Tangible geospatial modeling for collaborative solutions to invasive species management

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Abstract

Management of complex environmental problems, such as biological invasions, can be facilitated by integrating realistic geospatial models with user-friendly interfaces that stakeholders can use to make critical management decisions. However, gaps between scientific theory and application have typically limited opportunities for model-based knowledge to reach the stakeholders responsible for problem-solving. To address this challenge, we introduce Tangible Landscape, an open-source participatory modeling tool providing an interactive, shared arena for consensus-building and development of collaborative solutions for landscape-scale problems. Using Tangible Landscape, stakeholders gather around a geographically realistic 3D visualization and explore management scenarios with instant feedback; users direct model simulations with intuitive tangible gestures and compare alternative strategies with an output dashboard. We applied Tangible Landscape to the complex problem of managing an invasive forest epidemic, sudden oak death, in California and explored its potential to generate co-learning and collaborative management strategies among actors representing stakeholders with competing management aims.

Key words (max 6): *collaborative management, disease spread, geospatial modeling, invasive species management, plant disease, tangible user interface*

Software and data availability

Tangible Landscape is available under GNU General Public License and can be downloaded at http://tangible-landscape.github.io together with installation and setup instructions. Tangible Landscape was developed by Anna Petrasova and Vaclav Petras (Petrasova et al., 2014, 2015). The source code of the epidemiological spread model used in this study is available under GNU General Public License and can be downloaded at https://github.com/f-tonini/SOD-modeling with installation and setup instructions as well as set of GIS layers necessary to run the model. The code was developed by Francesco Tonini and based on the original epidemiological framework presented by Meentemeyer et al. (2011).

1. Introduction

Critically addressing complex environmental problems requires cross-disciplinary participatory approaches that facilitate stakeholder engagement and improve the development of collective management strategies (Cabin et al., 2010; Reed, 2008; Stokes et al., 2006; Voinov and Bousquet, 2010). However, the substantial research effort devoted to the study of large-scale problems such as biological invasions has overwhelmingly focused on generating model-based understanding of invasion dynamics, rather than implementation of management and intervention, creating what has become known as the knowledge-practice gap (Esler et al., 2010; Matzek et al., 2014). Biological invasions pose a severe threat to ecosystem services and public health worldwide (Daszak, 2000; Hatcher et al., 2012; Kilpatrick et al., 2010), with average annual global economic costs exceeding those of natural disasters (Lovett et al., 2016; Ricciardi et al., 2011). Yet, scholarly incentives to build knowledge irrespective of practice (Matzek et al., 2015), and mismatches between research and stakeholder priorities (e.g., academic priorities to publish ecological studies and stakeholder priorities to find management solutions, Bayliss et al., 2013) have limited the generation of evidence-informed solutions. In the management of invasive species, the application of knowledge-based tools has been problematic in landscapes that include a mosaic of management jurisdictions (Epanchin-Niell et al., 2010; Stokes et al., 2006), often resulting in competing interests between stakeholders and confusion as to who makes resource allocation decisions, who will benefit, and who pays (Voinov and Bousquet, 2010). In consequence, efforts to eradicate or control the spread of invaders have generally been unsuccessful (Simberloff et al., 2005).

One strategy for bridging the knowledge-practice gap involves making scientific models applicable by adding local context and easing accessibility (McCown, 2001). A suggested solution lies in the adoption of participatory modeling frameworks, which iteratively include stakeholders throughout the modeling process, and have been shown to maximize information transfer, generate buy-in, and create advocates for actions best supported by complex models (Perera et al., 2006). A special case, participatory simulation, has been proposed to move participants from passive or didactic learning about complex processes to experiential learning through immersion in what Colella (2000) calls the “computational sandbox,” i.e., simulations with realism adequate to temporarily suspend disbelief and constitute a shared experience. However, for complex, place-based problems like biological invasions, participatory modeling efforts have been hindered by a lack of realistic and intuitive geospatial modeling interfaces needed to generate contextualized understanding of spread dynamics among participants, thereby reducing barriers between specialists, management professionals, and stakeholders with varying levels of technical expertise. The availability of such interfaces could communicate complex system dynamics in clear visualizations, help all participants to understand and interpret multidimensional data, and facilitate decision-making consensus among stakeholders.

To address this need, we present Tangible Landscape (Petrasova et al., 2015), a flexible geospatial visualization and analysis platform that enables people with different backgrounds and levels of technical knowledge to direct dynamic computational simulations using simple tangible gestures. This novel approach seeks to bridge the knowledge-action gap by translating models of biological invasions into tools for strategic application to specific invasion challenges in real-world landscapes with targeted practitioner and stakeholder communities (Esler et al., 2010; Kueffer and Hadorn, 2008). Tangible Landscape allows individuals and groups to generate data-driven, spatially and temporally explicit projections of environmental management outcomes in near real-time in order to explore ramifications and risks associated with management action without threat of consequence.

In a pilot exercise to test the capacity of Tangible Landscape to facilitate learning and generate collaborative management strategies, we simulated the management of an emerging forest disease, sudden oak death (SOD, caused by the pathogen *Phytophthora ramorum*). From the onset of the SOD epidemic in California, delays in identifying the pathogen, understanding the mechanisms of spread, and developing management treatments have resulted in the disease becoming established well beyond initial introductions (Meentemeyer et al., 2011, 2015). Time to action is a critical determinant of eradication efficacy for any disease, and the critical time horizon for eradication has passed (Cunniffe et al., 2016); SOD infects 35% of its anticipated range, an increase of 500% from 2006 (Filipe et al. 2012; Meentemeyer et al., 2011). While modeling suggests that large-scale eradication in California is no longer possible, local to landscape-scale efforts are still very useful for protecting high-value trees in priority areas

(Cunniffe et al., 2016). There is widespread recognition that collective effort is needed to reach scales of management likely to succeed (Frankel, 2008).

We developed a customized deployment of Tangible Landscape that (1) adapted a dynamic spatially explicit model to a local study system parameterized using data on the spread of *P. ramorum*; (2) enabled place- and time-dependent interaction with the model using tangible representations of disease management actions on a physical model; (3) provided a shared environment for participants to discuss competing management perspectives and learn from each other; (4) created opportunities to develop and compare individual and collective management strategies; and (5) provided a graphic dashboard to track epidemic outcomes and cost of management treatments, providing feedback regarding how interactions influenced simulated disease spread. We roleplayed several stakeholder typologies associated with the study system and compared the performance of individual strategies with a strategy emerging from stakeholder consensus.

