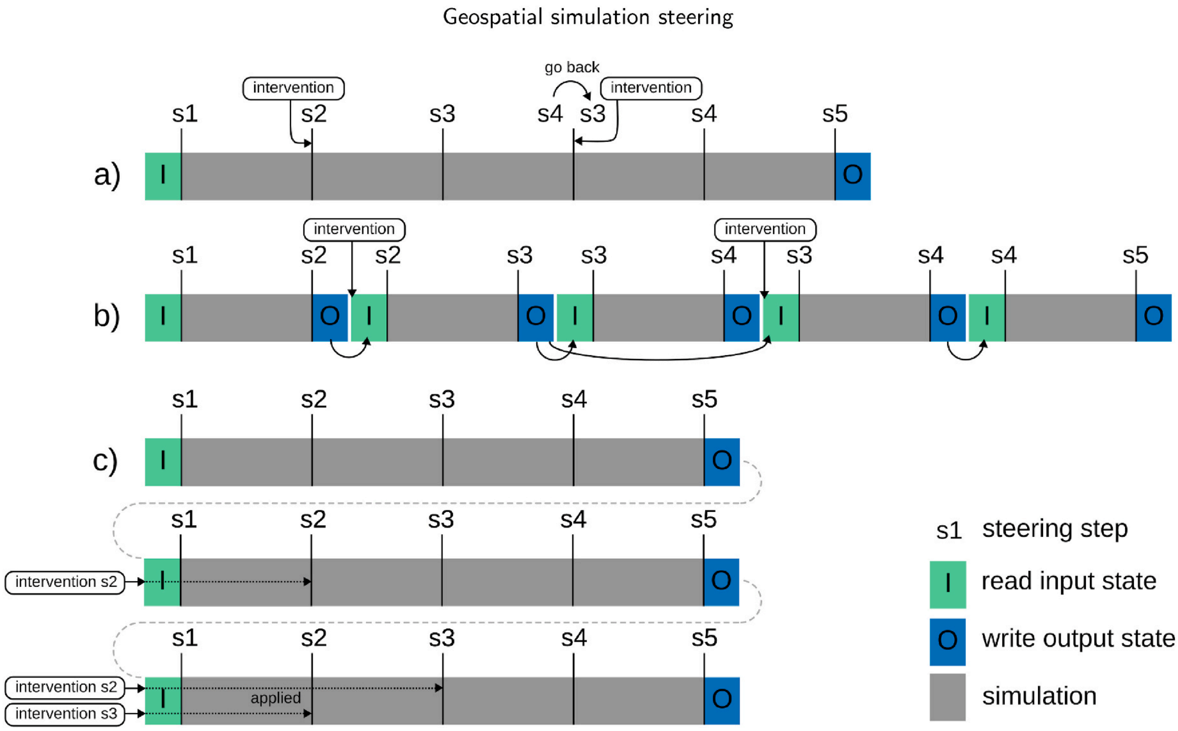

Fig. 3. Implementation of computational steering and alternative approaches to simulation steering: a) computational steering, b) steering by writing a complete simulation state after each steering step and reading a state modified by interventions before each step, c) steering by restarting the simulation with input modified by interventions. This example shows a situation in which we first intervene after step 1, and then after step 3 we decide to go back one step and run step 3 with a new intervention.

of the steering manager—a server—is to relay instructions and data between a steering interface client and a simulation client, without the interface or the simulation knowing any specific details about each other. The advantage of this approach is reduced complexity of the interface and simulation code and greater flexibility in combining different components. For example, the steering manager can instruct multiple simulations at the same time, each simulating a certain aspect of a modeled phenomenon. Alternatively, a simulation can be steered by multiple interfaces, e.g., steered through a tangible interface in a participatory workshop setting and at the same time through a web-based interface by remote workshop participants (Fig. 4). Additionally, this architecture allows for the alternative steering implementations described above. The steering manager can hide the particular implementation approach so that the steering interface works the same way regardless of the steering implementation.

