ABSTRACT

GAYDOS, DEVON ALANNA. Engaging Forest Stakeholders in Disease Management through Participatory Modeling. (Under the direction of Dr. Ross K. Meentemeyer).

Globally, invasive forest pests and pathogens kill millions of trees every year, triggering the long-term restructuring of forest ecosystems and how they function. These impacts can be far-reaching, not only ecologically, but socially and economically. In the United States alone, billions are lost annually through damage to valuable forest commodities, restricted trade of plant products, reduced property values in impacted areas, and expensive mitigation efforts. Management to minimize spread into new territories can potentially prevent the worst environmental and economic consequences, but decision-makers struggle to contain large-scale invasions with limited resources. Further, the ecological interconnectedness of land parcels means that effective management requires coordination between impacted stakeholders, which adds complex social dynamics and complicates efforts to unify control objectives. As outlined in Chapter 1, successful disease control may hinge on stakeholders' collective understanding spread patterns and how different treatment strategies are likely to impact those patterns. Fortunately, researchers have developed geospatial forecasts which project landscape-scale spread and impacts and enable the experimental evaluation of intervention strategies. However, the technological expertise required to develop and apply such tools makes them inaccessible to most decision-makers. This knowledge-practice gap is common in environmental modeling and limits forecasts' potential to guide coordinated, strategic responses. Studies are beginning to demonstrate the value of participatory modeling, or designing and applying models in collaboration with stakeholders, to bridge this gap. By guiding development, stakeholders ensure that the forecast meets their needs, while simultaneously learning about forecast functionality and how to interpret projections. Conversely, researchers can benefit from the added perspectives and local knowledge that stakeholders provide. Similar fields, such as watershed modeling and zoonotic epidemiology, have applied participatory modeling methods with great success, but there are little to no instances in plant disease forecasting. This dissertation investigates how participatory methods can fuel the collaborative development and application of forecasts for forest disease control. In Chapter 2, I discuss outcomes of a pilot participatory workshop where local stakeholders contributed to forecast development by supplying local knowledge of disease dynamics and suggesting improvements to the forecasting interface. This workshop established

the foundation for our participatory approach and guided subsequent forecast development. Working alongside stakeholders, I then collaboratively developed the integrated multi-strain disease forecast presented in Chapter 3. This multi-strain functionality is a novel forecasting approach which more accurately captures the effects of multiple, coexisting invasions, and allows us to explore the pressing policy questions raised by stakeholders. Results from Chapter 2 and 3 culminate in a final participatory workshop, reported in Chapter 4, where stakeholders used two interactive versions of the forecast to create and test novel disease intervention strategies. By reducing technological barriers and encouraging collaborative learning, such interactive forecasts could help fuel the kind of coordinated response necessary to tackle large-scale invasions. Here, I introduce two types of interfaces, web (an online forecasting platform where interactions are governed by computer mouse)and tangible, (a physical forecasting platform where interactions are governed by moving physical objects), and highlight how differences in design influenced collaborative evaluation of scenarios. Through this dissertation, I demonstrate how researchers can work alongside stakeholders to collaboratively develop geospatial forecasts to guide coordinated, strategic responses to invasive forest disease.

Engaging Forest Stakeholders in Disease Management Through Participatory Modeling

by
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DEDICATION

This is for my grandmother, Helen Gaydos, who has always been supportive of me. And to all the Loraxes out there who speak for the trees. Unless someone like you cares a whole awful lot, nothing is going to get better. It's not.

BIOGRAPHY

Devon was born and raised in the small suburban community of Hershey, Pennsylvania At 13, she moved to Albany, Georgia, where she mainly stayed indoors to avoid the heat and the gnats. Although she always loved animals and had a variety of pets, nature was more of an abstract concept. It wasn't until taking a field ecology class at the University of Georgia that she began to develop a deeper appreciation for the natural world. She decided to add ecology as a major and completed B.S. degrees in both Biology and Ecology. After her undergraduate studies, she pursued a Ph.D. with Dr. Ross Meentemeyer at the Center for Geospatial Analytics, North Carolina State University. Her initial focus was on the ecology of sudden oak death in Sonoma, California, where she spent several months conducting the most rigorous and rewarding fieldwork. Ultimately, she wanted to help stakeholders address the challenges posed by sudden oak death and developed a participatory approach to work alongside these stakeholders to forecast sudden oak death spread in Oregon.

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The idea of participatory research is that we're better when we work together, and that could not have been truer of this project. First and foremost, this work would not have been possible without the contributions of the stakeholders in Oregon – thank you for devoting your time to help guide this research. I especially want to highlight our main point of contact, Sarah Navarro, who contributed her expert knowledge of sudden oak death and helped organize both workshops. She's an absolute champ. Second, this project was truly interdisciplinary, and is a credit to the hard work of all my amazingly talented colleagues. Chris Jones was the main developer of the PoPS Forecasting System, including the PoPS R package and the PoPS Web Platform. Anna Petrasova was the main developer of the Tangible Landscape system. Vaclav Petras contributed to the development of Tangible Landscape and the PoPS Forecasting System and captured the best workshop photos. Nick Kruskamp developed the host maps used in the simulation. Garrett Millar provided substantial insights to the workshop surveys and the conceptualization of Chapter 4. Shannon Jones helped develop the PoPS Web Platform and designed some of the sleekest conceptual figures. Richard Cobb helped organize the first workshop and provided significant guidance. Ross Meentemeyer and Helena Mitasova guided this project by advising our research team. And members of the Center for Geospatial Analytics provided unending support throughout the whole dissertation. I would especially like to thank Whalen Dillon, Georgina Sanchez, and Lindsey Smart for showing me how to be a better student, a better professional, and a better person. You guys all rock. Lastly, I would like to thank my super chill partner, Brandon Kernan, and all my friends who helped me navigate the complexities of life in graduate school. Thanks for keeping things fun.

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CHAPTER 1

INTRODUCTION

1.1. INTRODUCTION

In 1912, scientists, policymakers, and stakeholders gathered at the capitol building in Harrisburg, Pennsylvania to debate a rapidly emerging environmental and economic threat: American chestnut blight. Introduced roughly 10 years prior, the invasive fungus *Cryphonectria parasitica* had already shown its destructive potential in New York City where it killed nearly every chestnut within a matter of years. As the disease rapidly expanded southward, millions of trees throughout the Appalachians were at risk (Freinkel 2007). At the time, chestnut was considered a keystone species due to its large stature, abundant population, and consistent, plentiful nutmast, which was a valuable food source for animals and humans alike (Ellison et al. 2005). Additionally, the wood was relatively cheap and adaptable, and was therefore used for a variety of purposes, including housing, furniture, telephone poles and railroad ties (Anagnostakis 1987). Contributing roughly $10 million dollars to the Appalachian economy annually, this was the age of peak chestnut production (Freinkel 2007). Many considered them an irreplaceable and iconic American species.

Stakeholders in Pennsylvania faced a critical decision. The disease had already taken hold in the eastern portion of the state but was still absent in the vast stands of chestnuts to the west and to the south. Some argued that the creation of a large host-free barrier along the Susquehanna River could potentially stop the spread and prevent the worst environmental and economic impacts. However, this would require significant resources and personnel without any guarantee of success. In fact, some rallied hard against management, with Franklin Stewart, a plant pathologist at the New York Agricultural Experiment Station, asserting “it is better to attempt nothing than to waste a large amount of public money on a method of control which there is every reason to believe cannot succeed” (Pennsylvania Chestnut Tree Blight Commission 1912). Others were more hopeful, wanting to manage out of a sense that something

had to be done and that it was “unAmerican” not to try. Ultimately, the latter argument won out and Pennsylvania allocated $275,000 (roughly $5.6 million by today’s standards) for the creation of a host-free disease barrier (Freinkel 2007).

The ambitious containment attempt faced several obstacles because: 1) there were several separate introductions along the Atlantic Coast, 2) the symptoms could be cryptic, complicating detection efforts, 3) it could be dispersed by several mechanisms, including wind and rain, sometimes over large distances, and 4) it could persist in other host species and the soil following treatments (Anagnostakis 1987, Freinkel 2007). In addition, there were no curative treatments. The only known method for reducing pathogen loads was cutting and burning infected trees (Anagnostakis 1987, Pennsylvania Chestnut Blight Commission 1912). This management was costly at large scales, but strategically targeting locations to reduce further spread was (and still is) a significant challenge (Forster and Gilligan 2007, Cunniffe et al. 2015). The landscape-scale nature of the disease also posed political challenges because land parcels with different ownerships and management objectives were inherently linked (Boyd et al. 2013, Epanchin-Niell et al. 2010). Spores could travel over large distances meaning that control efforts, or lack thereof, in one area could significantly affect disease in surrounding areas. Unfortunately, New York and Virginia allocated little funding for disease management which likely thwarted Pennsylvania’s efforts by providing a continuing source of new introductions (Freinkel 2007). These factors combined so that Pennsylvania found itself chasing an ever-expanding disease front. Unfortunately, Franklin Stewart had been correct; the management was unsuccessful, and the disease continued to spread, eventually causing the functional extinction of the American chestnut (Ellison et al. 2005).

This story has remained a classic lesson in forest pathology because it illustrates several key points. First, introduced pests and pathogens can rapidly cause the functional extinction of key species, leading to widespread shifts in forest community composition and related ecosystem services (Ellison et al. 2005, Orwig 2002, Schlarbaum et al. 1998). Second, the containment of forest pests and pathogens is often difficult for the reasons illustrated in the chestnut case: separate introduction events, cryptic infection, long-distance dispersal, and persistence in alternative reservoirs (Hyatt-Twynam et al. 2017, Filipe et al. 2012, Hansen 2008). Third, forest pests and pathogens can be just as much of an economic issue as they are an environmental one (Lovett et al. 2016, Pimentel et al. 2005). A recent study evaluating the costs associated with

forest pests found the economic repercussions to be worth billions annually in the United States alone (Pimentel et al. 2005). Lastly, the ecological interconnectedness of different land parcels means that effective large-scale control requires collaboration amongst several stakeholders. Each stakeholder brings different knowledge, values, management goals, regulatory frameworks and funding levels to the table, complicating efforts to create a unified vision of regional control (Epanchin-Niell et al. 2010, Mills et al. 2011, Marzano et al. 2025). These factors are common amongst many problematic forest pests and pathogens, as well as invasive species in general.

Today, scientists, policy makers, and stakeholders debate an analogous environmental and economic threat: sudden oak death (SOD). The causal pathogen, *Phytophthora ramorum*, was first discovered in the San Francisco Bay area in the mid-1990's when stakeholders raised concerns about the alarming numbers of dying trees in their community (Rizzo et al. 2005, Alexander and Lee 2010). Since then, sudden oak death has killed roughly 50 million trees, causing widespread shifts in forest composition and increasing regional wildfire risks (Cobb et al. 2012, Metz et al. 2011). Tanoak, the species most likely to die from infection, is a key component of the ecosystem because it provides habitat for several species, its ectomycorrhizal associations impact soil nutrient composition, and its consistent, plentiful nutmast serves as an important food source (Bowcutt 2015, Cobb et al. 2012, Long and Lake 2018). In part because of this, tanoak holds special significance to the indigenous peoples who historically relied on tanoak groves as foraging sites (Bowcutt 2015, Long and Lake 2018). And although tanoak holds little direct economic value, disease spread threatens billions of dollars through declining property values and losses to timber and nursery industries (Kovacs et al. 2011, Frankel 2008, Highland Economics and Mason, Bruce & Girard, Inc. 2019).

In many ways, sudden oak death has mirrored the trajectory of the American chestnut blight. There were several separate introductions along the Pacific Coast (Rizzo et al. 2005, Hansen et al. 2008). Infection symptoms are cryptic, often developing months to years following initial infection (Rizzo et al. 2005). It can be dispersed by wind and rain, sometimes over several kilometers (Meentemeyer et al. 2011). It is a generalist pathogen which can persist in many different species, as well as in soils and waterways (Rizzo et al. 2005). There is no known curative treatment and the only way to reduce pathogen spread is by cutting and burning infected trees; however, this management is cost-prohibitive at large scales, so management must be strategically dispersed across the landscape (Sweicki and Bernhardt 2013). Further spread would

have dramatic consequences for the ecosystem functioning and economic health. And, importantly, because of the landscape-scale nature of spread, control efforts require coordination amongst a complex mosaic of stakeholders. For these reasons, sudden oak death is proving as difficult to control as chestnut blight. Unfortunately, these are not cases in isolation. Variations of this story have played out with cases like Dutch Elm disease, Port Orford cedar root rot, Jarrah dieback, olive quick decline syndrome, sudden larch death, and spotted lanternfly (Hansen 2008, Schlarbaum et al. 1998, LeBoldus et al. 2019, Urban et al. 2019, Luvisi et al. 2017). And new threats are continually emerging, with one study finding that a new invasive plant pest or pathogen is introduced to the United States, on average, every 2.5 years (Aukema 2010).

Fortunately, the science of invasive pest and pathogen management has advanced considerably in the last one hundred years. We now have global databases of known pests and pathogens (Pasiecznik et al. 2005), a deeper understanding of their biology and ecology, better phytosanitary and early-detection protocols (Campbell 2001), and better spatial data of hosts, pathogens, and environmental factors (Ohmann et al. 2002, PRISM Climate Group). The field of computational modeling has capitalized on these advancements to develop dynamic geospatial simulations which replicate the spread patterns of invasive pests or pathogens. These simulations can be used to forecast pest and pathogen progression across the landscape to assess how fast spread might be, which areas will likely be affected, and what the potential environmental and economic impacts are (Meentemeyer et al. 2011, Cunniffe et al. 2015, Takeuchi et al. 2019). Importantly, management can be simulated by manipulating the underlying landscape data, which enables the experimental evaluation of different management scenarios without applying costly, destructive, or inefficient treatments (Filipe et al. 2012, Hyatt-Twynam et al. 2017, Cunniffe et al. 2016, Tonini et al. 2017). These computational experiments can help address critical questions, such as: 1) is eradication possible, 2) what budget is required to meet disease management goals, 3) where are the most high risk areas for disease, 4) where on the landscape should resources be focused, 5) and what shape and configuration of management is most effective (Cunniffe et al. 2015, Cunniffe 2016, Filipe et al. 2012). Researchers believe that the answer to these questions could be used to guide more effective policy and management decisions.

Yet, these forecasts alone do little to address the sociopolitical nature of management which remains one of the biggest hurdles to effective regional control (Meentemeyer et al. 2012).

Decision-makers are often not aware that such tools exist, nor do they have the technical geospatial and coding expertise required to use them. As such, their application to policy and management has been limited (Knight et al. 2016, Muscatello et al. 2017). This is a common problem in computational modeling, and many have noted a knowledge-practice gap where more accurate scientific models don't necessarily translate to better management outcomes (Voinov and Bousquet 2010). There have been two main suggestions, which often work in conjunction, to address this issue: 1) developing more user-friendly interfaces, and 2) using a participatory modeling framework which engages stakeholders throughout model and tool development. Intuitive, user-friendly interfaces could significantly reduce the technological barriers to use, allowing a wider range of stakeholders to explore management scenarios (Tonini et al. 2017, Radinsky et al. 2017). Similarly, participatory modeling democratizes the use of these simulation tools by engaging stakeholders throughout model and tool development (Voinov and Bousquet 2010, Voinov and Gaddis 2008). This approach has several demonstrated benefits. Stakeholders can bring new, diverse perspectives, in-depth local knowledge, and key observations which can be used to improve the simulations (Grant et al. 2016, Olabisi et al. 2016). In return, the stakeholders gain knowledge of key model processes and become more comfortable using the simulation for problem solving (Voinov and Bousquet 2010, Voinov et al. 2016, Blades et al. 2016). In addition, the collaborative nature of participatory modeling allows stakeholders to form connections with each other in a way that could build the capacity needed for cross-boundary management projects.

Despite several petitions for increased stakeholder engagement in forest pest and pathogen management, it is unclear to what extent participatory modeling has been used to develop interactive forecasting tools which could help decision-makers. Sudden oak death in Oregon is a prime case study for this work because: 1) decades of research have illuminated many of the ecological underpinnings of disease spread and impacts, 2) there are several years of observations available for model construction, 3) there are currently landscape-scale management operations underway, and 4) there is significant stakeholder concern from a wide array of different organizations. Through this case study, this dissertation addresses the following questions:

RQ1: *To what extent has participatory modeling been applied to plant disease management and how can stakeholders contribute to the development of invasive disease forecasts?*

RQ2: *How can multi-strain disease forecasts inform disease management in complex pathosystems?*

RQ3: *How do different types of forecasting interfaces enable groups of stakeholders to collaboratively explore disease management strategies?*

Together, these components will provide valuable decision support for sudden oak death management in Oregon, while simultaneously testing a participatory framework which could be applied to other systems. In the words of Winthrop Sargent, the Chairman of the Pennsylvania Commission on Chestnut Tree Blight, "This is not the last tree disease that will sweep over this State. All efforts to control this disease would be justified even if we only learned how to control the next one" (Pennsylvania Chestnut Commission 1912). Invasive pests and pathogens will continue to pose serious environmental and economic challenges, requiring cross-boundary cooperation by diverse stakeholders. By establishing a simulation co-development framework, we hope to democratize the use of these forecasts in a way that also addresses the sociopolitical challenges for management, both for this disease and for the next one.

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CHAPTER 2

FORECASTING AND CONTROL OF EMERGING INFECTIOUS FOREST DISEASE THROUGH PARTICIPATORY MODELLING

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2.1. INTRODUCTION

On the 100th year anniversary of the Spanish flu pandemic, there is a need to reflect on how well epidemiological models, a fundamental tool of disease research, meet the needs of stakeholders involved with the day-to-day control of emerging outbreaks. With 100 years of history for perspective, it is clear that understanding the pattern and rate of spread is fundamental for designing successful policies and interventions [1-7]. Epidemiological models are powerful tools for evaluating disease spread under a range of possible conditions, and are especially useful for comparing intervention strategies, as experimental studies may be unethical, impractical, or impossible [6-10]. However, the technical skill required to synthesize and operate these tools can restrict their use by the stakeholders who have the most to gain from them [10-11].

Several important examples highlight the value of models in guiding policy, especially regarding human diseases where forecast models have received great attention [12-14]. However, stakeholders rarely interact with such models directly, fueling the argument that models are underutilized by stakeholders [6-7,10-11,15-17]. Reasons commonly cited for this knowledge-practice gap include: 1) models don't address stakeholder concerns, 2) outputs cannot be clearly translated into policy or intervention, 3) processes are explained poorly and/or are too esoteric, 4) assumptions are considered invalid, and 5) models lack intuitive interfaces which facilitate stakeholder use [7,10-11,15-18]. These factors are compounded by the fact that models are often developed without systematic and transparent stakeholder input [11,15-17]. Essentially, modelling becomes a top-down exercise driven by the developers with limited opportunities for

stakeholders to guide model development, structure simulations, or apply counterfactual analysis. This presents a dilemma for the field of epidemiological modelling, as models without stakeholder confidence will be ineffective at addressing the environmental, economic, and social implications of disease [7,10-11].

Participatory research seeks to overcome this knowledge-practice gap by involving stakeholders who could be affected by research outcomes [15-17,19-22]. Owing to the rise of participatory approaches, there is an increased appreciation of the value of local knowledge, and an understanding that stakeholders and researchers have much to learn from each other [16-17,19-23]. Within the broader context of participatory research, we focus on two subdisciplines related to epidemiological modelling: participatory modelling (PM) and participatory epidemiology (PE). Originally developed to improve research and control of livestock diseases in data-scarce regions, PE uses techniques like semi-structured interviews, participatory mapping, and participatory disease surveillance to acquire fundamental data and situate epidemiological research in local contexts [22,24-26]. Importantly, PE may or may not include models. In contrast, PM arose to support decision-making in natural resource management where conflicting stakeholder interests play an integral role in management success [15-17]. By definition, PM involves stakeholders in modelling, but the types of models used can be variable, ranging from conceptual models to more complex geospatial simulation models [15-17]. Despite differences in focus, PE and PM share similar techniques and motivations for involving stakeholders. Further, when PE applications feature models, they fall within the sphere of PM.

Here we demonstrate through a systematic literature review and an ongoing case study of sudden oak death (SOD), that PM approaches are currently rare in studies of plant disease modelling, but have great value for collaboratively exploring control strategies. Since its introduction, *Phytophthora ramorum*, the cause of SOD, has precipitated significant ecological and economic damage along the Pacific coast of the United States, with impacts including loss of foundational tree species, increased wildfire hazards, and increased costs associated with plant trade [9,27-31]. Southwestern Oregon has recently experienced a resurgence of public concern because of a second introduction event, the potentially more aggressive European 1 (EU1) lineage [32-33]. Coordinated management to curb disease spread could reduce economic consequences associated with the quarantine of nursery and forestry products in surrounding counties [9,31,34]. Both in our example, and in epidemiology broadly, modelling tools can help

stakeholders address critical questions regarding where management will be most effective, when eradication becomes implausible, and if the pathogen is likely to escape quarantine. Using a PM approach, we worked with local stakeholders to collaboratively develop an interactive modelling tool for analysing *P. ramorum* management in Oregon. Here, we focus on how stakeholder involvement has shaped our research goals, the functionality and parameterization of the epidemiological simulation, and the development of Tangible Landscape, an interactive technology for decision-making (see: https://tangible-landscape.github.io/) [18,35]. This case study of model co-development illustrates the potential benefits of participatory modelling to empower stakeholders in the design, development and application of epidemiological models for disease control.

2.2. METHODS

2.2.1. Literature Review

Participatory modelling and participatory epidemiology share similar motivations for engaging stakeholders [16-17,22,24-26], but it is unclear how much overlap exists between these fields. To understand the extent and manner in which PM is currently employed within epidemiology, we conducted two systematic literature analyses using the ISI Web of Science Database. One search focused on areas of overlap between PE and PM across all disease systems (human, animal, and plant), with the other search focusing specifically on instances of stakeholder participation in plant epidemiology. Sources were first evaluated based on the modelling framework. Any sources that included models of disease spread or risk were assessed in-depth and categorized based on disease system (human, animal, or plant) and type of stakeholder participation. These searches can be reproduced with details included in Appendix A.

Engagement exists on a spectrum with varying degrees of stakeholder control [16,20,36-37], therefore we categorized sources into three broad categories of participation: 1) only mentioned, where there was no participation but it was mentioned that stakeholders would benefit the research or benefit from the research, 2) contributed data, where stakeholders provided disease locations, parameter estimates, or information about their actions, and 3) co-development, where stakeholder input significantly affected development of the model,

scenarios, or interface, often in an iterative manner. All levels of engagement can be valid and productive; however, participatory research ultimately strives for co-development where stakeholders increasingly steer research goals, processes, and outcomes [16-17,19-20,37].

2.2.2. Sudden Oak Death Reemergence

Consultation with stakeholders early in research development identified the potential for collaborative planning to improve *P. ramorum* management in southwestern Oregon. Although *P. ramorum* had been present in this region since 2001 [31,38], public concern had been reignited following the introduction and lab confirmation of the EU1 lineage [32-33], which is more virulent than the previously established North American (NA1) lineage [39]. There is also evidence that EU1 can infect Douglas fir (*Pseudotsuga menziesii*) and grand fir (*Abies grandis*) seedlings, potentially placing critically important regional timber products at risk [33]. Without a concerted and coordinated intervention, there is justified concern that this new strain could quickly spread into surrounding counties, making this an ideal case for leveraging the power of predictive models to explore the implications of proposed responses.

2.2.3. Tangible Landscape Modelling Tool

To simulate disease spread in Oregon, we adapted an existing modelling framework originally developed to explore disease dynamics in California [5,18,40]. These stochastic, spatially-explicit simulations integrate the effects of host density and weather conditions on pathogen transmission and establishment. For a detailed model description, including key data requirements, model processes, and links to source code, see Appendix B and [5,18,40].

Geospatial models can be perceived as inaccessible because their use requires substantial technological skill [7,16-17]. To overcome this barrier, the disease simulation was coupled with Tangible Landscape, a geospatial participatory modelling platform (see: https://tangible-landscape.github.io/). With Tangible Landscape, users guide the model intuitively through physical actions, rather than through code or software [18,35]. Stakeholders place markers on a visualization of the study area to designate the spatial allocation of host removal. These locations serve as input for the disease simulation by altering host density data. The resulting model outcomes are visualized on the study area, allowing users to quickly and intuitively assess how their actions affected disease spread [18,35]. A pilot study using Tangible Landscape to evaluate

SOD control measures found that users quickly learned model processes, intuitively explored management scenarios, and learned from other participants, making this system ideal for PM applications [18]. For further discussion of the Tangible Landscape tool, see Appendix B.

2.2.4. Participatory Modelling Workshops

Reciprocal feedback between model developers and stakeholders battling the EU1 infestation was engendered through a participatory workshop in October, 2017. Workshop goals were to: 1) assess how participants interact with the model, and 2) systematically collect stakeholder input to refine model dynamics and the Tangible Landscape interface. While PM strives to incorporate the full diversity of opinions, engaging stakeholders at all stages of model development may not be necessary or advisable as stakeholders often face significant time constraints or rely on developers for specific tasks [16,20,41]. In our case, there was an emphasis on refining the epidemiological model and we therefore concentrated on stakeholders with knowledge of local disease dynamics. Stakeholders with relevant expertise were invited from the U.S. Forest Service, Oregon Department of Forestry, and Oregon State University, and were encouraged to invite others who may be interested. We limited the maximum number of participants to 20, as previous experience suggests smaller groups allow for more personal interaction with the Tangible Landscape tool.

All participants were asked to complete questionnaires designed to assess participants' baseline knowledge, self-reported learning, interactions with Tangible Landscape, confidence in model processes and data, and recommended improvements. Because the aim of these surveys was to systematically collect suggestions for improvement, we strove for a broad spectrum of feedback. Questionnaires were developed following guidelines in [42-43], and included a mix of rank-choice, open-ended and Likert scale questions. Surveys were tested prior to the workshop by researchers not connected to the project. For further description, including participatory workshop outline and survey questions, see Appendix C.

2.3. RESULTS

2.3.1. Literature Review Results

Our two literature searches examined the role of PM in disease forecasting and control across all systems (human, animal, and plant), and stakeholder engagement in plant epidemiology in particular (Figure 2.1). Only sources about modelling disease spread or potential were considered, resulting in 29 and 14 sources, respectively. For data presented in Figure 2.1, sources could be counted more than once if they reported multiple case studies which fell under different disease or participation categories, for example [24]. A majority of studies focused on diseases of humans (17) and animals (14), with few touching on plant disease (3) (Figure 2.1A). Among all participatory studies, the majority of interactions revolved around contributing data (17) with fewer instances of co-development (10). Notably, there was only one plant disease study in the co-development or contributed data categories. This pattern was further illustrated by our second literature search examining how stakeholders are being engaged specifically in modelling of plant diseases (Figure 2.1B). Amongst these sources, the majority were classified in the lowest category of interaction "only mentioned" (11), with fewer instances of contributing data (1) or co-development (2).

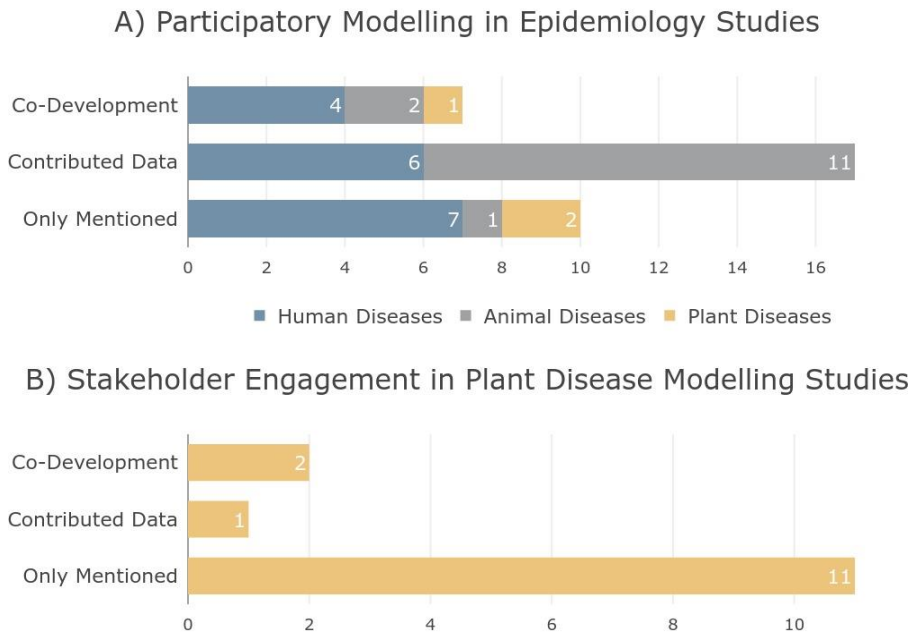

Figure 2.1. Summary of literature searches examining the role of participatory modelling across disease systems (A), and the role of stakeholder engagement in plant disease modelling (B).

2.3.2. Workshop Results

Twelve stakeholders from the U.S. Forest Service, Oregon Department of Forestry, and Oregon State University participated in a modelling workshop to perform management experiments with and provide feedback on an interactive tool for disease forecasting and control (Figure 2.2). Although the focus on this group restricts the range of stakeholder opinions, the approach produced highly-relevant feedback on epidemiological processes and management scenarios. Many of the participants indicated prior familiarity with disease forecasting models (7), although only 3 had used these tools in management planning (Appendix C). Survey results indicate that most participants found the modelling tool intuitive and easy to use (Figure 2.3D-E), aiding the perception that the tool would be useful for prioritizing treatment locations and facilitating communication amongst stakeholders (Figure 2.3F-G). Encouragingly, all stakeholders indicated that they learned something through the workshop, and that they would be likely to use the model to inform future management decisions (Figure 3.3H-I, Appendix C). While many aspects of the system and workshop were rated highly, the most valuable results were those indicating areas where the model could be improved. Participants were skeptical of the resolution and accuracy of the underlying host distribution data and felt inadequacies here could influence the spatial dynamics of the simulation (Figure 3.3A-B). Stakeholders provided guidance on ways to refine these aspects, amongst others, to make the tool more useful in management planning. Further details, including open-ended responses about self-assessed learning and suggested model changes, can be found in Appendix C.

