A Dissertation

entitled

Spatial Modeling as a Decision-making Tool for Invasive Species Management in the Great Lakes

by

Jennifer L. Sieracki

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the

Doctor of Philosophy Degree in Biology (Ecology Track)

____
Dr. Jonathan Bossenbroek, Committee Chair

____
Dr. Peter Lindquist, Committee Member

____
Dr. Christine Mayer , Committee Member

____
Dr. Darryl Moorhead, Committee Member

____
Dr. David Reid, Committee Member

____
Dr. Patricia R. Komuniecki, Dean
College of Graduate Studies

The University of Toledo

December 2014

An Abstract of

Spatial Modeling as a Decision-making Tool for Invasive Species Management in the Great Lakes

by

Jennifer L. Sieracki

Submitted to the Graduate Faculty as partial fulfillment of the requirements for the Doctor of Philosophy Degree in
Biology (Ecology Track)

The University of Toledo

December 2014

Due to recent recognition that ballast water is playing an important role in the spread of invasive species within the Great Lakes, there has been increasing interest in implementing management strategies that include a secondary spread component for ballast discharge. Using ballast water data for ships visiting U.S. ports in the Great Lakes, I created a dynamic spatial model to simulate the spread of invasive species based on recent shipping patterns. My goal in producing this model was to provide information to natural resource managers, scientists, and policy-makers to help effectively regulate invasive species issues. In testing the model, I determined that including the number of discharging ship visits that a location receives from previously infested areas and the ability of an organism to survive in the ballast tank were important in more accurately identifying the past spread of the fish virus, viral hemorrhagic septicemia virus (VHSV), zebra mussel (*Dreissena polymorpha*), and Eurasian Ruffe (*Gymnocephalus cernuus*), than discharge location alone. I also included and tested a localized spread distance that simulated the dispersal of an invasive species upon being discharged at a location. I first applied the model to identify if ballast water played a role in the secondary spread of

VHSV. Results indicated that ballast water movement has contributed to the spread of VHSV in the Great Lakes, albeit it is not the only vector of secondary spread. However, ballast water management would be an important part of any plan in preventing the future spread of VHSV in an ecosystem. Next, I applied the model to predict the future spread of Eurasian Ruffe, which already occurs in the Great Lakes, and two species that do not, golden mussel (*Limnoperna fortune*) and killer shrimp (*Dikerogammerus villosus*). The results of the prediction models are intended to be used to help direct early detection monitoring efforts. The Eurasian Ruffe results are currently being used by The Nature Conservancy in their eDNA monitoring efforts, and have led to the positive detection of ruffe eDNA in a location where ruffe has previously not been detected. Finally, I applied the model to identify potentially "safe" ballast water exchange (BWE) sites in Lake Michigan. The purpose of this exercise was to locate mid-lake sites where ships could exchange and flush their ballast tanks, so as to reduce the probability that species are able to survive and establish new populations in the Great Lakes. Potential BWE sites were identified by inputting the results of Lake Michigan circulation models into the ballast water model to determine which sites led to no or minimal spread throughout the Great Lakes. Results of model applications have led to specific predictions for species and management scenarios identified by invasive species managers that have previously not been made for ballast water management in the Great Lakes before.

This dissertation is dedicated to my grandmothers, Carleen and Rose. It is for them that I strive to make my dreams a reality.

Acknowledgements

I would like to take this opportunity to thank the many people who have made this degree possible. First, I would like to thank my advisor, Dr. Jonathan Bossenbroek, for guiding me through this process and encouraging me to accomplish that which seemed so out of reach over four years ago. He allowed me great independence while working on this project and was always there when I needed help. I would also like to thank my committee, Drs. Peter Lindquist, Christine Mayer, Daryl Moorhead, and David Reid, for all of their guidance and valuable input. They have been a wonderful group to work with and have provided insight into my future career, as well as my research. I am also grateful for the support provided by the Lake Erie Center's staff: Patricia Uzmann, Meredith Gray, Rachel Lohner, Pam Struffolino, and Tom Hodges. Further, I could not have survived this time without my fellow students and friends: Kristen Devanna Fussell, Rachel Kuhaneck Sullivan, Susan McCormick Olijnyk, Amanda Haponski, Lindsey Pierce Friedrich, Mark Dufour, Jeremy Pritt, and Tim Sullivan. For my parents, Mark and Lisa, I am grateful that they raised me to be independent and who continued to insist that I would get a PhD someday, even during my break from academia. I am also thankful for my grandfather, who not only provided me with incentive to complete my degree, but in doing so expressed his faith in me. Finally, I am grateful for my brother, Craig's, support and friendship. He has always believed in me, and that has meant the world to me.

Table of Contents

List of Tables

List of Figures

Preface

The chapters of this dissertation are organized in order of the date of acceptance for publication. Each chapter is identical to the published/submitted version.

Chapter 2 has been previously published as:

> Sieracki JL, Bossenbroek JM, and Faisal M (2014) Modeling the secondary spread of viral hemorrhagic septicemia virus (VHSV) by commercial shipping in the Laurentian Great Lakes. *Biological Invasions* **16**, 1043-53.

Chapter 3 is pending publication at *PLOS ONE* depending on major revisions:

> Sieracki JL, Bossenbroek JM, and Chadderton WL (In Review) A spatial modeling approach to predicting the secondary spread of invasive species due to ballast water discharge.

Chapter 4 has been formatted to be submitted concurrant with a related manuscript to the *Journal of Great Lakes Research*:

> Sieracki JL, Beletsky D, Beletsky R, and Bossenbroek JM (In Prep) Evaluating the effectiveness of mid-lake ballast water exchange at preventing the spread of invasive species in Lake Michigan.

This project was funded by grants from United States Department of Agriculture, National Institute of Food and Agriculture, Cooperative State Research, Education, and Extension Service, USDA-NIFA (CSREES) #2010-38927-21048 and National Oceanic and Atmospheric Agency, Center for Sponsored Coastal Ocean Research, NOAA-CSCOR #NA10NOS4780218. This is publication #2014-13 from the Lake Erie Research Center.

Chapter 1

Introduction

Prior to European settlement in North America, the Laurentian Great Lakes were a one-way conduit of water to the Atlantic Ocean with upstream travel blocked by natural obstacles. A series of rapids and a change in elevation of about 70 m prevented many organisms from travelling up the St. Lawrence River and into Lake Ontario. Niagara Falls further prevented species from travelling into Lake Erie and the remaining Great Lakes. However, from the time Europeans first reached the Great Lakes, they began to devise the means to turn them into the seaway they are today. First, the Erie Canal was completed in 1825, connecting the Hudson River in New York, and effectively the Atlantic Ocean, to Lake Erie (Finch 1925). Next, the First Welland Canal, added in 1829, connected Lake Ontario to the rest of the Great Lakes (The St. Lawrence Seaway Management Corporation 2014). This canal underwent several iterations until all but today's largest ships were able to lock through it and gain access to the lakes in the west. Beginning in the mid-1800s, the first known aquatic invasive species began to enter the Great Lakes, including alewife and sea lamprey, both believed to have entered the portion the Great Lakes from Lake Erie west via the canal system (NOAA Undated). Finally, after 64 years of planning and debating, the St. Lawrence Seaway was completed in 1959 (National Research Council 2008). The Seaway was the last step in opening up the Great Lakes to the Atlantic Ocean and the ports of the world. With the global trade that entered through the St. Lawrence Seaway came numerous species from around the world, some that have led to considerable economic and ecologic harm to the Great Lakes region.

Of the numerous vectors of species introduction to the Great Lakes, ballast water has been one of the most important contributers to invasive species introductions. Ship ballast has been a contributor to invasive species introductions to the Great Lakes since the mid-1800s (NOAA Undated). Ballast is required by ships travelling on large bodies of water to maintain the appropriate trim and stress loads (Committee on Ships' Ballast Operations et al. 1996). If a ship is ballasted improperly, it can break up due to high stresses on its hull and structure or be sunk during rough seas. During the early days of shipping on the Great Lakes, ships were made of wood and used solid ballast, usually composed of sand and rock (Transport Canada 2010). Despite solid ballast being an important contributor to the spread of invasive plants and some invertebrates, it was not a major source of aquatic invasive species introductions to the Great Lakes (NOAA Undated). However, by the early 1900s, ships were mostly being built of steel and used water as ballast, since it was easier to load and provided greater stability (Transport Canada 2010). This allowed for increased spread of species within the Great Lakes, which at that point were mostly introduced to the Great Lakes by intentional releases (NOAA Undated). However, after the opening of the St. Lawrence Seaway in 1959, the number of nonindigenous species being introduced into the Great Lakes, especially by ballast, drastically increased (NOAA Undated). From 1840 to 1959, the number of species being detected in the Great Lakes per year averaged 0.89, with 0.18 species per year identified as having been introduced via ballast exclusively (NOAA Undated). Since 1959, the average number of species detected per year has been 1.60 with 1.00 species per year due to ballast (NOAA Undated). In fact, since 1959 about 62% of species detected in the Great Lakes were introduced by ballast, as opposed to 21% prior to the opening of the St. Lawrence Seaway (NOAA Undated). The most evident jump in species introductions occurred in the mid- to late 1980s (NOAA Undated).

With the exception to those species that directly impacted economically important commercial and recreational fishers, such as sea lamprey and alewife, few policy makers had noticed the influx of invasive species to the Great Lakes. In the 1980s, the increasing number of invasive species detections began to raise the interests of scientists, natural resource managers, and policy makers; however, it was one small, bivalve introduced in the 1980s that is most well-known as the "poster child" of aquatic invasive species. The zebra mussel (*Dreissena polymorpha*) is a mollusk from the Ponto-Caspian region introduced via ballast water (NOAA Undated) that was first discovered in Lake St. Clair in 1988 (Benson 2014). By 1989, zebra mussels were found in all of the Great Lakes, except Lake Huron (Benson 2014). Since then, zebra mussels have spread to all Great Lakes, throughout the Mississippi, Ohio, and Hudson River basins, and into the western U.S. (Benson 2014). It was later determined that zebra mussels had been discovered in Lake Erie in 1986, but this information was recorded only in obscure references until published by Carlton in 2008. By the time zebra mussels were widespread in the Great Lakes, they had already fouled water intakes of power plants and municipal water suppliers. In fact, in 1989, Monroe, Michigan's water supply on the western end of Lake Erie was forced to shut down due to the clogging of its water intake pipes with zebra mussels (Beeton 2014). Zebra mussels have also had considerable impacts on the Great Lakes ecosystem, due to their large population sizes and ability to efficiently filter the water column (Adlerstein et al. 2007, Higgins 2014, Mayer et al. 2014). Zebra mussels have been identified as decreasing the diversity and abundance of native mussels and phyto- and zoo-planktons (Adlerstein et al. 2007, Lucy et al. 2014, Ward and Ricciardi 2014) and potentially increasing toxic algal blooms in the Great Lakes (Bierman et al. 2005). Because of the rapid expansion of the zebra mussel and the resulting economic and ecological loss, both the U.S. and Canada decided to take steps to prevent the future invasion of such species.

In order to prevent the introduction of species to the Great Lakes, both Canada and the U.S. have put forth ballast water management policies, which have evolved since their first inception. Prior to 1993, ballast water management policies involving invasive species were voluntary. However, in 1993, the U.S. Coast Guard (USCG) began requiring that all ships entering the Great Lakes undergo mandatory ballast water exchange (BWE; Buck 2010). In 2006, the Government of Canada were the first to begin requiring that all ships carrying residual ballast water and sediment (NOBOB-No Ballast On Board) flush their tanks with seawater prior to entering the Great Lakes (Government of Canada 2006). The USCG in 2012 and the U.S. Environmental Protection Agency (USEPA) in 2013 released further requirements for the management of ballast water in U.S. waters (USCG 2012, USEPA 2013). For the first time, U.S. policy listed management practice requirements for "Lakers", ships that only travel within the Great Lakes. These policies address the more recent concern that ballast water is playing a role in the "secondary spread" of invasive species within the Great Lakes (Rup et al. 2010, Briski et al. 2012). Secondary spread is the spread that occurs after the initial introduction of a species to a system. The USCG and USEPA further require that all new ships travelling in U.S. waters be equipped with approved ballast water management systems and that all ships visiting U.S. ports follow best management practices, such as avoiding taking in ballast water while at port when possible (USCG 2012, USEPA 2013).

Even though both the U.S. and Canada have taken steps to prevent the introduction of invasive species to the Great Lakes, it is important to also have a control plan in place for those species that either manage to slip past prevention efforts or are introduced via other means. Prediction and early detection need to be part of any control efforts and are particularly important for aquatic species, which are more difficult to detect than terrestrial species (Jerde et al. 2011). Detecting a species during the earliest stages of invasion is crucial in eradicating or controlling it, as this may be the only time that the reproducing population is small enough to treat at a manageable level (Simberloff et al. 2005, Lodge et al. 2006). Early detection also reduces the amount of time and money required to control a species (Lodge et al. 2006). Once a species has spread to multiple ports or lakes, it is much more difficult to control its spread. Because it is not possible to census the Great Lakes for invasive species using early detection techniques, such as eDNA methods, either due to lack of money, resources, or time, it is important to have tools that help to focus monitoring on locations that are most likely to be invaded by a species in the future. Using models to try to determine where a species may spread is a better option than actually introducing the species to a system, especially for a system as large as the Great Lakes. Prediction models have been used in the past to identify the potential future locations of species invasion. Many of these models have been developed to identify human behavior that would lead to long-distance spread based on the "attraction" of uninvaded areas to certain segments of the human population (Schneider et al. 1998, Bossenbroek et al. 2001, Carrasco et al. 2010, Drake and Mandrak 2010, Prasad et al. 2010). None of these models mapped the past pattern of movement of the vectors they were studying and instead assumed that human behavior is predictable based on the characteristics of the uninvaded location and infrastructure. While this may be a safe assumption with certain vectors of spread, such as recreational boaters, the movement of ballast water in the Great Lakes can change with the economy. However, because the movement of ballast water has been recorded and made available by the U.S. since 2004 (Smithsonian Environmental Research Center and USCG 2009), building a prediction model based on past behavior can result in fairly accurate predictions of long-distance secondary spread.

The goal of my dissertation is to build a ballast water model using past discharge data in the Great Lakes in order to inform a number of invasive species management questions. The model was tested to identify the most important information to include and to determine the best fit parameter values for each species studied as part of this dissertation. First, I used the ballast water model to identify the role ballast water was playing in spreading an invasive species, so as to ascertain if a ballast water management component would be important to consider in controlling the spread of the species. The species I modeled was Viral Hemorrhagic Septicemia Virus (VHSV), a fish virus first found in the Great Lakes in 2003. Despite regulations aimed at preventing the spread of VHSV via fish stocking and bait fish, it became widespread in the Great Lakes, potentially due to a lack of regulation of other vectors of spread. I used the model results to determine if ballast water may have led to the further spread of this fish disease. Next, I used the model to predict the future spread of invasive species in the Great Lakes to help direct monitoring efforts and inform management on how to proceed once a species invades. I tested and ran the model for three species, Eurasian Ruffe (*Gymnocephalus cernuus*), golden mussel (*Limnoperna fortunei*), and killer shrimp (*Dikerogammarus villosus*). Eurasian Ruffe currently already occurs in the Great Lakes, but is not yet widespread. Both golden mussel and killer shrimp have not yet been detected in the Great Lakes, but were identified by a collaborative group of scientists as at risk for being introduced. The modeling effort not only produced predictions for guiding monitoring efforts, but also allowed for the determination of the best options for preventing the spread of specific species in the Great Lakes. The results of the Eurasian Ruffe predictive model are currently being used by The Nature Conservancy in their early detection monitoring efforts. Finally, I input the results of a Lake Michigan circulation model devised by scientists at the National Oceanic and Atmospheric Administration (NOAA) into the ballast water model to identify potential mid-lake BWE sites within Lake Michigan that can reduce the risk of secondary spread of invasive species. By identifying mid-lake BWE sites within the Great Lakes, I hope to demonstrate the possibility for effective temporary solutions to ballast water spread until ballast water treatment systems have been approved for use in freshwater.

Chapter 2
Modeling the Secondary Spread of Viral Hemorrhagic Septicemia Virus (VHSV) by Commercial Shipping in the Laurentian Great Lakes

2.1 Abstract

Researchers have only begun to study the role of shipping in the spread of invasive species in the Laurentian Great Lakes despite a well-documented history of introductions in these lakes due to ballast water release. Here, we determine whether ballast water discharge was a likely vector of spread of the fish disease, viral hemorrhagic septicemia virus genotype IVb (VHSV-IVb), throughout the Great Lakes and St. Lawrence Seaway. Three models were developed to assess whether the spread of VHSV was due to 1) chance (random model), or 2) ballast water discharge (location model), and whether 3) increased propagule pressure, as measured by the number of visitations by ships carrying ballast water from VHSV infected areas, increased the likelihood of a discharge location becoming infected with VHSV (propagule pressure model). The third model was also used to assess the probable point of initial introduction of VHSV. Presence and absence accuracies and weighted Cohen's kappa were calculated to determine which models best

predicted observed presences and absences of VHSV. Location models explain the patterns of VHSV detections better than random models, and inclusion of "propagule pressure" often improved model fit; however, the relationship is weak likely because of a long lag time between introduction and detection, a high rate of false negatives in reporting, and the possible contribution of other vectors of spread. Montreal was also identified as the more likely introduction site of VHSV, rather than Lake St. Clair, the site where the virus was first detected.

2.2 Introduction

Commercial ship ballast water has been identified as a major component of non-native species spread globally (Molnar et al. 2008). For example, in the Laurentian Great Lakes, 62% of non-native species found are believed to have been introduced by ballast water since the opening of the St. Lawrence Seaway in 1959 (NOAA Undated). Commercial ships can carry between millions and billions of living organisms (i.e. propagules) in just 1 L of their ballast water (Drake et al. 2007; Leichsenring and Lawrence 2011; Ruiz et al. 2000). Even ships defined as carrying "no ballast on board (NOBOB)" may contain residual water and sediments harboring microorganisms (Drake et al. 2007). Not only can ships bring new species into the Great Lakes, but they have moved these species within the Great Lakes basin (Griffiths et al. 1991). "Secondary spread" of an invasive species, or the spread that occurs after the introduction of a species to a new region, can be a major contributor to dispersal within a region (Rup et al. 2010). Herein, we examine the role of shipping as a vector of secondary spread of viral hemorrhagic septicemia virus (VHSV) within the Great Lakes.

VHSV is a fish rhabdovirus that infects a wide range of fish species in North America, Europe, and Asia and is believed to have been introduced to the Great Lakes either via ballast water or migratory fish (Bain et al. 2010). VHSV has led to large fish kills, both in aquaculture and the wild (Kim and Faisal 2011; World Organisation for Animal Health 2011) and was first identified in eastern Lake Ontario in 2005 (Lumsden et al. 2007). Subsequent review of a rhabdovirus previously isolated from muskellunge in 2003 places the first verified record of VHSV in Lake St. Clair in 2003 (Elsayed et al. 2006; Faisal et al. 2012). The Great Lakes genotype of the virus was identified as being related to the North American and Japanese genotype (IVa); however, was distinct enough to be placed in its own sublineage (IVb) (Elsayed et al. 2006; Faisal et al. 2012). Since 2005, VHSV-IVb has spread rapidly across all five Great Lakes, with detections in Lakes Erie and Huron in 2006, Lake Michigan in 2007, and as far west as Duluth/Superior harbors in Lake Superior in 2009 (Figure 2-1). Despite a lack of detections prior to 2003, recent genetic research suggests that the virus may have been in the freshwaters of the Laurentian Great Lakes much earlier (Pierce and Stepien 2012). Moreover, there are eleven genetically distinct populations, or isolates, of the IVb strain found only in the Great Lakes and a few nearby inland waters (Pierce and Stepien 2012; Thompson et al. 2011). One of the isolates, U13653 (or vcG002), was originally found in eastern Lake Ontario and is the second most prevalent and widespread isolate as compared to the one originally found in Lake St. Clair (MI03GL) in 2003 (Pierce and Stepien 2012; Thompson et al. 2011). The prevalence of the U13653 isolate suggests the initial introduction of VHSV to the Great Lakes occurred via the St. Lawrence River. Since MI03GL and U13653 only diverge by one mutational step and both have been isolated from fish in eastern Lake Ontario, this hypothesis seems plausible (Pierce and Stepien 2012; Thompson et al. 2011). Regardless of genetic sequence, VHSV-IVb has become rapidly widespread in the Great Lakes.

One of the reasons VHSV-IVb has been successful in invading the Great Lakes is because of the presence of environmental conditions that are favorable for the transmission of the virus. VHSV-IVb is particularly likely to spread in fish populations with high densities that are experiencing stress, which usually occur when fish come together during spawning (Kane-Sutton et al. 2010). In the Great Lakes, many fish spawn in the spring and early summer, when temperatures are ideal for the transmission of VHSV-IVb (Eckerlin et al. 2011; Kane-Sutton et al. 2010; Kim and Faisal 2011). Additionally, VHSV has been found to survive in freshwater for up to 14 days at 15°C and 20 days at 10°C under controlled conditions (Hawley and Garver 2008; Kim and Faisal 2011), indicating that the virus may be carried by water currents for several days in the spring and fall.

While the actual dispersal capabilities of VHSV are relatively unknown, it is unlikely that it was able to invade the full length of the Great Lakes in such a short period without a human-mediated, long-distance vector of spread. On the other hand, Bain et al. (2010) found no relationship between VHSV occurrences and locations identified as "shipping centers". We thus hypothesize that commercial shipping may have been a vector of spread throughout the Great Lakes for VHSV. Ships in the Great Lakes generally draw in and discharge ballast water at ports as they unload and load cargo (Eames et al. 2008). They may also adjust their ballast mid-lake during bad weather and when entering connecting channels and rivers (Cangelosi and Mays 2006). This allows for many opportunities to pick up, move, and discharge invasive species. Moreover, because ships travelling exclusively within the Great Lakes make trips that happen over a short period of time, survival of invasive species may be greater than in those ships coming from outside the Great Lakes (Rup et al. 2010).

Here we set out to assess whether shipping played a role in the secondary spread of VHSV and whether we could use shipping spread models to identify the most likely location of initial VHSV introduction. To assess the role of Great Lakes shipping in the secondary spread of VHSV, we developed two primary questions: 1) Are VHSV occurrences related to the location and amount of ballast water being discharged throughout the Great Lakes?; 2) Is it possible to identify the site of initial introduction of VHSV based on ballast water discharge patterns? To answer the first question we developed three dynamic spatial models. The first two models, a random model and a location model, were built to determine if VHSV is related to ballast water discharge locations. The third model, a propagule pressure model, was built to determine if the number of visits from possibly infected ships increases the likelihood VHSV will become established at a discharge location. To answer the second question, the initial introduction location was changed in the propagule pressure model to identify the infection source that best fits the observed VHSV occurrences. Lake St. Clair was chosen as an initial introduction location, since it is the earliest detection of VHSV-IVb. Montreal was selected as a second possibility in order to determine if VHSV may have been introduced via the St. Lawrence River instead. By answering these questions, we hope to establish if Great Lakes shipping has been responsible for secondary spread of VHSV throughout the Great Lakes, and if Lake St. Clair was the first site of introduction in the Great Lakes.

2.3 Methods

2.3.1 Site Description

The Laurentian Great Lakes and the St. Lawrence Seaway are the areas of interest for the study. We defined the St. Lawrence Seaway as being the portion of the St. Lawrence River from the western edge of Anticosti Island west to its source at Lake Ontario.

2.3.2 Spatial Modeling

We developed three competing models to assess the role that shipping plays in the spread of VHSV. Each of the models were run to simulate the spread of the virus from 2003 to 2009 and had the same basic structure for each year of the model: 1) the number of VHSV introductions and their locations were selected using different stochastic processes, 2) each new introduction location was converted to an infection area based on the assumption that VHSV occurs in an area and not at a given point as identified by the presence data, and 3) the area of infection was further increased in each year to simulate the spread of the virus via natural means, such as by currents and fish hosts. The results of the models were areas of "predicted" infection, which were compared to the observed VHSV presence and absence data to assess model fit.

Our three models primarily differed in the way annual infection locations were chosen (i.e. Step 1 from above). The "random model" identified annual infection locations by randomly selecting locations throughout the entire study area. The number of infection locations was randomly drawn from a Poisson distribution with λ, the mean and variance of Poisson distributions, equal to the mean number of actual VHSV infections reported for the years 2003 to 2009. The total number of VHSV detections was 56, so λ=8. For the "location model", the number of infections per year was selected from a Poisson distribution as above; however, the infection locations were selected randomly only from known ballast water discharge locations.

The third model, the "propagule pressure model", was more complex and included data on VHSV sources, destinations, and number of trips made between source and discharge sites. As the first known location of VHSV-IVb was Lake St. Clair in 2003 (Elsayed et al. 2006), our first models initiated VHSV infection at that location. If a ship was identified as picking up ballast water in an area known to have VHSV, that ship was identified as carrying infected ballast water. Discharge locations receiving water from those infected ships in that year were next selected as possible locations of new VHSV infections. The total number of infected ships discharging at each location was calculated for each destination location. To determine if the discharge locations receiving at least one visit from an infected ship would become infected with VHSV that year we used a binomial distribution to determine if, for each ship visit, the discharge location became infected with VHSV. The number of binomial trials was equal to the total number of infected ships that discharged at the location in that year. The probability of infection for each binomial trial was calculated for each port based on a decay curve of virus-like particles (VLPs):

$$p(VLP) = 1 - e^{-0.11x}$$

where *p(VLP)* = proportion of VLPs remaining and *x* = day of the trip (Lovell and Drake 2009). Because of the lack of data on niche availability or the probability of establishment at each port, *p(VLP)* served as both the probability of infestation and the probability of establishment. Additional single probability values of 0.50 and 0.01 were tested as representing the probabilities of infestation and establishment; however, little improvement in model fit was detected and model ranks were unchanged. The number of days a trip took was determined by calculating the mode of the number of days for each trip between ballast water source and discharge locations. If one or more of the infected ship visits at each discharge location resulted in infection (i.e., at least one binomial trial = 1), then that location was identified as being infected.

The random and location models were built to test the hypothesis that VHSV occurrences are related to discharge locations, while the propagule pressure model was built to test the hypothesis that infection locations are related to the amount of ballast water discharge being released at each location. The propagule pressure model was also revised to identify if another location besides Lake St. Clair may have been a likely initial source of VHSV.

All three models include parameters that simulate the possible area of infection due to natural spread once VHSV has been introduced to a particular location (i.e. steps 2 and 3 above). It has been estimated that at least one strain of VHSV is capable of being moved outside of a host in seawater for up to 2-km (Meyers and Winton 1995). This distance might be somewhat arbitrary, as it depends on water current and wind which vary spatially and temporally; however, it was used as a reasonable estimate for identifying how far from a presence location VHSV may actually be found. The area created by a 2-km radius from the presence location was identified as the initial area of infection. Beyond the initial area of infection, it is unknown how far fish or currents carry the virus in any given year, so three distance values were tested to simulate the distance

VHSV would travel per year. Buffers of 10-, 20-, or 30-km radii were added to the infection areas every year to simulate the natural spread of the virus. Distances beyond 30-km were not considered, as VHSV would be predicted to have spread to the entire Great Lakes within the 7 years of infection modeled.

All models require VHSV occurrence data and all but the random model requires ballast water source and/or discharge location data. The VHSV occurrence data was collected from a variety of sources, including the Nonindigenous Aquatic Species (NAS) database (USGS 2009), Department of Pathobiology and Diagnostic Investigation in the College of Veterinary Medicine at Michigan State University (2011), Cornell University (2010), and Minnesota and Wisconsin Department of Natural Resources (2010; Figure 2-1). Other occurrence data were either unattainable or unidentified. Unattainable data included more recently published occurrences of VHSV in *Diporeia* spp. in Lakes Michigan and Ontario and in piscicolid leeches (*Myzobdella lugubris*) collected from Lakes St. Clair and Erie (Faisal et al. 2012; Faisal and Winters 2011). Both presences and absences were collected for the years 2003 to 2009 and were identified in all five Great Lakes, Lake St. Clair and its connecting waterways, and the St. Lawrence River in the Thousand Islands area. Ballast water source and discharge locations and number of trips were obtained from the National Ballast Information Clearinghouse (NBIC) data for 2004 to 2009 (Smithsonian Environmental Research Center and USCG 2009; Figure 2-2; Appendix A). The NBIC requires the reporting of the last location of ballast water pick-up (i.e. source information) and the location where that ballast water and potential propagules were then discharged for each individual ship. Source and discharge information was recorded at the U.S. port of arrival based on the NBIC data. All records containing source and/or discharge locations outside the Great Lakes were deleted. Remaining source and discharge locations were mapped using coordinates when available and location descriptions. Coordinates were obtained for location descriptions that included port and city names where possible. All other discharge and source points were located using topographic maps and aerial photographs. Four source locations (27 ship visits) were excluded from the data due to unclear location descriptions.

To identify the possibility of another likely location for the introduction of VHSV to the Great Lakes, the propagule pressure model was modified to initiate VHSV infection of the Great Lakes from Montreal. Due to recent genetic research by Thompson et al. (2011) and Pierce and Stepien (2012), we hypothesized that it was possible that VHSV may have initially been introduced to the St. Lawrence River. We chose Montreal as a possible introduction location since it is located on a part of the river that receives a large amount of ship traffic (National Research Council 2008). In particular, Montreal receives a large amount of traffic from the Atlantic coast of Canada, where VHSV-IVc, a closely related strain to VHSV-IVb was identified in 2000, 2002, and 2004 (Pierce and Stepien 2012). All strains of VHSV are hypothesized to have originated from a marine reservoir in the North Atlantic Ocean (Thompson et al. 2011; Pierce and Stepien 2012), and Strain IV appears to have originated specifically in the Northwest Atlantic Ocean (Pierce and Stepien 2012). Despite not receiving a large amount of ballast water sourced within the Great Lakes from ships visiting U.S. ports (Figure 2-2), Montreal receives numerous ship visits from areas where VHSV-IVb potentially could have originated.

All models were run for each natural spread distance (10-, 20-, and 30-km). Each model was built in the ArcGIS Model Builder and run for 100 iterations. A single iteration was comprised of a seven-year simulation (i.e. 2003 to 2009) with each year adding to the spread of the virus identified in the previous year. The predictions of the models were compared to the actual VHSV presence/absence locations for 2003 to 2009. The models have been exported to Python and included in Appendix B.

2.3.3 Analyses of Model Performance

In order to analyze the performance of the models, presence accuracy (i.e., sensitivity), absence accuracy (i.e., specificity), and weighted kappa were calculated for each iteration of each model. A confusion matrix was built for each iteration to identify the number of true positives and negatives and false positives and negatives produced by each model and to calculate the above measurements (Fielding and Bell 1997; Manel et al. 2001). The models' abilities to accurately predict presences and absences were calculated for each model iteration (Fielding and Bell 1997; Manel et al. 2001).

To determine the level of agreement between model predictions and actual VHSV presences and absences while correcting for chance we used a weighted Cohen's kappa statistic (Cohen 1968; Warrens 2011). The weighted kappa allows for weights to be applied to each cell in a confusion matrix, so that those cells calculated with data that is more uncertain than others will have less affect on the kappa statistic. We used a weighted kappa, as opposed to other calculations of fit (e.g. Cohen's kappa and AUC), due to the high false negative rate of the cell culture technique most frequently used in testing for VHSV. Despite cell culture being useful for identifying VHSV in fish that are carrying the active (positive-strand) virus (i.e. most likely to shed the disease), it was important that we identify all VHSV locations, even where the virus was inactive. A high false negative rate reduced our confidence in any reported absences. In experiments testing human viruses, cell culture was found to have false negative rates of 66 to 76% (Covalciuc et al. 1999; Wald et al. 2003). While not all of the VHSV presence/absence data were identified using cell culture tests, Hope et al. (2010) found even the more sensitive qRT-PCR test that was used on the remaining data did not detect VHSV in all fish exhibiting clinical signs of the infection. Because of this, an estimated false negative rate of 66% was used for our analysis.

Weighted kappa is calculated from the weighted proportions of observed and chance data for each cell of the confusion matrix. For our data, w_{11} = 1.00 (true positives) and w_{22} = 0.33 (true negatives). The weight for true negatives was based on the range of cell culture false negative rates. In order to test the sensitivity of the estimated false negative rate, weighted kappas were also calculated with w_{22} = 0.50 and 0.67. A level of agreement was assigned to each range of kappa values (Table 2.1; Gilchrist 2009; Landis and Koch 1977).

Presence accuracy, absence accuracy, and weighted kappa were calculated for each iteration, and averaged for comparison. Standard deviations were calculated for all means. In total, fifteen models were tested: random, location, Lake St. Clair only propagule pressure, Montreal only propagule pressure, and Lake St. Clair and Montreal propagule pressure models each run with 10-, 20-, and 30-km spread distances.

2.4 Results

The results of the weighted Cohen's kappa statistics indicate that VHSV spread is not random and that VHSV occurrences are related to ballast water discharge locations

(Table 2.2) although the strength of inference was slight. The location models tended to have higher presence accuracy at each spread distance than the random models (Table 2.3), indicating that the location models were better able to predict the presence of VHSV than the random models. Random models were better at predicting absences (Table 2.4); however, the location models were found to perform better overall with weighted kappas of 0.03, 0.04, and 0.05 at the 10-, 20-, and 30-km spread distances respectively (Table 2.2). All random models had weighted kappas between -0.04 and 0.00, suggesting that these models performed worse or equal to what would be expected by chance. Sensitivity analyses of the weighted w_{22} parameter only produced slight changes in the weighted kappa results with location models still performing better than random models. These results indicate that the spread of VHSV is related to ballast water discharge locations.

Further, locations that receive ballast water from infected ships were more likely to become infected with VHSV (Table 2.2). Most of the propagule pressure models performed better than the random and location models (Table 2.2). Sensitivity analyses of weighted kappas produced slightly higher measures of fit for most of the propagule pressure models, still resulting in better performance than the random and location models. Also, even though absence accuracies were generally lower than what was calculated for the random and location models (Table 2.4), presence accuracies were typically higher (Table 2.3). Additionally, propagule pressure models resulted in less variation overall (Tables 2.2, 2.3, and 2.4), since it repeatedly selected those locations that received large numbers of ship visits.

Not only do the results support the hypothesis that ports receiving more visits by infected ships are more likely to become infected, but they also indicate that Montreal is a more likely initial introduction location for VHSV (Table 2.2). The best performing model was the Montreal only 20-km model, even when considering the results of the weighted kappa sensitivity analysis. Additionally, combining Lake St. Clair and Montreal as simultaneous initial introduction locations produced very little change in the weighted kappas achieved by the Montreal only models (Table 2.2).

2.5 Discussion

The spread of VHSV within the Great Lakes has been aided by the secondary spread of ballast water. Though our model fit was only "slight" (based on the kappa scale used), the best fit model that we compared included the location, source, and amount of ballast water discharged, suggesting that these parameters are important indicators for identifying future VHSV infections. Furthermore, the results of our models also reveal that Lake St. Clair is a less likely initial location of VHSV to the Great Lakes than Montreal. We did not test other locations due to lack of information indicating alternatives; however, our results show that it is possible to use the model to identify locations that tend to be areas of initial introduction to the Great Lakes.

The performance of our models may have been limited in part by the data used for model validation and the quality of the data included in our model. For one, the tests that were used to detect VHSV have a high false negative rate (Chico et al. 2006; Covalciuc et al. 1999; Hope et al. 2010; Miller et al. 1998; Wald et al. 2003). Additionally, many absences that were identified were in areas where VHSV had been identified previously, suggesting that the potential to infect existed, but VHSV was not detected in the individual fish that was tested. For instance, the Minnesota Department of

Natural Resources had no positive tests for VHSV in the St. Louis River estuary between 2006 and 2010; however, researchers from Cornell University detected the virus in 2009. While we attempted to overcome this issue by measuring model fit using a weighted kappa statistic, absences that are not actually absences may have still been overly considered in the model. Incorrectly identified absences also would have been incorrectly identified for all remaining years in the model run. Error propagation would have affected both absence accuracy and weighted kappa statistics. The location from which infected fish were collected may also have added uncertainty to the presence/absence data. While many fish were collected live during monitoring efforts, others were collected during fish kills. Fish collected during fish kills would have mostly been found washed up on shore and likely far from the location where VHSV was actually contracted. Finally, the lack of Canadian ballast water data led to an incomplete dataset. This prevented us from establishing the complete pattern of ballast water movement in the Great Lakes. Whereas the limitations in the data used may not have been biased towards reducing the fit of any particular model over the other, it did prevent the accurate assessment of each model's ability to capture the past spread of VHSV.

Despite the limitations of the data used and the "slight" fit of even the best performing model, the pattern of secondary spread in the Great Lakes still indicates that shipping has played a role in the long-distance dispersal of VHSV. This is indicated by the Montreal models' abilities to capture VHSV presences at a higher rate than all of the other models. Further, at the best fit spread distance of 20-km, models that included ballast water discharge as a component of spread were able to explain the occurrence of VHSV at Duluth/Superior harbor at a much higher rate than the random models. In fact, the Montreal only model was the only model that correctly identified it 100% of the time at the 20-km spread distance. The only presences that the Montreal only model fails to predict with regularity are located in eastern Lake Ontario, a part of the Great Lakes that receives very little ballast discharge. However, if the St. Lawrence River is the actual source of VHSV, the virus has potentially persisted in eastern Lake Ontario longer than in other parts of the Great Lakes, leading to greater localized spread of the virus due to natural vectors. Other vectors of spread that have been identified are bait fishing and fish stocking, which potentially could contribute to long-distance spread along with ballast discharge. Nevertheless, we hypothesize that if bait and fish stocking were larger contributors to the long-distance spread of VHSV, more inland occurrences of the virus would have been detected. To date, only four inland waters that are not connected to the Great Lakes have positive occurrences of VHSV. Our conclusion that ballast water is a vector of spread for VHSV is contradictory to findings by Bain et al. (2010) who suggested there is no relationship between VHSV occurrences and centers of shipping. Their research only included shipping harbors as areas of shipping activity, and did not include actual ballast water discharge locations. Several locations that were identified as recreational boating or open shoreline by Bain et al. (2010) were identified by us as being close enough to ballast water discharge locations to become infected by discharged VHSV.

Even though we were not able to determine how much of a role ballast water plays in spreading VHSV, it was still identified as a vector that should be managed so as not to undermine other efforts that have been undertaken, such as through restrictions on bait and fish stocking (APHIS 2008). If ships had been required to treat there ballast water prior to entering the Welland Canal, VHSV could have potentially been isolated to Lake Ontario and the St. Lawrence River. However, most ballast water management systems that are currently being tested for oceangoing ships would be inefficient for use by ships in the Great Lakes, since much of the U.S. fleet have larger ballast tanks and higher pumping rates (Cangelosi and Mays 2006; USEPA Science Advisory Board 2011). Ships within the Great Lakes also tend to take shorter trips between ports, which may not allow enough time for chemical or physical treatments to sufficiently reduce propagule pressure (Cangelosi and Mays 2006). Without available ballast water treatment systems, there are a number of voluntary best management practices that ships in the Great Lakes may apply, such as drawing in water during the day or avoiding drawing in water where sediments are churned up (Shipping Federation of Canada 2000). However, these practices may not be effective in preventing the further spread of VHSV if not applied in the most suitable locations.

Our model can be used to identify the locations where the most promising best management practices would effectively be applied. One approach proposed by the shipping industry involves moving water uptake offshore, analogous to the requirements for ocean BWE outside the 200 nautical mile limit (Shipping Federation of Canada 2000). It is possible that invasive species may not be able to survive if released in deep waters offshore, far from required habitats and food resources. On the other hand, releasing invasive species in the deeper, offshore parts of the Great Lakes will only be effective if water currents do not carry the invasive species to more favorable habitats prior to mortality. Locations and times of year when water currents will not aid in the survival of invasive species will need to be identified. For example, our results could be combined with water circulation models that have been created by Beletsky and Schwab (2008) in order to identify those locations and times where and when ballast water may be released to reduce the probability of invasive species surviving. Further, our model can be used to identify those ports where the pick-up or discharge of ballast water should be avoided, or should be followed by ballast water exchange offshore.

Natural resource managers may also use our model to identify hotspots for invasive species. We expect to further validate our model by backcasting the secondary spread of zebra mussels (*Dreissena polymorpha*), an invasive bivalve, and ruffe (*Gymnocephalus cernuus*), an invasive fish. Both species are believed to have been introduced to the Great Lakes via ballast water (Grigorovich et al. 2003; Hebert et al. 1989; Simon and Vondruska 1991; Stepien et al. 2005). Once we parameterize our model for these species, predictions for the future spread of ruffe and other invasive species can be made. For example, managers are concerned about the introduction of killer shrimp (*Dikerogammerus villosus*), which has not yet been detected in the Great Lakes, but has been identified as a species that is likely to invade if ballast water management proves ineffective (Grigorovich et al. 2003). Our model can identify those areas where invasive species may occur next or may already occur, but may not be detected using conventional methods. Management practices can then be directed to those locations.

In summary, commercial ship ballast water movement and discharge patterns are likely contributing to the secondary spread of VHSV in the Great Lakes. Discharge locations that receive increasing visits from ships carrying ballast water from sources infected with VHSV are more likely to become infected with the virus itself. Additionally, Montreal is the more likely location of initial VHSV introduction, not Lake

St. Clair. Because ballast water is a component of long-distance spread in the Great Lakes, it is important that this vector be regulated along with bait and fish stocking. Our best fit model may be a tool that can aid managers and policy-makers in identifying locations where ballast water may best be managed.

2.6 Acknowledgements

We would like to thank Ling Shen of the Minnesota Department of Natural Resources and Drs. Mark Bain and Paul Bowser from Cornell University for providing VHSV occurrence information. We would also like to thank Dr. David Reid for providing technical knowledge on ballast water management. This project was funded by grants from United States Department of Agriculture, National Institute of Food and Agriculture, Cooperative State Research, Education, and Extension Service, USDA-NIFA (CSREES) #2010-38927-21048 and National Oceanic and Atmospheric Agency, Center for Sponsored Coastal Ocean Research, NOAA-CSCOR #NA10NOS4780218. This is publication #2013-XX from the Lake Erie Research Center.

Table 2.1 Level of agreement for each range of kappa values (Landis and Koch, 1977, Gilchrist, 2009).

Range of Kappa Value	**Level of Agreement**
$\geq$ 0.81	almost perfect
0.61 – 0.80	substantial
0.41 – 0.60	moderate
0.21 – 0.40	fair
0.00 – 0.20	slight
< 0.00	none

Table 2.2 Weighted Cohen's kappa for each natural spread distance tested of each model. Weighted Cohen's kappa is the proportion of agreement corrected by chance between the model predictions and actual presence/absence data (Cohen 1968; Warrens 2011). Numbers in parentheses are standard deviations.

	Natural Spread Distance		
Model	10-km	20-km	30-km
random	-0.04 (0.12)	-0.02 (0.12)	0.00 (0.09)
location	0.03 (0.07)	0.04 (0.08)	0.05 (0.07)
propagule pressure			
Lake St. Clair only	-0.14 (0.01)	0.03 (0.00)	0.11 (0.00)
Montreal only	0.07 (0.01)	0.13 (0.01)	0.12 (0.00)
Lake St. Clair and Montreal	0.09 (0.01)	0.12 (0.00)	0.11 (0.00)

Table 2.3 Presence accuracies for each natural spread of each model. Presence accuracies were calculated as the total number of actual presences that were accurately identified each year. Numbers in parentheses are standard deviations.

	Natural Spread Distance		
Model	10-km	20-km	30-km
random	0.23 (0.10)	0.50 (0.15)	0.71 (0.15)
location	0.39 (0.07)	0.61 (0.08)	0.73 (0.10)
propagule pressure			
Lake St. Clair only	0.38 (0.01)	0.64 (0.00)	0.77 (0.00)
Montreal only	0.65 (0.00)	0.73 (0.00)	0.79 (0.00)
Lake St. Clair and Montreal	0.65 (0.00)	0.72 (0.00)	0.77 (0.00)

Table 2.4 Absence accuracies for each natural spread distance of each model. Absence accuracies were calculated as the total number of actual absences that were accurately identified each year. Numbers in parentheses are standard deviations.