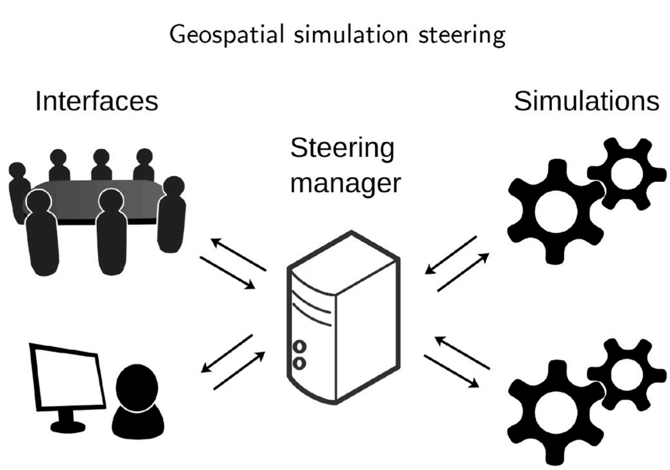

Fig. 4. Steering architecture: a steering manager allows receiving input from multiple interfaces and can control multiple simulations simultaneously.

3. Application for epidemiological simulation

We developed and applied the steering concepts described above by augmenting an existing epidemiological model for forecasting the spread of plant diseases. Based on stakeholders' feedback from a participatory workshop, we implemented the adaptive management approach, allowing them to steer the simulation by managing the disease yearly instead of only at the beginning of the simulation. We adapted an existing tangible user interface and a web interface to allow users to test realistic management strategies. The following sections describe the epidemiological simulation and the interfaces, including relevant technical details of the steering implementation.

3.1. Epidemiological simulation

We used the Pest or Pathogen Spread (PoPS) simulation (Jones et al., 2019) to forecast SOD dispersal in Oregon (Gaydos et al., 2019). PoPS is a stochastic, spatially explicit, susceptible-infected simulation that uses host distribution, seasonality, and weather patterns to project the spread of biological invasions. Stochastic components include pest reproduction, dispersal, and invasion probability. The open-source PoPS library—written in modern C++ language—has both R and GRASS GIS interfaces (Jones et al., 2019) and can run several stochastic simulations in parallel to leverage current computing infrastructures.

In close collaboration with stakeholders, we configured the PoPS model to reflect observed epidemiological processes and historical patterns of SOD spread in Oregon (Gaydos et al., 2019; Gaydos, 2020). Spread is simulated weekly and aggregated to yearly visual outputs representing a single stochastic iteration (Fig. 1b) and the probability of infection over multiple iterations (Fig. 1a). Users develop management scenarios by specifying spatial treatment polygons that alter the density or susceptibility of hosts. Treatments are designated yearly to match the timescale of decision-making.

3.2. Steering interfaces

We developed two steering interfaces to facilitate stakeholder use of the PoPS simulation: a web-based interface (PoPS Forecasting Platform) and a tangible interface (PoPS Tangible Landscape). Both interfaces allow users to intuitively run the forecast, visualize disease outcomes (both spatially and as summary statistics), and apply yearly interventions while effectively hiding the technical complexities of steering. However, differences in system architecture require different steering implementations, as described in Sec. 3.3. We present these two alternatives to demonstrate how steering approaches can be tailored to different system requirements while providing similar adaptive management capabilities for end-users.

The PoPS Forecasting Platform (Fig. 5) is an online interface that leverages cloud-computing to streamline plant pest risk assessments (Jones et al., 2020). On the backend, a Django framework links a centralized database with a dockerized cloud environment running the PoPS simulation using the R interface. This framework allows the simulation to access new data inputs, such as user-generated interventions, and store the resulting disease outcomes into the database from where they can be accessed and visualized via the Forecasting Platform front-end. In this way the Forecasting Platform also serves as a repository of scenarios to allow easy comparison of simulation outcomes using dynamic spread maps and summary charts.

The PoPS Tangible Landscape interface (Fig. 6) was designed with similar interactive capabilities, but a substantially different system architecture. Tangible Landscape is a type of tangible interface that uses physical objects to interact with a simulation (Petrasova et al., 2018). It is thought that tangible platforms may be more intuitive for less tech-savvy users and for group exploration of simulations (Gaydos et al., 2019; Gaydos, 2020). The main components of the system include the physical setup, projection-augmented physical model, interaction controls, and a steering dashboard (Fig. 6). The physical setup consists of a projector, an RGB-D scanner, and a computer with PoPS Tangible Landscape software built around GRASS GIS, an open-source geospatial analysis and modeling platform. Here, the communication between the Python-based tangible interface and the C++ GRASS GIS interface to PoPS simulation is controlled by the steering manager component written in Python.