2. Methodology

2.1. Model Development

2.1.1 The tangible geospatial modeling interface

Tangible Landscape (Petrasova et al., 2014, 2015), formerly TanGeoMS (Tateosian et al., 2010), is a tangible user interface (TUI) that allows participants to direct computational modeling through tangible gestures on a scaled physical model of a landscape, onto which raster and vector environmental data from a GIS are projected (Fig. 1).

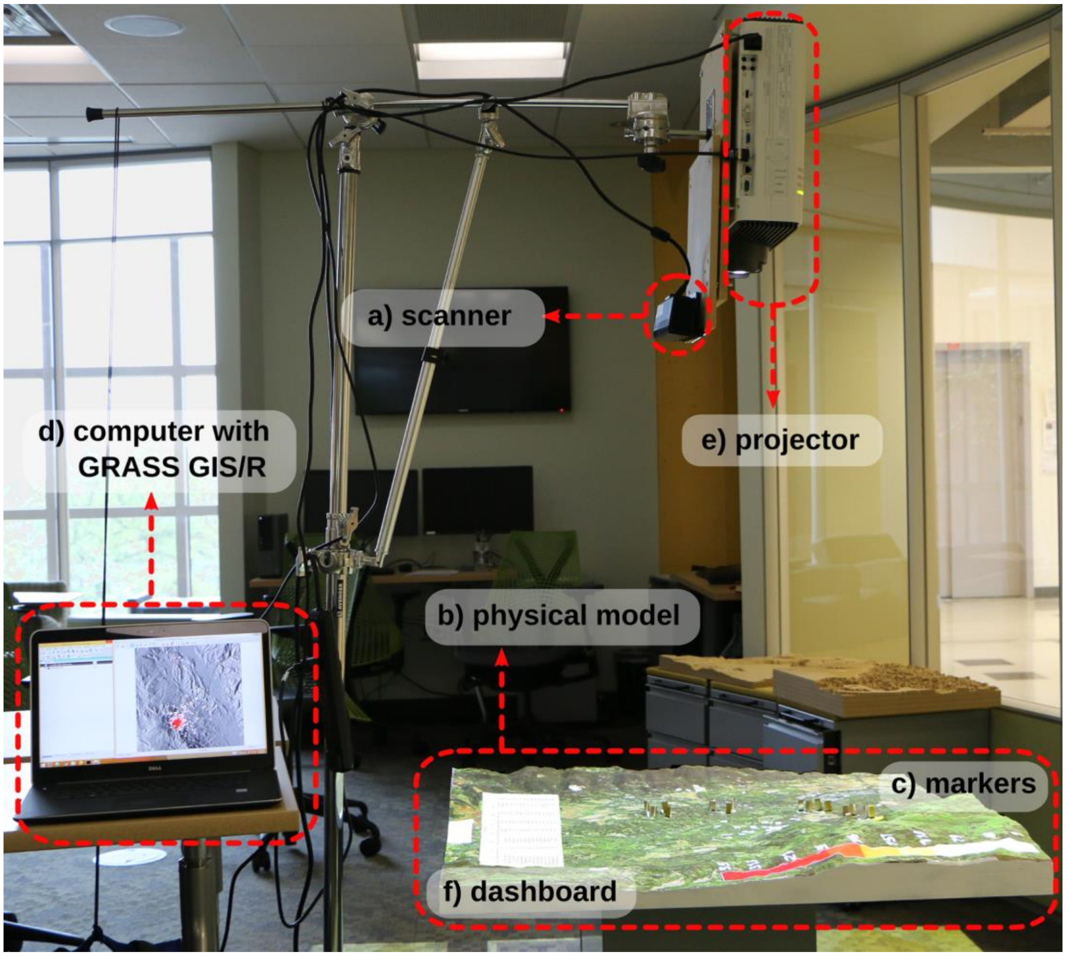

Figure 1. Tangible Landscape continuously scans (a) a physical terrain model (b), also "relief" in Fig. 6), identifies markers (c), computes geospatial analyses and simulations (d) and projects the resulting maps onto the model (e), together with the resulting analytics as a decision support dashboard (f). Available in color online.

Users conduct typical GIS functions on the projected data, including editing and parameterizing simulation models, as direct manual interactions with the scaled model are detected by continuous automated 3D scanning (Fig. 1a). Changes in the physical model are detected, recorded and input into GIS for visualization, analysis, and simulation, e.g., whenever a user alters model topography (such as sculpting with sand or plasticine), places markers, or moves building blocks. Tangible interaction frees participants from needing prior technical knowledge before directing sophisticated geospatial models. Maps or animations produced during tangible interaction are projected in near real-time, creating visuals that are readily understood and can inform future interaction. A decision support dashboard reports analytics and the results of queries using spreadsheets, charts, and infographics (Fig. 1f, Fig. 2d, Fig. 3). Tangible Landscape runs as a Python plugin for GRASS GIS that can be extended using the GRASS Python Scripting Library and R scripting (R Core Team, 2015). System hardware include a computer, a projector, a 3D scanner, and a physical model (Petrasova et al., 2015). Laptops and portable projectors allow Tangible Landscape deployments outside of the lab.

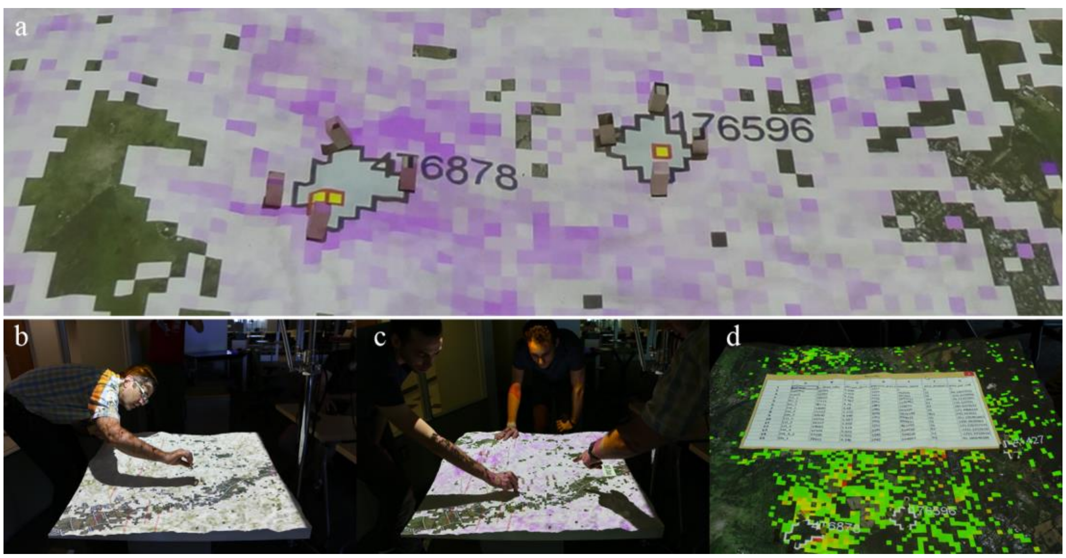

Figure 2: **Participants using Tangible Landscape to designate treatment areas and limit spread of the sudden oak death (SOD) epidemic in the Upper Sonoma Valley, California. (a) Markers digitized as treatment areas, (b) a single participant 3D-sketching a treatment area using a map of oak density as a guide, (c) a group of participants collaboratively 3D-sketching treatment areas using a map of California bay laurel density as a guide, and (d) a dashboard showing the cost and number of oaks saved. Available in color online.**

