The Spatial Dynamics of the Economic Impacts of an Aquatic Invasive Species: An Empirical Analysis

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ABSTRACT *This paper examines how the economic loss from an aquatic species invasion of a freshwater lake is allocated between users of the lake itself (own-lake effect) and users of neighboring lakes that become invaded because the lake is a new source of the invader (spillover effect). The empirical application concerns the Eurasian watermilfoil invasion in the lake-rich landscape of northern Wisconsin. Results suggest that coordinated management across lakes provides its highest economic value in the early years of an invasion, before high-value, high-traffic lakes are invaded, and drops quickly once the invasion claims these lakes.* (JEL Q51, Q57)

1. Introduction

Invasive species can have far-reaching impacts on natural ecosystems and the people who use them (Pimentel, Zuniga, and Morrison 2005; Lodge et al. 2006). As a result, invasive species have been the focus of intensive resource management efforts aimed at controlling or minimizing their spread. Recent empirical studies that quantify the economic impacts of aquatic invasive species have focused on estimating the welfare loss to users of an individual aquatic site from that site becoming invaded (Horsch and Lewis 2009; Zhang and Boyle 2010; Provencher, Lewis, and Anderson 2012; Olden and Tamayo 2014). However, the impacts from invasive species play out on complex landscapes and are influenced by dynamic-spatial processes that cause invasive species to spread to neighboring sites. The process of invasive species spread has led to recent interest in "scaling up" our understanding of site-level impacts to that of landscape-level impacts (Vander Zanden, Hansen, and Latzka 2017). Scaling up site-level impacts to the landscape level requires a quantitative understanding of two welfare effects arising from invasive species establishment on a new site: (1) a direct welfare loss to users of that site and (2) an indirect welfare loss due to the newly established population serving as a source population from which the species spreads to new sites, thereby inducing spillover effects, measured as welfare damages on neighboring sites. Economically optimal management of an invasive species requires knowledge of the damages of invasions, including spillover effects (Epanchin-Niell and Wilen 2015; Fenichel, Richards, and Shanafelt 2014).

This paper presents an empirical analysis of the spatial dynamics of the spillover costs—and corresponding total costs—of Eurasian watermilfoil (hereafter "milfoil") invasions in freshwater lakes in northern Wisconsin (Figure 1). Milfoil invasions, long considered "among the most troublesome submerged aquatic plants in North America" (Smith and Barko 1990), are characterized by dense mats of floating vegetation that interfere with navigation and water-based recreation, and may affect fisheries and waterfowl. Similar to most other aquatic invasive species (AIS), milfoil is largely spread inadvertently through the movement of recreational boaters from lake to lake (Rothlisberger et al. 2010; Chivers and Leung 2012). Since this mechanism occurs through the choices made by recreational

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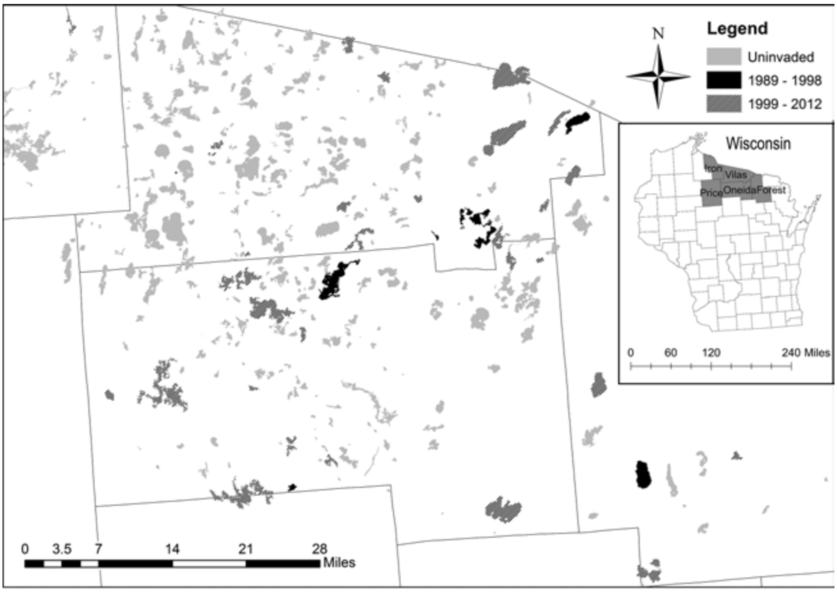
Figure 1
Location of the Northern Highlands Lake District in Wisconsin and the Lakes with Milfoil by Period of Discovery in Our Sample



boaters, AIS spread generates a patchy, leapfrog pattern of spatial spread that is influenced by the pattern of lake attractiveness to boaters. Therefore, simple deterministic spread mechanisms that are used in theoretical research for managing agricultural invasive species (e.g., Epanchin-Niell and Wilen 2015) are not applicable to the spread of aquatic invaders. Rather, understanding the spread of aquatic invaders requires a model of the primary vehicle of spread: recreational boater choices (Timar and Phaneuf 2009).

We empirically model the spread of aquatic invaders across a complex lake system by developing a coupled natural-human system model that combines (1) a behavioral model of recreational boater decisions; (2) recent ecological research regarding the biophysical properties of milfoil; (3) a stochastic empirical estimation of the probability of establishment of milfoil in lakes; and (4) prior estimates of direct welfare losses from milfoil for individual lakes. Our research makes contributions to two literatures on the spread and economic costs of invasive species. First, we provide the first empirical estimates to our knowledge of the spillover externality that occurs when an aquatic site becomes invaded. The current literature involving the site-level estimation of the economic cost of an invasion (e.g., Horsch and Lewis 2009; Lewis, Provencher, and Beardmore 2015; Provencher, Lewis, and Anderson 2012; Zhang and Boyle 2010; Olden and Tamayo 2014) ignores the spillover externality and thus underestimates the economic welfare loss from an invasion. Resource management agencies that use these site-level estimates as evidence of the damages from invasive species prevention[1] will underestimate the potential damages due to an invasion. Second, estimating the magnitude of the spillover externality has implications for the optimal management of AIS. Management of AIS is often conducted at the lake level. For example, AIS management in our study region of the Northern Highlands Lake District (NHLD) of northern Wisconsin is in part decentralized; approximately 69% of state spending on AIS is allocated to “local assistance” paid to eligible sponsors (e.g., lakes as-

[1] For example, see the State of Wisconsin’s Department of Natural Resources: http://dnr.wi.gov/files/PDF/pubs/ss/SS1113.pdf.

sociations, which comprise shoreline property owners around particular lakes).[2] Spillover effects from invasion of a particular lake are externalities to individual lake associations that make management decisions with regard to the benefits and costs that accrue to their lake. The theoretical literature on the spatial dynamics of invasions has suggested that such decentralized management at the site level that ignores or understates spillover costs will cause an invasion to spread more quickly, and decentralized management is most problematic when expected spillover costs are high (e.g., Epanchin-Niell and Wilen 2015, 2012; Finnoff, Potapov, and Lewis 2010; Macpherson, Moore, and Provencher 2006).

Building on and extending the framework developed by Timar and Phaneuf (2009), our coupled natural-human system model integrates a well-established recreation demand modeling framework from environmental economics with new ecological research on the life history of milfoil and the suitability of the recipient ecosystem. Specifically, we model the spread of invasions as involving the probability of taking a trip to an uninvaded lake *conditional* on having taken a trip to an invaded lake the day before. This is a critical feature of our approach because (1) recent evidence indicates that milfoil can survive out of water for approximately 24 hours (Bruckerhoff, Havel, and Knight 2014), and (2) our empirical analysis finds that, not surprisingly, the utility function for taking a trip changes if a trip was taken on the previous day. We are able to incorporate this intraseasonal dynamic into our model because we collected daily boater diary data during the summers of 2011 and 2012. Daily diary data enable the estimation of the daily probability of a recreational decision and give us the ability to differentiate trips on nonconsecutive days from trips on consecutive days, where the consecutive day trips from invaded to uninvaded lakes are the primary source of milfoil spread.