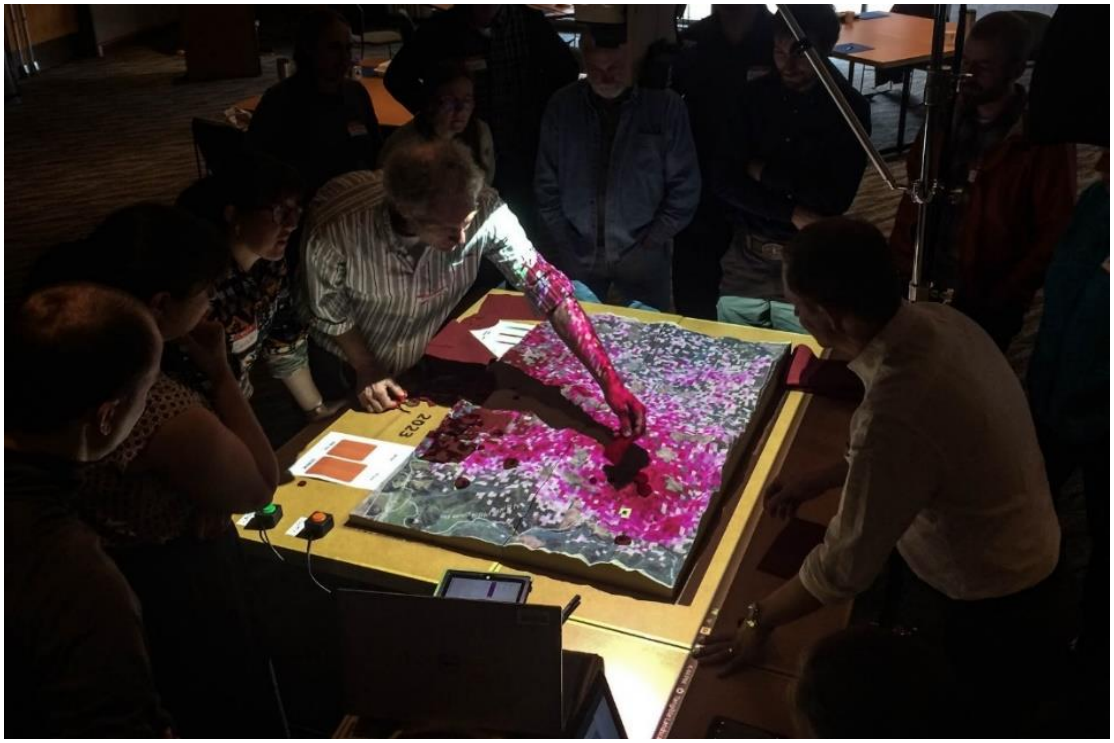

Figure 2.2. Participants interact with disease model at workshop. Credit: Rich Cobb

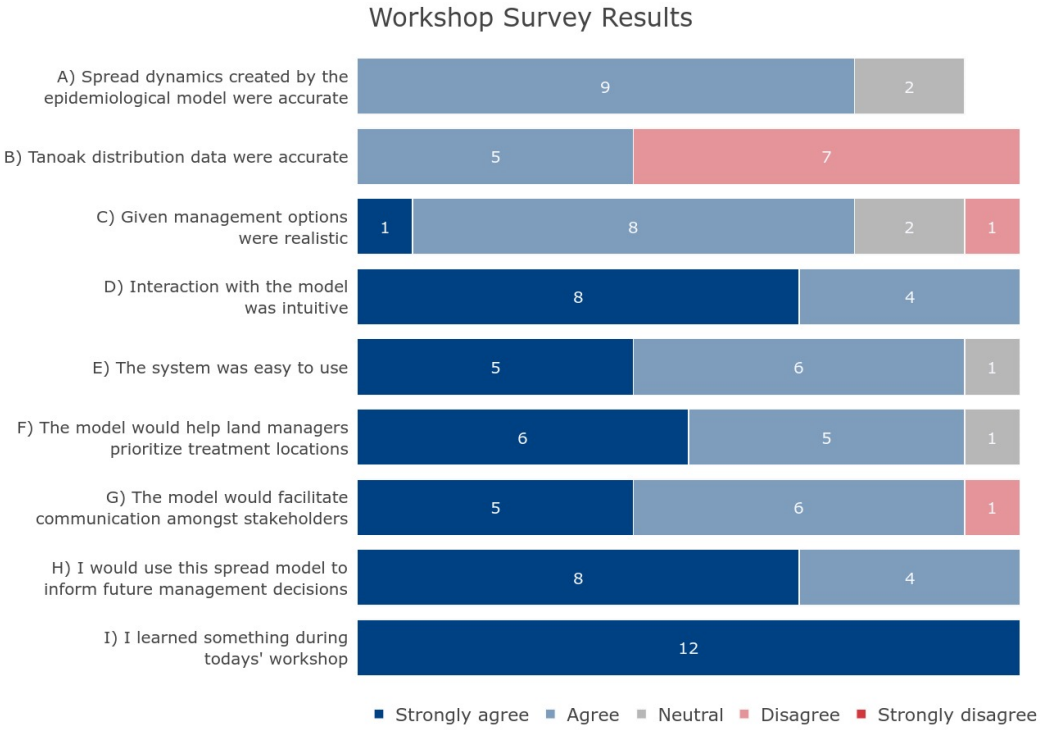

Figure 2.3. Survey responses evaluated core model components, including spread dynamics (3a), host data (3b), management options (3c), interaction (3d), accessibility (3e), ability to prioritize treatment locations (3f), and ability to facilitate communication (3g). Participants also reported willingness to use the model (3h) and perceived learning (3I).

2.4. DISCUSSION

It is increasingly recognized that stakeholders possess local knowledge of disease transmission, risk factors, and control strategies, and can be instrumental in guiding and implementing actionable epidemiological research [6,19,22-26]. Participatory modelling, which integrates these diverse perspectives throughout model development, encourages collaborative learning and empowers stakeholders to interact more directly with models [15-17,24]. We adapted the framework of Garner and Hamilton [1] to demonstrate how stakeholders can contribute to each stage of epidemiological model development (Figure 2.4). While this is not an exhaustive list of potential stakeholder contributions, each of these interactions have proven valuable in PE or PM research to date [16-17,22,24-26]. We engaged stakeholders at multiple stages of model development (Figure 2.4) and this resulted in a deeper understanding of the study system by the developers while making our model more applicable for a specific application by the stakeholders. In our case study, use of PM techniques is justified both in terms of model improvements as well as in increased usability and confidence from the stakeholders. More broadly for plant epidemiology, PM techniques are relatively underutilized and our example suggests it is a potential approach for empowering stakeholders to apply model insights to address disease spread and impacts [6,23,44-48].

Constructing overarching guidelines for PM applications is a growing research topic [15-17,20,41], but several principles have emerged which are highlighted by our example. Models which are inaccessible to stakeholders are likely to be overlooked; therefore, intuitive interfaces are essential for PM [7,16-18,48]. Coupling the epidemiological model with Tangible Landscape encouraged participants to collaboratively design management scenarios, visualize underlying spatial data, and assess the stochastic uncertainty of results [18,35]. In our surveys, participants overwhelmingly rated the system as intuitive and easy to use (Figure 2.3D-E) and we expect this was integral to promoting communication. The visualization capabilities proved especially beneficial, with one participant adding, “[it] reaffirmed [my] belief that effective visual displays are helpful in learning. Even more effective is the self-learning gained by ‘gaming’ the system. Would be extremely helpful with stakeholders” (Appendix C). A majority of participants agreed, indicating that the system would facilitate collaboration (Figure 2.3G). Previous work with Tangible Landscape [18] demonstrated that the platform can help users quickly grasp and

communicate essential model properties. For PM to be applied in other disease systems, assessing and improving the interface will likely be of critical importance.

Our workshop also highlighted a knowledge-practice gap that is likely common to many disease systems. Several participants indicated familiarity with disease models, but few had used them for management planning (Appendix C). Collaborative learning, a fundamental goal of the PM process, is theorized to help narrow this gap [15-17,41]. During the workshop, model exploration sparked discussions about disease dynamics, detection protocols, field operations, and local concerns. One participant noted "many aspects of spread and treatment dynamics came out from the various participants. It was very interesting to have the breadth of knowledge in the room" (Appendix C). All participants indicated they would be likely to use the spread model to inform future management decisions (Figure 2.3H) highlighting that collaboration between stakeholders and researchers can elucidate the value of epidemiological models.

Collaborative learning fundamentally affects all parties, and we found that engaging stakeholders impacted our research in considerable ways. Early discussions led us to refocus our attention on southwestern Oregon, where there is a pressing need for disease forecasting and control. Consequently, we worked with stakeholders to adapt a pre-existing disease model to represent local transmission dynamics and to address the most urgent needs of decision-makers. While participants rated many aspects of the Tangible Landscape highly, survey results were mixed considering the accuracy of the underlying epidemiological model specifically spread processes, host data, and management options (Figure 2.3A-C). Participants provided guidance on how to improve these areas, with suggestions including: 1) generating higher-resolution host maps which account for effects of prior timber harvest, 2) modelling pathogen strains separately, 3) adding management options, 4) allowing yearly management interventions, and 5) allowing easy parameter variations (Appendix C). These changes to the model structure or outputs represent unique contributions of the participants that the developers would not have pursued otherwise. Our subsequent research efforts have focused directly on these model deficiencies, and we believe that integrating these suggestions will make the modelling tool more applicable for disease forecasting and control in Oregon. Following the incorporation of these improvements, we will hold additional workshops with a larger, more diverse group of Oregon stakeholders to seek further input.

Participatory modelling is not the only way to increase collaboration between stakeholders and researchers, and whether or not to employ a participatory approach requires critical reflection and depends on the research and management goals. Model co-production can be expensive, time-consuming, and requires significant commitment from stakeholders and researchers alike [15-17,19,41]. Even with the best intentions, participatory research can fall short of achieving actionable science [19]. For these reasons, PM is best applied to problems with diverse actors and significantly complex socio-ecological interdependencies [15-17,41]. The management of epidemics frequently fits this definition [2-3,6,9-10,22]. Within epidemiology there are often substantial challenges associated with model or simulation complexity. Rigorous model development to assess validity is just as essential to PM as any other epidemiological model (Figure 2.4) [1,24]. Stakeholder engagement enhanced our model development by integrating new and diverse perspectives; we expect similar improvements in development efficiency and overall application can be made by employing the PM approach.

Our literature analysis supports the perspective that PM has not yet reached its full potential in epidemiology, especially in regards to plant disease modelling (Figure 2.1). As both a driver and deterrent of plant disease spread, stakeholders often determine the success of control strategies [6,23,44-48]. Other researchers have argued for increased stakeholder engagement within plant disease modelling, but PM methodologies are only beginning to be explored [6,23,44-48]. In our case study of *P. ramorum*, incorporating a PM framework resulted in a co-developed model and signs that this approach is changing perspectives on the role of models in management and policy decisions. Understanding if model co-development actually changes behavior, for example by changing field decisions in light of model results, remains to be seen. Regardless, stakeholder involvement clearly improved our modelling tool by guiding our research goals, model development, and by creating a forum for communication. This suggests that participatory modelling has potential to help bridge the knowledge-practice gap by facilitating collaborative learning and empowering stakeholders in the design, development, and application of epidemiological models for plant disease control.

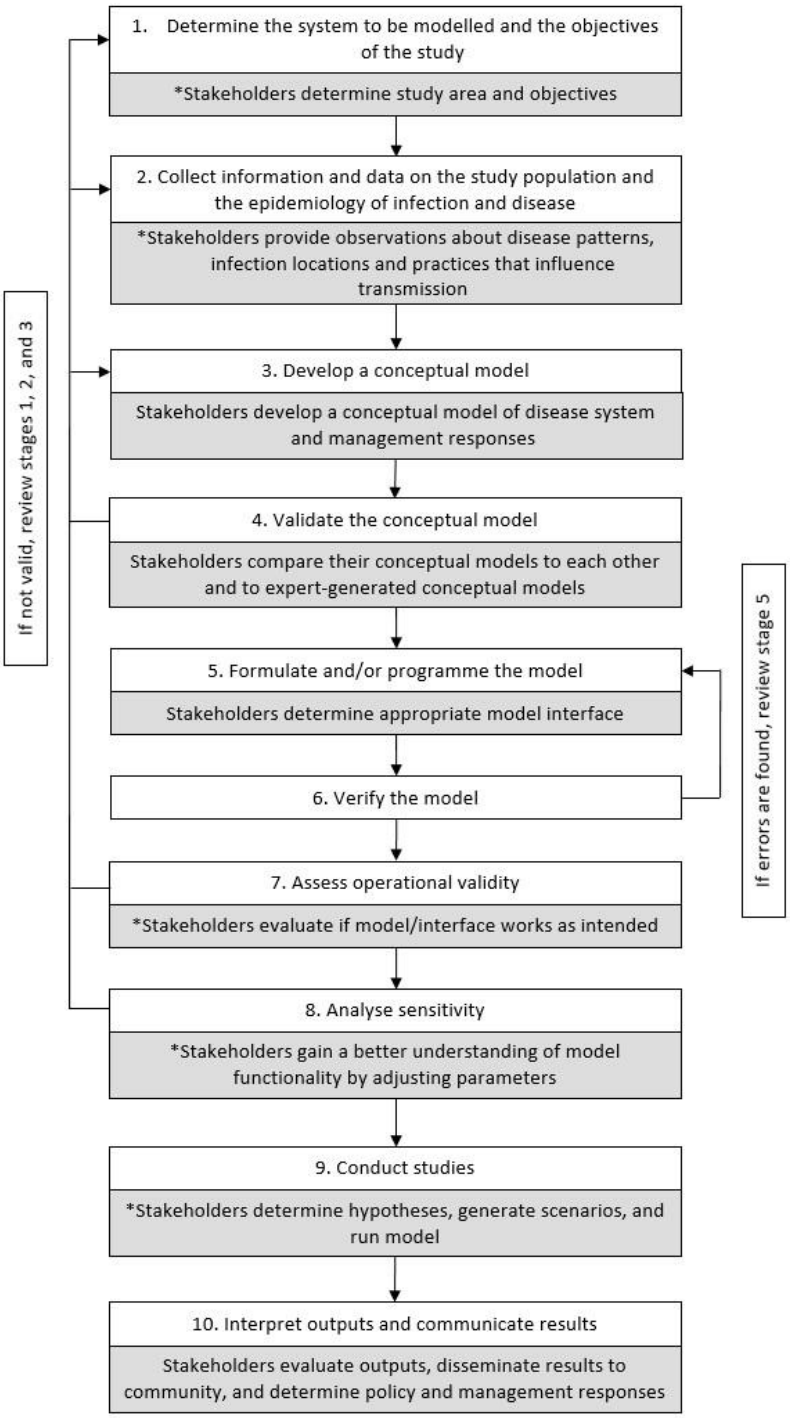

Figure 2.4. An adaptation of Garner and Hamilton's framework of epidemiological model development [1]. White boxes depict stages of model development [1], with grey boxes indicating how stakeholders can contribute to these stages. Asterisks highlight ways we have engaged stakeholder throughout this case study.

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CHAPTER 3

FORECASTING THE EFFECTS OF DISEASE CONTROL STRATEGIES ON THE SPREAD OF A MULTI-STRAIN FOREST PATHOGEN

3.1. INTRODUCTION

Although the environmental and economic impacts of invasive forest diseases are well-established (Boyd et al. 2013, Lovett et al. 2016, Pimentel et al. 2005, Hansen 2008), large-scale control programs often struggle to contain spread. High-profile failures, like American chestnut blight, Dutch elm disease, and citrus canker, illuminate common epidemiological, logistical, and socio-political challenges which impede management (Freinkel 2007, Tomlinson and Potter 2010, Gottwald 2007, Schlarbaum et al. 1998). Cryptic infections can delay detections and obscure the true geographic extent of infestation (Thompson et al. 2016, Cunniffe et al. 2015). Spread can occur along multiple pathways, sometimes over large distances (Filipe et al. 2012, Meentemeyer et al. 2011). And, often, these key epidemiological traits are unknown for emerging pathogens, handicapping control efforts (Hyatt-Twynam et al. 2017, Cunniffe et al. 2014). Research recommends rapid interventions (Vicent and Blaso 2017, Cunniffe et al. 2015), but logistical and legal hurdles can postpone treatments, enabling subsequent spread (Kanaskie et al. 2010, Gottwald 2007). Additionally, programs should match the scale of interventions with the scale of infectious spread (Gilligan et al. 2007, Cunniffe et al. 2016), which requires substantial resources and landscape-scale coordination. However, large-scale spatiotemporal treatment optimization remains a challenge (Forster and Gilligan 2007), and the ecological interconnectedness of parcels introduces complex socio-political dynamics as stakeholders struggle to create a unified vision of control (Mills et al. 2011, White et al. 2018, Epanchin-Niell et al. 2010).

Further, control strategies must adapt to changing epidemic conditions (Kanaskie et al. 2010, Thompson et al. 2018). Eradication, typically through culling infected hosts, is most feasible at early epidemic stages when disease is clustered near introduction points (Vicent and Blasco 2017, Cunniffe et al. 2015). As the epidemic progresses and the geographic extent grows, the potential of eradication dwindles (Pluess et al. 2012). However, control programs may contain the infestation by systematically culling outlying foci and blocking spread pathways, for example by regulating the movement of host plant materials (Rizzo et al. 2005, Filipe et al. 2012). If not contained, the disease eventually progresses into a widely-dispersed late-stage epidemic. Here, control programs should transition towards a "living with disease" alternative that focuses on protecting high-priority conservation areas, ameliorating negative effects of disease, and restoring biodiversity and ecosystem processes where possible (Cobb et al. 2017, Cobb et al. 2013). However, the transitions between these epidemic stages, as well as corresponding control strategies, can be unclear, meaning that control programs should routinely reassess their strategies as new information arises.

Although significant, these control challenges are not insurmountable. Success hinges on how well control programs understand spread patterns, how interventions impact those patterns, and how to respond to changing epidemic conditions (Cunniffe et al. 2015, Thompson et al. 2018). Fortunately, epidemiological forecasts provide powerful analytics to inform control strategies. Examples like Jones et al. (2019) and Meentemeyer et al. (2011) highlight how forecasts can integrate geospatial data with epidemiological processes to mimic disease spread and impacts across a landscape. With this information, control programs can pinpoint high-risk areas and investigate how patterns respond to changing environmental conditions. And by concurrently simulating interventions, we can conduct large-scale computational management experiments to explore how different treatment types or spatiotemporal arrangements are likely to impact spread trajectories (Filipe et al. 2012, Hyatt-Twynam et al. 2017, Gilligan et al. 2008). Further, with a Bayesian approach, forecasts can be rapidly updated as new information arises, helping programs respond as conditions evolve (Dietze et al. 2018, Jones et al. 2019). Traditionally, applying such forecasts required specialized expertise, deterring stakeholder use (Cunniffe et al. 2015). But novel, interactive interfaces make it possible for several stakeholders to collaboratively explore intervention strategies (Petrasova et al. 2018, Gaydos et al. 2019).

Through this “what-if” scenario testing, epidemiological forecasts reduce intervention uncertainties and enable the landscape-scale planning necessary for successful control.

However, in these forecasting examples, only one pathosystem was considered. In reality, diseases do not exist in isolation and sometimes pathosystems overlap. These cases pose an even greater challenge because we must anticipate multiple, potentially interacting, spread trajectories. When management resources are drawn from a common pool, programs must also consider how to prioritize interventions. Because of the time required to develop and run a forecast, as well as the logistical challenges of simulating multiple pathogens simultaneously, most studies have used a single-species or single-strain approach (Cunniffe et al. 2016, Hyatt-Twynam et al. 2017). However, moving beyond this single-species lens is flagged as a priority (Cunniffe et al. 2015), and is increasingly feasible thanks to technological advancements. For instance, researchers are developing modular forecasts where functions can be added, removed, or customized to fit different pathosystems, facilitating faster forecast development (Jones et al. 2019). With this, and the advancements in parallel computing, it is increasingly possible to develop multi-species forecasts that can better address how to strategically balance competing priorities.

Sudden oak death (SOD) in Oregon demonstrates the importance of a multi-strain approach to disease forecasting. To date, Oregon is the only place in the United States where two strains of the causal pathogen, *Phytophthora ramorum*, exist in wildland forests (Grunwald et al. 2016). While biology and spread patterns are largely similar, the strains differ in several key ways including virulence, spread rate, geographic distribution, and epidemic stage (Brasier and Webber 2010, Manter et al. 2010, Grunwald et al. 2012, LeBoldus et al. 2017) (Figure 3.1). First to be introduced, the North American-1 (NA1) strain was found outside of Brookings, Oregon in 2001 (Goheen et al. 2002), and has since spread to encapsulate the southwestern corner of Curry County (Hansen et al. 2008, Peterson et al. 2016) (Figure 3.1). In contrast, the European-1 (EU1) strain was detected in 2015 and because of intensive management has remained clustered near Pistol River, Oregon (Grunwald et al. 2016) (Figure 3.1). Laboratory and field observations suggest that EU1 is more aggressive and may have greater impact on timber commodities (Manter et al. 2010, Grunwald et al. 2012, LeBoldus et al. 2017, Søndreli et al. 2019). For these reasons, stakeholders consider EU1 a greater threat, but either strain could precipitate serious ecological and economic impacts. For control to be successful, the Oregon SOD Control Program must understand each strain’s spread trajectory and strategically prioritize interventions.

In close collaboration with the Oregon SOD Control Program, we developed an integrated multi-strain disease forecast to explore the individual and combined impacts of the two strains. Since the strains share a common host, this integrated approach was necessary to fully capture direct and indirect treatment effects. Here, we characterize key differences in the strain's spread trajectories and assess strategies currently under consideration by the Control Program (no management, prioritizing EU1, prioritizing NA1, and prioritizing neither strain)(Highland Economics et al. 2019). We evaluate how these strategies impacted total infected area and growth rate, and which strategy most effectively reduced infections near the northern quarantine boundary, an area of particular concern amongst stakeholders. We find that although the NA1 strain is likely to infect a greater area, targeting the aggressive EU1 strain may lead to a greater reduction in overall SOD infestation. Through this case study, we demonstrate how a synchronized multi-strain forecasting framework can be used to evaluate the impacts and interventions of multiple, interlaced invasions.

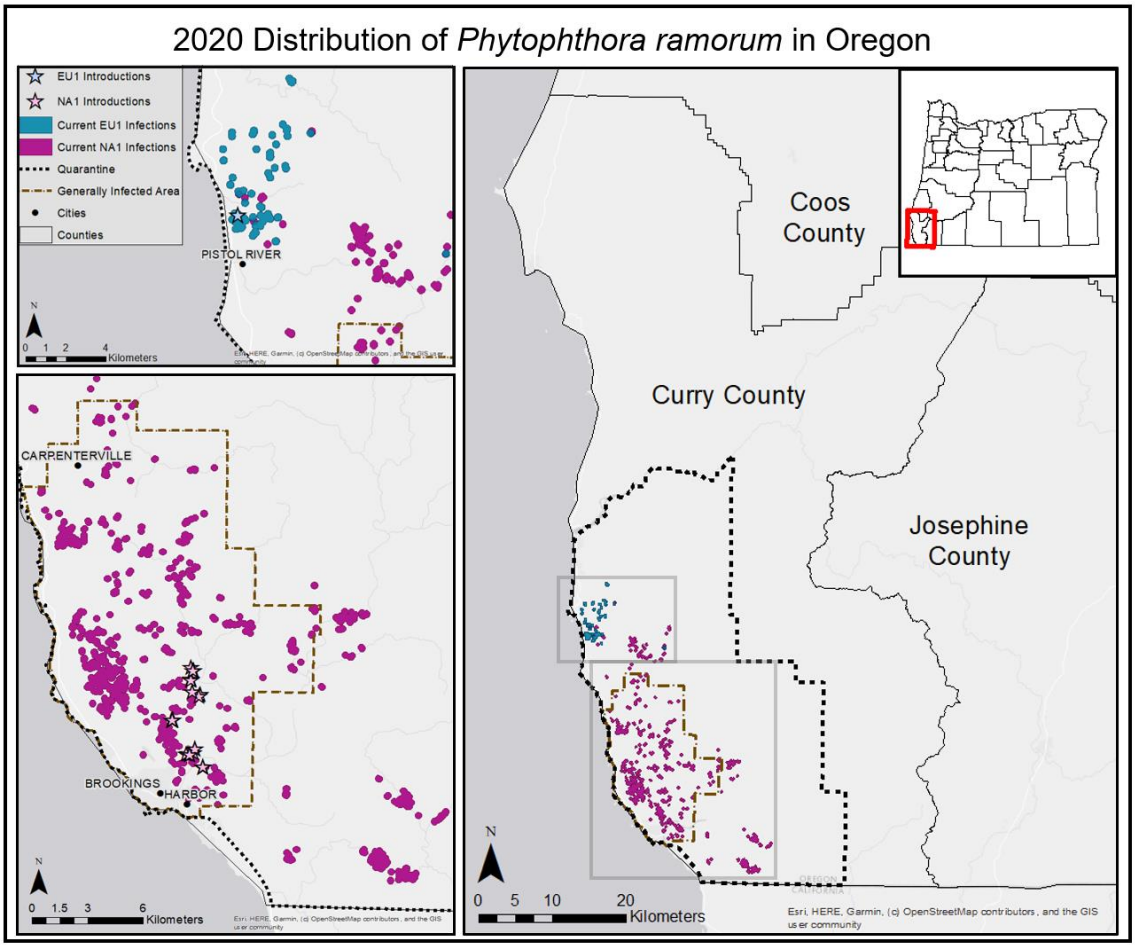

Figure 3.1. The current distribution of both strains (EU1 and NA1) of *Phytophthora ramorum* in Curry County, Oregon. Infected locations provided by the Oregon Department of Forestry.

3.2. CASE STUDY

Southwestern Oregon faces a unique challenge because it is the only place where the NA1 and EU1 strains of *P. ramorum* commingle in wildland forests. While the epidemiology is broadly similar, the strains differ in key ways (Brasier and Webber 2010). The NA1 strain was discovered in the mid-1990's as the causal agent of SOD in the San Francisco Bay area (Rizzo et al. 2005). Since then, it's killed millions of trees along the California coast, earning a reputation as one of the most destructive forest pathogens in the United States (Fei et al. 2019). In 2001, it was introduced to Brookings, Oregon via infected nursery stock (Goheen et al. 2002). Fearing the extensive mortality witnessed in California, the Oregon Department of Forestry (ODF) implemented a landscape-scale program to combat spread (Kanaskie et al. 2010). Although the

program failed to eradicate NA1, it contained damage to the southwestern corner of the state, an area referred to as the Generally Infested Area (Hansen et al. 2019) (Figure 3.1).

The control program faced a severe setback when EU1 was introduced, also via infected nursery stock, near Pistol River, Oregon in 2015 (Grunwald et al. 2016). O2bservations suggest that EU1 is even more aggressive than NA1 because it produces more spores, develops larger lesions, and spreads faster (Manter et al. 2010, Grunwald et al. 2012, Søndreli et al. 2019). Additionally, as the cause of sudden larch death in the United Kingdom, EU1 is known to attack conifers which are prominent in southwestern Oregon. Researchers have observed mortality in Douglas fir and grand fir seedlings in the wild, potentially compromising valuable timber products (Brasier and Webber 2010, LeBoldus et al. 2017). As with NA1, ODF swiftly implemented an intensive control strategy which, to date, has kept EU1 clustered near Pistol River (Figure 3.1).

The strains differ in another key way: they are different mating types. Generally, *Phytophthora*s are clonal, reproducing asexually via chlamydospores and sporangia. However, when exposed to the opposite mating type, they can reproduce sexually via oospores. In the case of *P. ramorum*, opposite mating types typically do not coexist and the functionality of the sexual system has been called into question (Grunwald et al. 2012). A laboratory study found that, although EU1 x NA1 crosses were possible, it was rare, most oospores were not viable, and the few surviving crosses were not more virulent than their parents (Xavier et al. 2010). Essentially, the risk of sexual recombination is low, but it is unclear how the strains may interact under nature's selective pressures. Since Oregon is the only area to date where opposite mating types coexist, areas of overlap could be of particular concern for management.

Due to EU1's aggressiveness, it's capacity to infect conifers, and it's recent introduction, stakeholders currently consider EU1 a greater threat. Nevertheless, either strain could precipitate the same environmental and economic impacts. Tanoak (*Notholithocarpus densiflorus*), the most susceptible host species, exists in high-densities throughout the region, putting over 2100 km^2 of forests at risk (Vaclavik et al. 2010). Widespread mortality has already occurred in some areas, and further spread could increase regional wildfire hazards, degrade biodiversity and habitat, and jeopardize cultural practices of native tribes who have traditionally utilized tanoak and other affected species (Bowcutt 2015, Long and Lake 2018, Cobb et al. 2012, Metz et al. 2011). Further, if either strain spread northward into neighboring Coos County, federal *P. ramorum*

quarantines could trigger severe economic repercussions by hindering timber trade through the Port of Coos Bay. The port, one of Oregon's largest, almost exclusively ships timber. An economic assessment found that if such trade were disrupted roughly 1,200 jobs and $57.9 million in annual wages could be lost (Highland Economics et al. 2019). Since either strain could induce impacts, the Oregon Control Program must figure out how to strategically prioritize the management of both strains to avoid the worst economic and environmental consequences.

