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Responsive Governance And Harmful Microbial Blooms On Lake Erie: An ABM Approach

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In general, decision makers tend to respond to problems rather than prevent them. In political science, this process is called responsive governance and is associated with complex dynamics such as availability cascades and punctuated equilibrium. Most authors treat problems as one-time events, like oil spills or political scandals. In this paper, we use an agent-based model of the Lake Erie watershed to explore how responsive governance evolves along with an on-going but noisy environmental problem: harmful microbial blooms. This conceptual model features a two-level decision process based on Jones and Baumgartner (2005). Meta-agents representing the individual level of analysis "perceive" blooms either directly via observation if they are near a bloom or indirectly through the media. As a meta-agent observes more blooms, their concern increases until it crosses an action threshold, at which point they use simple cost-benefit analysis to select from a range of options. One of these options is to send a signal to their policy agent, which aggregates these political signals based on a range of assumptions and then decides on actions in much the same way as the metapopulations themselves. We examine two major scenarios, one in which there is a single policy maker managing the entire region and one where there are 5 policy makers, each separately regulating a demographically and geographically distinct region. Although the model is relatively simple, it lets us explore how variability in risk perception and responsive governance shape the functioning of the entire coupled human and natural system, including biophysical feedbacks.

Keywords: harmful algal blooms; governance treadmill; responsive governance; social ecological systems; Lake Erie

Introduction

Harmful microbial blooms (HMBs) cause many problems in aquatic systems, both for ecosystems and for human life. Microbes like algae and bacteria are common in aquatic environments. Most use photosynthesis for energy. Thus, they need sunlight and nutrients like nitrogen and phosphorous to produce food. Given sufficient nutrients and warm temperatures, populations of micro-organisms should be consistent between microbes vs. micro-organisms can grow rapidly, creating blooms that cover large areas. Many blooms are healthy and can provide food for other organisms, but some blooms are harmful because they lead to oxygen depletion in the water or because the microbes in the bloom produce toxic substances. These are often referred to as harmful algal blooms, but we use the broader term harmful microbial blooms, which includes bacteria as well as algae (Wilson et al., 2019).

HMBs can be prevented through governance mechanisms that reduce the nutrient pollution that feeds blooms. Once high levels of nutrients are in a system, reducing bloom activity is much more difficult, both because of natural factors (nutrient pollution stored in lake sediments) and human factors (increased economic reliance on polluting processes such as the use of chemical fertilizers). Nevertheless, people and governments rarely intervene proactively to prevent blooms. Instead, rules to reduce nutrient pollution are only put in place after a series of large-scale HMBs that have significant impacts on human health or welfare (Bullerjahn et al., 2016; Paerl & Otten, 2013). According to Webster (2015a), this process of responsive governance is common in other environmental issue areas and can lead to a cycling back and forth between more and less effective response in a dynamic that she calls the governance treadmill.



Support for the concept of responsive governance comes from several literatures. It is fundamentally based on how people and organizations deal with problems. Research in psychology and decision science shows that, while people do respond proactively to risks that are easily imagined and important to them (practically or emotionally), the complexity of environmental issues tends to dampen the perception of risk until they experience the effects themselves or hear emotive stories about the effects on people like them (Keller, Siegrist, & Gutscher, 2006; Slovic, 1987). Responsive behavior is also observed in organizations, and can be further delayed by high transactions costs and other barriers to information sharing (March & Simon, 1993; Simon & Barnard, 1957).

In political science, responsive governance is used most often to explain how governments change. For instance, Higgs (1987) claims that as policy makers respond to problems they create bureaucratic agencies that persist, expanding the size of government unnecessarily. In his famous work, Hirschman (1993) shows how public responses to economic, environmental, and social problems pressure different types of governments to become more or less authoritarian over time. In an interesting expansion on that work, Kuran and Sunstein (1995) show how public response can display complex properties, such as when information cascades led to rapid transition away from Soviet dominance in Eastern Europe; as more people spoke out against these oppressive regimes, others were more willing to speak out as well, creating a positive feedback loop or cascade of response that culminated in the Velvet Revolution. For environmental management specifically, as early as the 1970s scholars showed that decisions makers tend to respond to environmental harm rather than prevent it, though patterns of responsive governance can be traced back much farther (Walters & Hilborn, 1978; Webster, 2015a).

More recently, political scientists started to develop theories around issue-attention cycles, showing that, in democracies, policy making tends to occur in response to high levels of attention from interests groups or the general public, usually in response to experienced effects or media coverage of some type of crisis situation. These authors adopted the concept of punctuated equilibrium, arguing that the policy process is punctuated by phases of high activity around periods of heightened attention (Baumgartner & Jones, 2009; Jones & Baumgartner, 2005a; Kingdon, 2011). Like Higgs, authors in this field generally assume that problems do not persist for very long, either because they were ephemeral to begin with or because governments enact effective policies to solve them. As shown by Webster (2015a), this assumption rarely holds for environmental issues, which are usually increasing in severity and are rarely "solved" by early responses. Indeed, it may take multiple periods of crisis and response before decision makers arrive at an effective combination of governance mechanisms and, even then, there is no guarantee that these rules will remain effective in perpetuity.

As a result of these shorter response cycles, in the long term environmental governance tends to shift between phases of more and less effective response in a process that Webster (2015a) calls the governance treadmill. As shown on the left-hand side of Figure 1, the treadmill starts in an ineffective cycle, where an increasing environmental problem sends more and more intense signals to scientists, decision-makers, firms, the public, and other actors. These signals are translated into political concern, which is increasing as long as signals are increasing. If policy remains ineffective, these cycles will continue until the system collapses. However, when concern is sufficient and solutions are available, governance can shift to a more effective cycle, where the problem is decreasing, signals are receding, and political concern is on the wane. The dampening of problem signals can generate a crisis rebound effect, which shifts policy back to the ineffective side of the treadmill.



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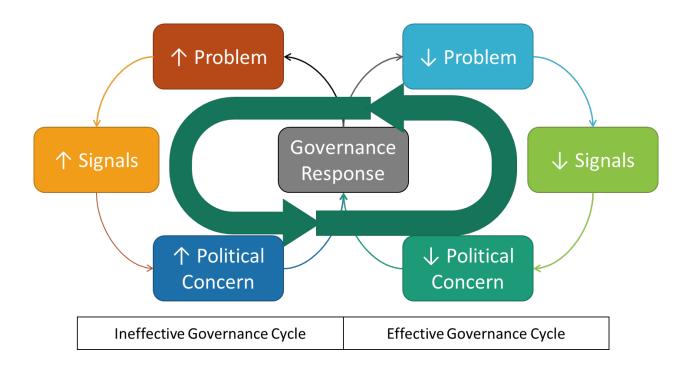


Figure 1 The Governance Treadmill. Source: Modified from Webster (2015a, fig 1.1)

Figure 2 compares the change in policy activity over time as predicted by the theory of punctuated equilibrium and the basic governance treadmill shown in Figure 1. As explained above, under punctuated equilibrium there is a flat trend in policy making that is punctuated by spikes of activity around crisis events that, while not completely random appear to occur randomly because they result from complex interactions within large socioeconomic systems. Although the apparent randomness remains, the governance treadmill predicts that spikes of attention will occur around an increasing trend as long as response is ineffective, and the problem is still sending out stronger and stronger signals. Attention and therefore policy-making will decrease substantially once an effective policy is implemented, and problem signals decline. Each spike in Figure 2 is a response cycle but only one round of the treadmill, or one transition from ineffective to effective governance is illustrated. if we extend the timeline long enough it is possible that policy will become ineffective again, either due to the rebound effect or because of exogenous changes like higher prices or new technologies that undermine existing policy. This would start another round of the treadmill, with growing spikes of response activity around an increasing trend.

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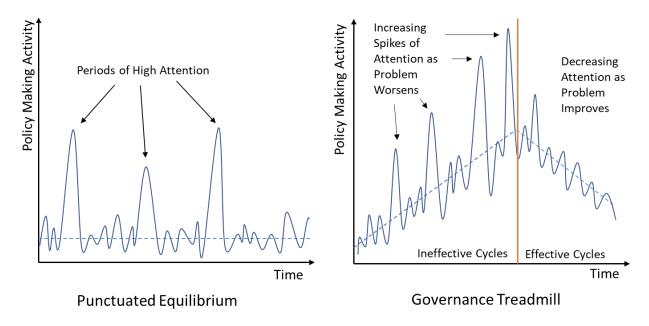


Figure 2 Two Perspectives on Responsive Governance over Time

Of course, there are many variations on the example shown in Figure 2. The governance treadmill can run smoothly, with relatively short periods of ineffectiveness and relatively long periods of effectiveness. This would be a healthy treadmill. When problems arise, they are dealt with in a timely and effective manner. Treadmills can also function poorly, getting mired in ineffective cycles as inaction or the implementation of palliative measures ensures that the problem continues to worsen over time. These dysfunctional treadmills can result in stagnation, crisis, and even a total system break, such as an ecological shift or a political revolution. They usually occur due to disconnects that prevent problem signals from reaching or influencing decision makers in a timely and effective way. Temporal disconnects like the threshold effects displayed by harmful microbial blooms (see below) are already well-recognized in the literature on complex systems, but there are many others.

This paper focuses on *power disconnects*, which occur when those who receive the strongest problem signals have little political influence or, in an alternative framing, when those who have political influence are insulated from the relevant problem signals (Webster, 2015a, 2015b). Essentially, power disconnects ensure that problem signals do not create sufficient concern to generate a governance response, thereby divorcing the problem from those who have the power to implement solutions and flattening the policy cycles shown in Figure 2. Thus, where there are power disconnects we can expect effective response to be substantially delayed, keeping the treadmill in an ineffective cycle until a major crisis closes the gap between those who are affected by the problem and those who have the ability to mitigate it. Such crises can be large-scale ecological failures that have broad-reaching impacts, but they can also be socioeconomic upheavals, such as the information cascades described by Kuran and Sunstein (1995) as explained above. Either way, these crisis events usually carry high human and environmental costs and may be destabilizing to other components of the system. This is why it is important to understand how power disconnects affect the governance treadmill and what can be done to reduce them.