	Natural Spread Distance		
Model	10-km	20-km	30-km
random	0.80 (0.07)	0.53 (0.11)	0.30 (0.10)
location	0.58 (0.08)	0.34 (0.09)	0.20 (0.07)
propagule pressure			
Lake St. Clair only	0.72 (0.00)	0.28 (0.00)	0.02 (0.00)
Montreal only	0.25 (0.01)	0.08 (0.01)	0.02 (0.00)
Lake St. Clair and Montreal	0.18 (0.01)	0.07 (0.00)	0.02 (0.00)

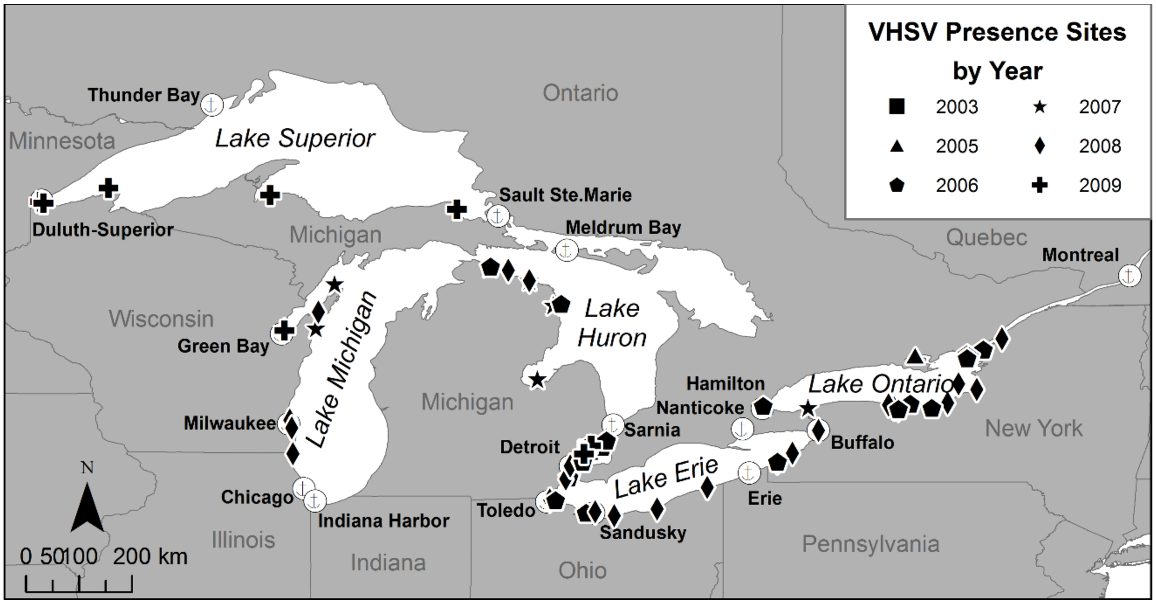


Figure 2-1 VHSV presence locations in the Great Lakes for 2003 to 2009. No known occurrences of VHSV are found east of the Thousand Islands area until the Atlantic coast. *Squares*, *triangles*, *pentagons*, *stars*, *diamonds*, and *crosses* represent VHSV occurrences for 2003 and 2005 to 2009 respectively.

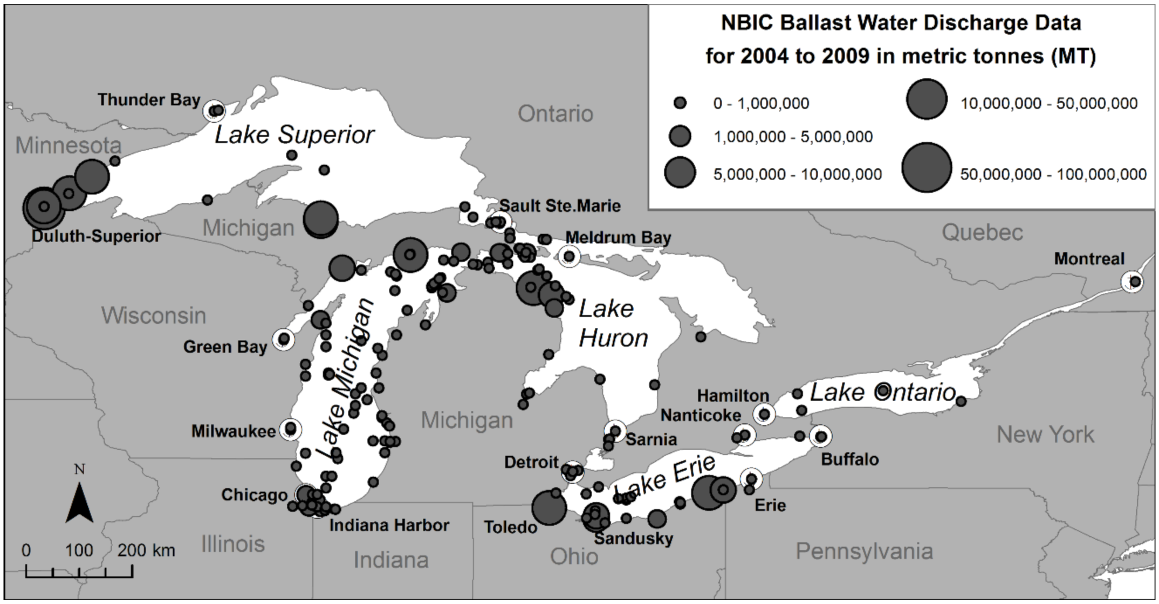


Figure 2-2 Location and amount of ballast water discharged by ships arriving at U.S. ports between 2004 and 2009 (from NBIC). Only discharge events involving ballast water picked-up in the Great Lakes are included. *Circles* of increasing size represent the amount of ballast water discharged at a location. Despite only receiving small amounts of ballast discharge from within the Great Lakes, the ports and river in and around Montreal receive large amounts of ship traffic (National Research Council 2008).

Chapter 3
A Spatial Modeling Approach to Predicting the Secondary Spread of Invasive Species Due to Ballast Water Discharge

3.1 Abstract

Ballast water in ships is an important contributor to the secondary spread of invasive species in the Laurentian Great Lakes. Here, we use a model previously created to determine the role ballast water management has played in the secondary spread of viral hemorrhagic septicemia virus (VHSV) to identify the future spread of one current and two potential invasive species in the Great Lakes, the Eurasian Ruffe (*Gymnocephalus cernuus*), killer shrimp (*Dikerogammarus villosus*), and golden mussel (*Limnoperna fortunei*), respectively. Model predictions for Eurasian Ruffe have been used to direct surveillance efforts within the Great Lakes and DNA evidence of ruffe presence was recently reported from one of three high risk port localities identified by our model. Predictions made for killer shrimp and golden mussel suggest that these two species have the potential to become rapidly widespread if introduced to the Great Lakes, reinforcing the need for proactive ballast water management. The model used here is flexible enough to be applied to any species capable of being spread by ballast water in marine or freshwater ecosystems.

3.2 Introduction

Invasive species have been identified as one of the major threats to the biodiversity of freshwater ecosystems, including the Laurentian Great Lakes (Beeton 2002, Millenial Ecosystem Assessment 2005). Since the opening of the St. Lawrence Seaway in 1959, ballast water has increasingly become the dominant pathway for non-native species to enter the Great Lakes (Holeck et al. 2004, Ricciardi 2006) and an important vector of secondary spread (i.e. spread that occurs upon invading a new location) of invasive species and diseases (Rup et al. 2010, Briski et al. 2012, Sieracki et al. 2014). However, despite ongoing regulatory efforts to prevent transoceanic introductions of species via ballast water, ships are not being regulated within the Great Lakes. At the same time, there is renewed interest in establishing basin wide surveillance programs to detect introductions early in the invasion process, in part generated by the potential of new genomic detection tools (Jerde 2011). In order to focus detection and monitoring efforts and plan prevention, response, and containment, it is important to predict locations of potential introduction and patterns of spread within the Great Lakes. The purpose of our study was to create a dynamic spatial model that predicts the secondary spread of invasive species by ballast water. In particular, we report the results of predictions made for one established, but localized, Great Lakes invader (Eurasian Ruffe, Gymnocephalus cernuus), and two predicted future invaders (killer shrimp, Dikerogammarus villosus, and golden mussel, Limnoperna fortunei). These three species were prioritized by Great Lakes resource managers and scientists as species whose spread around the Great Lakes may be enhanced by movement of ballast water. The species chosen are representative of probable future invasion management challenges in the region, but our approach may be applied to any species that may be moved via ballast water and to any ecosystem that may experience invasions due to commercial shipping.

To date, of the species we considered, only Eurasian Ruffe have been detected in the Great Lakes. Ruffe is a species of fish from Eurasia with a Great Lakes distribution limited to Lake Superior and the northern portions of Lakes Michigan and Huron (Stepien et al. 1998, Stepien et al 2005; Figure 3-1). The potential spread of ruffe is of concern because it is capable of competing with yellow perch, a native species of commercial importance (Savino and Kolar 1996, Sierszen et al. 1996, Fullerton et al. 1998). On the other hand, golden mussel and killer shrimp have not been detected in the Great Lakes. Golden mussel is a species of bivalve from Southeast Asia that has invaded Hong Kong, Japan, and South America (Miller and McClure 1931, Mizuno and Mori 1970, Brandt and Temcharoen 1971, Morton 1973, Darrigran 1995). Golden mussel is very similar to zebra mussel (Dreissena polymorpha), which is already widespread in the Great Lakes (Figure 3-2). Like the zebra mussel, it has the potential to generate similar economic and ecological costs (Karatayev et al. 2007a). Finally, killer shrimp is a species of amphipod from the Ponto-Caspian region that has already invaded parts of Europe via the Rhine-Main-Danube canal system (Dick et al 2002, Nesemann et al. 1995, Muskó 1994, Müller et al. 2002) and more recently the United Kingdom (MacNeil et al. 2010). Concern about an invasion by killer shrimp stems from its indiscriminate predation habits and ability to outcompete smaller, native amphipods (Dick et al 2002, Dick and Platvoet 2000, Boets et al. 2010). It has been reported that killer shrimp will at times kill prey as large as larval fish and do not always consume organisms upon killing them (Dick et al. 2002).

Predictive models are increasingly being used to identify how human-mediated vectors spread invasive species. For instance, Schneider et al. (1998) and Bossenbroek et al. (2007) used gravity models to identify lakes that were most at risk for future invasion of zebra mussels. On the other hand, Drake and Mandrak (2010) used least-cost transportation networks to identify how anglers may potentially spread invasive species throughout Ontario. Predictive models that include a human-mediated vector have also been applied to terrestrial invasive species. Prasad et al. (2010) used a spatially explicit cell-based model to identify the risk of emerald ash borer (Agrilus planipennis) spread in Ohio due to both natural and human-mediated vectors. Outside North America, Carrasco et al. (2010) discovered that both domestic and international human-mediated vectors were important in explaining the past spread of western corn rootworm (Diabrotica virgifera ssp. virgifera) in Austria. Previously, we explained past patterns of spread of the fish disease viral hemorrhagic septicemia virus (VHSV) in the Great Lakes, using a dynamic spatial model that incorporated the number of ballast water discharge events a location receives and species invasion probability. Our model differs from the examples listed here in that rather than identifying the pattern of spread by quantifying the "attractiveness" or likelihood of an area to become infested based on its characteristics, we used recent ballast water discharge data to establish a network of ballast water movement in the Great Lakes.

Ballast water discharge data has been used before to conduct risk assessments for ports in the Great Lakes and throughout North America. For example, Ruiz et al. (2013)

used the number of ship trips and amount of ballast water discharged at U.S. ports to determine if nonnative species richness is related to shipping activity. Their results found no difference in species richness between those areas with high and low shipping activity, indicating that such data would not provide for an accurate assessment of risk. Nonetheless, Ruiz et al. (2013) suggested that the inclusion of ballast water source data may have allowed for the differentiation of species richness between sites. Some risk assessments have included source information covering a variety of geographic extents to not only identify the probability that a port will be invaded in the future, but to also summarize from where that risk is likely to originate (Rup et al. 2010, McGee et al. 2006, Bailey et al. 2012, Keller et al. 2011). Unlike the risk assessments described here, we sought to create a ballast water spread model that identified the potential path of spread that a specific species could travel once it was introduced into the Great Lakes. Furthermore, unlike previous studies, our model not only includes site-specific source-discharge information, but also takes into consideration the results of species risk assessments and expert judgments, species biological requirements and behavior, known distribution of high risk invaders in source ports, and ballast water trip-specific information.

For this study, we adapt our dynamic spatial model to predict the future spread of Eurasian Ruffe, golden mussel, and killer shrimp. We used backcasting of the historic invasion pattern of zebra mussels and ruffe to identify the most important parameters and values that predicted their spread. We then predicted localities most at risk of future invasion by ruffe using the best parameter values that backcast historic ruffe spread, and those parameters that backcast historic zebra mussel dispersal were used to forecast the spread of golden mussel and killer shrimp. Based on the results of our models, we make recommendations for the future management of ballast water in the Great Lakes.

3.3 Methods

3.3.1 Site Description

The Great Lakes and St. Lawrence Seaway were the water bodies of interest for this study. The St. Lawrence Seaway was defined as the portion of the St. Lawrence River from Lake Ontario downstream to the western tip of Anticosti Island. The study area included Lake St. Clair and Niagara, Detroit, St. Clair, and St. Marys Rivers, as well. Despite water in the St. Lawrence Seaway flowing eastward towards the Atlantic Ocean, the trend of ballast water movement is westward, with Duluth-Superior Harbors receiving the most ballast water each year (Figure 3-1). As identified by data in the National Ballast Information Clearinghouse for the years 2004 to 2010, the top 5 U.S. ballast water discharge sources are: Nanticoke, ON (Lake Erie), Indiana Harbor, IN (Lake Michigan), Gary, IN (Lake Michigan), St. Clair, MI (St. Clair River), and Detroit, MI (Detroit River), top 5 U.S. discharge locations are: Superior, WI (Lake Superior), Two Harbors, MN (Lake Superior), Duluth, MN (Lake Superior), Calcite, MI (Lake Huron), and Marquette, MI (Lake Superior) (Smithsonian Environmental Research Center & USCG 2009).

3.3.2 Backcasting

We parameterized our models by backcasting the spread of two invasive species that already occur in the Great Lakes, zebra mussel and Eurasian Ruffe. Zebra mussel was backcast as a surrogate for golden mussel and killer shrimp, because golden mussel have life history traits and use habitats similar to zebra mussel (Karatayev et al. 2007, Karatayev et al. 2007b), and killer shrimp have similar physical and chemical tolerances (Bruijs et al. 2001). The three models based on Sieracki et al. (2014), a “random”, “location”, and “propagule pressure”, were developed for each of the two backcast species. The models have the same basic structure: (1) new infestation locations are selected for each year simulated, (2) an area of infestation is identified around each new location, and (3) the invasion front is further expanded given a possible rate of local spread that may occur each year. However, the three models differ in how new infestations (Step 1) are selected.

In order to determine if ballast water was contributing to species spread we compared the location model with a random model. The random model acts as the null model, and the location model needed to perform better than the random model in order to be able attribute spread to ballast water movement. The random model does not take into consideration other invasion pathways (e.g. recreational boating, sale of live organisms, etc.) that also contribute to spread in the Great Lakes. Both the random and location models selected the number of new annual infestations by randomly selecting from a Poisson distribution. The means and variances (λ) for the distributions were set equal to the mean number of new invasions potentially due to ballast water. For zebra mussel, λ was calculated as the mean number of occurrences per year for 1986 to 1992 as identified from records in the Nonindigenous Aquatic Species (NAS) database, thus $\lambda = 4$ (USGS 2009). Unlike zebra mussel, most Eurasian Ruffe occurrences identified in the NAS database appear to be due to natural spread by the fish themselves, particularly the spread that occurred along the south shore of Lake Superior. However, four independent invasion events that were potentially due to human-mediated spread were identified from the occurrence data. These independent invasions were determined to be "human-mediated", since they were long-distance (>50-km from the nearest infestation) and occurred in locations where large amounts of ballast water had been discharged in the past (Smithsonian Environmental Research Center and USCG 2009, USGS 2009). Therefore mean number of invasions per year for Eurasian Ruffe was calculated as $\lambda = 0.2$. Whereas the number of infestations per year were selected using the same method for both models, each model selected the location of each new infestation differently. The "random" model identified the location of each of the newly selected infestations randomly within the Great Lakes. The "location" model randomly selected infestation locations only from known ballast water discharge locations. The results of the models allowed us to determine whether or not species infestations were related to ballast water locations.

Upon determining if past infestations were related to ballast water discharge locations, the third model, the "propagule pressure" model, was used to determine if infestation locations could better be identified if ship trip information was included. First, ballast water source locations that occurred within an infested area were identified. Next, locations that received ballast water from those infested locations were selected. To determine if the selected discharge locations actually became infested upon receiving ballast water from infested sources, the potential invasion result was selected from a binomial distribution. A result of 0 meant a trip did not end in infestation and a result of 1 meant a trip did lead to infestation. The number of trials, n, was equal to the number of trips made to a discharge location that year by ships carrying infested ballast water. The probability of infestation for each day of the trip was varied for each species to identify the best value for the parameter. Probabilities of 0.000001, 0.0001, and 0.01 were tested for Eurasian Ruffe, and 0.05, 0.25, 0.50, and 0.75 for zebra mussels (Table 3.1). A single probability of invasion was used as opposed to multiple probabilities representing the rates of uptake, trip survival, and establishment in order to create a simple model that can be applied to multiple species despite the level of information available on biological and physical tolerances and habitat preferences. Probabilities for the two species differed in magnitude due to their differences in expected larval survival rates and length of reproductive period. Additional probabilities of infestation were tested; however, as these did not improve model accuracies, they were not included in this study. The length of the trip was determined by calculating the median of the trip lengths recorded between the source and discharge location. If at least one of the trips resulted in a binomial value of 1, then the discharge location was then considered infested.

Once infestation locations were selected for a year, the dispersal of the species from the initial invasion point was then identified for all models. First, an infestation area was identified from the new invasive species occurrence. Coordinates for ballast water discharge and source locations in the NBIC were recorded with a precision no less than one one-hundredths of a degree. We calculated that in the Great Lakes, the difference between two points that were one one-hundredths of a degree apart was approximately 1.4-km. This was identified as the estimated difference that could occur between the actual and recorded discharge locations due to rounding error, and was used as the radius of the area of infestation, since the species could have potentially been discharged anywhere within that circle. To identify the rate of natural spread that could occur upon being introduced to a new location, a second radius was used to expand the area of infestation. For ruffe, the natural spread distance was identified from the rate of secondary spread along the south shore of Lake Superior that was most likely due to fish dispersal. As identified from the occurrences recorded in the NAS database, the dispersal distance was most commonly ~25-km along the south shore of Lake Superior (USGS 2009). In addition to the 25-km distance, a 10-km spread distance was tested to determine if shorter dispersals were more common (Table 3.1). On the other hand, zebra mussels are not self-propelling even in the larval stages; however, veligers are capable of being carried great distances in water currents (Carlton 1993). Natural spread distances of 5-, 10- and 20-km were tested for the invasive bivalve (Table 3.1). The resulting areas of infestation were limited by lake depths identified as being inhabitable by ruffe (≤ 90-m) or zebra mussel (≤ 35-m) based on the maximum depth of occurrence locations obtained from the NAS Database for each of these species (USGS 2009).

Invasive species occurrences were required to run all three models, and ballast water data were needed for the “location” and “propagule pressure” models. Zebra mussel and Eurasian Ruffe presence locations for 1986 to 1992 and 1986 to 2011 respectively were obtained from the NAS Database (USGS 2009). The NAS Database is mostly compiled from U.S. occurrence records; however, does include some data for

Canada, as well. For the years prior to species detection, the species was considered to be absent from that location. Ballast water source, discharge, and trip data for the years 2004 to 2010 were obtained from the NBIC (Smithsonian Environmental Research Center and USCG 2009; Appendix A). Commercial ships that visit U.S. ports are required to report ballasting operations to the NBIC. Discharges at some Canadian ports are included, as the last discharge location prior to arriving at a U.S. port was not necessarily conducted in the U.S. The mean number of visits to discharge locations from each source location for 2004 to 2010 (Figure 3-3) and median number of trip days were calculated from the NBIC data. The limited amounts of Canadian data identified in the ANS Database and NBIC were included, since Canadian locations potentially served as ballast water sources for U.S. discharge locations, and some Canadian species occurrences were captured by the natural spread distance.

The models were developed in Python to be run in ArcGIS (see Appendix C). Scripting the models as opposed to creating them in ArcGIS ModelBuilder, as was done for the VHSV study (Sieracki et al. 2014), allowed for flexibility in the number of years the model could simulate and allowed for more specific trip information to be included for each source-discharge combination. The zebra mussel models were run to simulate secondary spread for 1986 to 1992, since they were widespread in the Great Lakes by 1992. The Eurasian Ruffe models simulated secondary spread for 1986 to 2011, because their rate of spread has been slow and their distribution in the Great Lakes is currently limited. Each of the models was run 100 iterations.

The model results were analyzed by calculating the overall, presence, and absence accuracies for each iteration of the model (Fielding and Bell 1997, Manel et al. 2001).

The means of each of the accuracies were calculated for each of the 28 models. The best fit model was selected as having the highest overall accuracy. Where overall accuracies were similar between models, the model with the highest presence accuracy was selected, unless absence accuracies were particularly low. Then, the model with the higher absence accuracy was used as an alternative model to capture a better range of predictions. Additionally, the length of time that would be required to spread the full extent of the current area invaded by each species if only natural spread is considered was identified. This was done by applying the largest spread distances tested above, 20-km for zebra mussel and 25-km for ruffe, to the initial introduction locations detected in 1986 for each species. The invasion front was identified for each year and was limited to the areas identified as being inhabitable by the species of interest.

3.3.3 Forecasting

Upon identifying the best fit model, the next step was to predict the future secondary spread of invasive species that either already occur in the Great Lakes or may occur in the Great Lakes in the future. The three species that predictions were simulated for were the Eurasian Ruffe, golden mussel, and killer shrimp.

Prediction models differed from the backcasting models in that the current Great Lakes distribution or possible initial introduction locations were used as the initial sources of infestation for each species. Also, instead of comparing the final distributions of the model predictions to the actual occurrences of the invasive species, the total number of model iterations a port was predicted to be invaded in the future was calculated. For each model iteration, once a port was identified as invaded in a given year, it continued to be invaded for all subsequent years. Each model simulated 10 time-steps of future invasion, and each simulation was run for 100 iterations. Time-steps were used in lieu of years, as the lag between a species introduction, establishment and potential for spread is uncertain. That uncertainty is also compounded by ballast water best management practices that are thought to reduce the likelihood of uptake and secondary spread within the basin (USEPA 2013, Shipping Federation of Canada 2000). The probability of that location becoming infested was calculated based on the 100 iterations.

The initial introduction locations, natural spread distances, and probability of infestation were different for each species. Unlike the other two species being modeled, Eurasian Ruffe already occurs in the Great Lakes. The actual occurrences of this species were used as the initial starting locations for future secondary spread. The best fit values for natural spread distance and probability of infestation were identified from the results of the backcasting exercise described above. For golden mussel and killer shrimp, the potential initial invasion locations were identified as those Great Lakes ports that received ballast water from international ports within the species' known current distribution. International ballast water source-discharge patterns were identified from the NBIC for 2004 to 2010 (Table 3.2; Smithsonian Environmental Research Center and USCG 2009). Predictions for both species were made using the parameters identified from the zebra mussel backcasting results; however, because we were uncertain as to how far killer shrimp would travel in the water column, no natural spread distance was used in forecasting this species. Further, by not including a natural spread distance, we were able to identify the secondary spread that was entirely due to the linkages between ballast water source and discharge locations, and not spread upon being discharged. Also, in the absence of a clear lower depth limit, no depth restrictions were placed on the killer shrimp models.

3.4 Results

3.4.1 Backcasting

Results of the Eurasian Ruffe backcasting identified the propagule pressure models as performing best overall, with mean overall accuracies between 0.69 and 0.72 (Figure 3-4A). Despite identifying absences at greater rates than the propagule pressure models, the random and location models identified very few ruffe presences, suggesting that these models would not be able to adequately predict the future spread of invasive species. (Figure 3-4B-C). Among the propagule pressure models, the 25-km models produced the highest presence accuracies (Figure 3-4B); however, also had the lowest absence accuracies (Figure 3-4C), suggesting that the model was over-predicting the spread of ruffe. On the other hand, the 10-km propagule pressure models produced presence accuracies that were somewhat lower than those for the 25-km model (Figure 3-4B), but still much higher than the location and random models. The 10-km propagule pressure models also produced higher absence accuracies than the 25-km models (Figure 3-4C), suggesting that these models are somewhat more conservative. Overall, the 25-km 0.0001 probability propagule pressure model performed best, but only at a rate of 0.02

over the next best performing model, the 10-km 0.01 probability propagule pressure model, so both models were identified as best fit. Further, if Eurasian Ruffe had only spread naturally at a rate of 25-km per year, it would have taken 55 years to reach the furthest extent of current invasion rather than the observed 26 years (Figure 3-1), signifying that the chosen models provided the most likely scenario for the secondary spread of Eurasian Ruffe. An example of the results of a single interation of the 10-km, 0.01 propagule pressure model is included in Figure 3-5. Based on the results of that model, Alpena was predicted to be invaded in 1993 1% of model runs (first detection was in 1995), Little Bay de Noc was predicted in 2000 (1%, first detection in 2002), and Green Bay was predicted in 1999 (1%, first detection in 2007).

The propagule pressure models were also the best performing in backcasting the spread of zebra mussel. Overall, the random and location models performed as well or nearly as well as the best performing propagule pressure models (Figure 3-4D); however, the addition of ballast water information increased the presence accuracy for each natural spread distance tested (Figure 3-4E). Furthermore, the probability of infestation proved to be an important parameter in backcasting zebra mussel. At the lower values tested, it reduced the ability of the model to predict presences, whereas at the highest value of 0.75 the presence accuracy was increased at all spread distances tested (Figure 3-4E). Despite an increase in presence accuracy generally leading to a decrease in absence accuracy, the lowest absence accuracy was still greater than 0.75, indicating that while some models may have been under-predicting occurrences, they were not over-predicting them (Figure 3-4F). Additionally, it would take 83 years (opposed to four) for zebra mussels to naturally disperse at a rate of 20-km per year (assuming they could spread upstream unaided – which seems unlikely) to reach the western most edge of their known 1992 extent (Figure 3-2). This suggests that zebra mussels spread much more rapidly than would be expected due to natural dispersal, and that the best fit model explained zebra mussel spread better when ballast water information was included.

3.4.2 Forecasting

In order to capture a range of possible outcomes for the future spread of Eurasian Ruffe, both models identified by Eurasian Ruffe backcasting above (10-km 0.01 probability and 25-km 0.001 probability) were used to forecast future secondary spread. The predictions made based on the two models depict relatively similar patterns of spread (Table 3.3; Figure 3-6A-B). Both models predict that Buffalo, New York, the Chicago, Illinois area, and the Saginaw Bay of Lake Huron are the most likely locations to be invaded by Eurasian Ruffe next (Table 3.3; Figure 3-6A-B). The ports predicted within the Chicago area varied for each model, but potentially include the Ports of Calumet, Illinois, Whiting, Indiana, and Chicago, Illinois, among others (Table 3.3). The Sandusky, Ohio area is also predicted by both models to have a small chance of becoming invaded. Milwaukee, Wisconsin, the Detroit, Michigan area, Cleveland, Ohio, and Prescott, Ontario were predicted to become invaded by Eurasian Ruffe in less than 10% of the model simulations.

In order to forecast the secondary spread of golden mussel and killer shrimp, the best performing model and parameters identified by backcasting zebra mussel were used. Since none of the models were found to over-predict zebra mussel occurrences, the model with the highest presence accuracy, the 20-km propagule pressure model with a probability of infestation of 0.75, was chosen. This model also had one of the highest overall accuracies.

Our analysis of the NBIC 2004-2010 data indicated seven ports historically received shipping from the global range of killer shrimp. Forecasting results predict that killer shrimp could become widespread within three to four time-steps of invasion. If the species invades Duluth first, it is predicted to most likely spread to Two Harbors (100 out of 100 model iterations) and Silver Bay (100), Minnesota, Marquette (98) and Alpena (100), Michigan, Indiana Harbor (93), Indiana, and Ashtabula (85), Ohio next (Table 3.3; Figure 3-7A). By the second and third time-steps after invasion, it is predicted to have a high probability of being widespread in Lakes Michigan, Huron, and Erie, and is predicted to invade Prescott, Ontario 74 out of 100 model iterations. By the fourth time-step killer shrimp is predicted to be widespread throughout the Great Lakes. If the initial invasion location for killer shrimp is Toledo, by the first time-step it is predicted to invade Duluth (99 out of 100 times), Two Harbors (99) and Silver Bay (99), Minnesota, much of the Upper Peninsula of Michigan (21-99), Alpena (99) and the Detroit area (99) in Michigan, Sturgeon Bay (87), Wisconsin, the Chicago area (27-99) in Illinois and Indiana, and Sarnia (96), Ontario (Table 3.3; Figure 3-7B). By the second time-step, killer shrimp is predicted to be widespread in Lakes Superior, Michigan, Huron, and Erie, and is predicted to invade Hamilton (53), in Lake Ontario and Prescott (73), in the St. Lawrence River. By the third time-step, killer shrimp is predicted to be widespread in the Great Lakes. Maps with the results of all predictions for the remaining invasion locations and years are included in Appendix D.

Results of golden mussel forecasting indicate that regardless of whether Duluth or Bay City (the two US ports receiving ships from invaded international ports) are invaded first, this invasive species will spread rapidly throughout the Great Lakes, much as zebra mussel did (Figure 3-2). By the first time-step, golden mussel is predicted to be found in all of the Great Lakes except Lake Ontario (Figure 3-8A). If golden mussel invades Duluth first, it is predicted to spread to Marquette (99 out of 100 model iterations), Ludington (99), Alpena (100), Saint Clair (93), and Detroit (100), Michigan, the Chicago area (49-100) in Illinois and Indiana, and Conneaut (100) and Ashtabula (84), Ohio (Table 3.3; Figure 3-8A). By the second time-step, golden mussel could potentially be widespread throughout the Great Lakes with predictions for invading Prescott, Ontario (78), and Oswego, New York (54). If golden mussel invades Bay City first, the species will become more widespread by the first time-step than if it were to invade Duluth first (Figure 3-8B). Locations that were predicted to be invaded by the first time-step include Duluth (100) and Two Harbors (99), Minnesota, Superior (100), Wisconsin, Marquette (100), Ludington (100), Detroit (100), Michigan, the northern portions of Lakes Michigan (91-100) and Huron (99-100) in Michigan, the Chicago area (68-100) in Illinois and Indiana, and Toledo (94), Cleveland (93), Conneaut (100), and Sandusky (75), Ohio (Table 3.3; Figure 3-8B). By the second time-step, Oswego, New York and Prescott, Ontario both are predicted to be invaded 57 and 70 model iterations out of 100, respectively.

3.5 Discussion

Our ballast water model simulates the potential spread of invasive species once they become established in the Great Lakes; whereas, previous assessments have focused on identifying the first ports of introduction to the basin. By applying source- and species-specific data to generate spread predictions, we were able to attribute ballast water as a vector of spread. Ruiz et al. (2013) previously found that there was no relationship between nonnative species richness and ballast water volume and number of ship arrivals at U.S. ports when data on ballast source locations were not considered. However, the risk of invasive species introductions from ballast water discharge varies, with the greatest risk posed from environmentally similar sources that also support harmful organisms (Ruiz et al. 2013, Keller et al. 2011). Additionally, transit time likely affects whether a species will be released alive (Ruiz et al. 2013). Although researchers have used broad source categories to assess the risk of invasion for ports in North America, few have analyzed the potential invasion risk from specific regions of the world (Rup et al. 2010, McGee et al. 2006, Miller et al. 2011). Those researchers that have identified risk from more specific source locations have not attempted to simulate the potential spread of specific species between source and discharge locations (Bailey et al. 2012, Keller et al. 2011). For these reasons, our modelling efforts are unique in that they not only include source- and species-specific information as a means to reduce the limitations of ballast water data as an effective predictor of invasion, but that they also may be used to establish the pattern of spread as opposed to identifying a location's risk to becoming invaded by any of a number of species in the future.

The inclusion of source information in predicting the spread of invasive species was important in identifying ports that may become invaded in the future. For instance, despite not being amongst the top 25 ports receiving the most visits by discharging ships (Table 3.3), both Saginaw Bay and Buffalo, New York were predicted to become invaded next by Eurasian Ruffe, even though their ballast water discharge history differ. Buffalo receives a sizeable amount of ballast water with an average of 73 ship visits a year (Figure 3.3), whereas Saginaw Bay receives very few ship visits. Nonetheless, the ballast water discharged in Saginaw Bay is frequently sourced from areas that are closer and identified as infested with Eurasian Ruffe, increasing the likelihood that each ballast discharge will contain live ruffe propagules. Another unusual prediction that our model made was the potential for Prescott, Ontario, on the St. Lawrence River, to become invaded by Eurasian Ruffe three out of 100 model iterations. Even though Prescott is a small port that receives few ship visits, during the course of our ballast water discharge time series it did receive a single ship visit from Alpena, which was enough for the model to predict the location to become invaded three times. Further predictions of invasion of killer shrimp and golden mussel for Prescott (73 and 78 iterations, respectively) were also driven by the earlier invasion of Alpena. The invasion of Prescott highlights the importance of including source information in our ballast water spread model, because if we had not, we may have overlooked a number of places within the Great Lakes with the potential of being invaded in the future.

The ability to predict the future spread of invasive species is an important part of any biosecurity surveillance and response program. Although prevention of new species invasions is expected to be the least expensive option for managing invasive species, early detection, containment, and eradication is the next best option when prevention has failed (Simberloff et al. 2005, Lodge et al. 2006). Delimiting the full extent of a recently discovered introduction is critical to the success of any incursion response (Panetta and Lawes 2005), but can be particularly problematic in aquatic environments where detection of rare organisms can be challenging (Jerde et al. 2011). Here we demonstrate how a ballast water spread model can be used to predict locations where a newly introduced invader is most likely to be spread, enabling what are usually limited surveillance resources to be focused onto a subset of high priority locations. Such information increases the probability that outlying populations can be identified, contained, and potentially eradicated (Collin et al. 2013).

The importance of prediction as part of a surveillance and response program is best illustrated by our predicted spread of Eurasian Ruffe across the remaining parts of the Great Lakes basin, namely southern Lakes Michigan and Huron, and Lakes Erie and Ontario. Our predictions identified three locations at high risk for invasion, and six additional sites with lower invasion risk based on current ballast water movement patterns (Figure 3-6A and B). These outputs can and have already been used to inform ruffe surveillance efforts across the Great Lakes Basin, and monitoring efforts motivated by our research has resulted in the detection of Eurasian Ruffe environmental DNA (eDNA) in Calumet Harbor in Chicago (Andrew Tucker, pers. comm.), which was predicted 95-97% of the time to be invaded next. Based on the remaining predictions modeled, shipping may potentially speed the spread of this invasive fish into regions of the Great Lakes that would otherwise not be affected for many years. However, if the shipping vector is managed, the regionally important yellow perch and walleye fisheries of Lake Erie could remain unaffected for many years.

Unlike Eurasian Ruffe, killer shrimp and golden mussels have not been detected in the Great Lakes; however, if they are introduced, they are predicted to spread rapidly. Golden mussel has life history traits similar to zebra mussel (Karatayev et al. 2007a), and we would expect spread to match that of zebra mussels, indicating that this species could become widespread within two years of introduction. Given that killer shrimp produce fewer young per individual compared to zebra mussels, the amount of time each time-step represents is uncertain. However, this species tends to be female-biased and reproduce early and frequently throughout the year (Devin et al. 2004), suggesting that it could potentially spread as quickly as zebra mussels did. Further limitations on our predictions for killer shrimp and golden mussel include increased uncertainty in the zebra mussel occurrence data, as opposed to the Eurasian Ruffe data, and rapid speed with which zebra mussels spread. Because detection of zebra mussels in the Great Lakes was at least two years behind actual invasion and occurred so rapidly, the actual pattern of spread is difficult to ascertain. In fact, the species was recorded in all Great Lakes within two years of its first detection, suggesting the data that our model is based upon may not be a fully accurate picture of how the actual spread occurred (USGS 2009, Benson 2014). However, model results were still able to capture a large proportion of past spread for zebra mussel, suggesting that it is capable of predicting future spread with enough accuracy to inform management decisions. Our results for killer shrimp and golden mussel further emphasize the need for protective binational (i.e. the United State and

Canada) ballast water treatment measures that minimize the potential for introduction of these and other species into the Great Lakes.

Shipping is the most important pathway of introduction and spread of invasive species in marine, freshwater, and estuarine environments (Ricciardi 2006, Keller et al. 2011, Karatayev et al. 2007b, Ruiz et al. 1997, Keller et al. 2009, Molnar et al. 2008). Globally there is increasing emphasis being placed on establishment of national port surveillance programs to detect incipient invasions from this pathway (Campbell et al. 2007), but these approaches need to be coupled with dynamic spread models because of the limitations of detecting species in aquatic environments (Jerde et al. 2011, Buchan and Padilla 2000). Additionally, limited resources typically constrain surveillance sampling efforts and periodicity, increasing the likelihood that secondary spread will have occurred by the time an incipient invasion is detected. The dynamic spatial model described here could easily be modified for new geographies. It has been built to run in ArcGIS, a commonly used program by government agencies and universities, is relatively easy to run, and requires few inputs, including the natural spread distance and probability of invasion. Further, other data can be readily added to the model in the future, such as habitat information. The model can also be retrofitted to run predictions for any aquatic system receiving ballast water discharges, so long as ballast water data exists. To date, ships visiting U.S. ports are required to submit ballast water management reports; however, many other countries do not collect this information. In fact, the predictions presented in this paper are incomplete as Canada does not require the reporting of ballast water discharge events for ships that only travel within Canadian waters, and any ballast water data that is collected is not readily available (Rup et al.

2010). If governing units are to make sound decisions about ballast water management, it is important that this information be made available in the future.

A further limitation to the model we have described here is the lack of rigorous occurrence data for invasive species. There is a tendency for aquatic species occurrence records to only be collected in port and marina locations; however, the spread of occurrences that we obtained from the NAS database are not limited to these areas, though some port bias may exist (USGS 2009; Figures 3.1 and 3.2). However, our goal was to identify the spread of invasive species due to ballast water alone. With this in mind, we were able to attribute a large portion of species occurrences using ballast water as the lone long-distance vector of dispersal. There is potential that other vectors of spread may contribute to the infestation of an area; however, ballast water would always serve as a potential disperser regardless of how the species was actually introduced to a port. We hypothesize that the larger issue with the data is the lack of timely detection, as illustrated by the spread of zebra mussel and VHSV (Sieracki et al. 2014), and the trend of not reporting absences. Because of these issues, it is difficult to fully capture the pattern of spread of an invasive species. We expect that our ballast water model will help to improve monitoring of secondary spread within the basin, and improved dispersal occurrence data should, in turn, enable model re-calibration and more accurate predictions.

The creation of a dynamic, spatial model simulating the secondary spread of invasive species due to ballast water in the Great Lakes has allowed us to identify the links between ballast water source and discharge locations. This information is already informing invasive species managers and policy-makers, motivating surveillance efforts, and illustrating the need to proactively manage ballast water to prevent or slow the spread of current and future invaders. With the model predictions for Eurasian Ruffe, we were able to identify the most likely locations where this invasive fish will invade next. For golden mussel and killer shrimp, we show that prevention is still the best policy for these species, as they both are expected to spread rapidly upon invasion. Also, given surveillance limitations, proactive management of intra-basin movement of ballast water is advisable if there is to be any hope that a new invader can be contained and eradicated.

3.6 Acknowledgements

We would like to acknowledge the support and information provided by David Lodge and Marion Wittman at the University of Notre Dame, Gust Annis at The Nature Conservancy, Dmitry Beletsky at the Cooperative Institute for Limnology and Ecosystems Research (CILER), Ed Rutherford at the National Oceanic and Atmospheric Administration, Lacey Mason at the University of Michigan, and Drew Kramer at the University of Georgia. We would also like to thank Dr. David Reid for providing technical knowledge on ballast water management. Additional thanks go to friendly reviewers Mark Dufour, Robert Mapes, Jeremy Pritt, and Jessica Sherman. This is publication #2014-XX from the Lake Erie Research Center.

TABLE 3.1. Model runs conducted in backcasting the spread of Eurasian Ruffe and zebra mussels.

Models	Spread Distance	Probability of Infestation	Species	
			Eurasian Ruffe	Zebra Mussel
Random	5-km			X
	10-km	NA	X	X
	20-km			X
	25-km		X	
Location	5-km			X
	10-km	NA	X	X
	20-km			X
	25-km		X	
Propagule Pressure	5-km	0.05		X
		0.25		X
		0.50		X
		0.75		X
	10-km	0.000001	X	
		0.0001	X	
		0.01	X	
		0.05		X
		0.25		X
		0.50		X
		0.75		X
	20-km	0.5		X
		0.25		X
		0.50		X
		0.75		X
	25-km	0.000001	X	
		0.0001	X	
		0.01	X	
		Total # of Models:	**10**	**18**

TABLE 3.2. Ports identified as having received ballast water from killer shrimp and golden mussel infested locations. The number of visits made by ships with potentially infested ballast water at each Great Lakes port was calculated from the NBIC data for 2004 to 2010 (Smithsonian Environmental Research Center and USCG, 2009).

	# Ship Visits
Killer Shrimp	
Duluth, Minnesota	147
Toledo, Ohio	47
Superior, Wisconsin	17
Ogdensburg, New York	8
Green Bay, Wisconsin	7
Goderich, Ontario	4
Detroit, Michigan	1
Golden Mussel	
Bay City, Michigan	9
Duluth, Minnesota	3

TABLE 3.3. Prediction results for the top 25 ports receiving the most visits by de-ballasting ships. Numbers represent the number of iterations out of 100 that were predicted to become invaded in the first year modeled. Ports that were outside of the area considered habitable for a species are indicated by NA.

				Ruffe: 10-km 1%	Ruffe: 25-km 0.01%	Golden Mussel: 10-km 75%		Killer Shrimp: 75%					
Rank	**Port**	**State**	**Waterbody**			Bay City	Duluth	Duluth	Toledo	Ogdensburg	Green Bay	Goderich	Detroit
1	Superior	WI	Superior	--	--	100	100	100	99	0	99	71	99
2	Two Harbors	MN	Superior	--	--	99	100	100	99	0	99	0	99
3	Calcite	MI	Huron	--	--	100	25	0	99	0	99	96	100
4	Marquette	MI	Superior	--	--	100	99	98	99	0	99	0	100
5	Duluth	MN	Superior	--	--	100	--	--	99	23	64	55	100
6	Presque Isle	MI	Superior	--	--	100	99	0	99	0	99	0	99
7	Toledo	OH	Erie	0	0	94	15	0	--	0	0	72	99
8	Stoneport	MI	Huron	95	0	100	11	0	99	0	99	64	99
9	Marblehead	OH	Erie	0	1	75	15	0	99	50	0	0	100
10	Silver Bay	MN	Superior	95	97	NA	NA	100	99	0	99	0	99
11	Sandusky	OH	Erie	0	1	75	15	0	96	53	0	61	99
12	Ashtabula	OH	Erie	0	0	0	84	85	99	98	0	0	100
13	Port Inland	MI	Michigan	95	97	100	0	0	97	0	99	0	98
14	Alpena	MI	Huron	--	--	99	100	100	99	0	99	79	100
15	Charlevoix	MI	Michigan	0	0	0	0	0	0	0	99	0	98
16	Port Dolomite	MI	Huron	95	100	100	12	0	99	0	99	0	100
17	Drummond Island	MI	Huron	16	2	NA	NA	0	99	0	99	62	100
18	Conneaut	OH	Erie	0	0	100	100	60	99	0	41	0	100
19	Escanaba	MI	Michigan	--	--	91	0	0	21	0	99	0	99
20	Chicago	IL	Michigan	0	97	68	49	0	99	0	0	0	29
21	Cleveland	OH	Erie	3	0	93	0	0	99	80	0	0	100
22	Calumet	IL	Michigan	95	97	100	100	0	27	0	0	0	1
23	Cedarville	MI	Huron	95	100	100	12	0	99	0	99	0	98
24	Whiting	IN	Michigan	95	97	100	100	0	93	0	85	0	19
25	Detroit	MI	Detroit River	4	0	100	100	0	99	0	0	0	--

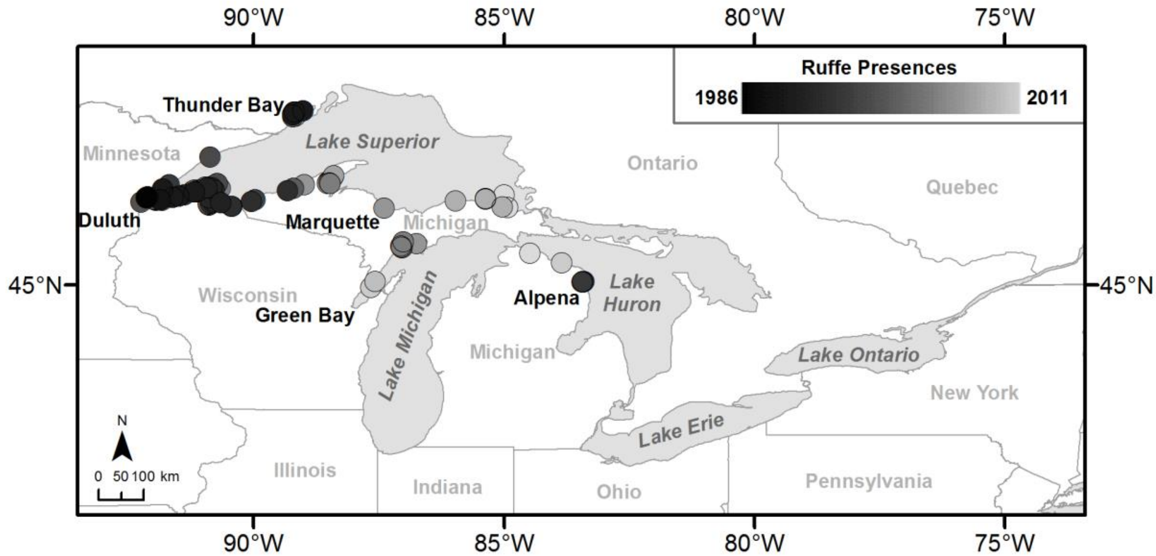


Figure 3-1. Eurasian Ruffe presences from 1986 to 2011. Ruffe data were obtained from the Nonindigenous Aquatic Species (NAS) database (USGS 2009).