We use this coupled model to scale up the site-level economic costs of invasions to a broader landscape, addressing the spatial dynamics of invasion across multiple sites, and estimate the systemwide costs of the spread of milfoil to both boaters and shoreline property owners. We have the luxury of drawing on recent literature concerning the welfare effect of milfoil invasions on both boaters and shoreline property owners within our own study region of northern Wisconsin lakes (Lewis, Provencher, and Beardmore 2015; Horsch and Lewis 2009; Provencher, Lewis, and Anderson 2012), and using this information in an extensive analysis of the spatial dynamics of the economic loss of a milfoil invasion. In particular, some of the economic cost of the invasion of a lake accrues to the users of the lake itself (hereafter the "own-lake effect"), and some is a spillover cost that accrues to the users of surrounding lakes, because an invaded lake increases the likelihood of future invasion of its neighbors. Distinguishing between the own-lake and spillover losses from a lake's invasion provides novel insight to how the economic gain from coordinated (or centralized) management of the landscape changes as the invasion progresses and is our paper's primary contribution.

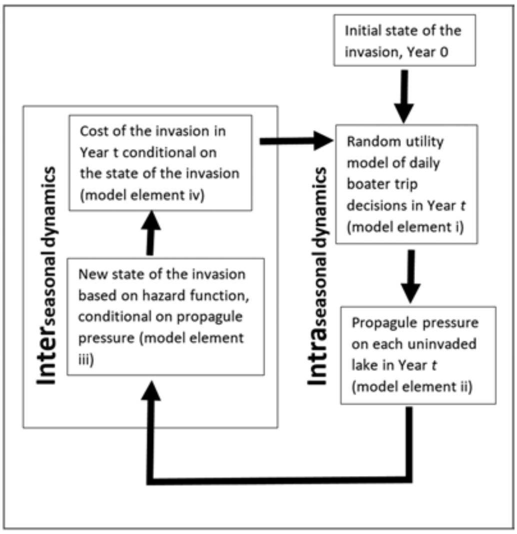
To operationalize our approach, we define the economic cost of a milfoil invasion of an individual lake (hereafter the "subject lake") over a 15-year period as the difference between (1) the regionwide expected cost of the invasion when the subject lake is invaded at the start of the period; and (2) the regionwide expected cost of the invasion when the subject lake is protected from invasion throughout the period.[3] In both the baseline (1) and the counterfactual (2) scenarios all lakes except the subject lake can become invaded. The dif-

[2] The DNR has a centralized, state-organized strategy and control program for some invasive species such as purple loosestrife. However, for other species such as milfoil, their approach is more decentralized, relying heavily on a competitive grant program to disperse funds to eligible sponsors, including highly motivated lake associations, municipalities, and counties. "We prioritize submitted projects based on the geographic location and size of waterbodies along with other priorities, but the DNR has little control over who submits an application or where those applications come from." (Personal communication with Alison Mikulyuk, Water Resources Management Specialist, Wisconsin Department of Natural Resources, May 2018).

[3] We use a 15-year period for the analysis because it is a reasonable planning horizon for lake management, and of sufficient length to clarify some of the basic bioeconomic issues associated with the management of aquatic species invasions.

Figure 2

Schematic of the 15-Year Simulation Used to Generate the Economic Cost of a Lake's Invasion



ference between these two values is allocated between the subject lake's own-lake cost and the spillover cost of the lake's invasion—the increase in the expected cost that accrues to other lakes when the subject lake is not protected compared to when it is protected. The spillover costs are spatial and dynamic; they depend on the movement of boaters between the subject lake and other lakes,[4] as well as the initial state of the invasion, defined as the lakes in the system that are already invaded in the initial time period.

To estimate the spread of a milfoil invasion through the NHLD and the associated economic cost of invasion, our simulation model involves four elements as depicted in Figure 2:[5] (i) A random utility model (RUM) of a boater's intraseasonal, day-by-day trip decisions; (ii) an accounting of lake-specific propagule pressure, which is the intraseasonal frequency that boaters carry viable milfoil propagules to a lake from invaded lakes; (iii) a hazard model of the probability of a lake's invasion in year $t+1$, conditional on the lake's ecological characteristics and propagule pressure on the lake in year t; and (iv) estimates from the published literature of the annual economic cost of a milfoil invasion to a lake's shoreline property owners and boaters (Horsch and Lewis 2009; Provencher, Lewis, and Anderson 2012; Lewis, Provencher, and Beardmore 2015).

Starting the simulation from the observed state of milfoil invasions in 1998, and averaging across all 453 lakes in our sample, we estimate that the 15-year economic cost of a lake's invasion is approximately \$2 million, with a spillover cost share of 20%. By comparison, starting the simulation from the observed state of milfoil invasions in 2013, the average economic cost of a lake's invasion is approximately \$1.5 million, with a spillover cost share of only 3%. These results suggest that coordinated AIS management across lakes provides its highest economic value in the early years of an invasion, before high-value, high-traffic lakes are invaded, and drops quickly once an invasion claims these lakes.

An additional level of complexity involves accounting for the behavioral response of humans to the spread of milfoil. Boaters may respond to an invasion by visiting the invaded lake less often, partially compensating for the reduction in trips by visiting uninvaded lakes more. We compared estimates of economic costs of lake invasions with and without the trip feedback effect for eight lakes in our sample. We found that the trip feedback effect reduces the estimate of the own-lake economic cost of an invasion slightly, but it can impact the estimates of spillover costs substantially, especially early in the invasion.[6]

[4] The diffusion process for milfoil involves boaters choosing to visit lakes and inadvertently spreading the invasive species. Therefore, the spatial aspect of the process is not a simple function of the spatial distance among lakes, but involves also the socioeconomic distance among lakes, such as lake size, fishing quality, and so forth.

[5] In the figure, the intraseasonal portion of the simulation accounts for boater's day-to-day trip decisions and the subsequent propagule pressure on all uninvaded lakes in the system; the interseasonal portion accounts for the spread of the invasive species across the lake system and the annual economic cost of this invasion.

[6] The welfare loss from a milfoil invasion is not only or even primarily suffered by boaters. Losses also accrue to shoreline property owners, and, like boaters, they can engage in averting behavior. Property price differentials between invaded lakes and uninvaded lakes can be expected to reflect the sorting response (if any) of property owners, and approximate the economic cost of a lake's invasion to the extent that the change in the invasion state under

2. The Coupled Natural-Human System Model for Lake Invasions

As illustrated in Figure 2, the 15-year, regionwide economic cost of a subject lake's invasion is based on a simulation exercise that combines the initial invasion state (i.e., the lakes in the system that are already invaded in the initial time period) in the NHLD with the following four model elements:

i. An RUM of a boater's intraseasonal, day-by-day trip decisions. This is the behavioral foundation of the analysis, estimated from diary surveys of 1,443 boaters intercepted at boat ramps during the 2011 and 2012 boating seasons.
ii. Lake-specific propagule pressure, which is the intraseasonal frequency that boaters carry viable milfoil propagules to a lake from invaded lakes. This is estimated from the RUM, using the result from Bruckerhoff, Havel, and Knight (2014) that milfoil can survive for approximately 24 hours out of water. Only trips from an invaded lake to an uninvaded lake on consecutive days can spread viable propagules.
iii. An interseasonal hazard function expressing the probability of a lake's invasion in year $t+1$ conditional on ecological variables and propagule pressure in year t. The function was estimated using the NHLD's invasion history over the period 1989–2012, with model elements (i) and (ii) applied to generate lake-specific propagule pressure for the period.
iv. The annual economic cost of a milfoil invasion to shoreline property owners and boaters. Costs are lake specific, reflecting the number of shoreline property owners and boaters. They are based on previously published research specific to milfoil and the NHLD study area, using contingent valuation (Provencher, Lewis, and Anderson 2012; Lewis, Provencher, and Beardmore 2015).

consideration affects a relatively small share of the relevant property market (Palmquist 1992).