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Because it encapsulates complex social ecological systems or coupled human and natural systems, modeling the governance treadmill is difficult and interpreting highly detailed models is problematic. In this study, we created a stylized agent-based model (ABM) of the treadmill for HMBs in the Lake Erie watershed that is relatively easy to understand and interpret. It will allow us to test two major scenarios, one in which there is a single policy maker managing the entire region and one where there are 5 policy makers, each separately regulating a demographically and geographically distinct region. Power disconnects are relatively narrow in the single regulator scenario because all actors have similar levels of influence, meaning that people who are affected by blooms have similar levels of influence to those who contribute to the nutrient pollution problem. Power disconnects are wider in the multidecision maker scenario because the farmers who contribute most to the problem of blooms and are affected the least by them are concentrated in a single governance region, giving them much more power over policy making in that region than they are able to wield in the single-decision-maker scenario. This mirrors state/province vs. national-level response as described in the next section, where we provide background information on HMBs in Lake Erie and a brief overview of governance response to this problem. We then describe our model and our testing methods. After presenting our results, we return to a discussion of the concept of the governance treadmill and methods for improving on this model in future work.

Background

Although they also occur naturally, HMBs are exacerbated by a number of human activities. Three are most important. First, humans add nutrients to the system by allowing human or animal waste to enter waterways and by oversaturating the land with (mainly synthetic) fertilizers, which then wash off into lakes and streams. Second and relatedly, land uses like farming and urban development increase runoff and erosion, moving more nutrients from the land into the water. Third, anthropogenic climate change can increase blooms through both higher temperatures and through larger amounts of rainfall. As described by Walker and Salt (2006), among others, by increasing the nutrient loads both in the water and in the lake sediment, human activities can push lakes past an ecological threshold, setting off a cascade of changes that ultimately results in the eutrophication of the lake. Essentially this means a rapid and sometimes irreversible transition from a high-oxygen plant and fish dominated system, which tends to be useful to humans, to a low-oxygen algae-dominated system, which reduces anthropogenic benefits such as recreation, fisheries, and clean water supply.

Because Lake Erie is very large, it is not as prone to such a complete transition, but the shallow western end of the lake is susceptible to blooms of Microcystis cyanobacteria (cyano blooms) that display similar but reversible threshold effects. Figure 3 shows a satellite image of a large-scale bloom event from 2011. Although there is a visible depositing of sediment from Lake Sinclair via the Detroit river, the majority of nutrient loading actually comes from the Maumee river basin, which enters the western-most tip of the lake as it passes through Toledo. Blooms can spread from there as far east as Cleveland. The Canadian section of the lake can also be affected, though their contribution to the nutrient load in the lake is much lower than the inflows from the US side of the boarder. In 2011, this cyano bloom event was considered to be one of the worst since the 1970s, but these large-scale blooms have increased in frequency since that time, including massive blooms in 2013, 2014, 2015, 2016, and 2017. In 2016 and 2017, double bloom events were observed, with an early bloom in June/July followed by a second bloom in September/October (Baker et al., 2019). There are other types of microbial blooms that occur in the deeper waters in the central and the north-eastern side of the lake, but these are not included in the model.



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Detroit Canada US Toledo Cleveland

Figure 3 Satellite view of October 2011 Cyano Bloom in Lake Erie Source: NOAA CoastWatch (MODIS)

This region has gone through one and a half rounds of the governance treadmill, with a historical switch from ineffective to effective governance, similar to the pattern shown in Figure 2, followed by a second transition back to the ineffective side. Harmful microbial blooms first flared up in the lake in the 1950s. Increasing bloom events caused growing socioeconomic costs that finally triggered management response in the form of improved sewage treatment and point-source controls in the 1960s and 1970s. In fact, large HMBs were well-publicized at the time and added to the national-level concern that culminated in the 1972 Clean Water Act. These responses improved sewage treatment and other urban sources, effectively reducing nutrient pollution and related bloom events in the 1980s but starting in the 1990s, non-point source pollution increased greatly due to the expansion of agriculture and proliferation of highly soluble chemical fertilizers (Wines, 2014). National-level legislation remains a primary driver of regulations to reduce HMBs in Lake (Wilson et al., 2019).

The return of large-scale blooms described above sends a number of different types of signals, some of which are noisier than others. The most direct signals are those sensed by people in close proximity to the lake. Large-scale cyano blooms turn the water bright green and they often are associated with a bad smell, green scums on the surface of the water and on beaches, and may cause irritation to bathers or pets that enter the water. Large blooms can suffocate fish and other wildlife and, in some cases, the cyanobacteria produce toxic chemicals that poison everything in the water (Paerl & Otten, 2013). This sends direct signals when dead animals or plans are perceptible, but indirect signals such as scientific reports, media coverage, and government warnings are more frequent. Scientists from the US National Ocean and Atmospheric Administration (NOAA) Great Lakes Environmental Research Laboratory collect bi-weekly samples from over 40 stations on the western end of the lake. They also monitor blooms using satellite imagery. This information is provided to the public through their HAB Tracker web-page. Though beaches are rarely closed due to HMBs, health advisories and other government warnings do occur. In fact, in 2014 a bloom forced the government to advise against using the municipal water supply, causing a severe water crisis for the city of Toledo (Neff et al., 2014; Pearson, 2014). In that case, media coverage made the bloom an event of nation-wide concern.

At a further remove from the core environmental problem, economic and political signals are also important. Blooms tend to discourage lake-based tourism and recreation, depressing lake-side economies. As noted above, major cities can also be affected through higher taxes to pay for clean-up

or alternative water sources. Economic analysis has also showed that property values near the lake decline with more blooms (Bingham, Sinha, & Lupi, 2015). People who experience these costs may send political signals to their representatives in several ways, most often through e-mails or phone calls, but also through protests, lobbying (esp. via professional organizations), and voting. Of course, these are not the only voices that politicians hear. Those people who might be affected by regulations may also send signals to protest potential new rules using similar channels. At the moment, most government action is aimed at reducing run-off from agriculture, so farmers are a very important interest group. While some farmers are environmentally concerned and already minimize their use of fertilizer and apply other practices to reduce run-off, other farmers feel economically threatened by regulations designed to curb HABs (Wilson, Howard, & Burnett, 2014). In this, they may receive signals from agro-business representatives and extension agents who are also politically opposed to regulations.

Decision makers must then aggregate all of these signals in some way. Lake Erie is embedded in a multi-scale governance system that ranges from community-based efforts at the local level to national-level legislation such as the Clean Water Act of 1972. There is even some international coordination via the Great Lakes Water Quality Agreement (Wilson et al., 2019). At this stage we cannot incorporate all of these different levels into our analysis, and so instead focus on developing a set of models that incorporate increasingly complicated governance decision processes.

We start with a single aggregator that simply sums the signals from all meta agents. This is somewhat representative of national-level response, although of course in the real world signals to the national government could come from other locations experiencing water quality issues as well. We compare this result to decisions made by 5 independent governance actors, each of which aggregates signals from different regions that have distinct geographic and demographic characteristics. Notably, one particular region—representative of the Maumee watershed in the Erie case—contributes the majority of the nutrient pollution driving the cyano blooms but is also home to a large population of farmers who will generally resist being regulated. Thus, our general expectation is that response will happen sooner in single decision maker mode and will be delayed or may not even occur in multiple decision maker mode. Although the model is relatively simple, it lets us explore how variability in risk perception and responsive governance shape the functioning of the entire coupled human and natural system, including biophysical feedbacks.

Model & Methods

Modeling responsive governance in a large, complex human and natural system like Lake Erie is a difficult task. Analyzing a high-resolution, detailed model would also be difficult because of the many different sources of variation and emergent properties in the system. Therefore, to maintain tractability in early stages of model development, we start with a relatively simple model that is easier to interpret. Figure 4 illustrates the basic logic of our model (see Appendix 1 for more detailed documentation of the model). Additional detail is provided in subsequent sections. Following the governance treadmill, the environmental problem (HMBs or Bloom Activity) sends signals to different metapopulations (Metapops in Figure 4) or agents that represent groups of similar individuals. We will refer to these types of agents as constituents throughout this text (e.g. farmers, coastal business owners, etc.). Signals occur either through direct observation of blooms or their effects, or indirectly through media reports on factors like the size and location of blooms. If bloom signals are strong enough to generate high levels of public or interest group attention, policy maker agents will also receive indirect signals from their constituents, pressuring them to take action to reduce bloom activity.



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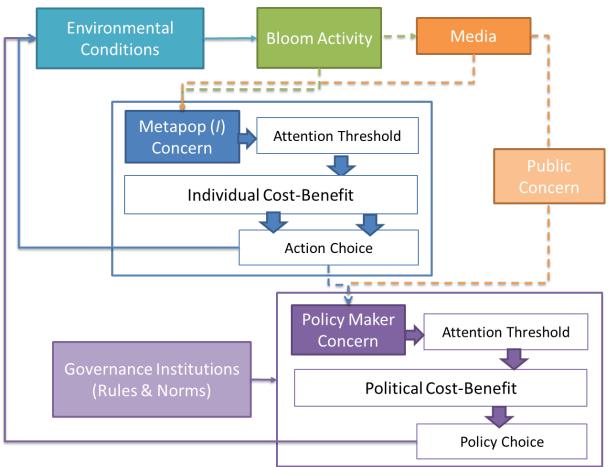


Figure 4 Basic Model Diagram

The internal decision processes for both constituent metapopulations and for policy makers are based on Jones and Baumgartner (2005b). We start by describing the constituent process. As shown in figure 3, signals from the bloom event and from the media increase the constituent's level of concern regarding the HMBs problem. Different types of signals are weighted differently across agents, depending on their pre-existing interests. Thus, total concern is the weighted sum of concern from multiple signals. Total concern will gradually dissipate, however, if no new signals are received by the agent. Once total concern reaches a pre-set attention threshold, the agent uses its own cost-benefit analysis to select from a preset suite of optional actions. In this case, they can choose to do nothing or they can choose to send a signal to the policy agent(s). The policy agent(s) then use a similar process to aggregate constituent concern and, once they cross their attention threshold, they select a policy option. Here, they decide on the maximum level of nutrients that farmer-agents can apply to patches within the watershed. Changes in the nutrient level then alter the environmental conditions, reducing the likelihood of bloom activity.