3.3. METHODS

3.3.1. Forecast Framework

We partnered with the Oregon SOD Control Program to collaboratively develop the forecasting framework presented in this section. The core functionality of the forecast was based on work by Meentemeyer et al. (2011) and Cunniffe et al. (2016) which simulated SOD spread in California. While epidemiological processes are largely consistent, some Oregon conditions warranted significant changes (Hansen et al. 2008). In 2017, we held a participatory modeling workshop with members of the Control Program to tailor these forecasts to Oregon epidemiology (Gaydos et al. 2019). In response to these local observations, we updated the forecast in the following ways. Although multiple species become infected, tanoak disproportionately influences landscape-scale spread and impacts in Oregon (Hansen et al. 2005, Peterson et al. 2015). Therefore, we switched from a multi-host framework to a single-host framework which only accounts for disease transmission in tanoak. Next, because SOD is more geographically-clustered in Oregon than in California, the long-distance dispersal kernel described in Meentemeyer et al. (2011) was not representative of the data and was removed. Further, we updated the short-distance kernel from a Cauchy function to a negative exponential function which better fit local dispersal patterns described in Peterson et al. (2015).

Importantly, the Control Program stressed the need for a multi-strain disease forecast which could simulate both the EU1 and NA1 strains concurrently (Gaydos et al. 2019). Because of observed differences between the strains (Manter et al. 2010, Grunwald et al. 2012, Søndreli et al. 2019), a single forecast could not capture the complex heterogeneities of the system. Rather, we needed to calibrate, validate, and run a forecast separately for each strain. However, because strains rely on a common host, treatments impact both systems and need to be

synchronized. To accomplish this, forecast outputs were combined at a yearly timestep. Treatment locations were determined based on the combined output and scenario heuristics. Treatments were applied, as described below, to both strains. Both forecasts were reinitialized with this "managed" data, and ran for another yearly timestep. This framework allowed us to capture key epidemiological differences between strains while also accounting for both direct and indirect treatment effects. This multi-strain forecast allowed us to test 4 intervention strategies under consideration by the Oregon Control Program: no management, prioritizing EU1, prioritizing NA1, and prioritizing neither strain (Highland Economics et al. 2019).

3.3.2. Forecast

The forecast is a stochastic, spatially-explicit susceptible-infected-removed (SIR) simulation which uses initial infection locations, host density, and weekly weather conditions to mimic pathogen dispersal and impacts across the landscape. It is composed of four core functions: 1) reproduction, 2) dispersal, 3) establishment, and 4) management. The first 3 functions encapsulate the epidemiological spread, and can be mathematically represented as:

$$\Psi_{ijt} = \beta P_{it} T_{it} I_{it} * K\left(\alpha, d_{ij}, D(\omega, \kappa)\right) * \ P_{jt} T_{jt} S_{jt} / N_j$$

where:

- Ψ_{ijt} represents infectious spread from cell i to cell j in timestep t;
- $\beta P_{it} T_{it} I_{it}$ represents pathogen reproduction in cell i;
- $K\left(\alpha, d_{jt}, D(\omega, \kappa)\right)$ represents pathogen dispersal from cell i to j; and,
- $P_{jt} T_{jt} S_{jt} / N_j$ represents pathogen establishment in cell j.

Further description of all terms, including parameter values, can be found in Table 3.1.

The simulation begins with the weekly reproductive function, represented by $\beta P_{it} T_{it} I_{it}$, where infected trees produce disease "spores" capable of generating new infection. The number of spores produced is stochastically determined by sampling a Poisson distribution based on the number of infected trees in the cell (I_{it}) multiplied by the strain's average reproductive rate (β) (Table 3.1). The reproductive rate (β) represents the amount of new infections each infected tree could create per week under optimal conditions and is calibrated as described below. Since SOD sporulation is heavily dependent on temperature (T_{it}) and precipitation (P_{it}), we moderate the number of spores produced by the weather coefficient ($T_{it} P_{it}$) for that location in that timestep

(Meentemeyer et al. 2011, Davidson et al. 2005). Importantly, the forecast only considers spores generated inside the study landscape (Curry County) and does not consider the potential for introductions from elsewhere.

The dispersal function, $K\left(\alpha, d_{ij}, D(\omega, \kappa)\right)$, distributes these spores across the landscape, and the establishment function, $P_{jt}T_{jt}S_{jt}/N_j$, determines whether they will establish a new infection. To determine where each spore will land, distance and direction traveled are stochastically sampled from probability distributions. Distance (d_{ij}) is sampled from a negative exponential function (K) with a mean of the 1/average dispersal distance (α), a calibrated parameter (Table 3.1). Given the shape of the negative exponential function, most disease dispersal will be local (within a few hundred meters) with some chances for longer-distance dispersal (within a few kilometers). Direction, $D(\omega, \kappa)$, is drawn from a Von Mises distribution (i.e., the circular approximation of a normal distribution) (Tonini et al. 2017). Because spread is driven by wind and rain, dispersal is an anisotropic process along the prevailing wind direction (ω) (Rizzo et al. 2005). In this region, southwinds dominate for much of the year, meaning that new infections are often located north of previous infections. Therefore, the Von Mises distribution was biased north with a strength of kappa (κ), as defined in Gaydos et al. (2019) and Tonini et al. (2017) (Table 3.1). Considering landscape heterogeneities, not all spores will land in suitable areas. The probability of establishment for each cell is determined by the density of susceptible hosts (S_{jt}/N_j) and the weekly weather coefficient ($P_{jt}T_{jt}$). Establishment is a stochastic process: if the probability of establishment is higher than a randomly generated number, a new infection will occur. Together, the spore generation, dispersal, and establishment functions control the transition from the susceptible to infected categories, thereby simulating weekly disease progression across the landscape.

The management function governs the human-induced removal of tanoak and occurs outside of the epidemiological component of the forecast. In ODF's protocols, treatments are typically 600m circular buffers in which all susceptible and infected tanoak are culled (Table 3.2). This polygonal nature of treatments is mismatched with the raster-based disease forecast. Therefore, treatment polygons are converted to rasters where the cell value represents the proportion of cell area covered by the treatment. When treatments intersect any segment of a cell, all infected trees and a proportion of susceptible trees relative to the treatment cell value. By

conducting treatments in this way, the management function assumes that all infected trees were targeted and removed, while also accounting for the fact that the entire cell was not treated and could therefore become reinfected. Unlike the previous functions, treatments are conducted in December of each simulation year. The rationale for this was three-fold: 1) treatment data from ODF is aggregated yearly, 2) treatments typically occur in winter months when there is less risk of wildfire, and 3) we are capturing realistic time-lags between detection and management (Kanaskie et al. 2010). Since treatments include herbicides to inhibit resprouting, we do not account for tanoak regrowth. Treatment costs of \$1.23/m^2 were based on average costs reported by ODF (Table 3.2)(Highland Economics et al. 2019). Costs were not tallied when treatments overlapped, or no hosts were present.

Table 3.1. Forecast parameter values for Equation 1. Calibrated parameters are designated by *

Parameters of Epidemiological Forecast			
Disease Strain	**Symbol**	**Meaning**	**Value or Range**
Both Strains	i, j	index of a particular cell, where i is the infectious cell and j is the receiving cell	---
	t	index of a particular week	---
	N^{max}	maximum numbe r of host units in any cell	100
	N_j	total number of hosts in cell j	$[0,N^{max}]$
	S_{jt}	number of susceptible hosts in cell j at time t	$[0,N^{max}]$
	I_{it}	number of infected hosts in cell i at time t	$[0,N^{max}]$
	P_{it}	precipitation suitability index in cell i at time t	[0,1]
	T_{it}	temperature suitability index in cell i at time t	[0,1]
	$K()$	exponential dispersal kernel	---

Table 3.1 (continued).

	d_{ij}	dispersal distance from cell i to j	---
	$D(\omega, \kappa)$	direction traveled	---
	ω	predominant wind direction	north
	κ	strength of wind direction	2
	Ψ_{ijt}	infectious pressure on cell i from cell ij at time t	---
EU1	$\beta*$	number of pests dispersing from a single host under optimal conditions	1.6 1/week
	α *	mean dispersal distance	242 m
NA1	$\beta*$	number of pests dispersing from a single host under optimal conditions	0.6 1/week
	α *	mean dispersal distance	354 m

Table 3.2. Heuristics for the management function.

Management Heuristics	
Treatment buffer distance	600ft
Cost	$1.23/m^2
Primary Prioritization Strategy	EU1, NA1, Do Not Prioritize by Strain
Secondary Prioritization Strategy	Shortest Distance from Northeastern Extent of Data
Annual Budget Limit	$2.5 million or $4.1 million

3.3.3. Data and Inputs

Host distribution data was adapted from an existing Oregon vegetation map representing the percent cover of tree species at a 30m resolution (Ohmann et al. 2011). Although *P. ramorum*

infects several species, tanoak disproportionately influences landscape-scale spread in Oregon (Hansen et al. 2008). Following the Control Program's advice, we focused solely on this critical species (Gaydos et al. 2019). Percent cover of tanoak was extracted and rescaled to 100m resolution using median values to avoid smoothing local heterogeneities. Local SOD experts observed that Ohmann et al. (2011) overestimated the spatial distribution of tanoak, suggesting instead that it's patchily-distributed based on disturbance history (Gaydos et al. 2019). Therefore, we used NLCD's 2016 Forest Disturbance Date product to remove tanoak in areas disturbed since 2000 (Jin et al. 2019). This product provides the date of disturbance but does not differentiate between disturbance types which may impact tanoak differently (Dillon et al. 2014, Tappeiner et al. 1990). In this region, timber harvesting generally overshadows other types of disturbances, such as urbanization (Bowcutt 2015, Robbins et al. 1985, Spies et al. 1994). Wildfires can also be significant, but happen sporadically and with mixed-effect on tanoak density (Tappeiner et al. 1990). In contrast, timber harvesting is annual, widespread, and consistently suppresses tanoak making it the largest driver of regional host density (Hansen et al. 2008). Therefore, all disturbances were assumed to be timber harvests that manually remove tanoak and prevent resprouting via herbicides. Additionally, we accounted for the effects of prior SOD management which also manually removes tanoak (Kanaskie et al. 2010, Hansen et al. 2019).

Yearly infection and treatment locations were obtained from ODF. Infection locations, differentiated by pathogen strain, were received as point vectors and converted to 100m raster by summing all infections within a cell. Yearly infection maps represent the cumulative distribution of infection (i.e., all infections discovered that year, plus any infections from previous years which had not been removed by treatments) to account for disease persistence in unmanaged stands. Infection data was current as of January 2020. At this time, some 2019 infections were awaiting genotyping and could not conclusively be assigned to a strain. In these cases, strain was assigned based on the closest genotyped infection, since most SOD spread is local (Rizzo et al. 2005). When the current distribution is converted to raster format, 53 pixels are infected with EU1, 461 pixels are infected with NA1, and 514 pixels are infected by either strain (Figure 3.2A). As with infections, yearly treatment polygons were converted to 100m rasters where the cell value corresponds to the cell area covered by the treatment. Treatment data was also current through January 2020.

Since weather patterns are known to drive SOD spread (Hansen et al. 2008, Davidson et al. 2005), we acquired daily temperature and precipitation maps through Daymet V3 at a 1km resolution from 2000 to 2019 (Thornton et al. 2017). These data were resampled to a 100m resolution and aggregated to a weekly timescale. Raw values were converted to temperature and precipitation coefficients using a formula from Meentemeyer et al. (2011), which was originally developed from laboratory observations of NA1 sporulation (Davidson et al. 2005). We further amended this formula to include linear decrease in suitability between 0-2℃. Temperature and precipitation coefficients were multiplied to create weekly weather suitability maps. Values range from 0-1, with 1 representing the most optimal conditions for pathogen sporulation and spread (Table 3.1). Future weather data spanning 2020-2025 was generated by resampling the historical data to simulate future weather, as described in Meentemeyer et al. (2011). The yearly 2000-2019 weather data was ranked by average coefficient value to create a distribution from most to least conducive for spread. To generate an average future weather scenario, we randomly selected weather years from the middle third of this distribution.

3.3.4. Calibration and Validation

Because the true values of dispersal distance and reproductive rate are unknown, we calibrated and validated these parameters for each strain. To calibrate, we used a Markov Chain Monte Carlo (MCMC) approximation to iteratively propose and evaluate parameter sets (Meentemeyer et al. 2011, Gilks et al. 1996). The fit of each parameter set was determined by the quantity and configuration disagreement between observed and simulated data. Quantity disagreement measures how well the forecast mimics the amount of infection, and is calculated as the difference between infected pixels in the simulated and observed data (Pontius and Millones 2011). Configuration disagreement, as calculated in Picard et al. (2017), is a value between 0-1 that measures how well the simulation mimics the spatial pattern of infection, with 0 being perfect pattern agreement. Together, these metrics provide a holistic picture of how well the simulation matches observed patterns (Hughes et al. 1997, Meentemeyer et al. 2012). Given the forecast's stochastic nature, quantity and configuration disagreement were averaged over 10 runs for each parameter set. If simulation fit was better than previously-tested parameters, or fell within a predetermined range of acceptability, parameters were recorded to a database of parameter values. The outcome was a distribution of potential parameter values, where the mode

represents the value with the best overall fit. We repeated this process 100,000 times, for a total of 1,000,000 iterations per strain. For EU1, calibration was initiated with 2016 data and ran for the two-year period of 2017 and 2018. For NA1, calibration was initiated with 2001 data and ran for the two-year period of 2002 and 2003. While more recent NA1 infections exist, data collected after 2010 was incomplete and could not be used for calibration or validation. At this time, the Control Program designated a heavily-infested zone, "generally infested area", and indefinitely suspended surveying and management in this location (Figure 3.1). Any records of NA1 distribution following 2010 underpredict disease in this area, which could skew calibration and validation results.

Ideally, calibration is conducted in undisturbed areas so parameters can be ascertained under natural spread conditions. However, no such areas exist in Oregon due to the intensive interventions. As described in Hansen et al. 2008, "the eradication effort precludes many classical epidemiological tests and observations." Yet, this is a realistic complication, as conventional wisdom favors swift and comprehensive management (Pluess et al. 2012, Cunniffe et al. 2016). Because treatments significantly alter infection density and pattern, they should not be ignored in the calibration. Therefore, treatment data from ODF was used to mimic tanoak removal in infected locations via the management function. Importantly, treatments were applied statically (i.e., did not vary by simulated outcomes). This was both computationally-efficient and represented the historical alteration of the landscape. In this way, we took both disease spread and management into account when calibrating forecast parameters.

To validate, we ran the forecast for each strain with the best fit parameter set 1,000 times over a period of 1 year. We used three validation metrics to assess distinct aspects of forecast functionality: 1) quantity disagreement, 2) configuration disagreement, and 3) proportion correct (Pontius and Millones 2011, Picard et al. 2017). As aforementioned, quantity and configuration disagreement examine the amount and spatial configuration of infected sites. Additionally, we assessed the locational accuracy of infections via proportion correct. Proportion correct is a common and easily-interpretable metric which is calculated as the proportion of correctly identified sites relative to all observed sites (Pontius and Millones 2011). Through this three-pronged validation, we can better understand not only prediction accuracy, but how well the forecast mimics the amount and spatial arrangement of infection to gain a more holistic sense of how the forecast functions. Validation was conducted using different data years to avoid

overestimation of accuracy (Pontius et al. 2004). For EU1, validation was initiated with 2018 data, run for 2019 and analyzed against 2019 field observations. For NA1, validation was initiated with 2004 data, run for 2005 and analyzed against 2005 field observations.

3.3.5. Computational Experiments

Management scenarios focused on 4 alternatives proposed by the Oregon SOD Control Program: no management, prioritizing EU1, prioritizing NA1, and prioritizing neither strain (Highland Economics et al. 2019). The No Management scenario is straightforward: both strains were simulated without interventions, representing a situation where the Control Program is no longer funded and all culling treatments cease. All other scenarios examine the effect of prioritizing treatments by disease strain. Currently, infected locations are prioritized by their distance to the northeastern quarantine boundary, regardless of strain (i.e., the No Priority scenario). However, given the aggressive nature of EU1, stakeholders question whether its management should take precedence over NA1 (Highland Economics et al. 2019). In the EU1 Priority scenario, EU1 infections are prioritized until either the budget is exhausted or all EU1 infections have been removed. If all locations are removed and budget remains, NA1 infections are treated as budget permits. The opposite applies for the NA1 Priority scenario: EU1 is only treated after all NA1 infections have been removed. There is less stakeholder interest in prioritizing NA1 treatments, but this scenario provides a valuable comparison. In all scenarios, a wave-front strategy is used where infections are prioritized by their distance to the northeastern quarantine boundary (Cunniffe et al. 2016). We tested these 3 prioritization scenarios under 2 annual budget limits ($2.5 million and $4.1 million) designated by ODF. All scenarios were run from 2020 to 2025 with 2019 setting the initial conditions.

Scenarios are compared by the following metrics: 1) infected area in 2025, 2) coexistence area in 2025, 3) the annual areal growth rate, 4) area saved, and 5) money spent per area saved. Area infected represents the area of infected pixels at the beginning of 2025. Coexistence area reflects the extent to which the NA1 and EU1 strains overlapped at the beginning of 2025. The growth rate represents how much the infected area is projected to grow annually, and is calculated by:

$$Growth\ Rate = \frac{(Infected\ Area\ in\ 2025 - Initial\ Infected\ Area)}{Initial\ Infected\ Area} * \frac{100}{5}$$

Both growth rate and infected area are reported for each strain individually and both strains combined. Area saved reflects the difference in total infection (both strains) between the No Management scenario and the managed scenario, and is calculated by:

$$Area\ Saved = No\ Management\ Combined\ Area - Scenario\ Combined\ Area$$

Money spent per area saved normalizes the cost of the scenario by its effectiveness at reducing tanoak loss, and is calculated by:

$$Money\ Spent\ per\ Area\ Saved = \frac{(Annual\ Budget * 5)}{Area\ Saved}$$

Lastly, we visually assessed the likelihood of either strain escaping the current quarantine boundary, which would trigger a quarantine on all of Curry County (Highland Economics et al. 2019).

We conducted ANOVA and Tukey HSD tests in R to further compare how the treatments altered the combined infected area in 2015 (R Core Team 2020). To focus on the differences in prioritization, we conducted the analysis separately for both budget limits. First, a one-way ANOVA determined whether any of the treated scenarios differed significantly from the No Management baseline. If significant at the .05 level, we conducted a Tukey HSD pairwise comparison of all scenarios within that budget limit, allowing us to compare scenarios to each other as well as the No Management control.

3.4. RESULTS

3.4.1. Calibration and Validation

Our calibration procedure determined different best-fit parameters for the EU1 and NA1 forecasts, reflecting laboratory and field observations of epidemiological differences (Table 3.1) (Søndreli et al. 2019, Manter et al. 2010). Importantly, the EU1 reproductive rate (1.6) was noticeably higher than the NA1 reproductive rate (.6), mirroring research which found that EU1 produces more spores (Manter et al. 2010). The strains had similar dispersal distances, with the NA1 strain having a slightly higher average distance (354m) than the EU1 strain (242m). Both distances are consistent with research suggesting that a new infection is, on average, 300m from a previous infection (Peterson et al. 2015).

We validated these parameters for both strains using three metrics to address different aspects of forecast functionality: 1) proportion correct, 2) quantity disagreement, and 3)

configuration disagreement (Table 3.3). Out of 1,000 iterations, the average proportion correct was 50.025 for the EU1 strain and 48.858 for the NA1 strain, meaning that both forecasts correctly identified roughly 50% of infected locations. The strains also had similar values of average configuration disagreement (.373 for EU1, .368 for NA1), which measures the similarity of landscape patterns (Picard et al. 2017). Here, configuration disagreement ranges from 0-1, where 0 indicates perfect agreement and 1 indicates perfect disagreement. Both strains have a configuration disagreement below .5, indicating that patterns are similar in the forecasted and observed data. Lastly, we assessed quantity disagreement, which reflects how well the forecast simulates the amount of infection on the landscape. Here, we note some differences between the strains, with EU1 (15.114 pixels) having a lower quantity disagreement than NA1 (40.407 pixels). This suggests that the EU1 forecast may more accurately project the amount of infected area.

Table 3.3. Validation outcomes showing proportion correct, quantity disagreement, and configuration disagreement. Proportion correct represents the locational accuracy of the forecast, and ranges from 0-100. Quantity disagreement represents how well the forecast matches the area of infection, and is reported as the number of pixels that differ in the observed and simulated data. Configuration disagreement represents how well the forecast matches infection patterns, and ranges from 0-1 with 0 indicating perfect pattern agreement. We report the average values from 1,000 forecast iterations with standard deviation in parentheses.

Disease Strain	Proportion Correct	Quantity Disagreement	Configuration Disagreement
EU1	50.025 (.008)	15.114 (8.196)	.373 (.083)
NA1	48.858 (.033)	40.407 (10.510)	.368 (.094)

3.4.2. Scenario Results

The No Management scenario presents an alternative where culling treatments are discontinued and stakeholders transition to living with the disease (Figure 3.2B). Under this scenario, the forecasts project an average total infected area of 4,974.64 ha by 2025, with the NA1 strain contributing the bulk of infection (4,058.60 ha on average) (Figure 3.3). However,

the EU1 strain increased the most dramatically (330.33%), more than quadrupling it's area each year (Table 3.4). While far lower, the NA1 growth rate is still substantial, increasing 156.08% annually (Table 3.4). When combined, we see an average annual growth rate of 173.57% of total SOD infection. Despite substantial increases in infected areas, we found relatively few areas where the strains coexist, with 12.33 ha supporting both strains on average (Figure 3.3). A visual analysis of the scenario found that at no point in the 5 year forecast did either strain of the pathogen escape the current quarantine boundary (Figure 3.2B).

We evaluated 3 treatment prioritizations at 2 annual budget limits (2.5 million and 4.1 million) for a total of 6 management scenarios (Figure 3.2). In all cases, we applied a wave-front approach which systematically targeted northeastern-most infections, the strategy most likely to reduce northeastern spread and which most accurately represents ODF's protocols (Highland Economics et al. 2019). As with the No Management scenario, we found no instances of the pathogen escaping quarantine during the 5 year study period (Figure 3.2C-H). On average, 193.75 ha were treated annually with a $2.5 million budget and 317.63 ha were treated annually with a $4.1 million budget. This area was consistent across years and scenarios. Several of these cells were only partially treated, meaning that susceptible hosts remained and could become infected in later simulation years. Budget limits did not factor in additional expenses and limitations, such as overhead costs, variable treatment rates, and the availability of contract crews. For these reasons, we expect actual treated areas to be lower than the treated areas simulated here.

Compared to the No Management scenario, all treated scenarios had significantly less infected areas (by each strain individually and both strains combined) according to ANOVA and Tukey HSD tests (Table 3.5). Under both budget limits, the NA1 Priority scenario saw the smallest decrease in combined infected area and annual growth rate (Figure 3.3), and came closest to escaping the northern quarantine boundary (Figure 3.2E-F), suggesting that this scenario is the least effective at combating spread. The remaining scenarios resulted in considerably less infection than the NA1 Priority scenario (Figure 3.3). With the 2.5 million budget, the No Priority scenario saw the lowest average combined infected area (4,110.59 ha) and growth rate (139.95%), with the EU1 Priority scenario projecting similar numbers (4,131.30 ha, 143.42%) (Table 3.4). Tukey HSD tests confirmed that these scenarios were not statistically different from one another (adjusted p value = .159). With $4.1 million, however, these results

were flipped, with the EU1 Priority showing the greatest decreases (3,662.98 ha, 122.53%), followed by the No Priority scenario (3,730.88 ha, 125.17%). In this case, Tukey HSD found significant differences between the scenarios (adjusted p value < .000000). A closer look at forecast outputs reveals several similarities between the EU1 and No Priority scenarios that explain their similar trajectories. Because the EU1 infestation is farther north, EU1 infections were often removed under the No Priority scenario, leading these scenarios to be functionally similar (Figure 3.2).

Of all the scenarios, the $4.1 million EU1 Priority scenario had the lowest overall infected area (3,662.98 ha), the lowest combined spread rate (122.53%), and the highest area saved (1,311.66 ha) (Figure 3.2D). Particularly notable, the EU1 growth rate dropped to -19.45% compared to 330.33% in the No Management scenario. This negative growth rate indicates that, on average, there was less infection in 2025 than when the forecast was initiated in 2019. Further, we found that in 332 of the 500 iterations (66.40%), EU1 had been eliminated entirely. In these cases, the remaining budget was used to treat NA1 infections, corresponding to 397.06 fewer ha of NA1 infection compared to the No Management scenario (Table 3.4). This also reduced the likelihood of infections near the northern quarantine boundary, although the No Priority scenarios saw the greatest overall reduction in this area (Figure 3.2G-H). Despite the higher annual budget limit, the high levels of area saved under this scenario contributed to the lowest money spent per area saved of all scenarios (Table 3.4).

Table 3.4. Comparison of scenario outcomes. All area metrics are in hectares. Annual growth rate represents the average yearly increase in infected areas in percentages. Money spent per area saved is reported in dollars. We report the average values from 500 forecast iterations with standard deviation in parentheses.

Annual Budget	Scenario	EU1 Infected Area	NA1 Infected Areas	Combined Infected Area	Co-existence Area	EU1 Annual Growth Rate	NA Annual Growth Rate	Combined Annual Growth Rate	Area Saved	Money Spent per Area Saved
---	Current Distribution	53	461	514	0	---	---	---	---	---
$0	No Management	928.37 (98.86)	4,058.60 (134.87)	4,974.64 (169.25)	12.33 (248.45)	330.33% (37.31)	156.08% (5.85)	173.57% (6.59)	---	---
$2.5 million	EU1 Priority	372.80 (49.37)	3,766.83 (141.18)	4,131.30 (156.88)	8.33 (135.55)	120.68& (18.63)	143.42% (6.13)	143.42% (6.10)	843.35 (232.01)	$16,403.94 (6,864.84)
	NA1 Priority	857.53 (95.47)	3,564.70 (121.56)	4,421.71 (158.05)	.52 (130.85)	303.59% (36.02)	134.65% (5.27)	152.05% (6.15)	552.93 (232.63)	$20,312.19 (189,721.6)
	No Priority	368.03 (49.85)	3,750.60 (129.51)	4,110.59 (143.61)	8.04 (125.92)	118.88% (18.81)	142.72% (5.62)	139.95% (5.59)	864.06 (224.27)	$21,823.06 (100,218.80)
$4.1 million	EU1 Priority	1.45 (3.86)	3,661.54 (138.57)	3,662.98 (139.02)	.01 (113.88)	-19.45% (1.46)	138.85% (6.01)	122.53% (5.41)	1,311.66 (222.63)	$16,132.66 (3,058.19)
	NA1 Priority	859.70 (99.43)	3,245.45 (143.42)	4,105.16 (177.78)	.01 (150.51)	304.42% (37.52)	120.80% (6.22)	139.73% (6.92)	869.49 (246.25)	$19,470.18 (154,500.90)
	No Priority	130.79 (62.71)	3,602.14 (125.76)	3,730.88 (150.32)	2.05 (143.5)	29.35% (23.66)	136.28% (5.46)	125.17% (5.85)	1,243.76 (243.74)	$17,139.21 (3,642.70)

Table 3.5. Results of the ANOVA and Tukey HSD analysis to determine if scenarios differ significantly. Values represent p-value for ANOVA and adjusted p-value for Tukey HSD.

Annual Budget	ANOVA	Tukey HSD Pairwise Comparisons					
		No Management - EU1 Priority	No Management - NA1 Priority	No Management - No Priority	EU Priority - NA Priority	EU Priority - No Priority	NA Priority - No Priority
$2.5 Million	$< 2 \times 10^{-16}$	.0000000	.0000000	.0000000	.0000000	.1590113	.0000000
$4.1 Million	$< 2 \times 10^{-1}$	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000

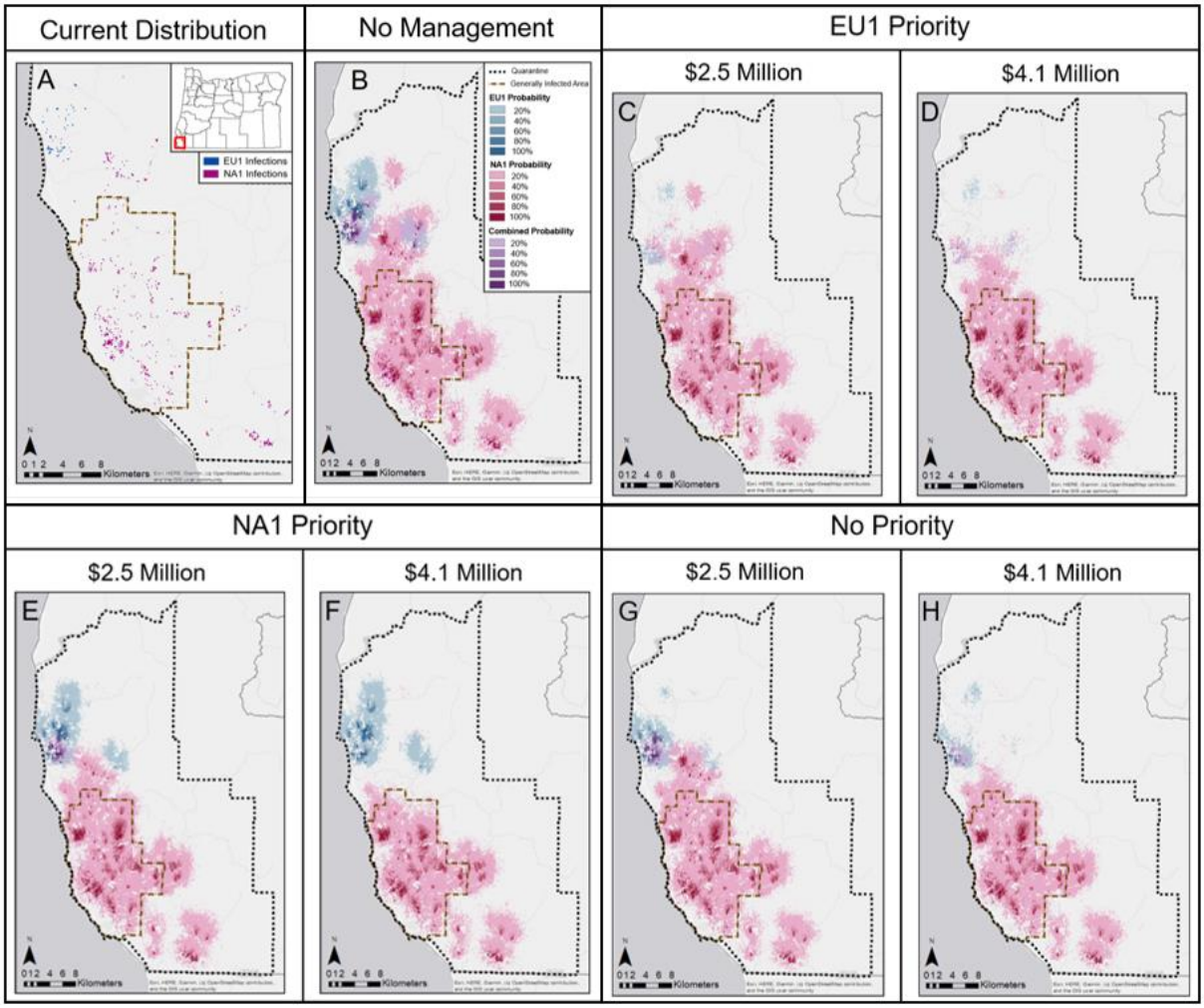

Figure 3.2. Comparison of the forecasted probability of infection by strain in 2025. In all projected scenarios (B-H), pink represents the NA1 stain, blue represents the EU1 strain, and purple represents coexistence of both strains. The current 2020 distribution of infections (A) is shown for comparison.