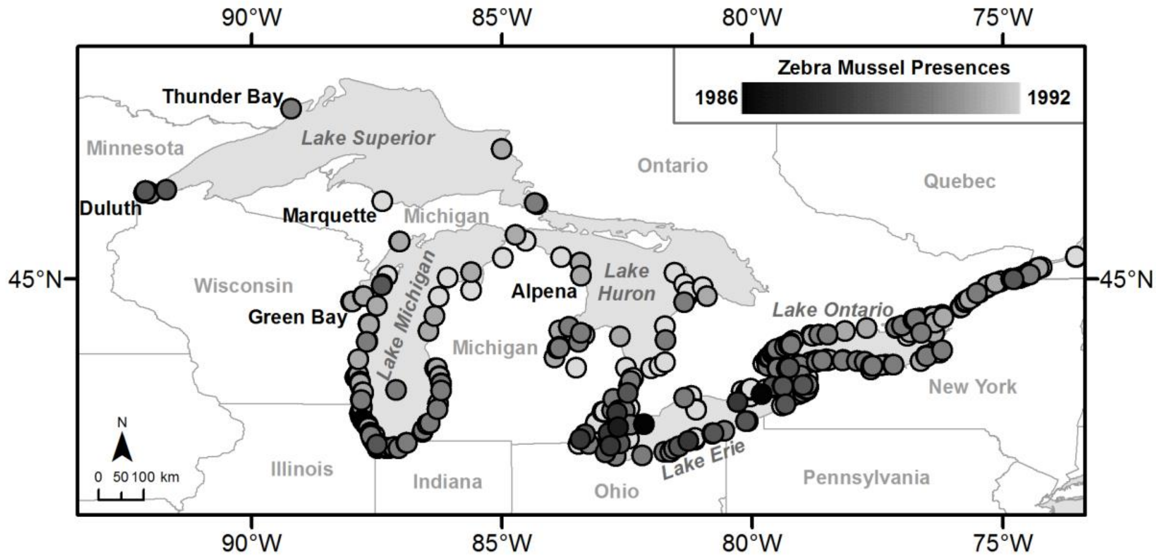


Figure 3-2. Zebra mussel presences from 1986 to 1992. Zebra mussel data were obtained from the Nonindigenous Aquatic Species (NAS) database (USGS 2009).

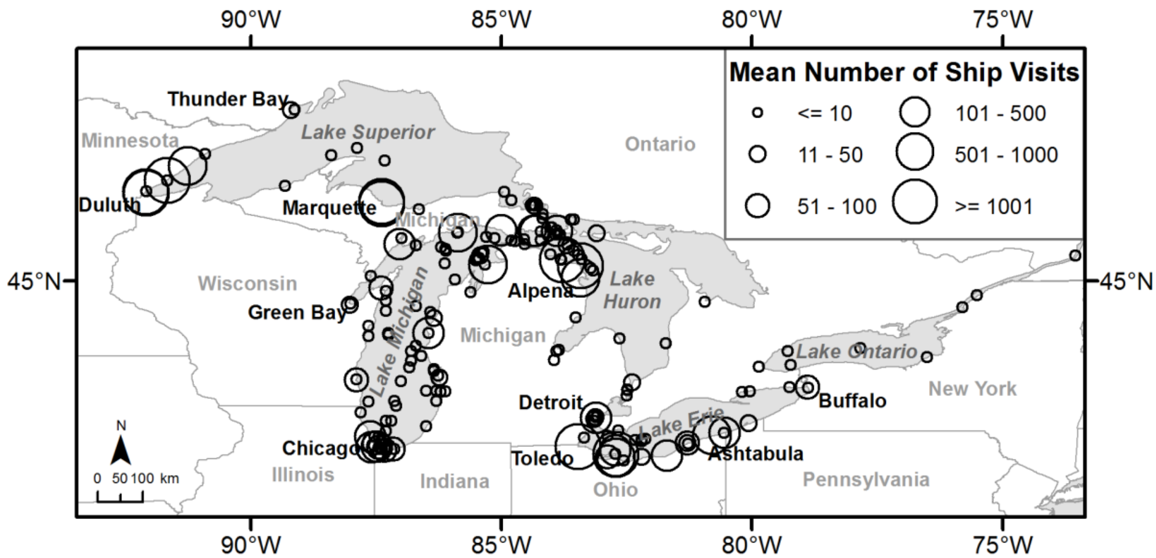


Figure 3-3. Mean number of discharging ship visits per year for each discharge location. Means between 0 and 1 were rounded up to 1. Ship visit data were obtained for ships visiting U.S. ports between 2004 and 2010 from the National Ballast Information Clearinghouse (Smithsonian Environmental Research Center and USCG 2009).

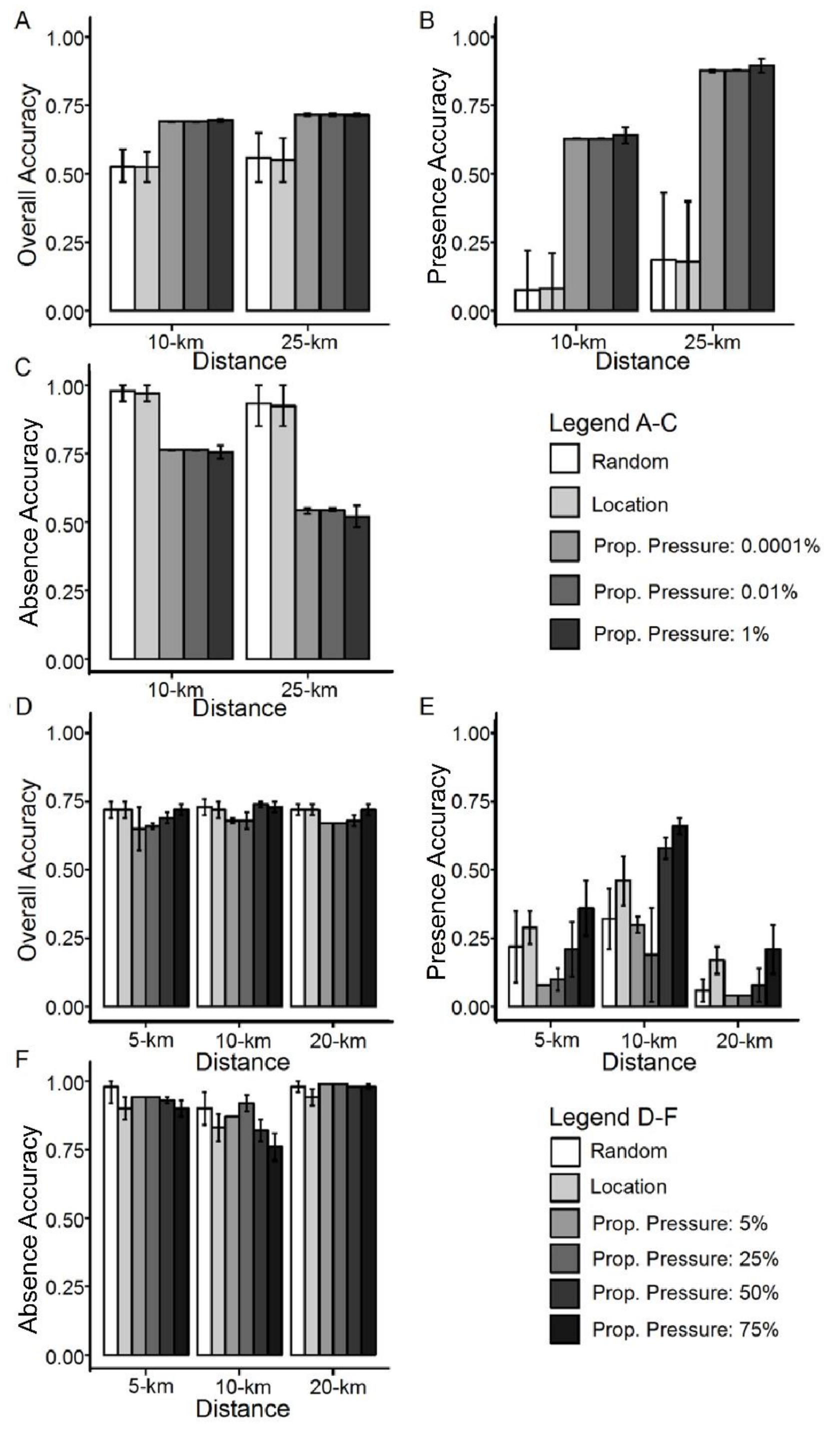


Figure 3-4. Backcasting results for Eurasian Ruffe and zebra mussel. Graphs A-C illustrate the results for Eurasian Ruffe, and graphs D-E illustrate the results for zebra

mussel. Graphs A and D depict the overall accuracy of the models tested. Graphs B and E depict the sensitivity, or ability to correctly identify presences correctly. Graphs C and F display the specificity, or ability to correctly identify absences correctly. Error bars represent standard deviations.

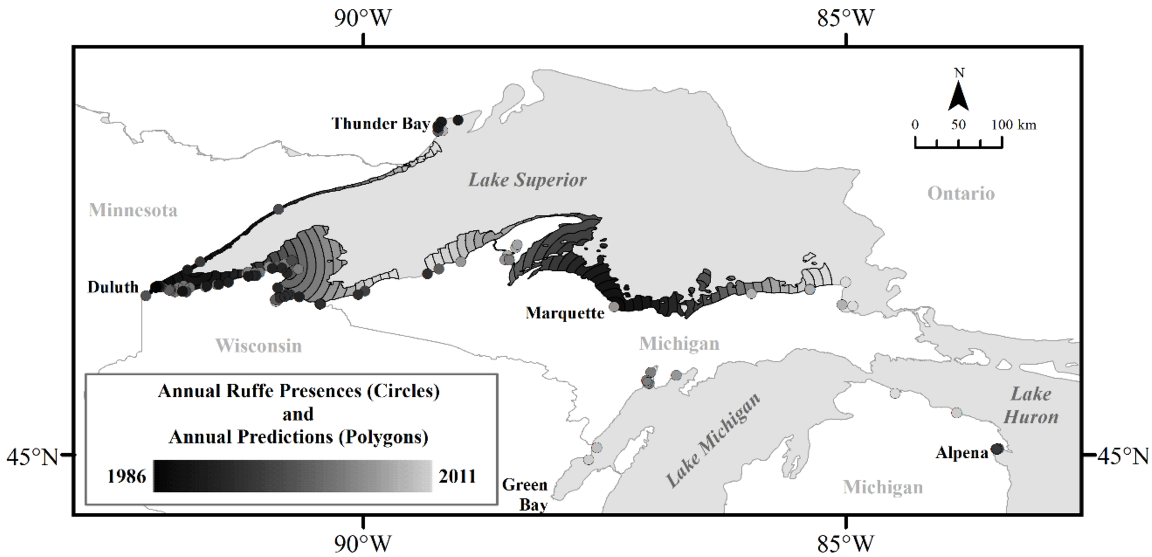


Figure 3-5. Results of a single iteration of the Eurasian Ruffe 10-km, 0.01 propagule pressure model. Eurasian Ruffe presences as recorded in the Nonindigenous Aquatic Species (NAS) database (USGS 2009) are depicted as circles. Model predictions are depicted as polygons. Where polygons are darker than circles, the model predicted presence earlier than detected. Where polygons are lighter than circles, the model predicted presences later than detected.

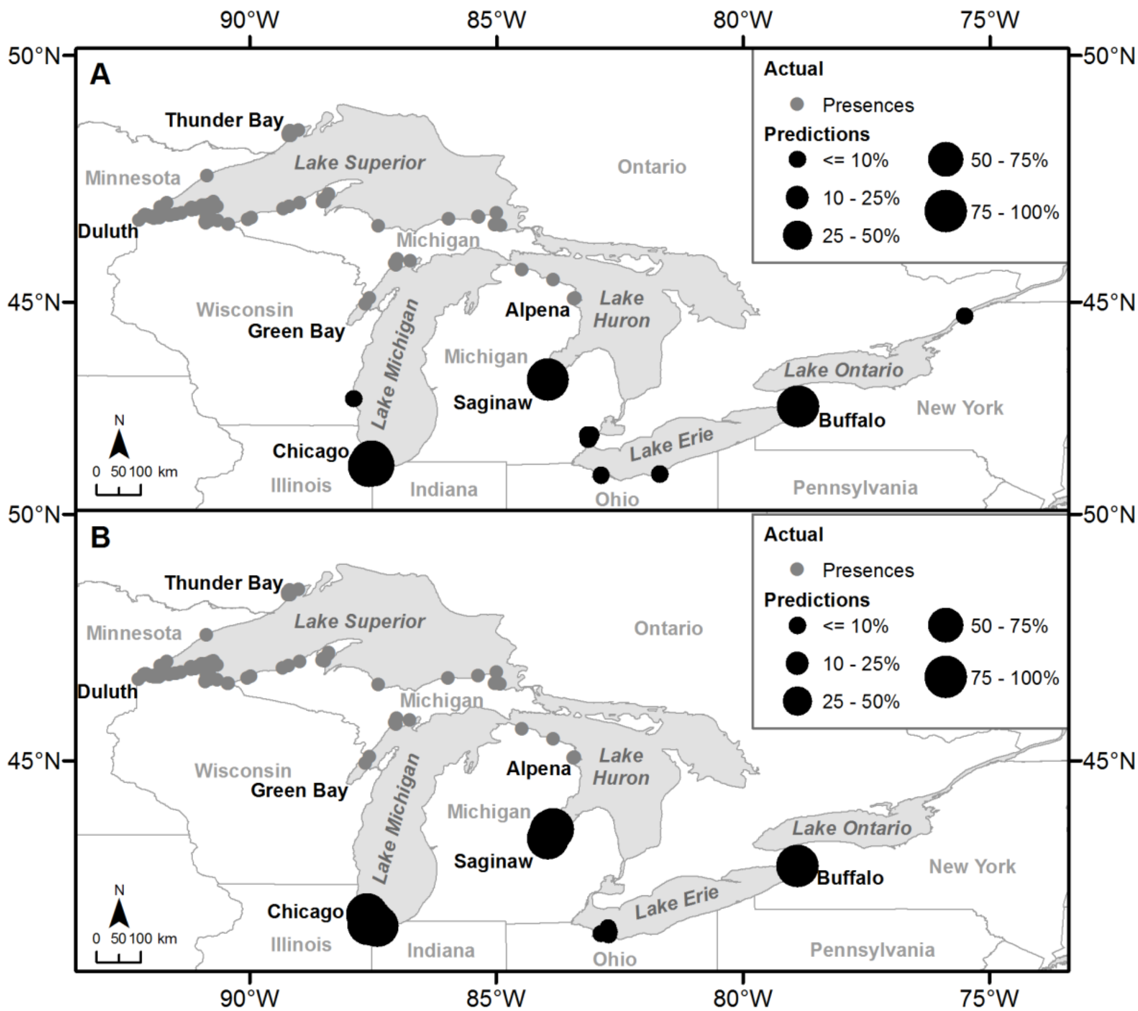


Figure 3-6. Eurasian Ruffe prediction results. The maps illustrate the results of the Eurasian Ruffe prediction models with Figure 3-5A dispersal distance = 10-km and probability of infestation = 0.01 and Figure 3-5B dispersal distance = 25-km and probability of infestation = 0.0001. The maps depict the next likely invaded locations from estimated presences.

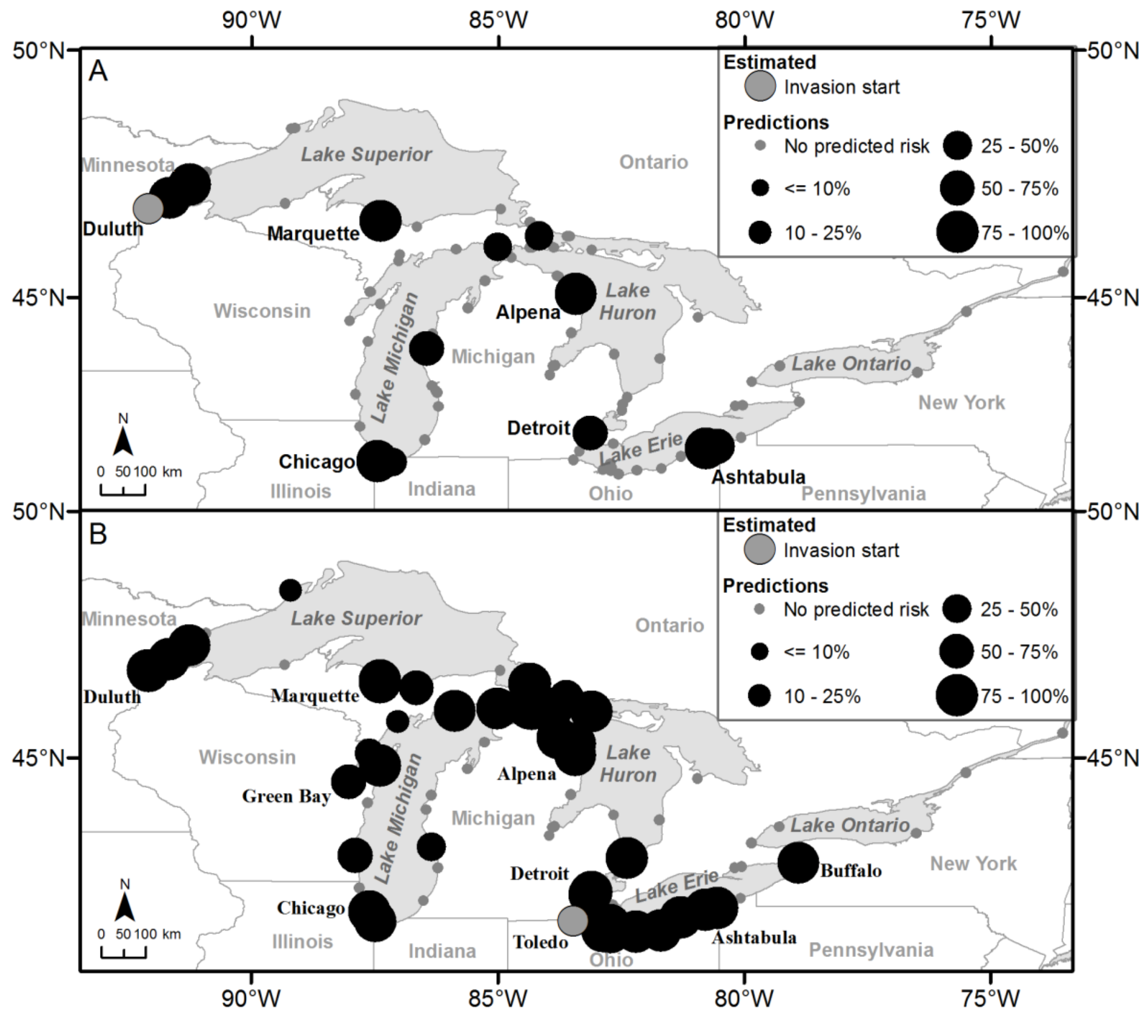


Figure 3-7. Killer shrimp prediction results. The maps illustrate the results of the killer shrimp prediction models with probability of infestation = 0.50 and no dispersal distance. Invasions were started from Figure 3-6A Duluth, Minnesota and Figure 3-6B Toledo, Ohio. The maps depict the next likely invaded locations from current observed presences.

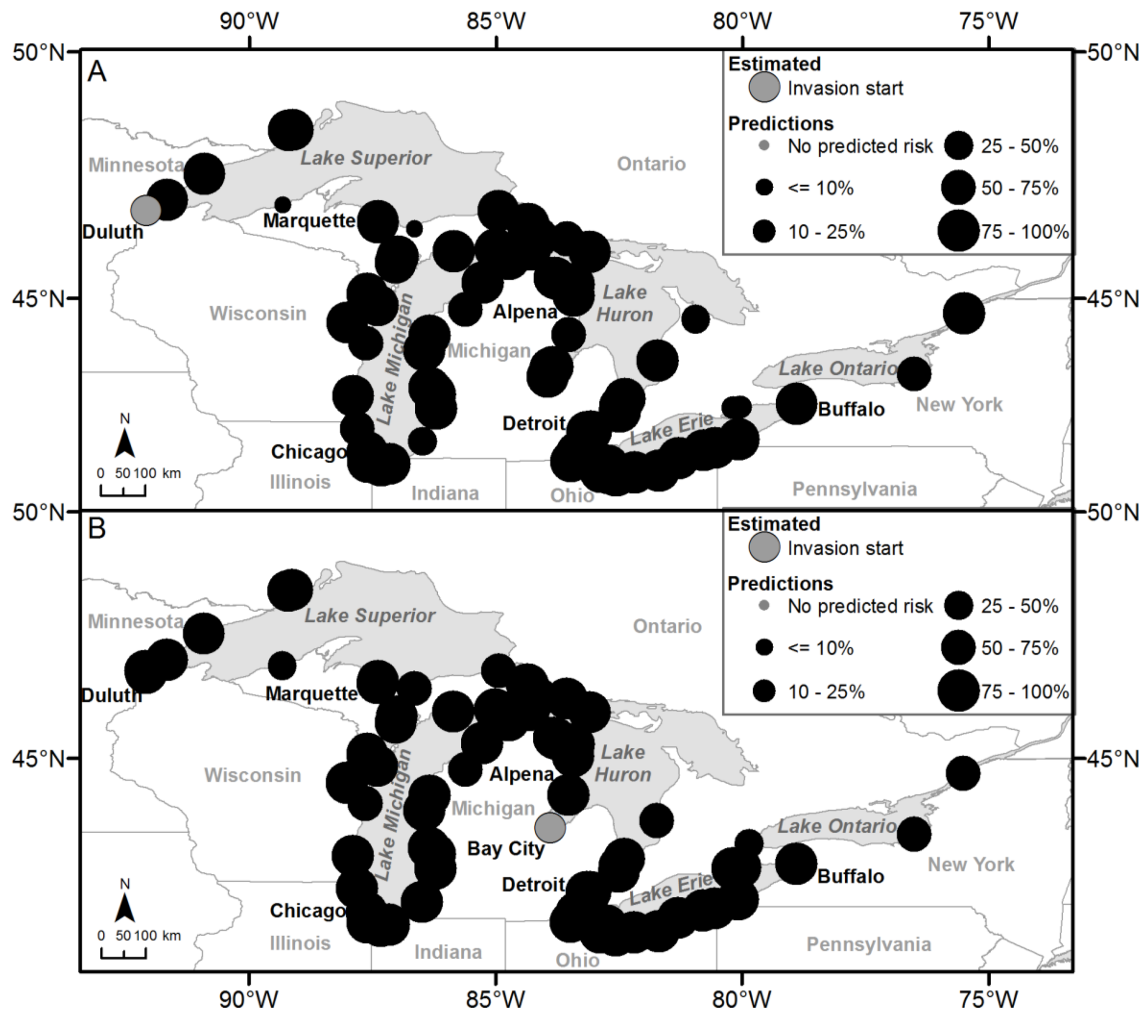


Figure 3-8. Golden mussel prediction results. The maps illustrate the results of the golden mussel prediction models with dispersal distance = 20-km and probability of infestation = 0.50. Invasions were started from Figure 3-7A Duluth, Minnesota and Figure 3-7B Bay City, Michigan. The maps depict the next likely invaded locations from estimated presences.

Chapter 4
Evaluating the Effectiveness of Mid-Lake Ballast Water Exchange at Preventing the Spread of Invasive Species in Lake Michigan

4.1 Abstract

Due to recent concerns over the role that ballast water has been playing in the secondary spread of invasive species in the Great Lakes, new efforts are being made to manage ballast water sourced within the Great Lakes. We applied a multi-model approach to determine the potential effectiveness of a suggested ballast water management technique, ballast water exchange (BWE). We identified 11 test BWE sites in Lake Michigan to ascertain the effectiveness of BWE in preventing the spread of Eurasian Ruffe (*Gymnocephalus cernuus*) and golden mussel (*Limnoperna fortune*). First, the natural spread of larvae for each species was simulated from each test BWE site using a 3D hydrodynamic model. The resulting distributions of settled larvae were then input into a ballast water spread model to determine where the invasive species may next be spread in the Great Lakes. The results indicate that BWE may be an effective means for managing the spread of ruffe. A single BWE test site also demonstrated to be effective at reducing the secondary spread of golden mussel; however, some larval settlement did still occur. While BWE shows promise as a temporary ballast water management technique, it is

important to continue to pursue the use of ballast water management systems, which are safer to implement.

4.2. Introduction

In response to the rising number of invasive species introduced to the Laurentian Great Lakes after the opening of the St. Lawrence Seaway in 1959, both the U.S. and Canada have introduced increasingly strict regulations in the management of ballast water. Although most of these regulations have focused on trans-oceanic vessels, recent research has begun to highlight the role that ballast water discharge plays in the "secondary spread" of invasive species within an aquatic system (Rup et al. 2010, Briski et al. 2012, Sieracki et al. 2014, Sieracki et al. In Review). Secondary spread is the dispersal of an invasive species that occurs after its initial introduction to a system. In order to minimize invasive species spread within the Great Lakes, the USEPA recently released new requirements that include management of ballast water specifically for "Lakers", or ships travelling exclusively within the Great Lakes (USEPA 2013). These requirements mandate that all Lakers built after January 1, 2009 must meet specific numeric ballast water discharge limits that are generally consistent with those established by the U.S. Coast Guard (USCG 2012) and the International Maritime Organization (IMO) D-2 standards (IMO 2004). However, no ballast water treatment systems have yet received type approval by the USCG for use in freshwater or under conditions similar to those in the Great Lakes. Further, the best management practices the USEPA is requiring as a temporary solution for ships without treatment systems are primarily designed to prevent the uptake of species in ports. However, there still remains the potential for taking up organisms in other areas in the Great Lakes, such as when entering locks or rivers.

Alternatively, mid-lake ballast water exchange and flushing (MLBWE) could reduce the spread of invasive species by ensuring that they are released in areas where they cannot survive. Mandatory MLBWE conducted in deep ocean waters has been evaluated as an effective means to prevent the introduction of new species to the Great Lakes (Bailey et al. 2011). Despite a lack of osmotic shock due to high salinity levels achieved by BWE performed at sea, MLBWE could still slow secondary spread by reducing the number of propagules in the ballast tank. In fact, Ruiz and Reid (2010) found that ballast water exchange replaced 88-99% of the original water in ballast tanks of several ships tested and removed between 75-99% of coastal plankton species. Due to its potential as a means to reduce propagules, the exchange of ballast water in deep portions of Lake Superior has been suggested in the past as a means to slow the spread of Eurasian Ruffe (*Gymnocephalus cernuus*) (Canadian Shipowners Association et al. 1996, Brown et al. 1998). We suggest that this may be a potential short-term ballast water management strategy to continue to slow the further spread of Eurasian Ruffe and other invasive species until ballast water treatment systems are approved for use in the Great Lakes.

Due to the recent advances in spatial modeling, it is possible to conduct initial assessments of the feasibility for using mid-lake BWE to prevent the spread of invasive species. Recent efforts to model long-term circulation in Lakes Michigan and Erie (Beletsky and Schwab 2001, Beletsky et al. 2013) have made it possible to identify the distance and direction that particles are likely to disperse if released in the Great Lakes The Lake Michigan 3D particle transport model has been applied to model the transport and settlement of yellow perch (*Perca flavescens*) larvae (Beletsky et al. 2007), and may be used to identify dispersal from potential MLBWE locations. Further, it is possible to identify whether or not organisms that are spread by lake circulation may then be picked-up and spread by ballast water once again by inputting larval transport model results into the ballast water model tested by Sieracki et al. (2014, In Review). The ballast water model identifies those locations that are most likely to receive ballast water from infested locations; therefore, allows us to determine whether a location may become in invaded in the future. Modeled settlement locations can then be assessed as to whether or not they can support the invasive species of interest, allowing for the identification of MLBWE locations most likely to reduce the risk of future secondary spread. By combining the predictions of the circulation and ballast water model, we are able to assess the potential effectiveness of MLBWE in Lake Michigan.

For this study, we identified locations in Lake Michigan that might serve as effective MLBWE sites for preventing the spread of one established, but localized species, Eurasian Ruffe, and one species that may invade the Great Lakes in the future, golden mussel (*Limnoperna fortunei*). Eurasian Ruffe was selected due to its continued spread in the Great Lakes and as being representative of other potential invasive species with slow dispersal capabilities and low survival rates in the ballast tank (Sieracki et al. In Review). Golden mussel was selected not only out of concern for its potential introduction, but also as a representative of invasive species with the ability to spread rapidly and survive in the ballast tank (Sieracki et al. In Review). Additionally, we modeled the further spread of ruffe and golden mussel due to ballast water that may occur from predicted settlement locations for each potential mid-lake BWE site.

4.3 Methods

To determine if MLBWE could be an effective management technique for preventing the spread of Eurasian Ruffe and golden mussel, we tested 11 potential MLBWE sites in Lake Michigan (Fig. 4-1). Lake Michigan was identified as the study area due to the existence of a thoroughly validated circulation model for the entire lake (Beletsky et al, 2006), and the lack of ballast water data for ships visiting Canadian ports in the remainder of the Great Lakes. The first species of interest, Eurasian Ruffe, is a Eurasian fish that was first detected in the Great Lakes in 1986 in the St. Louis estuary in Duluth, Minnesota. This species has since spread along the southern shore of Lake Superior, and has been found in the northern portions of Lakes Huron and Michigan (Fig. 4-2). Concern for the further spread of ruffe stems from its potential to outcompete yellow perch (*Perca flavescens*), which may negatively impact the popular Lake Erie fishery (Savino and Kolar 1996, Fullerton et al. 1998). Because adult ruffe are benthic and generally too large to be entrained through sea chest grates, this species is most likely to be spread during the larval phase. The other species of interest, golden mussel has not been detected in the Great Lakes, but has been identified as a species that could potentially become widespread if introduced (Sieracki et al. In Review). Golden mussel is a Southeast Asian species of bivalve that has already invaded Hong Kong, Japan, and South America

(Miller and McClure 1931, Mizuno and Mori 1970, Brandt and Temcharoen 1971, Morton 1973, Darrigran and Pastorino 1995). This species shares many reproductive traits and habitat requirements with zebra mussel and is expected to be just as damaging to an invaded ecosystem as its Ponto-Caspian counterpart in that it is expected to foul infrastructure and disrupt food webs (Karatayev et al. 2007a, Karatayev et al. 2007b). Like zebra mussel, the pelagic larval stage of golden mussel is most likely to be spread via ballast water.

4.3.1 *Larval Transport Model*

The larval transport model that was used as the first step in modeling the spread of larvae released at potential MLBWE sites was developed by Beletsky et al. (2007; Fig. 4-3). It has been applied for modeling aquatic invasive species from river mouths and ports in Lake Michigan by Beletsky et al. (to be submitted), and is briefly described here. We used a 3-dimensional particle transport model that predicts the transport and settlement of fish and mussel larvae. The model uses 3-hourly climatological currents (1998-2007 average) produced by the 3D hydrodynamic model of Lake Michigan (Beletsky and Schwab, 2008). Larvae are considered to be passive and neutrally buoyant. The 11 potential MLBWE locations were identified from National Ballast Information Clearinghouse (NBIC) data for 2004 to 2010 (Smithsonian Environmental Research Center and USCG 2009; Fig. 4-1; Appendix A). Any ship that visits a U.S. port must report its discharge activities to the NBIC, including ballast water source location and date, amount of water picked up (in metric tons), discharge location and date, and amount of water discharged. All 11 points were previously reported as actual ballast water discharge locations and were located with reported coordinates; therefore, have been identified as feasible locations for future ballast water discharge.

Both ruffe and golden mussel are most likely to be spread by ballast water during the larval period; hence, we limited the potential period of spread to the time of year when larvae are present. In the St. Louis estuary of Lake Superior, ruffe were found to spawn between 5 and 18°C, and larvae remained pelagic for 1-2 weeks (Brown et al. 1998). Therefore, the potential period of spread was limited from mid-April to late July based on nearshore bottom temperatures, and larvae were considered dead 14 days after having been discharged (Table 4.1). Additionally, potential spread was limited to only those parts of the Great Lakes at a depth of 10 meters or less, as the shallow littoral zone is the habitat where larval ruffe are most likely to feed (Bauer et al. 2007). Golden mussel has been found to reproduce at temperatures between 16 and 28°C, which corresponds with late June to mid-October (Cataldo and Boltovskoy 2000, Xu et al. 2013). This species may also survive in the pediveliger stage for up to 20 days at 20°C (Cataldo et al. 2005) and is expected to be found at depths similar to zebra mussels (T. Nalepa, pers. comm.). Because of this, golden mussels were limited to areas of the Great Lakes no greater than 50 meters (T. Nalepa, pers. comm.) and were tracked for 20 days until assumed dead.

A single larvae was released from each MLBWE site on each day during the modeled species' reproductive period. Locations where a larva could settle and survive after being discharged (henceforth termed "settlement locations") were selected by including only those points that fell within the period of survival and maximum depth identified for each species modeled. Any larva that was at depths greater than the maximum identified for the species at the end of the survival period was considered dead. Because larvae may not settle at the first suitable location, we continued to track the path each larva travelled until it was dead.

4.3.2 *Ballast Water Model*

If a potential MLBWE site resulted in the survival of at least a single larva, we assumed that a population could become established at that location. All locations where a larva could settle and survive were identified. From those settlement locations, we identified further spread that could occur upon being picked-up with ballast water (Fig. 4-3). Based on the NBIC data used to identify the pattern of ballast water spread for this model, three of the remaining four Great Lakes were identified as being directly connected to ballast water sources in Lake Michigan. (Fig. 4-4). The model was previously designed to predict the spread of invasive species due to ballast water in the Great Lakes (Sieracki et al. 2014, Sieracki et al. In Review). The model was tested by backcasting the past spread of Eurasian Ruffe and zebra mussel to identify parameter values that best captured the past spread of these two invasive species (Sieracki et al. In Review). The best fit parameter values were then used to predict the future spread of Eurasian Ruffe and golden mussel. For this study, the parameter values identified in Sieracki et al. (In Review) were used to predict the potential spread of each species from each of the settlement locations.

The ballast water model was designed to simulate the pattern of ballast water movement around the Great Lakes. Ballast water information was obtained from the NBIC for the years 2004 to 2010 (Smithsonian Environmental Research Center and USCG 2009). We derived ballast water source and discharge locations, mean number of trips between locations per year, and the median length of trips in days from the NBIC data. First, the model identifies locations invaded by the species of interest and creates an area with a 1.4-km radius around the location that may potentially be invaded due to the estimated error in mapping the location. Next, an area of potential localized spread is identified by applying a species-specific radius that was obtained from the previous testing of the model. The local spread distances of 25-km for Eurasian Ruffe and 20-km for golden mussel were pinpointed from previous testing and used for this study (Sieracki et al. In Review). Once the annual area of infestation has been established, the model then selects any ballast water source locations that occur within the infested areas. The model then identifies all discharge locations that received ballast water from the infested sources and uses a binomial distribution to calculate whether or not any trips between the source and discharge locations result in the discharge location becoming invaded. The binomial distribution calculated the sum of the trips that resulted in a failed invasion ($X = 0$) or a successful invasion ($X = 1$) using a species-specific infestation probability, which reduced exponentially as the median length of the trip increased. The infestation probability for Eurasian Ruffe was 0.0001 and for golden mussel was 0.75 as determined from Sieracki et al. (In Review). If at least one trip resulted in a successful invasion, the discharge location was considered invaded.

The ballast water model was coded in Python to be run in ArcGIS. Each of the models simulated only one time-step of invasion after the settlement of larva and was run 100 times. The results of the 100 runs were summed to determine the probability that a discharge location would next become invaded.

4.4 Results

For Eurasian Ruffe, six of the 11 ballast water exchange locations were modeled to result in settlement. Sites B02, B03, B04, B06, and B07 led to no survival of ruffe larvae upon being released (Table 2; Fig. 4-5). Site B11 led to the most larval settlement (78%) and highest number of locations that could potentially be settled (294; Table 2; Fig. 4-5), presumably due to its proximity to shoreline in multiple directions. The site that led to the second largest settlement, B05, led to 37 larvae settling at potentially 116 locations total. Additionally, B05 led to the greatest maximum distance of settlement for ruffe at 91.38 km, suggesting that larvae released at this site could be more widespread than at other sites (Table 2).

On the other hand, release of golden mussel at all 11 sites led to larger numbers of larval settlement, more locations potentially being settled, and locations at greater distances from the MLBWE site being settled (Table 2; Fig. 4-6). Both sites B01 and B11 led to 100% settlement of larvae (Table 2; Fig. 4-6) and the greatest number of locations with the potential for being settled (2,613 and 2,570, respectively; Table 2). Sites B05, B08, and B09 led to larval settlement greater than 80% (Table 2; Fig. 4-6). Similar to Eurasian Ruffe model runs, site B05 led to the greatest maximum distance of settlement at 159.08 km. However, sites B03 and B06 led to the least number of larvae being settled (4 and 5, respectively; Table 2; Fig. 4-6) and the least number of locations potentially being settled (6 for each release site; Table 2).

Overall, sites B03 and B06 led to the least amount of larval settlement and the number of potential settlement locations when results for both species were considered (Table 2; Fig. 4-4 and 4-5). Further, site B11 led to large numbers of larval settlement and potential settlement locations for both species, and site B05 led to the greatest distance of spread (Table 2; Fig. 4-5 and 4-6).

Among the potential ballast water exchange sites tested, those that led to less larval settlement did not necessarily lead to the least potential spread due to ballast water. While site B01 led to the most settlement modeled for golden mussel, it ranked only third for Eurasian Ruffe. However, B01 led to the invasion of the most ports for both species due to ballast water movement. This is most likely owing to B01's proximity to Chicago area ports, which are among the greatest contributors to ballast water discharged in the Great Lakes (Table 3; Smithsonian Environmental Research Center and USCG 2009). B01 also led to the invasion of four Great Lakes for golden mussel; yet, Eurasian Ruffe never left Lake Michigan. Conversely, sites B09 and B11 led to the most Great Lakes being invaded (2 each). B11 led to the invasion of Lake Huron due to its proximity to the Straits of Mackinac; while site B09 led to a concentration of spread at the downriver entrance to the St. Marys River. For golden mussel, a total of 8 MLBWE sites resulted in the modeled invasion of four Great Lakes at least 50% of model runs, and another two sites led to the invasion of three Great Lakes at least 50% of model runs. In particular, B06 led to the invasion of 25 ports and three Great Lakes at least 50% of model runs, despite resulting in such low larval settlement due to lake circulation. Ultimately, site B03 led to the least amount of spread due to circulation or ballast water for both species tested. An example of ballast water model results is shown in Figure 4-7.

4.5 Discussion

The results of the larval transport and ballast water models suggest that MLBWE may be an effective temporary alternative to ballast water treatment for preventing the spread of invasive species if strategically located. For Eurasian Ruffe, multiple sites were identified where ballast water may be exchanged in order to prevent the survival of any larvae entrained in ballast tanks. Indeed, past calls for the exchange of ballast water in the deeper regions of Lake Superior may have led to a reduction in the spread of ruffe from Duluth/Superior harbor (Brown et al. 1998). Requiring the implementation of BWE for ships leaving areas infested by ruffe will likely reduce the secondary spread of the invasive fish in the future. Despite MLBWE being predicted to be less effective at preventing the spread of golden mussel, at least one test site, B03, led to reduced spread due to lake currents and ballast water movement. Nevertheless, site B03 will only be an efficient BWE site for those ships that are passing through that area. If golden mussel were to become established in the Chicago area, we suggest that using site B03 to conduct BWE will help to reduce the number of propagules that a ship may carry to another port.

The results of our multi-model approach also demonstrate the importance of considering multiple vectors when trying to identify effective ballast water management techniques. When only taking the dispersion by lake currents into consideration, two ballast water test sites (B03 and B06) resulted in minimal golden mussel larval settlement in Lake Michigan. However, by inputting these results into the ballast water spread model, the six sites that were predicted to be settled due to lake circulation led to the future invasion of 25 ports and three Great Lakes at least 50% of the model runs. Even if a MLBWE site resulted in a small area becoming invaded, it could potentially lead to a large amount of spread as long as a population became established in a location that serves as a source of ballast water to multiple locations throughout the Great Lakes. In the case of site B06, the settled larvae were in close proximity to a major shipping lane and the port of Ludington, Michigan.

Though MLBWE may be a promising method for slowing the spread of invasive species, it is important to highlight that it should only be used temporarily while ballast water treatment options are going through the approval and implementation process. Despite high compliance to BWE policies by transoceanic ships (Bailey et al. 2011), not all individuals are killed or flushed out of the ballast tanks. Further, BWE practiced while still in saltwater provides a two-pronged attach by flushing organisms out of a ship's ballast tanks and providing for additional mortality by osmotic shock (Ruiz and Reid 2010). Currently, it is unknown how effective MLBWE with freshwater may be without testing it in the field; however, it is still expected to result in a noted decrease in the number of propagules available to establish a new population. Nevertheless, an approved ballast water treatment system will ultimately be more reliable and safer to the operation of ships than MLBWE.

The methods used in this study can be replicated for the remaining Laurentian Great Lakes and other aquatic and marine systems. Identifying MLBWE sites in Lake Superior, Huron, Erie, and Ontario will be important in devising an alternative to ballast water treatment for the next few years as treatment systems are certified for use in the Great Lakes and implemented on ships built after January 1, 2009. Further, MLBWE can be an effective best management practice applied by ships built prior to January 1, 2009. Considering that in 2012 the average age of the U.S. fleet was 46 years old with only four ships having been built since the 1990s (USDOT Maritime Administration 2013), it could be some time before the majority of lakers have a certified ballast water treatment system on board.

Until ballast water treatment systems are installed on all ships carrying ballast water in the Great Lakes, best management practices are going to form the backbone of invasive species prevention strategies. Our model results suggest that MLBWE is a feasible practice for slowing the spread of Eurasian Ruffe, golden mussel, and potentially other invasive species; however, it is important to state that preventing species from entering the Great Lakes in the first place is the most effective management plan. Nonetheless, techniques designed to prevent both the introduction of invasive species into the Great Lakes and secondary spread within the Great Lakes will be important in devising effective ballast water management policy.

4.6 Acknowledgements

We would like to acknowledge the support and information provided by David Lodge and Marion Wittman at the University of Notre Dame, Gust Annis at The Nature Conservancy, Ed Rutherford at the National Oceanic and Atmospheric Administration, Lacey Mason at the University of Michigan, and Drew Kramer at the University of Georgia. We would also like to thank Dr. David Reid for providing technical knowledge on ballast water management. Additional thanks go to friendly reviewers Kamalika Ganguly and Jessica Sherman. This project was funded by a grant from National Oceanic and Atmospheric Administration, Center for Sponsored Coastal Ocean Research, NOAA-CSCOR #NA10NOS4780218.This is publication #2014-XX from the Lake Erie Research Center.

Table 4.1. Larval transport model constraints identified for each species. The first and last release days represent the range of days that larvae may be found in the water column. The survival period represents the amount of time that larvae can survive in the water column without suitable habitat. The maximum depth is the depth beyond which larvae are not expected to survive.

	Eurasian Ruffe	**Golden Mussel**
First release (Julian day)	102	144
Last release (Julian day)	210	290
Survival period	14 days	20 days
Maximum depth	10 meters	50 meters

Table 4.2. Larval transport model results. The total number of larvae that settled (ruffe: *n=109*, golden mussel: *n=147*), total number of settlement locations, and maximum distance from each MLBWE site are reported. Settlement locations were identified as those locations at or below the maximum depth that larvae had reached prior to the end of the survival period.

	# Larvae Settled	# Settlement Locations	Max Dist from MLBWE Site (km)
Eurasian Ruffe			
B01	20	53	23.35
B02	0	0	NA
B03	0	0	NA
B04	0	0	NA
B05	37	116	91.38
B06	0	0	NA
B07	0	0	NA
B08	9	25	47.92
B09	11	35	35.66
B10	5	9	40.06
B11	85	294	28.67
Golden Mussel			
B01	147	2613	65.02
B02	27	144	112.77
B03	4	6	64.08
B04	46	102	139.81
B05	123	898	159.08
B06	5	6	64.40
B07	28	77	78.36
B08	144	558	64.46
B09	139	1024	66.03
B10	35	204	40.44
B11	147	2570	74.58

Table 4.3. Ballast water model results for all MLBWE sites that resulted in the settlement of at least one larva. The total number of ports and lakes invaded and the total number of ports and lakes that were predicted to become invaded at least half the time were counted.