Figure 3: Authors playing the role of local stakeholders visualizing results on Tangible Landscape and discussing implications of their collaborative management actions. Available in color online.

2.1.2 A socio-ecological dilemma: The SOD epidemic in Sonoma Valley

Circa 1995, conspicuous and unexplained tree mortality (Fig. 4) was observed in several locations within central-coastal California and spread to Sonoma Valley by 2000, generating a high degree of concern among the public (Rizzo and Garbelotto, 2003). Named sudden oak death (SOD) due to its rapid symptoms, the causal agent was traced to the pathogen *Phytophtora ramorum*. By 2013, *P. ramorum* had killed millions of oak (*Quercus spp.*) and tanoak (*Notholithocarpus densiflorus*) trees in California and Oregon (Cobb et al., 2013). Subsequent studies found a complex network of transmission and about two dozen naturally occurring host species (Meentemeyer et al., 2004), including a non-terminal (i.e. not suffering mortality from disease) “super spreader” foliar host, California bay laurel (*Umbellularia californica*). The broad variety of host species and the environmental resilience of the pathogen makes SOD extremely difficult to manage (Frankel 2008), and the few available management options are controversial among private and public stakeholders. Treatments include tree culling via cutting or herbicide application as well as the treatment of individual stems with prophylactic antifungal chemicals (phosphates) (Garbelotto and Schmidt, 2009). These treatments are costly and chemical treatments are often politically stigmatized in California.

Figure 4: Example of widespread oak mortality by sudden oak death (SOD) in the California wildlands. Available in color online.

The Sonoma Valley is a mixed landscape (Fig. 5a–c) of urbanized areas and widespread agriculture, especially wine grape production, and spans private and public ownerships including state and regional parks (e.g., Jack London State Historic Park). Forested areas are a mix of open oak (*Quercus spp.*) woodlands and denser mixed evergreens, with Coast redwood (*Sequoia sempervirens*) dominating cooler mesic drainages and north-facing slopes. California bay laurel, the most significant source of spore production and release by *P. ramorum*, is abundant in most forest types within the region (Meentemeyer et al., 2008).

Figure 5: Views of Upper Sonoma Valley, California. a) Forest trail intermixed with open forested landscape; b) urbanized areas surrounded by forested landscape; c) mix of open oak woodlands and denser forests of mixed evergreen species. Available in color online.

2.1.3 Adaptation of an epidemiological spread model

We adapted a previously validated stochastic, spatially-explicit susceptible-infected (SI) model developed to simulate the spread of the SOD pathogen *P. ramorum* in California (Meentemeyer et al., 2011) for use in Tangible Landscape. The raster-based model incorporates forest community structure, local weather conditions, seasonality, as well as transmission of the pathogen among host species. Increased spore production and pathogen transmission are the direct consequence of steady local moisture conditions (e.g., from consecutive days with precipitation events), thus fluctuations in local temperature and moisture conditions strongly affect outbreak patterns. With favorable weather conditions, spores are produced on the leaves of foliar hosts, such as bay laurel, and passively transmitted between trees and forest patches via wind-blown rain and rain splashes (Davidson et al., 2005; Václavík et al., 2010). Within each cell of the model, forest composition directly affects host susceptibility and pathogen production capacities; in the Sonoma Valley study area, transmission occurs primarily via spore production and release (sporulation) on bay laurel, which does not suffer mortality or any other known negative effects from infection (Cobb et al., 2010).

We adapted the simulation model to the Upper Sonoma Valley by first choosing a 1-ha (100 m x 100 m) resolution to match surveillance and field management for SOD (Valachovic et al., 2013) and partitioning the study area into a detailed lattice of contiguous 1-ha cells containing multiple susceptible and infected trees (bay laurel and oaks, Fig. 6e–f). The model was run for the interval 2000–2010 at discrete weekly time steps, using a predominant northeast wind direction typical for the chosen study area (Fig. 6a). In the model, sporulation within an infected site, the dispersal distance and direction, and the probability of successful infection of a susceptible host species are stochastic processes. The modeling framework involves a number of initial GIS layers and core sub-processes repeated at any generic time step (Appendix A). To account for uncertainty in simulation outcomes, the model was routinely run 100 times for a given scenario. Such a number represents a reasonable compromise between short computational time and higher precision in the estimated number of infected oaks, expressed as a Monte Carlo (or multi-run) average, i.e., as arithmetic mean of all simulation runs. The model was implemented in R and C++ using the *Rcpp* package (Eddelbuettel and Francois, 2011) and coupled with GRASS GIS through the *rgrass7* package (Bivand, 2015). The source code and a set of GIS layers necessary to run our model are freely available[3].