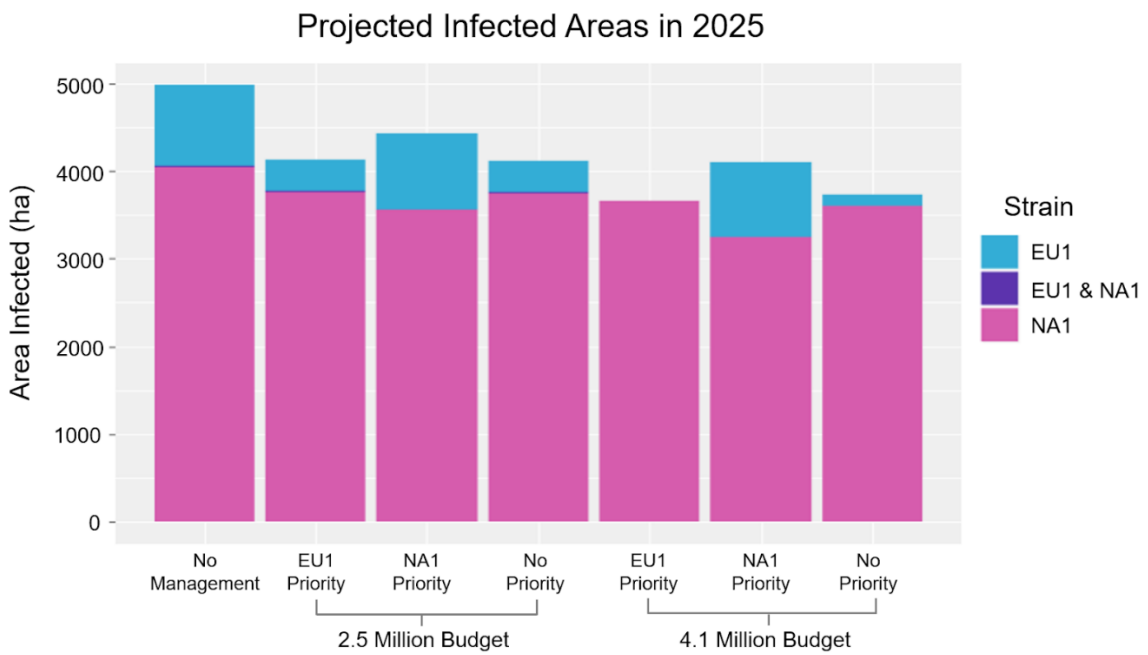

Figure. 3.3. Projected infected areas in 2025 for all scenarios, separated by strain and areas of coexistence.

3.5. DISCUSSION

Spatiotemporal forecasts of invasive forest disease can help control programs understand spread patterns, how interventions impact those patterns, and how to respond to changing epidemic conditions (Gilligan et al. 2008, Thompson et al. 2018). However, the common, single-species forecasting approach cannot fully capture the complexities of multiple, competing invasions, as is the case with *P. ramorum* in southwestern Oregon (Cunniffe et al. 2015, Hansen et al. 2019). In response, we developed a synchronized multi-strain forecast to assess how intervention strategies affect overall disease impacts through their combined effects on each strain. With this framework, we explored how to prioritize treatments in a complex, multi-strain pathosystem, and provided guidance on scenarios currently under consideration by the Oregon SOD Control Program.

Forecast results suggest that variations in pathogenicity and invasion history will drive considerable differences in the strains' spread trajectories with different implications for management (Figure 3.2). First, we consider the influence of invasion history. The NA1 strain was introduced in 2001, fourteen years prior to EU1. Over time, NA1 has grown into a

widespread invasion with thousands of infections scattered throughout the current quarantined area (Figure 3.1). In contrast, EU1 was introduced more recently and has remained confined to a small geographic extent (Figure 3.1). Driven by higher levels of initial infection, our forecasts consistently show NA1 contributing the vast majority of infected areas by 2025 (Table 3.4, Figure 3.3). For example, in the No Management scenario, NA1 generated 4 times the infected area compared to EU1 (Table 3.4). This indicates that NA1 is a serious threat which may cause widespread impacts over the next 5 years (Figure 3.2). However, results also suggest that the Control Program may receive fewer benefits from targeting NA1. Under both budgets, the highest infection levels were found in the NA1 Priority scenarios (Table 3.4). Even when NA1 was consistently targeted at the highest budget level, it still infected an average of 3,245.45 ha at an annual growth rate of 120.80%. Essentially, the forecast suggests that, at this point, NA1 is a widely-dispersed late-stage invasion which cannot be substantially reduced within realistic funding limits (Cunniffe et al. 2016). However, the control program may still see benefits from targeting some outlying NA1 infections with the potential to greatly expand the disease's range. For an example, we can consider the No Priority scenarios, which largely targeted EU1 and northern outliers of NA1. In these scenarios, we see both a considerable decrease in total infected area (Table 3.4) and the lowest probabilities of infection near the northeastern quarantine boundary (Figure 3.2G-H), which is of particular concern to stakeholders.

Pathogenicity also greatly influenced spread and impacts. The EU1 strain currently occupies a smaller geographic range, and results suggest that it does not have the capacity to infect as great an area as NA1 within the next 5 years. However, it's projected growth rate is substantially higher and is a significant cause for concern. In the No Management scenario, EU1 saw a growth rate of 330.33% compared to NA1's 156.08% (Table 3.4). At this rate, the EU1 strain is projected to quadruple in area annually. These projections support other observations that EU1 spreads faster and is more aggressive (LeBoldus et al. 2017, Søndreli et al. 2019). Over time, EU1 may be more damaging than NA1. However, this is also where we saw the greatest effect of treatments. Because EU1 has thus far remained a clustered early-stage invasion, limited treatment resources go farther towards reducing overall EU1 infections. And by removing infections with a high-growth rate, we see a corresponding reduction in total infection (Table 3.4). With a $4.1 million annual budget, the EU1 Priority scenario saw the greatest reduction in combined infected area and growth rate of all scenarios. This was driven by the massive

reduction in EU1 growth rate from 330.33% to -19.45%, which indicates that, on average, this scenario resulted in fewer EU1 infections than present day. While encouraging, we caution that eradication of the EU1 strain is unlikely. Prior attempts at *P. ramorum* eradication have failed because of complications including cryptic infections, new introductions, and pathogen persistence in other hosts, soils, and waterways (Peterson et al. 2015, Hansen et al. 2019). However, these results suggest that stakeholder's intuitions about the threat of EU1 are justified, and that a consistent, targeted treatment strategy could substantially reduce future SOD impacts throughout the county.

It is important to note that even when a strain was not directly targeted, we see a reduction in the average infected area. For example, in the NA1 Priority scenarios, we saw a roughly 70 ha drop in EU1 infection despite no direct treatments (Table 3.4). There are two underlying reasons for this effect. First, because the pathogens sometimes coexist, treatments in these areas directly reduce both strains simultaneously, and may be especially important to limit opportunities for unexpected sexual recombination (Grunwald et al. 2012). Second, because the strains share a common host, removing hosts anywhere can impact the future distribution of both strains, regardless of which strain was treated. These indirect treatment effects were found in all managed scenarios, suggesting they are common and have substantial effect on the disease trajectories (Table 3.4). A single-species approach where separate forecasts are aggregated post hoc would miss these indirect effects, and therefore would likely overpredict spread. However, by synchronizing our forecasts and applying treatments simultaneously to both strains, we were able to more realistically capture how treatments affect SOD's spread trajectory.

A common adage amongst modelers states that, "all models are wrong, but some are useful" (Box 1976). When models are used to guide policy, however, it is imperative that decision-makers fully comprehend the functionality and limitations (Cunniffe et al. 2015, Voinov and Bousquet 2010). We addressed this in two ways. First, we engaged the Oregon SOD Control Program throughout forecast and scenario development (Gaydos et al. 2019). This participatory approach not only guided our research, it gave stakeholders an opportunity to learn about forecast processes and data (Voinov and Bousquet 2010). Additionally, we conducted a robust assessment of forecast accuracy using 3 metrics (proportion correct, quantity disagreement, and configuration disagreement) to highlight different aspects of functionality (Pontius and Millones 2011, Picard et al. 2017). Similar studies have relied solely on odds ratio

to communicate accuracy (Meetemeyer et al. 2011, Cunniffe et al. 2016). However, this provides little context on the pattern and quantity of spread, which are important considerations from a policy perspective (Pontius and Millones 2011, Pontius et al. 2004). We found that our forecasts had moderate locational accuracy. Some errors can be attributed to inaccuracies in the host distribution data (Ohmann et al. 2011), which propagate locational uncertainty in the forecast (Dietze 2017). Additionally, intensive treatments obscured natural spread patterns and complicated parameter estimation (Hansen et al. 2008). Although our calibration procedure was a computationally-efficient method to account for treatment effects, it also introduced more variability and error. Future work will explore approximate Bayesian computing methods which may better capture treatment effects by updating parameters annually (Minter and Retkute 2019). Regardless, our validation revealed that the forecasted pattern and quantity of disease was representative of observed data. Therefore, our forecast is best-suited to assess trends in disease area and patterns, which we focus on throughout this analysis.

Considering the Control Program's goals of reducing SOD impacts and limiting northward spread, we recommend focusing on EU1 while reserving some funds to treat northernmost NA1 infections. Because of its aggressive nature and high spread rate, the EU1 strain will likely pose a greater long-term threat. However, it is an early-stage invasion and limited treatment resources have a substantial impact. We saw the greatest overall reduction in infected area and growth rate when EU1 was targeted. Yet, the Control Program must also consider the potential for northward spread into Coos County, which could trigger several economic impacts (Highland Economics et al. 2019). By removing northernmost NA1 outliers, we see the greatest reduction in northern spread in the No Priority Scenarios and the EU1 Priority $4.1 million scenario. So by consistently prioritizing EU1 treatments while retaining some funds to suppress northern NA1 infections, the Control Program may reduce overall SOD infestation while also delaying spread into Coos County. Unfortunately, projections also indicate that eradication of both *P. ramorum* strains in southwestern Oregon is unlikely and all scenarios showed substantial growth over the next 5 years (Figure 3.2). As spread and impacts increase, there may be more demand for the Control Program's current restoration, mitigation, and citizen science programs to help landowners to transition to living with the disease.

When multiple, co-occurring invasions complicate control efforts, approaches that explicitly consider each strain are necessary to fully capture treatment effects and to holistically

project disease impacts. Here, we worked alongside the Oregon SOD Control Program to develop an integrated multi-strain disease forecast to explore how alternative treatment strategies may alter the overall trajectory of *P. ramorum* invasion. Through this research, we provide guidance on scenarios under consideration by the Control Program and demonstrate how multi-strain simulation approaches can enable the forecasting of complex pathosystems.

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CHAPTER 4

EVALUATING TANGIBLE AND ONLINE USER INTERFACES FOR ENGAGING STAKEHOLDERS IN FORECASTING AND CONTROL OF BIOLOGICAL INVASIONS

4.1. INTRODUCTION

Sustainable natural resource management could benefit substantially from the ability to anticipate ecological trajectories and explore how humans may alter them. Accordingly, ecological forecasts are needed to explore trajectories and interventions on the timescales necessary for decision-making (Dietze et al. 2018). Biological invasions research showcases how scientific and technological advancements have merged to fuel responsive, near-term forecasts to address policy questions (Gilligan and van den Bosch 2008, Meentemeyer et al. 2012). We have better data than ever before on the biology, ecology, and distribution of pests, pathogens, and their hosts (Han et al. 2012, Pasiecznik et al. 2005). New technologies have bolstered rapid field detections and have empowered citizen scientists to join surveying efforts (Ristaino et al. 2019, Bargeron et al. 2007, Nugent 2018). And, substantial increases in computational efficiency have allowed researchers to capitalize on these advancements to develop sophisticated geospatial forecasts of invasive spread (Jones et al. 2019, Meentemeyer et al. 2011). Importantly, treatments can be simulated to evaluate how human interventions may impact spread trajectories, making these forecasts useful for understanding how biological invasions spread and what management tactics are most viable (Miller et al. 2017, Cunniffe et al. 2016, Gilligan and van den Bosch 2008).

These scientific and technological advancements may be moot, however, if decision-makers cannot explore the forecasts. This is a common challenge in computational modeling, often referred to as a knowledge-practice gap, where insights from models are rarely translated into on-the-ground decisions or policy (Matzek et al. 2014, Voinov and Bousquet 2010, Bayliss

et al. 2013). The reasons for this gap can be categorized under three major themes: 1) models are not directly relevant to the problem 2) insights from models rarely reach decision-makers, and 3) the models themselves are not accessible without considerable expertise (Voinov et al. 2016, Knight et al. 2016, Cunniffe et al. 2015, Muscatello et al. 2017, Matzek et al. 2014, Bayliss et al. 2013). Participatory modeling, or designing and applying models in collaboration with stakeholders, has been proposed to address these shortcomings (Voinov and Bousquet et al. 2010, Voinov et al. 2016). By guiding development, stakeholders ensure that the outcomes are relevant to decision-making while simultaneously learning about model processes and uncertainties, how to apply the model, and how to interpret findings (Olabisi et al. 2016, Blades et al. 2016, Jordan et al. 2018). On the flip side, researchers can capitalize on the new perspectives and local knowledge that stakeholders provide. This approach has been used to support decision-making in some cases of natural resource management (Blades et al. 2016, White et al. 2010, Voinov and Gaddis 2008), but is still relatively new in forecasting biological invasions (Gaydos et al. 2019).

Although participatory modeling empowers stakeholders to become amateur modelers, forecasts are often esoteric codes which inherently limit direct stakeholder interaction (Tonini et al. 2017, Cunniffe et al. 2015). For these cases, user-friendly interfaces are key to increasing stakeholder involvement. Interfaces can come in several forms, but should allow users to: 1) quickly and intuitively carry out model functions, 2) vary parameters to explore forecast uncertainty, 3) visualize ecological trajectories, and 4) carry out interventions which alter these trajectories (Petrasova et al. 2018, Jones et al. 2019, Cunniffe et al. 2015). With these capacities, interfaces can unmask the analytical power of forecasts, especially for less tech-savvy stakeholders, enabling them to more easily contribute their perspectives (Gaydos et al. 2019). Essentially, user-friendly interfaces can enable a bottom-up approach where researchers crowdsource diverse opinions to develop new intervention strategies (Voinov et al. 2016).

When designing forecasting interfaces for decision-making, one more aspect should be critically considered: *how the interface facilitates collaboration*. Large-scale environmental problems like biological invasions rarely affect only one stakeholder. Rather, a myriad of decision-makers operate under different jurisdictions and at different geographic and temporal scales (Miller et al. 2017, Crowley et al. 2017, Lovett et al. 2016, Mills et al. 2011). Yet, optimal control necessitates coordination among affected parties (Epanchin-Niell 2010, Crowley et al.

2017). An interface alone cannot solve this problem, but researchers should consider how an interface can support such coordination. Here, we can learn from the concept of boundary objects, which are flexible tools used to mediate communication and knowledge transfer between diverse groups (Star and Griesemer 1989, Star 2010). Because forecasts support the visualization of complex information under alternative scenarios, they can inherently function as boundary objects (Blades et al. 2016). Often, however, only the predetermined outcomes of forecasts are used in this capacity, limiting stakeholders' ability to fully explore dynamic processes (Blades et al. 2016, Cash et al. 2006, Miller at al. 2017). Forecasting interfaces which allow intuitive, on-the-fly interventions may better facilitate decision-making by enabling stakeholders to work together to develop dynamic and adaptive scenarios (Gaydos et al. 2019, Vukomanovic et al. 2019).

Yet, this is an emerging research domain, and little is known about how different forecasting interfaces function as boundary objects (Dix 2009, Boroushaki and Malczewski 2010). Graphical user interfaces (GUIs) have long been the paradigm of human-computer interactions because they are more intuitive than command-line interfaces (Dix 2009). This ubiquity is an advantage because they are familiar to researchers and users alike. Additionally, they can be web-based, enabling widespread access. For compelling examples of web-based GUI forecasting tools, see Cunniffe et al. (2015 B), Jones et al. (2020), and Takeuchi et al. (2019). However, it is unclear how GUIs function as boundary objects, and some human-computer interaction researchers have questioned the limitations of perceiving a 3-dimensional world through 2-dimensional interactions (Ishii 2008). Specifically, by confining users' input to a mouse and keyboard, and visual feedback to 2D graphics, GUIs limit users' ability to perceive, store, and effectively retrieve spatial information (Millar et al. 2018, Ishii 2008). In response, tangible user interfaces (TUIs) were designed so that users could see, feel, and directly experience data through the movement of physical objects (Ishii 2008, Ullmer and Ishii 2000). Theories of embodied cognition assert that by engaging our physical senses, TUIs inherently support more intuitive interaction than GUIs, which may be especially important with less tech-savvy users (Ishii 2008, Kirsh et al. 2013, Ratti et al. 2004). Interestingly, some TUIs are designed to mimic a traditional tabletop workbench to encourage multi-user interactions, which could naturally fit into a boundary object framework (Coors et al. 1999, Petrasova et al. 2018, Underkoffler and Ishii 1999, Higgins et al. 2012). As described by Geller, "tables are

approachable in ways that the standard keyboard-and-screen computer isn't" (2006). Gaydos et al. (2019) and Vukomanovic et al. (2019) detail two cases where TUIs engaged stakeholders in natural resource management. To date, comparisons of these different interface types are lacking and it is unclear which is more conducive for group exploration of forecasts. A better understanding of how such tools resonate with stakeholders could help guide the development of forecasting interfaces.

Under the umbrella of the broader PoPS (Pest or Pathogen Spread) Forecasting and Control Framework, we designed two interfaces for collaboratively exploring alternative spread trajectories: PoPS Tangible Landscape(TL)(a TUI) and PoPS Web Platform (WP)(a web-based GUI) (Figure 4.1) (Jones et al. 2019). These interfaces possess complementary functionality for running the simulation, adjusting parameters, visualizing spread trajectories, and applying interventions, but differ by the interaction modality which may, in turn, influence group dynamics. We evaluated how these technologies shape collaborative exploration of forecasts in the real-world context of sudden oak death (SOD) in Oregon. Sudden oak death, caused by the oomycete *Phytophthora ramorum*, is a remarkably disruptive forest disease responsible for the mortality of millions of trees along the Pacific Coast (Rizzo et al. 2005, Peterson et al. 2015, Cobb et al. 2012). In Oregon, SOD poses unique economic risks as further spread threatens to disrupt the trade of timber products, one of the region's biggest industries (Highland Economics et al. 2019). Accordingly, preventing spread into adjacent counties is of paramount importance to the Oregon Sudden Oak Death Task Force, a diverse collaboration of regional stakeholder interests (Peterson et al. 2015, Highland Economics et al. 2019). We held a workshop with members of the Oregon SOD Task Force to explore near-term trajectories of SOD spread, assess stakeholder perceptions of the forecast and interfaces, and compile suggestions for further research and development. Here, we report the findings from this workshop, including both the scenarios generated and stakeholder perceptions. We reflect on the strengths of both technologies, and suggest that workbench-style tangible interfaces which support multi-user interaction and dynamic geospatial visualization may be best suited for collaborative forecasting. This case study demonstrates how forecasting interfaces can facilitate the collaborative exploration of alternative ecological trajectories of a real-world biological invasion.

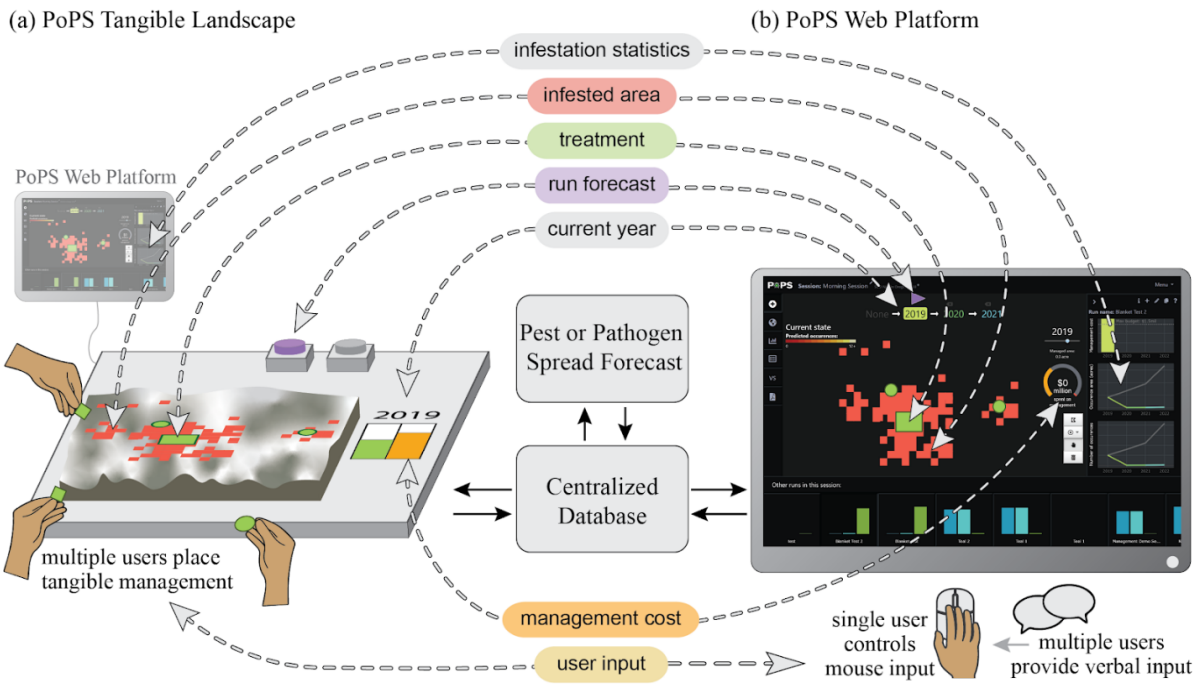

Figure 4.1. Schematic of the complementary functionality of the PoPS user interfaces, Tangible Landscape (TL) and the Web Platform (WP). The systems are linked by a centralized database and the PoPS forecast. PoPS TL (A) is a tangible interface where multiple users physically designate treatments on a representation of the study area. PoPS WP (B) is a web interface where a single user draws treatment based on verbal input from others. Connecting lines show the complementary functionality of the two interfaces. Additionally, PoPS TL displays treatment statistics via the PoPS WP. Figure Credit: Shannon Jones

4.2. CASE STUDY

Sudden oak death poses a substantial threat to southwestern Oregon, U.S.A. To date, two strains of the causal pathogen, *P. ramorum*, have been detected. While similar in many regards, the strains differ in several key ways including virulence, rate of spread, and current geographic distribution (Figure 4.2). The North American-1 (NA1) strain was detected in 2001 near Brookings, Oregon and has since spread to encompass the southwestern corner of the county (Hansen et al. 2008, Goheen et al. 2002, Peterson et al. 2015). In contrast, the European-1 (EU1) strain was detected in 2015 and has largely remained confined to the vicinity of Gold Beach, Oregon (Grunwald et al. 2016). Research suggests that EU1 is more aggressive because it causes larger lesions, produces more spores, and infects Douglas fir and Grand fir seedlings, placing valuable timber products at risk (Manter et al. 2010, Grunwald et al. 2012, LeBoldus et al. 2017).

For these reasons, and because of the novelty of the recent introduction, stakeholders consider EU1 a greater threat.

Nevertheless, either strain could cause considerable environmental and economic damage as spread continues. Tanoak (*Notholithocarpus densiflorus*), the species most likely to die from infection, occurs commonly throughout the region. This high host-density, coupled with a conducive climate, jeopardizes 2100 km^2 of high-risk forests throughout Curry, Coos, and Josephine counties (Vaclavik et al. 2010). Extensive tanoak mortality increases wildfire risks while degrading forest biodiversity and habitat (Cobb et al. 2012, Metz et al. 2011). Tanoak's decline also constitutes a loss of historical cultural practices, such as acorn gathering and basket weaving (Bowcutt 2015, Long and Lake 2018, Highland Economics et al. 2019). Of particular concern to many stakeholders, however, is the expansion of the current quarantine boundary. If either strain were to expand its range into Coos County, quarantine regulations could affect timber trade via the Port of Coos Bay, one of Oregon's largest ports. An economic assessment found that if trade were disrupted, it could affect 1,200 jobs and $57.9 million in annual wages (Highland Economics et al. 2019). These effects would likely ripple throughout the region, thus, preventing the northward spread of SOD into Coos County is of paramount importance to the Oregon SOD Task Force.

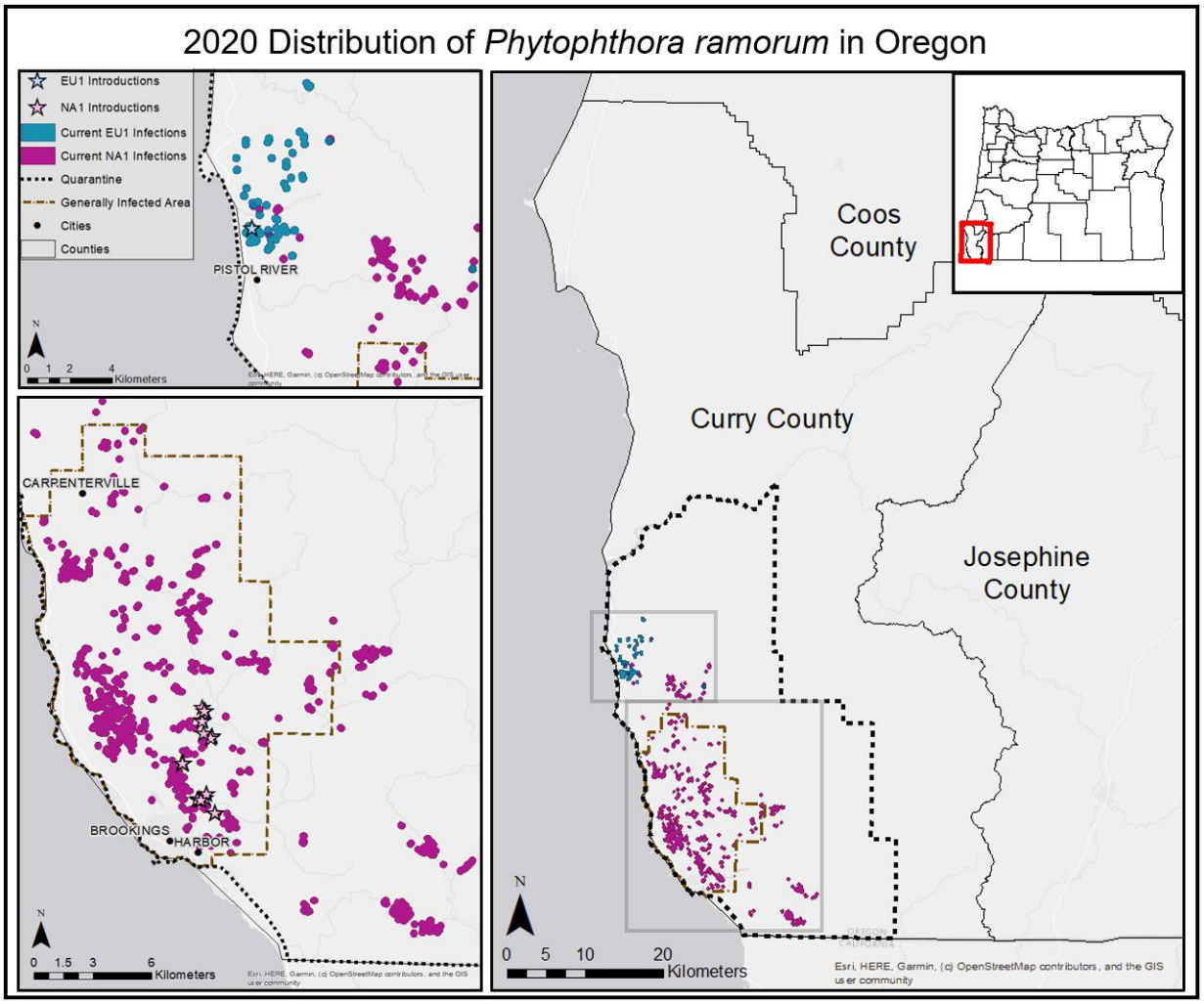

Figure 4.2. The current distribution of both strains (EU1 and NA1) of *Phytophthora ramorum* in Curry County, Oregon.