	Total Ports Invaded	**Total Lakes Invaded**	**Total Ports ≥ 50%**	**Total Lakes ≥ 50%**
Eurasian Ruffe	*(n=96)*	*(n=5)*	*(n=96)*	*(n=5)*
B01	14	1	13	1
B05	0	1	0	1
B08	2	1	2	1
B09	6	2	6	2
B10	1	1	1	1
B11	6	2	6	2
Golden Mussel	*(n=93)*	*(n=5)*	*(n=93)*	*(n=5)*
B01	63	4	56	4
B02	38	3	38	3
B03	1	1	1	1
B04	41	4	41	4
B05	30	4	30	4
B06	28	3	25	3
B07	1	4	1	4
B08	49	4	47	4
B09	48	4	47	4
B10	39	4	31	4
B11	37	4	37	4

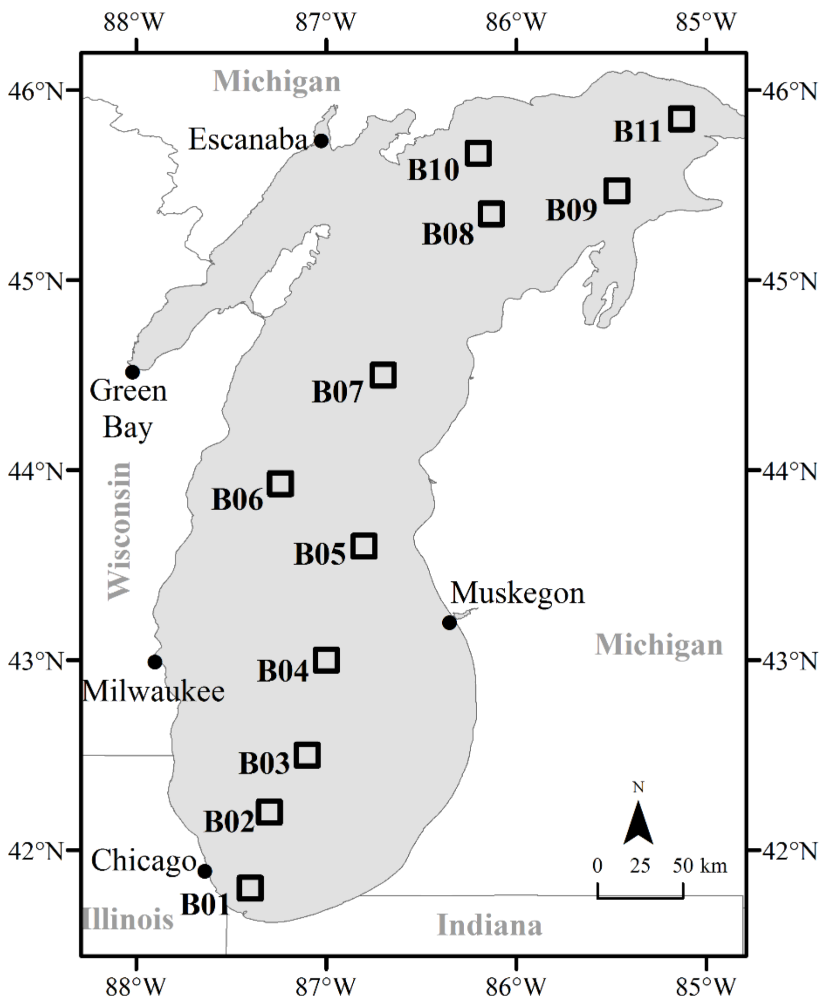


Figure 4-1. Lake Michigan mid-lake ballast water exchange (MLBWE) sites tested for effectiveness.

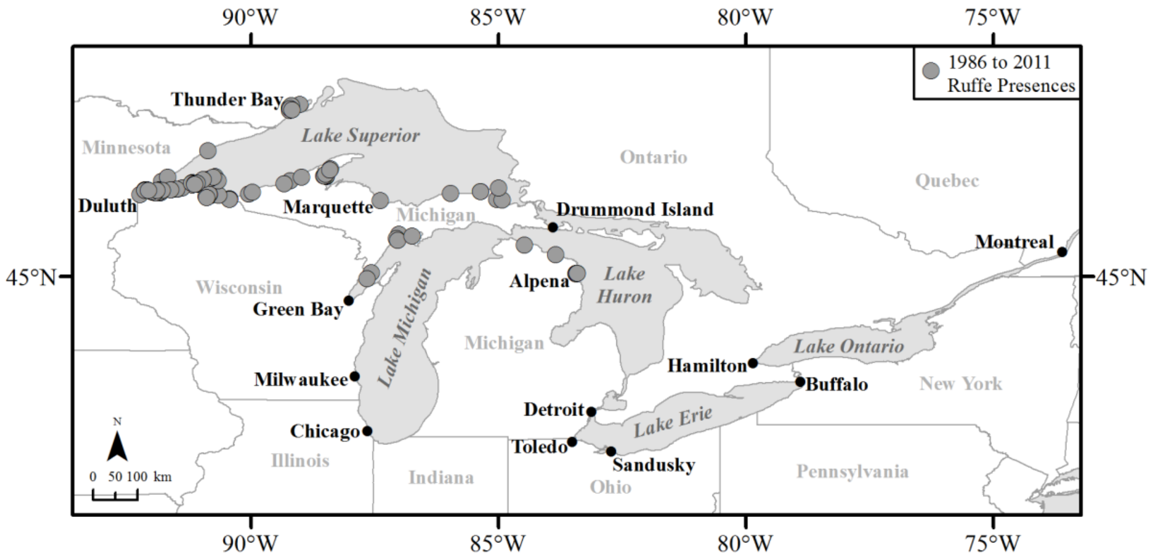


Figure 4-2. Eurasian Ruffe presences for the Great Lakes (USGS 2009).

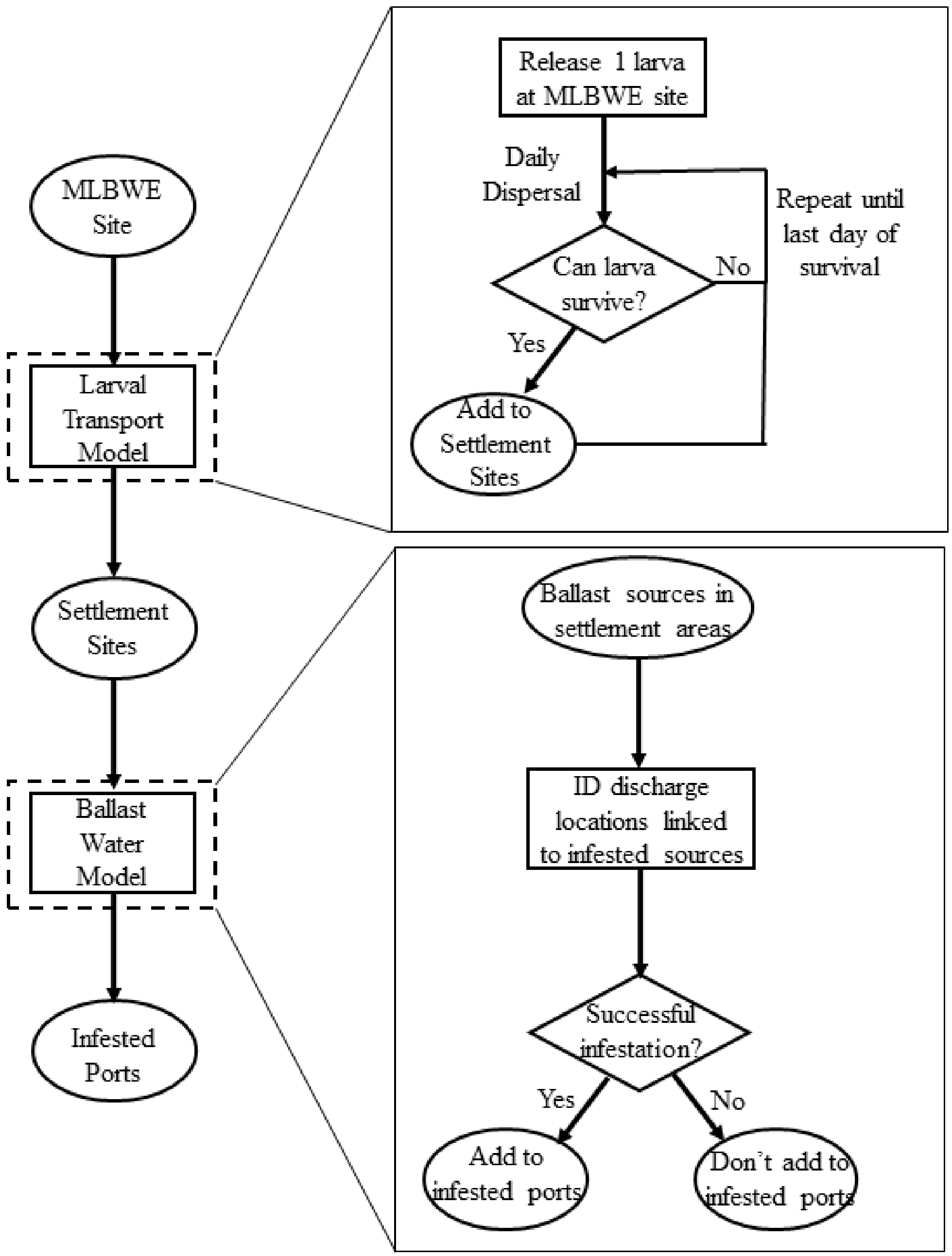


Figure 4-3. Conceptual model for predicting the effectiveness of MLBWE in Lake Michigan. Components of the larval transport and ballast water models are broken down in boxes to the right.

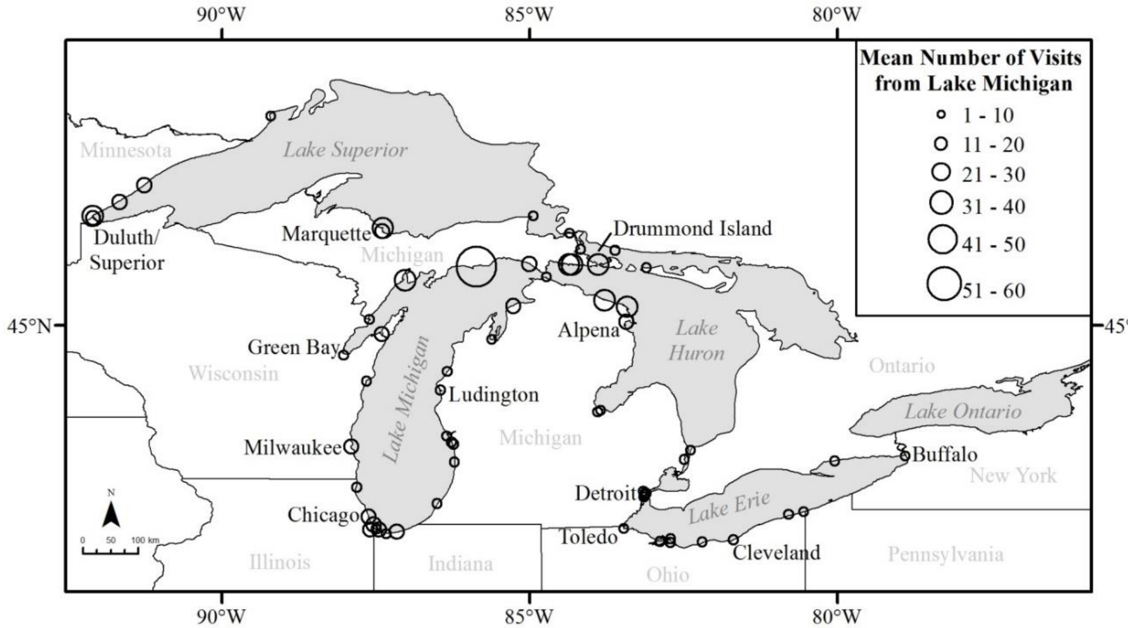


Figure 4-4. Ballast water discharge locations that received ballast water from Lake Michigan between 2004 and 2010 as recorded in the NBIC (National Ballast Information Clearinghouse 2009).

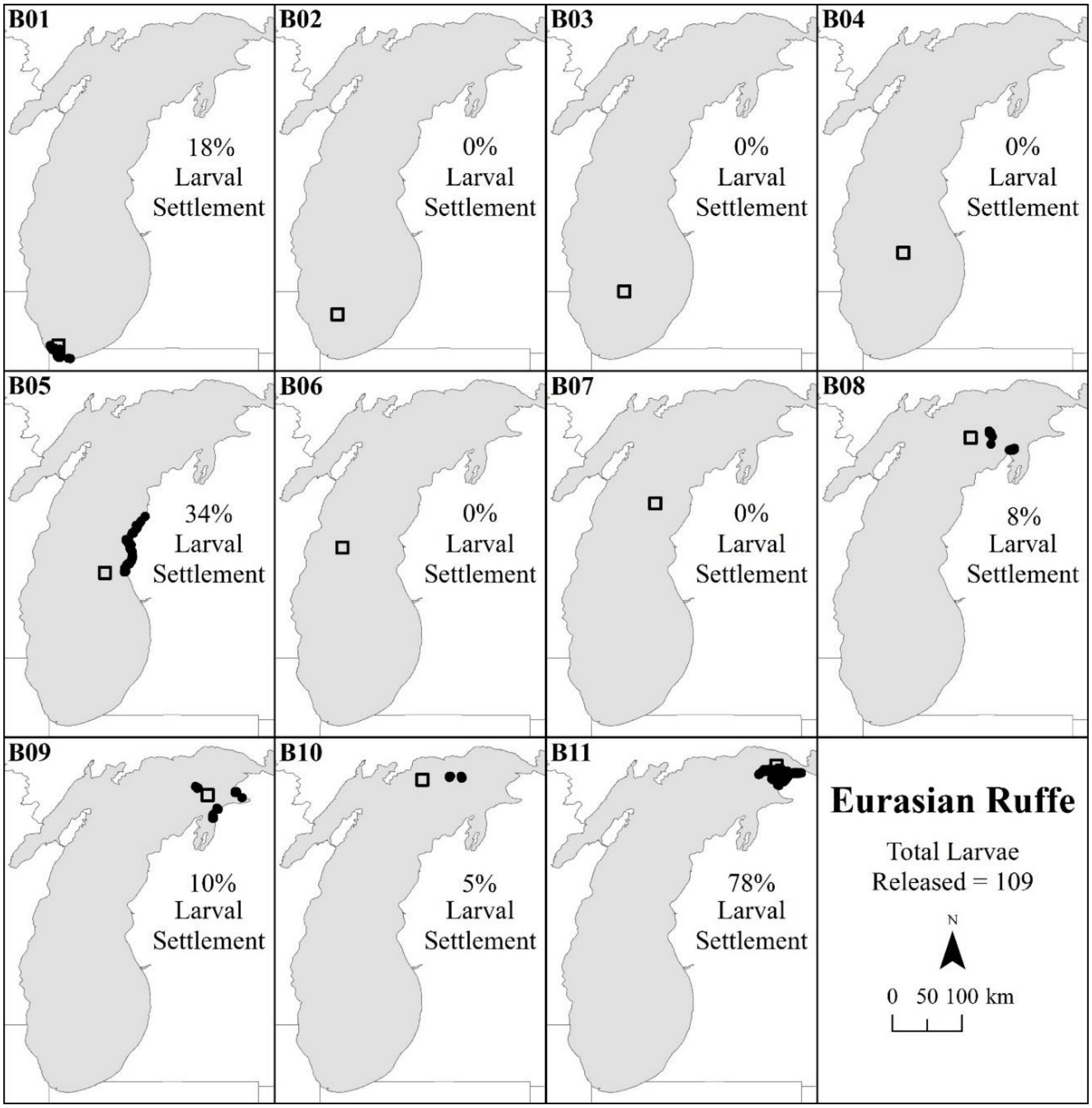


Figure 4-5. Eurasian Ruffe larval transport model results. As part of the simulation, one larva was released at each MLBWE site every day from mid-April to early July, resulting in 84 total larvae being released. Larvae were tracked for seven days after release and considered dead if they did not reach a safe depth of ≥ 10-m in that time. The total number of locations where a larva could settle was also calculated.

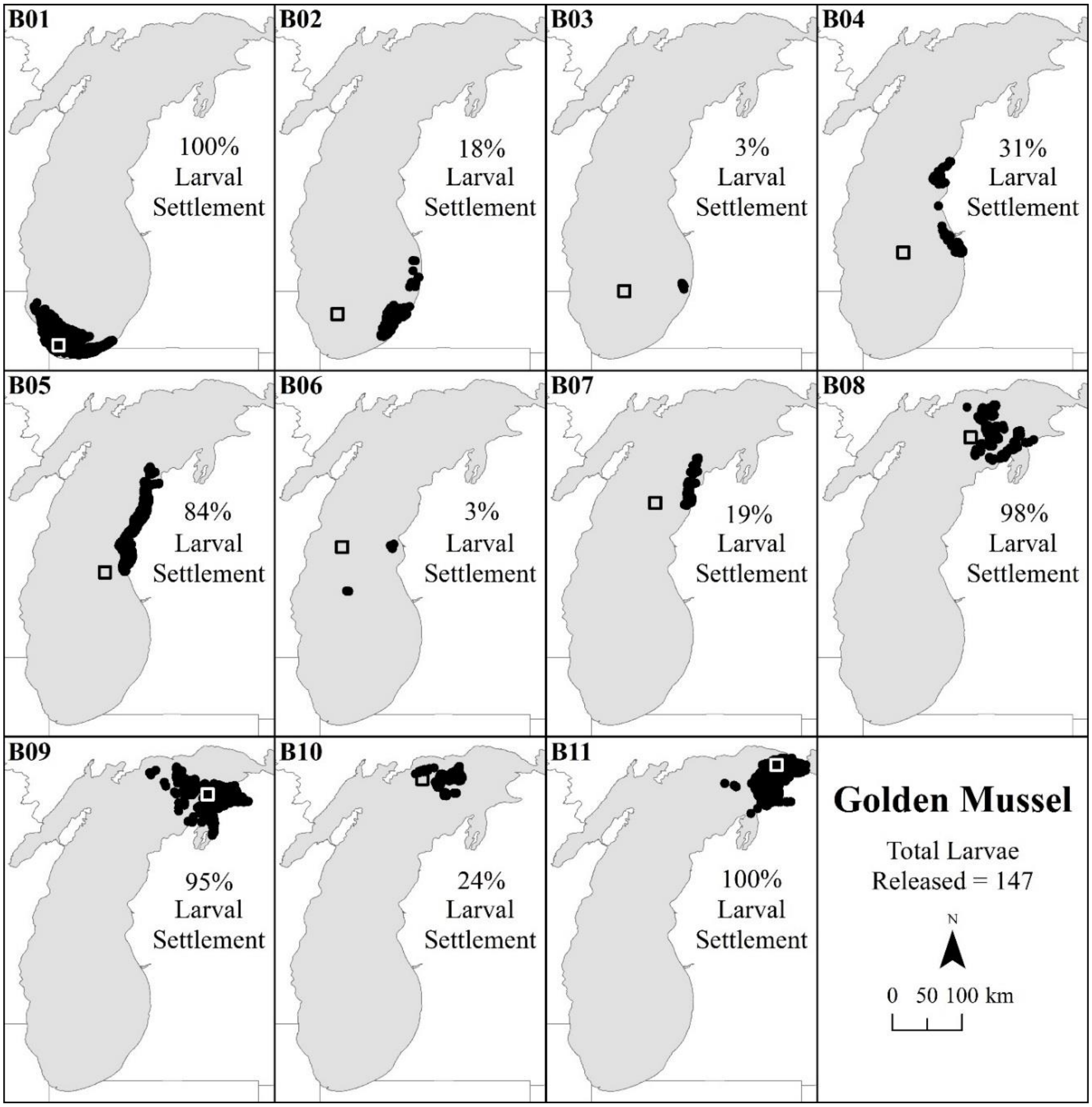


Figure 4-6. Golden mussel larval transport model results. As part of the simulation, one larva was released at each MLBWE site every day from mid-May to the end of September, resulting in 139 total larvae being released. Larvae were tracked for seventy days after release and considered dead if they did not reach a safe depth of ≥ 50-m in that time. The total number of locations where a larva could settle was also calculated.

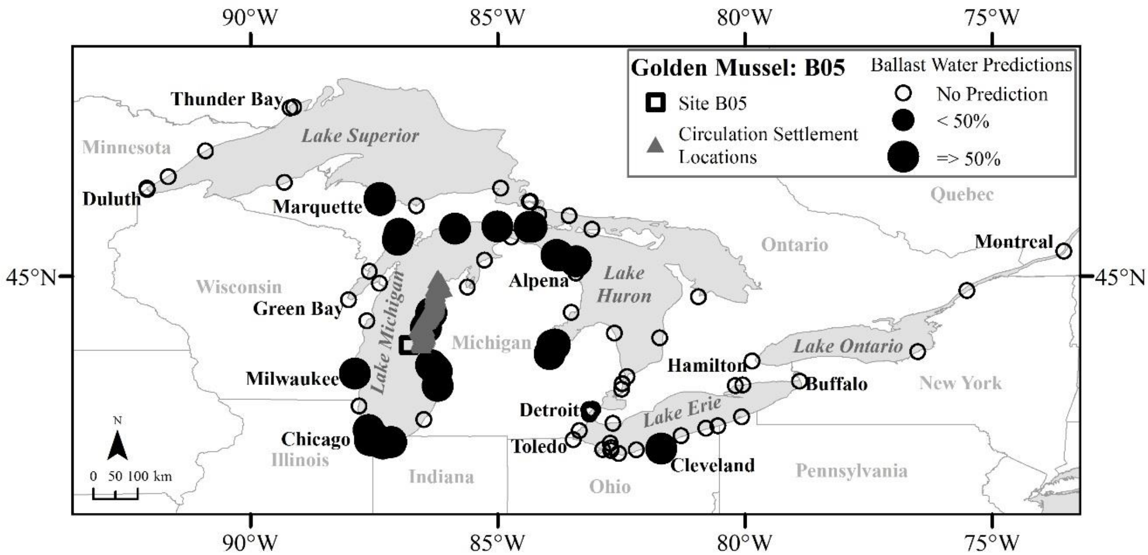


Figure 4-7. Golden mussel ballast water model results for Site B05. Ballast water predictions are the percentage of model runs that resulted in invasion for each port. Golden mussel were entrained from the settlement locations resulting from larvae being discharged at Site B05.

Chapter 5

Discussion

Ballast water and shipping data have been used in the past to conduct risk assessments for North American ports; however, they have not been used to create a spread model that can simulate the movement of specific species. Despite the frequent use of ballast data as a proxy for propagule pressure, Ruiz et al. (2013) recently found no relationship between U.S. ports that receive large amounts of ballast water or numerous ship arrivals and richness of nonnative species. Nonetheless, they hypothesized that the absence of a relationship may have been to due to the lack of ballast water source information considered in their study. Although large volumes of ballast water may be able to contain enough propagules to result in population establishment, those propagules may not necessarily be invasive if the ballast water was not picked-up in a location where nonnative species capable of inhabiting a discharge location are found (Ruiz et al. 2013). Further, source ports that are great distances from the discharge port are less likely to result in new invasions, since many organisms are likely to die prior to reaching their destination (Ruiz et al. 2013). A number of risk assessments have used varying levels of ballast water source information in order to over come these issues (McGee et al. 2006, Rup et al. 2010, Miller et al. 2011), but these risk assessments have lumped source data into broader categories rather than identifying specific regions. A risk assessment conducted by Bailey et al. (2012) identified specific domestic locations that served as ballast water sources in the Great Lakes and calculated a species invasion probability; however, they did not use a species-specific approach. Keller et al. 2010 also conducted a risk assessment for Great Lakes ports by identifying those global ports that have similar environmental conditions, but did not consider actual ballast water events. In order to overcome the limitations in using ballast water and shipping information, my model included specific source/discharge linkages, species-specific probabilities of infestation, and median trip lengths.

In using ballast water source and species-specific data, I was able to devise a model that not only explained the majority of secondary spread of at least two species, but that has also been useful in providing information to help guide monitoring and management of invasive species in the Great Lakes. In particular, the ballast water model was better able to capture long-distance spread events than the localized dispersal distance alone. Capturing these long-distance dispersal events can be key in controlling an invasive species. If those locations that are most likely to become invaded in the future are identified prior to invasion, it will allow time for the implementation of rigorous prevention methods (e.g. mid-lake BWE, ballast water treatment, etc.) and the development of early detection monitoring plans (Lodge et al. 2006). Additionally, the model I developed for this study can also be used to identify efficient and effective ballast water management techniques. In fact, there are many uses for the dynamic spatial ballast water model that have not been considered in this document.

One of the utilities of the ballast water model was in determining whether or not ballast water discharge was playing a role in the secondary spread of an invasive species in the Great Lakes. It was determined that VHSV occurrences were not simply related to the location of ballast water discharges, but they were located near those discharges that received numerous visits from ballast water sources that were previously identified as invaded. Despite ballast water discharge explaining only a small portion of VHSV spread, the model was able to capture long-distance spread and still demonstrated ballast water to be a vector of past spread. Because of this, any prevention program would need to include a ballast water management component in order to most effectively prevent the further spread of VHSV. Even though VHSV is already widespread in the Great Lakes, the information provided by the model may be applied to devising management strategies for the possible future invasion of other fish diseases. Additionally, the model was able to identify the St. Lawrence River as the more likely Great Lakes source of VHSV versus Lake St. Clair, as put forth by Thompson et al. (2011). Despite prevention methods being implemented in order to prevent the further spread of VHSV, such as prohibiting sale of bait across state lines (MDNR 2007, APHIS 2008), it still became widespread throughout the Great Lakes. Based on modeling results, lack of early detection, failure to focus control efforts on all source populations, and exclusion of ballast water management as part of the prevention program may have led to the ultimate pervasiveness of VHSV in the Great Lakes.

The ballast water model was also useful in predicting the secondary spread of three different invasive species in the Great Lakes. As with VHSV, including ship trip detail was important in identifying species occurrences. In addition, including a measure of an organism's ability to survive in the ballast tank during a trip was important in more accurately capturing the past spread of the species. Because of the accuracies obtained during backcasting, I was able to more reliably predict the future spread of ruffe, golden mussel, and killer shrimp based on ballast water movement alone than I would have if I had not created my models using past occurrences. Predictions of the future spread of these and any other species is important information to have in devising an early detection monitoring program (Simberloff et al. 2005, Lodge et al. 2006). Most agencies that conduct long-term monitoring do not have the time or money to census the entire system under their jurisdiction. For agencies, it is important to eliminate those areas that are least likely to be invaded by an invasive species and only focus on those locations that are most likely to become invaded in the future. The results of prediction modeling can help to guide early detection efforts, including but not limited to eDNA monitoring. Due to its current status in the Great Lakes, Eurasian Ruffe became an urgent test subject of the three species modeled. Preliminary results of prediction modeling were made available to The Nature Conservancy, who have been testing new eDNA methods to monitor for invasive species, including ruffe. Guided by my ballast water model results, ruffe eDNA was detected in Calumet Harbor in the summer of 2013. The ballast water model had predicted that ruffe would next invade Calumet Harbor in 95-97% of all model runs, suggesting that prediction modeling is a useful tool in directing early detection monitoring of invasive species.

Another application of the ballast water model was to determine its usefulness in identifying potential effective ballast water management practices. Using a hydrodynamic model to simulate the dispersal of ruffe and golden mussel larvae in combination with the ballast water model provided for a more complete picture of how those two species would spread upon being discharged at mid-lake locations. Inputting the circulation results into the ballast water model proved to be important, since the number of infestations due to ballast water spread was not necessarily positively related to the amount of circulation settlement. The combined modeling efforts led to the identification of potential mid-lake ballast water exchange (MLBWE) sites in Lake Michigan for Eurasian Ruffe and golden mussel. Despite not identifying as many effective MLBWE sites for golden mussel as for ruffe, MLBWE may still be an effective means of slowing the spread of the invasive bivalve depending on where it is first detected in the Great Lakes. For instance, if golden mussel were to invade the Chicago area first, it would be plausible for ships to conduct MLBWE prior to travelling to other ports. Further, MLBWE at even less desirable sites may prove to be effective in minimizing the number of larvae transported if combined with other management practices. Not only could the ballast water model be used to identify MLBWE locations in other lakes, but it could be used to test other management practices and potential locations of ballast water treatment in the Great Lakes as well.

Current limitations of the ballast water model lead to an incomplete picture for the Great Lakes. The lack of Canadian ballast water data results in the absence of accurate predictions for the Canadian shoreline and likely underestimates the total spread of a species within the Great Lakes. The mandatory reporting and release of this data would greatly enhance the accuracy of the ballast water model's predictions. It is also important to note that as the economy in the Great Lakes changes, the shipping patterns are also likely to change. In order to provide information that is timely, it will be important to update the discharge data on which the ballast water model relies to make accurate predictions. Further, the lack of good species occurrence data also limited our ability to identify appropriate parameter values and how well the models are predicting the spread of each of the species studied. Many species detections go unreported, either because it is assumed the species is already widespread or because it has been detected by a member of the public who does not where to report it. Mobile applications and online reporting systems have been developed to allow the public to report the locations of invasive plant species in the U.S. (e.g. IPAlert, EDDMapS West, What's Invasive, etc.). Similar applications may be developed for aquatic species, as well. In addition to better reporting of species occurrences, it is also important to include absence information as part of any reporting system. By reporting species absences, it is possible to more accurately determine if a lack of species presence is actually due to it not occurring in a location, or if it simply has not been looked for yet. Absence data also informs as to the degree of monitoring that has been undertaken in detecting a species.

Because the ballast water model has the potential to be a useful tool in making invasive species management decisions, it is important that it be made available to agencies. For this reason, the model has been coded in Python, a scripting language, to run in ESRI's ArcGIS. ArcGIS is available to and used by many federal, state, and local agencies, universities, and organizations to conduct spatial geoprocessing. The next stages in developing the ballast water model will include adding functionality to the code that allows for easier use by those with limited experience in ArcGIS. Further, a readily distributed package containing the model and all that is needed to run it (i.e. input data, tutorial, and help documentation) will be produced. Further, those with more advanced experience with Python and ArcGIS can readily modify the model's code to meet their own management needs and can create their own input data to run simulations in any freshwater or marine system where ballast water discharge data is available.

By modifying the ballast water model for use by others, the methods described here may be applied to other systems. In particular, the National Ballast Information Clearinghouse (Smithsonian Environmental Research Center and USCG 2009) maintains data for the entire U.S. Ballast water data for the Atlantic, Pacific, and Gulf Coasts may be summarized from the NBIC and used to simulate the pattern of secondary spread for each of these marine systems as well as it has been used for the Great Lakes. Additionally, the model is not limited to predicting the secondary spread of species, but may also be used to identify those ports most likely to be the initial invasion site of a specific species of interest. Because the NBIC maintains trans-oceanic as well as domestic ballast water source/discharge data, it is possible to simulate the movement of species into the U.S. from all global ports. The ballast water model may also be used in other countries and regions of the world so long as similar source/discharge data exists, as is the case for trans-oceanic travel in Canada (Rup et al. 2010, Bailey et al. 2011).

Further applications of the ballast water model have yet to be tested. The model may be used to determine how effective ballast water treatment or management practices would have been in preventing the spread of invasive species in the past. For instance, it may be used to determine what affect mandatory ballast water management may have had on the spread of zebra mussels in the Great Lakes. Model results could indicate the degree to which treatment may have slowed the spread of zebra mussels, potentially allowing time for control or eradication of the species at the initial infestation sites. The model results could also demonstrate when in the invasion process it would have been most effective to begin treating or managing ballast water. Furthermore, habitat and climate information can be added to the model to further narrow the spread predictions made for Eurasian Ruffe, golden mussel, killer shrimp, or any other species of interest. For instance, golden mussel tends to inhabit more tropical and subtropical regions. By adding habitat and climate constraints collected from both native and invaded golden mussel occurrences, it would be possible to determine if the limiting factor in the spread of golden mussel may actually be its own inability to survive throughout the Great Lakes. Additionally, ballast water model results may be used to inform secondary spread models designed to simulate inland invasions. The results of such modeling efforts will not only inform as to which inland waters a species is most likely to invade from a given port, but it can also inform as to how far a species may spread inland from a given port.

Because it is not possible or ethical to introduce a species to an ecosystem to study its spread patterns, we must rely on what we know about invasive species dispersal from past experiences. Predictive models organize data from the past in a way that allows us to infer how species and humans will behave in the future. Despite only being a representation of what may occur based on our current knowledge, the ballast water model still provides informed possible future scenarios of secondary spread of invasive species. By applying the ballast water model to three different management problems, I was able to provide more information to invasive species managers, scientists, and policy makers than previously available. As more data become available in the Great Lakes and beyond, our understanding of how invasive species spread will evolve, and the ballast water model will continue to increase in accuracy and applicability.

References

Adlerstein SA, Rutherford ES, Clevenger JA, Johnson JE, Clapp DF, and Woldt AP (2007) Lake trout movements in U.S. waters of Lake Huron interpreted from coded wire tag recoveries in recreational fisheries. *Journal of Great Lakes Research* **33**, 186-201.

APHIS (2008) Amended Federal Order: Viral Hemorrhagic Septicemia (VHS). Animal and Plant Health Inspection Service (APHIS), Washington, D.C.

Bailey SA, Chan F, Ellis SM, Bronnenhuber JE, JN Bradie, and Simard N (2012) Risk assessment for ship-mediated introductions of aquatic nonindigenous species to the Great Lakes and freshwater St. Lawrence River. DFO Canadian Science Advisory Secretariat Research Document 2011/104.

Bailey SA, Deneau MG, Jean L, Wiley CJ, Leung B, and MacIsaac HJ (2011) Evaluating efficacy of an environmental policy to prevent biological invasions. *Environmental Science & Technology* **45**, 2554-256.

Bain MB, Cornwell ER, Hope KM, Eckerlin GE, Casey RN, Groocock GH et al. (2010) Distribution of an invasive aquatic pathogen (viral hemorrhagic septicemia virus) in the Great Lakes and its relationship to shipping. *PLoSONE* **5**, 1-8.

Bauer CR, Bobeldyk AM, and Lamberti GA (2007) Predicting habitat use and trophic interactions of Eurasian Ruffe, round gobies, and zebra mussels in nearshore areas of the Great Lakes. *Biological Invasions* **9**, 667-78.

Beeton AM (2014) Foreward. In *Quagga and Zebra Mussels: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), 2nd (ed.), pp. xi-xii. CRC Press, Taylor & Francis Group, Boca Raton, FL.

Beeton AM (2002) Large freshwater lakes: present state, trends and future. *Environmental Conservation* **29**, 21-38.

Beletsky D, Hawley N, and Rao YR (2013) Modeling summer thermal structure and circulation in Lake Erie. *Journal of Geophysical Research* **118**, 1-5.

Beletsky D, Mason DM, Schwab DJ, Rutherford ES, Janssen J, Clapp DF et al. (2007) Biophysical model of larval yellow perch advection and settlement in Lake Michigan. *Journal of Great Lakes Research* **33**, 842-66.

Beletsky D and Schwab DJ (2001) Modeling circulation and thermal structure in Lake Michigan: Annual cycle and interannual variability. *Journal of Geophysical Research* **106**, 19745-71.

Beletsky D and Schwab D (2008) Climatological circulation in Lake Michigan. *Geophysical Research Letters* **35**, L2104.

Beletsky D, Schwab D, and McCormack M (2006) Modeling the 1998-2003 summer circulation and thermal structure in Lake Michigan. *Journal of Geophysical Research* **111**, C10010.

Benson AJ (2014) Chronological History of Zebra and Quagga Mussels (Dreissenidae) in North America, 1988-2010. In *Quagga and Zebra Mussels: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), 2nd (ed.), pp. 9-31. CRC Press, Taylor & Francis Group, Boca Raton, FL.

Bierman VJ, Kaur J, DePinto JV, Feist TJ, and Dilks DW (2005) Modeling the role of zebra mussels in the proliferation of blue-green algae in Saginaw Bay, Lake Huron. *Journal of Great Lakes Research* **31**, 32-55.

Boets P, Lock K, Messiaen M, and Goethals PLM (2010) Combining data-driven methods and lab studies to analyse the ecology of *Dikerogammarus villosus*. *Ecological Informatics* **5**, 133-9.

Bossenbroek JM, Johnson LE, Peters B, and Lodge DM (2007) Forecasting the expansion of zebra mussels in the United States. *Conservation Biology* **21**, 800-10.

Bossenbroek JM, Kraft CE, and Nekola JC (2001) Prediction of long-distance dispersal using gravity models: Zebra mussel invasion of inland lakes. *Ecological Applications* **11**, 1778-1788.

Brandt RAM and Temcharoen P (1971) The molluscan fauna of the Mekong at the foci of Schistosomiasis in South Laos and Cambodia. *Archiv fuer Hydrobiologic* **101**, 111-40.

Briski E, Wiley CJ, and Bailey SA (2012) Role of domestic shipping in the introduction or secondary spread of nonindigenous species: Biological invasions within the Laurentian Great Lakes. *Journal of Applied Ecology* **49**, 1124-30.

Brown WP, Selgeby JH, and Collins HL (1998) Reproduction and early life history of ruffe (*Gymnocephalus cernuus*) in the St. Louis River, a Lake Superior tributary. *Journal of Great Lakes Research* **24**, 217-27.

Bruijs MCM, Kelleher B, Velde Gvd, and Vaate Abd (2001) Oxygen consumption, temperature and salinity tolerance of the invasive amphipod *Dikerogammarus villosus*: Indicators of further dispersal via ballast water transport. *Archiv für Hydrobiologie* **152**, 633-46.

Buchan LAJ and Padilla DK (2000) Predicting the likelihood of Eurasian watermilfoil presence in lakes, a macrophyte monitoring tool. *Ecological Applications* **10**, 1442-55.

Buck EH (2010) Ballast water management to combat invasive species. In *Ballast water management: Combating aquatic invaders*. O'Sullivan EG (ed.), pp. 1-12. Nova Science Publishers, Inc., New York.

Campbell M, Gould B, and Hewitt C (2007) Survey evaluations to assess marine bioinvasions. Marine Pollution Bulletin 55: 360-378.

Canadian Shipowners Association, The Thunder Bay Harbour Commission, Shipping Federation of Canada, Lake Carriers' Association, Seaway Port Authority of Duluth, and U.S. Great Lakes Shipping Association (1996) Great Lakes maritime industry voluntary ballast water management plan for the control of ruffe in Lake Superior ports, 1993. In *Stemming the Tide: Controlling Introductions of Nonindigenous Species by Ships' Ballast Water*. Committee on Ships' Ballast Operations NRC (ed.), pp. 109-10. National Academy Press, Washington, D.C.

Cangelosi A and Mays N (2006) Great ships for Great Lakes?: Commercial vessels free of invasive species in the Great Lakes-St. Lawrence Seaway System. Northeast Midwest Institute, Washington, D.C.

Carlton JT (1993) Dispersal mechanisms of the zebra mussel (Dreissena polymorpha). In *Zebra Mussels: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), pp. 677-97. Lewis Publishers, Ann Arbor.

Carlton JT (2008) The zebra mussel *Dreissena polymorpha* found in North America in 1986 and 1987. *Journal of Great Lakes Research* **34**, 770-3.

Carrasco LR, Mumford JD, MacLeod A, Harwood T, Grabenweger G, Leach AW et al. (2010) Unveiling human-assisted dispersal mechanisms in invasive alien insects: Integration of spatial stochastic simulation and phenology models. *Ecological Modelling* **221**, 2068-75.

Cataldo D, Boltovskoy D, Hermosa JL, and Canzi C (2005) Temperature-dependent rates of larval development in *Limnoperna fortunei* (Bivalvia : Mytilidae). *Journal of Molluscan Studies* **71**, 41-6.

Cataldo DH and Boltovskoy D (2000) Yearly reproductive activity of *Limnoperna fortunei* (Bivalvia) as inferred from the occurrence of its larvae in the plankton of the lower Paraná River and the Río de la Plata estuary *Aquatic Ecology* **34**, 307-17.

Cohen J (1968) Weighted kappa: Nominal scale agreement with provision for scaled disagreement or partial credit. *Psychological Bulletin* **70**, 213-20.

Collin SB, Edwards PK, Leung B, and Johnson LE (2013) Optimizing early detection of non-indigenous species: Estimating the scale of dispersal of a nascent population of the invasive tunicate *Ciona intestinalis* (L.). *Marine Pollution Bulletin* **73**, 64-9.

Committee on Ships' Ballast Operations, Marine Board, Commission on Engineering and Technical Systems, and National Research Council (1996) In *Stemming the Tide: Controlling Introductions of Nonindigenous Species by Ships' Ballast Water*, pp. 158, Washington, D.C.

Covalciuc KA, Webb KH, and Carlson CA (1999) Comparison of four clinical specimen types for detection of influenza A and B viruses by optical immunoassay (FLU OIA test) and cell culture methods. *Journal of Clinical Microbiology* **37**, 3971-4.

Darrigran G and Pastorino G (1995) The recent introduction of a freshwater Asiatic bivalve, *Limnoperna fortunei* (Mytilidae) into South America. *The Veliger* **38**, 171-5.

Devin S, Piscart C, Beisel J-N, and Moreteau J-C (2004) Life history traits of the invader *Dikerogammarus villosus* (Crustacea: Amphipoda) in the Moselle River, France. *International Review of Hydrobiology* **89**, 21-34.

Dick JTA and Platvoet D (2000) Invading predatory crustacean *Dikerogammarus villosus* eliminates both native and exotic species. *Proceedings of the Royal Society B: Biological Sciences* **267**, 977-83.

Dick JTA, Platvoet D, and Kelly DW (2002) Predatory impact of the freshwater invader *Dikerogammarus villosus* (Crustacea: Amphipoda). *Canadian Journal of Fisheries and Aquatic Sciences* **59**, 1078-84.

Drake DAR and Mandrak NE (2010) Least-cost transportation networks predict spatial interaction of invasion vectors. *Ecological Applications* **20**, 2286-99.

Drake LA, Doblin MA, and Dobbs FC (2007) Potential microbial bioinvasions via ships' ballast water, sediment, and biofilm. *Marine Pollution Bulletin* **55**, 333-41.

Eames I, Landeryou M, Greig A, and Snellings J (2008) Continuous flushing of contaminants from ballast water tanks. *Marine Pollution Bulletin* **56**, 250-60.

Eckerlin GE, Farrell JM, Casey RN, Hope KM, Groocock GH, Bowser PR et al. (2011) Temporal variation in prevalence of viral hemorrhagic septicemia virus type IVb among Upper St. Lawrence River smallmouth bass. *Transactions of the American Fisheries Society* **140**, 529-36.

Elsayed E, Faisal M, Thomas M, Whelan G, Batts W, and Winton J (2006) Isolation of viral haemorrhagic septicaemia virus from muskelluge, *Esox masquinongy* (Mitchill), in Lake St Clair, Michigan, USA reveals a new sublineage of the North American genotype. *Journal of Fish Diseases* **29**, 611-9.

Faisal M, Shavalier M, Kim RK, Millard EV, Gunn MR, Winters AD et al. (2012) Spread of the emerging viral hemorrhagic septicemia virus strain, Gentoype IVb, in Michigan, USA. *Viruses* **4**, 734-60.

Faisal M and Winters AD (2011) Detection of viral hemorrhagic septicemia virus (VHSV) from *Diporeia* spp. (Pontoporeiidae, Amphipoda) in the Laurentian Great Lakes, USA. *Parasites & Vectors* **4**, 1-4.

Fielding AH and Bell JF (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* **24**, 38-49.

Finch RG (1925) The Story of the New York State Canals. New York State Canal Corporation, New York.

Fullerton AH, Lamberti GA, Lodge DM, and Berg MB (1998) Prey preferences of Eurasian Ruffe and yellow perch: Comparison of laboratory results with composition of Great Lakes benthos. *Journal of Great Lakes Research* **24**, 319-28.

Gilchrist JM (2009) Weighted 2 X 2 kappa coefficients: Recommended indices of diagnostic accuracy for evidence-based practice. *Journal of Clinical Epidemiology* **62**, 1045-53.

Government of Canada (2006) Ballast water control and management regulations. Department of Justice Canada, SOR/2006-129.

Griffiths RW, Schloesser DW, Leach JH, and Kovalak WP (1991) Distribution and dispersal of the zebra mussel (*Dreissena polymorpha*) in the Great Lakes region. *Canadian Journal of Fisheries and Aquatic Sciences* **48**, 1381-8.

Grigorovich IA, Colautti RI, Mills EL, Holeck K, Ballert AG, and MacIsaac HJ (2003) Ballast-mediated animal introductions in the Laurentian Great Lakes: retrospective and prospective analyses. *Canadian Journal of Fisheries and Aquatic Sciences* **60**, 740-56.

Hawley LM and Garver KA (2008) Stability of viral hemorrhagic septicemia virus (VHSV) in freshwater and seawater at various temperatures. *Diseases of Aquatic Organisms* **82**, 171-8.

Hebert PDN, Muncaster BW, and Mackie GL (1989) Ecological and genetic studies on Dreissena polymorpha (Pallas): A new mollusc in the Great Lakes. *Canadian Journal of Fisheries and Aquatic Sciences* **46**, 1587-91.

Higgins SN (2014) Meta-Analysis of Dreissenid Effects on Freshwater Ecosystems. In *Quagga and Zebra Mussels: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), 2nd (ed.), pp. 487-94. CRC Press, Taylor & Francis, Boca Raton, FL.

Holeck KT, Mills EL, MacIsaac HJ, Dochoda MR, Colautti RI, and Ricciardi A (2004) Bridging troubled waters: Biological invasions transoceanic shipping, and the Laurentian Great Lakes. *BioScience* **54**, 919-29.

Hope KM, Casey RN, Groocock GH, Getchell RG, Bowser PR, and Casey JW (2010) Comparison of quantitative RT-PCR with cell culture to detect viral hemorrhagic septicemia virus (VHSV) IVb infections in the Great Lakes. *Journal of Aquatic Animal Health* **22**, 50-61.

IMO (2004) International Convention for the Control and Management of Ships' Ballast Water and Sediments, 2004. In *Regulation D-2: Ballast water performance standard*. IMO, London.

Jerde CL, Mahon AR, Chadderton WL, and Lodge DM (2011) "Sight-unseen" detection of rare aquatic species using environmental DNA. *Conservation Letters* **4**, 150-7.

Kane-Sutton M, Kinter B, Dennis PM, and Koonce JF (2010) Viral hemorrhagic septicemia virus infection in Yellow Perch, *Perca flavescens*, in Lake Erie. *Journal of Great Lakes Research* **36**, 37-43.

Karatayev AY, Boltovskoy D, Padilla DK, and Burlakova LE (2007a) The invasive bivalves Dreissena polymorpha and Limnoperna fortunei: Parallels, contrasts, potential spread and invasion impacts. *Journal of Shellfish Research* **26**, 205-13.

Karatayev AY, Padilla DK, Minchin D, Boltovskoy D, and Burlakova LE (2007b) Changes in global economies and trade: The potential spread of exotic freshwater bivalves. *Biological Invasions* **9**, 161-80.