For each subject lake and each of the two initial invasion states (1998 and 2013), two cases are considered for each simulation run, the first for the case where the lake is invaded in the initial time period (that is, it is among the lakes that compose the initial invasion state), and the second for the case where it is protected from invasion for all 15 years of the invasion. The result of the simulation exercise is a frequency distribution of the economic cost of the lake's invasion status for each subject lake. Economic costs are probabilistic due to the stochastic behavior of recreational boaters as reflected in the RUM, and the stochastic colonization of a lake conditional on the level of propagule pressure as reflected in the hazard model of lake colonization.

Data

The five Wisconsin counties spanning the NHLD (Forest, Iron, Oneida, Price, and Vilas) include 2,407 lakes that are larger than 1 ha, of which 453 appear in our boater dataset. We collected two major datasets in the NHLD region: lake data and boater data. The features of the lake data that are relevant to our modeling include the year in which invaded lakes in the NHLD were first known to be invaded, and a lake's ecological suitability for milfoil. Several studies have shown that alkalinity, conductivity, and pH are important factors determining the presence of milfoil (Hutchinson 1970; Madsen and Sand-Jensen 1991).

Boater data were developed for boaters intercepted at boat ramps during 2011 and 2012 (see the Appendix). Intercepted boaters were recruited into a diary survey covering the 2011 and 2012 boating seasons (April–October), and sent an end-of-season (EOS) survey that included questions to identify the lakes in their boating choice set. We combined the diary survey data and the EOS survey data into a master dataset that contains, for each boater in our sample, (1) the boating trip in which the boater was intercepted by our surveyors; (2) the number of total trips per month for all months prior to the intercept date; (3) the dates for all boating trips in the previous two weeks before interception (but not boating trips prior to this two-week period), (4) the dates for all boating trips after interception; and (5) demographic data and a boater-specific choice set from the EOS survey.[7] The final dataset consists of 1,443 boaters (out of 3,010 total intercepts, a response rate of approximately 48%) taking 11,766 trips to 453 unique lakes over 117,298 choice occasions (respondent-days) across the 2011 and 2012 boating seasons.

Empirical Model of Recreational Boater Behavior (Model Element (i) in Figure 2)

The boater recreation model is a repeated RUM that provides estimates of the probability that boaters travel to each lake in their choice set on a given day in a season. Boaters $n = 1, \ldots, N$ maximize their utility by choosing a single boating destination[8] $j = 1, \ldots, J$ or deciding not to boat in the region ($j = 0$) on each day $t = 1, \ldots, \mathbf{T}_n$ that they are in the region during the boating season, April through October of year $s = 1, \ldots, S$.

The indirect utility (equation [1]) of boater n choosing to visit lake j on a given day t in season s is a function of day-specific attributes, $\mathbf{Z}_t'$ (weekend versus weekday, holidays, and a seasonal trend), boater-specific attributes, $\mathbf{X}_{njs}'$ (travel cost to lakes and, for boaters who targeted walleye, a measure of walleye abundance and the bag limit for walleye on a given lake), lake-specific fixed effects, $\boldsymbol{\gamma}_j$, which account for lake-specific attributes that remain fixed over the course of the two seasons of the data, and a vector of random variables with a known distribution that denotes the determinants of the boater's indirect utility that are not observed by the analyst, $\boldsymbol{\varepsilon}_{njts}$ (see Appendix Table A1 for a summary of the variables used in estimation).

[7] The appropriate identification of the choice set is critical in discrete-choice models. The inclusion of choices that are irrelevant or unknown to the boater, and the exclusion of relevant choices are a source of bias in choice models (Haab and Hicks 1997). In our model, the lakes in a boater's choice set include the lakes the respondent reported visiting in the two weeks before intercept, the lakes they recorded visiting in their diary, and the lakes identified in the following two questions in the EOS survey: "Are there any lakes in the NHLD that you have not yet visited, but that you have heard about and would like to visit?" and "Are there any lakes in the NHLD that you have visited in the past but did not get to this year?"

[8] We do observe boaters going to multiple lakes within a day, and these are treated as separate trip occasions.

$$\mathbf{V}_{njts} = \mathbf{U}_{njts} + \boldsymbol{\varepsilon}_{njts} = \mathbf{X}_{njs}'\boldsymbol{\beta} + \mathbf{Z}_t'\boldsymbol{\delta}_{j\neq0} + \boldsymbol{\gamma}_j + \boldsymbol{\varepsilon}_{njts};$$
$$n = 1, \ldots, N;\ j = 0, \ldots, J;\ t = 1, \ldots, \mathbf{T}_n;\ s = 1, \ldots, S, \qquad [1]$$

where $\boldsymbol{\beta}$ and $\boldsymbol{\delta}_{j\neq0}$ are coefficient vectors to be estimated. Because $\mathbf{X}_{njs}'$ varies across sites and individuals, the parameter set $\boldsymbol{\beta}$ is not indexed by site. However, since $\mathbf{Z}_t'$ does not vary across sites, the parameter set $\boldsymbol{\delta}_{j\neq0}$ is indexed by whether the boater chose to boat ($j \neq 0$) rather than not boat ($j = 0$). As is standard in random utility modeling for recreation demand, the utility associated with not taking a trip is normalized to zero ($\mathbf{U}_{n0ts} = 0$).

The lake-specific fixed effects capture all intraseasonal fixed observable and unobservable attributes associated with a lake (including the lake's milfoil status), and have been shown to be an important tool to reduce omitted variables bias in modern recreation demand models (Murdock 2006). Examples of lake attributes captured by these lake-specific fixed effects include the lake's size, water quality, scenery, and the size and composition of the lake's fish stock. Further, lake-specific fixed effects better predict in-sample decisions by ensuring that a lake's predicted share of boaters equals the lake's actual share of boaters for the two seasons over which the trip demand model is estimated.

If we assume that the random variables, $\boldsymbol{\varepsilon}_{njts}$, are independent and identically distributed type I extreme value, then the conditional logit model arises (see Train 2009, ch. 3 for a general overview), and the probability of observing a particular choice is

$$\mathbf{P}_{njts} = \frac{\exp(\mathbf{X}_{njs}'\boldsymbol{\beta} + \mathbf{Z}_t'\boldsymbol{\delta}_{j\neq0} + \boldsymbol{\gamma}_j)}{\sum_{k\in J}\exp(\mathbf{X}_{nks}'\boldsymbol{\beta} + \mathbf{Z}_t'\boldsymbol{\delta}_{k\neq0} + \boldsymbol{\gamma}_k)};$$
$$n = 1, \ldots, N;\ j, k = 0, \ldots, J;\ t = 1, \ldots, \mathbf{T}_n;\ s = 1, \ldots, S. \qquad [2]$$

The parameters of the model are estimated with maximum likelihood. The sample log-likelihood function for a single day t *is*

$$\mathbf{LL}_t = \sum_{n=1}^{N}\sum_{j=0}^{J}\mathbf{y}_{njts}\mathbf{P}_{njts}, \qquad [3]$$

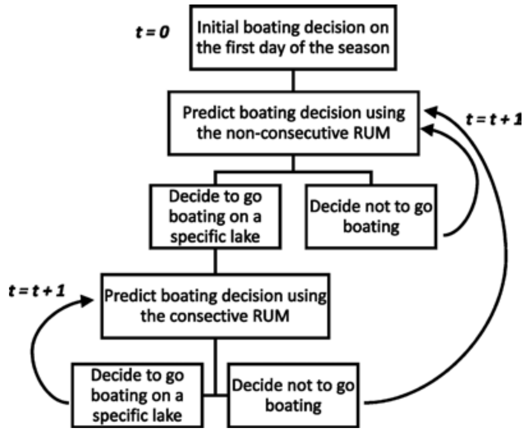
where $\mathbf{y}_{njts} = 1$ if boater n is observed visiting site j at time t and zero otherwise. The parameter vector $\boldsymbol{\beta}$ is estimated by maximizing the likelihood function (equation [3]). Given the magnitude of vacationing recreational boaters in this region, and given potential differences in lake preferences across vacationers and permanent local residents, we separately estimate [3] for vacationers and permanent residents (see the Appendix).