4.3. METHODS

4.3.1. Participatory Approach

Routine and consistent engagement with stakeholders is a central feature of participatory modeling (Voinov et al. 2016). Following these principles, the research presented here has arisen from a long-term collaborative engagement with Oregon stakeholders. In 2017, we conducted an initial participatory workshop with the Core Science Team of the Oregon SOD Task Force (Gaydos et al. 2019). At the time, SOD forecasts existed solely for California where epidemiological conditions are different (Meentemeyer et al. 2011, Cunniffe et al 2016). Through this workshop, we gathered critical observations of local epidemiology to tailor the

forecast for Oregon conditions. In particular, stakeholders honed in on the underlying host data and differences between the two pathogen strains, suggesting that we account for disturbance-based effects on host density and forecast the strains separately (Gaydos et al. 2019). Additionally, we debuted the PoPS TL platform and chronicled suggested improvements, including incorporating yearly management interventions and developing an additional GUI interface (Gaydos et al. 2019). This has subsequently guided our research in the following ways: 1) we refined the host data by reducing density in unsuitable and disturbed areas, (2) we calibrated and validated the epidemiological forecast separately for the two pathogen strains (Chapter 2), 3) we incorporated an adaptive management capacity, and 4) we developed packages for R (R Core Team 2019) and GRASS GIS (GRASS Development Team 2019), and the PoPS WP as additional interfaces (Jones et al. 2019).

Our collaboration with the Core Science Team continued throughout forecast and interface development to ensure that new developments met stakeholders needs and expectations and were consistent with the ever-changing conditions of SOD management. To stay connected, we participated in regularly-scheduled meetings, research symposiums, and semi-structured interviews. Additionally, the Core Science Team helped us overcome the challenge of geographic distance by acting as an intermediary between us and the larger Oregon SOD Task Force. By relaying information, they kept us abreast of any new scientific developments and changes in the political realities of management. Further, they kept the Task Force informed about our interface development which helped maintain the bidirectional flow of information that is key to participatory research (Voinov and Gaddis 2008). This consistent and routine engagement contributed directly to the development of the forecast and interfaces, as well as the collaborative forecasting workshop described below.

4.3.2. Forecasts

To forecast the spread of SOD in Oregon, we updated forecasts developed for California (Meentemeyer et al. 2011) based on local observations provided by the Oregon SOD Task Force as described in Gaydos et al. 2019 and Chapter 3. The forecast is a stochastic, spatially-explicit, susceptible-infected-removed (SIR) simulation which uses raster-based initial infection locations, relative host density, and weekly weather conditions to mimic pathogen dispersal and establishment across the landscape. Forecasts are largely controlled by two parameters,

reproductive rate and dispersal distance, which were calibrated for the EU1 and NA1 strains separately (Chapter 3). It is important to note that, in congruence with field observations, the EU1 strain spreads faster in the forecast than the NA1 strain. For this workshop, we forecasted a 3-year period from 2020 to 2022, starting with 2019 infections. Infection locations, obtained from the Oregon Department of Forestry, portray the current distribution of each strain as of September 2019. Some 2019 infections were still pending genotyping and could not be definitively assigned to a strain. For these cases, the closet genotyped strain served as a proxy since most SOD dispersal is local (Rizzo et al. 2005, Peterson et al. 2015). Host data representing the proportion of tanoak in a cell was originally acquired as forest species maps from Ohmann et al. 2011 and processed as described in Chapter 2. We assumed an average future weather scenario, generated by resampling historical DayMet weather data (Thornton et al. 2017) using a revised version of Meentemeyer et al. (2011 which accounts for reduced fitness at temperatures between 0-2°C. All raster data was processed at a 100m resolution and represented the extent of Curry County, Oregon.

Regardless of interface, treatments are carried out the same way. The user designates treatment polygons using either felt markers in PoPS TL or a point-and-click draw tool in the PoPS WP (Petrasova et al. 2018, Jones et al. 2019) (Figure 4.1). If a cell intersects a treatment polygon, all infected trees are removed and a proportion of susceptible trees relative to the area of the cell covered by the polygon are removed. By conducting treatments in this way, we are giving users the benefit of the doubt that infected trees were located and removed, while simultaneously acknowledging that cells which were not fully treated could become reinfected later. These treatments are designated by users in January of the forecast year, but not applied until the following December of that year to account for realistic time-lags between detection and treatment, during which the disease has the opportunity to spread (Kanaskie et al. 2011). Treatments cost \$1.23/m^2 (Highland Economics et al. 2019), but were not counted where treatments overlapped or no hosts were present.

In previous studies, treatments could only be conducted in the first year of the forecast (Tonini et al. 2017, Gaydos et al. 2019). Through iterative feedback from Oregon stakeholders, we developed an adaptive management capacity which allows for yearly interventions (Gaydos et al. 2019). The stochasticity made this particularly challenging because individual iterations of the forecast can be quite different. Visualizing several stochastic iterations as a probability of

infection can help users understand the potential range of outcomes. However, real-world decisions are based on known infections, represented as a single stochastic iteration. To meet both of these needs, we developed an iterative framework where management was conducted on a single stochastic iteration, but future disease spread was visualized as a probability. Users place treatments based on the current 2019 infections and then run 10 stochastic iterations until the final year (2022). The single iteration that is closest to the average of all iterations is selected and replaces 2019 as the new starting point, essentially the new "simulated reality." To see how this current trajectory may play out into the future assuming no new treatments, users can visualize the infection probabilities in 2021 and 2022. With this information, users decide how to treat the 2020 infections, repeating this process until the final management year (2021) and the final visualization year (2022). This adaptive management capacity allows a user to walk through a simulated reality where they can explore the direct effect of treatments while simultaneously forecasting likely disease spread and impacts.

4.3.3. Forecast Interfaces

The forecast, composed of R and C++ code, can be run via two open-source interfaces: PoPS TL and the PoPS WP. The interfaces share an underlying simulation, can be linked via the web platform, and were designed with complementary functionality for running the simulation, adjusting parameters, visualizing spread trajectories, and applying interventions. And, importantly, stakeholder feedback was iteratively incorporated throughout development of both systems to improve usability (Gaydos et al. 2019, Jones et al. 2019). PoPS TL is a TUI where users intuitively guide a geospatial simulation via physical actions (Ishii 2008). It was designed as a general geospatial modeling tool and has been used in several applications besides pest and pathogen spread (Petrasova et al. 2018). The system consists of a scanner, a projector, a physical representation of the study area landscape, and a computer equipped with GRASS GIS (Petrasova et al. 2018) (Figure 4.1A). Current infection locations, host density, and aerial imagery are projected onto the physical landscape for visualization. With this information, stakeholders designate the spatial allocation of treatments by cutting out piece of felt (or using prepared circular shapes) and placing them on the landscape. A steering dashboard next to the landscape displays the timeline and the cost of proposed treatments to guide scenario development. Users run the forecast one year into the future with the click of a button and scroll

through past observations and future probability forecasts using a clicker. All scenario information is stored on a web-based summary dashboard (linked to PoPS WP) which helps users quickly compare scenarios by infected area, cost of treatment, and spread rate. This interface has been successfully applied in multiple case studies of pest and pathogen spread (Gaydos et al. 2019, Tonini et al. 2017).

During our prior workshop with the PoPS TL interface, stakeholders expressed interest in a standalone web system with similar management functionality (Gaydos et al. 2019). This sparked the development of the PoPS WP (Figure 4.1B). Rather than interacting with a physical representation of the study area, users interact via a web map and a traditional mouse tool. Users designate treatments via a point-and-click draw tool with some common shapes, such as circular buffers, preloaded. As with PoPS TL, the cumulative cost of proposed treatments is displayed via the cost widget to help users develop scenarios within budget limits. The run forecast button is analogous to the physical button, moving the forecast one year into the future. Users scroll through future forecasts using the display year toggle. Importantly, the PoPS WP also functions as a summary dashboard for PoPS TL with detailed information about all scenarios, linking these standalone systems (Figure 4.1).

Although the interfaces function similarly, there are some key differences concerning modes of interaction. As a TUI, it is theorized that PoPS TL could naturally facilitate group interaction as users gather around the physical landscape to negotiate scenarios (Petrasova et al. 2019, Coors et al. 1999, Underkoffler and Ishii 1999, Geller 2006). Importantly, this also enables users to simultaneously place treatments with ease (Figure 4.1A). In contrast, the PoPS WP draws participants' attention towards a mounted computer monitor and because it is controlled by one computer mouse, groups must designate someone to draw the proposed treatments (Figure 4.1B). So although the forecast is the same, the group dynamic generated by the interface can be different. Another key difference is that the PoPS TL study area is static due to the physical landscape (Petrasova et al. 2018). A tradeoff exists where increasing the scale of the study area inherently increases the scale of treatments. To conduct realistic, targeted treatments, the study area must remain relatively compact. In comparison, the PoPS WP offers much more flexibility to zoom and pan around large study areas. For these reasons, PoPS TL was better suited to modeling the confined EU1 outbreak, while the PoPS WP was more appropriate for the widely-dispersed NA1 strain.

4.3.4. Workshop

We used our long-standing relationship with members of the Core Science Team to organize a Sudden Oak Death Management Scenarios Workshop on September 10th, 2019 at the Oregon Department of Forestry Headquarters in Salem, Oregon (Figure 4.3). Our goals were to: 1) provide decision support for SOD management in Oregon, 2) assess stakeholder perceptions of the forecast and interfaces, and 3) collect suggestions to guide further forecast and interface development. We incorporated the entire Oregon SOD Task Force (including our collaborators on the Core Science Team) to ensure a diversity of perspectives was represented. The workshop was strategically scheduled to coincide with a routine Task Force meeting to encourage participation. Participants were invited from each of the 37 Task Force organizations, starting with the main contacts provided by Task Force organizers. If a participant could not attend, they were encouraged to recommend another individual to represent their organization. All organizations were contacted at least 3 times: twice by researchers and once by Task Force administrators.

Similar research suggests that smaller groups promote more participatory interaction (Gaydos et al. 2019, Blades et al. 2016, Kaner 2010). Prior to the workshop, we split participants into two subgroups, A and B, using a stratified random sample. We categorized each organization into the following groups: federal government, state and local government, tribal government, timber industry, nonprofits, and academia. We chose this classification scheme based on a priori knowledge and on the hypothesis that these groups would share similar decision-making purviews. Within each organizational grouping, participants were randomly assigned to either group A or B until the participant list was exhausted. This approach allowed us to create a small group dynamic while still preserving the organizational diversity that exists within the Task Force.

The full-day workshop was partitioned into several activities. After completion of the pre-workshop questionnaire, researchers gave a thorough, but brief, project overview covering the history of the project, our participatory work with the Core Science team, and how the forecast and interfaces work. It is well known that clear communication is key in participatory modeling, as “black box” systems are less likely to be considered credible, salient, or legitimate (Beier et al. 2017, Voinov et al. 2016, Rambaldi et al 2006, Voinov and Gaddis 2008). To avoid this perception, we made the code open source and encouraged questions and carefully explained

forecast processes, assumptions, and uncertainties (Van Voorn et al. 2016, Rambaldi et al. 2006). Stakeholders were then split into predefined groups. Group A started at the PoPS TL station where they assessed EU1 spread, while Group B started at the PoPS WP assessing NA1 spread. Researchers walked participants through the functionality of the interfaces, demonstrated the adaptive management workflow, and encouraged participants to test management scenarios. Following lunch, the groups switched stations to ensure that all participants interacted with both interfaces. Each modeling session lasted 90 minutes, the upper-limit recommended for group activities (Kaner 2010). We administered the post-workshop questionnaire following the afternoon session. To conclude, we held a semi-structured group discussion to summarize key insights and promote convergent thinking, a creative-thinking activity shown to aid group decision-making (Cropley 2006, Kaner 2010). Following the workshop, the Task Force held a meeting to review the current treatment plan in light of what was learned via the forecast. A report detailing the scenarios was distributed to the Task Force following the workshop.

4.3.5. Questionnaires

Participants were asked to complete questionnaires before and after the modeling sessions, a common technique in participatory modeling (Blades et al. 2016, Morisette et al. 2017, White et al. 2010). Importantly, questionnaires were adapted from our prior work with the PoPS TL interface (Gaydos et al. 2019). Questionnaires were expanded considerably, however, to apply to both interfaces and to include a more robust assessment of usability. Questionnaires were a combination of open-ended questions, 5-point Likert-items, and yes/no questions, designed by the standards in Dillman et al. (2014) and Fowler (2013).

The pre-workshop survey gauged the participants' expertise with GIS and disease forecasts, and whether they had used these tools relating to forest disease management. This is important, as a participant’s technological expertise may influence how they perceive the forecast and interfaces (Harvey and Chrisman 1998, Gaydos et al. 2019). The post-workshop questionnaire collected participants’ perceptions of credibility, salience, and legitimacy (Van Voorn et al. 2016). Forecast credibility (i.e., scientific accuracy) was measured by perceptions of processes, assumptions, and underlying host data. These metrics were chosen because the accuracy of processes and assumptions are well-established measures of model credibility (Van Voorn et al. 2016) and host data was previously identified as an area for improvement (Gaydos

et al. 2019). Salience (i.e., usability and relevance) was assessed by interface usability (described in-depth below), how the interface supported treatment prioritization, and if the forecast's management capabilities enabled testing of all relevant scenarios. Legitimacy (i.e., respectfulness and mediation of stakeholder's values) was assessed via how the interfaces facilitated discussion and collaboration, if the treatment functionality was designed to meet decision-makers' needs, and if the workshop facilitated open discussion. Since the forecast and treatment type were the same for both interfaces, questions about processes, assumptions, underlying host data, and treatments were asked only once. In contrast, questions about interface usability, and how the interfaces facilitated treatment prioritization, discussion, and collaboration were asked for each to allow comparison.

The usability of both PoPS TL and PoPS WP was assessed via the System Usability Scale (SUS) which we integrated into the post-workshop questionnaire. Often described as a "quick and dirty" usability scale, the SUS questionnaire provides a broad, subjective measure of usability, which has proven to be a reliable and valid industry standard (Brooke 1996, Bangor et al. 2008). It is composed of ten 5-point Likert-scale questions, alternating between positive and negative concepts to limit response bias (Dillman et al. 2014, Fowler 2013). Overall scores are converted to a 0-100 scale, with 100 being the most positive (Brooke 1996). This numeric rating can be further differentiated by an adjective rating scale with categories including: best imaginable, excellent, good, okay, poor, awful, and worst imaginable (Bangor et al. 2008). While other assessments of usability exist, we found that the SUS questionnaire provided a reasonable tradeoff between reliability and the time taken to complete the survey. Additionally, the SUS questionnaire has been applied to a wide range of technologies and has been used to assess the difference between interfaces, making it highly applicable for our case (Bangor et al. 2008).

Lastly, we collected open-ended responses to inform further interface development and future collaborative forecasting workshops. Collaborative learning is considered a fundamental goal of participatory modeling (Voinov et al. 2016, Jordan et al. 2018). We asked stakeholders to record what they learned, if anything, to better understand stakeholders' perceptions of the workshop. Additionally, participants were also asked to describe any additional scenarios that could not be tested as-is with the goal of expanding forecast functionality. Lastly, participants were asked to give broad feedback on any aspects of the forecast, interfaces, or workshop to guide future collaborative forecasting workshops. Qualitative survey responses were inductively

categorized into themes which emerged during the workshop. Two researchers independently categorized responses, and then collectively negotiated any disagreements to reach the categorizations presented here (Zhang and Wildemuth 2009, Campbell et al. 2013).

4.4. RESULTS

4.4.1. Workshop

In total, 34 participants represented 21 organizations at the Sudden Oak Death Management Scenarios Workshop on September 10th, 2019. Participants represented state/local government (11), federal government (9), academia (5), nonprofits (5), timber industry (3), and tribal governments (1). Three participants were members of the Core Science Team of the Task Force who were present at the first participatory model building workshop (Gaydos et al. 2019). Through a stratified random sample, this organizational diversity was captured in two smaller subgroups. Group A had 15 total participants with representation from federal government (4), state/local government (4), academia (3), timber industry (2), and nonprofits (2). It should be noted that all three members of the Core Science Team who were part of our first workshop were randomly assigned to Group A (Gaydos et al. 2019). Group B had 17 total participants with representation from federal government (4), state/local government (6), academia (2), timber industry (1), nonprofits (3), and tribal government (1). Two participants could only attend one of the two modeling sessions, and were therefore not assigned to a group. Instead, they switched between groups to interact with both technologies.

Figure 4.3. Workshop participants developing intervention scenarios using PoPS TL (A) and PoPS WP (B). Photo credit: Vaclav Petras.

4.4.2. Questionnaire Analysis

Of the 34 workshop participants, 32 completed the pre-workshop questionnaire and 29 completed the post-workshop questionnaire for response rates of 94% and 85%, respectively. Due to an omitted page, all direct comparisons of PoPS WP and PoPS TL had an N=28. All survey responses were coded from 1 to 5, with 3 as neutral and 5 as the most positive. While Groups A and B returned a similar number of questionnaires (Group A: 15 pre, 14 post; Group B: 15 pre, 13 post), Group B had a slightly lower response rate due to a larger group size (Group A: 100% for pre, 93% for post; Group B: 88% for pre, 76% for post). Participants who missed any part of either the pre- or post-workshop surveys were given two opportunities to respond via an online-version. While nonresponses could potentially bias our results, especially if these participants had differing views, we find this response rate comparable to other similar workshops (Blades et al. 2016).

We characterized participants' familiarity with GIS and disease forecasts, which may impact their overall perceptions of the forecasting and interfaces (Harvey and Chrisman 1998). Most stakeholders considered themselves familiar with GIS (average = 4.38), but only a third (34%) had used it for forest disease management. Participants were less familiar overall with disease forecasts (average = 3.34), and fewer than a third (28%) had used them. Only 7 of the 32 participants who completed the pre-workshop questionnaire had used both GIS and disease forecasts, suggesting that most participants were new to the geospatial disease forecasts used in the workshop.

Participants predominantly found the forecast credible. Forecast processes were considered the most credible (average = 4.20), followed closely by the assumptions which underlie these processes (average = 4.12). Responses were more varied, but still positive, regarding the accuracy of the host distribution data (average = 3.85), suggesting this may still be an area for improvement. However, it should be noted that a handful of participants (4-5) chose the "don't know" option for these questions, so while most participants felt confident in the scientific accuracy of the forecast and data, others felt that they did not have enough information to comment. Mann Whitney U tests were conducted to assess whether there were significant differences in ratings given by participants who had used GIS or disease forecasts prior to the workshop and those who had not. Results revealed no significant difference (Table 4.2),

suggesting that prior use of such tools had no bearing on how credible participants found the forecast and data.

An analysis of 206 studies found a global average SUS score of 69.69 (Bangor et al. 2008). Based on the 28 participants who completed the SUS questionnaire, both PoPS TL (71.34) and PoPS WP (68.26) had an average usability. When converted to the adjective scale described by Bangor et al. (2008), both systems are considered "good". While the usability ratings were similar, a majority of individuals (16) rated PoPS TL more favorably. We used a paired Wilcoxon signed rank test to compare individuals' preferences. Results reveal a statistically significant difference in the usability ratings, with stakeholders considering PoPS TL more user-friendly (Table 4.1). Usability ratings did not differ significantly based on prior GIS or disease model use according to Wilcoxon signed rank tests (Table 4.2).

Other measures of salience were also rated positively. Participants found both interfaces useful for prioritizing treatment locations (PoPS TL average = 4.53, PoPS WP average = 4.25), with ratings for PoPS TL being particularly positive. This difference was observed through paired Wilcoxon tests, finding that participants preferred PoPS TL for prioritizing treatments (Table 4.1) over PoPS WP. The lowest measure of salience related to whether or not the forecast was able to address all relevant scenarios (average = 4.06). A majority of participants (58%) did not offer suggestions for additional management capabilities. For those that did, comments were inductively coded into 6 themes by 2 researchers: 1) scenarios involving landowner information [3], 2) additional treatment customizations [3], 3) something other than SOD management [3], 4) more variation in funding [1], 5) longer timeframes [1], and 6) including other SOD hosts [1] (Appendix E). In examinations of prior use of GIS and disease forecasts, we found no significant relationships to overall ratings, nor how likely a person was to suggest additional scenarios (Table 4.2).

When considering forecast legitimacy, the management capabilities and whether or not they met stakeholders needs had the lowest, but still positive, rating (average = 3.79). The interfaces' abilities to facilitate discussion and collaboration, however, the results were broadly positive. Both interfaces were rated higher in their ability to facilitate discussion (PoPS TL average = 4.57, PoPS WP average = 4.39) than their ability to enable collaboration (PoPS TL average = 4.45, PoPS WP average = 4.14). PoPS TL was rated higher in both metrics, but this relationship was significant only for enabling collaboration (Table 4.1). For the PoPS TL

interface, we found no effect of prior GIS or disease model use (Table 4.2). Interestingly, we found that those who had used GIS before were more likely to consider PoPS WP effective at facilitating discussion (Table 4.2), but this relationship was not found for disease model expertise.

We also assessed participants' perceptions of the workshop itself. Participants overwhelmingly agreed that the workshop encouraged open discussion of ideas (average = 4.44) and that they learned something (average = 4.58). Additionally, 86% of participants provided comments about what they learned, which were inductively coded into 5 themes: 1) about the forecasting tools [14], 2) about the effectiveness of treatments [7], 3) about the importance of collaborative learning [5], 4) about the potential use as teaching tools [3], 5) and about sudden oak death in general [3] (Appendix E). All organization types mentioned the forecasting tools and the effectiveness of treatments, suggesting that these were the most ubiquitous takeaways.

Ten participants (34%) suggested improvements to either the forecast, interfaces, or workshop. Responses were inductively coded into 5 themes: 1) additional data visualizations [6], 2) restructuring group modeling activities [5, 3) additional success metrics [3], 4) alternative scenarios [3], and 5) adding management features [2] (Appendix E). Several comments overlapped with previous suggestions for additional management capacities, reinforcing need for improvement. Several of the suggestions reflected the need for additional flexibility in visualizations and types of management, which are case-specific and easily-changed. We also received some suggestions regarding the workshop format. Stakeholders recommended that we shorten the forecast sessions and incorporate more structured scenarios, which will inform future workshops. Lastly, several participants offered compliments that contained no suggestions [8]. In most cases, both interfaces were mentioned, but PoPS TL [3] was singled out in comments more than the PoPS WP [1]. Outside of the workshop, some participants inquired about using the interfaces for other case studies, including teaching, citizen science, and other pest and pathogen systems. Intriguingly, more participants expressed interest in using PoPS WP [3] than PoPS TL [1], likely because of the ease of accessing from a standard laptop.

Table 4.1. Comparison of how participants perceived PoPS Tangible Landscape and PoPS Web Platform. The System Usability Scale ranges from 0-100 with 100 being most positive. All other metrics range from 1-5, with 5 being the most positive. We report average scores with standard deviation in parentheses. Significant differences are denoted with an *.

Stakeholder Perception	Rating of Tangible Interface	Rating of Web Interface	Paired Wilcoxon Test of Difference
Salience: System Usability Scale	71.34 (9.48)	68.26 (12.15)	p = .04*
Salience: Prioritizing Treatments	4.53 (.51)	4.25 (.59)	p = .02*
Legitimacy: Facilitating Discussion	4.57 (.69)	4.39 (.50)	p = .20
Legitimacy: Enabling Collaboration	4.45 (.51)	4.14 (.71)	p = .04*

Table 4.2. Comparison of how participants with different technological expertise rated the forecast and interfaces. Participants were divided by whether or not they had used geospatial information systems or disease models prior to the workshop. The System Usability Scale ranges from 0-100 with 100 being most positive. All other metrics range from 1-5, with 5 being the most positive. We report average scores with standard deviation in parentheses. Significant differences between those with and without prior experience are denoted by a *.

		Forecast		Tangible Interface		Web Interface	
	Perception Metric	With/ Without GIS Experience	With / Without Disease Model Experience	With/ Without GIS Experience	With/ Without Disease Model Experience	With/ Without GIS Experience	With/ Without Disease Model Experience
Credibility	forecast processes	3.8 (.67) / 4.3 (.77)	4.3 (.71) / 4.2 (.75)	---	---	---	---
		p = .66	p = .89				
	forecast assumptions	4.3 (.48) / 4.0 (.58)	4.1 (.35) / 4.1 (.64)	---	---	---	---
		p = .22	p = .94				
	host data	3.8 (1.09) / 4.0 (.88)	4.1 (.83) / 3.8 (1.01)	---	---	---	---
		p = .64	p = .52				

Table 4.2 (continued).

Salience	management capabilities	4.4 (.70) / 4.0 (.84)	4.0 (.83) / 4.2 (.76)	---	---	---	---
		p = .23	p = .53				
	system usability scale	---	---	75.3 (8.70) / 71.0 (9.78)	74.1 (9.25) / 71.9 (9.73)	68.61 (11.18) / 70.75 (12.90)	74.38 (10.50) / 67.38 (12.42)
				p = .35	p = .76	p = .14	p = .21
	prioritizing treatments	---	---	4.6 (.52) / 4.5 (.51)	4.5 (.53) / 4.5 (.51)	4.5 (.53) / 4.1 (.58)	4.4 (.52) / 4.2 (.62)
				p = .63	p = .83	p = .10	p = .53
Legitimacy	facilitating discussion	---	---	4.6 (.52) / 4.5 (.78)	4.6 (.52) / 4.6 (.76)	4.7 (.48) / 4.2 (.43)	4.5 (.53) / 4.4 (.49)
				p = .84	p = .10	p = .01*	p = .48
	enabling collaboration	---	---	4.4 (.52) / 4.5 (.51)	4.5 (.53) / 4.5 (.51)	4.5 (.53) / 3.9 (.73)	4.2 (.71) / 4.1 (.72)
				p = .64	p = .84	p = .04*	p = .66
	management capabilities designed for stakeholder	3.9 (.57) / 3.8 (.65)	3.9 (.64) / 3.8 (.62)	---	---	---	---
		p = .60	p = .79				

4.4.3. Scenario Analysis

Stakeholders generated a total of 13 scenarios for SOD management in Oregon (Table 4.3). A majority of the scenarios [9] focused on the more-aggressive EU1 strain which has been of particular concern to the Task Force. All EU1 scenarios were conducted via PoPS TL. The remaining four scenarios focused on the NA1 strain and were conducted via PoPS WP. Scenarios were analyzed by total costs, infected area in 2022, applied management tactics, and how they distributed their budget (Table 4.3). Several epidemiological modeling studies have documented spatial management strategies, both in the case of SOD and elsewhere, creating a typology of

tactics (Filipe et al. 2012, Cunniffe et al. 2016, Hyatt-Twynam et al. 2017). Stakeholders explored the following tactics: 1) wave front: removing infections along the spreading-front of the disease, 2) foci: removing densely-infected areas near the disease epicenter, 3) eradication: removing all or nearly-all infections in a single year, 4) host barrier: removing a line of hosts ahead of the spreading-front, and 5) preemptive host removal: removing uninfected areas with high host density that were nonadjacent to current infections. Importantly, scenarios often contained a combination of several tactics. Apart from the spatial organization of treatments, there was the question of how to distribute the 3-year budget. Some modeling studies have demonstrated that front-loading a budget (i.e., spending a majority of the budget early in disease management) is a cost-effective way to reduce long-term disease impacts (Cunniffe et al. 2016, Thompson et al. 2018). Stakeholders tested this front-loading strategy in 4 of the scenarios. Additionally, stakeholders tested some extreme budget scenarios which are unrealistic, such as NA1 Scenario 4, but provide insights into disease control.

Table 4.3. Stakeholders developed 13 scenarios of SOD management in Oregon, with 9 focusing on the EU1 strain and 4 focusing on the NA1 strain. Scenarios are differentiated by money spent, area infected in 2022, tactics applied, and how budget was distributed. The most cost-effective and least cost-effective scenarios for each strain are designated with a * and †, respectively.

	Scenario Name	**Interface**	**Disease Management Tactics**	**Budget Division**	**Money Spent**	**Acres Infected in 2022**
	EU1 No Management Scenario		---	---	---	1,282
Group A	EU1 Scenario 1	tangible	1. Eradication 2. Eradication 3. eradication	evenly divided	2,801,314	66
	EU1 Scenario 2	tangible	1. Eradication, host barrier 2. Eradication, host barrier, preemptive host removal 3. eradication	evenly divided	2,780,255	27
	EU1 Scenario 3	tangible	1. Wave front 2. Wave front 3. Wave front, foci	evenly divided	2,117,724	596

Table 4.3 (continued).

Group B	EU1 Scenario 4	tangible	1. host barrier, wave front 2. Wave front 3. Wave front, foci	evenly divided	2,812,770	511
	EU1 Scenario 5	tangible	1. Eradication 2. wave front 3. eradication	evenly divided	2,736,891	160
	EU1 Scenario 6*	tangible	1. Wave front 2. Wave front 3. Wave front, host barrier	evenly divided	1,344,419	487
	EU1 Scenario 7	tangible	1. Eradication 2. Eradication 3. Eradication	front loaded	2,384,983	34
	EU1 Scenario 8†	tangible	1. Eradication 2. Eradication 3. eradication	front loaded	5,038,509	54
	EU1 Scenario 9	tangible	1. Eradication 2. Eradication 3. eradication	front loaded	4,624,446	34
	NA1 No Management Scenario		---	---	---	6,766
Group A	NA1 Scenario 1*	web	1. Wave front 2. Wave front 3. Wave front	evenly divided	7,979,514	6,009
Group B	NA1 Scenario 2	web	1. Host barrier, wave front 2. Host barrier, wave front 3. Host barrier, wave front	evenly divided	7,152,207	6,401
	NA1 Scenario 3	web	1. Wave front 2. Wave front 3. Wave front	evenly divided	8,320,519	5,974
	NA1 Scenario 4†	web	1. Eradication 2. No management 3. No management	front loaded	520,626,142	91

4.5. DISCUSSION

Forecasts are effective for exploring alternative trajectories of biological invasions, but will have less impact on control strategies if inaccessible to decision-makers (Voinov and Bousquet 2010). Reflecting other studies, our survey results show that despite familiarity with forecasting tools, there has been little adoption amongst SOD stakeholders in Oregon (Gaydos et al. 2019). This knowledge-practice gap is common and limits forecasts' potential to address ecological challenges (Matzek et al. 2014, Cunniffe et al. 2015, Knight et al. 2016). Here, we show how user-friendly interfaces and participatory approaches can reduce this gap by enabling adaptive experimentation, driving future research, and promoting collaborative learning.