Keller RP, Drake JM, Drew MB, and Lodge DM (2011) Linking environmental conditions and ship movements to estimate invasive species transport across the global shipping network. *Diversity and Distributions* **17**, 93-102.

Keller RP, Ermgassen PSEZ, and Aldridge DC (2009) Vectors and timing of freshwater invasions in Great Britain. *Conservation Biology* **23**, 1526-34.

Kim R and Faisal M (2011) Emergence and resurgence of the viral hemorrhagic septicemia virus (*Novirhabdovirus, Rhabdoviridae, Mononegavirales*). *Journal of Advanced Research* **2**, 9-23.

Landis JR and Koch GG (1977) The measurement of observer agreement for categorical data. *Biometrics* **33**, 159-74.

Leichsenring J and Lawrence J (2011) Effect of mid-oceanic ballast water exchange on virus-like particle abundance during two trans-Pacific voyages. *Marine Pollution Bulletin* **62**, 1103-8.

Lodge DM, Williams S, MacIsaac HJ, Hayes KR, Leung B, Reichard S et al. (2006) Biological invasions: Recommendations for U.S. policy and management. *Ecological Applications* **16**, 2035-54.

Lovell SJ and Drake LA (2009) Tiny stowaways: Analyzing the economic benefits of a U.S. Environmental Protection Agency permit regulating ballast water discharges. *Environmental Management* **43**, 546-55.

Lumsden JS, Morrison B, Yason C, Russell S, Young K, Yazdanpanah A et al. (2007) Mortality event in freshwater drum *Aplodinotus grunniens* from Lake Ontario, Canada, associated with viral haemorrhagic septicemia virus, Type IV. *Diseases of Aquatic Organisms* **76**, 99-111.

MacNeil C, Platvoet D, Dick JTA, Fielding N, Constable A, Hall N et al. (2010) The Ponto-Caspian 'killer shrimp', *Dikerogammarus villosus* (Sowinsky, 1894), invades the British Isles. *Aquatic Invasions* **5**, 441-5.

Manel S, Williams HC, and Ormerod SJ (2001) Evaluating presence-absence models in ecology: The need to account for prevalence. *Journal of Applied Ecology* **38**, 921-31.

Mayer CM, Burlakova LE, Eklöv P, Fitzgerald D, Karatayev AY, Ludsin SA et al. (2014) Benthification of Freshwater Lakes: Exotic Mussels Turning Ecosystems Upside Down. In *Quagga and Zebra Mussels: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), 2nd (ed.), pp. 575-85. CRC Press, Taylor & Francis Group, Boca Raton, FL.

McGee S, Piorkowski R, and Ruiz G. 2006. Analysis of recent vessel arrivals and ballast water discharge in Alaska: Toward assessing ship-mediated invasion risk. *Marine Pollution Bulletin* **52**, 1634-1645.

MDNR (2007) Fish Disease Control. Michigan Department of Natural Resources, FO-245.07A.

Meyers TR and Winton JR (1995) Viral hemorrhagic septicemia virus in North America. *Annual Review of Fish Diseases* **5**, 3-24.

Millenial Ecosystem Assessment (2005) Ecosystems and Human Well-being: Wetlands and Water Synthesis. Washington, D.C.

Miller RC and McClure FA (1931) The fresh-water clam industry of the Pearl River. *Lingnan Science Journal* **10**, 307-22.

Miller TA, Rapp J, Wastlhuber U, Hoffmann RW, and Enzmann PJ (1998) Rapid and sensitive reverse transcriptase-polymerase chain reaction based detection and differential diagnosis of fish pathogenic rhabdoviruses in organ samples and cultured cells. *Diseases of Aquatic Organisms* **34**, 13-20.

Miller AW, Minton MS, Ruiz GM (2011) Geographic limitations and regional differences in ships' ballast water management to reduce marine invasions in the contiguous United States. *BioScience* **61**, 880-887.

Mizuno T and Mori S (1970) Preliminary hydrobiological survey of some Southeast Asia inland waters. *Biological Journal of the Linnean Society* **2**, 77-117.

ML C, B G, and CL H (2007) Survey evaluations to assess marine 547 bioinvasions. *Marine Pollution Bulletin* **55**, 360-78.

Molnar JL, Gamboa RL, Revenga C, and Spalding MD (2008) Assessing the global threat of invasive species to marine biodiversity. *Frontiers in Ecology and the Environment* **6**, 485-92.

Morton B (1973) Some aspects of the biology and functional morphology of the organs of feeding and digestion of *Limnoperna fortunei* (Dunker) (Bivalvia: Mytilacea). *Malacologia* **12**, 265-81.

Müller JC, Schramm S, and Seitz A (2002) Genetic and morphological differentiation of *Dikerogammarus* invaders and their invasion history in Central Europe. *Freshwater Biology* **47**, 2039-48.

Muskó IB (1994) Occurrence of Amphipoda in Hungary since 1853. *Proceedings of the First European Crustacean Conference, 1992* **66**, 144-52.

National Research Council (2008) *Great Lakes Shipping, Trade, and Aquatic Invasive Species*. 291, p. 202, National Academy of Sciences, Nation.

NOAA (Undated) GLANSIS: Great Lakes aquatic nonindigenous species infor- mation system. http://www.glerl.noaa. gov/res/Programs/glansis/glansis.html. Accessed 11 Sept 2012.

Nesemann H, Pöckl M, and Wittmann KJ (1995) Distribution of epigean Malacostraca in the middle and upper Danube (Hungary, Austria, Germany). *Miscellanea Zoologica Hungarica* **10**, 49-68.

Panetta FD and Lawes R (2005) Evaluation of weed eradication programs: The delimitation of extent. *Diversity and Distributions* **11**, 435-42.

Pierce LR and Stepien CA (2012) Evolution and biogeography of an emerging quasispecies: Diversity patterns of the fish viral hemorrhagic septicemia virus (VHSV). *Molecular Phylogenetics and Evolution* **63**, 327-41.

Prasad AM, Iverson LR, Peters MP, Bossenbroek JM, Matthews SN, Sydnor TD et al. (2010) Modeling the invasive emerald ash borer risk of spread using a spatially explicit cellular model. *Landscape Ecology* **25**, 353-69.

Ricciardi A (2006) Patterns of invasion in the Laurentian Great Lakes in relation to changes in vector activity. *Diversity and Distributions* **12**, 425-33.

Ruiz GM, Carlton JT, Grosholz ED, and Hines AH (1997) Global invasions of marine and estuarine habitats by non-indigenous species: Mechanisms, extent, and consequences. *American Zoologist* **37**, 621-32.

Ruiz GM, Fofonoff PW, Ashton G, Minton MS, and Miller AW (2013) Geographic variation in marine invasions among large estuaries: Effects of ships and time. *Ecological Applications* **23**, 311-320.

Ruiz GM, Rawlings TK, Dobbs FC, Drake LA, Mullady T, Huq A et al. (2000) Global spread of microorganisms by ships. *Nature* **408**, 49-50.

Ruiz GM and Reid DF (2010) Current state of understanding about the effectiveness of ballast water exchange (BWE) in reducing aquatic nonindigenous species (ANS) introductions to the Great Lakes Basin and Chesapeake Bay, USA: Synthesis and analysis of existing information. In *Ballast water management: Combating aquatic invaders*. O'Sullivan EG (ed.), pp. 25-148. Nova Science Publishers, Inc., New York.

Rup MP, Bailey SA, Wiley CJ, Minton MS, Miller AW, Ruiz GM et al. (2010) Domestic ballast operations on the Great Lakes: Potential importance of lakers as a vector for introduction and spread of nonindigenous species. *Canadian Journal of Fisheries and Aquatic Sciences* **67**, 256-68.

Savino JF and Kolar CS (1996) Competition between nonindigenous ruffe and native yellow perch in laboratory studies. *Transactions of the American Fisheries Society* **125**, 562-71.

Schneider DW, Ellis CD, and Cummings KS (1998) A transportation model assessment of the risk to native mussel communities from zebra mussel spread. *Conservation biology* **12**, 788-800.

Shipping Federation of Canada (2000) Code of best practices for ballast water management. Shipping Federation of Canada, Montreal.

Sieracki JL, Bossenbroek JM, and Chadderton WL (In Review) A spatial modeling approach to predicting the secondary spread of invasive species due to ballast water discharge.

Sieracki JL, Bossenbroek JM, and Faisal M (2014) Modeling the secondary spread of viral hemorrhagic septicemia virus (VHSV) by commercial shipping in the Laurentian Great Lakes. *Biological Invasions* **16**, 1043-53.

Sierszen ME, Keough JR, and Hagley CA (1996) Trophic analysis of ruffe (*Gymnocephalus cernuus*) and white perch (*Morone americana*) in a Lake Superior coastal food web, using stable isotope techniques. *Journal of Great Lakes Research* **22**, 436-43.

Simberloff D, Parker IM, and Windle PN (2005) Introduced species policy, management, and future research needs. *Frontiers in Ecology and the Environment* **3**, 12-20.

Simon TP and Vondruska JT (1991) Larval identification of the ruffe, *Gymnocephalus cernuus* (Linnaeus) (Percidae: Percini), in the St. Louis River Estuary, Lake Superior drainage basin, Minnesota. *Canadian Journal of Zoology* **69**, 436-42.

Smithsonian Environmental Research Center and USCG (2009) National Ballast Information Clearinghouse. http:// invasions.si.edu/nbic/search.html. Accessed Aug 2012.

Stepien CA, Brown JE, Neilson ME, and Tumeo MA (2005) Genetic diversity of invasive species in the Great Lakes versus their Eurasian source populations: Insights for risk analysis. *Risk Analysis* **25**, 1043 - 60.

Stepien CA, Dillon AK, and Chandler MD (1998) Genetic identity, phylogeography, and systematics of ruffe *Gymnocephalus* in the North American Great Lakes and Eurasia. *Journal of Great Lakes Research* **24**, 361-78.

The Seaway: Seaway History (2014) The St. Lawrence Seaway Management Corporation. http://www.greatlakes-seaway.com/en/seaway/history/index.html. Accessed 24 May, 2014.

Thompson TM, Batts WN, Faisal M, Bowser P, Casey JW, Phillips K et al. (2011) Emergence of *Viral hemorrhagic septicemia virus* in the North American Great Lakes region is associated with low viral genetic diversity. *Diseases of Aquatic Organisms* **96**, 29-43.

Transport Canada (2010) Ballast Water Defined. https://www.tc.gc.ca/eng/marinesafety/oep-environment-ballastwater-defined-249.htm. Accessed 24 May, 2014.

USCG (2012) Ballast Water Management for Control of Nonindigenous Species in the Great Lakes and Hudson River. 33 C.F.R § 151(c).

USDOT Maritime Administration (2013) Status of the U.S.-Flag Great Lakes Water Transportation Industry. USDOT, Maritime Administration, Washington, DC.

USEPA (2013) Vessel General Permit for Discharges Incidental to the Normal Operation of Vessels (VGP). USEPA,, Washington, D.C.

USEPA Science Advisory Board (2011) *Efficacy of ballast water treatment systems: a report by the EPA Science Advisory Board*. USEPA, EPA-SAB-11-009.

USGS (2009) NAS-Nonindigenous aquatic species database. http://nas.er.usgs.gov. Accessed 30 July 2011.

Chico V, Gomez N, Estepa A, and Perez L (2006) Rapid detection and quantitation of viral hemorrhagic septicemia virus in experimentally challenged rainbow trout by real-time RT-PCR. *Journal of Virological Methods* **132**, 154-9.

Wald A, Huang M-L, Carrell D, Selke S, and Corey L (2003) Polymerase chain reaction for detection of herpes simplex virus (HSV) DNA on mucosal surfaces: Comparison with HSV isolation in cell culture. *Journal of Infectious Diseases* **188**, 1345-51.

Ward JM and Ricciardi A (2014) Impacts of *Dreissena* on Benthic Macroinvertebrate Communities Predictable Patterns REvealed by Invasion History. In *Quagga and Zebra Musses: Biology, Impacts, and Control*. Nalepa TF and Schloesser DW (ed.), 2nd (ed.), pp. 599-610. CRC Press, Taylor & Francis Group, Boca Raton, FL.

Warrens MJ (2011) Cohen's linearly weighted kappa is a weighted average of 2 x 2 kappas. *Psychometrika* **76**, 471-86.

World Organisation for Animal Health (2011) Chapter 2.3.9.: Viral haemorrhagic septicaemia. In *Manual of Diagnostic Tests for Aquatic Animals 2011: Summary*. World Organisation for Animal Health, Paris, France.

Xu M, Wang Z, Lin CC, Pan B, and Zhao N (2013) Experimental study of invasion and biofouling of freshwater mussel *Limnoperna fortunei*. *International Journal of Geosciences* **4**, 7

Appendix A

Compiled National Ballast Information Clearinghouse (NBIC) Data for 2004-2010

The following tables contain the compiled NBIC data that was used to establish the pattern of spread for both the location and propagule pressure models. The data is recorded here as it was input the models described in Chapters 3 and 4; however, data used in Chapter 2 can also be derived from the tables included here.

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
41.55 -82.73	-82.73000000	41.55000000	0	0	0	0	0	6	0	6	1
41.63 -87.32	-87.32000000	41.63000000	1	0	0	0	0	0	0	1	0
41.64 -87.14	-87.14000000	41.64000000	0	0	0	0	0	10	0	10	1
41.68 -87.30	-87.30000000	41.68000000	0	1	0	0	0	0	0	1	0
41.68 -87.45	-87.45000000	41.68000000	0	6	0	0	0	3	0	9	1
41.71 -87.54	-87.54000000	41.71000000	1	0	0	0	0	0	0	1	0
41.75 -81.28	-81.28000000	41.75000000	1	0	0	0	0	0	0	1	0
41.80 -82.20	-82.20000000	41.80000000	0	28	0	0	0	0	0	28	4
41.80 -87.40	-87.40000000	41.80000000	0	1	0	0	0	0	0	1	0
41.82 -82.33	-82.33000000	41.82000000	0	0	2	0	0	0	0	2	0
41.83 -82.20	-82.20000000	41.83000000	0	34	8	0	0	0	0	42	6
41.85 -82.12	-82.12000000	41.85000000	8	0	0	0	0	0	0	8	1
41.89 -87.45	-87.45000000	41.89000000	1	0	0	0	0	0	0	1	0
41.89 -87.53	-87.53000000	41.89000000	9	6	0	0	0	1	0	16	2
41.90 -82.88	-82.88000000	41.90000000	0	2	0	0	0	0	0	2	0
41.97 -80.55	-80.55000000	41.97000000	10	7	0	0	0	0	0	17	2
42.00 -87.30	-87.30000000	42.00000000	1	0	0	0	0	0	0	1	0
42.20 -87.20	-87.20000000	42.20000000	0	0	1	0	0	0	0	1	0
42.20 -87.30	-87.30000000	42.20000000	0	0	0	4	0	0	0	4	1
42.50 -87.10	-87.10000000	42.50000000	0	0	1	0	0	0	0	1	0

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
42.59 -87.65	-87.65000000	42.59000000	0	0	12	0	0	0	0	12	2
42.60 -86.30	-86.30000000	42.60000000	0	1	0	0	0	0	0	1	0
42.60 -87.13	-87.13000000	42.60000000	0	1	0	0	0	0	0	1	0
42.79 -86.12	-86.12000000	42.79000000	2	1	0	0	0	8	0	11	2
42.79 -86.21	-86.21000000	42.79000000	1	0	0	0	0	0	0	1	0
42.80 -86.30	-86.30000000	42.80000000	0	2	0	0	0	0	0	2	0
42.80 -86.50	-86.50000000	42.80000000	0	1	0	0	0	0	0	1	0
42.87 -78.88	-78.88000000	42.87000000	0	2	0	0	0	0	0	2	0
42.88 -79.25	-79.24733500	42.88038071	0	1	0	0	0	0	0	1	0
43.00 -87.00	-87.00000000	43.00000000	0	0	0	1	0	1	0	2	0
43.03 -87.90	-87.89405135	43.03000000	0	0	0	0	0	2	0	2	0
43.23 -86.35	-86.35000000	43.23000000	0	0	0	0	0	1	0	1	0
43.27 -86.83	-86.83000000	43.27000000	6	0	0	0	0	0	0	6	1
43.32 -79.22	-79.22000000	43.32000000	0	1	0	0	0	0	0	1	0
43.40 -86.80	-86.80000000	43.40000000	0	0	1	0	0	0	0	1	0
43.50 -86.60	-86.60000000	43.50000000	0	0	1	0	0	0	0	1	0
43.60 -86.80	-86.80000000	43.60000000	0	1	0	0	0	0	0	1	0
43.65 -77.83	-77.83000000	43.65000000	0	0	0	0	1	0	0	1	0
43.70 -86.70	-86.70000000	43.70000000	1	0	0	0	0	0	0	1	0
43.74 -86.70	-86.70000000	43.70000000	0	0	0	1	0	0	0	1	0

Table A.1. Ballast water discharge location information

			Number of Discharging Ship Visits								
NBIC Discharge Location	**Longitude**	**Latitude**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**	**Mean**
43.90 -87.65	-87.65000000	43.90000000	1	0	0	0	0	0	0	1	0
43.92 -87.26	-87.26000000	43.92000000	0	0	0	0	1	0	0	1	0
43.93 -87.24	-87.24000000	43.93000000	0	0	0	0	1	0	0	1	0
43.94 -87.26	-87.26000000	43.94000000	0	0	0	0	1	0	0	1	0
43.95 -86.45	-86.45000000	43.95000000	1	0	0	0	0	0	0	1	0
43.95 -87.26	-87.26000000	43.95000000	0	0	0	0	2	0	0	2	0
44.10 -87.65	-87.64583594	44.09821540	1	0	0	0	0	0	0	1	0
44.37 -86.42	-86.42000000	44.37000000	0	0	1	0	0	0	0	1	0
44.40 -87.30	-87.30000000	44.40000000	0	1	0	0	0	0	0	1	0
44.465 -75.79833	-75.79833000	44.46500000	0	0	0	0	0	0	4	4	1
44.50 -86.70	-86.70000000	44.50000000	0	1	0	0	0	0	0	1	0
44.54 -88.01	-88.01000000	44.54000000	0	0	0	0	0	1	0	1	0
44.60 -87.30	-87.30000000	44.60000000	0	0	0	1	0	0	0	1	0
44.80 -87.30	-87.30000000	44.80000000	0	0	0	1	0	0	0	1	0
45.02 -85.92	-85.92000000	45.02000000	6	0	0	0	0	0	0	6	1
45.10 -87.60	-87.59900573	45.09758533	2	0	0	0	0	0	0	2	0
45.20 -83.17	-83.17000000	45.20000000	6	0	0	0	0	0	0	6	1
45.25 -83.22	-83.22000000	45.25000000	0	0	0	0	0	1	0	1	0
45.32 -85.32	-85.32000000	45.32000000	17	16	0	0	0	0	0	33	5
45.35 -86.13	-86.13000000	45.35000000	6	0	0	0	0	0	0	6	1

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
45.40 -85.50	-85.50000000	45.40000000	0	12	0	1	0	0	0	13	2
45.41 -83.82	-83.80953037	45.42142141	1	2	0	0	0	1	0	4	1
45.43 -83.40	-83.40000000	45.43000000	2	0	0	0	0	0	0	2	0
45.43 -85.50	-85.50000000	45.43000000	4	0	0	0	0	0	0	4	1
45.45 -85.45	-85.45000000	45.45000000	2	0	0	0	0	0	0	2	0
45.47 -85.47	-85.47000000	45.47000000	2	0	0	0	0	0	0	2	0
45.50 -85.42	-85.42000000	45.50000000	2	44	32	0	0	0	0	78	11
45.51 -83.47	-83.47000000	45.51000000	0	0	0	0	0	0	3	3	0
45.53 -84.02	-84.02000000	45.53000000	0	0	0	0	0	0	3	3	0
45.55 -85.38	-85.38000000	45.55000000	2	0	0	0	0	0	0	2	0
45.57 -85.35	-85.35000000	45.57000000	0	0	0	0	0	2	3	5	1
45.60 -83.55	-83.55000000	45.60000000	2	0	0	0	0	0	0	2	0
45.60 -86.10	-86.10000000	45.60000000	0	0	1	0	0	1	0	2	0
45.63 -86.12	-86.12000000	45.63000000	0	4	0	0	0	0	0	4	1
45.67 -86.20	-86.20000000	45.67000000	0	2	0	0	0	0	0	2	0
45.70 -83.70	-83.70000000	45.70000000	0	78	0	0	0	0	0	78	11
45.70 -86.70	-86.70000000	45.70000000	1	0	0	0	0	0	0	1	0
45.72 -83.68	-83.68000000	45.72000000	2	0	0	0	0	0	0	2	0
45.73 -84.53	-84.53000000	45.73000000	1	0	0	0	0	0	0	1	0
45.80 -84.80	-84.80000000	45.80000000	0	0	0	1	0	0	0	1	0

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
45.81 -84.21	-84.21000000	45.81000000	1	0	0	0	0	0	0	1	0
45.83 -84.55	-84.55000000	45.83000000	6	0	0	0	0	0	0	6	1
45.85 -85.13	-85.13000000	45.85000000	0	0	0	0	7	0	0	7	1
45.87 -85.30	-85.30000000	45.87000000	6	0	0	0	0	0	0	6	1
45.92 -83.83	-83.83000000	45.92000000	0	6	0	0	0	0	0	6	1
45.92 -83.92	-83.92000000	45.92000000	0	3	0	0	0	0	0	3	0
45.95 -83.88	-83.88000000	45.95000000	8	0	0	0	0	0	0	8	1
45.96 -85.88	-85.88000000	45.96000000	4	14	0	0	0	26	0	44	6
45.97 -85.87	-85.87000000	45.97000000	1	0	0	0	0	0	0	1	0
45.98 -84.21	-84.21000000	45.98000000	3	7	0	0	0	23	0	33	5
45.98167 -84.20834	-84.20890816	45.97882922	0	0	0	0	0	0	1	1	0
46.00 -83.90	-83.90000000	46.00000000	2	0	0	0	0	0	0	2	0
46.07 -84.00	-84.00000000	46.07000000	3	0	0	0	0	0	0	3	0
46.07 -84.02	-84.02000000	46.07000000	15	0	0	0	0	0	0	15	2
46.33 -84.18	-84.18000000	46.33000000	0	1	0	0	0	0	0	1	0
46.5 -84.33334	-84.33334000	46.50000000	0	0	0	0	0	0	1	1	0
46.52 -84.41	-84.41571071	46.50929243	0	1	0	0	0	0	0	1	0
46.60 -84.80	-84.80000000	46.60000000	0	0	0	0	0	1	0	1	0
46.78 -92.09	-92.09000000	46.78000000	0	0	0	0	0	1	0	1	0
47.00 -91.67	-91.67000000	47.00000000	0	5	0	0	0	0	0	5	1

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	2004	2005	2006	2007	2008	2009	2010	Total	Mean
			Number of Discharging Ship Visits								
47.40 -87.33	-87.33000000	47.40000000	0	0	0	1	0	0	0	1	0
47.5 -88.4	-88.40000000	47.50000000	0	0	0	0	0	0	1	1	0
47.65 -87.88	-87.88000000	47.65000000	0	0	0	0	5	0	0	5	1
Alpena	-83.42248041	45.05617658	297	903	819	903	705	552	755	4934	705
Ashtabula	-80.79284082	41.92097164	321	927	829	855	1279	632	771	5614	802
Bay City	-83.89436423	43.59458002	0	1	29	2	8	5	0	45	6
Brevort	-85.00525546	46.00228847	99	214	225	172	143	93	138	1084	155
Bruce Mines	-83.61040038	46.22432871	0	0	0	7	2	4	0	13	2
Buffalo	-78.89352308	42.87302286	6	57	62	70	154	62	93	504	72
Buffington	-87.41681132	41.64609891	18	9	0	0	0	0	8	35	5
Burns Harbour	-87.15627276	41.64309038	34	63	93	64	49	57	88	448	64
Calcite	-83.78375307	45.41256739	945	2328	2127	2125	1972	1472	1513	12482	1783
Calumet	-87.59000000	41.68000000	200	529	273	270	305	189	51	1817	260
Cedarville	-84.35573909	45.99432933	70	250	253	388	153	129	236	1479	211
Charlevoix	-85.26665891	45.32060596	281	788	802	813	678	328	467	4157	594
Chicago	-87.61117156	41.88766995	83	254	222	276	338	370	649	2192	313
Cleveland	-81.69326296	41.51123219	162	398	272	194	209	207	430	1872	267
Conneaut	-80.54845446	41.96742176	311	737	685	598	238	2	225	2796	399
Dearborn (USA, MI)	-83.15466718	42.29710166	0	0	9	0	0	12	31	52	7
Detroit	-83.11071510	42.26993213	104	177	167	184	186	229	157	1204	172

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits 2004	2005	2006	2007	2008	2009	2010	Total	Mean
Drummond Island	-83.88710041	45.99347694	197	512	525	530	422	352	352	2890	413
Duluth	-92.09559323	46.77757890	382	1629	1389	1964	1494	1081	1403	9342	1335
Ecorse	-83.13897379	42.24038919	9	48	13	11	10	18	11	120	17
Erie	-80.06813164	42.15154000	0	12	36	20	26	31	37	162	23
Escanaba	-87.02521064	45.73393228	91	278	371	382	544	202	387	2255	322
Essexville	-83.84551468	43.61709960	0	0	7	9	0	0	0	16	2
Fairport (USA, OH)	-81.29216737	41.76733212	0	29	66	33	18	74	84	304	43
Fairport Harbor	-81.29216737	41.76733212	33	77	58	61	75	115	136	555	79
Ferrysburg	-86.26650485	43.10245213	0	0	1	1	1	0	6	9	1
Gary	-87.32625606	41.61279472	20	15	18	12	18	36	269	388	55
Gladstone (USA, MI)	-86.99229658	45.85194417	0	0	0	0	0	0	1	1	0
Goderich	-81.72245295	43.74750157	0	0	6	0	6	0	0	12	2
Grand Haven	-86.23588202	43.06723122	22	63	26	96	34	52	25	318	45
Green Bay	-88.01915727	44.51623062	10	37	33	24	27	2	79	212	30
Hamilton (Canada)	-79.85843165	43.28144106	0	1	15	6	0	0	8	30	4
Harbor Beach	-82.64308647	43.84544313	8	0	0	0	0	0	0	8	1
Holland	-86.21816734	42.77769307	0	0	11	1	10	0	28	50	7
Huron	-82.55901593	41.41169036	15	0	2	0	1	0	1	19	3
Indiana Harbor	-87.44565848	41.67603000	116	100	60	42	16	13	171	518	74
Kelleys Island	-82.72822529	41.61511955	43	352	404	308	88	0	0	1195	171

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
Kingsville	-82.66864816	42.01795767	0	0	0	4	0	0	0	4	1
Lorain	-82.19633670	41.48326690	13	31	26	6	37	14	144	271	39
Ludington	-86.45153054	43.95140843	43	155	178	149	146	31	71	773	110
Mackinaw City	-84.72777778	45.78867507	0	0	18	0	0	0	0	18	3
Manistee	-86.34252995	44.24989629	4	10	7	0	0	7	80	108	15
Manitowoc	-87.64732600	44.09402244	0	0	1	1	2	0	16	20	3
Marblehead	-82.70903179	41.52939236	454	1236	1220	1337	1106	759	1128	7240	1034
Marine City	-82.49429312	42.70757559	0	3	14	0	0	0	9	26	4
Marinette	-87.60021134	45.09407405	0	0	8	1	1	20	6	36	5
Marquette	-87.38781613	46.53254391	489	1727	1722	1451	1629	1112	1952	10082	1440
Marysville	-82.48166352	42.82705600	8	10	9	2	7	0	1	37	5
Meldrum Bay	-83.09738910	45.94401979	0	35	17	1	6	9	19	87	12
Menominee	-87.60105220	45.09754051	0	0	0	16	0	30	16	62	9
Milwaukee	-87.89178675	43.02572009	19	51	97	91	36	51	75	420	60
Monroe	-83.35105572	41.87523576	19	4	0	10	0	7	3	43	6
Montreal	-73.54699411	45.50183563	0	0	1	1	0	0	0	2	0
Munising	-86.64650415	46.42047134	0	0	0	0	0	0	8	8	1
Muskegon	-86.35028973	43.19498154	1	7	12	2	15	0	1	38	5
Nanticoke	-80.04217491	42.79599297	0	16	7	0	5	0	5	33	5
Ontonagon	-89.31749707	46.88971051	0	0	2	0	0	0	0	2	0

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
Oswego	-76.50826842	43.47142499	0	0	3	8	0	0	4	15	2
Owen Sound	-80.94082864	44.58165727	0	0	0	0	2	0	0	2	0
Port Arthur	-89.12874868	48.41386870	0	0	0	10	0	0	0	10	1
Port Colborne	-80.19576040	42.78104103	0	11	0	0	1	0	0	12	2
Port Dolomite	-84.31318454	45.99126085	155	710	454	437	556	426	549	3287	470
Port Gypsum	-82.87557503	41.48920047	22	97	124	76	66	31	12	428	61
Port Inland	-85.86311644	45.95479905	209	1005	1166	821	978	617	702	5498	785
Prescott	-75.51131288	44.70595909	0	0	0	0	0	0	1	1	0
Presque Isle	-87.38546026	46.57723878	647	1587	1479	1448	1195	955	1006	8317	1188
River Rouge	-83.11753054	42.27423857	10	10	7	2	7	15	118	169	24
Rogers City	-83.81228929	45.42400641	0	0	0	0	0	0	7	7	1
Saginaw	-83.94945883	43.42000938	0	7	11	1	0	0	10	29	4
Saint Clair	-82.48365223	42.82030872	8	2	0	0	8	0	38	56	8
Saint Joseph	-86.49758743	42.09997281	14	0	15	8	6	0	11	54	8
Saint Marys River (USA, Great Lakes)	-84.17254652	46.24113045	7	0	0	0	0	0	0	7	1
Sandusky	-82.71433826	41.47022000	363	1198	1072	927	945	544	806	5855	836
Sarnia	-82.38542117	42.96761211	0	41	29	5	11	7	9	102	15
Sault Ste. Marie (Canada)	-84.33910563	46.50623582	0	0	0	0	4	0	5	9	1
Sault Ste. Marie (Unknown)	-84.36187160	46.50619995	1	0	0	0	0	0	0	1	0

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Total**	**Mean**
Sault Ste. Marie (USA, MI)	-84.34547400	46.49697400	0	14	6	57	2	14	0	93	13
Silver Bay	-91.26094919	47.28134631	260	1052	967	1210	1401	519	1308	6717	960
Soo Locks (Sault Ste. Marie, MI)	-84.34850000	46.50250000	0	0	0	0	2	0	0	2	0
South Chicago	-87.53339626	41.76514493	0	51	66	84	104	64	126	495	71
Stoneport	-83.41958130	45.29548266	354	855	1340	1340	1511	870	1056	7326	1047
Sturgeon Bay	-87.39444444	44.85416667	34	145	68	84	98	138	121	688	98
Superior	-92.09088501	46.74762037	1710	5248	5277	5387	5242	3104	4285	30253	4322
Taconite Harbor	-90.91119577	47.52896843	7	0	0	9	12	0	1	29	4
Tawas City	-83.51796162	44.26569244	0	5	0	0	0	0	6	11	2
Thessalon	-83.55487011	46.21785730	0	0	8	0	7	0	0	15	2
Thunder Bay	-89.20142133	48.39932926	13	27	0	0	2	15	22	79	11
Toledo (USA)	-83.47027097	41.69149353	473	1355	1236	1323	1115	1185	1390	8077	1154
Toronto	-79.28754265	43.59849232	0	0	0	0	0	1	0	1	0
Traverse City	-85.61232349	44.77196180	0	1	0	0	0	0	0	1	0
Two Harbors	-91.66378092	47.00456203	581	2049	2400	2468	2365	1024	2473	13360	1909
Waukegan	-87.80620035	42.37250000	1	3	0	0	9	4	10	27	4
Whitefish Point	-84.94140188	46.77351513	10	0	0	0	0	0	0	10	1
Whiting	-87.48350532	41.68859648	85	194	138	162	353	256	187	1375	196
Windsor	-83.07957510	42.30398452	0	7	9	0	0	0	5	21	3

Table A.1. Ballast water discharge location information

NBIC Discharge Location	Longitude	Latitude	Number of Discharging Ship Visits								
			2004	2005	2006	2007	2008	2009	2010	Total	Mean
Wyandotte	-83.14414366	42.20734516	0	0	2	0	0	0	0	2	0
Zug Island (USA, MI)	-83.10734880	42.28139564	0	0	0	0	1	1	0	2	0

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
41.46 -71.37	-82.16000000	41.46000000	2
41.46 -82.16	-82.16000000	41.46000000	3
41.52 -81.71	-81.71000000	41.52000000	1
41.62 -87.30	-87.30000000	41.62000000	2
41.63 -87.14	-87.14000000	41.63000000	1
41.67 -87.16	-87.16000000	41.67000000	4
41.67 -87.43	-87.43000000	41.67000000	1
41.68 -82.17	-82.17000000	41.68000000	12
41.69 -87.55	-87.55000000	41.69000000	1
41.75 -81.28	-81.28000000	41.75000000	1
41.78 -87.45	-87.45000000	41.78000000	1
41.80 -82.43	-82.43000000	41.80000000	12
41.87 -82.60	-82.60000000	41.87000000	2
41.89 -87.53	-87.53000000	41.89000000	12
41.90 -82.87	-82.87000000	41.90000000	1
41.90 -87.10	-87.10000000	41.90000000	1
41.90 -87.40	-87.40000000	41.90000000	2
41.90 -87.60	-87.60000000	41.90000000	1
41.92 -80.80	-80.80000000	41.92000000	3
41.92 -81.33	-81.33000000	41.92000000	1
41.95 -82.00	-82.00000000	41.95000000	1
41.95 -87.15	-87.15000000	41.95000000	2
41.97 -80.55	-80.55000000	41.97000000	2
41.97 -81.77	-81.77000000	41.97000000	1
42.00 -87.50	-87.50000000	42.00000000	1
42.10 -87.32	-87.32000000	42.10000000	1
42.11 -87.47	-87.47000000	42.11000000	3
42.21 -83.14	-83.14000000	42.21000000	3
42.22 -81.05	-81.05000000	42.22000000	2
42.28 -83.11	-83.11000000	42.28000000	1
42.31 -80.72	-80.72000000	42.31000000	2
42.33 -83.02	-83.02000000	42.33000000	4
42.36 -86.53	-86.53000000	42.36000000	4

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
42.36 -87.72	-87.72000000	42.36000000	7
42.37 -87.78	-87.78000000	42.37000000	7
42.40 -82.40	-82.41408641	42.39847715	2
42.42 -81.63	-81.63000000	42.42000000	1
42.45 -87.15	-87.15000000	42.45000000	2
42.47 -87.08	-87.08000000	42.47000000	12
42.47 -87.71	-87.71000000	42.47000000	7
42.59 -87.65	-87.65000000	42.59000000	12
42.60 -87.15	-87.15000000	42.60000000	1
42.62 -80.03	-80.03000000	42.62000000	2
42.66 -79.70	-79.70000000	42.66000000	1
42.68 -80.03	-80.03000000	42.68000000	6
42.73 -79.51	-79.51000000	42.73000000	4
42.79 -86.12	-86.12000000	42.79000000	16
42.82 -79.33	-79.33000000	42.82000000	3
42.88 -79.25	-79.24733500	42.88038071	18
42.90 -87.00	-87.00000000	42.90000000	1
43 -87.86667	-87.86667000	43.00000000	1
43.00 -86.50	-86.50000000	43.00000000	1
43.00 -87.00	-87.00000000	43.00000000	1
43.00 -87.60	-87.60000000	43.00000000	1
43.02 -87.87	-87.87000000	43.02000000	7
43.03 -87.90	-87.89405135	43.03000000	6
43.05 -86.25	-86.25000000	43.05000000	1
43.07 -86.23	-86.23000000	43.07000000	36
43.08 -82.40	-82.40000000	43.08000000	7
43.10 -82.40	-82.40000000	43.10000000	75
43.10 -82.42	-82.42000000	43.10000000	4
43.10 -87.87	-87.87000000	43.10000000	5
43.17 -82.42	-82.42000000	43.17000000	6
43.20 -82.42	-82.42000000	43.20000000	2
43.23 -86.35	-86.35000000	43.23000000	11
43.23 -86.79	-86.79000000	43.23000000	1

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
43.28 -79.56	-79.56000000	43.28000000	1
43.28 -79.67	-79.67000000	43.28000000	6
43.28 -79.83	-79.83000000	43.28000000	6
43.30 -79.30	-79.30000000	43.30000000	3
43.30 -79.77	-79.77000000	43.30000000	3
43.33 -79.83	-79.81380124	43.31056149	6
43.35 -86.55	-86.55000000	43.35000000	1
43.39 -86.65	-86.65000000	43.39000000	8
43.40 -83.96	-83.96484639	43.39976359	1
43.43 -87.19	-87.19000000	43.43000000	1
43.48 -78.57	-78.57000000	43.48000000	2
43.48 -82.47	-82.47000000	43.48000000	6
43.50 -86.70	-86.70000000	43.50000000	2
43.50 -86.80	-86.80000000	43.50000000	1
43.50 -86.82	-86.82000000	43.50000000	1
43.52 -78.42	-78.42000000	43.52000000	2
43.55 -87.37	-87.37000000	43.55000000	1
43.60 -78.08	-78.08000000	43.60000000	2
43.63 -77.95	-77.95000000	43.63000000	1
43.64 -83.86	-83.84929243	43.64666249	6
43.68 -77.75	-77.75000000	43.68000000	1
43.71 -77.54	-77.54000000	43.71000000	1
43.73 -86.72	-86.72000000	43.73000000	1
43.77 -77.26	-77.26000000	43.77000000	4
43.80 -77.14	-77.14000000	43.80000000	1
43.94 -76.67	-76.67000000	43.94000000	6
43.94667 -86.44833	-86.44833000	43.94667000	1
43.95 -86.45	-86.45000000	43.95000000	21
43.97 -82.58	-82.58000000	43.97000000	2
43.98 -86.98	-86.98000000	43.98000000	1
44.0 -87.4	-87.40000000	44.00000000	2
44.05 -82.62	-82.62000000	44.05000000	10
44.10 -82.48	-82.48000000	44.10000000	1

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
44.10 -87.48	-87.48000000	44.10000000	12
44.16 -76.32	-76.32000000	44.16000000	1
44.25 -82.72	-82.72000000	44.25000000	3
44.25 -86.30	-86.30000000	44.25000000	1
44.26 -86.79	-86.79000000	44.26000000	1
44.30 -86.50	-86.50000000	44.30000000	1
44.33 -87.08	-87.08000000	44.33000000	1
44.40 -82.78	-82.78000000	44.40000000	6
44.40 -86.50	-86.50000000	44.40000000	1
44.465 -75.79833	-75.79833000	44.46500000	4
44.52 -86.50	-86.50000000	44.52000000	1
44.52 -86.57	-86.57000000	44.52000000	3
44.54 -88.01	-88.01000000	44.54000000	1
44.55 -82.85	-82.85000000	44.55000000	1
44.62 -80.92	-80.92000000	44.62000000	4
44.67 -82.83	-82.83000000	44.67000000	1
44.70 -82.95	-82.95000000	44.70000000	10
44.70 -86.40	-86.40000000	44.70000000	2
44.90 -87.40	-87.40000000	44.90000000	2
44.90 -87.43	-87.43000000	44.90000000	1
45.00 -86.75	-86.75000000	45.00000000	1
45.10 -87.60	-87.59900573	45.09758533	11
45.20 -86.20	-86.20000000	45.20000000	1
45.20 -86.40	-86.40000000	45.20000000	1
45.20 -87.50	-87.50000000	45.20000000	2
45.23 -86.28	-86.28000000	45.23000000	2
45.26 -85.18	-85.18000000	45.26000000	4
45.30 -83.32	-83.32000000	45.30000000	1
45.30 -86.10	-86.10000000	45.30000000	1
45.32 -85.32	-85.32000000	45.32000000	1
45.32 -86.10	-86.10000000	45.32000000	1
45.40 -85.60	-85.60000000	45.40000000	1
45.40 -86.10	-86.10000000	45.40000000	3

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
45.43 -86.73	-86.73000000	45.43000000	1
45.47 -86.96	-86.96000000	45.47000000	9
45.50 -86.10	-86.10000000	45.50000000	6
45.50 -86.37	-86.37000000	45.50000000	1
45.50 -86.60	-86.60000000	45.50000000	5
45.6 -86.3	-86.30000000	45.60000000	2
45.60 -85.10	-85.10000000	45.60000000	3
45.60 -86.10	-86.10000000	45.60000000	43
45.67 -86.20	-86.20000000	45.67000000	1
45.68 -83.65	-83.65000000	45.68000000	7
45.70 -83.70	-83.70000000	45.70000000	3
45.70 -84.30	-84.30000000	45.70000000	1
45.70 -86.00	-86.00000000	45.70000000	1
45.70 -86.30	-86.30000000	45.70000000	1
45.80 -85.82	-85.82000000	45.80000000	1
45.80 -86.10	-86.10000000	45.80000000	2
45.85 -86.13	-86.13000000	45.85000000	6
45.87 -85.18	-85.18000000	45.87000000	1
45.90 -84.00	-84.00000000	45.90000000	2
46.03 -73.03	-73.04142141	46.06319348	1
46.08 -82.40	-82.40000000	46.08000000	8
46.13 -72.96	-72.96000000	46.13000000	3
46.20 -84.11	-84.11000000	46.20000000	6
46.20 -84.20	-84.20000000	46.20000000	26
46.30 -84.20	-84.20000000	46.30000000	176
46.33 -84.18	-84.18000000	46.33000000	71
46.37 -84.20	-84.20000000	46.37000000	4
46.38 -84.22	-84.22000000	46.38000000	85
46.40 -84.23	-84.23535379	46.39892924	3
46.47 -84.30	-84.29801145	46.47085224	2
46.47 -84.57	-84.57000000	46.47000000	6
46.5 -84.33334	-84.33334000	46.50000000	2
46.50 -84.60	-84.60000000	46.50000000	39

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
46.50 -84.61	-84.61000000	46.50000000	5
46.50 -86.70	-86.70000000	46.50000000	1
46.51 -84.62	-84.62000000	46.51000000	9
46.52 -84.41	-84.41571071	46.50929243	3
46.52 -84.62	-84.62000000	46.52000000	5
46.53 -84.67	-84.67000000	46.53000000	16
46.53 -84.70	-84.70000000	46.53000000	5
46.57 -72.05	-72.05000000	46.57000000	1
46.57 -84.73	-84.73000000	46.57000000	6
46.65 -84.95	-84.95000000	46.65000000	4
46.66 -71.64	-71.64000000	46.66000000	1
46.80 -85.10	-85.10000000	46.80000000	1
46.80 -85.20	-85.20000000	46.80000000	1
46.83 -71.07	-71.07000000	46.83000000	1
46.83 -85.17	-85.17000000	46.83000000	40
46.88 -85.30	-85.30000000	46.88000000	6
47.00 -85.08	-85.08000000	47.00000000	1
47.00 -85.60	-85.60000000	47.00000000	10
47.00 -85.70	-85.70000000	47.00000000	1
47.15 -90.73	-90.73000000	47.15000000	32
47.16667 -90.43333	-90.43333000	47.16667000	144
47.17 -90.42	-90.42000000	47.17000000	191
47.17 -90.43	-90.43000000	47.17000000	757
47.18 -86.48	-86.48000000	47.18000000	10
47.18 -90.38	-90.38000000	47.18000000	10
47.20 -86.51	-86.51000000	47.20000000	1
47.20 -90.40	-90.40000000	47.20000000	112
47.20 -90.60	-90.60000000	47.20000000	28
47.28 -89.57	-89.57000000	47.28000000	1
47.37 -89.33	-89.33000000	47.37000000	190
47.40 -70.45	-70.45000000	47.40000000	1
47.42 -87.33	-87.33000000	47.42000000	5
47.45 -87.45	-87.45000000	47.45000000	1

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
47.45 -88.63	-88.63000000	47.45000000	11
47.52 -87.83	-87.83000000	47.52000000	6
47.57 -87.92	-87.92000000	47.57000000	6
47.62 -70.03	-70.03000000	47.62000000	1
47.77 -69.87	-69.87000000	47.77000000	1
48.20 -69.88	-69.88000000	48.20000000	1
48.50 -88.35	-88.35000000	48.50000000	1
49.20 -64.62	-64.62000000	49.20000000	1
49.40 -64.63	-64.63000000	49.40000000	2
49.40 -64.93	-64.93000000	49.40000000	1
49.52 -65.78	-65.78000000	49.52000000	1
Algoma (Sault Ste. Marie, Canada)	-84.33361492	46.50466286	40
Alpena	-83.42248041	45.05617658	1044
Ashland (USA, WI)	-90.93552749	46.59105680	62
Ashtabula	-80.79284082	41.92097164	4316
Baie Comeau	-68.13973134	49.19135042	130
Bath (Canada)	-76.68894110	44.17367638	59
Bay City	-83.89436423	43.59458002	1492
Bay of Quinte	-77.05079839	44.11765182	5
Becancour	-72.53506616	46.30870794	86
Benton Harbor	-86.48558983	42.12544394	19
Blind River (Canada)	-83.07691993	46.16530079	16
Bowmanville (Ontario)	-78.68750000	43.82904512	222
Brevort	-85.00525546	46.00228847	106
Bruce Mines	-83.61040038	46.22432871	1
Buffalo	-78.89352308	42.87302286	1743
Buffington	-87.41681132	41.64609891	2169
Burns Harbour	-87.15627276	41.64309038	5652
Calcite	-83.78375307	45.41256739	190
Calumet	-87.59000000	41.68000000	630
Cardinal	-75.46528268	44.73883423	9
Cedarville	-84.35573909	45.99432933	23
Charlevoix	-85.26665891	45.32060596	515