Milfoil is dispersed when boaters visit an invaded lake, become "carriers" by inadvertently transporting milfoil propagules out of the invaded lake, and then visit an uninvaded lake while propagules are still viable. Recent research found evidence that milfoil can survive for only 24 hours outside of the water (Bruckerhoff, Havel, and Knight 2014). Given this result, the only trips that matter for the spread of milfoil are trips taken on consecutive days. It is important, then, that our analysis accurately predict both the number of trips over the course of the season and also the number of trips taken on consecutive days over the course of the season. Consequently, we separately estimated two boater recreation models: one for the case where the boater took a trip on the previous day, and one for the case where the boater did not (the consecutive day model and nonconsecutive day model, respectively).[9] This implies that indirect utility from taking a trip is different if a trip was taken the day before than if a trip was not taken the day before—a reasonable relaxation of the model. It follows that we estimate two RUM models, one for days when a trip was taken the day before (consecutive trip model) and one for days when a trip was not taken the day before (nonconsecutive day trip). We use the same general form embodied by equations [1]–[3] for both but allow them to have different parameters. Altogether, we achieve modeling flexibility by estimating four different RUM models, differentiated across vacationers and permanent residents, and across consecutive and nonconsecutive day trips to lakes.

[9]As an alternative to estimating the consecutive day model and nonconsecutive day model separately, we also tried to estimate one model and include a dummy variable if the boater took a trip on the previous day. However, the single model with a dummy variable was not able to accurately capture the decision to take consecutive trips, and underpredicted the number of consecutive trips by 17% for permanent residents and 7% for vacationers.

Figure 3

Schematic of the Boater Trip Decision Simulation (Model Element (ii) in Figure 2)



Linkage between Boater Behavior and Milfoil Propagule Dispersal (Model Element (ii) in Figure 2)

In 2011, project researchers inspected 1,496 boats leaving 27 invaded lakes for milfoil propagules on their boat or trailer, finding that approximately 3% of boats/trailers carried viable propagules. We therefore assume in our modeling that boats inadvertently carry milfoil out of invaded lakes 3% of the time. We use the boater recreation models to simulate boater trip behavior on each day of a given season (see Figure 3) and estimate the number of times viable propagules are deposited in each uninvaded lake in each season—3% of trips to an invaded lake within one day of a trip to an uninvaded lake will carry a viable propagule according to our model—using the following stepwise procedure:

1. Select the lakes $j \in \mathbf{J}_s^{\mathrm{I}}$ that were reported as invaded before season s. We assume that lakes that become invaded in season s are not observed to be invaded until season $s+1$.
2. Count the number of boaters who visit an invaded lake, $j \in \mathbf{J}_s^{\mathrm{I}}$. Boater behavior on a given day depends on whether the boater went boating on the previous day. Therefore, we need to know what the boater did on the previous day $t-1$ in order to predict

boater behavior on day t. To do this, we take the following steps (see Figure 3):

a. Starting with the first day of the season, randomly draw values of the error term from a type I extreme value distribution and estimate the indirect utility of each choice in a boater's choice set on the first day of the season, using equation [1].
b. Identify the choice that maximizes the boater's indirect utility.
c. Return to step (a) for the second day of the season, where the calculation of indirect utility for each choice depends on the choice on the first day of the season. If a trip was taken on the previous day, we use the parameters from the consecutive day model. Otherwise we use the parameters from the nonconsecutive day model.
d. Continue this iterative process through the last day of the season.

3. Count the number of boats that carry milfoil out of the invaded lake. We assume that 3% of the boats that travel to an invaded lake become inadvertent carriers.
4. Count the number of boats inadvertently transporting milfoil that visit an uninvaded lake while the propagule is still viable (within 24 hours of the trip to the invaded lake).
5. Generalize our sample predictions to the entire population of boaters using the expected number of trips to the NHLD by the general population (Kovski 2015) from an estimated 854,954 trips (95% confidence interval of 731,019 to 978,872 trips) to any lake in the NHLD during one summer season. See Appendix Section A.1.3 "Intercept and follow sampling considerations" for more details.
6. Sum the total number of times a propagule is deposited by the population of boaters in season s in each uninvaded lake.

Empirical Estimate of the Effect of Milfoil Propagule Pressure on Milfoil Colonization (Model Element (iii) in Figure 2)

We use historical lake invasion data to estimate the probability that a lake becomes invaded in a given season, conditional on the expected number of boats carrying viable propagules (estimated as described in the preceding subsection) and relevant lake characteristics. We estimate the following hazard model of the probability that an uninvaded lake becomes invaded in season s given that it is uninvaded in season $s-1$:

$$\boldsymbol{\pi}_{ks} = \frac{\exp(c + \eta'\mathbf{L}_{ks} + \rho'\mathbf{W}_{ks} + \boldsymbol{\xi}_s + \omega'\mathbf{L}_{ks}\cdot\boldsymbol{\xi}_s)}{1+\exp(c + \eta'\mathbf{L}_{ks} + \rho'\mathbf{W}_{ks} + \boldsymbol{\xi}_s + \omega'\mathbf{L}_{ks}\cdot\boldsymbol{\xi}_s)};\quad k = 1,\ldots J,\ s = 1,\ldots,S, \qquad [4]$$

where c is a constant term, $\mathbf{L}_{ks}$ is the total number of propogules delivered to the lake in season s by boaters, $\mathbf{W}_{ks}$ is the relevant lake characteristics, $\boldsymbol{\xi}_s$ is a trend, and $\mathbf{L}_{ks}\cdot\boldsymbol{\xi}_s$ is a trend interacted with propagule pressure.[10] Ecological studies have found that milfoil is most common in hard, alkaline, shallow, and clear waters (Dale 1981; Nichols and Shaw 1986) and grows well under nutrient-rich conditions (Lind and Cottam 1969). We use alkalinity, percentage forest cover in the drainage basin, pH, water clarity (Secchi depth), maximum lake depth, and lake size to control for lake characteristics that affect the colonization of milfoil. We also use the trend terms to control for the number of invaded lakes in a given year and for increasing awareness and education about milfoil over time, which may decrease the effect of propagule pressure on milfoil colonization.

Now let $\mathbf{z}_{ks}=1$ if lake k was invaded in by the end of season s.[11] Because we are estimat-

[10] There are two components of propagule pressure measure $\mathbf{L}_{ks}$: (1) the number of consecutive trips that boaters make from invaded to uninvaded lakes (potential contamination trips) and (2) the probability that a boater visiting an invaded lake leaves with an invasive species (the uptake probability). The RUM captures how boaters adjust (1) in response to the spread of the invasive species. The trend term captures awareness and education leading to a change in (2), in other words, as boaters become more aware of invasive species and inspect their boats after visiting an invaded lake, then it is likely that over time a smaller and smaller percentage of consecutive trips from invaded to uninvaded lakes will carry the AIS.