Setup

Initial setup involves creating global variables, breeds of agents, and assigning patch- and breedspecific variables (see Appendix 2 for a list of all variables, their initial values, and the sources used to parameterize these values). The only global variables fixed in the setup code are related to lake and bloom variables. Other global variables are controlled by sliders in the user interface. These variables relate to how different agents perceive and are affected by different signals. They include the



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magnitude of a signal, how susceptible an agent is to that signal, how long they care about that type of signal for, how quickly an agent loses concern, and at what level of concern an agent takes action (see Appendix 3 for a list of these variables and the values used in the simulations described here). Patch-specific variables include land-cover type and blooming conditions. They will be described in greater detail below.

There are seven breeds of agents in the model: "urban.dwellers", "rural.non.farmers", "coastal.busines.owners", "farmers", "government.actors", "media.sources", and "scientists". Variables assigned to each breed primarily control their internal decision processes, particularly signal processing and internal levels of concern. Of these breeds, "urban.dwellers", "rural.non.farmers", "coastal.busines.owners", and "farmers" are metapopulations of constituents that respond to direct and indirect signals from bloom events as described above; "government.actors" aggregate signals from constituents in the areas that they control (see below) and from "media.sources"; there is only one "media.source" agent that monitors bloom events and reports on specific characteristics to other breeds of agents in the model; "scientist" is also a single agent that uses bloom-related variables to calculate the range of nutrient application levels that are likely to minimize bloom activity and then passes this information to "government.actors".

Patch setup is largely based on maps of the Lake Erie watershed and features deemed to be important based on our review of the literature on HABs in the region (see Background section). First, each patch is assigned a land cover type, delineating between "*lake*" patches, "*coast*" patches, and "*land*" patches. All patches outside of the Lake Erie watershed have no land cover type. Next, major cities are placed on the map in approximately their location in real life. Smaller cities are then distributed randomly throughout the remaining land area. "*Beaches*" and "*water intakes*" are created in coastal and lake patches respectively, and are distributed in areas proximate to their real-world locations. Of the remaining land patches, those within the approximate contour of the Maumee River Watershed are designated as "*farms*". Of course, there are many other farms outside this watershed, but the Maumee is the primary source of nutrient pollution in the Western Basin, as described above, so we keep the analysis tractable by only modeling nutrient application on farms in this area. Patches are given population characteristics according to their land cover type and the presence or absence of a city. These characteristics include population size and the proportions of urban dwellers, coastal business owners, farmers, urban non-farmers, and "*tourists*". Note that "*tourists*" are not agents in the model but are an attribute of coastal patches that changes with bloom activity.

We populate the model landscape by placing constituent agents in their respective positions and assigning appropriate population proportions (see Figure 5). "*urban.dweller*" agents are located in the major cities and represent the relevant proportion of population in each patch. For instance, Toledo, OH, is represented by 5 patches, each of which sprouts an "*urban.dweller*" agent that is assigned to represent 1/5 of the total population of Toledo. Smaller cities and towns are only one patch, each of which sprouts a single "*urban.dweller*" agent with a population randomly drawn from a distribution based on the actual population sizes of small to medium sized cities in the region.

Coastal cities near beaches also sprout a "*coastal.business.owner*" agent that tracks the number of "tourists" in neighboring patches as well as other blooms signals. Non-farm "*land*" patches sprout "*rural.non.farmer*" agents and "farm" patches sprout "farmer" agents. This nomenclature is a bit misleading, as "*rural.non.farmers*" can represent people who farm in areas outside of the watershed, but it follows with our designation of "*farmers*" agents that control the level of nutrients in the

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Maumee watershed only. The "*media.source*" agent and "*scientist*" are placed in patches outside of the Erie watershed.

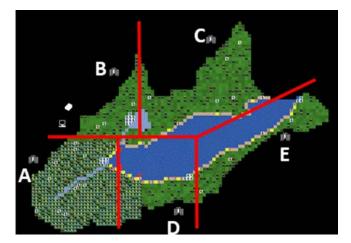


Figure 5 Landscape and Governance Districts

Finally, regional boundaries are created (red lines in Figure 5) and five "government.actor" agents are placed within their regions but outside of the area occupied by active watershed patches. Regional boundaries are drawn and five "government.actor" agents are created on patches outside of the Erie watershed. When the model is run with a single decision maker, the "government.actor" labeled "A" received signals from all constituent agents in the model and its policy decisions apply to all agents in the model. In the multiple decision-maker version of the model, each of the "government.actor" agents only receives signals from constituents in its region and can only apply policies to agents in said region.

Processes

The processes run by the model proceed in the following order: 1) track time and seasons, 2) farming, 3) microbial blooms, 4) track tourists visiting beaches, 5) determine what signals the media will present, and 5) calculate the level of concern of and actions taken by urban dwellers, rural non-farmers, coastal business owners, farmers, and the government. We should note that each agent type has a procedure for calculating concern and whether they take action.

Bloom-related procedures

Farming contains the decision of farmers about how much nutrients they apply while farming. This is relevant to the simulation in two ways: it is the source of nutrient pollution to the lake, and the level of nutrients applied can be regulated by policy. Farmers apply nutrients to their fields during the growing season, between calendar weeks 18 and 42 to represent the Ohio farming season.

Farmers apply 10 units of nutrients under normal conditions, and lower amounts if the government is regulating nutrient application. (See description of the nutrient regulation procedure



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below.) Farmers have a certain probability of applying nutrients at each time step, controlled by the variable *"fertilizer.application.rate,"* whose values range from 0 to 1.

Microbial blooms can occur if the sum of all "*nutrients*" on the landscape times the "*rainfall.factor*" (takes values between 0-1) exceeds the threshold required to have a bloom ("*nutrient.threshold*"), and if the time of year is within the warm season ("*temperature*" = "*hot*"; there are only 2 seasons, "*hot*" and "*cold*"). When the conditions are met, a bloom is seeded in a specified number of lake patches ("*bloom.seeds*" number of patches set "*blooming*?" = 1) within the Western Basin of the lake ("*pxcor*" <= 46). The bloom then spreads to a certain number of its neighbors ("*num.neighbors.bloom.spread*"), which can be selected by the user using a slider in the interface. Values for bloom spread range between 1 and 8, with a default level of 4. A patch remains blooming for a certain number of time steps ("*max.time.blooming*"), which can be set anywhere between 1 and 20 with a default level of 7. Patches stop blooming if the temperature changes to "low" or nutrients drop below the threshold.

Coastal tourism declines if blooms occur near public beaches. If the season is warm and none of the lake patches neighboring a beach are blooming, the number of tourists is calculated using the following equation:

$$tourists = population * prop_{tourists}$$
(1)

Where "*prop*tourists" is the proportion of people at a patch that are normally tourists. As noted above, "*tourists*" are not agents but are a patch-related variable.

If any of a beach's neighboring lake patches are blooming, "*tourists*" are calculated with the following equation:

$$tourists = population * prop_{tourists} -$$

$$tourism. loss. by. bloom * population * prop_{tourists}$$
(2)

Where "*tourism.loss.by.bloom*" is the proportion of tourists who no longer visit beaches when there is a nearby bloom.

There is also a "*scientist*" agent that provides advice to decision-makers based on bloom characteristics. Specifically, this agent sets the maximum advisable level of nutrients per application as:

$$nutrients.MAX.RECOMMENDED = \frac{nutrient.threshold}{\frac{(1-rainfall.factor+nutrient.decay)}{(count.farmers)/(fertilizer.application.rate)}}$$
(3)



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In order to account for some uncertainty created by the potential build-up of nutrients on farms, the scientist agent sets a minimum advisable level of nutrients per application as:

if rainfall.factor > 0.4: nutrients.MIN.RECOMMENDED = nutrients.MAX.RECOMMENDED - 1 (4)

if rainfall factor is <= 0.4: nutrients.MIN.RECOMMENDED = nutrients.MAX.RECOMMENDED – 2 (5)

Basically, when rainfall is higher, it is more likely that the nutrients on a given patch will be depleted within the two-week on average period between applications, so with more rainfall the buildup of nutrients is less likely, and the lower bound on scientific advice will be higher. With less rainfall, nutrient build-up is more likely, meaning that a lower minimum application rate is needed to prevent a bloom event is lower. This is counter-intuitive if you think about real-world systems, where rainfall is not a constant factor but rather higher average rainfall can mean more storm events that carry large nutrient loads into the lake. For tractability, we do not represent such realism in the model. Rainfall is a constant percentage removed from the nutrients on the land and therefore sudden large inflows are more likely if nutrients are allowed to build up over several ticks in the model.

Concern

"Concern" is a variable held by each agent that calculates and stores their level of concern regarding the microbial blooms. Concern at each time step is generated from the multiple signals agents receive according to the following equation:

$$concern = \sum_{signal.types} susceptibility_{signal.type} * signal.value_{signal.type}$$
(6)

For calculations of concern, there are 13 types of signals in the model. Four types of signals are directly assessed by constituent agents in coastal regions through commands to ask neighboring patches for information or through information gathered from other agents ("signal.value.intake", "signal.value.seeing", "signal.value.tourism", and "signal.value.regulation"). Five types of signals are calculated by the media agent and then called by other agents in the model ("signal. Toledo", "signal.Sandusky", "signal.large.bloom", "signal.intakes", and "signal.beaches").

Each of the four types of constituent agents can also send signals to government agents, though these are interpreted using a somewhat different equation (see below). We describe each signal in greater detail in the next section.