[3] https://github.com/f-tonini/SOD-modeling

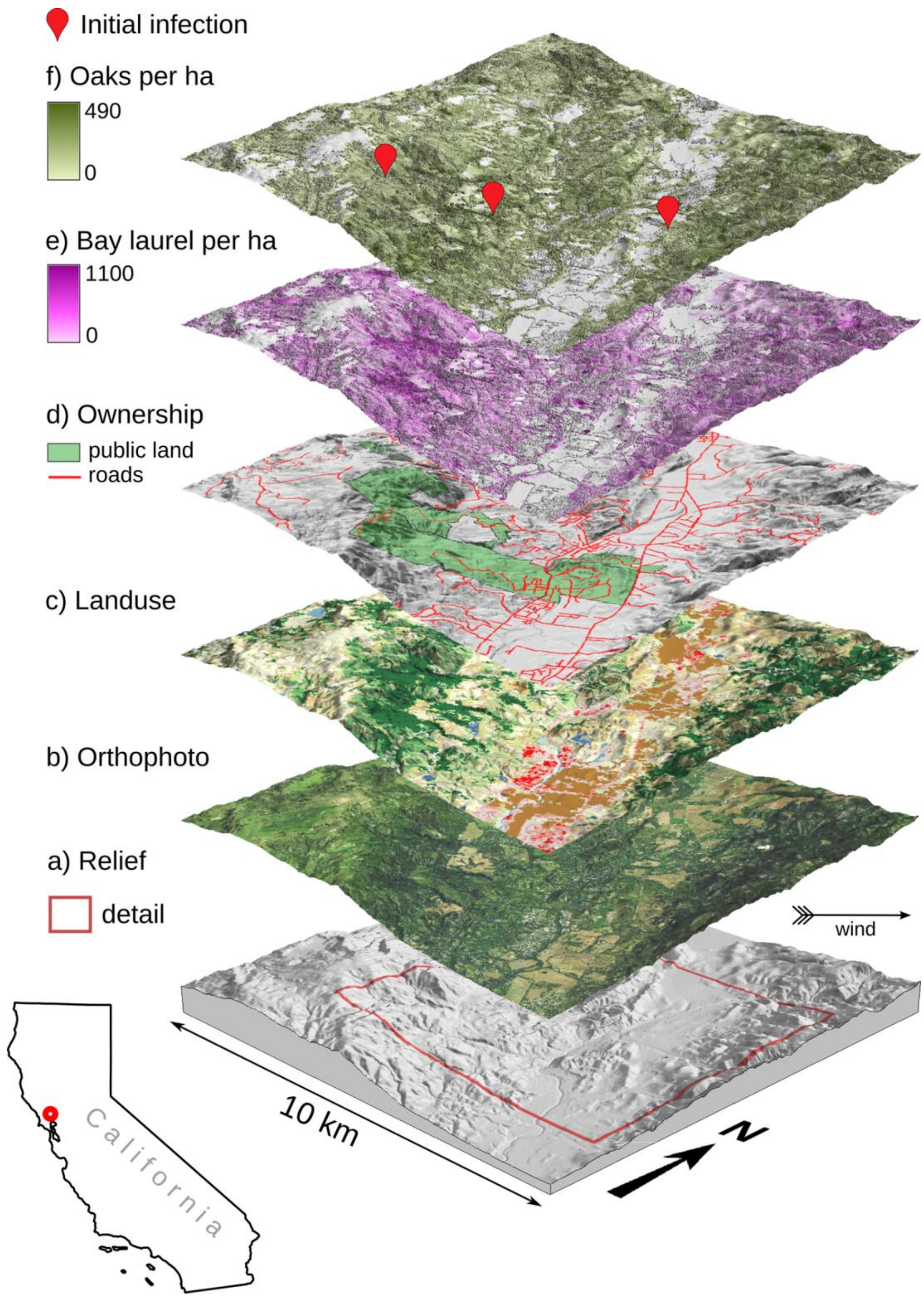

Figure 6: Data representations used in a deployment of Tangible Landscape to explore collaborative management of SOD in Upper Sonoma Valley, CA. This illustration mimics the overlay of multiple physical, human, and environmental GIS maps projected onto a 3D

physical model base. a) Relief map of the 10 km x 10 km Upper Sonoma Valley study area, noting prevailing wind direction; b) orthophoto of the region (USGS HRO 2011); c) land use map (Fry et al. 2011); d) land tenure including public roads (California Department of Parks and Recreation 2015, US Census Bureau 2015); e) Vegetative mapping of super spreader host California bay laurel (Ohmann and Gregory 2002, LEMMA 2016) and f) terminal hosts *Quercus spp*. (Ohmann and Gregory 2002) with first known sites of pathogen *Phytophtora ramorum* infection (Kelly et al. 2004). See text for details. Available in color online.

For this deployment of Tangible Landscape, we used computer numeric control (CNC) machining to fabricate a 1:10,000 m scale physical model for a 10 km^2 region of the Upper Sonoma Valley, onto which the GIS layers were projected (Fig. 6a). To create the physical model, we first exported a digital elevation model (DEM) of the region as a point cloud using GRASS GIS, and then generated a toolpath for CNC machining from a computed mesh. We used a 3-axis CNC router to carve a landscape topography model from a block of medium density fiberboard. The model was sanded and coated with magnetic paint so that magnetized markers would hold to its sloping topography (see Petrasova et al. 2015 for a guide to CNC machining topographic models). GIS layers (Fig. 6b–f) including orthoimagery, vegetation cover, land use and ownership, and initial sites of *P. ramorum* infection were projected onto the physical model, creating a contextually immersive 3D environment with information relevant to the management problem.

2.2 Application

2.2.1 Choice of stakeholder types for roleplaying

We identified a diverse subset of stakeholders within the study area and categorized them into three idealized typologies for roleplay—Forest Manager, Landowner, and Conservationist—with different goals for disease containment. The *Forest Manager* was concerned with forest health within national and state park boundaries and motivated to manage a forest epidemic with the responsibility of maintaining public safety and biodiversity. The *Landowner* was not concerned with the overall size and extent of the infested areas unless the epidemic directly affected their properties; rather, they were most likely to manage disease by reducing host numbers in narrow bands on their own land, to reduce fuel accumulation for fire management. Despite the presence of multiple private properties over the area, we restricted ourselves to a single representative landowner for simplicity. The *Conservationist* was concerned with preservation, restoration or improvement of the natural environment, generally not in favor of deforestation, but in favor of disease management that preserved limited resources such as old growth trees and species of conservation concern. With these roles, we conducted a mock planning workshop to address the SOD epidemic in the study area. Another co-author helped players with details of the basic working principles of the spread model and provided assistance and facilitated interaction with Tangible Landscape when necessary. Although several details about the spread dynamics of an emerging infectious disease can be intuitively learned by visualizing them directly on a physical model, we acknowledge that pre-training may be necessary to provide actual stakeholders with additional information about the main processes and assumptions involved in the model.

2.2.2. Rules of the roleplaying exercise

After observing the average outcome of a baseline (no treatment) simulated scenario and locations of pathogen introductions in the year 2000 (Fig. 8), the players sought to maximize the number of oaks saved by the year 2010 and to minimize management costs (total and cost per oak saved, described below). The sole control method was removal of susceptible foliar host trees, defined as 99% culling of bay laurel trees within 1-ha units. Players accomplished this by placing small wooden markers on the physical model (Fig. 2b, c; Fig. 7). When scanned, each marker generated a vector point within the GIS, and an automated algorithm digitized those points as nodes in a convex shell polygon or linear polygon representing the area, shape, and geo-referenced position of culling. Treatment polygons directed the epidemiological simulation model by reducing mapped bay laurel density in those units to 1% regardless of starting value, an action analogous to culling the trees. The sole option of culling bay laurel reflects the paucity of real-world options for controlling *P. ramorum* as, to date, no curative chemical treatment or comprehensive biological control has been found (Garbelotto and Schmidt, 2009; Rizzo et al., 2005).