[11] We have historical lake invasion data that identify the year that milfoil was reported and confirmed present. The Wisconsin Department of Natural Resources collects records on the status of aquatic invasions (for milfoil invasions see http://dnr.wi.gov/lakes/invasives/AISLists.aspx?species=EWM).

ing a hazard function of the probability that an uninvaded lake becomes invaded, a lake remains in the sample only in that portion of the available historical record (1989–2013) during which it is not invaded. We estimate the following log-likelihood function:

$$LL(\eta,\rho)=\sum_{s}\sum_{k}\begin{bmatrix}(1-\mathbf{z}_{ks})\times\ln(1-\boldsymbol{\pi}_{ks})\\+\mathbf{z}_{ks}\times\ln(\boldsymbol{\pi}_{ks})\end{bmatrix}. \qquad [5]$$

The log-likelihood function is composed of (1) the survival probability $(1-\boldsymbol{\pi}_{ks})$, or the probability that an uninvaded lake remains uninvaded, for each season that a lake is uninvaded, and (2) the hazard probability, $\boldsymbol{\pi}_{ks}$, or the probability that an uninvaded lake becomes invaded in season *s* given that it has not been invaded in all previous seasons, for the season that a lake becomes invaded.

Cost of Milfoil Invasions (Model Element (iv) in Figure 2)

We estimate the cost of milfoil invasions for two populations—recreational boaters and shoreline property owners—using previous research conducted in our NHLD region, as explained below.[12]

The Welfare Effect of Milfoil Invasions on Boaters

It is common in the literature to regress the lake-specific fixed effects from a typical RUM on the time-invariant variables of interest to estimate the welfare impacts of these variables. Because only 4 of the 453 lakes in our sample became invaded in the two years (2011–2012) boater data were collected, the lake-specific fixed effects capture whether each lake has milfoil. However, in the current context the presence of milfoil is (possibly) endogenous: boater's trip decisions (possibly) depend on the presence of milfoil in a lake, which depends on the past trip decisions of boaters, which were determined in part by the constituent variables of the lake-specific fixed effects. Therefore, more attractive lakes are more likely to have milfoil, and so in a regression of the lake-specific fixed effects on its constituent variables, the milfoil variable would capture in part the general attractiveness of the lake. Statistically correcting for milfoil endogeneity in the RUM requires an instrumental variable—a variable correlated with the presence of milfoil but not the attractiveness of a lake to boaters. It is difficult to conjure what that variable would be. For example, ecological attributes such as alkalinity, water clarity (Secchi depth), maximum lake depth, and lake size that affect the suitability of a lake to a milfoil invasion, and are therefore correlated with the presence of milfoil, are also likely to affect the attractiveness of the lake to boaters by influencing, among other things, the lake's fishing productivity.

Rather than integrating an instrumental variable approach in the RUM estimation to identify the welfare cost of a milfoil invasion to boaters, we use an approach similar to that used by Von Haefen and Phaneuf (2008).[13] We simply use an estimate of the cost of milfoil invasions to boaters developed in a stated preference contingent valuation study in the NHLD (Lewis, Provencher, and Beardmore 2015). The contingent valuation study drew on our sample of boaters to ascertain their willingness to pay for milfoil control/prevention on their "favorite" lake. The estimated annual welfare loss was $98, which, given that on average sample boaters take nine trips per year, is an average of $10.89 per trip. Importantly, the estimated annual welfare loss is high to the extent that boaters' willingness to pay for milfoil control on their favorite lake is higher than that on other lakes in their choice set. Of course, to the extent that a milfoil invasion affects boater welfare, it is also likely to

[12] An issue in estimation of costs is whether we incorrectly include shoreline property owners among the set of boaters visiting a lake, leading to double counting of some costs. Less than 5% of our boater sample owns shoreline property. Moreover, most shoreline property owners put their boats into their own lakes from their own property, while our sample was generated via intercepts at boat ramps. Taken together, these observations indicate that such double counting is not an issue for our study.

[13] In their analysis, von Haefen and Phaneuf (2008) remark, "For example, professional judgment and accumulated knowledge might suggest that some parameters are more credibly identified from one or the other data source. In the recreation context, we may have more confidence in the travel cost parameter estimated off the RP (revealed preference) data, but prefer nonprice attribute parameters estimated off the experimental SP (stated preference) design" (29, 30–31).

affect boater behavior; we address this issue in the discussion of the simulation of milfoil spread below, in the subsection "Adjusting Boater Behavior for Feedbacks."

The Welfare Effect of Milfoil Invasions on Property Owners

We use previous studies in the NHLD as the basis for estimates of the annual economic welfare loss of a milfoil invasion for shoreline property owners. In a contingent valuation study in the NHLD, Provencher, Lewis, and Anderson (2012) estimate that the annual welfare loss of a milfoil invasion to residential shoreline property owners is an average of $1,373 per year. This estimate is very similar to the estimated reduction in residential shoreline property values in a hedonic model in the same region (Horsch and Lewis 2009). That such different valuation methods yield similar estimates is a source of confidence that the true value of the average annual loss is somewhere near these values. We round this welfare loss to residential shoreline property owners associated with the spread of milfoil through the NHLD to $1,400 per year.

Simulations of Invasion and the Economic Costs of Milfoil

Using the model elements described above and illustrated in Figure 2, we developed simulations for baseline and counterfactual scenarios to examine the spatial dynamics of the milfoil invasion of the NHLD and the associated welfare loss to shoreline property owners and boaters in two initial states of the system—the actual state of the invasion in 1998, or the actual state of the invasion in 2013—and extended over a 15-year horizon (see Appendix Section A.2 for an overview of this simulation process). Simulations starting in 1998 ran through 2013, and simulations starting in 2013 ran through 2028. In the baseline, we simulated boater behavior and subsequent propagule pressure when particular subject lakes were invaded at the initial states of the system using the simulation procedure described earlier in this section. In the corresponding counterfactual scenarios, the subject lakes were protected from invasion. A discussion of the subject lakes chosen for examination in the analysis, and the rationale for choosing them, is presented below in the subsection "Adjusting Boater Behavior for Feedbacks."

The average difference between the value of the lake system under the counterfactual simulation and the value of the lake system under the baseline simulation is the expected benefit to shoreline property owners and boaters of protecting the subject lake from invasion. It is, in other words, the answer to the question, "What do boaters and shoreline property owners gain (in expectation) by protecting subject lake $\tilde{\jmath}$ from invasion over a 15-year period, conditional on the initial extent of the invasion in the NHLD?" This gain can be separated into the "own-lake" benefit—the benefit to the shoreline property owners of lake $\tilde{\jmath}$ and the boaters visiting lake $\tilde{\jmath}$—and the "spillover" benefit to neighboring lakes that are less likely to become invaded because lake $\tilde{\jmath}$ is protected. This benefit can be cast instead, as we do below, as the welfare loss from failing to protect the subject lake from invasion. This loss is naturally separated into an own-lake loss and a spillover loss.