The "susceptibility signal.type" (range = 0-1) variable accounts for differences in how much people care about different aspects of the bloom. For example, farmers might not care if coastal tourism decreases ("signal.value.tourism"), whereas coastal business owners care a lot. In contrast, farmers often react negatively to regulations that limit their use of fertilizer ("signal.value.regulation"), while coastal business owners do not. Each type of agent has a different level of susceptibility to each type of signal

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that they receive. Thus, media signals, which are the same across all agent types, will affect types of agents differently because of the variation in susceptibility. This interacts with signal variability for direct experience with the bloom, which does vary by agent location.

Urban dwellers' concern comes from four types of signals: contaminated water intakes, blooms that occur close enough to the shoreline of their cities for people to see, decreases in coastal tourism, and media signals on blooms.

Rural non-farmers' concern comes from media signals only. This assumes they are not directly impacted by the blooms, but may care about the health of the lake or other people who are impacted.

Coastal business owners' concern comes from three sources: blooms that occur close enough to the shoreline for people to see, decreases in tourism in adjacent beaches caused by nearby blooms, and media signals on blooms.

Farmers' concern comes from two sources: regulation of nutrient application and media signals. Media signals generate concern in two ways; farmers have concern for the health of the lake and that they may face further regulations that will hurt their business.

Government actors are susceptible to signals from the media, but they also receive signals from constituent agents directly. This variable is named with the following format in the code: *"susceptibility.agent.type.GOVERNMENT"*. An example is *"susceptibility.farmers.GOVERNMENT"* for government susceptibility to farmers. Because constituent agents represent different proportions of the population and because population characteristics vary by region, we calculate government concern from signals received from each breed using this equation:

concern = (susceptibility.agent.type.GOVERNMENT *
count agent.type with [countact.government? = 1]/(count agent.type) (7)

By using the proportion rather than the total number of constituents of a given type that contact government to calculate concern we are able to restrict the political influence of each agent type to the variable "*susceptibility*.agent.type.*GOVERNMENT*".

While it is likely that groups with larger populations in a governance region will have more influence if they are activated, the scale of the difference in population sizes would wash out all impacts of the susceptibility variable at high levels of concern (where most constituents are contacting the government agents). Thus, we instead assume that population size is one of the factors that determines the magnitude of *"susceptibility*.agent.type.*GOVERNMENT"* while the proportion of the population contacting the government is a better indicator of the level of concern regarding the environmental problem for that type of agent. This also makes it easier to interpret the results of the model, though alternative methods of calculating government concern should be considered in future work (see Conclusion).

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Total concern for each government agent was calculated by summing across the weighted signals received. Since farmer agents tend to be more concerned with the negative effects of regulation, their signals end up reducing rather than increasing government concern.

For all signal and agent types, multiplying the signal value by a constant level of susceptibility implies that each additional unit of signal creates the same amount of concern. More complex models could be used if there were theory or evidence to support them.

Concern decays over time linearly. Each agent type has a different rate at which concern decreases, referred to as *"decay.of.*agent.type".

$$concern_t = decay * concern_{t-1} + concern_{new}$$
(8)

Concern over each signal type disappears completely if enough time passes without a new signal; the time threshold is called "*attention.span.*signal.type".

Signals

The "*signal.value*_{signal.type}" variable allows for variability in the strength of signals at different points in time. Signal values range from 0 to 1. Direct signal variables are binary while media signals are calculated as proportions. Table 1 describes how each signal type is calculated in the model.

Table 1 Calculating Signal Types in the Model

Direct Signals	Description
signal.value.intake	If any patches that has a water intake on it and is within a radius of four from an agent, the signal value for intakes equals one. Otherwise, this signal equals 0.
signal.value.seeing	If any neighboring patches are blooming, the signal value for seeing the bloom equals 1. Otherwise, this signal equals 0.
signal.value.tourism	If it is the hot, tourists are counted at coastal beaches. If there is a bloom in any of a beach's neighboring patches, tourism declines by the proportion <i>"tourism.loss.by.bloom"</i> . The signal value for tourism loss is one minus the proportion of tourists currently compared to the number of that would be there had there not been a nearby bloom.



signai.vaiue.reguiation	value for regulation is 1. Otherwise, this signal equals 0.
Indirect (Media) Signa	ls
signal.Toledo	Proportion of patches that are blooming in lake patches neighboring Toledo's coastal patches
signal.Sandusky	Proportion of patches that are blooming in lake patches neighboring Sandusky's coastal patches
signal.large.bloom	Reports the proportion of patches blooming if the total size of the bloom is > "large.bloom.threshold"
signal.intakes	Proportion of water intake patches where a bloom is occurring
signal.beaches	Proportion of beach-adjacent patches where a bloom is occurring

If government actors are currently regulating nutrients, the signal

As noted above, signal values of constituents' concern, received by government actors, are calculated as the proportion of constituents with "*contact.government*?" = 1. For instance, if every farmer was concerned enough to contact the government, the government would receive a signal of 1 from farmers.

Action

signal value regulation

There are two main types of actions in the model: constituents can send signals to government agents and government agents can regulate nutrient levels, and farmer agents change the nutrients applied to their patches once regulations are put in place. Both types of action only occur when the agent's concern crosses an action threshold, triggering their action routine. We limit the actions available to each agent type severely in this preliminary model to maintain tractability and transparency. More elaborate choices among different types of action could be modeled in future work.

Urban dwellers, rural non-farmers, coastal business owners, and farmers can take action by contacting the government (*"contact.government?"* = 1). They do so when their concern exceeds their type-specific threshold, *"concern.threshold.*agent.type". These signals are then aggregated in government concern as described above.

Government actors take action by setting the regulated level of nutrient application. Government agents only regulate once per year, in the 40th week (just before the end of the growing season). This is a simple representation, but it reflects the fact that decision makers can rarely change agricultural policy in the middle of a growing season and that in any case it often takes time to collect scientific

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information and move policies through the process. Of course, regulation is often much harder to pass than is depicted in this model, but we believe this is a good place to start.

If government concern remains less than their action threshold for an entire season, they choose not to regulate, leaving the nutrient level where it is. If no regulations are in place, this will be the default level of nutrient application. If there are prior regulations, then they will simply remain in place for another season.

If government concern was greater than their action threshold during the season, government agents will choose to regulate by reducing the amount of nutrients that farmer agents are allowed to apply to their patches. To determine the new level of nutrients, the government agent follows a set of conditions that is designed to gradually align regulated nutrient levels with levels that are close to those recommended by the scientist agent:

If the average nutrients per field is greater than the maximum amount recommended by scientists plus one (*"nutrients.MAX.RECOMMENDED"* + 1), the government agents will set

$$nutrients. REGULATED = nutrients. MAX. RECOMMENDED + \frac{nutrients.applied-nutrients.MAX.RECOMMENDED}{2}$$
(9)

If the average nutrients per field is greater than the max amount recommended but less than or equal to the max amount recommended plus one,

$$nutrients. REGULATED = nutrients. MAX. RECOMMENDED$$
(10)

If the average nutrients per field is greater than the minimum amount recommended but less than the maximum amount recommended,

$$nutrients. REGULATED = nutrients. applied - 1$$
(11)

If the average nutrients per field is less than the minimum amount recommended, government agents will not change the regulated level of nutrients. In other words, the minimum level of nutrient application recommended by the scientist agent serves as a lower bound for the government agents' regulatory algorithm.

There are two options for the process of how government actors make decisions: either as a single decision maker for the entire watershed, or with five decision makers, each representing a defined



geographic area. If there is a single decision maker, the concerns of all stakeholders affect the government actor's concern and, hence, level of nutrient regulation. Under the multiple-decision-maker option, each government actor receives signals from the agents within its district, as well as media signals that are globally available. In this case, the regulated level of nutrient application is particular to each government actor and their district. Farmers' nutrient application is then governed by the regulation set for their district.

Parameterization, Validation, and Verification

Where possible, we used real-world data to parameterize the model (see Appendix 2 for detailed descriptions of variables and sources). This provided some grounding in reality for factors like population size, but data were not available for many variables. For most of the variables in the decision process, we set parameters to reflect the relative importance of cyanos to the groups in question, using best-guesses based on our review of the literature (above). We then hand-tuned many of the variables to create our working model.

Because this is a stylized model, we were not able to validate against real-world behaviors. Model verification was done through systematic evaluation of coding logic and model behavior (Yilmaz, 2006). We started with bloom-related procedures, checking that nutrient application was occuring at expected rates, that the nutrient decay function was working properly, and that blooms were occuring as expected in the absense of regulation. At unregulated levels of nutrient application, even our simple model produced blooms that are physically similar to actual blooms observed in Lake Erie in recent years, though bloom duration tends to be longer, lasting for multiple ticks or "weeks". We then tracked the relationships between bloom activity and the signals received by different agent sets and finally verfied that the regulation algorithm was working correctly and that farmer agents were applying only the regulated level of nutrients when regulations were in place. We found and eliminated multiple artifacts in this process.

Results

Model results generally support the expectations laid out in the introduction. Response occurred more quickly in single-regulator mode than in multiple-regulator mode. When there was a single regulator aggregating signals from the entire area, regulation started after only 1-2 major bloom events and regulated nutrient levels quickly stepped down to scientifically recommended levels as new regulations were enacted each season. This, in turn, reduced bloom activity and represents a transition to an effective management cycle. In model runs with multiple decision makers, the disconnect between farmers and other actors in "*Region A*" prevented a transition to more effective governance like the one shown in Figure 2.

Instead, while all other regions quickly implemented regulations to reduce nutrient levels, the government agent in charge of "*Region A*" was never sufficiently motivated to take action. Because most of the nutrient pollution in the modeled lake comes from "*Region A*", the end result was that large bloom events continued much as in the unregulated version of the model.