Figure 7: Disease management treatments for sudden oak death (SOD) in the field (upper) and their equivalent on Tangible Landscape (right) via culling of "super spreader" California bay laurel. In the field, culling of bay laurel trees can be achieved with hand clippers for saplings (a) or chainsaws for older trees (b). On Tangible Landscape, wooden dowels are arranged in order to enclose areas where culling treatments are needed. Available in color online.

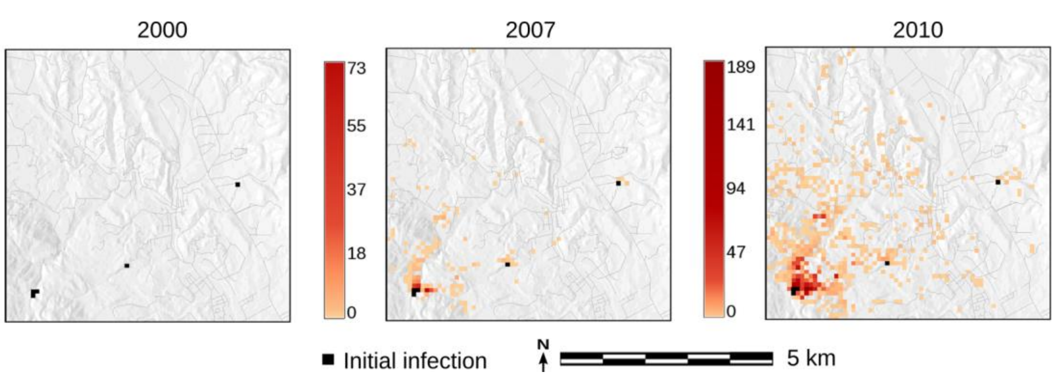

Figure 8: Number of infected oaks predicted by a baseline (no treatment) simulated scenario between 2000 and 2010. The chosen geographical extent matches the smaller area outlined on the physical model, Fig. 1. Values are averaged over 100 model runs. Darker values correspond to higher oak mortality: by 2007, a total of 430 oaks were expected to die, and by 2010 a total of 2770. Available in color online.

Players could cull up to a total of 62 ha (≈ 150 ac) per simulation, acknowledging the real-world limitation that treatments in excess of this amount require a lengthy and costly application process as part of the California Environmental Quality Act (CEQA) or National Environmental Policy Act (NEPA) (Buck, 1991). We based the estimated costs of culling on those associated with a trial treatment at the University of California Big Creek Reserve, where 99% of bay laurel was culled from 1 ha with a crew of 16 people. Site planning by personnel had included locating suitable sites using aerial orthophotography, scouting, and purchasing materials to locate plot centers and boundaries; hand culling of bay laurel had required 13 person hours per 1% cover. Disregarding capital costs (e.g., purchase of chainsaws) and transportation expense to and from the site, we arrived at the following formula to use in the model:

Cost ($ USD)/ha = (Relative cover in whole numbers/ha x 13.0 person hours x $18.00/person hour) + $800 planning fee.

After examining the average outcome of a baseline (no treatment) simulated scenario 2000–2010 (Fig. 8), players were allowed three trials to individually create a management strategy, and the epidemiological model was run after each trial to generate maps of infection outcomes by 2010. These maps were projected onto the physical model (Fig. 2d, Fig. 3) and used for comparison with the no-treatment scenario. A graphic dashboard further tracked oaks saved and costs (Fig. 2a, d; Fig 3), providing feedback of how management decisions influenced the simulated spread of the disease. Near-instant feedback after each trial provided opportunities for the players to test placement of culling. For each player, we quantified the average amount of infected oaks for each grid cell and the average amount of total infected area (i.e., infected bay laurel and oaks), as well as the cost of treatments (total and per tree saved). The three players performed treatments and viewed outcomes in the presence of all other participants, allowing co-learning. After each player performed three trials, we worked together for three trials as a collaborative team. We then compared individual participant results with those of the group.

3. Results

3.1. Outcomes of simulated management

Forest Manager was the first player to deploy a strategy and noticed in the no-treatment scenario that little oak mortality was predicted to occur near the easternmost initial infection site; so they placed treatments close to the southwestern foci (Fig. 1f). Concerned with park management, they chose to cull bay laurel from groves of oaks near frequently visited state park trails and entrances. On average, these simulated management actions saved 68 oaks per hectare (Fig. 9a) and a total of 400 oak trees over the entire study area (Fig. 10) at a cost of $251,759 USD, or $693 per oak (Table 1).

Landowner deployed their strategy next and restricted culling to linear treatments along minor roads bordering their private property, reflecting legacy management behaviors that emphasize managing fuel accumulation as part of a rural fire protection program. The simulation demonstrated, however, that establishing defensible space along property boundaries did not control the spread of *P. ramorum*. Management away from the three infection foci, in areas with little bay laurel near personal property, had no significant impact on preventing oak mortality ahead of the culling treatments (Fig. 9b, Fig. 10, Appendix B). Despite a lower overall cost ($190,158), this treatment produced a high average cost per saved oak due to the negligible number of oaks saved from mortality (Table 1).

After observing the strategies of *Forest Manager* and *Landowner*, *Conservationist* decided to use a containment strategy typical of reactive culling (i.e., culling of all host species around detected infection sites, in this case bay laurel). This was the most successful approach among the players, with an average of 189 oaks saved per hectare, about 2,000 trees saved over the entire study area (Fig. 9c, Fig. 10, Appendix B), and a cost of $159 per oak saved (Table 1). High overall treatment costs were compensated by the large number of oaks saved from mortality, thus lowering the average cost per saved oak (Table 1). Despite targeted culling around infection foci, the pathogen was still able to spread beyond the treated areas due to small amounts (1%) of remaining bay laurel and the occurrence of long-distance dispersal events. This is analogous to real-world evidence that even under the best practices *P. ramorum* is rarely eradicated, with success rates often measured in terms of the degree to which disease outbreaks are slowed down.