For a given year of a given simulation run, the calculation of the welfare loss due to milfoil is simply the sum of the loss to shoreline property owners around each invaded lake ($1,400 per property) and the loss to boaters visiting invaded lakes ($10.89 per boater per trip). For context, the property value impact of milfoil is equivalent to an 8% reduction in total property value (Horsch and Lewis 2009). while the per trip welfare loss is equivalent to a 4% reduction in the estimated economic value of a boating trip (Lewis, Provencher, and Beardmore 2015; Kovski 2015). Each simulation run generates a 15-year sequence of NHLD invasions using the hazard model developed earlier in this section,[14] and, therefore, a 15-year sequence of welfare loss due

[14] The hazard model predicts the probability that a lake becomes invaded, given that it has not become invaded yet. In order to use these probabilities to predict which lakes become invaded, we draw a random uniform number between 0 and 1, r_j, for each lake j, and if the probability of invasion for lake j is greater than r_j then lake j becomes invaded that simulation.

to milfoil. We then disentangle the own-lake effect from the spillover effect. The own-lake effect in season s of a given simulation run m is the welfare loss to property owners around the subject lake $\tilde{j}$ and boaters who visit the subject lake $\tilde{j}$ when lake $\tilde{j}$ is invaded, in the baseline case. The own-lake effect is zero in the counterfactual case because $\tilde{j}$ is protected from invasion.

$$\mathbf{WL}_{\tilde{j},s,m}^{\text{own}} = \$1,400 * \text{shoreline properties}_{\tilde{j}} + \$10.89 * \mathbf{trips}_{\tilde{j},s,m}. \quad [6]$$

The spillover effect in season s of a given simulation run m is the welfare loss to lakes that experience a higher probability of invasion, given that lake $\tilde{j}$ is invaded in the baseline case. The spillover effect is measured as the difference between the total welfare loss in the baseline case minus the total welfare loss in the counterfactual case minus the own-lake effect:

$$\mathbf{WL}_{\tilde{j},s,m}^{\text{spillover}} = \sum_{j}^{J} \mathbf{WL}_{j,s,m}^{\text{base}} \mid \tilde{j} \text{ is invaded} - \sum_{j}^{J} \mathbf{WL}_{j,s,m}^{\text{counter}} \mid \tilde{j} \text{ is protected} - \mathbf{WL}_{\tilde{j},s,m}^{\text{own}}. \quad [7]$$

Adjusting Boater Behavior for Feedbacks

The calculation of the welfare loss from failing to protect a subject lake from invasion depends on whether boaters respond to the presence of milfoil by changing their trip behavior. The willingness of boaters to pay to prevent a milfoil invasion, as expressed in the contingent valuation study by Lewis, Provencher, and Beardmore (2015), does not imply a behavioral response to the presence of milfoil[15]; it depends on whether the values expressed are use values, in which case we might expect a behavioral response, or nonuse values, in which case a behavioral response is not implied. The behavioral response of boaters to milfoil also assumes that boaters are aware of the presence of milfoil on lakes. Even though 87% of boaters reported that they were somewhat to very familiar with milfoil, only 50% correctly reported that their favorite lake was infested with milfoil, and 73% correctly reported that their favorite lake was not infested with milfoil, with an average of 65% of boaters correctly identifying the milfoil status of their favorite lake. In our analysis we consider the two extreme cases. In the first, boaters do not respond to a milfoil invasion (no-feedback model), and in the second they do (feedback model).

For the model without feedback we assume that milfoil does not affect daily boating decisions; however, if a lake in a boater's choice set becomes invaded, the boater is \$10.89/trip worse off. For the case with feedback, we assume that as soon as a lake becomes invaded, the cost to boaters from visiting the lake is \$10.89/trip higher, and the boater's trip decision changes correspondingly.[16] In particular, the boater recreation model uses distance as a proxy for travel cost, and we convert the \$10.89/trip annual welfare loss into an equivalent additional roundtrip distance that a boater would have to travel to an invaded lake, using the American Automobile Association's cost of \$0.60/mile (American Automobile Association 2012). Thus, if lake j becomes invaded, we increase each boater's distance to lake j by \$10.89/\$0.60 = 18.15 miles round-trip (or about 9 miles one way). Using the estimated marginal effects for distance from the recreational boater model, a milfoil invasion on a lake would reduce the average probability of visiting that lake by 11%. Estimates of the

[15] The behavioral response of boaters to milfoil also assumes that boaters are aware of the presence of milfoil on lakes. Our survey elicited boaters' familiarity with milfoil, and 87% were somewhat to very familiar. Therefore, we assume that boaters are aware of milfoil invasions. We thank an anonymous reviewer for this comment.

[16] If boaters change their trip behavior due to the presence of milfoil in lakes, then the lake-specific fixed effects will reflect the effect of milfoil on the utility boaters receive from choosing to take a boating trip. These lake-specific fixed effects will be higher before a lake becomes invaded with milfoil. In our simulation exercise, we do not account for changes in the lake-specific fixed effects before a lake becomes invaded. Following Train (2009, section 2.8), we recalibrate the lake-specific fixed effects for each lake that was invaded to find the preinvasion lake-specific fixed effects. On average the lake-specific fixed effects would be adjusted by 2.5% in the preinvasion state. Given the small magnitude of this adjustment, we keep the lake-specific fixed effects constant over all simulations.

economic cost of a lake's invasion without trip feedback effects are a good approximation of the actual cost if boaters change their trip behavior relatively little as lakes become invaded.

Incorporating the feedback effect increases the computational cost of the simulation exercise enormously, as it requires that the within-year distribution of trips be resimulated for each year within each 15-year simulation run. By contrast, in the absence of a feedback effect, the within-year distribution of trips across lakes must be simulated only once, because trip behavior is not conditional on the distribution of milfoil across lakes. Therefore, in the model without feedbacks we estimate the economic costs of milfoil invasions for each of the 453 lakes in our sample. However, in the model with feedbacks we estimate the economic costs of milfoil invasions for eight subject lakes (see Appendix Table A6 for characteristics of lakes selected for the coupled model). Unless otherwise noted, regionwide summaries of the economic cost of a milfoil invasion reported hereafter are based on simulations with no trip feedback effect. See Appendix Section A.2 (Simulations of the Effects of Milfoil Invasions on Economic Welfare Using a Fully Coupled Model and an Uncoupled Model) for more information about the simulation procedure.

3. Results

A full set of parameter estimates for the RUM of boater movement for permanent residents is reported in Appendix Table A2, and for vacationers in Appendix Table A3 for $S=2$ (2011–2012). As expected, the results from the RUM indicate that higher travel costs lower the probability of visiting lakes for all boaters, and all boaters are more likely to visit a lake on weekends and holidays. Additionally, the intraseasonal trend of boating trips is an inverted U-shape with a peak of boating trips in mid-July. The parameter estimates for the hazard model for the probability of lake invasions are presented in Appendix Table A4 for $S=23$ (1990–2012). The results from the hazard model indicate that lakes have a higher probability of being invaded by milfoil if they receive more propagule pressure from boaters, are smaller, have high alkalinity, and have less water clarity.[17]

Using the RUM estimates of boater behavior and hazard model estimates of the impact of this boater behavior on the probability that a lake becomes invaded, we examine the spillover costs of individual lakes—the difference in the systemwide economic value with and without a specific lake invaded for $S=15$ (either 1998–2013 or 2013–2028). Figure 4[18] provides a summary of the 15-year economic cost of a lake's invasion for each lake examined in the study, and the share of each lake's economic cost that is spillover cost.[19] Averaged across all 453 NHLD lakes, we estimate that for the 1998 initial invasion state, the average 15-year economic cost of a lake's invasion is \$2.14 million, with a minimum of \$3,635 and a maximum of \$45.27 million. For the 2013 initial invasion state, the average 15-year economic cost of a lake's invasion is \$1.53 million, with a minimum of \$3,629 and a maximum of \$31.33 million.