Despite differences, the PoPS Forecasting Platform and PoPS Tangible Landscape interfaces provide complementary functionality for stakeholders. The display year toggle in the Forecasting Platform and the clicker in Tangible Landscape allow users to step through simulation years to visualize disease projections and select when to apply treatments. Users design intervention strategies by arranging treatment polygons (either free-form or predefined shapes) on the landscape. In Tangible Landscape, these treatments are applied by placing felt indicators on the 3D projection-augmented physical model (Fig. 6), while in the Forecasting Platform, this same functionality is achieved by drawing treatment polygons on the dynamic web map (Fig. 5). As treatments are placed, users are given instant-feedback on cost and area of management to help plan their strategies. Control buttons (physical USB buttons in Tangible Landscape or widget buttons in the Forecasting Platform) allow users to start and progress through the simulation. Tangible Landscape is linked to Forecasting Platform in order to store the scenarios created with the tangible interface, and compare them using different metrics.

3.3. Steering implementation

In order to enable dynamic implementation of treatments in different years of the simulation, we integrated spatio-temporal steering capabilities into our modeling platform. Given that different technologies are used in the back-end of the tangible and web-based interfaces, we implemented spatio-temporal steering using approaches best suited to each prototype.

When customizing Tangible Landscape and the underlying GRASS GIS interface to PoPS library, we implemented the full computational

Fig. 5. PoPS Forecasting Platform. Dynamic web map shows disease occurrences and estimated probability of infection in a selected year, given the designed treatments up to that year. Charts on the right summarize budget spent, disease occurrence area, intensity, and spread rate. With the results overview at the bottom of the page users can compare scenarios and select and visualize individual scenarios.

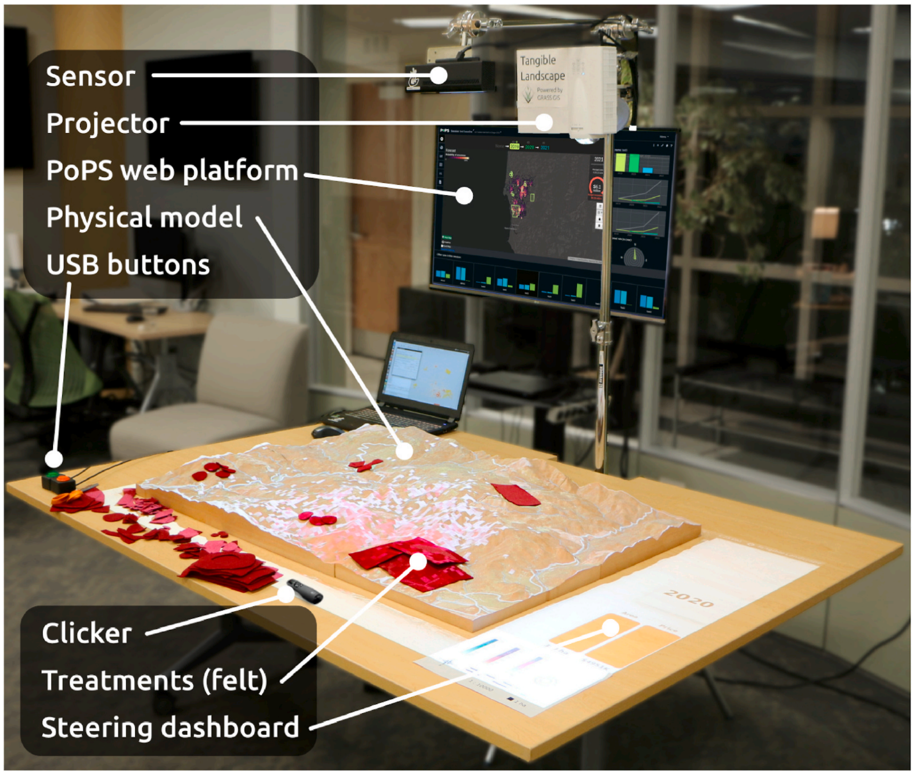

Fig. 6. PoPS Tangible Landscape setup. The sensor (3D scanner) scans the physical model to capture the location and shape of felt patches representing interventions on the landscape. The projector projects GIS layers on the physical model and a steering dashboard next to it. USB buttons invoke a simulation, which takes into account current interventions; its results are projected on the physical model and logged and displayed on a summary dashboard.