On-the-fly collaborative exploration of intervention strategies would have been tedious, if not nearly-impossible, with the code-based versions of the forecast. Both interfaces were a significant improvement in this regard. Both were broadly considered credible, salient, and legitimate, and had "good" usability scores, reflecting a participant's comment that the forecast was "extremely useful from a planning perspective." We found that, for most metrics, ratings were unaffected by prior experience with GIS and disease forecasts, suggesting that the interfaces successfully reduced the traditional technological barriers to use (Table 4.2). Further, the adaptive management capacity, which arose from our previous participatory workshop, empowered stakeholders to generate novel intervention scenarios (Table 4.3) (Gaydos et al. 2019). Although the tactics themselves were not novel, and had been tested in the case of SOD (Cunniffe et al. 2016, Filipe et al. 2012), stakeholders combined the tactics in unique ways. Most forecasting studies only apply one tactic per scenario, which explores a tactic's stochastic effectiveness, but prevents the kind of adaptive experimentation which is encouraged in natural resource management (Serrouya et al. 2019). Here, stakeholders combined several tactics and changed their approaches through time, which may better reflect the realistic-complexities of control (Kanaskie et al. 2010, Walters and Holling 1990). Lastly, stakeholders had to negotiate their diverse perspectives in order to design scenarios, representing an innovative, bottom-up approach to forecasting which one participant described as, "hands-on learning amongst stakeholders to deal with natural resource issues." In this way, we demonstrate how user-friendly interfaces, regardless of mode of interaction, can empower stakeholders in the forecasting and control of biological invasions.

We observed some key differences, however, in how stakeholders used and perceived the two interfaces. Both groups generated more scenarios using PoPS TL, which exceeded PoPS WP in all survey comparisons. Further, this preference was statistically significant for three metrics: system usability, prioritizing treatments, and enabling collaboration (Table 4.1). So, while both interfaces provided advantages over the code-based versions, participants preferred PoPS TL for collaborative forecasting. Our observations suggest that this preference was driven by the physical setup and the multi-user interaction. The physical setup energized the group dynamic as participants physically gathered around the system to develop scenarios (Figure 4.3A), echoing suggestions that workbench-style tangible interfaces naturally promote group interaction (Coors et al. 1999, Underkoffler and Ishii 1999, Petrasova et al. 2018, Millar et al. 2018, Geller 2006). Additionally, this workbench layout allowed several participants to access the interface, paving the way for the multi-user input which was likely the greatest collaborative advantage of PoPS TL (Figs. 1A and 2A). Essentially, stakeholders could simultaneously construct interventions which facilitated teamwork and reduced the time taken to develop scenarios. We also found that, like other tangible systems (Underkoffler and Ishii 1999), PoPS TL stimulated playful interactions, with one participant commenting, “the tangible landscape really gets stakeholders talking and engaging in a fun and constructive manner”. This playful dynamic may be especially important, as studies have shown that stakeholders are more likely to prioritize fun or novel engagement activities (White et al. 2018). These factors combined to make PoPS TL a particularly effective forecasting boundary object.

However, PoPS WP outperformed PoPS TL in some areas. Both researchers and participants observed that PoPS WP provoked in-depth dialogue, with one participant commenting, “I was fascinated with the Tangible Landscape, but PoPS WP seemed to trigger more inclusive discussion.” As with PoPS TL, this is partly due to how the interface influenced group dynamics. The single-user input necessitated greater verbal communication as groups dictated scenarios to the individual drawing treatments (Figure 4.1B). However, we also observed how the dynamic data visualization fueled communication. As participants panned and zoomed around the flexible study extent, they analyzed fine-scale details of the treatments and the underlying GIS data. This sparked conversations about the patterns of disease spread, the accuracy of the underlying host data, the spatial configuration of treatments, and what other data would be relevant for decision-making, which ultimately inspired participants’

recommendations. Essentially, PoPS WP became a platform to analyze the GIS data, which may explain why those with GIS experience rated it more favorably for facilitating discussion (Table 4.2). Since mediating knowledge transfer is a central function of boundary objects, this aspect of the PoPS WP warrants recognition.

Given the strengths of both systems, we suggest developing workbench-style interfaces which support intuitive multi-user interactions and dynamic geospatial visualizations. Multitouch tables, like those commonly found in interactive museum displays, naturally fit into this context (Geller 2006). They are intuitive, responsive to touch, and enable simultaneous data exploration (Higgins et al. 2012, Antle et al. 2011). They could be powerful tools for collaborative forecasting of biological invasions. However, there are several limitations. Commercially-available products can be expensive, difficult to transport, and sometimes rely on proprietary software which can limit applications. Researchers can build low-cost alternatives, but this requires time and expertise (Schöning et al. 2008). In addition to exploring multi-touch tables, we are developing low-cost alternatives which build upon our existing framework. We are implementing zoom functionality to improve the dynamic visualization of PoPS TL and are exploring websockets, commonly used in online chatrooms, to enable simultaneous treatment placement from either interface (Lombardi 2015). By linking dynamic data visualization with simultaneous interactions, each alternative route of development is promising for increasing the collaborative capacity of biological forecasts.

Additionally, our participatory approach allowed stakeholders to drive research and development of the broader PoPS Forecasting and Control Framework (Jones et al. 2019). Survey results indicated that stakeholders desired more flexibility in terms of visualizations and treatment options. For example, stakeholders recommended visualizations of roads, land ownerships, and weather suitability to better inform decision-making, and requested more options in terms of management buffers and treatment types. This suggests that incorporating a high-degree of flexibility into visualizations and interventions may strengthen stakeholders' perceptions of salience and legitimacy. Survey results also highlighted the underlying host distribution data as an area for improvement, reflecting findings from our previous workshop (Table 4.2) (Gaydos et al. 2019). Despite advancements in remote sensing, the fine-scale mapping of individual hosts remains a challenge (Xie et al. 2008). Not only can such errors propagate forecast uncertainty (Dietze 2017), they may be especially prominent to stakeholders

who live and work in the study landscape (Voinov and Gaddis 2008, Vukomanovic et al. 2019). New techniques to automate tree detection and species recognition are promising for increasing the spatial accuracy of host data and should be a top priority for biological invasions researchers (Branson et al. 2018). Implementing these improvements should increase the accuracy of the forecast and its relevance for decision-making.

Collaborative learning is considered a fundamental aspect of participatory modeling (Jordan et al. 2018, Voinov et al. 2016). Not only did we learn what decision-makers desire from forecasts and interfaces, the participants overwhelmingly reported that the workshop encouraged open discussion and learning. Comments suggest that participants learned about a broad range of topics, with the effectiveness of treatments as one of the most ubiquitous takeaways. For example, one participant commented that "it made more sense that a wide buffer may not be a silver bullet for stopping the spread northeast." This comment was particularly compelling because host barrier strategies had been discredited by other SOD models (Cunniffe et al. 2016, Filipe et al. 2012). Essentially, this is a classic example of the knowledge-practice gap because the critical information from these modeling studies did not reach these decision-makers. However, through interactive forecasting, participants discovered the effectiveness (or in this case, ineffectiveness) of tactics in a matter of hours, demonstrating the power of this hands-on learning. When collaborative, this hands-on approach may also teach participants about each other (Jordan et al. 2018, White et al. 2019). Several participants commented that they "learned a lot about what stakeholders value most in containing SOD," suggesting that there may be ancillary socio-political outcomes of the participatory process.

Encouragingly, we have seen continued interest in the forecast and interfaces following the workshop. Four participants reached out about using PoPS TL and PoPS WP in other applications, including teaching, citizen science, and forecasting other socio-ecological systems. Additionally, the Oregon SOD Task Force has been mobilizing to expand their management capacity in response to what was learned at the workshop (Sarah Navarro, personal communication). We consider these positive indications that stakeholders saw direct value in forecasting and experimenting with "what if" management scenarios. Unfortunately, intuitive forecasting interfaces which enable such experimentation are still rare, limiting forecasts' impact on decision-making. Through this case study, we demonstrate how participatory methods and user-friendly interfaces can unmask the analytical capacity of forecasts and empower

stakeholders to collaboratively develop novel and adaptive management strategies to inform control of biological invasions.

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APPENDICES

APPENDIX A

SYSTEMATIC LITERATURE REVIEW

We conducted systematic literature reviews addressing two questions: 1) how is participatory modelling being applied in studies modelling disease spread or potential across all systems (plant, animal, and human)? and, 2) how are stakeholders being engaged specifically in studies of plant disease modelling? Searches were conducted in the ISI Web of Science database during the months of July and August 2018. We did not consider any sources that were not in English.

For our first question about participatory modelling in epidemiology, we compiled three searches using the following terms: 1) participatory model* epidemiolog*, 2) participatory model* with the infectious disease category selected, and 3) participatory epidemiolog* simulation model* *OR* participatory disease simulation model* *OR* participatory pathogen simulation model* *OR* participatory epidemiolog* spread model* *OR* participatory disease spread model* *OR p*articipatory pathogen spread model*. Some sources were found under multiple searches. In total, there were 103 sources. One source couldn't be located, and one source was eliminated because it was not in English. For a source to be considered, it had to be about modelling of disease spread or potential. Twenty-nine sources fit this criteria and were considered more in-depth (Table A.1).

For our second question about stakeholder engagement in plant disease modelling studies, we conducted one search with the terms: plant stakeholder* model* disease OR plant stakeholder* model* pathogen OR plant stakeholder* simulation disease OR plant stakeholder* simulation pathogen. In total, there were 43 sources. One source couldn't be located, and one source was eliminated because it was not in English. For a source to be considered, it had to be about modelling of disease spread or potential. Fourteen sources fit this criteria and were considered more in-depth (Table A.2).

We recognise important limitations to these kinds of literature reviews, most significantly the bias against publishing negative results. There may be an even greater disincentive to publish

negative participatory modelling results, as ‘bad press’ can jeopardize management funding and erode essential interpersonal connections between stakeholders and modellers. Furthermore, by focusing specifically on models of disease spread or potential, we may have missed relevant participatory research with other types of models or in epidemiology more broadly. Lastly, it is possible that there are applicable developments reported in other languages or under different names.

Table A.1. Sources considered for first search examining overlap between participatory modelling and participatory epidemiology.

Participatory Modelling in Epidemiology Studies				
Source Title	**First Author**	**Study Topic**	**Disease System**	**Participatory Category**
A heterogeneous population model for contagious bovine pleuropneumonia transmission and control in pastoral communities of East Africa	Mariner, J.C.	contagious bovine pleuropneumonia	animal	contributed data
A model of lineage-1 and lineage-2 rinderpest virus transmission in pastoral areas of East Africa	Mariner, J.C.	rinderpest virus	animal	contributed data
Moving alcohol prevention research forward Part 1: introducing a complex systems paradigm	Apostolopoulos, Y.	alcoholism	human	just mentioned
Moving alcohol prevention research forward Part 2: new directions grounded in community-based systems dynamics modeling	Apostolopoulos, Y.	alcoholism	human	just mentioned

Table. A.1 (continued).

How to reach the poor? Surveillance in low-income countries, lessons from experiences in Cambodia and Madagascar	Goutard, F.L.	various zoonotics	human and animal	contributed data
Impacts of climate change on plant diseases- opinions and trends	Pautasso, Marco	various plant diseases	plant	just mentioned
A model of contagious bovine pleuropneumonia transmission dynamics in East Africa	Mariner, J.C.	contagious bovine pleuropneumonia	animal	contributed data
Web-based participatory surveillance of infectious diseases: the Influenzanet participatory surveillance experience	Paolotti, D.	flu	human	contributed data
Application of system dynamics and participatory spatial group model building in animal health: A case study of East Coast Fever interventions in Lundazi and Monze districts of Zambia	Mumba, C.	East Coast fever	animal	co-development
Tangible geospatial modeling for collaborative solutions to invasive species management	Tonini, F.	sudden oak death	plant	just mentioned
Moving interdisciplinary science forward: integrating participatory modelling with mathematical modelling of zoonotic disease in Africa	Grant, C.	various zoonotic diseases including henipavirus, Lassa fever, Rift Valley fever, and trypanosomiasis	human and animal	contributed data and co-development

Table A.1 (continued).

The economic and poverty impacts of animal diseases in developing countries: new roles, new demands of economics and epidemiology	Rich, K.M.	Rift Valley fever, avian influenza, and food and mouth disease	animal	just mentioned
An analytics framework to support surge capacity for planning emerging epidemics	Curran, M.	epidemics in general	human	just mentioned
Metapopulation dynamics and determinants of H5N1 highly pathogenic avian influenza outbreaks in Indonesian poultry	Farnsworth, M.L.	H5N1 avian influenza	animal	contributed data
Description and analysis of the poultry trading network in the Lake Alaotra region, Madagascar: implications for the surveillance and control of Newcastle disease	Rasamoelina-Andriamanivo, H.	Newcastle disease	animal	contributed data
Situated knowledge of pathogenic landscapes in Ghana: understanding the emergence of Buruli ulcer through qualitative analysis	Tschakert, P.	Buruli ulcer	human	co-development
Evaluating the efficiency of participatory epidemiology to estimate the incidence and impacts of foot-and-mouth disease among livestock owners in Cambodia	Bellet, C.	foot and mouth disease	animal	contributed data
Uncertainty in epidemiology and health risk and impact assessment	Briggs, P.J.	uncertainty in epidemiology	human	just mentioned

Table A.1 (continued).

Identifying risk factors of highly pathogenic avian influenza (H5N1 subtype) in Indonesia	Leo, L.	avian influenza	animal	contributed data
A participatory approach to design spatial scenarios of cropping systems and assess their effects on phoma stem canker management at a regional scale	Hossard, L.	phoma stem canker	plant	co-development
Dynamic simulation modelling of policy responses to reduce alcohol-related harms: rationale and procedure for a participatory approach	Atkinson, J.A.	alcohol-related diseases	human	co-development
A blockchain-enabled participatory decision support framework	Laskowski, M.	disease in general	human	just mentioned
A participatory simulation model for studying attitudes to infection risk	Maharaj, S.	attitudes towards disease risk	human	just mentioned
A participatory model of the paradox of primary care	Homa, L.	various illnesses	human	co-development
Avian Cholera emergency in Arctic-nesting northern Common Eiders: using community-based, participatory surveillance to delineate disease outbreak patterns and predict transmission risk	Iverson, S.A.	avian cholera	animal	contributed data
Expert knowledge sourcing for public health surveillance: national tsetse mapping in Uganda	Berrang-Ford, L.	Human African typanosomiasis	human	contributed data

Table A.1 (continued).

Combining public participatory surveillance and occupancy modelling to predict the distributional response of Ixodes scapularis to climate change	Lieske, D.J.	mapping tick prevalence	human and animal	contributed data
Spontaneous social distancing in response to a simulated epidemic: a virtual experiment	Kleczkowski, A.	social distancing in response to infection	human	contributed data

Table A.2. Sources considered for second search examining stakeholder engagement in plant disease modelling.

Stakeholder Engagement in Plant Disease Modelling Studies			
Source Title	**First Author**	**Study Topic**	**Participatory Category**
When prevention fails. Toward more efficient strategies for plant disease eradication.	Vicent, A.	citrus canker	just mentioned
Risk-based management of invading plant disease	Hyatt-Twynam, S.R.	citrus canker	just mentioned
Monitoring invasive pathogens in plant nurseries for early-detection and to minimise the probability of escape	Chavez, A.	sudden oak death, HLB, citrus canker, ash dieback	just mentioned
A set of software components of the simulation plant airborne diseases	Bregaglio, S.	wheat brown rust and rice blast epidemics	just mentioned
Citizen science helps predict risk of emerging infectious disease	Meentemeyer, R.K.	sudden oak death	contributed data
Optimising and communicating options for the control of invasive plant disease when there is epidemiological uncertainty	Cunniffe, N.J.	citrus canker	just mentioned

Table A.2 (continued).

Addressing the implementation problem in agricultural decision support systems: the example of vite.net (R)	Rossi, V.	viticultural diseases	co-development
Impacts of climate change on plant diseases - opinions and trends	Pautasso, M.	various plant diseases	just mentioned
Potential and limitations of plant virus epidemiology: lessons from the potato virus Y pathosystem	Doring, T.F.	potato virus Y	just mentioned
Tracking the distribution and impacts of diseases with biological records and distribution modelling	Purse, B.V.	various plant, animal, and human diseases	just mentioned
Epidemiology and population biology of Pseudoperonospora cubensis: a model system for management of downy mildews	Ojambo, P.S.	cucurbit downy mildew	co-development
Predicting the benefits of banana bunchy top virus exclusion from commercial plantations in Australia	Cook, D.C.	banana bunchy top virus	just mentioned
Plant pathogens, insect pests and weeds in a changing global climate: a review of approaches, challenges, research gaps, key studies and concepts	Juroszek, P.	various plant diseases	just mentioned
Clubroot of cruciferous crops - new perspectives of an old disease	Howard, R.J.	clubroot disease of brassicas	just mentioned

APPENDIX B

EPIDEMIOLOGICAL MODELLING TOOL

B.1. DISEASE SPREAD MODEL

B.1.1. Model

To model disease spread in Oregon, we expanded upon a pre-existing modelling framework originally developed to simulate the spread of *P. ramorum* in California [1-3]. While most epidemiological processes are the same in these two regions, key differences exist. In California, disease spread is predominantly influenced by two high-competency host trees: California bay laurel (*Umbellularia californica*) and tanoak (*Notholithocarpus densiflorus*). For unknown reasons, California bay laurel is found to be a low-competency host in Oregon which does not contribute significantly to disease spread [4-6]. Therefore, we amended the original multi-host framework to reflect a single-host system driven by tanoak. Evidence also suggests that *P. ramorum* is able to produce spores year-round in Oregon, likely due to wetter climatic conditions. Therefore, we removed the seasonality component which prevented spread during winter months in the California models.

The intensive management in Oregon presents a challenge for model parameterization and validation because it obscures natural patterns of disease transmission [5]. Due to this limitation, the model was parameterized based on natural spread conditions in Northern California following the Markov chain Monte Carlo (MCMC) process described in [2]. While there are some differences in epidemiology, this area is a tanoak-heavy ecosystem and we felt it provided a reasonable approximation for this case study. Prior to the workshop, we performed a qualitative analysis as described in [2], where we compared model outputs to: 1) known infection locations in Oregon, and 2) to a map of *P. ramorum* risk [7]. We found there was good visual correspondence between model outputs, the risk map, and known infection locations, and felt this was suitable for this stage of model development. We are currently pursuing more intensive quantitative validations which take into account the Oregon's extensive treatments.

B.1.2. Data Requirements

This geospatial model requires raster inputs of host density, weekly weather conditions, and initial infection locations. Host density data for the main host, tanoak, was derived from detailed raster structure maps from the Landscape Ecology, Modeling, Mapping and Analysis (LEMMA) [8] project webpage (https://lemma.forestry.oregonstate.edu/) using the density calculation presented in [1]. Daily values of precipitation, minimum temperature and maximum temperature were obtained as raster data from the PRISM Climate Group [9] webpage (http://www.prism.oregonstate.edu/). Minimum and maximum temperature were converted to a measure of average temperature. These data were aggregated to a weekly timestep, and converted to an index of weather suitability for disease spread based on laboratory studies as reported in [1-2]. Infection locations were acquired from the Oregon Department of Forestry's annual survey program for 2001 through 2017. These point locations were converted to raster data representing number of infected host trees per pixel.

B.1.3. Model Processes

The model is a spatially-explicit susceptible-infected (SI) model consisting of three stochastic processes: sporulation, spore dispersal, and spore establishment. The amount of spores produced by an infected host is sampled each week from a Poisson distribution as described in [2]. This spore-rate corresponds to the maximum number of new infections that could be produced from an infectious host, and is moderated by the weather conditions during that week.

Spore dispersal is controlled by a particle-emission anisotropic process as described in [1]. The direction of dispersal is sampled from a Von Mises circular probability distribution. The predominant wind direction for this study area is north, which was used to parameterize the angular distribution for the Von Mises distribution. The dispersal distance was sampled from a Cauchy probability distribution parameterized with values from [2]. Given the comparatively small study area, we did not include the long-distance component of the dispersal kernel (which accounts for human-mediated spread on a regional scale).

Spore establishment is governed by a stochastic process which probabilistically challenges the cell based on the amount of susceptible hosts and weekly weather conditions as described in [1]. If the value of hosts and weather suitability is higher than a randomly sampled

number, one new infection will occur in that pixel. Infections can occur both in new cells, and within a cell that the spore originated.

B.1.4. Case study

The disease simulation was run in a 12x8 km area surrounding Gold Beach, Oregon, where the recent European-1 (EU1) strain locations were found. Model resolution was 100m. The model was run at a weekly timestep for a period of 5 years, from 2016 to 2021, and from 2017 to 2022.

B.1.5. Source Code

This sudden oak death disease spread model is available as a GRASS GIS add-on module [10] (see user documentation: https://grass.osgeo.org/grass74/manuals/addons/r.spread.sod.html).

B.2. TANGIBLE LANDSCAPE SYSTEM

B.2.1. Description of Interface

Tangible Landscape is a tangible user interface (TUI) which allows users to intuitively guide a geospatial model through a series of physical actions [11]. The system consists of a scanner, a projector, a computer with GRASS GIS software, a physical landscape terrain model, and USB-enabled buttons (Figures B.1 and B.2). Tangible Landscape can be used for modelling many geospatial processes, but here we are using a customized set up specifically for pest and pathogen modelling [11]. Geospatial data layers, including aerial imagery, roads, property boundaries, infection locations, and host data are projected onto the physical landscape model to provide context. Users place felt markers on the landscape to represent management (e.g., culling hosts). These markers are detected by a scanner and converted to GIS polygons, which are then used to alter the host data used in the disease spread model. Disease spread is calculated using this new host input, and spread locations are projected back into the terrain model to give users a sense of how the proposed management scenario alters landscape-scale disease spread. Using the two USB-enabled buttons, users can switch back and forth between an animation of a single stochastic model iteration and a probability surface showing likelihood of infection within 10

model runs, giving users both a sense of how the disease may progress across the landscape and the stochastic uncertainty of that outcome.

B.2.2. Dashboards

Tangible Landscape is linked with two interactive dashboards to aid in designing and comparing management strategies. As users designate management locations, information about the area and cost of management is displayed next to the physical landscape to help guide scenario development (see steering dashboard, Figure B.2). Data from each scenario are stored in a web-based dashboard that allows users to compare dozens of scenarios simultaneously (see summary dashboard, Figures B.2 and B.3). Scenarios are tracked by the name of the user who designated management locations, allowing people to track their individual model runs and compare their results to others'. Metrics in the web-based dashboard include number of infected trees, number of infected hectares, money spent, area treated, and price per protected tree.

B.2.3. Equipment and Code

All equipment and code for Tangible Landscape is open-source and runs with GRASS GIS platform [10]. For more information about Tangible Landscape, see https://tangible-landscape.github.io/ or Tangible Modeling with Open Source GIS: Second Edition [11].

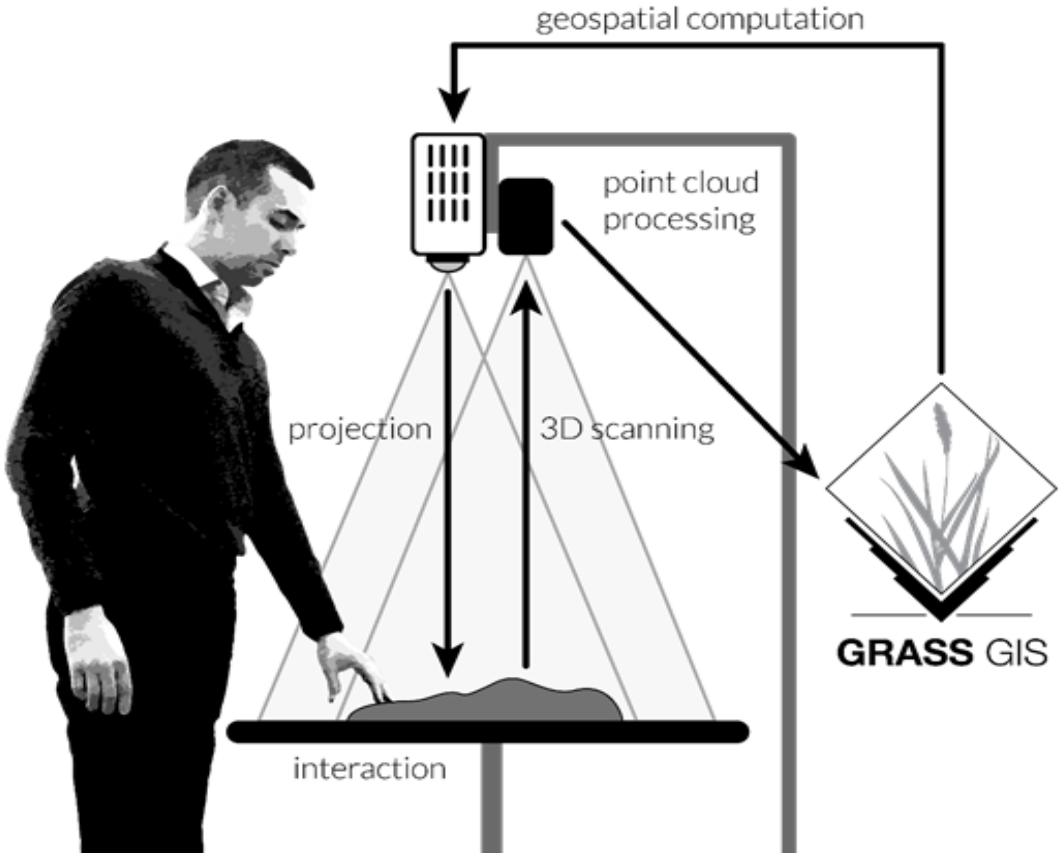

Figure B.1. Schema of Tangible Landscape design. Credit: Brendan Harmon

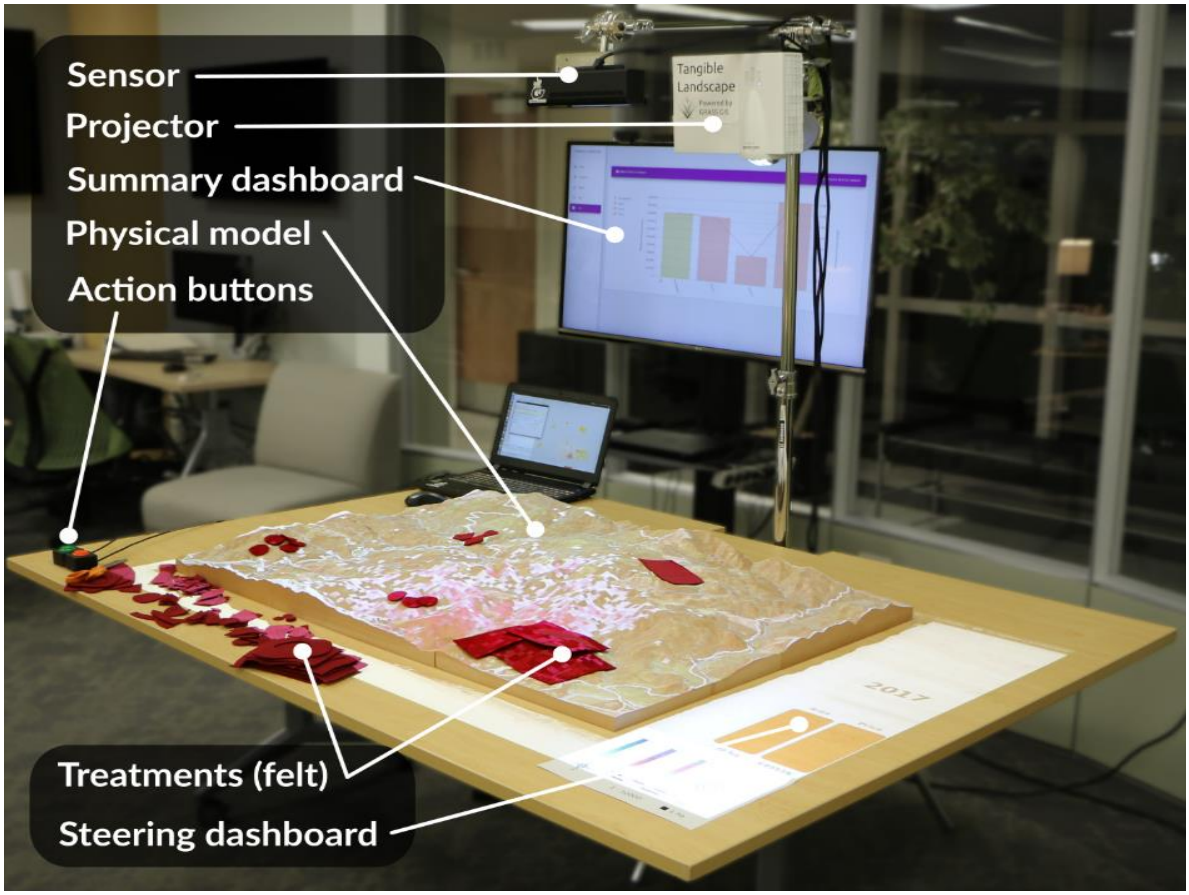

Figure B.2. Example of Tangible Landscape setup for pathogen modelling. Credit: Anna Petrasova

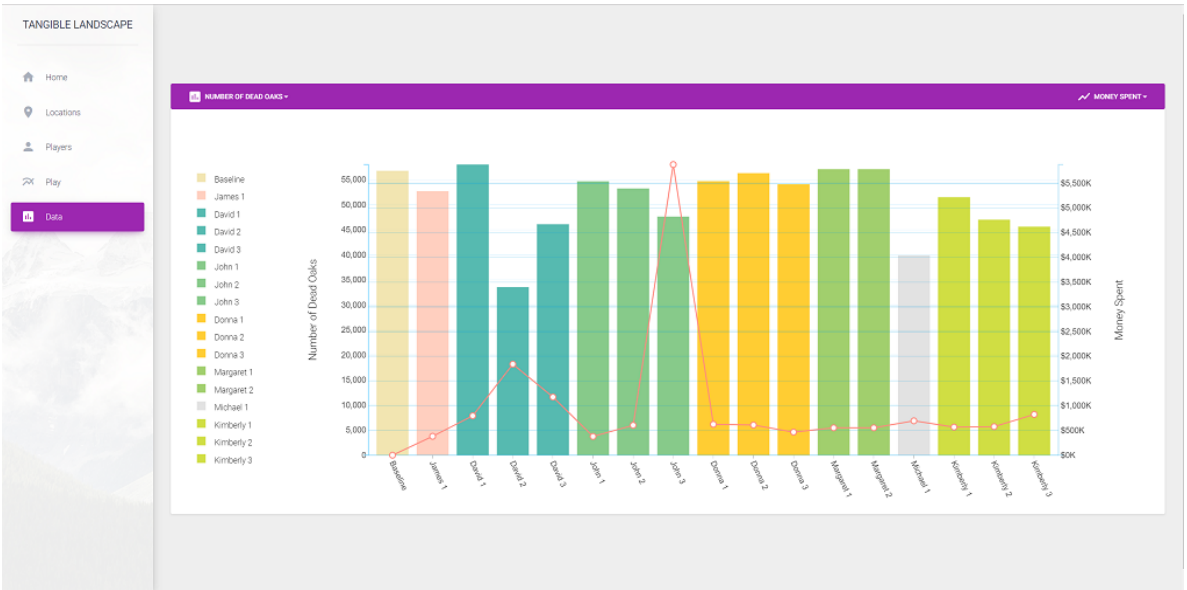

Figure B.3. Example of web-based dashboard output. The bar graph and line graphs represent number of infected trees and money spent in each scenario, respectively. Bar colors represent which stakeholder designed each scenario. Credit: Makiko Shukunobe

B.3. REFERENCES

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APPENDIX C

PARTICIPATORY MODELLING WORKSHOP

C.1. DESCRIPTION OF WORKSHOP

We held the first of a series of participatory modelling workshops with stakeholders at the Oregon Department of Forestry headquarters in Salem, Oregon in October, 2017. Twelve participants from Oregon State University (5), Oregon Department of Forestry (6), and the United States Forest Service (1) attended. The workshop lasted the entire day, and was divided into discrete sections. In the morning prior to interaction with the model, participants were asked to take a pre-workshop survey to assess their baseline knowledge of both the disease system and disease modelling tools. Then we held a group discussion focused on the implications of disease spread and the challenges of management. This discussion served two purposes: 1) to get participants thinking about the disease system, and 2) to give researchers valuable context on the participants' disease concerns. We then familiarized participants with model functionality by giving a short presentation detailing all of the input data, input parameters, and model functions. To get everyone on a common page, participants were encouraged to ask clarifying questions and challenge aspects of the model or data they did not understand or did not agree with during this presentation and throughout the rest of the workshop.