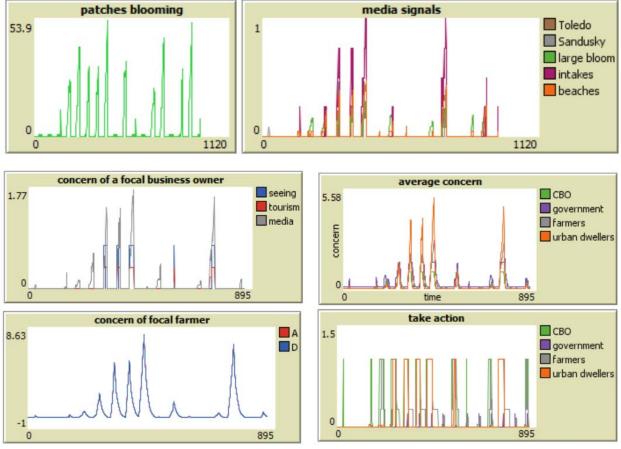


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No Regulation

Figure 5 shows typical model results over a period of 1000 ticks (weeks). Note the seasonal fluctuation in bloom activity, which can only occur when temperatures are above a certain threshold (summer months). At first, bloom activity is relatively low because there are not a lot of nutrients built up in the field patches but toward the end of the third "summer" the size of the bloom starts to increase. Large bloom events like the one shown in figure 6 become common without regulation, though there is still a large degree of interannual variability in bloom size. This matches what is observed in the real world, though the mechanism is different; in reality large blooms tend to be correlated with major rainfall events but in our case large blooms reflect the build-up of nutrients in the soil and random/contagion effects in the bloom algorithm.



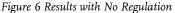


Figure 5 also shows how various signals from the bloom are received by different agents. As expected, the media is tracking the overall size of the bloom (large bloom), and the proportion of blooming patches near major urban areas (Toledo, Sandusky), beaches, and water intakes. This information is distributed to other agents and is part of their concern function. The two charts on the bottom right track the level of concern for a randomly selected business owner (top) and farmer Complexity, Governance & Networks – Vol. 5, No 1 (2019) Special Issue: Adaptive Governance of Coupled Social-Ecological Systems, p. 24-64 DOI: http://dx.doi.org/10.20377/cgn-72

(bottom). Note that the ranges are quite different for these agents but that these numbers are normalized and weighted by population size in the graph labeled average concern. The last graph shows the proportion of the agent set that is motivated to "take action" (send a signal to their decision maker) at any given point in time. Urban dwellers and coastal business owners are the most motivated while farmers are the least motivated, as would be expected.

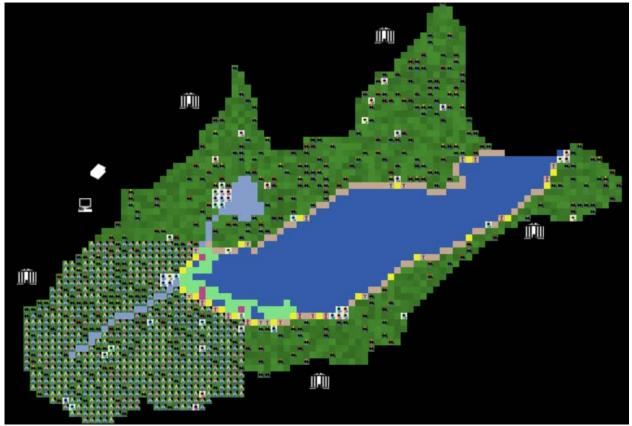


Figure 7 Large Bloom event with no regulation

Individual (National-level) Regulator

Figure 7 shows the results with the same configuration as above but with an individual regulator collecting signals from all agents in the region and then regulating the level of nutrients applied by farmers. In this run a large bloom randomly occurs in the second "season", triggering considerable concern by urban agents because it is near water intakes. This triggers the first stage of governance, setting the allowed level of fertilizer per application to the maximum recommended by scientists plus the mean difference between the current level and the scientifically recommended level.

This reflects the responsive or trial-and-error nature of governance as well as the often observed desire of policy makers to cushion the impacts of regulations on business via gradual implementation. However, because this reduction is not sufficient, the government agent is forced to regulate again, gradually reducing the amount of fertilizer allowed per application until it is close to the minimum



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level recommended by scientists. Nutrients applied go down with the regulations and eventually blooms are eliminated from the lake.

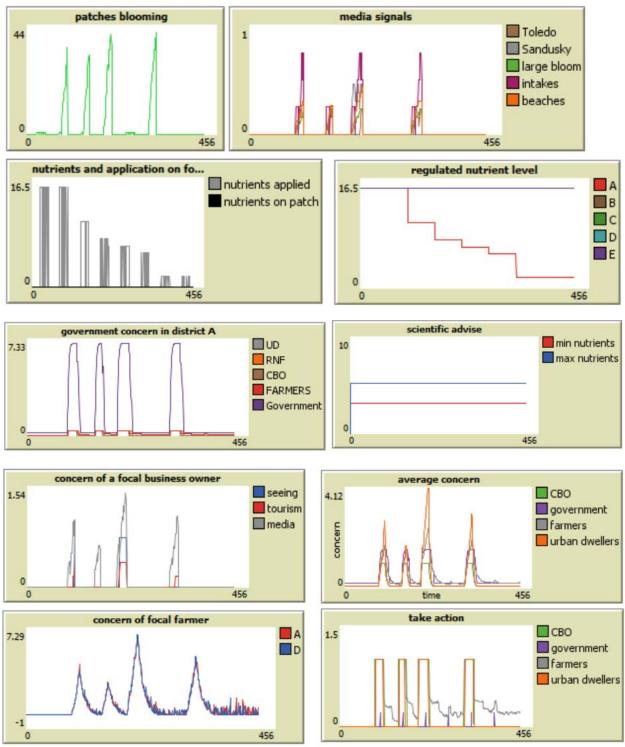


Figure 8 Results with single government agent



Multiple (5 Regional) Regulators

When we allow the five regional regulators to operate independently, the results change drastically, even though all other parameters remain the same. Note that even though we ran the simulation for much longer, blooms continued to be a problem, much as in the unregulated case. The reason for this can be seen in the chart showing the "regulated nutrient level" by region. Because they have no farmers, even though they are least directly affected by blooms, regions E and C (north-east and south-east) quickly set nutrient application limits at the minimum level recommended by scientists. However, as this had no effect on the flow of nutrients into the lake it does not reduce bloom activity. Regions B and D (central north and south) do have some farmers, but signals from media, urban dwellers, and coastal businesses pushing for regulation outweighed signals from farmers against regulation. Thus, these regions followed a gradual decline similar to that of the single-regulator described above. Interestingly, region B, which has fewer coastal businesses took longer to enact minimum regulations, which would be expected based on relative levels of concern for these agents. Here again, too few farmers are actually regulated to make much difference. Finally, area A, (western basin) is dominated by farmer agents and so regulators never required any reductions in fertilizer rates. Since this is where most of the farmers are located, nutrient pollution remained high and blooms remained a problem.



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patches blooming media signals Toledo 53.9 Sandusky large bloom intakes beaches 0 0 1400 1400 0 0 nutrients and application on foc... regulated nutrient level nutrients applied A 16.5 16.5 nutrients on patch В C D E 0 0 1400 1400 0 0 scientific advise government concern in district A min nutrients UD 10 RNF max nutrients СВО FARMERS Government 0 -3.93 1400 0 1400 0 concern of a focal business owner average concern seeing СВО 1.91 5.21 tourism government media farmers concern urban dwellers 0 -8.2 1400 n 1400 0 time take action concern of focal farmer СВО A 1.5 13.8 D government farmers urban dwellers 0 1400 0 1400 0

Figure 9 Results from the multi-regulator model

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Discussion and Conclusions

The two scenarios we tested with our models (single regulator, and multiple regulators) show how the governance treadmill can switch to an effective cycle fairly quickly when disconnects are narrow (single regulator) but get stuck in ineffective cycles when disconnects are wide (multiple regulators). In the single regulator scenario, the signals from those agents that were most concerned about the bloom events (urban dwellers, coastal businesses) outweighed the signals from agents that were more concerned about the costs of regulation (farmers) and so response was relatively quick. In the multiregion scenario, the region that contributed most to the problem (A) was also politically dominated by agents that were most concerned about the costs of regulation and therefore the decision maker for that region never chose to regulate and blooms continued, even though other regions with narrower disconnects did choose to enact strict regulations after a time.

While these results are interesting, they are not unexpected. The real value of this model is as a means to decompose the various elements of the governance treadmill and to plan for the development of more advanced models in the future. For instance, while we see seemingly random cycles of policy concern in the results, there is no positive underlying trend in policy attention (approximated by concern in the model) as shown in Figure 2. This can be attributed to several elements of the model specification. Most important, agents in the model had fairly short memories, so concern did not last much beyond the bloom events themselves. This may be indicative of public attention spans, but we know that some interest groups retain concern for much longer and could even evince step-wise increases in concern. On the other hand, people may also become desensitized to bloom events, such that susceptibility is actually decreasing with exposure to blooms. Much more research is needed to be able to appropriately specify and parameterize these components of the model. In particular, longitudinal data on how people's attitudes and willingness to participate in political processes or other response options with repeated exposure to extreme events is needed.

The trend in concern was also relatively flat because of decisions that we made in order to maintain the transparency of the model. For instance, while there was some randomness in the application of fertilizer, its effect was minimal compared to either the farmer agent's pre-set level of nutrient application or the allowed levels once regulations were in place. Furthermore, we did not model any legacy nutrients in lake sediments, ensuring that after only a few years, bloom activity would be fairly stable at a level that could be generally predicted based on nutrient application rates. While this made it much easier to tell what was going on in the model, it assumed away a number of factors that would make bloom activity—and therefore agent concern—follow an increasing trend instead of the flat plateaus observed in our results. For instance, in the absence of regulation nutrient application rates have been increasing over time, rather than remaining constant, and even when regulations are in place their effects on nutrient levels are not uniformly effective. Furthermore, nutrient storage in lake sediments can also lead to an increase in the severity of blooms and resulting concern even after regulations lead to lower inflows of nutrients (Wilson et al., 2019).