steering approach (Fig. 3a). In this case, the combination of programming languages used by Tangible Landscape, GRASS GIS and PoPS—C, C++, and Python—is well suited for computational steering implementation. More specifically, we used Python and C implementation of sockets to build a custom communication protocol to control the progress of the simulation, including pausing, resuming, going back, or running a single step of the simulation. Through this communication protocol, the simulation is also informed when new treatments need to be loaded into current data structures. Since disease treatments are conducted yearly, we selected the steering step—the step when interventions can be performed—to be one year and thus different from the shorter simulation step (one week).

Another important aspect of instrumenting the model—a checkpointing mechanism—allows going back to previous steps of the simulation by saving the states of the simulation, similarly to how a person can go back and forward when navigating websites in a browser. Thanks to this mechanism, users can decide to go back in time in the simulation and test different treatments or the same ones at a different time. Finally, to simulate adaptive management as described in section 2.1.3, the simulation can synchronize the infected and susceptible host data among the multiple runs, so that after synchronization, all of the stochastic simulation runs start from the same state but progress individually, each with different random number generator seed. The run to which all other runs are synchronized is the one with the median value of the sum of infected hosts. This selection ensures that extreme cases aren't selected, but this criterion can be easily adjusted if more extreme scenarios are actually desirable. To maintain the sustainability of the model code, we have a single code base allowing us to use the model with or without computational steering. Without computational steering, the treatments can still be provided for specific years and thus used for scenario modeling without the need for a special steering interface.

Given the higher complexity of the web technologies used in PoPS Forecasting Platform, we chose a simpler steering approach that does not require direct communication with the simulation (described in Fig. 3b). After each step, we end the simulation, output the raster layers of infected and susceptible hosts, and restart the simulation for the following step with the input consisting of the output from the previous step and any treatments for the following step. This approach supports all of the steering mechanisms described above, including controlling the progress, checkpointing, and synchronization; they are simply implemented outside of the simulation. The disadvantage of this solution is the extra time spent writing intermediate data to disk and loading it back to memory, as apparent from Fig. 3b. Although a part of this output data is used for visualization of the intermediate results, a large portion of it serves only to save the simulation steps and would not be exported in cases of computational steering.

Given our need to compare the outcomes of different treatment strategies, we run the simulation with each new set of treatments until the end step of the simulation and then it is paused. Using the checkpointing mechanism we can then go back and resume the simulation from any point. Having such a tree structure of end results for all decisions allows us to easily compare the outcomes and better understand the effect of individual treatments. Additionally, users can see estimates of multiple alternative futures and use them to inform their decisions. All of the results are saved in PoPS Forecasting Platform database and can be reloaded on the dashboard to review them.

4. Case study

We applied our modeling framework with stakeholders in Oregon who must make decisions regarding the management of Sudden Oak Death (SOD), an emerging forest disease that has killed millions of trees in California and Oregon. Based on their feedback from a prior workshop (Gaydos et al., 2019), we extended our epidemiological model to enable them to spatio-temporally steer the simulation by managing the disease at yearly intervals, rather than managing only at the beginning of the simulation. During a full-day participatory workshop we introduced stakeholders to this novel adaptive management modeling approach using PoPS Tangible Landscape and PoPS Forecasting Platform (Fig. 7). Stakeholders were to work in groups to collaboratively develop management strategies. To make the strategies relevant for stakeholders and their organizations' funding cycles, we simulated the disease for 3 years, starting with known 2019 infections. To account for delays in detection and treatment of the disease, participants designed their treatments in the beginning of each year, but the treatments were not applied until the end of that year. We applied the adaptive management approach to steering (Sec. 2.1.3) and simulated 10 stochastic realizations, which were sufficient to communicate uncertainty while avoiding time delays. More details about the workshop itself can be found in Gaydos (2020).

4.1. Adaptive management workflow

To better convey how adaptive management was incorporated into our participatory modeling exercise, we describe here the steering workflow using one example of how workshop participants progressed through the simulation (Fig. 8). This particular scenario was created by participants using PoPS Tangible Landscape.