For the final series of simulations, the three players collaboratively designed a management strategy (Fig. 3). By observing the outcomes of previous strategies, we learned that treatments near individually valued resources, such as oak groves or properties, did not perform as well as targeted reactive culling approaches meant to contain the disease at its origins, regardless of land ownership. The resulting collaborative effort led to a high average number of oaks saved per hectare as well as total amount saved over the study area (Fig. 9d, Fig. 10, Appendix B). Total overall costs and average cost per oak saved were similar to that observed for *Conservationist*. Although the spatial configuration of areas partially saved from the disease was similar between the collaboration exercise and *Conservationist* (Fig. 9c–d), the *Conservationist*'s strategy saved more oaks per weekly time step than the collaborative strategy (Fig. 10), ultimately resulting in more total oaks saved. This was likely due to the cumulative effect of slower disease spread in the first years of simulation as pathogen accumulation was reduced by targeted treatments around the three initial infection foci.

Table 1. Treatment outcomes and costs associated with disease management scenarios implemented by roleplaying, individually and collaboratively.

Stakeholder typology	**Trial**	**Treatment size (ha)**	**Saved oaks (average)**	**Cost (USD)[a]**	**Price per saved oak (average) [a]**
Forest manager	1	62	51	**$187,382**	$3,680
	2 [b]	59	363	$251,759	**$693**
	3	62	8	$249,377	$29,973
Landowner	1	57	43	$274,945	$6,359
	2	52	104	**$190,158**	**$1,822**
	3 [b]	60	73	$280,857	$3,865
Conservationist	1 [b]	62	1991	$315,863	**$159**
	2	59	236	**$300,862**	$1,276
	3	61	1270	$480,678	$378
Collaboration	1	61	1196	$326,528	$273

2 *	62	1275	**$315,371**	**$225**
3	62	615	$334,937	$545

[a] Costs were calculated based on site planning, labor, materials, and transportation necessary for culling treatments (see formula in *Rules of the roleplaying exercise* section). Costs per saved oak are averaged over 100 model runs. Lowest costs within each stakeholder typology are in bold.

[b] Shown in Figures 9–10

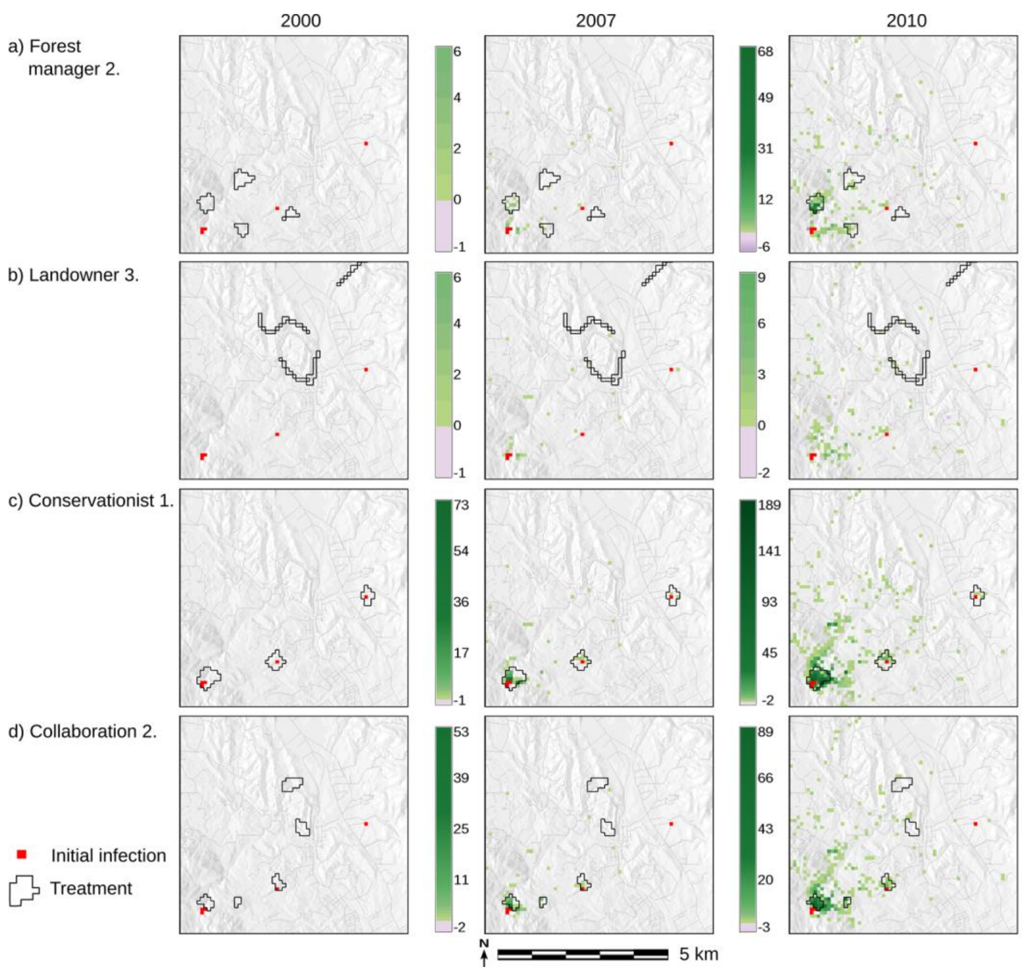

Figure 9: Number of oaks saved from mortality compared to the baseline (no treatment) scenario between 2000 and 2010. The color ramp is the same for all maps: legends show minimum and maximum values for the specific simulation year and trial. The small

negative values are caused by residual stochastic differences between average outcomes of the baseline (no treatment) and the management scenarios under consideration. (a) *Forest Manager* with treatments centered on trails, campgrounds, and other high-use areas within state parks boundaries, (b) *Landowner* with treatments along roads, (c) *Conservationist* with treatments placed around initial known foci of infection (red squares), and (d) collaborative action, with treatments placed according to shared interests. Values represent per-pixel averages over 100 model runs. The chosen geographical extent matches the smaller area outlined on the physical model, Fig. 6a. Only the most successful trial for each category is shown. Available in color online.

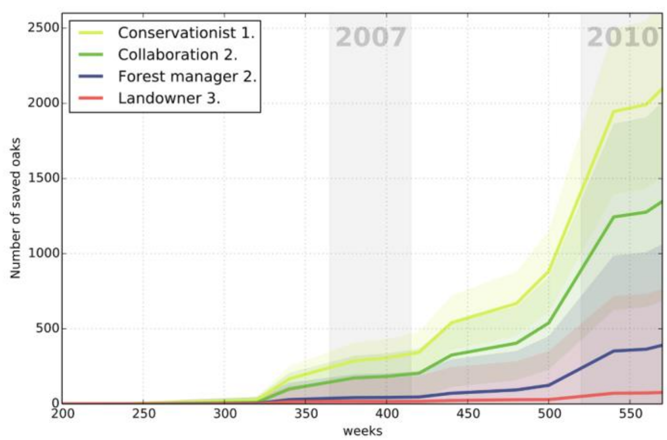

Figure 10: Total number of oaks saved from mortality over the entire study area compared to a baseline (no treatment) simulated scenario between 2000 and 2010. Lines represent averages over 100 model runs, enclosed by their Monte Carlo confidence interval (shaded areas). Available in color online.