Thus, instead of being a real result of the governance treadmill, the step-wise changes in regulation shown in the models where power disconnects are narrow are really an artifact of our programming. In other words, while we captured spikes in concern and resultant changes in the need to regulate, as predicted by the treadmill, the form of regulatory response was dictated by model specifications. This highlights the needs for additional data on representation and influence as well as better modeling of the policy process itself. A first step would be to allow for de-regulation in the current model. This would at least let us examine the rebound effect and multiple full cycles of the treadmill. More realistic representations could also include an array of possible policies, each of which has different cost and benefits for different sets of agents. Then constituent agents could communicate not just their concern but also their support for particular regulatory options. The model could also be improved with more accurate representations of decision making, including periods in which decision

makers could communicate or negotiate with each other and then make decisions using voting or some other rules.

Indeed, there are many avenues for enquiry through refinement of this simple model. We designed it specifically to serve as the foundation of a suite of experiments around the governance treadmill, starting with the Lake Erie case study but eventually generalizable to other regions and types of issues (Janssen & Ostrom, 2006). By keeping most of components relatively simple, it will be easier to observe the effects of changes or experiments in sections of the model where there are high levels of variation or uncertainty, like public attention or interest group influence. Of course, model results must be interpreted accordingly, and it will still be difficult to trace causal connections as the model becomes more complex, but a systematic exploration of the governance treadmill through these models is still worthwhile. Extreme events like harmful microbial blooms are expected to surge with population growth, increasing affluence, and climate change, so we need a better understanding of the way such events will affect environmental governance of social ecological systems.

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Appendix 1 Overview, Design concepts, and Details Documentation

Overview

This model was created to help explore the ways citizens perceive and respond to the risks associated with harmful algal blooms (HABs), the way government officials respond to their constituents, and the policy and environmental outcomes of these processes.

To simulate this action-response dynamic, we first setup a lake comprised of patches that can become colonized by harmful algae or "bloom." The processes used to create the simulated bloom do not represent actual biophysical processes, but they do produce blooms that display common characteristics of real blooms (random seeding, threshold effects, contiguous spread).

Agents live in the land area surrounding the lake. There are several types of agents representing different types of people with different interests and incentives. Each agent can perceive blooms in the lake through various signals. They can also become concerned about the blooms if they receive signals that the bloom will affect them negatively. If enough concern accumulates, the agents can take action by engaging with policy makers.

Policy makers, known as "government actors" in the model, receive signals from the media, scientists, and people who are concerned enough to contact the government about algal blooms. These signals create concern in the policy makers, and they can decide to regulate nutrient use by farmers if the government actors become concerned enough.

Setup

Global variables can be used by any patch or agent in the model. In this model, we created global variables for two reasons: to allow more than one agent type to use the variables' values to run a procedure, or to give the model user the ability to change variable values through sliders on the user

interface. The only global variables fixed in the setup code are related to lake and bloom variables; these are the nutrients in the lake 'nutrients.lake', the total nutrients on all farms 'nutrients.farms', a tracker of warm and cold seasons 'temperature', a tracker of precipitation 'rain', the number of patches that are farms 'farm patches', and the proportion of each of three types of farmers represented in the model 'proportion.farmers.X', 'proportion.farmers.Y', and 'proportion.farmers.Z'. All other global variables are controlled by sliders on the user interface. These variables relate to how different agents perceive and are affected by different signals. They include the magnitude of a signal, how susceptible an agent is to that signal, how long they care about that type of signal for, how quickly an agent loses concern, and at what level of concern an agent takes action. These variables are described below in the section on the calculation of conern.

Next, seven different breeds of agents are created: 'urban.dwellers', 'rural.non.farmers', 'coastal.busines.owners', 'farmers', 'government.actors', 'media.sources', and 'scientists'.

The variables owned by patches and each agent type are setup next. These variables are either characteristics of the agents or elements of the world that are specific to individual agents and change over time. Patches own a variable that corresponds to the map assigning patch type 'land.cover.code'; the type of patch set by the code 'land.cover.type'; 'city.name' which is left blank if the patch is not part of a city; binary variables that equal one if true named 'major.city', 'minor.city?', 'farm?', and 'intake?'; the watershed to which the patch belongs 'watershed'; represented human population 'population'; the proportion of different agent types at each patch 'prop.farmer', 'prop.urban', 'prop.rural.non.farmer', 'prop.tourist', and 'prop.coastal.business'; the nutrients at that point in time 'nutrients.here'; the number of tourists at that point in time 'tourists.now'; whether the patch has an algal bloom happening, which is only applicable for lake patches 'blooming?', and the number of time steps the patch has been blooming for 'time.blooming'; and the district to which the patch belongs 'pdistrict'.

All agents or "turtles" own a few common variables; these are setup next. All agents have a 'district', a number of time steps they are affected by media signals 'attention.span.media', 'conern', and a threshold of concern over which they take action 'concern.threshold'.

Agents also own variables specific to their type. These are defined next in the model, beginning with urban dwellers. Agents keep record of signals they have received over the course of their attention span, coded as 'signal.history.TYPE' where TYPE is replaced with the type of signal. For instance, urban dwellers have four signal history variables: 'signal.history. intake', 'signal.history.seeing', 'signal.history.tourism', and 'signal.history.media'. Agents have variables that represent the amount of concern they have from each type of signal, coded as 'concern.TYPE'. For urban dwellers, these are 'concern.intake', 'concern.seeing', 'concern.tourism', and 'concern.media'. The four agent types that represent constituencies, i.e. urban dwellers, rural non-farmers, coastal business owners, and farmers, have a variable that denotes whether their concern threshold has been crossed and if they are triggered to contact the government 'contact.government?'.

Rural non-farmers have concern-related variables for media signals. Coastal business owners have concern variables for intake, seeing, tourism, and media signals.



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Farmers have concern-related variables for regulation and media signals. They also have a variable denoting the type of farmer 'farmer.type', and the nutrients they applied to their fields at that point in time 'nutrients.APPLIED'.

Government actors own signal-history and concern variables for different signal types, with these signals coming from their constituents. These variables, 'signal.history.TYPE' and 'conern.TYPE', replace TYPE with 'UD' for urban dwellers, 'RNF' for rural non-farmers, 'CBO' for coastal business owners, and 'FARMERS.X', 'FARMERS.Y', and 'FARMERS.Z' for farmers of type X, Y, and Z. government actors own a variable denoting whether they are the top decision maker, 'top.decision.maker?'. They also own variables related to regulating nutrient application by farmers.

Whether they regulate nutrients at that point in time is tracked by the binary variable 'regulate.nutrients?; the maximum amount of nutrients farmers can apply at any time step is 'nutrients.REGULATED'; and if the conditions are met for government actors to regulate nutrients that year, the variable 'need.to.regulate' is set to one, and zero otherwise.

Media sources own variables that represent media coverage of different types of signals: 'signal.large.bloom', 'signal.Toledo', 'signal.Sandusky', 'signal.intakes', and 'signal.beaches'.

Scientists own two variables that convey the scientific recommendations for the lower limit of nutrients famers should be allowed to apply, 'nutrients.MIN.RECOMMENDED', and the upper limit 'nutrients.MAX.RECOMMENDED'.

Next, we setup the world. First, all information from previous runs is cleared. Next, we set the size of the world to a 100 by 100 grid. We set the patch size to 7 so that the map is a usable size in the user interface. Then, we set up land cover codes for the world and create beaches, major cities, minor cities, farms, and water intakes. The location of large cities – Toledo, Cleveland, Erie, Buffalo, Detroit, and Sandusky – and water intakes corresponds to their locations in the real world. Beaches are distributed at intentional intervals along the coast to represent their approximate distribution in the real world. Minor cities and farms are distributed randomly over the land. We then define watersheds and set patch colors according to their cover type. Finally, we give patches population characteristics include population size and the proportions of urban dwellers, coastal business owners, farmers, and tourists.

Finally, we create seven different types of agents: urban dwellers, rural non-farmers, coastal business owners, three subtypes of farmers ("X", "Y", and "Z"), and government actors. In this version of the model (8 May 2018), farmers are considered a single group. These agents populate the modeled landscape in approximately the same way they populate the real-life landscape. However, the numbers of each agent type in the model does not represent the number of each type of people in real life.

Urban dwellers represent people living in major cities and small cities.

Rural non-farmers represent people who live in rural areas but do not farm.

Coastal business owners represent people who live near coastal tourist attractions, namely beaches. In the model, they occupy land patches with at least one neighboring patch that is a beach.

There is potential to add different types of farmers, but this has not yet been implemented. The three types of farmers represent categorizations made by Robyn Wilson from Ohio State University, based on farmer surveys conducted in the Maumee river basin, which is the main source of nutrient pollution in Erie. They are currently conducting a latent variable analysis to generate up to three categories of farmers that will be distinguished by their age, income, education, and, most important, attitudes toward HABs risk and nutrient-reducing policies. Once this is finished we will use it to develop the farmer types. Similar analysis is also planned from a public survey in the Erie region that should help parameterize the other agent types.

There are two versions of how the government operates: via single or multiple decision makers. In the single-decision-maker version, a single government actor receives signals and creates nutrientuse policy. In the multiple-decision-maker version, the landscape is divided into five districts, each with its own assigned government actor. Here, policy is made in response to the concerns of constituents within each district, and that policy applies only to farmers within that district. More details about the differences between government processes are described below.

Processes

The processes in the model proceed in the following order: 1) track time and seasons, 2) farming, 3) algal blooms, 4) track tourists visiting beaches, 5) generate media signals, and 5) calculate the level of concern of and actions taken by urban dwellers, rural non-farmers, coastal business owners, farmers, and the government. Each agent type has a procedure for calculating concern and whether they take action).

Bloom-related procedures

Blooms only occur during warm months, roughly weeks 22 through 43 of the calendar year, which we designate with 'temperature' = "high" in the model. For all other months, 'temperature' = "low".