By switching among the displayed years, participants explored the probability of infection, which would rapidly increase within three years without any management (Fig. 8a). Using PoPS Forecasting Platform, they then created a new scenario by specifying various settings, including budget constraint or treatment efficiency. To reduce the forecasted infection probability, participants decided to split their 2019 budget between treating outbreaks in northern parts of the landscape and treating some of the core infected areas in the south (Fig. 8 b-2019). They designated the treatments (Fig. 7) and adjusted them based on real-time feedback on the treatments' size and cost. When participants pressed the USB button, the treatment was registered in the database and the simulation ran from that year until the end year, 2021, taking into consideration the new treatments.

At that point, the participants moved within the scenario to the beginning of 2020 and a newly simulated infection layer representing one stochastic realization for that year was displayed. Despite the treatment of most 2019 infected areas, the disease escaped and spread northward (Fig. 8 b-2020). This spread occurred due to the delay between the treatment decision at the beginning of 2019 and actual management happening at the end of 2019, representing realistic delays between detection and taking action. Taking into account the future probability of spread extent (Fig. 8 b-2021 and b-2022) and the ineffectiveness of small buffers to completely prevent outbreaks, as in 2019, participants decided to treat the remaining infections and allocate half of their 2020 budget to treat larger areas in the north that were likely to become infected later (Fig. 8 c-2020).

At the beginning of 2021, all northward infection was successfully eradicated and the remaining infection was greatly reduced (Fig. 8 c-2021). In the last simulated year, participants were able to spend a much smaller budget to treat the few remaining infections (Fig. 8 d-2021). Although the beginning of year 2022—the end of the simulation—showed a few remaining infections (Fig. 8 d-2022), these could be easily treated by future management efforts.

This example demonstrates that allowing participants to manage throughout the simulation is essential for representing adaptive management decisions. Although a disease spread forecast based solely on initial treatment (Fig. 8b) is useful in planning, there are limits to using it to explore strategies. Without the option to treat in subsequent years, participants would not be able to test realistic management strategies, such as how much budget to allocate in different years, when and where to treat given the spatial distribution of the infection, or whether it is even possible to eradicate the disease given a realistic budget.

5. Discussion

Given the large uncertainties associated with forecasting social-ecological phenomena, researchers have been advocating for management "experiments" that could both develop scientific knowledge and lead to improved management policies and practices (Serrouya et al., 2019). Adaptive management has been shown to accomplish both through continuous "learning-by-doing" that takes into account the outcomes of previous strategies and models system behavior using updated knowledge (Walters and Holling, 1990). Given that successful implementation of this approach requires effective communication across science, policy and management (Bosch et al., 2003), participatory modeling has been used to engage stakeholders in learning, model development and creating management strategies (Lynam et al., 2010; Fujitani et al., 2017; Smith et al., 2007). However, participatory modeling efforts have been lacking in methods that allow stakeholders to explore how different spatially and temporally explicit interventions may impact a complex social-ecological system. In our work, we demonstrated how using simulation steering allows stakeholders to explore more realistic decisions through adopting an adaptive

Fig. 7. Participants using PoPS Tangible Landscape to steer simulation by placing felt on top of infected areas. PoPS Forecasting Platform with results is in the background.