4. Discussion

For the first time, we demonstrated how a 3D interface such as Tangible Landscape can facilitate decision-making among management stakeholders with different initial objectives collectively facing the spread of an invasive plant pathogen. In this pilot exercise, we deployed a real-world epidemiological model using Tangible Landscape and compared individual and collaborative performances for decreasing the spread of sudden oak death. When working together, players compromised where they would each prefer to enact management in order to maximize the overall number of oaks saved. We found that directing computation by simply placing markers on a 3D physical model of the study system enabled us to quickly and easily explore management alternatives and engage in active discussions while evaluating “what-if” scenarios. The near-real time assessment of alternative management interventions inspired discussion and co-learning, thus building consensus when making decisions.

The Tangible Landscape framework constitutes a novel methodology designed to bridge the knowledge-practice gap and make model-based research actionable. In translating the spread model to Tangible Landscape, we considered how participants might interact with and manipulate the driving parameters. For example, recognizing weather as a key SOD spread driver beyond human control, we held climatic parameters constant and instead allowed participants to alter the abundance host density via culling treatments. Further, we developed and reported metrics relevant to stakeholders groups (e.g. treatment costs based on host density and labor), not just researchers, to ease the communication of trade-offs associated with alternative management strategies.

4.1. Lessons learned from roleplay

Using Tangible Landscape, we were able to explore some of the substantial challenges facing those charged with managing SOD. A key question, acknowledging the generalist nature of *P. ramorum*, was whether it was more effective to deploy preemptive treatments downwind from the sites of known introduction or attempt to contain the disease at its source (Cunniffe et al., 2016; Filipe et al., 2012; Hansen et al., 2008). In our case study, the Conservationist's management strategies aimed at culling the reservoir host solely around the three known infection foci (Fig. 9c) did not contain the spread of the disease, most likely due to the practical impossibility of fully removing the reservoir host. The containment strategy did, however, slow down the disease in the short term and reduce overall oak mortality (Fig. 10). The location and spatial extents of areas saved from the disease were similar between *Conservationist*'s approach and the alternative collaborative strategy (Fig. 9d). The latter resulted in slightly higher costs but brought a high degree of realism to the management effort by considering the necessary trade-offs and multiple local interests involved (Cobb et al., 2013b; Rizzo et al., 2005).

In order to develop collaborative strategies, management practices initially favored by representative interest groups (i.e., *Landowner, Forest Manager*, and *Conservationist*) were modified, abandoned, or exchanged to accommodate competing interests. For example, participants noticed that treatments placed around the easternmost infected site (see *Conservationist*, Fig. 9c) had little to no effect on reducing oak mortality in the surrounding areas. As a consequence, ~10 ha of land were re-allocated near the central portion of the study area to prevent part of the disease outbreak projected to hit by year 2010 (Fig. 8) should no management action be taken. *Landowner* abandoned linear road treatments after seeing how the investment did not save many trees. *Forest Manager* re-allocated 20 ha of treatments in order to better protect oak groves downwind from the central source of infection (Fig. 9d), while accommodating the treatment area originally placed by *Conservationist* around the same infected site. Although a single individually developed strategy (as seen here by *Conservationist*) might achieve the best outcome in terms of number of oaks saved (Fig. 9c, Fig. 10), the overall treatment costs can easily exceed those of a carefully planned collaborative strategy (Table 1; Hansen et al. 2008).

4.2. Technical considerations

This pilot application of Tangible Landscape to a management planning scenario revealed technical challenges for us to address. In particular, the variability observed between stochastic runs of the same scenario (Fig. 10) still leaves an open question concerning the optimal compromise between model replications and computational burden. The three main components implemented in the epidemiological model (i.e. sporulation, dispersal, infection) are stochastic processes in which differences between any two simulations can grow between successive time steps, and sometimes even lead to snowballing divergences. The presence of small positive and negative values in the *Landowner* strategy (Fig. 9b) exemplifies this problem. Increasing the number of model replications leads to a more accurate average outcome while reducing variability and accounting for a range of extreme possibilities (Monte Carlo simulation). However, the purpose of Tangible Landscape is to offer the user a near real-time interaction with the physical model and the layers of spatial information projected onto it, thus necessitating a reduced computational burden (Petrasova et al., 2015). A method to deal with large numbers of independent model runs may be to launch them in parallel on multiple processors possibly on a remote infrastructure. The results would then be averaged into a single outcome and presented to stakeholders. In the future, we intend to explore computational improvements that could enable inclusion of multiple adaptive disease interventions through time in Tangible Landscape.

5. Conclusions

Our pilot exercise demonstrated the potential for Tangible Landscape to run a responsive epidemiological model with user input through an easy-to-use 3D interface. Our next step for exploring collaborative decision-making with Tangible Landscape is to deploy this model in a real-world setting out of the lab, with real stakeholders that include private citizens and representatives from state and national government agencies, academia, and industry, exploring control scenarios for the SOD epidemic in a focal area of pressing concern. As we observed in our pilot study, we expect that the participatory tangible modeling environment will empower stakeholders to experiment, granting them freedom to make mistakes, evaluate outcomes, and negotiate costs and benefits in order to reach individual and collective objectives.

Our mock planning workshop illustrated some of the challenges of uniting multiple stakeholders with overlapping jurisdictional boundaries and exposed some of the difficult trade-offs required to arrive at consensus in management decisions. We predict that in a real-world setting, several technical and visual advantages of Tangible Landscape will help reduce barriers between participants with varying objectives and types of expertise: Tangible Landscape provides the degree of information density and realism needed for participants to 1) quickly and intuitively learn the salient details and dynamics of a complex epidemiological spread model, 2) virtually place themselves into a landscape they know and care about and allow their decision making to be geographically and contextually informed, 3) quickly develop and test management strategies, often by observing and learning from each other, and 4) receive near-real time feedback as to the efficacy of their actions over time. This leads us to suggest that customized deployments of Tangible Landscape will facilitate understanding, interpretation, and compromise when examining complex ecological interactions and potential solutions for management.

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Appendix A.