Farming contains the decision of farmers about how much nutrients they apply while farming. This is relevant to the simulation in two ways: it is the source of nutrient pollution to the lake, and nutrient additions can be regulated by policy. Farmers apply nutrients to their fields during the growing season, between calendar weeks 18 and 42 to represent the Ohio farming season. Farmers apply 10 units of nutrients under normal conditions, and lower amounts if the government is regulating nutrient application (see description of the nutrient regulation procedure below). We chose 10 units of nutrients as a starting point arbitrarily. Farmers have a certain probability of applying nutrients at each time step, controlled by the variable 'fertilizer.application.rate', that ranges from 0 to 1. The default value for the fertilizer application rate is 0.5, i.e., every other week on average, which is also arbitrary. There are two possible scenarios for government structure and, therefore, regulated levels for farmers in all districts. If there are multiple government decision makers, the decision maker from each district sets the regulated level for farmers in their district only. In this case, farmers from the different districts could all have different regulated levels.

The procedure for farming proceeds as follows. First, we temporarily set the beginning and ending weeks of the farming season and the rate at which nutrients leave the patch where they were applied. Next, farmers determine whether there are multiple or a single decision maker, which is based on a switch in the user-interface.

The answer to this question determines which government actor farmers look to for the regulated nutrient level. Then, if farmers are located in the Western Basin, representing the Maumee River Basin, and the week is within the growing season and a random draw between 0 and 1 is less than the



fertilizer application rate, the farmer sets their 'nutrients.APPLIED' variable to the 'nutrients.REGULATED' level of the appropriate government actor. If all three of those previously mentioned conditions are not met, farmers set 'nutrients.APPLIED' to 0.

Patches calculate the amount of nutrients they have in the next step of the farming procedure. Patches gain nutrients from the application by farmers, and they lose nutrients to natural processes we encapsulate with the term 'nutrient.decay' and by runoff from rainfall.

If the farmer or farmers on a patch applied nutrients that week, the patch's 'nutrients.here' variable is set according to the following formula:

```
\begin{aligned} nutrients.here_{t+1} &= nutrients.here_t - nutrient.decay * nutrients.here_t - rainfall.factor \\ &* nutrients.here_t + \sum_{farmers} nutrients.APPLIED \end{aligned}
```

If the farmer or farmers on a patch do not apply nutrients on a patch that week, the patch's nutrients are set according to the following formula: nutrients. $here_{t+1} = nutrients$. $here_t - nutrients$. $here_t - rainfall$. factor * nutrients. $here_t$

The procedure for producing harmful algae blooms has several components. First, two conditions have to be met: the nutrients entering the lake, 'nutrients.farms * rainfall.factor', must exceed the minimum threshold for a bloom to occur, and the temperature must be "high". If so, and there isn't a bloom already occurring, the western end of the lake where the x-coordinates are less than 55 has 'bloom.seeds' number of patches turned on by setting 'blooming?' = 1. The 'time.blooming' variable of the newly blooming patch is set to 1 as well.

Next, the bloom spreads to neighboring patches. А number, set by 'num.neighbors.bloom.spread', of lake patches also bloom. If the bloom occurs along the coast and there are fewer lake patches available to bloom than 'num.neighbors.bloom.spread', all of the neighboring lake patches bloom. Within this sub-procedure, each patches' 'time.blooming' variable advances by 1. Any patches with 'time.blooming >= max.time.blooming' return to their regular state, i.e., 'blooming? = 0'. If the conditions for a bloom are not met, i.e. 'nutrients.farms * rainfall.factor <= nutrient.threshold', or temperature is "low", any blooming patches are returned to their regular state.

Coastal tourism declines if blooms occur near public beaches. If the season is warm and none of the lake patches neighboring a beach are blooming, the number of tourists is calculated using the following equation:

$tourists = population * prop_{tourists}$

Where '*prop*tourists' is the proportion of people at a patch that are normally tourists.

If any of a beach's neighboring lake patches are blooming, tourists are counted with the following equation:

 $tourists = population * prop_{tourists} - tourism. loss. by. bloom * population * prop_{tourists}$

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Where 'tourism.loss.by.bloom' is the proportion of tourists who no longer visit beaches when there is a nearby bloom.

Media signals are calculated next in the NetLogo script. We describe them within the "Signals" section below.

Next, we calculate scientific advice on setting regulated nutrients levels. We set the rate at which nutrients leave the landscape and do not enter the lake at 0.1. The highest level of nutrient application scientists recommend is calculated according to the following equation:

> nutrients.MAX.RECOMMENDED = nutrient. threshold $* (1 - rainfall. factor + nutrient. decay)^{-1}$ * number of farmers⁻¹ * fertilizer.application.rate⁻¹

The lowest level of nutrient application scientists recommend differs based on the amount of rainfall, according to the following logic: if 'rainfall.factor' > 0.4, 'nutrients.MIN.RECOMMENDED = nutrints.MAX.RECOMMENDED - 1'; if 'rainfall.factor' <=0.4, 'nutrients.MIN.RECOMMENDED = nutrients.MAX.RECOMMENDED - 2'.

Concern

'Concern' is a variable held by each agent that calculates and stores their level of concern regarding the algal blooms. Concern at each time step is generated from the multiple signals agents receive according to the following equation:

$$concern = \sum_{signal.types} susceptibility_{signal.type} * signal.value_{signal.type}$$

Urban dwellers, rural non-farmers, and coastal business owners have only positive levels of concern, representing how much they are worried about undesirable effects of the bloom. Farmers concern can be positive or negative. Positive concern in farmers represents concern that their farming business will be negatively impacted by nutrient regulation, and negative concern represents concern over undesirable effects from the bloom.

The 'susceptibility_{signal.type}' variable accounts for differences in how much people care about different aspects of the bloom. For example, farmers might not care if coastal tourism decreases, whereas coastal business owners care a lot. Because all signals are between 0 and 1, with 1 being full signal strength, the susceptibility variables determine the maximum amount of concern a signal can generate.

The susceptibility of government actors to a constituency contacting them is the maximum amount of concern that constituency can create in the government actor. Note that this variable accounts for multiple factors such as number of constituents of each type and the political power they wield as a group. This variable is named with the following format in the code:

'susceptibility.agent.type.GOVERNMENT'.

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An example is 'susceptibility.farmers.x.GOVERNMENT' for government susceptibility to farmers of type X. A susceptibility of 1 would mean that if all farmers, for example, contacted the government, the government actor would become maximally concerned, i.e. 'concern' = 1. If urban dwellers were also concerned and contacted the government, no additional concern would accumulate, because there would be no ability to become more concerned.

Multiplying the signal value by susceptibility implies that each additional unit of signal creates the same amount of concern. More complex models could be used if there were theory or evidence to support them.

Concern decays over time linearly. Each agent type has a different rate at which concern decreases, referred to as 'decay.of.*agent.type*'.

 $concern_t = decay * concern_{t-1} + concern_{new}$

Concern over each signal type disappears completely if enough time passes without a new signal; the time threshold is called 'attention.span.*signal.type*'. In the model, a list is created for each signal type that keeps track of whether there was a signal at each time step for as long as the agent's attention span for each signal type. If none of the lists contain any signals greater than one, no signals have occurred within the agent's attention span and their concern goes to zero.

Urban dwellers' concern comes from four sources: contaminated water intakes, blooms that occur close enough to the shoreline of their cities for people to see, decreases in coastal tourism, and media signals on blooms.

Rural non-farmers' concern comes from media signals only. This assumes they are not directly impacted by the blooms, but may care about the health of the lake or other people who are impacted.

Coastal business owners' concern comes from three sources: blooms that occur close enough to the shoreline for people to see, decreases in tourism in adjacent beaches caused by nearby blooms, and media signals on blooms.

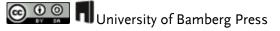
Farmers' concern comes from two sources: regulation of nutrient application and media signals. Media signals generate concern in two ways; farmers have concern for the health of the lake and that they may face further regulations that will hurt their business.

Signals

Signal values, which feed into the calculation of agents' concern, range from 0 to 1, with some variables being binary, i.e. either 0 or 1. The 'signal.value_{signal.type}' variable allows for variability in the strength of signals at different points in time.

If any patches that has a water intake on it and is within a radius of four from an agent, the signal value for intakes equals one. Otherwise, this signal equals 0.

If any neighboring patches are blooming, the signal value for seeing the bloom equals 1. Otherwise, this signal equals 0.



If it is the hot season, tourists are counted at coastal beaches. If there is a bloom in any of a beach's neighboring patches, tourism declines by the proportion *'tourism.loss.by.bloom'*. The signal value for tourism loss is one minus the proportion of tourists currently compared to the number of that would be there had there not been a nearby bloom.

If government actors are currently regulating nutrients, the signal value for regulation is 1. Otherwise, this signal equals 0.

Media signals are calculated for five phenomena: if the bloom is 1) large (patches blooming > '*large.bloom.threshold'*); 2) near Toledo (patches blooming and neighbor to Toledo's coastal patch); 3) near Sandusky (patches blooming and neighbor to Sandusky's coastal patch); 4) at a drinking water intake; or 5) adjacent to any beach. The value or strength of each media signal is the proportion of patches blooming that meet the given condition relative to the number that could possibly meet the conditions. All agents have access to media signals because they are global variables.

For government actors, signals from each type of constituent are calculated as the proportion of constituents with 'contact.government?' = 1. If every farmer was concerned enough to contact the government, the government would receive a signal of 1 from farmers.

Action

Agents take action if their level of concern reaches a threshold. Taking action is binary; an agent can either take action or not.

Urban dwellers, rural non-farmers, coastal business owners, and farmers can take action by contacting the government ('contact.government' = 1). They do so when their concern exceeds a threshold, 'concern.threshold.*agent.type*'.

Government actors take action by regulating nutrient application by farmers. At each time step, government actors either leave the amount of nutrients that can be applied the same or change it. The decision making process of government actors begins with the calculation of concern generated by signals from urban dwellers, rural non-farmers, coastal business owners, farmers, the media, and scientific advice. If these signals generate enough concern to cross government actors' concern threshold, the government actors decide to regulate nutrients. The level of regulation set depends on a series of conditions.