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
Cheboygan	-84.46585477	45.65776119	655
Chicago	-87.61117156	41.88766995	2589
Clarkson	-79.61190320	43.49132751	317
Cleveland	-81.69326296	41.51123219	12241
Conneaut	-80.54845446	41.96742176	4352
Contrecoeur	-73.28247989	45.83320316	142
Corunna (Canada)	-82.41464676	42.82488741	9
Cote-Sainte-Catherine	-73.56843367	45.40850618	95
Courtright	-82.41496672	42.81714631	1670
Dearborn (USA, MI)	-83.15466718	42.29710166	1330
Detroit	-83.11071510	42.26993213	9961
Detroit River	-83.11765426	42.27439197	3
Drummond Island	-83.88710041	45.99347694	47
Duluth	-92.09559323	46.77757890	1456
Ecorse	-83.13897379	42.24038919	1045
Erie	-80.06813164	42.15154000	1481
Escanaba	-87.02521064	45.73393228	748
Essexville	-83.84551468	43.61709960	2391
Fairport (USA, OH)	-81.29216737	41.76733212	1048
Fairport Harbor	-81.29216737	41.76733212	1526
Ferrysburg	-86.26650485	43.10245213	486
Fisher Harbour (Canada)	-81.73722000	45.99611000	159
Gary	-87.32625606	41.61279472	7173
Georgean Bay	-80.87397041	45.39087031	2
Gladstone (USA, MI)	-86.99229658	45.85194417	287
Goderich	-81.72245295	43.74750157	189
Grand Haven	-86.23588202	43.06723122	1491
Green Bay	-88.01915727	44.51623062	5469
Hamilton (Canada)	-79.85843165	43.28144106	6693
Harbor Beach	-82.64308647	43.84544313	313
Harsens Island	-82.55138889	42.59000000	7
Heron Bay	-86.39017448	48.67459505	105
Holland	-86.21816734	42.77769307	865

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
Huron	-82.55901593	41.41169036	1452
Indiana Harbor	-87.44565848	41.67603000	7581
Kelleys Island	-82.72822529	41.61511955	4
Kingston (Canada)	-76.49714465	44.21905448	1
Kingsville	-82.66864816	42.01795767	536
Lac Saint Louis	-73.81513042	45.39436709	2
Lackawanna	-78.86207808	42.83423693	114
Lambton	-82.47920461	42.64038857	413
Little Current (Canada)	-81.89984218	45.96757995	16
Lorain	-82.19633670	41.48326690	3158
Ludington	-86.45153054	43.95140843	206
Manistee	-86.34252995	44.24989629	1462
Manitowoc	-87.64732600	44.09402244	834
Marblehead	-82.70903179	41.52939236	221
Marine City	-82.49429312	42.70757559	1238
Marinette	-87.60021134	45.09407405	67
Marquette	-87.38781613	46.53254391	2532
Marysville	-82.48166352	42.82705600	1606
Meldrum Bay	-83.09738910	45.94401979	40
Menominee	-87.60105220	45.09754051	157
Midland	-79.85555482	44.75078016	162
Milwaukee	-87.89178675	43.02572009	4391
Mississauga	-79.50937666	43.51726883	9
Monroe	-83.35105572	41.87523576	2541
Montreal	-73.54690197	45.50176771	276
Morrisburg	-75.23956040	44.86924119	43
Munising	-86.64650415	46.42047134	154
Muskegon	-86.35028973	43.19498154	2187
Nanticoke	-80.04217491	42.79599297	10321
Oak Creek	-87.84038218	42.88414701	18
Ogdensburg	-75.47261276	44.71526377	17
Ontonagon	-89.31749707	46.88971051	296
Oshawa	-78.84528071	43.81505268	181

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
Oswego	-76.50826842	43.47142499	106
Owen Sound	-80.94082864	44.58165727	90
Parry Sound	-80.03333333	45.33333333	25
Picton (Canada)	-77.12696413	44.02759104	106
Pointe Noire (Canada)	-66.78607740	50.01145496	1
Port Alfred	-70.86699147	48.33498894	53
Port Arthur	-89.12874868	48.41386870	2
Port Cartier	-66.86699147	50.01599900	139
Port Colborne	-80.19576040	42.78104103	588
Port Credit	-79.57873374	43.54908909	27
Port Dolomite	-84.31318454	45.99126085	125
Port Gypsum	-82.87557503	41.48920047	20
Port Huron	-82.42587631	42.99383875	1
Port Inland	-85.86311644	45.95479905	211
Port St. Joseph	-86.49758743	42.09997281	1
Port Stanley (Canada)	-81.27399400	42.60804952	20
Port Washington (USA, WI)	-87.86289882	43.39226202	3
Port Weller	-79.21805556	43.22138889	51
Prescott	-75.51131288	44.70595909	60
Presque Isle	-87.38546026	46.57723878	354
Quebec City	-71.20563303	46.82496808	373
River Rouge	-83.11753054	42.27423857	2689
Saginaw	-83.94945883	43.42000938	3406
Saint Clair	-82.48365223	42.82030872	6211
Saint Joseph	-86.49758743	42.09997281	1372
Saint Marys River (USA, Great Lakes)	-84.17254652	46.24113045	261
Sandusky	-82.71433826	41.47022000	117
Sarnia	-82.38542117	42.96761211	746
Sault Ste. Marie (Canada)	-84.33910563	46.50623582	7728
Sault Ste. Marie (Unknown)	-84.36187160	46.50619995	437
Sault Ste. Marie (USA, MI)	-84.34547400	46.49697400	459
Sept-Iles	-66.38542117	50.20000100	29
Serpent Harbor	-82.65322423	46.15486084	135

Table A.2. Ballast Water Source Locations

Location	Longitude	Lattitude	Number of Visits Made
Silver Bay	-91.26094919	47.28134631	177
Sombra	-82.43720344	42.69949068	173
Soo Locks (Sault Ste. Marie, MI)	-84.34850000	46.50250000	14
Sorel	-73.11640454	46.04971699	298
South Chicago	-87.53339626	41.76514493	339
Stoneport	-83.41958130	45.29548266	150
Sturgeon Bay	-87.39444444	44.85416667	744
Sun Oil (Sarnia, Canada)	-82.38542117	42.96761211	6
Superior	-92.09088501	46.74762037	1334
Taconite Harbor	-90.91119577	47.52896843	179
Thessalon	-83.55487011	46.21785730	3
Thorold	-79.19116996	43.12935985	203
Three Rivers	-72.54203874	46.32313076	38
Thunder Bay	-89.20142133	48.39932926	306
Toledo (USA)	-83.47027097	41.69149353	4821
Tonawanda	-78.89255812	43.02062150	153
Toronto	-79.28754265	43.59849232	387
Tracy	-73.09968855	46.05076174	122
Traverse City	-85.61232349	44.77196180	378
Trenton (USA, MI)	-83.17405164	42.13844715	112
Trois Rivieres	-72.54203874	46.32313076	52
Two Harbors	-91.66378092	47.00456203	435
Valleyfield	-74.08333300	45.21666700	193
Waukegan	-87.80620035	42.37250000	1193
Welland	-79.21953640	42.98278146	10
Whitefish Falls, Ontario	-81.74939033	46.07802524	254
Whitefish River	-81.75000000	46.06666700	7
Whiting	-87.48350532	41.68859648	27
Windsor	-83.07957510	42.30398452	2159
Wyandotte	-83.14414366	42.20734516	357
Zilwaukee	-83.91263584	43.47877068	86
Zug Island (USA, MI)	-83.10734880	42.28139564	5

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
41.46 -82.16	41.75 -81.28	1	0	1
41.46 -82.16	42.87 -78.88	1	1	1
41.46 -82.16	45.81 -84.21	1	2	1
41.52 -81.71	41.97 -80.55	1	1	1
41.62 -87.30	41.89 -87.53	1	1	1
41.62 -87.30	45.98 -84.21	1	2	1
41.63 -87.14	45.10 -87.60	1	2	1
41.67 -87.16	Duluth	4	4	1
41.67 -87.43	45.97 -85.87	1	2	1
41.68 -82.17	Charlevoix	12	1	2
41.69 -87.55	42.79 -86.21	1	1	1
41.69 -87.87	41.69 -87.87	1	0	1
41.73 -81.28	Burns Harbour	1	0	1
41.75 -81.28	41.71 -87.54	1	1	1
41.78 -87.45	Traverse City	1	2	1
41.80 -82.43	Charlevoix	12	2	2
41.87 -82.60	Duluth	2	6	1
41.89 -87.53	41.64 -87.14	3	0	1
41.89 -87.53	41.68 -87.45	1	0	1
41.89 -87.53	42.79 -86.12	1	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
41.89 -87.53	43.30 -83.42	1	1	1
41.89 -87.53	45.96 -85.88	6	2	1
41.90 -82.87	Superior	1	2	1
41.90 -87.10	Port Inland	1	1	1
41.90 -87.40	43.70 -86.70	1	1	1
41.90 -87.40	46.00 -83.90	1	1	1
41.90 -87.60	45.60 -86.10	1	1	1
41.92 -80.80	Superior	3	2	1
41.92 -81.33	Toledo (USA)	1	1	1
41.95 -82.00	Superior	1	7	1
41.95 -87.15	Duluth	2	5	1
41.97 -80.55	41.55 -82.73	1	1	1
41.97 -80.55	42.88 -79.25	1	1	1
41.97 -81.77	River Rouge	1	5	1
42.00 -87.50	Port Inland	1	1	1
42.08 -82.83	41.55 -82.73	4	0	1
42.08 -82.83	45.96 -85.88	1	2	1
42.08 -82.83	45.98 -84.21	1	2	1
42.10 -87.32	Duluth	1	3	1
42.11 -87.47	41.64 -87.14	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
42.11 -87.47	41.68 -87.45	2	0	1
42.21 -83.14	41.55 -82.73	1	1	1
42.21 -83.14	45.98 -84.21	2	2	1
42.22 -81.05	Toledo (USA)	2	0	1
42.28 -83.11	41.97 -80.55	1	1	1
42.31 -80.72	Toledo (USA)	2	0	1
42.33 -83.02	45.32 -85.32	4	12	1
42.35 -64.00	Sturgeon Bay	1	8	1
42.36 -86.53	Alpena	4	1	1
42.36 -87.72	Alpena	7	1	1
42.37 -87.78	Alpena	7	1	1
42.40 -82.40	Duluth	1	3	1
42.40 -82.40	Superior	1	5	1
42.42 -81.63	Superior	1	3	1
42.45 -87.15	Duluth	2	5	1
42.47 -87.08	Superior	6	3	1
42.47 -87.08	Two Harbors	6	3	1
42.47 -87.71	Alpena	7	2	1
42.57 -83.74	Toledo (USA)	2	6	1
42.57 -84.53	River Rouge	1	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
42.59 -87.65	42.59 -87.65	12	0	2
42.60 -87.15	Port Inland	1	0	1
42.62 -80.03	Cleveland	2	1	1
42.66 -79.70	Superior	1	3	1
42.68 -80.03	Superior	6	3	1
42.73 -79.51	Superior	4	2	1
42.79 -86.12	41.68 -87.45	2	1	1
42.79 -86.12	41.89 -87.45	1	1	1
42.79 -86.12	41.89 -87.53	7	1	1
42.79 -86.12	44.10 -87.65	1	1	1
42.79 -86.12	45.96 -85.88	3	1	1
42.79 -86.12	45.98 -84.21	2	1	1
42.79 -87.90	46.52 -84.41	1	1	1
42.82 -79.33	Conneaut	3	0	1
42.87 -82.33	46.07 -84.00	3	0	1
42.88 -79.25	41.97 -80.11	2	0	1
42.88 -79.25	41.97 -80.55	14	1	2
42.88 -79.25	42.87 -78.88	1	0	1
42.88 -79.25	45.98 -84.21	1	2	1
42.90 -87.00	45.80 -84.80	1	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
43 -87.86667	46.5 -84.33334	1	27	1
43.00 -82.00	Two Harbors	1	2	1
43.00 -86.50	44.50 -86.70	1	1	1
43.00 -87.00	Port Inland	1	1	1
43.00 -87.60	Port Inland	1	0	1
43.02 -87.87	Charlevoix	7	2	1
43.03 -87.90	41.89 -87.53	1	1	1
43.03 -87.90	45.32 -85.32	4	87	1
43.03 -87.90	45.98 -84.21	1	1	1
43.05 -86.22	45.32 -85.32	8	0	1
43.05 -86.25	43.90 -87.65	1	1	1
43.07 -86.23	41.64 -87.14	2	0	1
43.07 -86.23	41.68 -87.30	1	1	1
43.07 -86.23	41.68 -87.45	3	1	1
43.07 -86.23	41.89 -87.53	3	1	1
43.07 -86.23	42.79 -86.12	7	1	1
43.07 -86.23	43.03 -87.90	1	1	1
43.07 -86.23	43.23 -86.35	1	0	1
43.07 -86.23	43.30 -83.42	1	1	1
43.07 -86.23	45.96 -85.88	8	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
43.07 -86.23	45.98 -84.21	9	1	1
43.08 -82.40	Duluth	7	2	1
43.08 -84.40	Duluth	1	2	1
43.10 -82.40	45.70 -83.70	42	0	6
43.10 -82.40	Duluth	16	2	2
43.10 -82.40	Sturgeon Bay	1	2	1
43.10 -82.40	Superior	4	2	1
43.10 -82.40	Two Harbors	12	2	2
43.10 -82.42	Sturgeon Bay	4	39	1
43.10 -87.87	Charlevoix	5	1	1
43.17 -82.42	41.82 -82.33	2	1	1
43.17 -82.42	45.60 -83.55	2	1	1
43.17 -82.42	Superior	2	2	1
43.18 -82.92	45.43 -83.40	2	0	1
43.20 -82.42	45.72 -83.68	2	1	1
43.23 -86.35	41.64 -87.14	2	1	1
43.23 -86.35	42.79 -86.12	2	1	1
43.23 -86.35	45.10 -87.60	1	1	1
43.23 -86.35	45.41 -83.82	1	1	1
43.23 -86.35	45.96 -85.88	2	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
43.23 -86.35	45.98 -84.21	2	1	1
43.23 -86.35	46.78 -92.09	1	2	1
43.23 -86.79	Superior	1	3	1
43.28 -79.56	Sandusky	1	1	1
43.28 -79.67	Conneaut	3	1	1
43.28 -79.67	Superior	3	3	1
43.28 -79.83	Conneaut	3	1	1
43.28 -79.83	Superior	3	3	1
43.30 -79.30	Duluth	3	4	1
43.30 -79.77	Duluth	3	9	1
43.33 -79.83	Conneaut	6	1	1
43.33 -84.50	Superior	2	1	1
43.35 -86.55	Escanaba	1	1	1
43.39 -86.65	Charlevoix	8	1	1
43.40 -83.96	45.98 -84.21	1	1	1
43.43 -87.19	Port Inland	1	1	1
43.48 -78.57	Toledo (USA)	2	1	1
43.48 -82.47	Two Harbors	6	2	1
43.50 -86.70	Port Inland	2	0	1
43.50 -86.80	41.70 -87.70	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
43.50 -86.82	Port Inland	1	0	1
43.52 -78.42	Duluth	2	55	1
43.55 -87.37	Duluth	1	2	1
43.60 -78.08	Duluth	2	4	1
43.63 -77.95	Burns Harbour	1	4	1
43.64 -83.86	41.97 -80.55	1	1	1
43.64 -83.86	45.96 -85.88	3	2	1
43.64 -83.86	45.98 -84.21	2	1	1
43.64 -83.96	45.41 -83.82	1	1	1
43.68 -77.75	Superior	1	40	1
43.71 -77.54	Toledo (USA)	1	1	1
43.77 -77.26	Toledo (USA)	4	6	1
43.80 -77.14	Superior	1	7	1
43.94 -76.67	Toledo (USA)	6	6	1
43.94667 -86.44833	45.98167 -84.20834	1	1	1
43.95 -86.45	41.64 -87.14	2	1	1
43.95 -86.45	41.68 -87.45	1	1	1
43.95 -86.45	41.89 -87.53	1	1	1
43.95 -86.45	42.79 -86.12	1	1	1
43.95 -86.45	43.03 -87.90	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
43.95 -86.45	45.41 -83.82	1	1	1
43.95 -86.45	45.96 -85.88	11	1	2
43.95 -86.45	45.98 -84.21	3	2	1
43.97 -82.58	Silver Bay	2	2	1
43.98 -86.98	Duluth	1	2	1
44.0 -87.4	Port Dolomite	2	1	1
44.05 -82.62	43.00 -83.42	10	0	1
44.10 -82.48	45.32 -85.32	1	2	1
44.10 -87.48	45.32 -85.32	12	1	2
44.16 -76.32	Toledo (USA)	1	1	1
44.25 -82.72	Silver Bay	3	2	1
44.25 -86.30	45.96 -85.88	1	1	1
44.26 -86.79	Escanaba	1	0	1
44.30 -86.50	Port Inland	1	1	1
44.33 -87.08	Escanaba	1	0	1
44.40 -82.78	45.20 -83.17	6	0	1
44.40 -86.50	Port Inland	1	0	1
44.465 -75.79833	44.465 -75.79833	4	0	1
44.52 -86.50	Marinette	1	6	1
44.52 -86.57	Marinette	3	6	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
44.54 -88.01	45.96 -85.88	1	1	1
44.55 -82.85	Silver Bay	1	2	1
44.62 -80.92	45.32 -85.32	4	2	1
44.67 -82.83	Whiting	1	1	1
44.70 -82.95	Duluth	10	2	1
44.70 -86.40	Port Inland	2	1	1
44.90 -87.40	44.40 -87.30	1	0	1
44.90 -87.40	Port Inland	1	1	1
44.90 -87.43	Escanaba	1	1	1
44.98 -61.02	47.50 -60.22	1	6	1
45.00 -86.75	Escanaba	1	1	1
45.10 -87.60	41.89 -87.53	3	1	1
45.10 -87.60	43.95 -86.45	1	3	1
45.10 -87.60	45.96 -85.88	5	1	1
45.10 -87.60	45.98 -84.21	2	1	1
45.20 -86.20	Port Inland	1	0	1
45.20 -86.40	Port Inland	1	0	1
45.20 -87.50	44.60 -87.30	1	1	1
45.20 -87.50	44.80 -87.30	1	1	1
45.23 -86.28	Marinette	2	6	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
45.26 -85.18	44.54 -88.01	1	1	1
45.26 -85.18	45.96 -85.88	2	0	1
45.26 -85.18	45.98 -84.21	1	1	1
45.30 -83.32	Brevort	1	0	1
45.30 -86.10	Port Inland	1	1	1
45.32 -85.32	43.05 -86.22	1	1	1
45.32 -86.10	Port Inland	1	0	1
45.33 -60.37	47.45 -59.83	1	6	1
45.40 -85.60	Indiana Harbor	1	1	1
45.40 -86.10	44.60 -86.10	1	0	1
45.40 -86.10	Port Inland	2	0	1
45.41 -83.82	Duluth	1	2	1
45.43 -86.73	45.73 -84.53	1	9	1
45.43 -88.73	Monroe	1	12	1
45.47 -86.96	Escanaba	9	0	1
45.50 -86.10	41.80 -87.40	1	0	1
45.50 -86.10	42.60 -86.30	1	0	1
45.50 -86.10	42.80 -86.30	2	0	1
45.50 -86.10	42.80 -86.50	1	0	1
45.50 -86.10	Port Inland	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
45.50 -86.37	Port Inland	1	1	1
45.50 -86.60	Port Inland	5	0	1
45.6 -86.1	Port Dolomite	1	0	1
45.6 -86.3	Port Dolomite	2	0	1
45.60 -85.10	42.20 -87.30	1	1	1
45.60 -85.10	Escanaba	1	0	1
45.60 -85.10	Port Inland	1	0	1
45.60 -86.10	42.20 -87.20	1	1	1
45.60 -86.10	42.20 -87.30	3	0	1
45.60 -86.10	42.50 -87.10	1	2	1
45.60 -86.10	43.50 -86.60	1	0	1
45.60 -86.10	43.70 -86.40	1	0	1
45.60 -86.10	Port Dolomite	5	1	1
45.60 -86.10	Port Inland	31	0	4
45.60 -86.20	Port Inland	1	0	1
45.60 -86.30	Port Dolomite	2	5	1
45.67 -86.20	46.33 -84.18	1	0	1
45.68 -83.65	Drummond Island	7	1	1
45.70 -83.70	Sturgeon Bay	3	3	1
45.70 -84.30	Calcite	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
45.70 -86.00	43.60 -86.80	1	1	1
45.70 -86.10	Port Inland	1	1	1
45.70 -86.30	Port Inland	1	0	1
45.80 -85.82	Duluth	1	6	1
45.80 -86.10	Port Inland	2	0	1
45.85 -86.13	Superior	6	2	1
45.87 -85.18	Duluth	1	6	1
45.9 -84.0	47.5 -88.4	1	1	1
45.90 -84.00	46.60 -84.80	1	0	1
46.03 -73.03	Toledo (USA)	1	2	1
46.08 -82.40	45.95 -83.88	8	0	1
46.13 -72.96	Toledo (USA)	3	2	1
46.2 -84.2	Two Harbors	2	1	1
46.20 -84.11	45.51 -83.47	3	0	1
46.20 -84.11	45.53 -84.02	3	0	1
46.20 -84.20	Duluth	4	2	1
46.20 -84.20	Two Harbors	20	1	3
46.3 -84.2	Superior	4	2	1
46.3 -84.2	Two Harbors	56	1	8
46.3 -84.4	Duluth	20	2	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
46.3 -84.4	Two Harbors	13	0	2
46.30 -84.20	Duluth	32	0	5
46.30 -84.20	Superior	12	0	2
46.30 -84.20	Two Harbors	72	0	10
46.30 -84.40	Conneaut	4	5	1
46.30 -84.40	Duluth	135	1	19
46.30 -84.40	Superior	54	0	8
46.30 -84.40	Two Harbors	354	1	51
46.33 -84.18	41.83 -82.20	4	31	1
46.33 -84.18	45.57 -85.35	3	0	1
46.33 -84.18	Duluth	6	1	1
46.33 -84.18	Superior	6	2	1
46.33 -84.18	Two Harbors	52	1	7
46.33 -84.33	Superior	138	1	20
46.33 -84.50	Superior	1	1	1
46.37 -84.20	Two Harbors	4	1	1
46.38 -84.22	45.50 -85.42	28	0	4
46.38 -84.22	Duluth	2	2	1
46.38 -84.22	Superior	15	2	2
46.38 -84.22	Two Harbors	40	1	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
46.40 -84.23	Superior	3	1	1
46.40 -84.40	Two Harbors	1	3	1
46.40 -84.50	Duluth	14	1	2
46.40 -84.50	Superior	24	1	3
46.40 -84.50	Two Harbors	26	1	4
46.47 -84.30	Superior	2	2	1
46.47 -84.57	Superior	6	1	1
46.5 -84.33334	Duluth	2	2	1
46.50 -83.60	Two Harbors	1	1	1
46.50 -84.60	Superior	39	1	6
46.50 -84.61	Marquette	5	1	1
46.50 -86.70	Duluth	1	1	1
46.51 -84.62	Duluth	9	1	1
46.52 -84.41	45.41 -83.82	1	1	1
46.52 -84.41	45.96 -85.88	1	0	1
46.52 -84.41	Duluth	1	31	1
46.52 -84.62	47.65 -87.88	5	1	1
46.53 -84.67	Superior	6	1	1
46.53 -84.67	Two Harbors	10	1	1
46.53 -84.70	Duluth	5	4	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
46.56 -83.92	45.98 -84.21	1	1	1
46.57 -84.50	Duluth	1	1	1
46.57 -84.73	Superior	6	1	1
46.65 -84.95	Superior	4	1	1
46.66 -71.64	Toledo (USA)	1	3	1
46.67 -86.67	Marquette	15	0	2
46.80 -85.10	Two Harbors	1	1	1
46.80 -85.20	Two Harbors	1	1	1
46.83 -85.17	Duluth	5	2	1
46.83 -85.17	Two Harbors	35	1	5
46.88 -85.30	Superior	6	1	1
47.00 -85.08	Two Harbors	1	1	1
47.00 -85.60	Two Harbors	10	1	1
47.00 -85.70	Two Harbors	1	1	1
47.15 -90.73	Duluth	4	0	1
47.15 -90.73	Two Harbors	28	1	4
47.16667 -90.43333	Superior	36	1	5
47.16667 -90.43333	Two Harbors	108	1	15
47.17 -90.42	Duluth	10	0	1
47.17 -90.42	Superior	5	362	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
47.17 -90.42	Two Harbors	176	1	25
47.17 -90.43	Duluth	120	0	17
47.17 -90.43	Superior	24	0	3
47.17 -90.43	Two Harbors	613	0	88
47.18 -86.48	Superior	10	2	1
47.18 -90.38	Two Harbors	10	1	1
47.20 -86.51	Duluth	1	1	1
47.20 -90.40	Duluth	40	0	6
47.20 -90.40	Sturgeon Bay	4	2	1
47.20 -90.40	Superior	12	0	2
47.20 -90.40	Two Harbors	56	0	8
47.20 -90.60	Superior	8	1	1
47.20 -90.60	Two Harbors	20	0	3
47.28 -89.57	45.25 -83.22	1	14	1
47.37 -89.33	Duluth	5	0	1
47.37 -89.33	Sturgeon Bay	5	1	1
47.37 -89.33	Two Harbors	180	0	26
47.42 -87.33	Silver Bay	5	0	1
47.45 -87.45	Duluth	1	3	1
47.45 -88.63	Two Harbors	11	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
47.52 -87.83	Two Harbors	6	1	1
47.57 -87.92	Two Harbors	6	1	1
48.50 -88.35	Bay City	1	2	1
49.38 -64.42	Duluth	2	9	1
49.40 -64.63	Duluth	2	9	1
49.40 -64.93	Duluth	1	9	1
Algoma (Sault Ste. Marie, Canada)	Marquette	40	2	6
Alpena	Alpena	23	2	3
Alpena	Brevort	23	1	3
Alpena	Calcite	287	0	41
Alpena	Calumet	1	2	1
Alpena	Cedarville	69	1	10
Alpena	Chicago	7	2	1
Alpena	Drummond Island	92	1	13
Alpena	Marquette	25	2	4
Alpena	Milwaukee	8	1	1
Alpena	Port Dolomite	69	0	10
Alpena	Port Gypsum	45	1	6
Alpena	Port Inland	28	1	4
Alpena	Prescott	1	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Alpena	Presque Isle	132	1	19
Alpena	Silver Bay	49	2	7
Alpena	South Chicago	2	0	1
Alpena	Stoneport	148	0	21
Alpena	Superior	13	2	2
Alpena	Taconite Harbor	5	2	1
Alpena	Thunder Bay	7	2	1
Alpena	Two Harbors	10	2	1
Ashland (USA, WI)	Duluth	16	1	2
Ashland (USA, WI)	Presque Isle	7	1	1
Ashland (USA, WI)	Silver Bay	14	1	2
Ashland (USA, WI)	Two Harbors	25	1	4
Ashtabula	Ashtabula	47	0	7
Ashtabula	Calcite	647	2	92
Ashtabula	Cedarville	23	2	3
Ashtabula	Chicago	21	3	3
Ashtabula	Cleveland	129	1	18
Ashtabula	Conneaut	29	0	4
Ashtabula	Detroit	14	1	2
Ashtabula	Drummond Island	45	1	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Ashtabula	Duluth	237	4	34
Ashtabula	Erie	6	0	1
Ashtabula	Escanaba	59	2	8
Ashtabula	Fairport (USA, OH)	18	0	3
Ashtabula	Fairport Harbor	23	0	3
Ashtabula	Grand Haven	1	2	1
Ashtabula	Lorain	42	1	6
Ashtabula	Marblehead	245	1	35
Ashtabula	Marine City	8	0	1
Ashtabula	Marquette	161	3	23
Ashtabula	Milwaukee	8	4	1
Ashtabula	Port Dolomite	59	2	8
Ashtabula	Port Gypsum	15	2	2
Ashtabula	Port Inland	21	2	3
Ashtabula	Presque Isle	233	2	33
Ashtabula	Saint Joseph	6	3	1
Ashtabula	Sandusky	455	0	65
Ashtabula	Silver Bay	606	3	87
Ashtabula	Stoneport	96	1	14
Ashtabula	Superior	423	3	60

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Ashtabula	Toledo (USA)	456	1	65
Ashtabula	Two Harbors	183	3	26
Baie Comeau	Ashtabula	16	4	2
Baie Comeau	Burns Harbour	9	6	1
Baie Comeau	Chicago	31	7	4
Baie Comeau	Duluth	3	9	1
Baie Comeau	Milwaukee	9	7	1
Baie Comeau	Superior	19	7	3
Baie Comeau	Toledo (USA)	43	5	6
Bath (Canada)	Alpena	1	4	1
Bath (Canada)	Ashtabula	23	2	3
Bath (Canada)	Conneaut	6	2	1
Bath (Canada)	Ludington	15	5	2
Bath (Canada)	Oswego	2	12	1
Bath (Canada)	Sandusky	6	2	1
Bath (Canada)	Silver Bay	6	5	1
Bay City	Calcite	232	1	33
Bay City	Cedarville	65	1	9
Bay City	Cleveland	5	3	1
Bay City	Conneaut	1	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Bay City	Detroit	20	4	3
Bay City	Drummond Island	57	1	8
Bay City	Duluth	8	2	1
Bay City	Ecorse	2	1	1
Bay City	Indiana Harbor	1	5	1
Bay City	Ludington	80	2	11
Bay City	Marquette	44	2	6
Bay City	Meldrum Bay	2	2	1
Bay City	Port Dolomite	142	1	20
Bay City	Port Gypsum	5	1	1
Bay City	Port Inland	85	2	12
Bay City	Presque Isle	38	2	5
Bay City	River Rouge	5	1	1
Bay City	Silver Bay	35	2	5
Bay City	Stoneport	518	1	74
Bay City	Sturgeon Bay	2	2	1
Bay City	Superior	8	2	1
Bay City	Toledo (USA)	22	2	3
Bay City	Two Harbors	7	2	1
Bay City	Whiting	108	3	15

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Bay of Quinte	Chicago	5	5	1
Becancour	Calumet	6	8	1
Becancour	Duluth	51	7	7
Becancour	Erie	6	12	1
Becancour	Milwaukee	6	12	1
Becancour	Superior	10	6	1
Becancour	Toledo (USA)	7	7	1
Belledune	Duluth	8	12	1
Belledune	Superior	15	8	2
Belledune	Toledo (USA)	32	6	5
Benton Harbor	Brevort	5	2	1
Benton Harbor	Port Inland	8	1	1
Benton Harbor	South Chicago	6	0	1
Blind River (Canada)	Port Dolomite	15	1	2
Blind River (Canada)	Stoneport	1	1	1
Bowmanville (Ontario)	Ashtabula	86	1	12
Bowmanville (Ontario)	Buffalo	6	0	1
Bowmanville (Ontario)	Conneaut	14	1	2
Bowmanville (Ontario)	Duluth	13	4	2
Bowmanville (Ontario)	Fairport (USA, OH)	7	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Bowmanville (Ontario)	Fairport Harbor	13	1	2
Bowmanville (Ontario)	Ferrysburg	1	4	1
Bowmanville (Ontario)	Sandusky	44	2	6
Bowmanville (Ontario)	Silver Bay	6	4	1
Bowmanville (Ontario)	Superior	31	4	4
Bowmanville (Ontario)	Toledo (USA)	1	2	1
Brevort	Buffalo	54	3	8
Brevort	Cleveland	52	2	7
Britt	Toledo (USA)	6	2	1
Bruce Mines	Toledo (USA)	1	1	1
Buffalo	Alpena	32	2	5
Buffalo	Ashtabula	76	1	11
Buffalo	Buffalo	4	0	1
Buffalo	Calcite	298	2	43
Buffalo	Cedarville	7	1	1
Buffalo	Cleveland	87	1	12
Buffalo	Conneaut	50	1	7
Buffalo	Duluth	27	3	4
Buffalo	Fairport (USA, OH)	18	0	3
Buffalo	Fairport Harbor	44	1	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Buffalo	Lorain	7	1	1
Buffalo	Marblehead	140	1	20
Buffalo	Owen Sound	2	2	1
Buffalo	Port Dolomite	18	60	3
Buffalo	Port Inland	1	3	1
Buffalo	Presque Isle	10	2	1
Buffalo	River Rouge	1	34	1
Buffalo	Sandusky	273	1	39
Buffalo	Silver Bay	58	3	8
Buffalo	Stoneport	27	2	4
Buffalo	Superior	291	4	42
Buffalo	Thunder Bay	2	2	1
Buffalo	Toledo (USA)	239	1	34
Buffalo	Two Harbors	31	3	4
Buffington	Burns Harbour	27	0	4
Buffington	Calcite	589	1	84
Buffington	Calumet	160	1	23
Buffington	Cedarville	7	2	1
Buffington	Chicago	67	1	10
Buffington	Drummond Island	105	2	15

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Buffington	Duluth	9	3	1
Buffington	Escanaba	31	2	4
Buffington	Gary	4	2	1
Buffington	Marquette	9	2	1
Buffington	Menominee	8	2	1
Buffington	Port Dolomite	134	1	19
Buffington	Port Inland	103	1	15
Buffington	Presque Isle	533	1	76
Buffington	Silver Bay	8	3	1
Buffington	South Chicago	18	0	3
Buffington	Stoneport	339	1	48
Buffington	Sturgeon Bay	9	1	1
Buffington	Two Harbors	9	3	1
Burns Harbour	44.10 -86.60	1	1	1
Burns Harbour	Brevort	31	1	4
Burns Harbour	Bruce Mines	5	2	1
Burns Harbour	Burns Harbour	39	0	6
Burns Harbour	Calcite	238	2	34
Burns Harbour	Calumet	267	0	38
Burns Harbour	Cedarville	39	1	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Burns Harbour	Chicago	286	1	41
Burns Harbour	Cleveland	3	2	1
Burns Harbour	Drummond Island	34	1	5
Burns Harbour	Duluth	242	4	35
Burns Harbour	Escanaba	133	1	19
Burns Harbour	Gary	33	1	5
Burns Harbour	Grand Haven	16	3	2
Burns Harbour	Indiana Harbor	1	1	1
Burns Harbour	Lorain	14	3	2
Burns Harbour	Ludington	60	2	9
Burns Harbour	Marquette	30	2	4
Burns Harbour	Milwaukee	78	1	11
Burns Harbour	Port Dolomite	55	2	8
Burns Harbour	Port Inland	221	1	32
Burns Harbour	Presque Isle	72	2	10
Burns Harbour	Silver Bay	189	3	27
Burns Harbour	South Chicago	60	0	9
Burns Harbour	Stoneport	32	2	5
Burns Harbour	Sturgeon Bay	33	1	5
Burns Harbour	Superior	3287	3	470

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Burns Harbour	Toledo (USA)	42	3	6
Burns Harbour	Two Harbors	83	3	12
Burns Harbour	Whiting	28	2	4
Calcite	Ashtabula	9	55	1
Calcite	Bay City	2	4	1
Calcite	Buffalo	1	0	1
Calcite	Buffington	18	1	3
Calcite	Burns Harbour	18	7	3
Calcite	Calcite	21	3	3
Calcite	Cedarville	4	2	1
Calcite	Chicago	13	2	2
Calcite	Cleveland	11	1	2
Calcite	Conneaut	12	3	2
Calcite	Detroit	12	1	2
Calcite	Duluth	4	2	1
Calcite	Gary	1	1	1
Calcite	Marblehead	3	2	1
Calcite	Marine City	9	1	1
Calcite	Marysville	9	1	1
Calcite	Port Dolomite	2	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Calcite	Saginaw	1	0	1
Calcite	Sandusky	2	2	1
Calcite	Sarnia	11	2	2
Calcite	Silver Bay	12	3	2
Calcite	South Chicago	1	2	1
Calcite	Superior	10	3	1
Calcite	Toledo (USA)	4	2	1
Calumet	Alpena	95	2	14
Calumet	Burns Harbour	7	0	1
Calumet	Calcite	42	1	6
Calumet	Calumet	25	0	4
Calumet	Charlevoix	32	1	5
Calumet	Detroit	10	12	1
Calumet	Drummond Island	24	2	3
Calumet	Duluth	28	3	4
Calumet	Escanaba	23	1	3
Calumet	Green Bay	21	2	3
Calumet	Holland	19	0	3
Calumet	Mackinaw City	9	1	1
Calumet	Manistee	14	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Calumet	Manitowoc	1	1	1
Calumet	Marquette	51	2	7
Calumet	Muskegon	1	0	1
Calumet	Port Inland	51	2	7
Calumet	Presque Isle	112	2	16
Calumet	Stoneport	9	2	1
Calumet	Superior	47	3	7
Calumet	Two Harbors	1	2	1
Calumet	Waukegan	1	731	1
Calumet	Whiting	5	1	1
Calumet	Wyandotte	2	2	1
Cardinal	Cleveland	2	2	1
Cardinal	Sandusky	7	3	1
Cedarville	Calcite	3	2	1
Cedarville	Duluth	2	2	1
Cedarville	Indiana Harbor	1	1	1
Cedarville	Marblehead	1	2	1
Cedarville	Muskegon	1	3	1
Cedarville	Port Inland	9	1	1
Cedarville	Silver Bay	1	4	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Cedarville	Superior	5	1	1
Charlevoix	Brevort	17	2	2
Charlevoix	Calcite	46	1	7
Charlevoix	Calumet	3	2	1
Charlevoix	Cedarville	16	1	2
Charlevoix	Charlevoix	6	3	1
Charlevoix	Chicago	24	2	3
Charlevoix	Conneaut	1	2	1
Charlevoix	Drummond Island	8	0	1
Charlevoix	Duluth	8	3	1
Charlevoix	Ferrysburg	7	1	1
Charlevoix	Green Bay	30	1	4
Charlevoix	Indiana Harbor	1	1	1
Charlevoix	Manitowoc	10	1	1
Charlevoix	Marquette	8	2	1
Charlevoix	Milwaukee	11	1	2
Charlevoix	Port Dolomite	22	1	3
Charlevoix	Port Gypsum	1	1	1
Charlevoix	Port Inland	168	1	24
Charlevoix	Presque Isle	43	2	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Charlevoix	Silver Bay	29	2	4
Charlevoix	South Chicago	1	2	1
Charlevoix	Stoneport	19	1	3
Charlevoix	Sturgeon Bay	7	1	1
Charlevoix	Superior	5	3	1
Charlevoix	Two Harbors	23	2	3
Charlevoix	Waukegan	1	18	1
Cheboygan	Brevort	7	1	1
Cheboygan	Cedarville	8	0	1
Cheboygan	Chicago	10	17	1
Cheboygan	Presque Isle	8	0	1
Cheboygan	Sarnia	9	1	1
Cheboygan	Stoneport	7	0	1
Cheboygan	Sturgeon Bay	3	6	1
Cheboygan	Toledo (USA)	187	3	27
Cheboygan	Whiting	416	2	59
Chicago	Alpena	45	3	6
Chicago	Brevort	38	1	5
Chicago	Burns Harbour	18	1	3
Chicago	Calcite	79	2	11

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Chicago	Cedarville	1	1	1
Chicago	Charlevoix	1542	2	220
Chicago	Chicago	120	1	17
Chicago	Detroit	6	3	1
Chicago	Drummond Island	25	2	4
Chicago	Duluth	131	4	19
Chicago	Escanaba	9	1	1
Chicago	Gary	36	1	5
Chicago	Grand Haven	27	1	4
Chicago	Green Bay	18	1	3
Chicago	Holland	26	1	4
Chicago	Indiana Harbor	36	1	5
Chicago	Ludington	36	4	5
Chicago	Manistee	55	1	8
Chicago	Marquette	14	2	2
Chicago	Port Dolomite	53	1	8
Chicago	Port Inland	42	1	6
Chicago	Presque Isle	22	2	3
Chicago	Sandusky	6	2	1
Chicago	Sarnia	10	14	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Chicago	Silver Bay	18	3	3
Chicago	Stoneport	73	2	10
Chicago	Sturgeon Bay	5	1	1
Chicago	Superior	58	3	8
Chicago	Toledo (USA)	12	7	2
Chicago	Two Harbors	14	2	2
Chicago	Waukegan	1	0	1
Chicago	Whiting	13	2	2
Clarkson	Ashtabula	79	1	11
Clarkson	Conneaut	27	1	4
Clarkson	Duluth	4	4	1
Clarkson	Erie	12	4	2
Clarkson	Fairport Harbor	36	1	5
Clarkson	Marblehead	15	2	2
Clarkson	Sandusky	56	2	8
Clarkson	Stoneport	7	2	1
Clarkson	Superior	44	4	6
Clarkson	Toledo (USA)	37	1	5
Cleveland	41.80 -82.20	6	0	1
Cleveland	45.70 -83.70	6	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Cleveland	Alpena	399	2	57
Cleveland	Ashtabula	258	0	37
Cleveland	Burns Harbour	36	3	5
Cleveland	Calcite	1166	1	167
Cleveland	Cedarville	74	2	11
Cleveland	Charlevoix	36	2	5
Cleveland	Chicago	65	3	9
Cleveland	Cleveland	187	0	27
Cleveland	Conneaut	133	1	19
Cleveland	Detroit	90	1	13
Cleveland	Drummond Island	102	1	15
Cleveland	Duluth	312	5	45
Cleveland	Escanaba	18	2	3
Cleveland	Fairport (USA, OH)	38	0	5
Cleveland	Fairport Harbor	100	0	14
Cleveland	Green Bay	37	2	5
Cleveland	Hamilton (Canada)	8	3	1
Cleveland	Huron	8	1	1
Cleveland	Indiana Harbor	8	4	1
Cleveland	Kelleys Island	958	1	137

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Cleveland	Lorain	41	0	6
Cleveland	Ludington	21	4	3
Cleveland	Marblehead	3010	1	430
Cleveland	Marinette	5	8	1
Cleveland	Marquette	145	2	21
Cleveland	Marysville	8	2	1
Cleveland	Meldrum Bay	15	2	2
Cleveland	Milwaukee	47	3	7
Cleveland	Monroe	10	0	1
Cleveland	Nanticoke	20	2	3
Cleveland	Port Dolomite	133	2	19
Cleveland	Port Gypsum	184	1	26
Cleveland	Port Inland	16	2	2
Cleveland	Presque Isle	368	1	53
Cleveland	River Rouge	41	1	6
Cleveland	Sandusky	626	0	89
Cleveland	Sarnia	26	2	4
Cleveland	Silver Bay	1453	3	208
Cleveland	Stoneport	301	2	43
Cleveland	Sturgeon Bay	10	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Cleveland	Superior	302	3	43
Cleveland	Taconite Harbor	7	3	1
Cleveland	Tawas City	6	2	1
Cleveland	Thunder Bay	3	9	1
Cleveland	Toledo (USA)	1091	1	156
Cleveland	Two Harbors	262	3	37
Cleveland	Waukegan	5	2	1
Cleveland	Whiting	26	3	4
Cleveland	Windsor	14	1	2
Conneaut	41.83 -82.20	38	1	5
Conneaut	41.85 -82.12	8	0	1
Conneaut	41.90 -82.88	2	1	1
Conneaut	46.50 -84.50	10	2	1
Conneaut	Alpena	4	1	1
Conneaut	Ashtabula	146	0	21
Conneaut	Calcite	401	2	57
Conneaut	Cedarville	9	2	1
Conneaut	Cleveland	35	0	5
Conneaut	Conneaut	1	2	1
Conneaut	Detroit	36	1	5

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Conneaut	Drummond Island	17	1	2
Conneaut	Duluth	392	3	56
Conneaut	Ecorse	45	1	6
Conneaut	Erie	63	1	9
Conneaut	Escanaba	9	51	1
Conneaut	Grand Haven	1	3	1
Conneaut	Lorain	9	1	1
Conneaut	Manistee	9	2	1
Conneaut	Marblehead	97	0	14
Conneaut	Marquette	4	3	1
Conneaut	Meldrum Bay	2	1	1
Conneaut	Muskegon	2	3	1
Conneaut	Port Dolomite	89	2	13
Conneaut	Port Gypsum	4	0	1
Conneaut	Port Inland	2	4	1
Conneaut	Presque Isle	101	1	14
Conneaut	Saint Marys River (USA, Great Lakes)	1	6	1
Conneaut	Sandusky	310	1	44
Conneaut	Silver Bay	101	3	14

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Conneaut	Stoneport	163	2	23
Conneaut	Sturgeon Bay	12	2	2
Conneaut	Superior	280	3	40
Conneaut	Toledo (USA)	306	1	44
Conneaut	Two Harbors	1643	3	235
Contrecoeur	Ashtabula	6	2	1
Contrecoeur	Duluth	23	5	3
Contrecoeur	Escanaba	6	5	1
Contrecoeur	Lorain	1	5	1
Contrecoeur	Marquette	12	5	2
Contrecoeur	Sandusky	6	3	1
Contrecoeur	Silver Bay	25	5	4
Contrecoeur	Superior	29	5	4
Contrecoeur	Thunder Bay	6	12	1
Contrecoeur	Toledo (USA)	14	5	2
Contrecoeur	Two Harbors	14	5	2
Corunna (Canada)	Escanaba	9	1	1
Cote-Sainte-Catherine	Ashtabula	46	2	7
Cote-Sainte-Catherine	Duluth	17	11	2
Cote-Sainte-Catherine	Marblehead	6	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Cote-Sainte-Catherine	Superior	17	4	2
Cote-Sainte-Catherine	Toledo (USA)	9	4	1
Courtright	Ashtabula	56	1	8
Courtright	Calcite	28	1	4
Courtright	Cedarville	1	1	1
Courtright	Chicago	21	2	3
Courtright	Cleveland	7	1	1
Courtright	Conneaut	30	1	4
Courtright	Drummond Island	58	1	8
Courtright	Duluth	104	3	15
Courtright	Escanaba	8	0	1
Courtright	Goderich	2	4	1
Courtright	Marquette	27	2	4
Courtright	Port Dolomite	10	2	1
Courtright	Port Inland	12	1	2
Courtright	Presque Isle	115	1	16
Courtright	Sandusky	21	1	3
Courtright	Silver Bay	11	3	2
Courtright	Stoneport	18	1	3
Courtright	Sturgeon Bay	26	2	4