We held two modelling sessions, each lasting a few hours. In the first, participants worked together to control disease spread starting with infection locations from 2016. Since there were less infections in 2016, it was easier for participants to learn model functions and explore different spatial management scenarios. In the second session, participants worked together to manage the 2017 infections, which were more challenging to control. After each of these sessions, there was a short debrief where we collectively examined the model outputs and discussed which scenarios worked best and why. After both modelling sessions, participants took a post-workshop survey designed to capture participant's opinions of the system and any

suggested updates. Following this workshop, we held one final group discussion to provide a forum for any final comments or feedback.

C.2. SURVEY RESULTS

All workshop participants completed pre- and post-workshop surveys designed to assess participants' knowledge of forest and disease dynamics, perception of the model and Tangible Landscape, and to systematically collect recommended changes. Survey questions were a mix of rank-choice, open-ended, and Likert scales. We report a subset of these survey responses most related to credibility of model functions, interactivity and accessibility of the system, and potential applications in Figure 2.3 in the main text. We further report here on familiarity with disease simulation models (Figure C.1), self-assessed learning (Table C.1), and suggestions for model improvement (Table C.2).

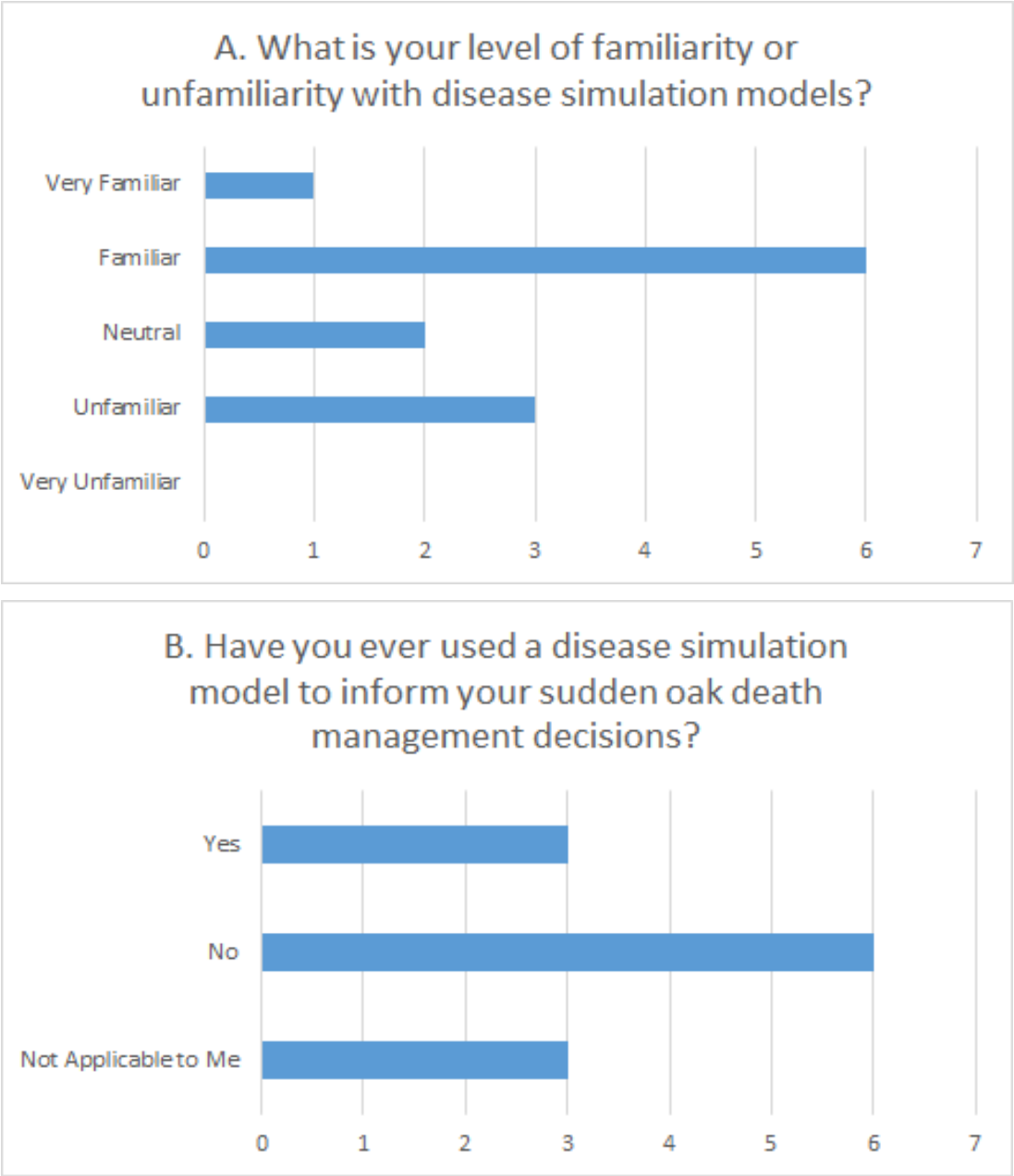


Figure C.1. Survey results indicating participant's familiarity (A) and prior experience with (B) disease simulation models.

Table C.1. Participants' open-end responses about what they learned during the workshop.

Things Learned from Workshop:
The potential effectiveness of alternative treatments (ie: host elimination). Unlikely to eradicate EU1 regardless of treatment if model predictions are accurate.
The many aspects of spread and treatment dynamics came out from the various participants. It was very interesting to have the breadth of knowledge in the room. I would like to have the system to "game" many different projects.
Reaffirmed belief that effective visual displays are helpful in learning. Even more effective is the self-learning gained by "gaming" the system. Would be extremely helpful with stakeholders.
The model is beginning to approach reality. Confirmed my suspicion that eradication is nearly impossible.
I learned about the model and getting to use tangible landscapes with respect to SOD. I also learned how important adequate funding was to disease management.
The model was interesting and the ability to compare treatment proposals would be very valuable. With a refinement in vegetation type, I think the model has a lot of potential for identifying areas at high risk for infection.
Management of SOD is going to be successful only if agencies, public, industry, and funding enables it to be so. The potential for eradication is small and may be unrealistic as a goal. But, confinement and treating new outbreaks could reduce the severity and landscape distribution of SOD. In short, SOD won't go away but perhaps it can be managed.
Eradicating EU1 in Oregon is going to be almost impossible, even with budget surpassing 10 or 20 million dollars.
The simulations highlighted our uncertainty of detecting rare dispersal events - ie, at low frequencies are we accurately describing the distribution or must greater local intensification occur before detection.
How the tangible landscape model works and it's possibilities. New way of displaying data (target). We are still uncertain about spread dynamics. Different ways we can use the model.
I learned the value of pre-emptive removal of tanoak in a high risk area. I learned the value of managing disease foci (isolated outbreaks). I learned the importance of strategic choice of management sites for cost effectiveness. Great workshop!!! What a wonderful tool to explore management strategies!

Table C.1 (continued).

Better understanding of disease spread over time, especially in the absence of treatments. The epidemiological model needs to be adjusted to specifically reflect SOD spread in Oregon forests. The technology is fantastic as a tool for handling large amounts of information and displaying results effectively.

Table C.2. Participants' open-ended suggestions for model improvement.

Suggested Model Changes:
As was discussed, the need for more accurate, reliable and spatially fine scale inputs is a needed factor. These would help to refine the models and increase applicability.
Add adaptive management. Conduct model validation from real outbreaks.
I think the workshop would be great if the model was refined in terms of tanoak density, weather, and the ability to conduct treatments on a yearly basis. Great first workshop.
I think that it would be interesting to be able to add treatments on a yearly basis.
I think it might be interesting to have an example of a recalcitrant landowner. Either as a means to understand how a hole in treatment would or wouldn't impact SOD control effectiveness. I also think it might be helpful to have some parameter variations (span a range of uncertainty) that might give a better idea of how robust or variable simulations might be for specific scenarios given uncertainty about phenomenological parameters (eg, reinfection rates for treatment areas).
It was a great opportunity to learn. Thank you for all your hard work. It would be interesting to adjust/validate the model to Oregon-specific data, in particular, or historical treatment data, refined climate/weather data and refined host distribution data. Then, a follow-up workshop or report of findings disseminated to Oregon to OR natural resource agencies.
Adjust length of LDD tail to match weather phenomenon of a given simulated year (allow to vary) (ex wetter spring = longer tail). Better host distribution. Allow for larger scale reduction in tanoak (ie tanoak thinning vs total removal) to either (a) decrease change of infection or (b) reduce local transmission rate. Allow adaptive management. Overall need for validation. Use to get at the question of the validity of the assumptions notably that sites remain infective and weather condition variation between years is negligible. Overall very cool and, importantly, fun. I love the idea of scorer. Consider online tool (maybe simplify). Conceptually it map be a leap for some people to translate the number of infected trees/ha to a risk map.
Use dataset from one of the expansions and treatment scenarios and compare model with reality. Use untreated site data on expansion and compare.

Table C.2 (continued).

Validate model assumptions (for example, spores/tree) by comparing predicted rate of spread with actual rate of spread using Oregon epidemiological data. Add capability for adaptive management (the ability to manage each year, not just the first year). Superimpose a risk map on the landscape, and use finer scale vegetation map and climate/weather map to fine tune the risk map. This would really help to inform the management decisions. Make the tanoak distribution more obvious (finer scale, visually obvious). Some number of years after trees are initially infected, have them die and no longer produce spores. Allow for separately modelling NA1 and EU1 genotypes.
Improve the tanoak distribution layer. Improve vegetation layer by accounting for Douglas-fir plantations. Allow for treatments to occur during each year of the simulation, rather than only at the beginning. Add an optimization function to help determine where and how big to make treatments.

APPENDIX D

SURVEY INSTRUMENTS

D.1. SURVEY INSTRUMENTS FOR FIRST PARTICIPATORY WORKSHOP

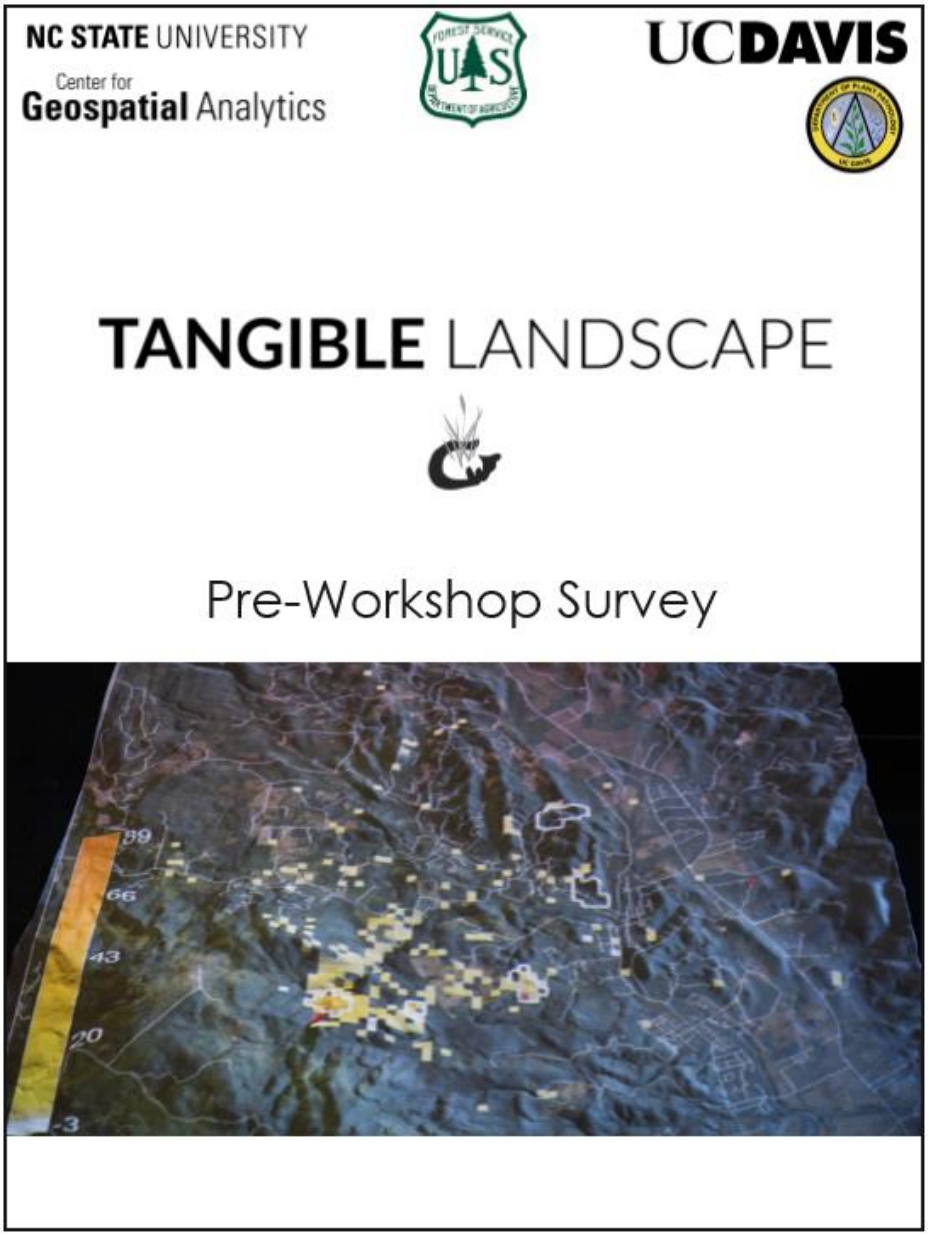


Figure D.1. Pre-workshop survey for first participatory workshop.

QUESTIONS ABOUT MANAGEMENT

These questions will help us understand the management goals for the region.

1. Please use the letter corresponding to the following statements to rank these potential management goals by order of importance with 1 being the most important and 10 being the least important. If a goal is not important, do not add it to the list.

Goals:	Your Ranking:
A. Eliminating the EU1 infection	1.
B. Conserving tanoak	2.
C. Minimizing damage to conifers	3.
D. Reducing regional fire risk	4.
E. Reducing disease spread in Curry County	5.
F. Preventing spread into Coos County	6.
G. Preventing spread into Douglas County	7.
H. Preventing spread into Josephine County	8.
I. Preventing spread into Del Norte County	9.
J. Other, please fill in: _____	10.

2. Please use the letter corresponding to the following statements to rank these potential impediments to disease control by order of significance with 1 being the most significant factor and 7 being the least significant factor. If an option is not an impediment to disease control, do not add it to the list.

Goals:	Your Ranking:
A. Long distance dispersal through wind and rain	1.
B. Human-mediated pathogen introduction	2.
C. Lack of funding	3.
D. Lack of collaboration amongst landowners	4.
E. Inadequate information about the pathogen dynamics	5.
F. Sexual reproduction between EU1 and NA1	6.
G. Other, please fill in: _____	7.

2

Figure D.1 (continued).

3. Sudden oak death can be contained through management. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

4. Do you support or oppose using state funds to treat sudden oak death disease? Please choose one:

- ☐ Strongly support
- ☐ Support
- ☐ Neither support nor oppose
- ☐ Oppose
- ☐ Strongly oppose

5. Have there been any negative ecological effects of sudden oak death management in Oregon? Please circle one:

Yes No Don't know

If yes: Please describe these effects: _____

_____

_____

_____

_____

_____

_____

_____

3

Figure D.1 (continued).

QUESTIONS ABOUT SOD DYNAMICS

These questions will help us understand how stakeholders understand and perceive sudden oak death disease dynamics.

6. Most disease spread is local, but rare long-distance dispersal events (greater than 1km) are thought to have occurred driven by wind gusts during storms. Are you concerned that disease might spread within the quarantine area from a long-distance dispersal event? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

7. Are you concerned that the disease might leave the quaratine area from a long-distance dispersal event, affecting another region? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

8. Are you concerned that there may be a new introduction from a nursery within the quaratine area? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

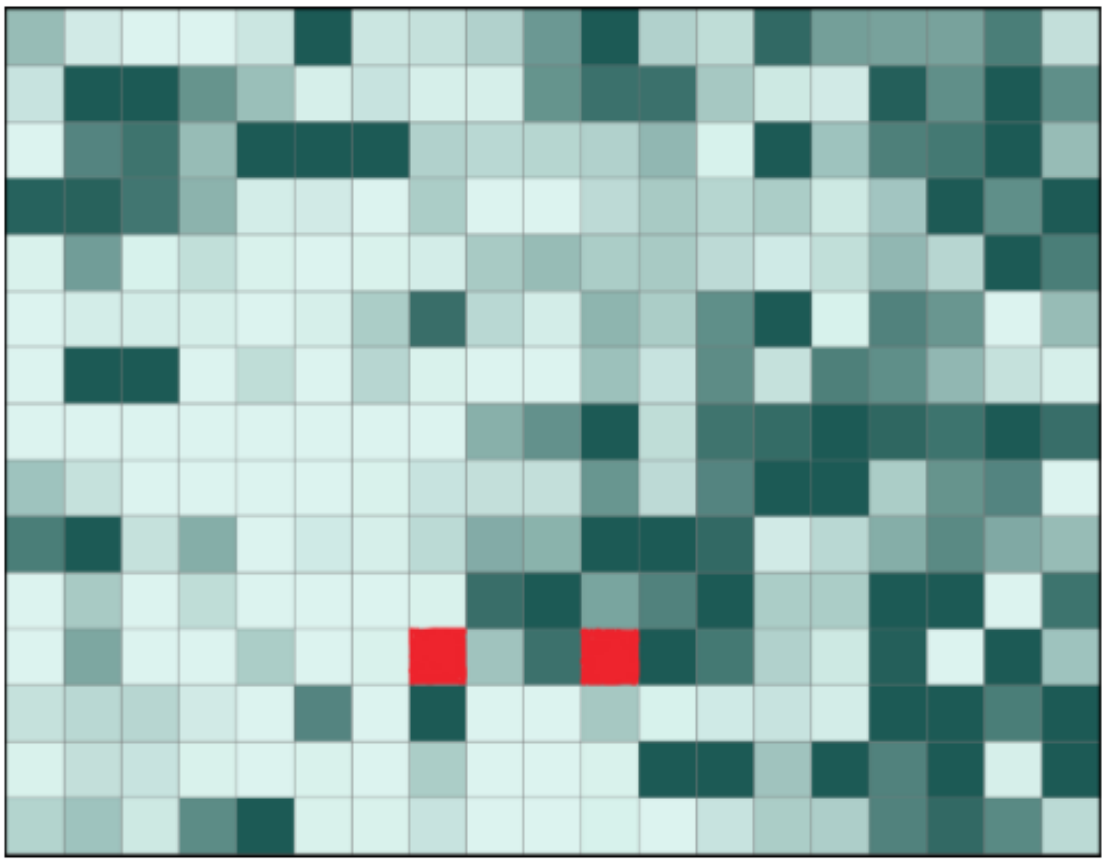
4

Figure D.1 (continued).

9. Are you concerned that there may be a new introduction from a nursery outside of the quaratine area? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

For the next two questions, consider the landscape below. Each pixel represents an area of 1 hectare (100m²). The darker green a square is, the more tanoak it has. All tanoak trees in the red pixels are infected with SOD.



10. Considering the goal of limiting spread from these infections, please mark 10 squares with an X on this image to indicate where you would place management. Management will remove all tanoak within the pixel.

5

Figure D.1 (continued).

11. What percentage of this landscape will likely be infected after 5 years, assuming average weather conditions? Please choose one:

- ☐ Less than 25%
- ☐ Between 25 and 49%
- ☐ Between 50 and 75%
- ☐ Over 75%

QUESTIONS ABOUT THE ROLE OF SCIENCE

These questions will help us understand the role of science in informing management decisions.

12. What is your level of familiarity or unfamiliarity with geographic information systems (GIS)? Please choose one:

- ☐ Very familiar
- ☐ Familiar
- ☐ Neutral
- ☐ Unfamiliar
- ☐ Very unfamiliar

13. Have you ever used a geographic information system (GIS) to inform your SOD management decisions? Please choose one:

- ☐ Yes
- ☐ No
- ☐ Not applicable to me

14. What is your level of familiarity or unfamiliarity with disease simulation models? Please choose one:

- ☐ Very familiar
- ☐ Familiar
- ☐ Neutral
- ☐ Unfamiliar
- ☐ Very unfamiliar

Figure D.1 (continued).

15. Have you ever used a disease simulation model to inform your SOD management decisions? Please choose one:

- ☐ Yes
- ☐ No
- ☐ Not applicable to me

16. Consider a geospatial model that uses the following inputs: host density, current infection locations, weather conditions, and management locations. The model then runs, showing likely SOD spread across the landscape for a span of 10 years. How likely or unlikely would you be to use this model to inform future SOD management decisions? Please choose one:

- ☐ Very likely
- ☐ Somewhat likely
- ☐ Neutral
- ☐ Somewhat unlikely
- ☐ Very unlikely
- ☐ Not applicable to me

QUESTIONS ABOUT TANOAK

These questions will help us understand how people value tanoak.

17. To your knowledge, is conserving tanoak an important goal for a majority of landowners in the generally infested area? Please choose one:

- ☐ Yes
- ☐ No
- ☐ Don't know

Figure D.1 (continued).

Please indicate your agreement or disagreement with the following three statements about tanoak:

18. I consider tanoak ecologically valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

19. I consider tanoak economically valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

20. I consider tanoak spiritually valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

Figure D.1 (continued).

QUESTIONS ABOUT COLLABORATION

These questions will help us understand how collaboration amongst a group of stakeholders affects successful disease management.

Please indicate your agreement or disagreement with the following four statements about collaboration regarding the spread of SOD:

21. Collaboration with a diverse group of stakeholders (ex: foresters, timber companies, private landowners, conservation agencies, tribal agencies, etc) improves management outcomes. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

22. Lack of communication between stakeholders has been an impediment to successful disease management in Oregon. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

23. A diversity of management goals amongst stakeholders has been an impediment to successul disease management in Oregon. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

9

Figure D.1 (continued).

24. Management would be more effective at limiting the spread of SOD if one person or organization made all the decisions. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

BACKGROUND INFORMATION

25. What organization are you associated with?

_____

26. What is your current position at that organization?

_____

27. How many years have you been in your current position?

_____ years

Figure D.1 (continued).

TANGIBLE LANDSCAPE PRE-WORKSHOP SURVEY

Thank you for your help!

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This project has been reviewed and approved by the Institutional Review Board at NC State University.

Questions concerning your rights as a participant in this research may be addressed to the NC State IRB Administrator Debbie Paxton at dapaxton@ncsu.edu or (919) 515-4514.

Figure D.1 (continued).

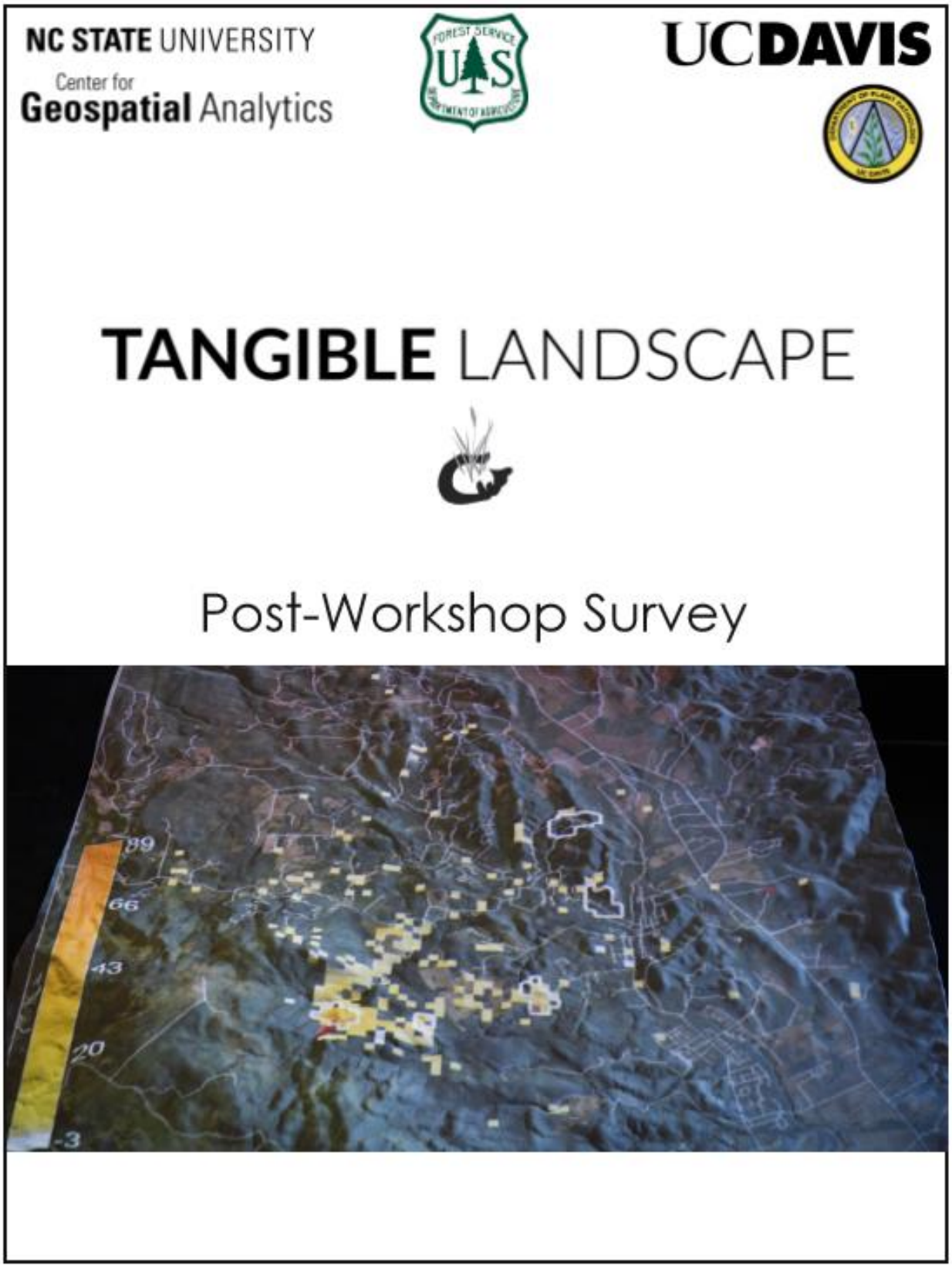


Figure D.2. Post-workshop survey for first participatory workshop.