If the nutrients applied by farmers at that time step is greater than the amount recommended by scientists,

nutrients. REGULATED

= nutrients.MAX.RECOMMENDED + <u>nutrients.applied – nutrients.MAX.RECOMMENDED</u> 2

If nutrients applied by farmers is greater than the max amount recommended but less than or equal to the max amount recommended plus one,

nutrients. REGULATED = nutrients. MAX. RECOMMENDED

If nutrients applied is greater than the minimum amount recommended but less than the max amount recommended,

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nutrients. *REGULATED* = *nutrients*. *applied* - 1

If nutrients applied is less than the minimum amount recommended, nutrients are not regulated. There are two options for the process of how government actors make decisions: either as a single decision maker for the entire watershed, or with five decision makers, each representing a defined geographic area. If there is a single decision maker, the concerns of all stakeholders affect the government actor's concern and, hence, level of nutrient regulation. Under the multiple-decisionmaker option, each government actor receives signals from the agents within its district, as well as media signals that are globally available, but which may be more or less important in their district (e.g. signals that a bloom is near a significant city in their jurisdiction). In this case, the regulated level of nutrient application is particular to each government actor and their district. Farmers' nutrient application is then governed by the regulation set for their district. There is no "cheating" in the model. Farmers always apply the regulated amount of nutrients, though the total amount of nutrients will sometimes go above the regulated amount due to the probabilistic process farmer agents use to decide when to apply nutrients.

Variable in code	Estimated/base value	Data source
land.cover.code	NA	Lake Erie map (see web address in Notes)
land.cover.type	NA	Lake Erie map
city.name	NA	estimated position from google earth
major.city?	5 major cities	estimated position from google earth
minor.city?	25 minor cities	guestimate
farm?	1846 farms	determined by remaining patches after other patch types assigned
beach?	8 beaches	estimated number of beaches from google earth
intake?	4 intakes	https://www.google.com/mymaps/viewer?mi d=18-6xXsAz10DOxCWfaZRp_u- qNw8&hl=en_US
watershed		Lake Erie map
population	721 agents	generated from pixelation of Lake Erie watershed map

Appendix 2 Model variables, values, and sources



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prop.urban	varies by patch type	guestimate
prop.coastal.business	varies by patch type	guestimate
prop.farmer	varies by patch type	guestimate
prop.tourist	varies by patch type	guestimate
nutrient.decay	0.1	none
nutrients.here	max ~31000	NA
tourists.now	max 12776	NA
time.blooming	calculated	NA
blooming?	reporter	guestimate
bloom.seeds	1	NA
num.neighbors.bloom.spread	3	NA
max.time.blooming	5	NA
signal.value.intake	reporter	NA
signal.value.seeing	reporter	NA
signal.value.tourism	2	NA
signal.value.regulation	2	NA
signal.Toledo	reporter	NA
signal.Sandusky	reporter	NA
signal.large.bloom	reporter	NA
signal.intakes	reporter	NA



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signal.beaches	reporter	NA
signal.history.intake	calculated	NA
signal.history.seeing	calculated	NA
signal.history.tourism	calculated	NA
signal.history.media	calculated	NA
signal.history.regulation	calculated	NA
signal.history.UD	calculated	NA
signal.history.RNF	calculated	NA
signal.history.CBO	calculated	NA
signal.history.farmers	calculated	NA
susceptibility.media.Toledo	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.media.Sandusky	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.media.large.bloom	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.media.intakes	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.media.beaches	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.seeing	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.tourism	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.UD	2	set to values that reflect the variability in the impact of signals on agents



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	-	
susceptibility.RNF	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.farmers	2	set to values that reflect the variability in the impact of signals on agents
susceptibility.CBO	2	set to values that reflect the variability in the impact of signals on agents
attention.span.media	5	set to reflect a reasonable attention span
attention.span.intake	5	set to reflect a reasonable attention span
attention.span.seeing	5	set to reflect a reasonable attention span
attention.span.tourism	5	set to reflect a reasonable attention span
attention.span.regulation	5	set to reflect a reasonable attention span
concern	0	calculatd in model
concern.media	0	calculatd in model
concern.intake	0	calculatd in model
concern.seeing	0	calculatd in model
concern.tourism	0	calculatd in model
concern.regulation	0	calculatd in model
concern.UD	0	calculatd in model
concern.RNF	0	calculatd in model
concern.CBO	0	calculatd in model
concern.farmers	0	calculatd in model
concern.threshold	20	tuned
decay.of.UD	0.9	estimated to produce a reasonable decay curve

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decay.of.RNF	0.9	estimated to produce a reasonable decay curve
decay.of.CBO	0.9	estimated to produce a reasonable decay curve
decay.of.farmers	0.9	estimated to produce a reasonable decay curve
decay.of.government	0.9	estimated to produce a reasonable decay curve
apply.nutrients	NA	arbitrary
contact.government?	NA	0
regulate.nutrients?	NA	0



Regulatory Options		Initial Setting
Base Concern	base.concern.UD	0.1
	base.concern.RNF	0.1
	base.concern.CBO	0.1
	base.concern.FARMERS.X	0.1
	base.concern.FARMERS.Y	0.1
	base.concern.FARMERS.Z	0.1
	base.concern.GOVERNMENT	0.2
Susceptibility	susceptibility.intake.UD	0.75
	susceptibility.intake.CBO	0.75
	susceptibility.seeing.UD	0.5
	susceptibility.seeing.CBO	0.75
	susceptibility.tourism.UD	0.5
	susceptibility.tourism.CBO	0.75
	susceptibility.regulation.FARMERS.X	0.75
	susceptibility.regulation.FARMERS.Y	0.75
	susceptibility.regulation.FARMERS.Z	0.69
	susceptibility.ud.GOVERNMENT	0.35
	susceptibility.rnf.GOVERNMENT	0.35
	susceptibility.cbo.GOVERNMENT	0.35
	susceptibility.farmers.x.GOVERNMENT	0.35
	susceptibility.farmers.Y.GOVERNMENT	0.35
	susceptibility.farmers.Z.GOVERNMENT	0.35
	susceptibility.media.intakes.UD	0.75
	susceptibility.media.intakes.RNF	0.75
	susceptibility.media.intakes.CBO	0.75

Appendix 3 Initial settings for all three Regulatory options (none, individual, multiple)



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 susceptibility.media.intakes.FARMERS.X	0.25
 susceptibility.media.intakes.FARMERS.Y	0.75
 susceptibility.media.intakes.FARMERS.Z	0.75
 susceptibility.media.intakes.GOVERNMENT	1
 susceptibility.media.Toledo.UD	0.75
 susceptibility.media.Toledo.RNF	0.75
 susceptibility.media.Toledo.CBO	0.5
 susceptibility.media.Toledo.FARMERS.X	0.25
 susceptibility.media.Toledo.FARMERS.Y	0.66
 susceptibility.media.Toledo.FARMERS.Z	0.75
 susceptibility.media.Toledo.GOVERNMENT	1
 susceptibility.media.Sandusky.UD	0.75
 susceptibility.media.Sandusky.RNF	0.75
 susceptibility.media.Sandusky.CBO	0.75
 susceptibility.media.Sandusky.FARMERS.X	0.25
 susceptibility.media.Sandusky.FARMERS.Y	0.74
 susceptibility.media.Sandusky.FARMERS.Z	0.71
 susceptibility.media.Sandusky.GOVERNMENT	1
 susceptibility.media.beaches.UD	0.5
 susceptibility.media.beaches.RNF	0.75
susceptibility.media.beaches.CBO	0.75
 susceptibility.media.beaches.FARMERS.X	0.25
 susceptibility.media.beaches.FARMERS.Y	0.75
 susceptibility.media.beaches.FARMERS.Z	0.75
 susceptibility.media.beaches.GOVERNMENT	1
susceptibility.media.large.bloom.UD	0.5
susceptibility.media.large.bloom.RNF	0.25

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	susceptibility.media.large.bloom.CBO	0.75
	susceptibility.media.large.bloom.FARMERS.X	0.25
	susceptibility.media.large.bloom.FARMERS.Y	0.75
	susceptibility.media.large.bloom.FARMERS.Z	0.75
	susceptibility.media.large.bloom.GOVERNMENT	1
	susceptibility.media.regulation.FARMERS.X	0.75
	susceptibility.media.regulation.FARMERS.Y	0.75
	susceptibility.media.regulation.FARMERS.Z	0.75
Attention Span	attention.span.intake.UD	66
	attention.span.intake.CBO	66
	attention.span.seeing.UD	66
	attention.span.seeing.CBO	66
	attention.span.tourism.UD	66
	attention.span.tourism.CBO	66
	attention.span.regulation.FARMERS.X	63
	attention.span.regulation.FARMERS.Y	63
	attention.span.regulation.FARMERS.Z	66
	attention.span.media.UD	66
	attention.span.media.RNF	26
	attention.span.media.CBO	66
	attention.span.media.FARMERS.X	66
	attention.span.media.FARMERS.Y	66
	attention.span.media.FARMERS.Z	70
	attention.span.media.GOVERNMENT	66
	attention.span.ud.GOVERNMENT	62
	attention.span.rnf.GOVERNMENT	62
	attention.span.cbo.GOVERNMENT	62



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	attention.span.farmers.x.GOVERNMENT	62
	attention.span.farmers.y.GOVERNMENT	62
	attention.span.farmers.z.GOVERNMENT	62
Decay	decay.of.UD	0.7
	decay.of.RNF	0.8
	decay.of.CBO	0.9
	decay.of.FARMERS.X	0.9
	decay.of.FARMERS.Y	0.9
	decay.of.FARMERS.Z	0.9
	decay.of.GOVERNMENT	0.9
Concern Threshold	concern.threshold.UD	0.5
	concern.threshold.RNF	0.4
	concern.threshold.CBO	0.2
	concern.threshold.FARMERS.X	0.3
	concern.threshold.FARMERS.Y	0.3
	concern.threshold.FARMERS.Z	0.3
	concern.threshold.GOVERNMENT	6.02
Bloom Variable	bloom.seeds	5
	num.neighbors.bloom.spread	4
	max.time.blooming	7
	nutrient.threshold	1000
	large.bloom.threshold	5
	rainfall.factor	0.4
	fertilizer.application.rate	0.5
	nutrients.DESIRED	15
	nutrients.REGULATED.slidebar	2