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Courtright	Superior	1092	3	156
Courtright	Toledo (USA)	7	1	1
Courtright	Two Harbors	16	2	2
Dearborn (USA, MI)	Calcite	57	1	8
Dearborn (USA, MI)	Dearborn (USA, MI)	12	0	2
Dearborn (USA, MI)	Detroit	9	0	1
Dearborn (USA, MI)	Drummond Island	59	1	8
Dearborn (USA, MI)	Duluth	32	2	5
Dearborn (USA, MI)	Escanaba	12	1	2
Dearborn (USA, MI)	Marblehead	93	1	13
Dearborn (USA, MI)	Marquette	170	2	24
Dearborn (USA, MI)	Presque Isle	289	2	41
Dearborn (USA, MI)	Sandusky	166	1	24
Dearborn (USA, MI)	Silver Bay	13	5	2
Dearborn (USA, MI)	Stoneport	154	1	22
Dearborn (USA, MI)	Sturgeon Bay	12	2	2
Dearborn (USA, MI)	Superior	135	3	19
Dearborn (USA, MI)	Toledo (USA)	116	0	17
Dearborn (USA, MI)	Zug Island (USA, MI)	1	1	1
Detroit	Alpena	322	2	46

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Detroit	Ashtabula	63	1	9
Detroit	Brevort	6	1	1
Detroit	Bruce Mines	2	1	1
Detroit	Burns Harbour	2	4	1
Detroit	Calcite	1194	1	171
Detroit	Cedarville	165	1	24
Detroit	Charlevoix	85	1	12
Detroit	Chicago	4	5	1
Detroit	Cleveland	102	1	15
Detroit	Conneaut	48	1	7
Detroit	Detroit	33	1	5
Detroit	Drummond Island	207	1	30
Detroit	Duluth	556	3	79
Detroit	Escanaba	46	2	7
Detroit	Fairport (USA, OH)	12	1	2
Detroit	Fairport Harbor	19	1	3
Detroit	Goderich	6	1	1
Detroit	Green Bay	8	0	1
Detroit	Lorain	22	0	3
Detroit	Ludington	20	2	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Detroit	Marblehead	508	1	73
Detroit	Marquette	767	2	110
Detroit	Marysville	10	1	1
Detroit	Meldrum Bay	13	1	2
Detroit	Milwaukee	6	4	1
Detroit	Port Dolomite	296	1	42
Detroit	Port Gypsum	25	1	4
Detroit	Port Inland	33	2	5
Detroit	Presque Isle	771	1	110
Detroit	Sandusky	602	1	86
Detroit	Sault Ste. Marie (Canada)	9	3	1
Detroit	Sault Ste. Marie (USA, MI)	8	2	1
Detroit	Silver Bay	476	2	68
Detroit	Stoneport	683	1	98
Detroit	Sturgeon Bay	37	2	5
Detroit	Superior	1406	3	201
Detroit	Thunder Bay	8	7	1
Detroit	Toledo (USA)	690	1	99
Detroit	Two Harbors	686	3	98
Detroit	Whiting	5	5	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Detroit River	Two Harbors	3	12	1
Drummond Island	Bay City	1	2	1
Drummond Island	Buffington	9	3	1
Drummond Island	Detroit	1	1	1
Drummond Island	Escanaba	7	1	1
Drummond Island	Fairport Harbor	9	1	1
Drummond Island	Presque Isle	3	2	1
Drummond Island	Saginaw	9	1	1
Drummond Island	Stoneport	8	0	1
Duluth	47.00 -91.67	5	2	1
Duluth	Alpena	107	2	15
Duluth	Ashtabula	18	3	3
Duluth	Brevort	3	4	1
Duluth	Burns Harbour	2	3	1
Duluth	Conneaut	13	3	2
Duluth	Duluth	63	1	9
Duluth	Ecorse	1	2	1
Duluth	Indiana Harbor	35	3	5
Duluth	Ludington	12	4	2
Duluth	Marquette	18	1	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Duluth	Saint Marys River (USA, Great Lakes)	1	2	1
Duluth	Silver Bay	259	0	37
Duluth	Superior	268	0	38
Duluth	Two Harbors	651	0	93
Ecorse	41.80 -82.20	2	0	1
Ecorse	45.70 -83.70	10	1	1
Ecorse	Calcite	102	1	15
Ecorse	Drummond Island	28	1	4
Ecorse	Duluth	43	3	6
Ecorse	Fairport Harbor	7	0	1
Ecorse	Gary	2	3	1
Ecorse	Lorain	18	1	3
Ecorse	Marblehead	16	1	2
Ecorse	Marquette	60	2	9
Ecorse	Port Dolomite	39	1	6
Ecorse	Presque Isle	122	1	17
Ecorse	Sandusky	63	1	9
Ecorse	Stoneport	66	1	9
Ecorse	Sturgeon Bay	29	3	4

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Ecorse	Superior	86	3	12
Ecorse	Toledo (USA)	27	1	4
Ecorse	Two Harbors	325	2	46
Erie	Ashtabula	64	0	9
Erie	Calcite	363	2	52
Erie	Cedarville	32	2	5
Erie	Cleveland	127	1	18
Erie	Conneaut	77	0	11
Erie	Detroit	7	1	1
Erie	Drummond Island	34	2	5
Erie	Duluth	58	3	8
Erie	Erie	5	3	1
Erie	Escanaba	8	1	1
Erie	Fairport Harbor	27	0	4
Erie	Kelleys Island	4	1	1
Erie	Marblehead	152	1	22
Erie	Marinette	8	2	1
Erie	Marquette	7	2	1
Erie	Port Dolomite	26	2	4
Erie	Port Gypsum	5	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Erie	Port Inland	1	19	1
Erie	Presque Isle	19	2	3
Erie	Sandusky	122	1	17
Erie	Silver Bay	43	3	6
Erie	Stoneport	39	2	6
Erie	Superior	44	3	6
Erie	Toledo (USA)	176	1	25
Erie	Two Harbors	33	3	5
Escanaba	Ashtabula	1	2	1
Escanaba	Calcite	151	1	22
Escanaba	Cedarville	1	1	1
Escanaba	Dearborn (USA, MI)	19	1	3
Escanaba	Drummond Island	36	1	5
Escanaba	Duluth	16	3	2
Escanaba	Escanaba	11	1	2
Escanaba	Indiana Harbor	11	1	2
Escanaba	Marquette	17	2	2
Escanaba	Meldrum Bay	9	1	1
Escanaba	Port Dolomite	28	1	4
Escanaba	Port Inland	99	0	14

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Escanaba	Presque Isle	142	1	20
Escanaba	Silver Bay	29	2	4
Escanaba	Stoneport	121	1	17
Escanaba	Sturgeon Bay	18	0	3
Escanaba	Superior	30	2	4
Escanaba	Two Harbors	9	2	1
Essexville	Brevort	7	1	1
Essexville	Calcite	183	1	26
Essexville	Cedarville	19	1	3
Essexville	Cleveland	10	2	1
Essexville	Drummond Island	79	1	11
Essexville	Duluth	133	3	19
Essexville	Escanaba	8	1	1
Essexville	Indiana Harbor	35	3	5
Essexville	Marquette	70	1	10
Essexville	Port Dolomite	94	1	13
Essexville	Port Inland	1	1	1
Essexville	Presque Isle	112	1	16
Essexville	Silver Bay	28	2	4
Essexville	Stoneport	113	1	16

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Essexville	Superior	1388	2	198
Essexville	Toledo (USA)	10	1	1
Essexville	Two Harbors	89	2	13
Essexville	Whiting	12	3	2
Fairport (USA, OH)	Ashtabula	14	0	2
Fairport (USA, OH)	Calcite	56	2	8
Fairport (USA, OH)	Cedarville	7	2	1
Fairport (USA, OH)	Cleveland	117	0	17
Fairport (USA, OH)	Conneaut	27	0	4
Fairport (USA, OH)	Detroit	55	1	8
Fairport (USA, OH)	Drummond Island	84	2	12
Fairport (USA, OH)	Erie	9	0	1
Fairport (USA, OH)	Escanaba	8	10	1
Fairport (USA, OH)	Kelleys Island	90	0	13
Fairport (USA, OH)	Kingsville	4	1	1
Fairport (USA, OH)	Lorain	6	1	1
Fairport (USA, OH)	Marblehead	252	1	36
Fairport (USA, OH)	Marquette	7	4	1
Fairport (USA, OH)	Port Dolomite	5	1	1
Fairport (USA, OH)	Port Inland	7	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Fairport (USA, OH)	Presque Isle	7	2	1
Fairport (USA, OH)	Rogers City	7	1	1
Fairport (USA, OH)	Sandusky	28	0	4
Fairport (USA, OH)	Silver Bay	1	2	1
Fairport (USA, OH)	Stoneport	154	2	22
Fairport (USA, OH)	Superior	8	3	1
Fairport (USA, OH)	Toledo (USA)	95	1	14
Fairport Harbor	Ashtabula	35	0	5
Fairport Harbor	Calcite	126	2	18
Fairport Harbor	Cedarville	6	7	1
Fairport Harbor	Cleveland	274	0	39
Fairport Harbor	Conneaut	25	1	4
Fairport Harbor	Detroit	35	1	5
Fairport Harbor	Drummond Island	25	1	4
Fairport Harbor	Erie	27	1	4
Fairport Harbor	Fairport Harbor	9	1	1
Fairport Harbor	Green Bay	1	2	1
Fairport Harbor	Kelleys Island	12	1	2
Fairport Harbor	Lorain	2	1	1
Fairport Harbor	Marblehead	559	1	80

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Fairport Harbor	Port Dolomite	18	2	3
Fairport Harbor	Port Gypsum	5	1	1
Fairport Harbor	Presque Isle	58	2	8
Fairport Harbor	Saginaw	9	1	1
Fairport Harbor	Sandusky	123	0	18
Fairport Harbor	Silver Bay	8	2	1
Fairport Harbor	Stoneport	48	2	7
Fairport Harbor	Superior	9	4	1
Fairport Harbor	Toledo (USA)	112	1	16
Ferrysburg	Brevort	5	1	1
Ferrysburg	Calcite	8	2	1
Ferrysburg	Cedarville	10	1	1
Ferrysburg	Charlevoix	398	1	57
Ferrysburg	Drummond Island	8	2	1
Ferrysburg	Duluth	6	2	1
Ferrysburg	Ferrysburg	1	9	1
Ferrysburg	Milwaukee	1	1	1
Ferrysburg	Port Inland	49	1	7
Fisher Harbour (Canada)	Brevort	8	3	1
Fisher Harbour (Canada)	Calcite	14	3	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Fisher Harbour (Canada)	Cedarville	11	1	2
Fisher Harbour (Canada)	Drummond Island	37	1	5
Fisher Harbour (Canada)	Duluth	7	2	1
Fisher Harbour (Canada)	Port Dolomite	7	1	1
Fisher Harbour (Canada)	Port Inland	1	1	1
Fisher Harbour (Canada)	Presque Isle	14	0	2
Fisher Harbour (Canada)	Silver Bay	6	2	1
Fisher Harbour (Canada)	Stoneport	25	1	4
Fisher Harbour (Canada)	Superior	24	2	3
Fisher Harbour (Canada)	Toledo (USA)	5	1	1
Gary	41.63 -87.32	1	3	1
Gary	43.27 -86.83	6	1	1
Gary	45.02 -85.92	6	1	1
Gary	45.35 -86.13	6	1	1
Gary	45.40 -85.50	12	1	2
Gary	45.43 -85.50	4	0	1
Gary	45.45 -85.45	2	2	1
Gary	45.47 -85.47	2	0	1
Gary	45.50 -85.42	50	1	7
Gary	45.55 -85.38	2	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Gary	45.57 -85.35	2	1	1
Gary	45.63 -86.12	4	1	1
Gary	45.67 -86.20	2	1	1
Gary	45.83 -84.55	6	2	1
Gary	45.85 -85.13	7	1	1
Gary	45.87 -85.30	6	1	1
Gary	Brevort	32	1	5
Gary	Burns Harbour	28	1	4
Gary	Calcite	556	1	79
Gary	Calumet	165	1	24
Gary	Cedarville	12	4	2
Gary	Charlevoix	9	1	1
Gary	Chicago	236	0	34
Gary	Cleveland	9	4	1
Gary	Conneaut	6	6	1
Gary	Drummond Island	18	1	3
Gary	Duluth	824	3	118
Gary	Ecorse	18	2	3
Gary	Escanaba	90	1	13
Gary	Grand Haven	1	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Gary	Indiana Harbor	1	1	1
Gary	Marquette	46	2	7
Gary	Milwaukee	25	3	4
Gary	Muskegon	1	0	1
Gary	Port Dolomite	159	2	23
Gary	Port Inland	40	1	6
Gary	Presque Isle	383	1	55
Gary	Saint Marys River (USA, Great Lakes)	5	3	1
Gary	Silver Bay	39	2	6
Gary	South Chicago	72	0	10
Gary	Stoneport	440	1	63
Gary	Sturgeon Bay	110	1	16
Gary	Superior	650	3	93
Gary	Two Harbors	3070	3	439
Gary	Whitefish Point	10	1	1
Georgean Bay	Conneaut	2	4	1
Gladstone (USA, MI)	Ashtabula	9	2	1
Gladstone (USA, MI)	Brevort	36	0	5
Gladstone (USA, MI)	Calcite	66	1	9

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Gladstone (USA, MI)	Cedarville	18	1	3
Gladstone (USA, MI)	Drummond Island	16	1	2
Gladstone (USA, MI)	Port Dolomite	19	1	3
Gladstone (USA, MI)	Port Inland	37	1	5
Gladstone (USA, MI)	Presque Isle	27	1	4
Gladstone (USA, MI)	Stoneport	32	1	5
Gladstone (USA, MI)	Sturgeon Bay	9	1	1
Gladstone (USA, MI)	Whiting	18	2	3
Goderich	Alpena	1	1	1
Goderich	Brevort	1	2	1
Goderich	Calcite	14	1	2
Goderich	Drummond Island	2	2	1
Goderich	Duluth	8	2	1
Goderich	Gladstone (USA, MI)	1	1	1
Goderich	Ludington	115	2	16
Goderich	Manistee	1	2	1
Goderich	Marinette	6	1	1
Goderich	Milwaukee	7	2	1
Goderich	Saint Joseph	2	2	1
Goderich	Sandusky	13	4	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Goderich	Stoneport	2	2	1
Goderich	Superior	15	3	2
Goderich	Toledo (USA)	1	1	1
Grand Haven	45.40 -85.50	1	2	1
Grand Haven	Brevort	105	1	15
Grand Haven	Burns Harbour	27	0	4
Grand Haven	Calcite	73	1	10
Grand Haven	Calumet	138	1	20
Grand Haven	Cedarville	33	1	5
Grand Haven	Charlevoix	30	1	4
Grand Haven	Chicago	242	1	35
Grand Haven	Drummond Island	93	1	13
Grand Haven	Escanaba	11	1	2
Grand Haven	Gary	5	0	1
Grand Haven	Grand Haven	7	0	1
Grand Haven	Holland	1	0	1
Grand Haven	Indiana Harbor	18	1	3
Grand Haven	Marinette	1	1	1
Grand Haven	Marquette	8	2	1
Grand Haven	Meldrum Bay	2	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Grand Haven	Milwaukee	1	0	1
Grand Haven	Muskegon	1	0	1
Grand Haven	Port Dolomite	41	1	6
Grand Haven	Port Inland	420	1	60
Grand Haven	Presque Isle	56	1	8
Grand Haven	Sault Ste. Marie (USA, MI)	1	2	1
Grand Haven	Silver Bay	8	3	1
Grand Haven	South Chicago	86	1	12
Grand Haven	Stoneport	59	1	8
Grand Haven	Sturgeon Bay	8	1	1
Grand Haven	Superior	8	2	1
Grand Haven	Thunder Bay	7	2	1
Green Bay	Alpena	777	1	111
Green Bay	Bay City	20	2	3
Green Bay	Brevort	154	1	22
Green Bay	Calcite	877	1	125
Green Bay	Cedarville	82	1	12
Green Bay	Charlevoix	52	2	7
Green Bay	Conneaut	9	4	1
Green Bay	Drummond Island	134	1	19

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Green Bay	Duluth	12	3	2
Green Bay	Escanaba	107	1	15
Green Bay	Green Bay	13	1	2
Green Bay	Indiana Harbor	5	1	1
Green Bay	Ludington	5	2	1
Green Bay	Manitowoc	9	1	1
Green Bay	Marquette	91	2	13
Green Bay	Meldrum Bay	9	1	1
Green Bay	Menominee	16	1	2
Green Bay	Milwaukee	19	1	3
Green Bay	Nanticoke	7	2	1
Green Bay	Port Dolomite	338	1	48
Green Bay	Port Gypsum	5	0	1
Green Bay	Port Inland	1051	1	150
Green Bay	Presque Isle	973	1	139
Green Bay	Saint Joseph	7	1	1
Green Bay	Silver Bay	91	2	13
Green Bay	South Chicago	16	2	2
Green Bay	Stoneport	367	1	52
Green Bay	Sturgeon Bay	38	1	5

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Green Bay	Superior	43	2	6
Green Bay	Two Harbors	109	3	16
Green Bay	Waukegan	3	1	1
Green Bay	Whiting	30	3	4
Hamilton (Canada)	Ashtabula	1230	1	176
Hamilton (Canada)	Buffalo	150	1	21
Hamilton (Canada)	Burns Harbour	37	5	5
Hamilton (Canada)	Calcite	14	3	2
Hamilton (Canada)	Calumet	15	5	2
Hamilton (Canada)	Cedarville	7	2	1
Hamilton (Canada)	Chicago	19	4	3
Hamilton (Canada)	Cleveland	6	1	1
Hamilton (Canada)	Conneaut	349	1	50
Hamilton (Canada)	Detroit	38	3	5
Hamilton (Canada)	Duluth	896	4	128
Hamilton (Canada)	Escanaba	7	4	1
Hamilton (Canada)	Fairport (USA, OH)	67	1	10
Hamilton (Canada)	Fairport Harbor	41	1	6
Hamilton (Canada)	Gary	7	3	1
Hamilton (Canada)	Green Bay	13	5	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Hamilton (Canada)	Hamilton (Canada)	12	2	2
Hamilton (Canada)	Indiana Harbor	1	5	1
Hamilton (Canada)	Lorain	11	2	2
Hamilton (Canada)	Marblehead	268	1	38
Hamilton (Canada)	Marquette	126	3	18
Hamilton (Canada)	Milwaukee	60	4	9
Hamilton (Canada)	Oswego	7	1	1
Hamilton (Canada)	River Rouge	5	3	1
Hamilton (Canada)	Sandusky	599	1	86
Hamilton (Canada)	Silver Bay	177	4	25
Hamilton (Canada)	Sturgeon Bay	1	13	1
Hamilton (Canada)	Superior	1266	4	181
Hamilton (Canada)	Toledo (USA)	1038	2	148
Hamilton (Canada)	Two Harbors	139	4	20
Hamilton (Canada)	Whiting	77	5	11
Hamilton (Unknown)	Duluth	5	4	1
Hamilton (Unknown)	Superior	5	4	1
Harbor Beach	Calcite	117	1	17
Harbor Beach	Cedarville	6	0	1
Harbor Beach	Drummond Island	22	1	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Harbor Beach	Duluth	16	2	2
Harbor Beach	Marquette	9	2	1
Harbor Beach	Presque Isle	24	1	3
Harbor Beach	Silver Bay	29	2	4
Harbor Beach	Stoneport	27	1	4
Harbor Beach	Superior	28	2	4
Harbor Beach	Toledo (USA)	9	1	1
Harbor Beach	Two Harbors	26	2	4
Harsens Island	Calcite	7	1	1
Heron Bay	Alpena	105	1	15
Holland	Brevort	40	1	6
Holland	Burns Harbour	17	1	2
Holland	Calcite	23	1	3
Holland	Calumet	68	0	10
Holland	Cedarville	45	1	6
Holland	Chicago	219	0	31
Holland	Drummond Island	24	1	3
Holland	Escanaba	1	0	1
Holland	Gary	9	0	1
Holland	Grand Haven	18	0	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Holland	Indiana Harbor	41	1	6
Holland	Milwaukee	2	0	1
Holland	Port Dolomite	26	1	4
Holland	Port Inland	217	1	31
Holland	Presque Isle	20	1	3
Holland	South Chicago	57	1	8
Holland	Stoneport	25	3	4
Holland	Sturgeon Bay	1	2	1
Holland	Superior	12	3	2
Huron	Alpena	2	3	1
Huron	Ashtabula	44	0	6
Huron	Calcite	149	1	21
Huron	Conneaut	18	0	3
Huron	Detroit	57	0	8
Huron	Drummond Island	137	2	20
Huron	Duluth	38	4	5
Huron	Ecorse	18	1	3
Huron	Erie	7	1	1
Huron	Escanaba	15	2	2
Huron	Huron	1	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Huron	Lorain	9	0	1
Huron	Mackinaw City	9	2	1
Huron	Marblehead	134	0	19
Huron	Marquette	38	3	5
Huron	Port Dolomite	59	1	8
Huron	Port Inland	7	2	1
Huron	Presque Isle	321	1	46
Huron	Sandusky	54	1	8
Huron	Silver Bay	21	2	3
Huron	Stoneport	156	1	22
Huron	Superior	43	3	6
Huron	Toledo (USA)	93	0	13
Huron	Two Harbors	22	4	3
Indiana Harbor	41.60 -87.40	1	1	1
Indiana Harbor	41.73 -81.28	1	1	1
Indiana Harbor	42.00 -87.30	1	0	1
Indiana Harbor	42.60 -87.13	1	0	1
Indiana Harbor	43.00 -87.00	2	0	1
Indiana Harbor	43.40 -86.80	1	1	1
Indiana Harbor	43.74 -86.70	1	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Indiana Harbor	44.37 -86.42	1	1	1
Indiana Harbor	45.60 -86.10	1	0	1
Indiana Harbor	46.00 -83.90	1	2	1
Indiana Harbor	Ashtabula	12	5	2
Indiana Harbor	Brevort	15	1	2
Indiana Harbor	Burns Harbour	60	1	9
Indiana Harbor	Calcite	131	2	19
Indiana Harbor	Calumet	262	0	37
Indiana Harbor	Cedarville	11	1	2
Indiana Harbor	Chicago	115	1	16
Indiana Harbor	Drummond Island	38	2	5
Indiana Harbor	Duluth	733	3	105
Indiana Harbor	Escanaba	1211	1	173
Indiana Harbor	Gary	18	1	3
Indiana Harbor	Green Bay	10	1	1
Indiana Harbor	Indiana Harbor	20	2	3
Indiana Harbor	Ludington	1	2	1
Indiana Harbor	Marquette	340	2	49
Indiana Harbor	Menominee	7	2	1
Indiana Harbor	Milwaukee	42	1	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Indiana Harbor	Port Dolomite	77	1	11
Indiana Harbor	Port Inland	630	1	90
Indiana Harbor	Presque Isle	168	2	24
Indiana Harbor	Saint Clair	8	4	1
Indiana Harbor	Sault Ste. Marie (USA, MI)	1	1	1
Indiana Harbor	Silver Bay	473	3	68
Indiana Harbor	South Chicago	64	0	9
Indiana Harbor	Stoneport	85	2	12
Indiana Harbor	Sturgeon Bay	121	1	17
Indiana Harbor	Superior	1770	3	253
Indiana Harbor	Toledo (USA)	33	3	5
Indiana Harbor	Two Harbors	1114	3	159
Kelleys Island	Cleveland	4	0	1
Kingston (Canada)	Marblehead	1	0	1
Kingsville	Ashtabula	8	0	1
Kingsville	Calcite	14	1	2
Kingsville	Cedarville	12	1	2
Kingsville	Cleveland	23	1	3
Kingsville	Detroit	11	1	2
Kingsville	Drummond Island	16	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Kingsville	Fairport (USA, OH)	8	0	1
Kingsville	Huron	1	0	1
Kingsville	Kelleys Island	39	0	6
Kingsville	Marblehead	226	0	32
Kingsville	Sandusky	16	0	2
Kingsville	Stoneport	7	1	1
Kingsville	Toledo (USA)	151	0	22
Kingsville	Windsor	4	1	1
Lac Saint Louis	Duluth	2	6	1
Lackawanna	Ashtabula	8	1	1
Lackawanna	Calcite	16	2	2
Lackawanna	Cedarville	8	2	1
Lackawanna	Lorain	7	1	1
Lackawanna	Marblehead	5	2	1
Lackawanna	Sandusky	20	0	3
Lackawanna	Silver Bay	16	4	2
Lackawanna	Superior	7	3	1
Lackawanna	Toledo (USA)	27	1	4
Lake Huron	Drummond Island	2	1	1
Lake Michigan	Alpena	12	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Lambton	Ashtabula	6	1	1
Lambton	Calcite	6	1	1
Lambton	Chicago	1	3	1
Lambton	Conneaut	7	1	1
Lambton	Duluth	5	11	1
Lambton	Marblehead	9	1	1
Lambton	Marquette	13	1	2
Lambton	Sandusky	6	1	1
Lambton	Silver Bay	6	2	1
Lambton	Stoneport	24	1	3
Lambton	Superior	330	3	47
Lemont	Ludington	158	3	23
Lemont	South Chicago	3	21	1
Little Current (Canada)	Ludington	16	2	2
Lorain	Ashtabula	58	1	8
Lorain	Buffalo	1	1	1
Lorain	Calcite	426	1	61
Lorain	Cedarville	31	1	4
Lorain	Cleveland	71	1	10
Lorain	Conneaut	46	1	7

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Lorain	Detroit	53	1	8
Lorain	Drummond Island	90	1	13
Lorain	Duluth	87	3	12
Lorain	Ecorse	1	0	1
Lorain	Escanaba	1	3	1
Lorain	Fairport (USA, OH)	13	1	2
Lorain	Fairport Harbor	1	1	1
Lorain	Huron	7	0	1
Lorain	Kelleys Island	80	0	11
Lorain	Lorain	14	1	2
Lorain	Marblehead	624	0	89
Lorain	Marquette	49	2	7
Lorain	Port Dolomite	59	1	8
Lorain	Port Gypsum	35	1	5
Lorain	Port Inland	8	2	1
Lorain	Presque Isle	137	2	20
Lorain	Sandusky	259	0	37
Lorain	Silver Bay	207	3	30
Lorain	Stoneport	124	1	18
Lorain	Superior	218	3	31

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Lorain	Toledo (USA)	296	1	42
Lorain	Two Harbors	162	3	23
Ludington	Bay City	1	2	1
Ludington	Brevort	37	1	5
Ludington	Burns Harbour	2	5	1
Ludington	Calcite	29	1	4
Ludington	Cedarville	8	1	1
Ludington	Chicago	7	1	1
Ludington	Drummond Island	7	0	1
Ludington	Escanaba	1	0	1
Ludington	Indiana Harbor	2	1	1
Ludington	Milwaukee	1	0	1
Ludington	Muskegon	2	1	1
Ludington	Port Dolomite	26	1	4
Ludington	Port Inland	72	1	10
Ludington	Presque Isle	9	1	1
Ludington	South Chicago	2	1	1
Manistee	Brevort	217	1	31
Manistee	Calcite	182	1	26
Manistee	Calumet	7	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Manistee	Cedarville	24	1	3
Manistee	Chicago	38	1	5
Manistee	Cleveland	1	2	1
Manistee	Drummond Island	104	1	15
Manistee	Escanaba	7	0	1
Manistee	Grand Haven	9	1	1
Manistee	Marquette	21	1	3
Manistee	Port Dolomite	67	1	10
Manistee	Port Inland	478	1	68
Manistee	Presque Isle	142	1	20
Manistee	Silver Bay	15	2	2
Manistee	South Chicago	7	1	1
Manistee	Stoneport	143	1	20
Manitowoc	Brevort	7	1	1
Manitowoc	Calcite	22	2	3
Manitowoc	Calumet	19	0	3
Manitowoc	Cedarville	22	1	3
Manitowoc	Charlevoix	577	1	82
Manitowoc	Chicago	7	1	1
Manitowoc	Drummond Island	38	1	5

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Manitowoc	Escanaba	9	1	1
Manitowoc	Green Bay	5	0	1
Manitowoc	Marquette	7	21	1
Manitowoc	Port Dolomite	17	1	2
Manitowoc	Port Inland	38	1	5
Manitowoc	Presque Isle	31	2	4
Manitowoc	Stoneport	9	1	1
Manitowoc	Sturgeon Bay	8	3	1
Manitowoc	Superior	9	2	1
Manitowoc	Waukegan	9	1	1
Marblehead	Ashtabula	36	0	5
Marblehead	Calcite	4	2	1
Marblehead	Cleveland	48	0	7
Marblehead	Fairport (USA, OH)	18	0	3
Marblehead	Fairport Harbor	91	0	13
Marblehead	Port Dolomite	1	1	1
Marblehead	Sandusky	6	1	1
Marblehead	Silver Bay	5	33	1
Marblehead	Stoneport	9	2	1
Marblehead	Toledo (USA)	3	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Marine City	45.98 -84.21	4	1	1
Marine City	Brevort	7	0	1
Marine City	Calcite	202	1	29
Marine City	Cedarville	75	1	11
Marine City	Detroit	9	1	1
Marine City	Drummond Island	118	1	17
Marine City	Ecorse	7	0	1
Marine City	Goderich	2	8	1
Marine City	Indiana Harbor	1	3	1
Marine City	Marblehead	54	0	8
Marine City	Marquette	206	2	29
Marine City	Port Dolomite	80	1	11
Marine City	Port Inland	8	1	1
Marine City	Presque Isle	179	1	26
Marine City	Silver Bay	30	2	4
Marine City	Stoneport	229	1	33
Marine City	Toledo (USA)	27	1	4
Marinette	Burns Harbour	1	1	1
Marinette	Calcite	6	0	1
Marinette	Chicago	12	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Marinette	Duluth	3	8	1
Marinette	Holland	2	1	1
Marinette	Milwaukee	2	1	1
Marinette	Port Dolomite	19	1	3
Marinette	Port Inland	7	1	1
Marinette	South Chicago	1	0	1
Marinette	Superior	14	2	2
Marquette	Calcite	1	5	1
Marquette	Cleveland	1	61	1
Marquette	Dearborn (USA, MI)	21	2	3
Marquette	Detroit	10	2	1
Marquette	Duluth	489	1	70
Marquette	Escanaba	1	0	1
Marquette	Indiana Harbor	1	1	1
Marquette	Marblehead	1	1	1
Marquette	Marquette	63	0	9
Marquette	Presque Isle	143	0	20
Marquette	River Rouge	77	2	11
Marquette	Silver Bay	304	1	43
Marquette	Sturgeon Bay	3	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Marquette	Superior	1052	1	150
Marquette	Toledo (USA)	28	2	4
Marquette	Two Harbors	337	1	48
Marysville	Brevort	13	2	2
Marysville	Calcite	404	1	58
Marysville	Cedarville	5	1	1
Marysville	Detroit	15	1	2
Marysville	Drummond Island	146	1	21
Marysville	Duluth	7	2	1
Marysville	Ecorse	7	1	1
Marysville	Escanaba	8	2	1
Marysville	Fairport (USA, OH)	7	3	1
Marysville	Marblehead	9	1	1
Marysville	Marquette	63	2	9
Marysville	Port Dolomite	82	1	12
Marysville	Port Inland	20	1	3
Marysville	Presque Isle	254	1	36
Marysville	Sandusky	7	0	1
Marysville	Silver Bay	27	3	4
Marysville	Stoneport	408	1	58

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Marysville	Superior	66	3	9
Marysville	Thessalon	7	1	1
Marysville	Toledo (USA)	25	1	4
Marysville	Two Harbors	26	2	4
Meldrum Bay	Buffington	8	1	1
Meldrum Bay	Calcite	2	2	1
Meldrum Bay	Cleveland	2	2	1
Meldrum Bay	Ecorse	1	2	1
Meldrum Bay	Marysville	1	1	1
Meldrum Bay	Port Dolomite	1	2	1
Meldrum Bay	Presque Isle	17	1	2
Meldrum Bay	Stoneport	8	0	1
Menominee	Brevort	7	4	1
Menominee	Calcite	47	1	7
Menominee	Drummond Island	5	1	1
Menominee	Duluth	27	2	4
Menominee	Port Dolomite	23	2	3
Menominee	Port Inland	17	1	2
Menominee	Presque Isle	16	2	2
Menominee	Stoneport	15	4	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Midland	Brevort	1	1	1
Midland	Calcite	19	1	3
Midland	Cleveland	7	2	1
Midland	Conneaut	5	4	1
Midland	Drummond Island	30	1	4
Midland	Duluth	20	2	3
Midland	Port Inland	6	2	1
Midland	Stoneport	18	1	3
Midland	Superior	49	2	7
Midland	Toledo (USA)	7	2	1
Milwaukee	Alpena	461	2	66
Milwaukee	Brevort	66	1	9
Milwaukee	Burns Harbour	5	1	1
Milwaukee	Calcite	129	1	18
Milwaukee	Calumet	298	1	43
Milwaukee	Cedarville	55	1	8
Milwaukee	Charlevoix	1233	1	176
Milwaukee	Chicago	109	1	16
Milwaukee	Conneaut	11	5	2
Milwaukee	Detroit	19	3	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Milwaukee	Drummond Island	45	1	6
Milwaukee	Duluth	199	3	28
Milwaukee	Escanaba	125	1	18
Milwaukee	Gary	6	2	1
Milwaukee	Grand Haven	41	0	6
Milwaukee	Indiana Harbor	109	1	16
Milwaukee	Ludington	6	3	1
Milwaukee	Marinette	6	2	1
Milwaukee	Marquette	89	2	13
Milwaukee	Milwaukee	26	1	4
Milwaukee	Muskegon	3	1	1
Milwaukee	Port Dolomite	52	1	7
Milwaukee	Port Inland	428	1	61
Milwaukee	Presque Isle	80	2	11
Milwaukee	Saint Joseph	7	0	1
Milwaukee	Silver Bay	122	3	17
Milwaukee	South Chicago	25	1	4
Milwaukee	Stoneport	93	2	13
Milwaukee	Sturgeon Bay	18	0	3
Milwaukee	Superior	244	2	35

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Milwaukee	Thunder Bay	2	5	1
Milwaukee	Toledo (USA)	26	5	4
Milwaukee	Two Harbors	54	3	8
Milwaukee	Whiting	199	1	28
Monroe	Ashtabula	30	1	4
Monroe	Calcite	111	1	16
Monroe	Cedarville	5	1	1
Monroe	Cleveland	16	0	2
Monroe	Conneaut	9	1	1
Monroe	Detroit	14	0	2
Monroe	Duluth	42	3	6
Monroe	Erie	9	1	1
Monroe	Harbor Beach	8	1	1
Monroe	Indiana Harbor	5	3	1
Monroe	Marblehead	18	0	3
Monroe	Marquette	93	2	13
Monroe	Monroe	16	0	2
Monroe	Port Dolomite	27	1	4
Monroe	port gypsum	3	1	1
Monroe	Port Gypsum	2	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Monroe	Presque Isle	37	1	5
Monroe	Sandusky	21	31	3
Monroe	Silver Bay	76	3	11
Monroe	Stoneport	16	1	2
Monroe	Sturgeon Bay	8	2	1
Monroe	Superior	1765	3	252
Monroe	Toledo (USA)	37	0	5
Monroe	Two Harbors	153	3	22
Monroe	Whiting	20	3	3
Montreal	47.40 -87.33	1	4	1
Montreal	Ashtabula	19	3	3
Montreal	Buffalo	28	3	4
Montreal	Chicago	1	9	1
Montreal	Cleveland	2	3	1
Montreal	Detroit	11	4	2
Montreal	Duluth	67	10	10
Montreal	Marblehead	1	3	1
Montreal	Sault Ste. Marie (USA, MI)	8	7	1
Montreal	Superior	50	6	7
Montreal	Thunder Bay	4	10	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Montreal	Toledo (USA)	74	4	11
Montreal	Whiting	10	8	1
Morrisburg	Ashtabula	6	2	1
Morrisburg	Conneaut	12	2	2
Morrisburg	Marblehead	12	2	2
Morrisburg	Sandusky	13	2	2
Munising	Duluth	8	1	1
Munising	Marquette	16	0	2
Munising	Silver Bay	97	1	14
Munising	Superior	16	1	2
Munising	Toledo (USA)	8	1	1
Munising	Two Harbors	9	1	1
Muskegon	Alpena	230	2	33
Muskegon	Brevort	49	1	7
Muskegon	Burns Harbour	5	1	1
Muskegon	Calcite	54	1	8
Muskegon	Calumet	57	1	8
Muskegon	Cedarville	33	1	5
Muskegon	Chicago	72	1	10
Muskegon	Drummond Island	18	1	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Muskegon	Duluth	21	3	3
Muskegon	Escanaba	104	1	15
Muskegon	Gary	15	1	2
Muskegon	Grand Haven	41	0	6
Muskegon	Holland	2	1	1
Muskegon	Indiana Harbor	13	1	2
Muskegon	Marquette	64	2	9
Muskegon	Meldrum Bay	5	1	1
Muskegon	Milwaukee	7	4	1
Muskegon	Muskegon	2	0	1
Muskegon	Port Dolomite	70	1	10
Muskegon	Port Inland	450	1	64
Muskegon	Presque Isle	111	2	16
Muskegon	Silver Bay	42	2	6
Muskegon	South Chicago	19	1	3
Muskegon	Stoneport	66	1	9
Muskegon	Sturgeon Bay	7	1	1
Muskegon	Superior	545	2	78
Muskegon	Two Harbors	70	2	10
Muskegon	Whiting	15	2	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Nanticoke	41.80 -82.20	20	1	3
Nanticoke	45.70 -83.70	20	2	3
Nanticoke	Ashtabula	2406	1	344
Nanticoke	Buffalo	181	1	26
Nanticoke	Calcite	40	2	6
Nanticoke	Cleveland	31	1	4
Nanticoke	Conneaut	1145	1	164
Nanticoke	Detroit	47	1	7
Nanticoke	Duluth	752	3	107
Nanticoke	Erie	7	1	1
Nanticoke	Escanaba	9	2	1
Nanticoke	Fairport (USA, OH)	37	1	5
Nanticoke	Fairport Harbor	38	1	5
Nanticoke	Green Bay	9	2	1
Nanticoke	Hamilton (Canada)	10	0	1
Nanticoke	Lorain	21	1	3
Nanticoke	Marblehead	17	0	2
Nanticoke	Marquette	30	3	4
Nanticoke	Milwaukee	7	4	1
Nanticoke	Nanticoke	1	4	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Nanticoke	Port Dolomite	18	2	3
Nanticoke	Sandusky	1052	1	150
Nanticoke	Silver Bay	41	3	6
Nanticoke	Stoneport	15	4	2
Nanticoke	Sturgeon Bay	17	3	2
Nanticoke	Superior	3198	3	457
Nanticoke	Toledo (USA)	709	1	101
Nanticoke	Two Harbors	443	3	63
Oak Creek	Milwaukee	5	0	1
Oak Creek	Port Dolomite	2	1	1
Oak Creek	Port Inland	11	1	2
Ogdensburg	43.65 -77.83	1	1	1
Ogdensburg	Ashtabula	7	2	1
Ogdensburg	Duluth	7	4	1
Ogdensburg	Marblehead	2	2	1
Ontonagon	Duluth	32	1	5
Ontonagon	Silver Bay	37	1	5
Ontonagon	Superior	47	1	7
Ontonagon	Two Harbors	180	0	26
Oshawa	Ashtabula	5	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Oshawa	Cleveland	4	1	1
Oshawa	Detroit	57	6	8
Oshawa	Duluth	8	6	1
Oshawa	Ludington	45	5	6
Oshawa	Marblehead	7	1	1
Oshawa	Milwaukee	5	4	1
Oshawa	Superior	1	1	1
Oshawa	Toledo (USA)	34	5	5
Oshawa	Whiting	15	4	2
Oswego	Cleveland	38	2	5
Oswego	Detroit	34	4	5
Oswego	Duluth	1	7	1
Oswego	Ludington	22	6	3
Oswego	Manistee	4	8	1
Oswego	Sarnia	5	4	1
Oswego	Toledo (USA)	2	4	1
Owen Sound	Brevort	1	1	1
Owen Sound	Cedarville	33	1	5
Owen Sound	Drummond Island	36	1	5
Owen Sound	Marquette	7	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Owen Sound	Sandusky	7	2	1
Owen Sound	Stoneport	5	1	1
Owen Sound	Sturgeon Bay	1	1	1
Parry Sound	Calcite	8	1	1
Parry Sound	Cedarville	1	0	1
Parry Sound	Drummond Island	14	1	2
Parry Sound	Port Dolomite	1	1	1
Parry Sound	Stoneport	1	1	1
Picton (Canada)	Ashtabula	54	1	8
Picton (Canada)	Buffalo	6	2	1
Picton (Canada)	Conneaut	22	2	3
Picton (Canada)	Detroit	6	0	1
Picton (Canada)	Sandusky	6	2	1
Picton (Canada)	Superior	5	5	1
Picton (Canada)	Toledo (USA)	7	2	1
Point Tupper	Montreal	1	4	1
Port Alfred	Duluth	46	10	7
Port Alfred	Toledo (USA)	7	11	1
Port Cartier	Ashtabula	6	4	1
Port Cartier	Burns Harbour	6	7	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Port Cartier	Duluth	13	8	2
Port Cartier	Gary	6	21	1
Port Cartier	Silver Bay	7	6	1
Port Cartier	Superior	51	7	7
Port Cartier	Toledo (USA)	50	4	7
Port Colborne	Ashtabula	91	1	13
Port Colborne	Calcite	1	2	1
Port Colborne	Cedarville	6	1	1
Port Colborne	Cleveland	69	1	10
Port Colborne	Conneaut	120	1	17
Port Colborne	Detroit	2	1	1
Port Colborne	Drummond Island	1	2	1
Port Colborne	Duluth	37	6	5
Port Colborne	Ecorse	3	1	1
Port Colborne	Fairport Harbor	12	1	2
Port Colborne	Lorain	13	1	2
Port Colborne	Marblehead	33	1	5
Port Colborne	Montreal	1	1	1
Port Colborne	Port Colborne	11	0	2
Port Colborne	Port Inland	1	3	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Port Colborne	River Rouge	1	1	1
Port Colborne	Sandusky	64	2	9
Port Colborne	Sarnia	1	62	1
Port Colborne	Silver Bay	7	4	1
Port Colborne	Superior	44	4	6
Port Colborne	Toledo (USA)	70	2	10
Port Credit	Ashtabula	21	1	3
Port Credit	Conneaut	6	2	1
Port Dolomite	Burns Harbour	1	1	1
Port Dolomite	Calcite	3	2	1
Port Dolomite	Cleveland	32	2	5
Port Dolomite	Duluth	12	2	2
Port Dolomite	Erie	9	3	1
Port Dolomite	Indiana Harbor	3	3	1
Port Dolomite	Meldrum Bay	1	3	1
Port Dolomite	Port Inland	44	1	6
Port Dolomite	Stoneport	18	0	3
Port Dolomite	Superior	1	3	1
Port Dolomite	Toledo (USA)	1	3	1
Port Gypsum	Calcite	6	0	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Port Gypsum	Chicago	2	2	1
Port Gypsum	Cleveland	5	1	1
Port Gypsum	Waukegan	7	2	1
Port Huron	Green Bay	1	1	1
Port Inland	Burns Harbour	9	1	1
Port Inland	Calcite	10	1	1
Port Inland	Cedarville	4	0	1
Port Inland	Cleveland	15	2	2
Port Inland	Detroit	8	2	1
Port Inland	Escanaba	3	1	1
Port Inland	Essexville	9	1	1
Port Inland	Green Bay	7	2	1
Port Inland	Indiana Harbor	37	1	5
Port Inland	Ludington	9	0	1
Port Inland	Manistee	9	32	1
Port Inland	Marblehead	1	4	1
Port Inland	Marquette	7	2	1
Port Inland	Muskegon	13	14	2
Port Inland	Port Dolomite	26	2	4
Port Inland	Port Inland	34	0	5