Vegetation Maps

We derived tree densities from detailed GIS structure (species-size) maps from the Landscape Ecology, Modeling, Mapping & Analysis (LEMMA) project webpage (Ohmann and Gregory 2002; http://lemma.forestry.oregonstate.edu/). Tree densities (per hectare) for bay laurel and oak species of interest (coast live oak, black oak, canyon live oak) were calculated using the live tree density attribute (*TPH_GE_3*) multiplied by fractions of total basal area (*BA_GE_3*) as follows:

$$Density_K = TPH\_GE\_3 * \frac{BA_K}{BA\_GE\_3},$$

where the index *K* indicates the species of interest and *BA* indicates basal area (m^2/ha). This resulted in maps of oak and bay laurel density (Fig. 6e and f, respectively) that informed stakeholders as to the location of susceptible tree populations and super-spreaders of *P. ramorum*, aiding the development of management strategies.

Initial Disease Records

To initiate the model, we used empirical records of the disease collected in three different appelocations within the study area (Fig. 6f) around year 2000. These records include plot-level data on *P. ramorum* incidence collected by Phytosphere Research and the California Oak Mortality Task Force (Kelly et al. 2004), which reports infections confirmed by the California Department of Food and Agriculture (Meentemeyer et al. 2008).

Weather Conditions and Seasonality

Fluctuations in temperature and moisture conditions strongly affect sporulation rates and transmission of *P. ramorum* in forests (Davidson et al. 2005, Václavík et al. 2010). Specifically, increased pathogen production is the direct consequence of steady local moisture conditions (e.g. from consecutive days with precipitation events) that coincide with mild temperatures. These conditions are typical of spring precipitation events in the study region. In this work, we used weekly maps of weather condition indices derived from average temperature and consecutive days of precipitation as described in Meentemeyer et al. (2011). The combined index is defined in [0, 1], where zero corresponds to unsuitable conditions for spore production and transmission. Seasonality is included in the model by restricting pathogen spread and infection in forests between the months of January and September, following the start of the rainy season in California's Mediterranean climate.

Sporulation and Pathogen Dispersal

The amount of spores produced each week within each infected site is sampled from a Poisson distribution with rate equal to 4.4 spores/week as calibrated in Meentemeyer et al. (2011). This rate corresponds to the maximum expected number of spores an infectious host can produce if weather conditions were most suitable. Weather conditions affect sporulation by reducing the amount of spores produced through a low value of the weather condition index. Pathogen intensification and transmission are controlled by a probabilistic kernel that describes the spatial spread over short distances (≤ 1 km) as well as occasional jumps (1-100 km) caused by anthropogenic activity (Rizzo et al. 2005). Although SOD is a "spillover" disease, where outbreaks on oaks are caused by transmission of the pathogen from foliar hosts in close-proximity, it is crucial to account for occasional long-range dispersal events. In fact, these types of rare jumps ultimately drive pathogen spread over regional extents, complicating the implementation of effective management and control strategies for invasive species (Frankel 2008). Further, because wind-driven rain is thought to be a major dispersal process at local scales (Rizzo et al. 2005), we considered wind direction as an additional component to the spread model. In contrast with Meentemeyer et al. (2011), we used a particle-emission anisotropic reformulation of the dispersal kernel: the spores produced within each infected cell of the landscape are dispersed in a direction sampled from a Von Mises circular probability distribution on $[0, 2\pi)$ by a distance distributed according to the dispersal kernel. The predominant wind direction for the study area (Northeast = 45 degrees or ≈ 0.78 rad) was used to parameterize the mean of the angular distribution and we set its concentration value equal to 2 ($k = 2$). The dispersal distance was sampled from a Cauchy probability distribution parameterized with values from Meentemeyer et al. (2011). Because the study area is relatively small (10 km x 10 km), in this work we ignored the long-distance component of the dispersal kernel.

Infection

Susceptible host species are probabilistically challenged for infection by the pathogen proportionally to their density and adjusted by a variable indicating the suitability of weather conditions. Transmission and mortality are independent processes within the model which provides the flexibility to reflect the epidemiology of this disease in real forests. For example, the parameter values for bay laurel provide relatively high rates of sporulation on bay laurel with mortality rates set to zero. In contrast, transmission is set to zero for oaks, but mortality is the greatest relative to other species within the host landscape. Spread of infection is approximated as a function describing the probability of infection $p(I)$ given spatial location - distance and angle from infection at the previous time step - climate factors, and sporulation rate. Changes in probability of dispersal of new infections is included as a Cauchy distribution conditioned on distance to the target cell. Within cell infection is allowed across bay laurel and oak species while dispersal outside of the cell is to bay laurel only. These rules are consistent with spatially extensive datasets on pathogen spread.

Within cell infection (d < 1) is taken as:

$$p(I) = \frac{S}{N} * w * \sum(\beta_{i,j} * x_{i,j})$$

where beta is a species (i) and location (j) specific rate of new potential infections per species. This introduces independence between acquisition of infection and transmission. Species with beta = 0 can acquire but cannot transmit infection which, in this case, would represent oak species. The probability of new infections is dependent on the susceptible population size (*S*) and the suitability of weather conditions (*w*). Dispersal outside of target cell follows a similar construction but restricted to acquisition of infections in bay laurel and adjustments for spatial relationships:

$$p(I) = \frac{S_{bay}}{N} * w * \theta * \varphi * \sum(\beta_{bay\,j} * x_{bay\,j})$$

Where theta is a standard normal Cauchy probability distribution and phi is a function describing the effect of wind velocity (v) and direction (δ). This takes the form:

$$\varphi = v * \delta$$

which provides the additional flexibility to restrict dispersal direction according to dominant storm tracks and observed dominant dispersal directions.

Appendix B.

Forest manager 1.
Forest manager 2.
Forest manager 3.
Landowner 1.
Landowner 2.
Landowner 3.
Conservationist 1.
Conservationist 2.
Conservationist 3.
Collaboration 1.
Collaboration 2.
Collaboration 3.
2000
2007
2010
Initial infection
Treatment
N
5 km

Figure B.1: Number of oaks saved from mortality by each player in multiple attempts, compared to the baseline (no treatment) simulated scenario between 2000 and 2010. The color ramp is the same for all maps: legends show minimum and maximum values for the specific simulation year and trial. The small negative values are caused by residual stochastic differences between average outcomes of the baseline (no treatment) and the management scenarios under consideration. Initial known foci of infection are shown (red squares). Values represent per-pixel averages over 100 model runs. The chosen geographical extent matches the smaller area outlined on the physical model, Fig. 6a. Available in color online.