Spillover shares are noticeably larger for the 1998 initial invasion state than for the 2013 initial invasion state. For the 1998 initial invasion state, the average spillover cost was \$0.66 million, with a minimum of \$0 and a maximum of \$20.15 million. For the 2013 initial invasion state, the average spillover cost was \$37,977—1/17th of the average of the 1998 initial invasion state—with a minimum of \$0 and a maximum of \$0.93 million. To visualize the estimated spillover losses, Figure

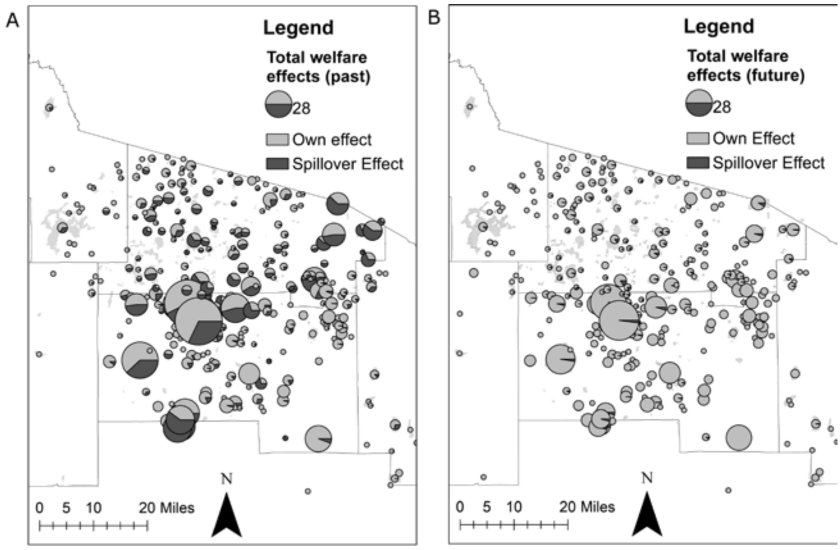
[17] The yearly trend of milfoil invasions is an inverted U-shape. Initially, the trend term is large and positive, indicating that having more invaded lakes in the system increases the likelihood of invasion for uninvaded lakes, holding the propagule pressure from boating trips constant. However, the squared trend term is negative and the marginal effect of the trend term becomes negative around 2004, indicating that education and awareness might have led to a decreased the effect of propagule pressure on milfoil colonization.

[18] The sizes of the pie charts represent the total 15-year economic cost (millions of dollars). The *darker* share represents the proportion of the total economic cost that accrues to the users of neighboring lakes (the spillover cost).

[19] We use a 0% discount rate, which is fairly consistent with the 0.42% 10-year real interest rate (http://www.multpl.com/10-year-real-interest-rate/). The results are robust across specifications of the discount rate, see Appendix Table A5.

Figure 4

Spillover Costs for Each Lake in Our Sample, as a Proportion of the Total 15-Year Economic Cost: (A) 1998 Initial Invasion State; (B) 2013 Initial Invasion State



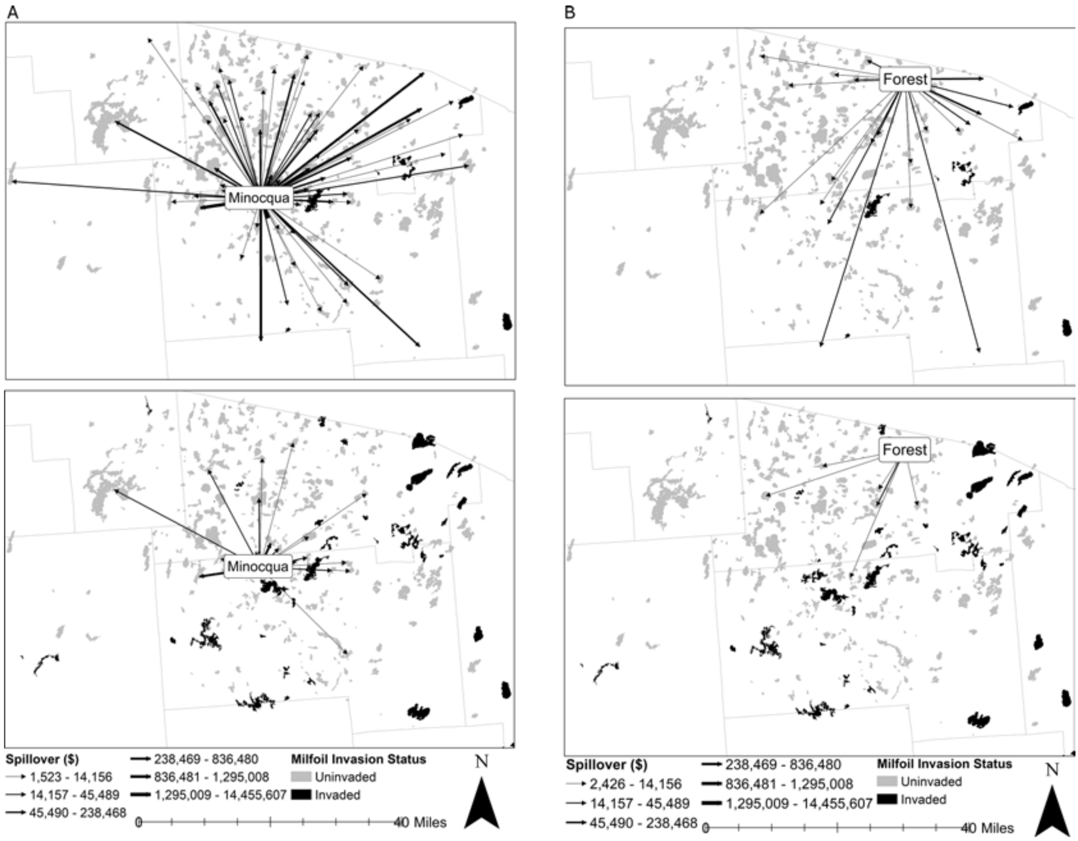
5 presents a mapped depiction of the spatial dynamics of the spillover losses arising from a milfoil invasion in one of the system's most visited lakes (Lake Minocqua, panel A) and a lake with far less boat traffic (Forest Lake, panel B). The width of the "spokes" in the figure represents the magnitude of the spillover losses. A striking result from Figure 5 is that there are far fewer "spokes" in the latter period (2013–2028) than in the earlier period (1998–2013), since many of the lakes susceptible to a milfoil invasion in the earlier period had been invaded by the beginning of the latter period.

Table 1 provides estimates of invasion costs with and without boater trip feedback effects for the eight lakes in the study area selected for the comparison. For all lakes, the own-lake cost of an invasion is lower in the model with feedback effects because boaters substitute away from the lake, thereby mitigating the cost of an invasion compared to the case where such substitution is not possible. Across the eight lakes, the average spillover cost for the 1998 initial invasion state was approximately \$5 million for the model without trip feedbacks and approximately \$4.19 million for the model with trip feedback effects, a difference of 16%. For the 2013 initial invasion state, the average spillover cost was approximately \$0.46 million for the model without trip feedback effects and \$0.39 million for the model with trip feedback effects, a difference of approximately 15%. With respect to total economic costs, the model with trip feedback effects generates average values that are 10% lower than those for the model without trip feedback effects for the 1998 initial invasion state, and 5% lower for the 2013 initial invasion state.

Although one would expect the trip feedback effect to mitigate spillover costs—fewer trips to an invaded lake mean fewer propagules are carried to uninvaded lakes—the results in Table 1 indicate the extent of mitigation can vary considerably, and that it can actually increase spillover costs. For Dam Lake the spillover effect is higher when trip feedbacks are modeled for the 1998 initial invasion state, and the same is true for Lake Minocqua for the 2013 initial invasion state. The explanation is that trip substitution away from the lake due to the milfoil invasion includes fewer consecutive-day trips to the lake (such as occurs on weekends), replaced to some extent by trips to the lake on one day and to another (uninvaded) lake the next (it bears repeating that in the model, milfoil propagules

Figure 5

Spillover Costs to Individual Lakes: (A) From Minocqua Lake, 1998 Initial State *(upper)* and 2013 Initial State *(lower)*; (B) From Forest Lake, 1998 Initial State *(upper)* and 2013 Initial State *(lower)*



are a source of invasion only if a boater visits an uninvaded lake the day after picking up the propagule on an invaded lake). This particular type of substitution serves to increase spillover costs, and it appears that in some cases it is significant enough to generate an overall increase in spillover costs.