QUESTIONS FROM PRE-WORKSHOP SURVEY

These questions will help us understand how knowledge and opinions may differ before and after the workshop.

1. Sudden oak death can be contained through management. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

2. Do you support or oppose using state funds to treat sudden oak death disease. Please choose one:

- ☐ Strongly support
- ☐ Support
- ☐ Neither support nor oppose
- ☐ Oppose
- ☐ Strongly oppose

3. Most disease spread is local, but rare long-distance dispersal events (greater than 1km) are thought to have occurred driven by wind gusts during storms. Are you concerned that disease might spread within the quaratine area from a long-distance dispersal event? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

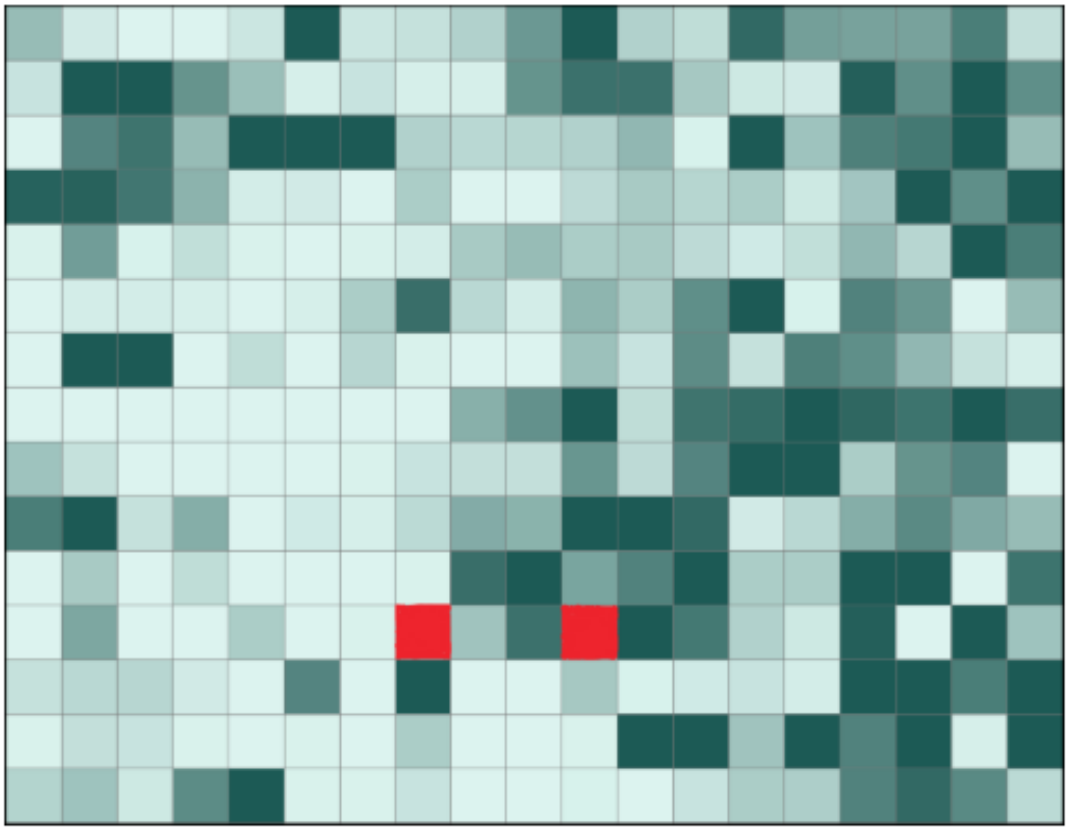
4. Are you concerned that the disease might leave the generally infested area from a long-distance dispersal event, quaratine another region? Please choose one:

- ☐ Extremely concerned
- ☐ Moderately concerned
- ☐ Somewhat concerned
- ☐ Slightly concerned
- ☐ Not at all concerned

2

Figure D.2 (continued).

For the next two questions, consider the landscape below. Each pixel represents an area of 1 hectare (100m²). The darker green a square is, the more tanoak it has. All tanoak trees in the red pixels are infected with SOD.



5. Considering the goal of limiting spread from these infections, please mark 10 squares with an X on this image to indicate where you would place management. Management will remove all tanoak within the pixel.

6. What percentage of this landscape will likely be infected after 5 years, assuming average weather conditions? Please choose one:

- ☐ Less than 25%
- ☐ Between 25 and 49%
- ☐ Between 50 and 74%
- ☐ Over 75%

3

Figure D.2 (continued).

Please indicate your agreement or disagreement with the following three statements about tanoak:

7. Tanoak is ecologically valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

8. Tanoak is economically valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

9. Tanoak is spiritually valuable. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

4

Figure D.2 (continued).

QUESTIONS ABOUT TODAY'S WORKSHOP

These questions will help us understand how you felt about the Tangible Landscape system, and how we can improve future workshops.

10. Consider the spread model we used today. How likely or unlikely is it that you would use this model to inform future SOD management decisions? Please choose one:

- ☐ Very likely
- ☐ Somewhat likely
- ☐ Neutral
- ☐ Somewhat unlikely
- ☐ Very unlikely

11. How interested or disinterested would you be in attending future workshops? Please choose one:

- ☐ Very interested
- ☐ Somewhat interested
- ☐ Neutral
- ☐ Somewhat disinterested
- ☐ Very disinterested

12. The 3D landscape model helped orient you to the landscape. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

5

Figure D.2 (continued).

13. How respected or disrespected did you feel your opinions were by the researchers? Please choose one:

- ☐ Very respected
- ☐ Somewhat respected
- ☐ Neutral
- ☐ Somewhat disrespected
- ☐ Very disrespected

14. How respected or disrespected did you feel your opinions were by other participants? Please choose one:

- ☐ Very respected
- ☐ Somewhat respected
- ☐ Neutral
- ☐ Somewhat disrespected
- ☐ Very disrespected

15. How accurate or inaccurate was the tanoak distribution data used in the model? Please choose one:

- ☐ Very accurate
- ☐ Somewhat accurate
- ☐ Neutral
- ☐ Somewhat inaccurate
- ☐ Very inaccurate
- ☐ Don't know

16. How realistic or unrealistic were the management options given? Please choose one:

- ☐ Very realistic
- ☐ Somewhat realistic
- ☐ Neutral
- ☐ Somewhat unrealistic
- ☐ Very unrealistic
- ☐ Don't know

6

Figure D.2 (continued).

17. How accurate or inaccurate were the spread dynamics created by the epidemiological model? Please choose one:

- ☐ Very accurate
- ☐ Somewhat accurate
- ☐ Neutral
- ☐ Somewhat inaccurate
- ☐ Very inaccurate
- ☐ Don't know

18. How intuitive or counterintuitive was the interaction with the model? Please choose one:

- ☐ Very intuitive
- ☐ Somewhat intuitive
- ☐ Neutral
- ☐ Somewhat counterintuitive
- ☐ Very counterintuitive

19. How useful or useless was the data presented in the dashboard? Please choose one:

- ☐ Very useful
- ☐ Somewhat useful
- ☐ Neutral
- ☐ Somewhat useless
- ☐ Very useless

20. What type of workshop outputs would you like to be given? Please check all that apply:

- ☐ Epidemiological model
- ☐ Maps from simulation runs
- ☐ A summary report of outcome metrics
- ☐ The whole Tangible Landscape system
- ☐ Other. Please specify: _____

7

Figure D.2 (continued).

21. How easy or difficult was it to use the system? Please choose one:

- ☐ Very easy
- ☐ Somewhat easy
- ☐ Neutral
- ☐ Somewhat difficult
- ☐ Very difficult

22. The model used today would help land managers prioritize treatment locations. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

23. The model used today would facilitate communication amongst stakeholders. Please choose one:

- ☐ Strongly agree
- ☐ Agree
- ☐ Neither agree nor disagree
- ☐ Disagree
- ☐ Strongly disagree

8

Figure D.2 (continued).

24. Do you feel like you learned anything from today's workshop? Please circle one:

Yes No

If yes, please explain what you learned:

_____

_____

_____

_____

_____

_____

_____

_____

_____

_____

_____

_____

_____

9

Figure D.2 (continued).

25. Do you have any other suggestions or comments that could be used to improve the Tangible Landscape system and inform future workshops?

10

Figure D.2 (continued).

TANGIBLE LANDSCAPE POST-WORKSHOP SURVEY

Thank you for your help!

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Figure D.2 (continued)

D.2. SURVEY INSTRUMENTS FOR SECOND PARTICIPATORY WORKSHOP

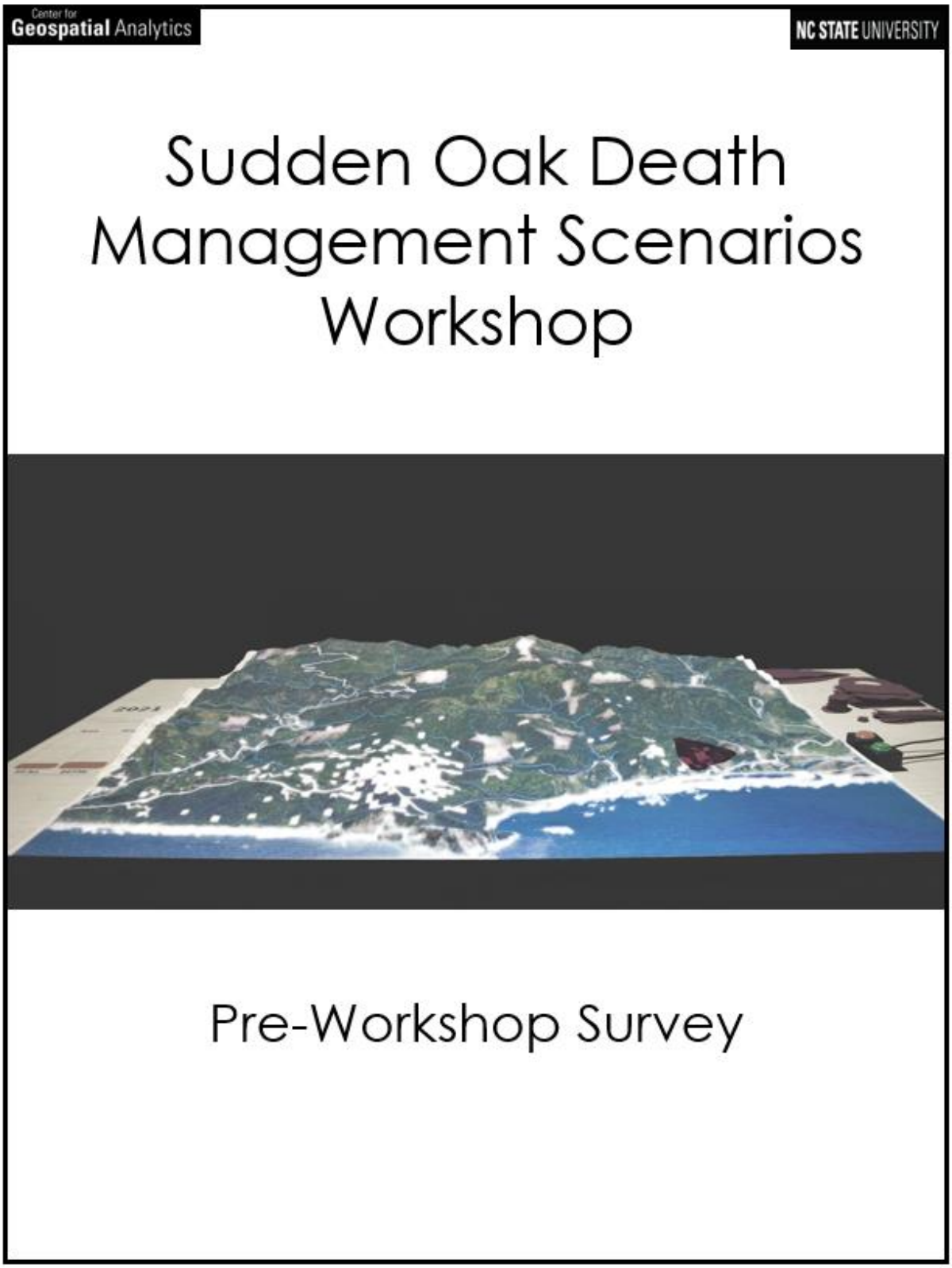

Figure D.3. Pre-workshop survey for second participatory workshop.

Background Questions

1. What organization are you associated with? _____

2. What is your current position at that organization? _____

3. Please describe how sudden oak death has impacted or could impact your organization:

_____

_____

_____

_____

_____

_____

_____

	Very Familiar	Somewhat Familiar	Neutral	Somewhat Unfamiliar	Very Unfamiliar
4. What is your level of familiarity or unfamiliarity with geographic information systems (GIS)?	○	○	○	○	○
5. What is your level of familiarity or unfamiliarity with simulations of pest or pathogen spread?	○	○	○	○	○

	Yes	No	Not Applicable
6. Have you ever used a geographic information system to inform pest or pathogen management?	○	○	○
7. Have you ever used a simulation of pest or pathogen spread to inform pest or pathogen management?	○	○	○

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
8. I think that sudden oak death in Oregon can be contained through management.	○	○	○	○	○

Figure D.3 (continued).

Center for Geospatial Analytics

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Thank you for your help!

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This project has been reviewed and approved by the Institutional Review Board at North Carolina State University.

Questions concerning your rights as a participant in this research may be addressed to the NC State IRB at irb-director@ncsu.edu or (919) 515-4514.

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Figure D.3 (continued).

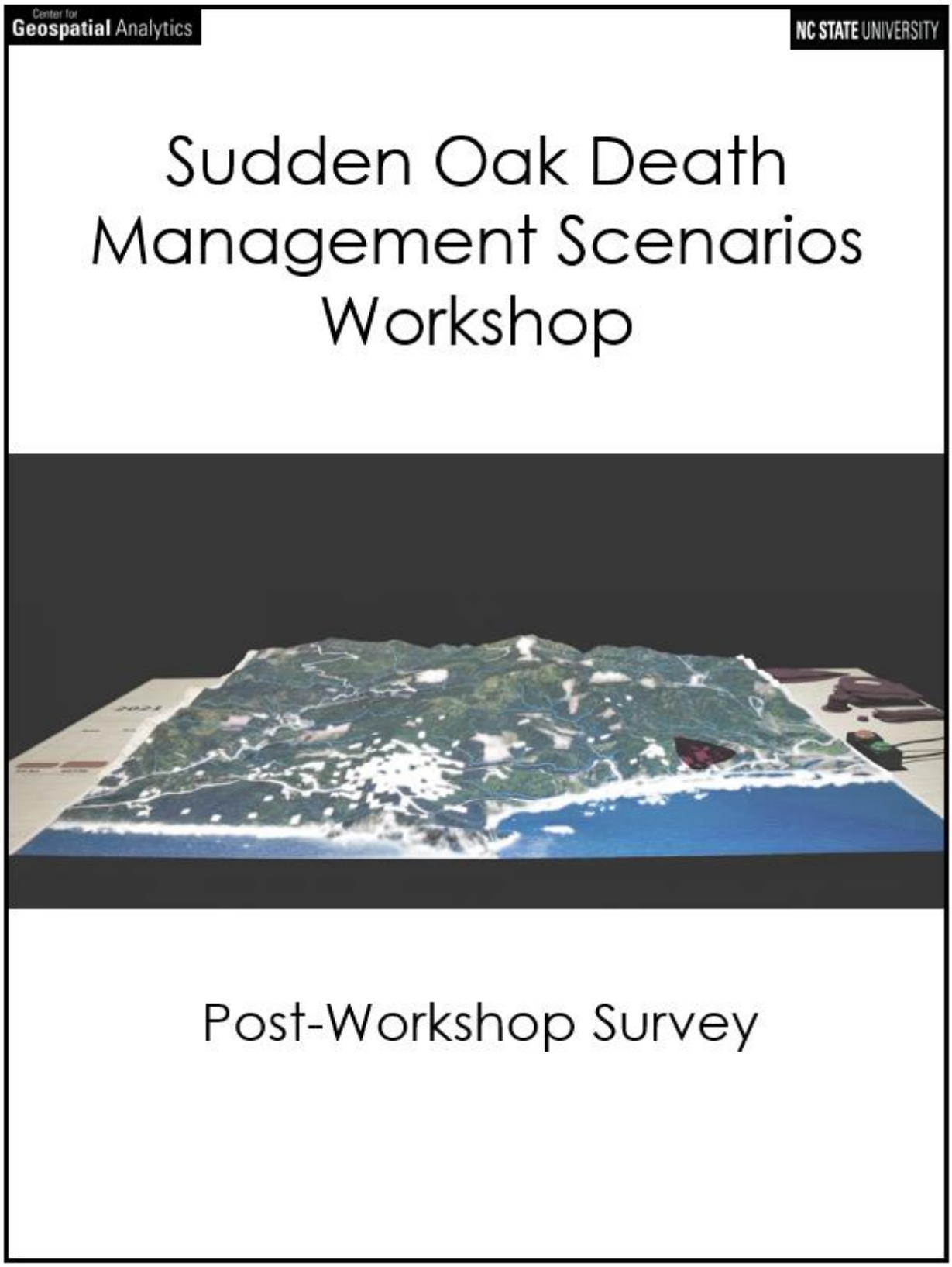

Figure D.4. Post-workshop survey for second participatory workshop.

Questions about Disease Simulation

	Very Accurate	Somewhat Accurate	Neutral	Somewhat Inaccurate	Very Inaccurate	Don't Know
1. How accurate or inaccurate were the patterns of disease spread produced by the simulation?	○	○	○	○	○	○
2. How accurate or inaccurate were the assumptions behind the simulation?	○	○	○	○	○	○
3. How accurate or inaccurate was the host tree map used in the simulation?	○	○	○	○	○	○

Questions about Tangible Landscape System

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
4. I think that I would like to use Tangible Landscape frequently.	○	○	○	○	○
5. I found Tangible Landscape unnecessarily complex.	○	○	○	○	○
6. I thought Tangible Landscape was easy to use.	○	○	○	○	○
7. I think that I would need the support of a technical person to be able to use Tangible Landscape.	○	○	○	○	○
8. I found the various functions of Tangible Landscape to be well integrated.	○	○	○	○	○
9. I thought there was too much inconsistency in Tangible Landscape.	○	○	○	○	○
10. I would imagine that most people would learn to use Tangible Landscape very quickly.	○	○	○	○	○
11. I found Tangible Landscape very cumbersome to use.	○	○	○	○	○
12. I felt very confident using Tangible Landscape.	○	○	○	○	○

Figure D.4 (continued).

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
13. I needed to learn a lot of things before I could get going with Tangible Landscape.	○	○	○	○	○
14. I think that Tangible Landscape would help stakeholders prioritize treatment locations for pest and pathogen management.	○	○	○	○	○
15. I think that Tangible Landscape would facilitate communication amongst stakeholders managing pests and pathogens.	○	○	○	○	○
16. I think that working with Tangible Landscape encouraged collaborative decision making.	○	○	○	○	○
17. I think that working with Tangible Landscape allowed everyone's interests to be considered.	○	○	○	○	○

Questions about PoPS Web Platform

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
18. I think that I would like to use the PoPS Web Platform frequently.	○	○	○	○	○
19. I found the PoPS Web Platform unnecessarily complex.	○	○	○	○	○
20. I thought the PoPS Web Platform was easy to use.	○	○	○	○	○
21. I think that I would need the support of a technical person to be able to use the PoPS Web Platform.	○	○	○	○	○
22. I found the various functions of the PoPS Web Platform to be well integrated.	○	○	○	○	○
23. I thought there was too much inconsistency in the PoPS Web Platform.	○	○	○	○	○
24. I would imagine that most people would learn to use the PoPS Web Platform very quickly.	○	○	○	○	○
25. I found the PoPS Web Platform very cumbersome to use.	○	○	○	○	○

Figure D.4 (continued).

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
26. I felt very confident using the PoPS Web Platform.	○	○	○	○	○
27. I needed to learn a lot of things before I could get going with the PoPS Web Platform.	○	○	○	○	○
28. I think that the PoPS Web Platform would help stakeholders prioritize treatment locations for pest and pathogen management.	○	○	○	○	○
29. I think that the PoPS Web Platform would facilitate communication amongst stakeholders managing pest and pathogens.	○	○	○	○	○
30. I think that the PoPS Web Platform encouraged collaborative decision making.	○	○	○	○	○
31. I think that working with the PoPS Web Platform allowed everyone's interests to be considered.	○	○	○	○	○

Questions about Management Scenarios

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
32. I think that sudden oak death in Oregon can be contained through management.	○	○	○	○	○
33. I think that the management capabilities were designed with stakeholder's needs in mind.	○	○	○	○	○
34. The disease simulation allowed me to explore the sudden oak death management scenarios that I wanted to test.	○	○	○	○	○

35. Please describe any scenarios you would have liked to test but that were not possible today:

_____

_____

_____

_____

_____

_____

_____

Figure D.4 (continued).

Questions about Today's Workshop

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
36. The workshop encouraged open discussion and evaluation of ideas.	○	○	○	○	○
37. I feel like I learned something from today's workshop.	○	○	○	○	○

38. If yes, please describe what was learned:

_____

_____

_____

_____

_____

_____

_____

_____

39. Do you have any suggestions or comments that could be used to improve anything about today's workshop, including the workshop format, disease simulation, or interfaces?

_____

_____

_____

_____

_____

_____

_____

_____

_____

_____

Figure D.4 (continued).

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Figure D.4 (continued)**.**

APPENDIX E

QUALITATIVE SURVEY RESPONSES FOR CHAPTER 4

Table E.1. Participants' open-ended responses about what other management scenarios to test.

Theme	Participants' Open-Ended Response
Include information on land ownership	Need ownership info.
	Have and shown different landowners, fed lands, private land owners, and industry.
	Include generally infested area (GIA) scenarios and no treatment in some land ownerships at the same time with matching treatment priorities.
Include other treatment customizations	I'd like to take a closer look at treatment buffer sizes.
	In PoPS, it would be great to have a function to create buffers around all infection sites.
	I was expecting to learn about the treatments that is commonly applied for the management of sudden oak death in Oregon. Based on what I would like to test the treatment combinations which is applied to a given management scenario.
Including more funding variations	I would have liked to test management with no boundaries in terms of funding.
Include more variation in time frames	Longer timeframes.
Include other SOD hosts	Possible sporulation by Oregon myrtle

Table E.1 (continued).

Expand Application Range of Forecasting Platform	Insert new known SOD infection and then run model
	I am very curious how both the tangible landscape and PoPS platform could be used beyond disease/pathogen pests, for example seed spread for noxious weeds such as gorse on the south coast
	As this is developed I'd like to known APHIS's intent or list of pest to try this on next. Rapid ohia death in Hawaii would be a good next step

Table E.2. Participants' open-ended suggestions for further developments to the forecast, interfaces, or workshop.

Theme	Participants' Open-Ended Response
Additional data visualizations	Include multi land uses. Owners. Roads.
	I think that including land ownership shapefiles would be very useful for stakeholder
	Include the GIA perimeter and ownership (fed/nonfed) on platform for context.
	Retain the existing occurrence locations on platform when out year projections are displayed (maybe as diff color?) – this informs/differentiates existing v new occurrences so you can see direction/extent of spread
	Add current state of Oregon 1 ft resolution aerial photography
	Disease simulation including GIA
Clarify metrics	Keep going! Tell "metric" of success tools providing answers to complex invasive and national pest.
	Explain/define the 'area', 'total area' fields – wasn't clear about that initially
	Allow default measurement in English or Metric units

Table E.2 (continued).

Comments about group modeling activities	Think the interactive time with model could have been better spent – with more structure
	Breakout groups: mode than enough time to run simulations
	Less sim time per session
	More opportunity for people to try PoPS on their own laptop
	I was in the first group with the Tangible Landscape, and it seemed there was less group discussion about treatments. Our group opened up a lot more in the afternoon while using PoPS. I'm not sure why the difference? I was fascinated with the Tangible Landscape but PoPS seemed to trigger more inclusive discussion.
Test alternative scenarios	All work on one scenario – outlying areas N and E, large area where SOD occurs, water drainages, go through multiple scenarios
	Mention potential to use as tool for reporting results of work already done (vs nonaction)
	A more simple graphics/tabular output of various scenarios over time would be useful
Add management features	Add ruler/measure tool in web tool to aid in drawing appropriately sized polygons
	Various polygon options in PoPS
Compliments/no suggestions	None!
	It was all good. Thanks!
	You all did a very comprehensive and informative presentation, well done.
	Thank you! Facility was comfortable, presenters were friendly/interesting. Very good experience.
	So far, the system (both tangible and web based) is well enough to describe the spread of the disease and management. This looks more user friendly than I thought about it.

	Thank you! If you ever want to venture into weeds (seed spread) please come back to Oregon. Oregon department of agriculture. The gorse action group. We have lots of great preliminary GIS data to feed a model 😊
	Tangible landscape simulation super cool
	Good tools; decision needs help at local, regional, and national planning

Table E.3. Participants' open-ended responses to what they learned at the workshop,

Theme	Participants' Open-Ended Response
About the effectiveness of treatments	Treatment options with tradeoffs on approaches both time and money
	It made more sense that a wide buffer may not be a silver bullet for stopping the spread NE
	In the first tangible landscape run (cost/acre was incorrect) and that shows EU1 can be contained
	Interesting to see management/treatment options to halt EU1
	The difference of treatment vs non-treatment
	Compare different management scenarios along with their predicted cost
	I have a much better understanding of SOD spread vs treatments.
Potential as teaching tools	The potential use of the PoPS web platform as a teaching tool
	Potential for landowner education and communications
	It is great the way it is now (no improvements) for displaying 'no action' vs 'action' – which is hugely valuable for communicating and teaching. Improvements were suggested, which will make it even more valuable (easier?) to use

Table E.3 (continued).

The importance of stakeholder engagement/collaborative learning	Value of hands-on learning amongst stakeholders to deal with natural resource issue.
	Disease management and control are best designed and produce better results when inputs from stakeholder, forest managers, and phytosanitary agencies are taken into account
	Ability to understand differing points of view
	I learned a lot about what different stakeholders value most in containing SOD
	Met a lot of different stakeholders and folks concerned with this disease
About the forecasting tools	Tools being developed to help in management of SOD
	Ability to project scenarios and test out response ideas is much further along than I expected
	I also learned the different ways in which the two interfaces can be applied
	Modelling approaches
	All of this – was not aware of these predictive tools. Extremely useful from a planning perspective and a very effective tool for collaboration and prioritization. Great group from NC!
	The value of modeling is not new to me, but this particular model was new to me. I think you've done a great job of displaying a very difficult subject.
	I learned about the PoPS, both tangible and web platform. Got ideas on the variables considered for model building, assumptions made and the ways to run simulations. Possibility to extend thi system to other pathosystems.
	Cool new technology that could be used for a lot of scenarios.
	Availability of software analysis and its use to predict possible future growth through treatment

Table E.3 (continued).

About the forecasting tools (continued)	How this model can better inform our treatment decisions
	The tangible landscape model was very helpful to visualize predicted occurrences by seeing the topography and past management areas such as clearcuts, road, etc
	The ability to model and produce visual evidence of the importance of cross boundary work was very helpful. Also, a tool to focus limited resources for the greatest return was helpful.
	The tangible landscape really gets stakeholders talking and engaging in a fun and constructive manner
	Good to know that such things are being explored or tested.
About sudden oak death	I was somewhat a novice on SOD. I learned a lot about the situation and treatment.
	I knew very little about SOD. This was eye opening. Thank you.
	Pathology and treatment of SOD. Management options and relative costs, scope of work needed for containment.

APPENDIX F

IRB Approval

The research in this dissertation was approved under North Carolina State University IRB Protocol Number 12270. The research was originally categorized as exempt (category b.2) on September 28th, 2017. An amendment was submitted on May 15th, 2018, and approved on November 16th, 2018.

NC STATE

Devon Gaydos <dagaydos@ncsu.edu>

Meentemeyer - 12270 - IRB Protocol assigned Exempt status

IRB Administrative Office <pins_notifications@ncsu.edu> Thu, Sep 28, 2017 at 1:02 PM
Reply-To: debra_paxton@ncsu.edu
To: dagaydos@ncsu.edu

Dear Devon Gaydos:

Date: September 28, 2017
IRB Protocol 12270 has been assigned Exempt status
Title: Developing the Tangible Landscapes GIS Tools to Better Inform Management Decisions: Sudden Oak Death Collaborative Management Planning for the Oregon – California Border Region
PI: Meentemeyer, Ross Kendall

The research proposal named above has received administrative review and has been approved as exempt from the policy as outlined in the Code of Federal Regulations (Exemption: 46.101. Exempt b.2). Provided that the only participation of the subjects is as described in the proposal narrative, this project is exempt from further review. This approval does not expire, but any changes must be approved by the IRB prior to implementation.

1. This committee complies with requirements found in Title 45 part 46 of The Code of Federal Regulations. For NCSU projects, the Assurance Number is: FWA00003429.
2. Any changes to the protocol and supporting documents must be submitted and approved by the IRB prior to implementation.
3. If any unanticipated problems or adverse events occur, they must be reported to the IRB office within 5 business days by completing and submitting the unanticipated problem form on the IRB website: http://research.ncsu.edu/sparcs/compliance/irb/submission-guidance/.
4. Any unapproved departure from your approved IRB protocol results in non-compliance. Please find information regarding non-compliance here: http://research.ncsu.edu/sparcs-docs/irb/non-compliance_faq_sheet.pdf.

Please let us know if you have any questions.

Sincerely,

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Jennie Ofstein
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Figure F.1. NCSU IRB categorization as exempt research.