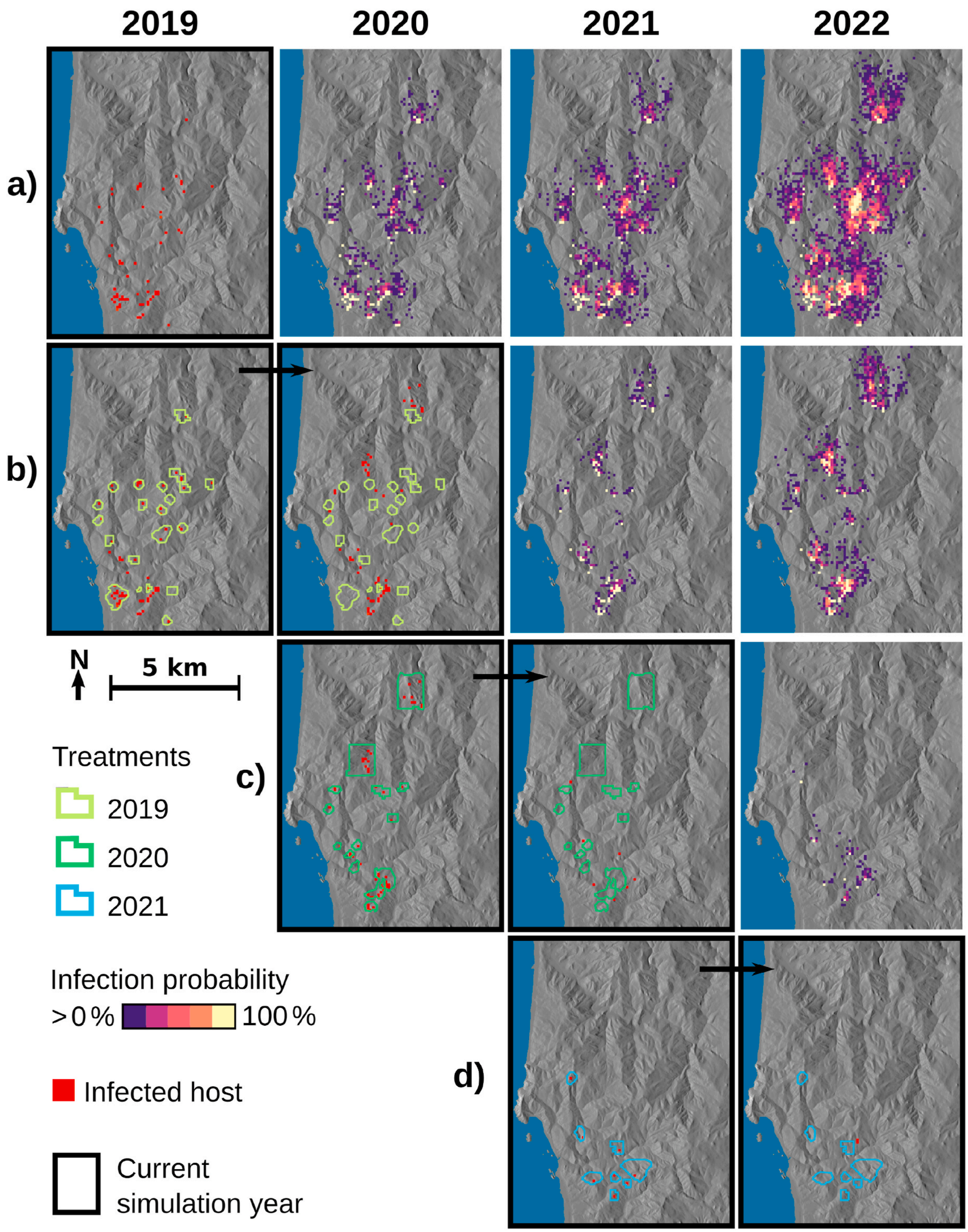

Fig. 8. An example of an adaptive management scenario developed by workshop participants demonstrating the steering workflow: a) no management scenario, b) treatments introduced in 2019, c) followed up by treatments in 2020, and d) 2021.

management approach.

As aforementioned, this work was motivated by the needs of stakeholders, voiced at an initial participatory modeling session (Gaydos et al., 2019) at which stakeholders could manage the infection only in the initial year of the simulation. That exercise helped them to learn about disease spread behavior and strategies to reduce spread but also revealed that the disease cannot be contained without continued yearly interventions, leading us to integrate adaptive management capabilities into the modeling framework. The new approach allowed stakeholders to ask more questions about their ability to eradicate the disease, how much of a yearly budget to allocate, and which areas should be treated first. At the workshop described here, participants used the new approach to, for example, experiment with front-loading the budget to see whether that would be more effective to eradicate the disease (Fig. 8). As an analysis of the workshop reports (Gaydos, 2020), the adaptive management approach "empowered stakeholders to generate novel intervention scenarios", and participants "combined several tactics and changed their approaches through time, which may better reflect the realistic-complexities of control."