4. Discussion and Conclusion

The results presented here, combined with current theory and empirical evidence about the management of common property resources, provide several insights to the question of cost-effective management of AIS. First, because spillover costs are dynamic, declining rapidly as an invasion spreads across a lake system, coordinated management of an invasive species at the system level is most important early in the invasion (Finnoff, Potapov, and Lewis 2010; Albers, Fischer, and Sanchirico 2010; Epanchin-Niell et al. 2010; Epanchin-Niell and Wilen 2012; Epanchin-Niell and Hastings 2010). While the argument for the efficiency of early intervention has been made in previous theoretical studies, this paper presents the first empirical illustration of this point through examination of the dynamics of the spillover effect of an invasion. In 2013, only 13% of the NHLD lakes in our sample were invaded, and yet spillover costs averaged only a 3% share of a lake's economic cost of invasion, reflecting that 8 out of the top 10 most-visited lakes were invaded by 2013. Our results suggest that the potential efficiency gains from coordinated management are potentially quite low

Table 1
A Comparison of the Economic Cost of Invasion in the Uncoupled and Coupled Models (dollars)

		1998 Invasion State			2013 Invasion State		
Lake	Trip Feedback	Own-Lake Effect	Spillover Effect	Spillover Percentage	Own-Lake Effect	Spillover Effect	Spillover Percentage
Big Arbor Vitae	No	4,925,978	9,015,315	65	4,926,818	932,428	16
	Yes	4,777,000	6,496,000	58	4,707,000	812,200	15
Little Arbor Vitae	No	1,773,875	5,345,252	75	1,773,408	548,763	24
	Yes	1,704,000	2,700,000	61	1,663,000	285,000	15
Rhinelander Flowage	No	17,833,785	13,247	0	17,833,951	626	0
	Yes	16,780,000	1,913	0	17,100,000	605	0
Dam	No	5,249,109	1,409,634	21	5,249,203	54,610	1
	Yes	4,894,000	1,884,000	28	4,895,000	31,840	1
Minocqua	No	25,118,372	20,152,521	45	25,118,372	672,963	3
	Yes	23,660,000	19,650,000	45	24,002,759	775,170	3.1
Squash	No	3,824,295	65,777	2	3,824,295	682	0
	Yes	3,584,000	26,320	0.7	3,562,000	600	0
Twin, South	No	1,767,563	3,046,594	63	1,767,320	70,898	4
	Yes	1,630,000	2,160,000	57	1,614,000	51,640	3
Forest	No	3,132,675	927,395	23	3,132,675	27,971	1
	Yes	2,565,000	597,400	19	2,909,000	4,779	0.2

in a system for which at least a moderate share of valuable sites already are invaded.

Second, the significant spatial heterogeneity in both the own-lake and spillover economic costs of a milfoil invasion (Figure 4) indicates the need for a spatially responsive management strategy. Returning to Figure 5, it is clear that allocating more management effort to protecting a popular lake (Lake Minocqua) from an invasion compared to a less popular lake (Forest Lake) would be justified not only because the annual own-lake damage from an invasion would be higher (about \$1.5 million compared to \$0.17 million), but because popular lakes are major hubs for recreational boating and so their invasion can generate substantial spillover costs to other lakes.

Third, not only is it likely that, with a fixed budget for systemwide management, spending the incremental dollar on prevention and control on certain hub lakes generates greater value than spending it on an "endpoint" lake tied to the hub, it is possible that the value is greater even from the perspective of the residents of the endpoint lake. This possibility arises because of the significant spillover costs associated with the hub lake, and because of the potential for lake-level management economies of scale and scope (e.g., economy of scope from joint management of several AIS) (Drury and Rothlisberger 2008).

Fourth, lake users are more likely to invest time and energy collaborating with the system management agency to prevent an invasion on their own lake than to control its spread from the lake after invasion, because they gain from the former and do not gain (or gain much less) from the latter. An implication of this is that the system management agency can leverage resources dedicated to prevention to enlist lake users to the effort, but cannot leverage resources dedicated to controlling the spread. A set of related propositions requiring additional study concerns what characteristics of uninvaded lakes are associated with greater leveraging of system management resources. For instance, an extensive empirical literature (see, e.g., Poteete and Ostrom 2004; Yang et al. 2013 and references therein) has investigated the role of group size and heterogeneity in collective action of common property resources. Is a system management agency engaged in AIS prevention likely to receive a greater total contribution of effort from lake users on a large lake than a small lake, that is, on a hub lake than an endpoint lake? How does the contribution change in response to the spatial heterogeneity of the milfoil infestation within a lake? It seems quite possible—though to reiterate, a matter of additional research—that the system management agency can rely heavily on local lake users to provide prevention resources, even on the large hub lakes, allowing the agency to concentrate its resources on controlling the spread of AIS from invaded lakes.

Fifth, the damages that can be avoided by preventing AIS invasions dwarfs the state of Wisconsin's expenditure on AIS management. In 2015, the Wisconsin Department of Natural Resources spent a total of $5.8 million on all aquatic invasive species programs in the state—all species and all bodies of water, including all 3,620 inland lakes greater than 20 acres, all rivers, and all wetlands (Wisconsin Department of Natural Resources 2015). As a thought experiment, suppose that this same amount had been spent annually on only the 48 lakes that became invaded in the NHLD during the period 1998 through 2013—more than $120,000 per lake per year[20]—and that this expenditure was enough to assure milfoil would not invade these lakes over the 15-year period. Then according to our results, the expenditure would have positive net benefits at any reasonable discount rate. For instance, at a 3% discount rate the net present value of this expenditure would have been $69 million, whereas we estimate that the net present value of the benefit in terms of avoiding the damages actually sustained by shoreline property owners and boaters on these lakes during this period would have been $96 million.[21] Whether the current expenditure should be increased turns on the question of whether AIS management is cost-effective. Spending $5.8 million each year to prevent milfoil invasions on the aforementioned 48 lakes would make little economic sense if it had little effect on the probability of invasion.[22]

Our analysis could be improved in several ways. More research is needed to better understand how the transport of invasive species from invaded lakes to uninvaded lakes is influenced by the phenology and life history of a species, and management options such as educational signs, boat washing stations, and volunteers monitoring lakes. This additional information will allow policy simulations to predict the effect of management options that may not lead to complete protection against invasion. Further research could also apply the methodology outlined in this paper to use existing RUMs to model the spread of invasive species and estimate the magnitude of the spillover effect with three main components: (1) the survival time of the invasive species out of water and a RUM that can predict recreational trips across this time frame, (2) a hazard model of the probability of invasion given the number of trips from invaded sites to uninvaded sites and the uptake probability, and (3) welfare damages given invasion.

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[20] For reference, a typical boat washing station costs between $8,000 and $16,500 (Kovski 2015).

[21] It is important to note that given the spillover externalities, the damages from multiple lakes becoming invaded is not simply the sum of the estimated damages when each lake becomes invaded individually. Therefore, in order to understand the damages from the invasion of the 48 lakes from 1998 to 2013, we simulate damages from a baseline state with the 48 invasions to a counterfactual state without these 48 invasions.

[22] The effectiveness of invasive species management is unlikely to be 100%; however, the effectiveness has been estimated to be quite high, ranging from 88% ± 5% for visually inspecting and removing invasive plants by hand to 83% ± 4% for high-pressure boat washing in controlled experiments (Rothlisberger et al. 2010).

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