Workshop participants gave good usability scores to both interfaces—PoPS Tangible Landscape and PoPS Forecasting Platform—and perceived them as useful for targeting treatment areas (Gaydos, 2020). These results show us that using sophisticated, realistic, steerable spatio-temporal simulations does not have to be difficult for stakeholders without modeling expertise. Indeed, studies developing interactive visual interfaces affirm that complexities of the model and the steering implementation can be hidden behind intuitive, visual interfaces that expose only information and behavior that are meaningful and practical for the stakeholders (Afzal et al., 2011; Ribičić et al., 2013; Niño-Ruiz et al., 2017). In our case, both interfaces provided the stakeholders the same steering capabilities, despite featuring different implementations of steering due to the practicalities of their different (web vs. desktop) deployments. Although the behavior of the simulation is the same, PoPS Forecasting Platform currently requires more time to progress through each steering step. That is to be expected given the steering implementation (Fig. 3b), but we are currently working on minimizing the delay by using better web deployment strategies. Nevertheless, this delay did not negatively impact the workshop, as participants used that time for more discussion. To help stakeholders develop and evaluate more scenarios in the allotted time, we decided to limit their ability to go back in time and change past interventions. Although this prevented them from fine-tuning individual scenarios, they managed to test a wider range of strategies. The option to change past treatments to fine-tune approaches is likely more important for analysts working with PoPS Forecasting Platform to finalize treatment plans.

Although considerable research has been devoted to overcoming the technological challenges of computational steering, the conceptual challenges of steering stochastic simulations have been overlooked. The common aggregation approach (Ribičić et al., 2013) (Fig. 1a) is limited in its ability to represent spatial structure and patterns explicitly modeled by many urban growth, disease, or wildfire simulations. Moreover, this approach is problematic when differences in the intermediate states of multiple stochastic realizations would result in significantly different steering decisions. The developed steering approaches—single-realization, aggregation, and adaptive management approach—provide a framework to address these challenges by better defining the role of each method in modeling and the associated implications for interpreting results. Since this work focused on the adaptive management approach, future work could further investigate the applicability and limitation of each of the developed methods for different spatio-temporal simulations (such as urban growth, flooding) based on their specific behavior and questions researchers and decision-makers are interested in answering. Additionally, a possible avenue to mitigate the limitation associated with using single stochastic realization in the adaptive management approach can be using a more sophisticated mechanism for selecting the single run. To mitigate any concerns about representing a likely reality, the run could be selected by weighing several of its characteristics, including e.g., its size, pattern, or value range, while at the same time the more extreme runs can be visualized alongside to provide a more complete picture of the stochastic variations. To facilitate further research, we envision developing a geospatial library with a simple steering interface that would streamline integrating spatio-temporal steering into current and new geospatial simulations (e.g., Peckham et al. (2013); Neteler and Mitasova (2008)). Such a library would encourage more interactive modeling in geospatial research, making the research process and results more accessible to domain experts and decision-makers.

6. Conclusions

In this study we addressed the often overlooked conceptual and implementation challenges of steering stochastic spatio-temporal simulations. Our suggested approach—combining aggregate views of future estimates with a single realization representing the past—provides a novel solution to steering multiple stochastic realizations and one that is particularly applicable for testing adaptive management strategies. The adaptive management modeling approach—developed to help stakeholders design more realistic management scenarios—can better represent the realities of decision-making by allowing stakeholders to decide when and where they manage based on past actions, current observations, and future forecasting. The participatory modeling case study demonstrated that the stakeholders were able to ask better, more realistic questions about the feasibility of disease eradication, budget allocations, and management priorities. Given the large uncertainties typically associated with social-ecological phenomena, the adaptive management modeling approach focuses attention on developing strategies that decision-makers can adopt based on the current, on-ground situation. Although our case study highlights the application and importance of spatio-temporal steering for disease management, the described approach is generally applicable and relevant for a variety of stochastic, geospatial models.

7. Software and data availability

This work is based on PoPS Forecasting and Control System, an open source project composed of several software components under GNU GPL v2 and later:

- C++ library *PoPS*
- R package *rpops*
- C++ GRASS GIS addon *r.pops.spread*
- *PoPS Forecasting Platform* based Django web framework

Links to GitHub repositories are accessible from OSF project osf.io/q32p9. Additionally, Tangible Landscape—tangible geospatial modeling and visualization system integrated with GRASS GIS licensed under GNU GPL v2 and later—was customized for steering and the code is available under a separate branch on GitHub (github.com/tangible-landscape/grass-tangible-landscape/tree/pops-steering). Data used for SOD modeling are accessible from r.pops.spread tutorial page (grasswiki.osgeo.org/wiki/SOD_Spread_tutorial).

Declaration of competing interest

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

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