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Port Inland	River Rouge	1	1	1
Port Inland	Stoneport	7	1	1
Port Inland	Superior	2	2	1
Port Stanley (Canada)	Detroit	20	3	3
Port Washington (USA, WI)	Valleyfield	3	8	1
Port Weller	Ashtabula	11	1	2
Port Weller	Conneaut	11	6	2
Port Weller	Duluth	15	4	2
Port Weller	Escanaba	7	4	1
Port Weller	Superior	6	3	1
Port Weller	Toledo (USA)	1	4	1
Prescott	Ashtabula	25	2	4
Prescott	Cleveland	4	1	1
Prescott	Duluth	5	5	1
Prescott	Fairport Harbor	5	1	1
Prescott	Marblehead	8	2	1
Prescott	Sandusky	6	2	1
Prescott	Two Harbors	7	49	1
Presque Isle	Chicago	1	2	1
Presque Isle	Cleveland	3	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Presque Isle	Detroit	1	1	1
Presque Isle	Duluth	28	1	4
Presque Isle	Fairport Harbor	9	1	1
Presque Isle	Grand Haven	1	1	1
Presque Isle	Huron	1	1	1
Presque Isle	Marquette	7	1	1
Presque Isle	Port Dolomite	1	2	1
Presque Isle	Presque Isle	1	2	1
Presque Isle	River Rouge	14	2	2
Presque Isle	Saginaw	7	0	1
Presque Isle	Superior	257	1	37
Presque Isle	Toledo (USA)	1	3	1
Presque Isle	Two Harbors	22	0	3
Quebec City	Ashtabula	38	3	5
Quebec City	Burns Harbour	26	6	4
Quebec City	Chicago	18	6	3
Quebec City	Detroit	2	11	1
Quebec City	Duluth	27	7	4
Quebec City	Gary	5	7	1
Quebec City	Indiana Harbor	7	6	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Quebec City	Lorain	14	4	2
Quebec City	Milwaukee	2	0	1
Quebec City	Silver Bay	79	6	11
Quebec City	Sturgeon Bay	5	5	1
Quebec City	Superior	77	6	11
Quebec City	Toledo (USA)	73	4	10
River Rouge	Alpena	3	0	1
River Rouge	Ashtabula	9	0	1
River Rouge	Calcite	124	1	18
River Rouge	Cleveland	33	0	5
River Rouge	Conneaut	8	0	1
River Rouge	Drummond Island	15	2	2
River Rouge	Duluth	216	3	31
River Rouge	Escanaba	24	2	3
River Rouge	Marblehead	43	1	6
River Rouge	Marquette	537	2	77
River Rouge	Port Dolomite	29	1	4
River Rouge	Port Gypsum	10	1	1
River Rouge	Presque Isle	495	1	71
River Rouge	River Rouge	2	10	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
River Rouge	Sandusky	186	1	27
River Rouge	Sarnia	1	8	1
River Rouge	Silver Bay	123	3	18
River Rouge	Stoneport	83	1	12
River Rouge	Sturgeon Bay	7	1	1
River Rouge	Superior	305	3	44
River Rouge	Toledo (USA)	197	1	28
River Rouge	Two Harbors	239	2	34
Saginaw	Alpena	112	1	16
Saginaw	Brevort	46	1	7
Saginaw	Bruce Mines	2	1	1
Saginaw	Calcite	644	1	92
Saginaw	Cedarville	107	1	15
Saginaw	Cleveland	4	1	1
Saginaw	Conneaut	1	0	1
Saginaw	Detroit	11	2	2
Saginaw	Drummond Island	261	1	37
Saginaw	Duluth	23	2	3
Saginaw	Ecorse	1	2	1
Saginaw	Escanaba	8	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Saginaw	Marquette	12	2	2
Saginaw	Meldrum Bay	5	2	1
Saginaw	Menominee	8	2	1
Saginaw	Port Dolomite	227	1	32
Saginaw	Port Inland	96	2	14
Saginaw	Presque Isle	701	1	100
Saginaw	Saginaw	1	1	1
Saginaw	Sault Ste. Marie (USA, MI)	14	62	2
Saginaw	Silver Bay	38	2	5
Saginaw	South Chicago	2	1	1
Saginaw	Stoneport	1008	1	144
Saginaw	Superior	59	2	8
Saginaw	Taconite Harbor	7	3	1
Saginaw	Thessalon	8	1	1
Saint Clair	45.92 -83.83	6	1	1
Saint Clair	45.92 -83.92	3	1	1
Saint Clair	46.07 -84.02	15	1	2
Saint Clair	Duluth	316	2	45
Saint Clair	Escanaba	10	2	1
Saint Clair	Marquette	19	2	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Saint Clair	Monroe	13	1	2
Saint Clair	Saint Clair	8	0	1
Saint Clair	Silver Bay	133	2	19
Saint Clair	Sturgeon Bay	48	2	7
Saint Clair	Superior	5315	3	759
Saint Clair	Toledo (USA)	8	2	1
Saint Clair	Two Harbors	317	2	45
Saint Joseph	Alpena	500	2	71
Saint Joseph	Brevort	27	1	4
Saint Joseph	Burns Harbour	26	0	4
Saint Joseph	Calcite	28	1	4
Saint Joseph	Calumet	165	1	24
Saint Joseph	Cedarville	6	1	1
Saint Joseph	Chicago	240	1	34
Saint Joseph	Drummond Island	3	2	1
Saint Joseph	Escanaba	5	1	1
Saint Joseph	Gary	8	0	1
Saint Joseph	Grand Haven	147	0	21
Saint Joseph	Indiana Harbor	18	0	3
Saint Joseph	Muskegon	4	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Saint Joseph	Port Dolomite	22	1	3
Saint Joseph	Port Inland	116	1	17
Saint Joseph	Saint Joseph	7	1	1
Saint Joseph	Silver Bay	5	4	1
Saint Joseph	South Chicago	36	1	5
Saint Joseph	Stoneport	8	1	1
Saint Joseph	Sturgeon Bay	1	1	1
Saint Marys River (USA, Great Lakes)	Duluth	52	1	7
Saint Marys River (USA, Great Lakes)	Superior	6	2	1
Saint Marys River (USA, Great Lakes)	Two Harbors	203	1	29
Sandusky	Calcite	6	2	1
Sandusky	Chicago	3	3	1
Sandusky	Cleveland	9	0	1
Sandusky	Duluth	2	19	1
Sandusky	Green Bay	19	2	3
Sandusky	Marblehead	28	0	4
Sandusky	Marquette	12	2	2
Sandusky	Ontonagon	2	3	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sandusky	Sault Ste. Marie (USA, MI)	18	5	3
Sandusky	Silver Bay	5	3	1
Sandusky	Stoneport	1	1	1
Sandusky	Superior	11	3	2
Sandusky	Toledo (USA)	1	2	1
Sarnia	Ashtabula	1	0	1
Sarnia	Bay City	4	4	1
Sarnia	Brevort	18	1	3
Sarnia	Buffalo	15	4	2
Sarnia	Calcite	119	1	17
Sarnia	Cedarville	23	1	3
Sarnia	Chicago	6	2	1
Sarnia	Conneaut	6	1	1
Sarnia	Detroit	74	1	11
Sarnia	Drummond Island	50	1	7
Sarnia	Duluth	29	6	4
Sarnia	Goderich	2	5	1
Sarnia	Huron	1	1	1
Sarnia	Indiana Harbor	5	4	1
Sarnia	Marblehead	3	1	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sarnia	Marysville	2	1	1
Sarnia	Meldrum Bay	4	1	1
Sarnia	Monroe	2	1	1
Sarnia	Port Colborne	1	5	1
Sarnia	Port Dolomite	31	1	4
Sarnia	Port Inland	8	1	1
Sarnia	Presque Isle	7	2	1
Sarnia	River Rouge	1	6	1
Sarnia	Sandusky	25	1	4
Sarnia	Sarnia	5	0	1
Sarnia	Sault Ste. Marie (USA, MI)	3	2	1
Sarnia	Silver Bay	20	2	3
Sarnia	Soo Locks (Sault Ste. Marie, MI)	2	1	1
Sarnia	Stoneport	36	1	5
Sarnia	Superior	160	3	23
Sarnia	Toledo (USA)	78	1	11
Sarnia	Whiting	5	3	1
Sault Ste. Marie (Canada)	Ashtabula	8	2	1
Sault Ste. Marie (Canada)	Bay City	6	1	1
Sault Ste. Marie (Canada)	Brevort	14	0	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sault Ste. Marie (Canada)	Calcite	216	1	31
Sault Ste. Marie (Canada)	Calumet	7	2	1
Sault Ste. Marie (Canada)	Cedarville	108	1	15
Sault Ste. Marie (Canada)	Chicago	6	2	1
Sault Ste. Marie (Canada)	Cleveland	16	3	2
Sault Ste. Marie (Canada)	Conneaut	30	2	4
Sault Ste. Marie (Canada)	Detroit	7	2	1
Sault Ste. Marie (Canada)	Drummond Island	73	1	10
Sault Ste. Marie (Canada)	Duluth	194	2	28
Sault Ste. Marie (Canada)	Ludington	7	2	1
Sault Ste. Marie (Canada)	Marquette	5689	1	813
Sault Ste. Marie (Canada)	Port Dolomite	34	1	5
Sault Ste. Marie (Canada)	Port Inland	66	1	9
Sault Ste. Marie (Canada)	Presque Isle	257	1	37
Sault Ste. Marie (Canada)	Saginaw	1	1	1
Sault Ste. Marie (Canada)	Sandusky	15	134	2
Sault Ste. Marie (Canada)	Sarnia	6	2	1
Sault Ste. Marie (Canada)	Silver Bay	135	1	19
Sault Ste. Marie (Canada)	Stoneport	38	1	5
Sault Ste. Marie (Canada)	Sturgeon Bay	7	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sault Ste. Marie (Canada)	Superior	693	1	99
Sault Ste. Marie (Canada)	Toledo (USA)	13	2	2
Sault Ste. Marie (Canada)	Two Harbors	82	2	12
Sault Ste. Marie (Unknown)	Calcite	5	1	1
Sault Ste. Marie (Unknown)	Duluth	27	1	4
Sault Ste. Marie (Unknown)	Marquette	253	1	36
Sault Ste. Marie (Unknown)	Port Dolomite	7	1	1
Sault Ste. Marie (Unknown)	Presque Isle	3	1	1
Sault Ste. Marie (Unknown)	Sarnia	15	6	2
Sault Ste. Marie (Unknown)	Silver Bay	25	2	4
Sault Ste. Marie (Unknown)	Superior	72	2	10
Sault Ste. Marie (Unknown)	Two Harbors	30	1	4
Sault Ste. Marie (USA, MI)	Ashtabula	7	2	1
Sault Ste. Marie (USA, MI)	Calcite	8	1	1
Sault Ste. Marie (USA, MI)	Duluth	64	2	9
Sault Ste. Marie (USA, MI)	Marquette	61	1	9
Sault Ste. Marie (USA, MI)	Nanticoke	5	3	1
Sault Ste. Marie (USA, MI)	Presque Isle	26	0	4
Sault Ste. Marie (USA, MI)	Sault Ste. Marie (USA, MI)	2	0	1
Sault Ste. Marie (USA, MI)	Silver Bay	7	28	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sault Ste. Marie (USA, MI)	Stoneport	8	1	1
Sault Ste. Marie (USA, MI)	Superior	253	1	36
Sault Ste. Marie (USA, MI)	Two Harbors	18	1	3
Sept-Iles	Detroit	4	11	1
Sept-Iles	Duluth	4	12	1
Sept-Iles	Ludington	17	10	2
Sept-Iles	Sandusky	1	6	1
Sept-Iles	Toledo (USA)	3	6	1
Serpent Harbor	Brevort	6	2	1
Serpent Harbor	Calcite	35	1	5
Serpent Harbor	Calumet	3	2	1
Serpent Harbor	Duluth	12	2	2
Serpent Harbor	Port Dolomite	14	0	2
Serpent Harbor	Presque Isle	18	0	3
Serpent Harbor	Silver Bay	13	1	2
Serpent Harbor	Superior	27	2	4
Serpent Harbor	Two Harbors	7	2	1
Silver Bay	45.70 -86.70	1	1	1
Silver Bay	Ashtabula	33	2	5
Silver Bay	Calcite	1	5	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Silver Bay	Cleveland	13	3	2
Silver Bay	Duluth	10	1	1
Silver Bay	Gary	11	3	2
Silver Bay	Marquette	6	1	1
Silver Bay	Port Gypsum	2	4	1
Silver Bay	Silver Bay	2	5	1
Silver Bay	Sturgeon Bay	1	3	1
Silver Bay	Superior	73	1	10
Silver Bay	Two Harbors	24	1	3
Sombra	Calcite	54	1	8
Sombra	Cedarville	1	1	1
Sombra	Drummond Island	10	2	1
Sombra	Duluth	12	2	2
Sombra	Marquette	7	2	1
Sombra	Port Dolomite	26	1	4
Sombra	Port Inland	2	1	1
Sombra	Stoneport	30	1	4
Sombra	Superior	17	2	2
Sombra	Toledo (USA)	8	3	1
Sombra	Two Harbors	6	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Soo Locks (Sault Ste. Marie, MI)	Duluth	14	1	2
Sorel	Burns Harbour	10	7	1
Sorel	Chicago	7	5	1
Sorel	Duluth	43	6	6
Sorel	Marquette	13	4	2
Sorel	Menominee	14	6	2
Sorel	Milwaukee	10	8	1
Sorel	Silver Bay	51	5	7
Sorel	Superior	97	6	14
Sorel	Toledo (USA)	53	4	8
South Chicago	Alpena	71	3	10
South Chicago	Brevort	9	2	1
South Chicago	Burns Harbour	2	0	1
South Chicago	Calcite	17	2	2
South Chicago	Charlevoix	12	1	2
South Chicago	Drummond Island	51	2	7
South Chicago	Escanaba	7	1	1
South Chicago	Grand Haven	7	1	1
South Chicago	Green Bay	10	2	1
South Chicago	Indiana Harbor	19	0	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
South Chicago	Ludington	3	1	1
South Chicago	Manistee	9	1	1
South Chicago	Marinette	1	1	1
South Chicago	Milwaukee	1	1	1
South Chicago	Muskegon	1	0	1
South Chicago	Port Inland	31	2	4
South Chicago	Presque Isle	72	2	10
South Chicago	South Chicago	1	0	1
South Chicago	Stoneport	7	2	1
South Chicago	Superior	8	3	1
Stoneport	Burns Harbour	1	1	1
Stoneport	Calcite	19	0	3
Stoneport	Cleveland	10	2	1
Stoneport	Detroit	10	2	1
Stoneport	Essexville	7	1	1
Stoneport	Fairport Harbor	27	2	4
Stoneport	Grand Haven	1	1	1
Stoneport	Manistee	7	0	1
Stoneport	Marine City	9	1	1
Stoneport	Marquette	18	2	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Stoneport	Marysville	7	1	1
Stoneport	Monroe	1	1	1
Stoneport	Port Dolomite	1	3	1
Stoneport	Saginaw	1	1	1
Stoneport	Saint Joseph	25	2	4
Stoneport	Silver Bay	1	3	1
Stoneport	Stoneport	4	1	1
Stoneport	Toledo (USA)	1	3	1
Sturgeon Bay	Alpena	23	1	3
Sturgeon Bay	Brevort	1	1	1
Sturgeon Bay	Calcite	15	1	2
Sturgeon Bay	Calumet	32	1	5
Sturgeon Bay	Cedarville	6	3	1
Sturgeon Bay	Charlevoix	12	1	2
Sturgeon Bay	Chicago	32	1	5
Sturgeon Bay	Duluth	83	2	12
Sturgeon Bay	Escanaba	45	1	6
Sturgeon Bay	Lorain	9	4	1
Sturgeon Bay	Ludington	6	22	1
Sturgeon Bay	Marquette	39	2	6

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Sturgeon Bay	Port Dolomite	19	2	3
Sturgeon Bay	Port Inland	19	1	3
Sturgeon Bay	Presque Isle	36	1	5
Sturgeon Bay	Silver Bay	46	3	7
Sturgeon Bay	Stoneport	25	1	4
Sturgeon Bay	Sturgeon Bay	3	353	1
Sturgeon Bay	Superior	177	2	25
Sturgeon Bay	Toledo (USA)	2	4	1
Sturgeon Bay	Two Harbors	108	3	15
Sturgeon Bay	Whiting	6	2	1
Sun Oil (Sarnia, Canada)	Port Dolomite	6	1	1
Superior	Alpena	338	2	48
Superior	Ashtabula	1	6	1
Superior	Brevort	6	2	1
Superior	Buffalo	11	4	2
Superior	Burns Harbour	9	2	1
Superior	Calcite	12	7	2
Superior	Conneaut	55	3	8
Superior	Detroit	2	0	1
Superior	Duluth	135	0	19

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Superior	Ecorse	9	3	1
Superior	Gary	11	2	2
Superior	Indiana Harbor	33	3	5
Superior	Ludington	62	4	9
Superior	Marblehead	2	6	1
Superior	Marquette	39	1	6
Superior	Port Dolomite	1	7	1
Superior	Presque Isle	15	1	2
Superior	Saint Clair	40	3	6
Superior	Silver Bay	265	1	38
Superior	South Chicago	3	3	1
Superior	Stoneport	1	7	1
Superior	Sturgeon Bay	9	3	1
Superior	Superior	124	1	18
Superior	Taconite Harbor	10	0	1
Superior	Toledo (USA)	6	6	1
Superior	Two Harbors	135	0	19
Taconite Harbor	Duluth	36	0	5
Taconite Harbor	Silver Bay	9	0	1
Taconite Harbor	Superior	116	1	17

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Taconite Harbor	Two Harbors	18	0	3
Tawas City	Chicago	3	2	1
Thessalon	Calcite	1	14	1
Thessalon	Erie	2	2	1
Thorold	Ashtabula	29	1	4
Thorold	Calcite	5	3	1
Thorold	Cedarville	1	3	1
Thorold	Cleveland	28	1	4
Thorold	Conneaut	20	1	3
Thorold	Detroit	7	41	1
Thorold	Drummond Island	1	3	1
Thorold	Fairport (USA, OH)	3	1	1
Thorold	Marblehead	64	1	9
Thorold	Presque Isle	7	21	1
Thorold	River Rouge	7	3	1
Thorold	Sandusky	14	1	2
Thorold	Toledo (USA)	17	1	2
Three Rivers	Burns Harbour	1	7	1
Three Rivers	Duluth	20	7	3
Three Rivers	Ludington	5	7	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Three Rivers	Sturgeon Bay	9	97	1
Three Rivers	Superior	3	11	1
Thunder Bay	43.92 -87.26	1	4	1
Thunder Bay	43.93 -87.24	1	4	1
Thunder Bay	43.94 -87.26	1	4	1
Thunder Bay	43.95 -87.26	2	3	1
Thunder Bay	43.96 -87.26	1	3	1
Thunder Bay	Bay City	5	2	1
Thunder Bay	Buffalo	5	3	1
Thunder Bay	Detroit	6	0	1
Thunder Bay	Duluth	86	2	12
Thunder Bay	Ludington	11	5	2
Thunder Bay	Silver Bay	6	2	1
Thunder Bay	Superior	153	1	22
Thunder Bay	Thunder Bay	13	1	2
Thunder Bay	Toledo (USA)	15	4	2
Toledo (USA)	Alpena	240	2	34
Toledo (USA)	Ashtabula	249	1	36
Toledo (USA)	Brevort	18	2	3
Toledo (USA)	Bruce Mines	4	2	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Toledo (USA)	Buffalo	32	1	5
Toledo (USA)	Calcite	346	1	49
Toledo (USA)	Calumet	7	4	1
Toledo (USA)	Cedarville	47	2	7
Toledo (USA)	Chicago	72	3	10
Toledo (USA)	Cleveland	139	1	20
Toledo (USA)	Conneaut	135	1	19
Toledo (USA)	Detroit	74	1	11
Toledo (USA)	Drummond Island	67	1	10
Toledo (USA)	Duluth	258	3	37
Toledo (USA)	Ecorse	7	0	1
Toledo (USA)	Escanaba	8	6	1
Toledo (USA)	Fairport (USA, OH)	44	1	6
Toledo (USA)	Fairport Harbor	17	1	2
Toledo (USA)	Green Bay	9	2	1
Toledo (USA)	Kelleys Island	4	0	1
Toledo (USA)	Lorain	6	0	1
Toledo (USA)	Marblehead	334	0	48
Toledo (USA)	Marquette	160	2	23
Toledo (USA)	Meldrum Bay	12	1	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Toledo (USA)	Menominee	9	3	1
Toledo (USA)	Milwaukee	11	4	2
Toledo (USA)	Munising	8	2	1
Toledo (USA)	Muskegon	1	3	1
Toledo (USA)	Port Dolomite	60	1	9
Toledo (USA)	Port Gypsum	25	1	4
Toledo (USA)	Port Inland	19	1	3
Toledo (USA)	Presque Isle	166	2	24
Toledo (USA)	Sandusky	442	1	63
Toledo (USA)	Sarnia	12	1	2
Toledo (USA)	Sault Ste. Marie (Unknown)	1	1	1
Toledo (USA)	Sault Ste. Marie (USA, MI)	8	1	1
Toledo (USA)	Silver Bay	270	3	39
Toledo (USA)	Stoneport	268	1	38
Toledo (USA)	Sturgeon Bay	18	2	3
Toledo (USA)	Superior	710	3	101
Toledo (USA)	Thunder Bay	25	9	4
Toledo (USA)	Toledo (USA)	276	1	39
Toledo (USA)	Two Harbors	141	3	20
Toledo (USA)	Whiting	61	4	9

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Toledo (USA)	Zug Island (USA, MI)	1	244	1
Tonawanda	Cleveland	28	1	4
Tonawanda	Conneaut	70	0	10
Tonawanda	Detroit	25	2	4
Tonawanda	Fairport (USA, OH)	7	1	1
Tonawanda	River Rouge	2	17	1
Tonawanda	Sarnia	1	1	1
Tonawanda	Toledo (USA)	15	1	2
Tonawanda	Whiting	5	5	1
Toronto	43.32 -79.22	1	1	1
Toronto	Ashtabula	76	1	11
Toronto	Chicago	8	4	1
Toronto	Cleveland	24	1	3
Toronto	Conneaut	8	2	1
Toronto	Detroit	14	2	2
Toronto	Duluth	43	5	6
Toronto	Fairport (USA, OH)	7	2	1
Toronto	Fairport Harbor	17	1	2
Toronto	Marblehead	24	1	3
Toronto	Sandusky	30	2	4

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Toronto	Sault Ste. Marie (USA, MI)	19	4	3
Toronto	Superior	43	4	6
Toronto	Toledo (USA)	66	4	9
Toronto	Toronto	1	1	1
Toronto	Two Harbors	6	4	1
Tracy	Bay City	5	5	1
Tracy	Cleveland	5	3	1
Tracy	Detroit	41	4	6
Tracy	River Rouge	10	8	1
Tracy	Toledo (USA)	20	4	3
Tracy	Whiting	41	8	6
Traverse City	Sturgeon Bay	4	4	1
Traverse City	Toledo (USA)	131	3	19
Traverse City	Whiting	243	3	35
Trenton (USA, MI)	Calcite	60	1	9
Trenton (USA, MI)	Drummond Island	8	1	1
Trenton (USA, MI)	Port Gypsum	5	1	1
Trenton (USA, MI)	Presque Isle	8	1	1
Trenton (USA, MI)	Sandusky	7	1	1
Trenton (USA, MI)	Silver Bay	24	2	3

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Trois Rivieres	Ashtabula	6	3	1
Trois Rivieres	Duluth	6	9	1
Trois Rivieres	Ludington	35	7	5
Trois Rivieres	Superior	5	5	1
Troy (USA, NY)	Oswego	4	2	1
Two Harbors	Conneaut	163	3	23
Two Harbors	Detroit	2	2	1
Two Harbors	Escanaba	1	4	1
Two Harbors	Gary	211	3	30
Two Harbors	Indiana Harbor	49	2	7
Two Harbors	Lorain	5	2	1
Two Harbors	Silver Bay	2	8	1
Two Harbors	Two Harbors	2	0	1
Valleyfield	Cleveland	5	2	1
Valleyfield	Detroit	121	3	17
Valleyfield	Duluth	28	6	4
Valleyfield	Fairport Harbor	6	2	1
Valleyfield	Marinette	3	11	1
Valleyfield	Milwaukee	6	7	1
Valleyfield	Sault Ste. Marie (USA, MI)	11	5	2

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Valleyfield	Toledo (USA)	3	8	1
Valleyfield	Whiting	10	6	1
Waukegan	Alpena	731	2	104
Waukegan	Burns Harbour	5	0	1
Waukegan	Calcite	20	1	3
Waukegan	Calumet	112	1	16
Waukegan	Cedarville	5	1	1
Waukegan	Charlevoix	101	1	14
Waukegan	Chicago	31	0	4
Waukegan	Escanaba	10	1	1
Waukegan	Milwaukee	6	1	1
Waukegan	Muskegon	5	1	1
Waukegan	Port Dolomite	30	1	4
Waukegan	Port Gypsum	5	2	1
Waukegan	Port Inland	79	1	11
Waukegan	Presque Isle	5	2	1
Waukegan	Silver Bay	30	2	4
Waukegan	South Chicago	13	1	2
Waukegan	Sturgeon Bay	5	1	1
Welland	Duluth	3	4	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Welland	Sandusky	5	1	1
Welland	Toledo (USA)	2	18	1
Whitefish bay	Alpena	7	1	1
Whitefish Falls, Ontario	Alpena	253	1	36
Whitefish Falls, Ontario	Superior	1	3	1
Whitefish River	Alpena	7	1	1
Whiting	Toledo (USA)	26	4	4
Whiting	Whiting	1	1	1
Windsor	Alpena	8	2	1
Windsor	Ashtabula	21	1	3
Windsor	Buffalo	10	1	1
Windsor	Burns Harbour	10	2	1
Windsor	Calcite	482	1	69
Windsor	Cedarville	58	1	8
Windsor	Chicago	11	5	2
Windsor	Cleveland	17	1	2
Windsor	Conneaut	9	1	1
Windsor	Detroit	64	1	9
Windsor	Drummond Island	8	1	1
Windsor	Duluth	94	3	13

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Windsor	Fairport Harbor	4	1	1
Windsor	Green Bay	1	2	1
Windsor	Kelleys Island	8	1	1
Windsor	Ludington	6	6	1
Windsor	Marblehead	215	1	31
Windsor	Marquette	87	2	12
Windsor	Meldrum Bay	8	2	1
Windsor	Milwaukee	1	14	1
Windsor	Muskegon	1	2	1
Windsor	Oswego	2	2	1
Windsor	Port Dolomite	111	1	16
Windsor	Port Gypsum	50	1	7
Windsor	Port Inland	16	2	2
Windsor	Presque Isle	24	1	3
Windsor	Sandusky	55	1	8
Windsor	Silver Bay	45	2	6
Windsor	Stoneport	173	1	25
Windsor	Superior	62	3	9
Windsor	Tawas City	5	1	1
Windsor	Thunder Bay	2	4	1

Table A.3. Trip Data

Source Location	Discharge Location	Number of Trips	Median Trip Length	Mean Trips per Year
Windsor	Toledo (USA)	466	1	67
Windsor	Two Harbors	17	2	2
Windsor	Whiting	5	4	1
Windsor	Windsor	3	1	1
Wyandotte	Calcite	149	1	21
Wyandotte	Cedarville	7	1	1
Wyandotte	Marquette	31	2	4
Wyandotte	Port Dolomite	26	2	4
Wyandotte	Presque Isle	17	1	2
Wyandotte	Sandusky	9	1	1
Wyandotte	Silver Bay	11	2	2
Wyandotte	Stoneport	27	1	4
Wyandotte	Superior	14	2	2
Wyandotte	Toledo (USA)	58	1	8
Wyandotte	Two Harbors	8	4	1
Zilwaukee	Calcite	15	1	2
Zilwaukee	Drummond Island	18	1	3
Zilwaukee	Port Dolomite	26	1	4
Zilwaukee	Stoneport	27	1	4
Zug Island (USA, MI)	Stoneport	5	1	1

Appendix B

Chapter 2 Model Code

All models were built in ArcGIS 10 ModelBuilder. We have exported the models to Python and included the code in this appendix. The code has been modified to remove file paths and eliminate repetition. The random selection tool used in the Location Model (RandomSelection.tbx) was downloaded from the ESRI website: http://arcscripts.esri.com/details.asp?dbid=15441 (last accessed: 3/29/2011). It was modified to select from a Poisson distribution.

Random Model

```
# ---------------------------------------------------------------------------
# vhs_rand_model.py
# Created on: 2013-06-28 14:30:05.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: vhs_rand_model <Distance__value_or_field_> <final_layer>
# Description:
# ---------------------------------------------------------------------------

# Set the necessary product code
# import arcinfo


# Import arcpy module
import arcpy

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "\\base"

# Script arguments

# Input natural spread distance and units
Distance__value_or_field_ = arcpy.GetParameterAsText(0)
if Distance__value_or_field_ == '#' or not Distance__value_or_field_:
    Distance__value_or_field_ = "20 Kilometers" # provide a default value if unspecified

# Input final layer that will contain model results
final_layer = arcpy.GetParameterAsText(1)
if final_layer == '#' or not final_layer:
    final_layer = "\\final_layer" # provide a default value if unspecified

# Local variables:
```

```
# List of variables defined by ArcGIS removed for publication
# Variables used in following code may include the following:
#    CY = 2-digit Current Year
#    PY = 2-digit Previous Year
#    YYYY = 4-digit Current Year

### CALCULATE THE NUMBER OF NEW INFECTIONS FOR EACH YEAR SIMULATED ###

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2003
arcpy.CalculateField_management(gl_sls_boundary__9_, "randct03", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n")

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2004
arcpy.CalculateField_management(gl_sls_boundary__8_, "randct04", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n")

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2005
arcpy.CalculateField_management(gl_sls_boundary, "randct05", "numpy.random.poisson(lam=8)", "PYTHON_9.3",
"import numpy.random\\nfrom numpy.random import poisson")

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2006
arcpy.CalculateField_management(gl_sls_boundary__2_, "randct06", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n")

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2007
arcpy.CalculateField_management(gl_sls_boundary__5_, "randct07", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n")

# Process: Calculate Field
```

```
# Calculate the number of new infections to be selected for 2008
arcpy.CalculateField_management(gl_sls_boundary__3_, "randct08", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n\\n")

# Process: Calculate Field
# Calculate the number of new infections to be selected for 2009
arcpy.CalculateField_management(gl_sls_boundary__7_, "randct09", "numpy.random.poisson(lam=8)",
"PYTHON_9.3", "import numpy.random\\nfrom numpy.random import poisson\\n")


### 2003: INDENTIFY NEW INFECTIONS ###

# Process: Create Random Points
# Create random points within the Great Lakes boundary using number of infections identified for 2003
arcpy.CreateRandomPoints_management(scratch_data__2_, "rand_pt_03", gl_sls_boundary__4_, "0 0 250 250",
"randct03", "0 Unknown", "POINT", "0")

# Process: Buffer
# Apply the 2-km spread distance to each new infection point
arcpy.Buffer_analysis(rand_pt_03, rand_py_03, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(rand_py_03, spread1_03, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a “prediction” field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_03, "pred", "SHORT", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute “prediction” filed to identify infected areas
arcpy.CalculateField_management(spread1_03__2_, "pred", "1", "VB", "")
```

```
### 2003: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###

# Process: Identity
# Overlay the actual 2003 VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_2003, spread1_03__3_, detection_03, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(detection_03, "iter", "LONG", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(detection_03__4_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\detection_03", final_layer, "NO_TEST", "", "")


### 2003: REMOVE INFECTED LOCATIONS FROM POSSIBILITY OF BEING SELECTED AGAIN ###

# Process: Buffer
# Add a small buffer to the newly infected locations
arcpy.Buffer_analysis(rand_pt_03, rand_erase_2003, "1 Feet", "FULL", "ROUND", "NONE", "")

# Process: Erase
# Erase the newly infected locations from the Great Lakes boundary to prevent being used again
arcpy.Erase_analysis(gl_sls_boundary__9_, rand_erase_2003, gl_sls_boundary_2004, "")


### 2004-2009: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Create Random Points
```

```
# Create random points in the Great Lakes boundary using number of infections identified for current year
arcpy.CreateRandomPoints_management(scratch_data__2_, "rand_pt_CY", gl_sls_boundary_YEAR, "0 0 250 250",
"randctCY", "0 Unknown", "POINT", "0")

# Process: Buffer
# Apply the 2-km spread distance to each new infection point
arcpy.Buffer_analysis(rand_pt_CY, rand_py_CY, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Union
# Combine the current year's newly infected areas to the previous year's infected areas
arcpy.Union_analysis("\\spread1_PY #;\\rand_py_CY #", spread1_CY, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(spread1_CY, spread2_CY, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread2_CY, "pred", "SHORT", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread2_CY__4_, "pred", "1", "VB", "")


### 2004-2009: REMOVE INFECTED LOCATIONS FROM POSSIBILITY OF BEING SELECTED AGAIN ###

# Process: Buffer
# Add a small buffer to the newly infected locations
arcpy.Buffer_analysis(rand_pt_CY, rand_erase_YYYY, "1 Feet", "FULL", "ROUND", "NONE", "")

# Process: Erase
# Erase the newly infected locations from the Great Lakes boundary to prevent being used again
arcpy.Erase_analysis(gl_sls_boundary_YYYY, rand_erase_YYYY, gl_sls_boundary_YYYY, "")
```

```
### 2004-2009: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###

# Process: Identity
# Overlay the actual current year's VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_YYYY, spread2_CY__3_, detection_CY, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(detection_CY, "iter", "LONG", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(detection_CY__4_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\detection_CY", final_layer, "NO_TEST", "", "")
```

Location Model

```
# ---------------------------------------------------------------------------
# vhs_loc_model.py
# Created on: 2013-06-28 14:30:24.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: vhs_loc_model <Distance__value_or_field_> <final_layer>
# Description:
# ---------------------------------------------------------------------------

# Set the necessary product code
# import arcinfo


# Import arcpy module
import arcpy

# Load required toolboxes
arcpy.ImportToolbox("/RandomSelection.tbx")

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "\\base"

# Script arguments

# Input natural spread distance and units
Distance__value_or_field_ = arcpy.GetParameterAsText(0)
if Distance__value_or_field_ == '#' or not Distance__value_or_field_:
    Distance__value_or_field_ = "10 Kilometers" # provide a default value if unspecified

# Input final layer that will contain model results
final_layer = arcpy.GetParameterAsText(1)
if final_layer == '#' or not final_layer:
```

```
    final_layer = "\\final_layer" # provide a default value if unspecified

# Local variables:
# Local variables:
# List of variables defined by ArcGIS removed for publication
# Variables used in following code may include the following:
#    CY = 2-digit Current Year
#    PY = 2-digit Previous Year
#    YYYY = 4-digit Current Year
#    NEXT = 4-digit Next Year


### 2003: IDENTIFY NEW INFECTIONS

# Process: Random selection
# Randomly select the number of infections for 2003 from a Poisson distribution
# Select locations from the feature class containing discharge locations
arcpy.gp.toolbox = "/RandomSelection.tbx";
arcpy.gp.RandomSelection(gl_discharge_loc_red, ship_dis_03_lyr)

# Process: Buffer
# Apply the 2-km spread distance to each new infection point
arcpy.Buffer_analysis(ship_dis_03_lyr, rand_ship_py_03, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(rand_ship_py_03, spread1_03, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_03, "pred", "SHORT", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
```

```
arcpy.CalculateField_management(spread1_03__2_, "pred", "1", "VB", "")


### 2003: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###

# Process: Identity
# Overlay the actual 2003 VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_2003, spread1_03__3_, detection_03, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(detection_03, "iter", "LONG", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(detection_03__4_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\detection_03", final_layer, "NO_TEST", "", "")


### 2003: REMOVE INFECTED LOCATIONS FROM POSSIBILITY OF BEING SELECTED AGAIN ###

# Process: Join Field
# Join the 2003 infected locations layer created under Random Selection (8) to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red, "Location", ship_dis_03_lyr, "Location", "Location")

# Process: Select
# Create a new feature class of those locations that have not already been infected
arcpy.Select_analysis(gl_discharge_loc_red__3_, gl_discharge_loc_2004, "\"Location_1\" IS NULL")

# Process: Delete Field
```

```
# Delete the field added to the discharge feature class during Join Field
arcpy.DeleteField_management(gl_discharge_loc_2004, "Location_1")


### 2004-2009: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Random selection
# Randomly select the number of infections for the current year from a Poisson distribution
# Select locations from the feature class containing discharge locations with previous infections removed
arcpy.gp.toolbox = " /RandomSelection.tbx";
arcpy.gp.RandomSelection(gl_discharge_loc_YYYY__2_, ship_dis_CY_lyr)

# Process: Buffer
# Apply the 2-km spread distance to each new infection point
arcpy.Buffer_analysis(ship_dis_CY_lyr, rand_ship_py_CY, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Union
# Combine the current year's newly infected areas to the previous year's infected areas
arcpy.Union_analysis("\\spread1_PY #;\\rand_ship_py_CY #", spread1_CY, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(spread1_CY, spread2_CY, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread2_CY, "pred", "SHORT", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread2_CY__3_, "pred", "1", "VB", "")


### 2004-2009: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###
```

```
# Process: Identity
# Overlay the actual VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_2004, spread2_04__2_, detection_04, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(detection_04, "iter", "LONG", "", "", "1", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(detection_04__5_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\detection_04", final_layer, "NO_TEST", "", "")


### 2004-2009: REMOVE INFECTED LOCATIONS FROM POSSIBILITY OF BEING SELECTED AGAIN ###

# Process: Join Field
# Join the current year's infected locations identified by Random Selection to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_YYYY__2_, "Location", ship_dis_CY_lyr, "Location", "Location")

# Process: Select
# Create a new feature class of those locations that have not already been infected
arcpy.Select_analysis(gl_discharge_loc_YYYY__3_, gl_discharge_loc_NEXT, "\"Location_1\" IS NULL")

# Process: Delete Field
# Delete the field added to the discharge feature class during Join Field
arcpy.DeleteField_management(gl_discharge_loc_NEXT, "Location_1")
```

Propagule Pressure Model: Lake St. Clair Only

```
# ---------------------------------------------------------------------------
# vhs_pplsc_model.py
# Created on: 2013-07-08 09:47:27.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: vhs_pplsc_model <Distance__value_or_field_> <final_layer>
# Description:
# ---------------------------------------------------------------------------

# Set the necessary product code
# import arcinfo


# Import arcpy module
import arcpy

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "\\base"

# Script arguments

# Input natural spread distance and units
Distance__value_or_field_ = arcpy.GetParameterAsText(0)
if Distance__value_or_field_ == '#' or not Distance__value_or_field_:
    Distance__value_or_field_ = "20 Kilometers" # provide a default value if unspecified

# Input final layer that will contain model results
final_layer = arcpy.GetParameterAsText(1)
if final_layer == '#' or not final_layer:
    final_layer = " \\final_layer" # provide a default value if unspecified

# Local variables:
```

```
# List of variables defined by ArcGIS removed for publication
# Variables used in following code may include the following:
#    CY = 2-digit Current Year
#    PY = 2-digit Previous Year
#    YYYY = 4-digit Current Year
#    PREV = 4-digit Previous Year
```

2003: BEGIN INVASION FROM 1ST LAKE ST. CLAIR OCCURRENCE

```
# Process: Select
# Create feature class with Lake St. Clair as the initial invasion locations
arcpy.Select_analysis(vhs_pasites_2003, vhs_possites_2003, "\"actual\" = 1")

# Process: Buffer
# Apply the 2-km spread distance to each new infection point
arcpy.Buffer_analysis(vhs_possites_2003, ship_py_03, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_03, spread1_03, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_03, "pred", "SHORT", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_03__2_, "pred", "1", "VB", "")
```

2004: IDENTIFY NEW AND CONTINUING INFECTIONS

```
# Process: Identity
# Identify source locations that fall within the infected boundary
```

```
arcpy.Identity_analysis(gl_discharge_source_red, spread1_03__3_, source_inf_03, "ALL", "",
"NO_RELATIONSHIPS")

# Process: Join Field
# Join infected sources with table containing source-to-discharge trip information
arcpy.JoinField_management(sourcedis_freq_2003, "Source_Location", source_inf_03, "Location", "pred")

# Process: Table Select
# Select discharge locations that have received ballast water from an infected source
arcpy.TableSelect_analysis(sourcedis_freq_2003__2_, sourcedis_inf_2003, "\"pred\" = 1")

# Process: Delete Field
# Delete prediction files from tables that contain source-to-discharge trip information
arcpy.DeleteField_management(sourcedis_freq_2003__2_, "pred;pred")

# Process: Summary Statistics
# Calculate the number of visits discharge locations received from infected sources
arcpy.Statistics_analysis(sourcedis_inf_2003, dis_inf_2003, "FREQUENCY SUM", "Discharge_Location")

# Process: Join Field
# Join the table from Summary Statistics to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red__10_, "Location", dis_inf_2003, "Discharge_Location",
"SUM_FREQUENCY")

# Process: Add Field
# Create a field to hold the number of visits each location received from an infected source
arcpy.AddField_management(gl_discharge_loc_red, "inf_visits", "LONG", "", "", "", "", "NULLABLE",
"NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the field with the number of visits each location received from an infected source
arcpy.CalculateField_management(gl_discharge_loc_red__3_, "inf_visits", "[SUM_FREQUENCY]", "VB", "")

# Process: Delete Field
```

```
# Delete the field added to the discharge feature class from Join Field
arcpy.DeleteField_management(gl_discharge_loc_red__4_, "SUM_FREQUENCY")

# Process: Calculate Field
# Calculate the number of visits that resulted in infection for 2004 by drawing from binomial distribution
# n = number of visits, p = p(VLP)
arcpy.CalculateField_management(gl_discharge_loc_red__5_, "inf03", "numpy.random.binomial(n= !inf_visits!,
p= !decay_per!  )", "PYTHON_9.3", "import numpy.random\\nfrom numpy.random import binomial")

# Process: Buffer
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(gl_discharge_loc_red__14_, dis_inf_py_04, "2 Kilometers", "FULL", "ROUND", "LIST",
"inf03")

# Process: Select
# Select areas that were newly infected for 2004
arcpy.Select_analysis(dis_inf_py_04, dis_inf_yes_04, "inf03 >= 1")

# Process: Union
# Combine the 2004 newly infected areas to the previous years infected areas
arcpy.Union_analysis("\\spread1_03 #;\\dis_inf_yes_04 #", ship_py_04, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_04, spread1_04, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_04, "pred", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_04__2_, "pred", "1", "VB", "")
```

```
### 2005-2009: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Identity
# Identify source locations that fall within the infected boundary
arcpy.Identity_analysis(gl_discharge_source_red, spread1_PY__3_, source_inf_PY, "ALL", "",
"NO_RELATIONSHIPS")

# Process: Join Field
# Join infected sources with table containing source-to-discharge trip information
arcpy.JoinField_management(sourcedis_freq_PREV__4_, "Source_Location", source_inf_PY, "Location", "pred")

# Process: Table Select
# Select discharge locations that have received ballast water from an infected source
arcpy.TableSelect_analysis(sourcedis_freq_PREV, sourcedis_inf_PREV, "\"pred\" = 1")

# Process: Delete Field
# Delete prediction files from tables that contain source-to-discharge trip information
arcpy.DeleteField_management(sourcedis_freq_PREV__2_, "pred;pred")

# Process: Summary Statistics
# Calculate the number of visits discharge locations received from infected sources
arcpy.Statistics_analysis(sourcedis_inf_PREV, dis_inf_PREV, "FREQUENCY SUM", "Discharge_Location")

# Process: Join Field
# Join the table from Summary Statistics to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red__14_, "Location", dis_inf_PREV, "Discharge_Location",
"SUM_FREQUENCY")

# Process: Calculate Field
# Attribute the field with the number of visits each location received from an infected source
arcpy.CalculateField_management(gl_discharge_loc_red__7_, "inf_visits", "[SUM_FREQUENCY]", "VB", "")
```

```
# Process: Delete Field
# Delete the field added to the discharge feature class from Join Field (4)
arcpy.DeleteField_management(gl_discharge_loc_red__8_, "SUM_FREQUENCY")

# Process: Calculate Field
# Calculate number of visits that resulted in infection for the year by drawing from binomial distribution
# n = number of visits, p = p(VLP)
arcpy.CalculateField_management(gl_discharge_loc_red__18_, "infPY", "numpy.random.binomial(n= !inf_visits!,
p= !decay_per! )", "PYTHON_9.3", "import numpy.random\\nfrom numpy.random import binomial")

# Process: Buffer
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(gl_discharge_loc_red__2_, dis_inf_py_CY, "2 Kilometers", "FULL", "ROUND", "LIST",
"inf04")

# Process: Select
# Select areas that were newly infected for the year
arcpy.Select_analysis(dis_inf_py_CY, dis_inf_yes_CY, "infPY >= 1")

# Process: Union
# Combine the current year's newly infected areas to the previous year's infected areas
arcpy.Union_analysis("\\spread1_PY #;\\dis_inf_yes_CY #", ship_py_CY, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_CY, spread1_CY, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_CY, "pred", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_CY__2_, "pred", "1", "VB", "")
```

2005-2009: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES

```
# Process: Select
# Create feature class with all presence/absence locations except Lake St. Clair
arcpy.Select_analysis(vhs_pasites_YYYY, vhs_pasites_ship_YYYY, "\"Location\" <> 'Lake St. Clair-1'")

# Process: Identity
# Overlay the actual VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_ship_YYYY, spread1_YY__3_, ship_pred_CY, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(ship_pred_CY, "iter", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(ship_pred_CY__2_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\ship_pred_CY", final_layer, "NO_TEST", "", "")
```

Propagule Pressure Model: Montreal Only

```
# ---------------------------------------------------------------------------
# vhs_ppmon_model.py
# Created on: 2013-07-03 14:48:04.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: vhs_ppmon_model <Distance__value_or_field_> <final_layer>
# Description:
# ---------------------------------------------------------------------------

# Set the necessary product code
# import arcinfo


# Import arcpy module
import arcpy

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "\\base"

# Script arguments

# Input natural spread distance and units
Distance__value_or_field_ = arcpy.GetParameterAsText(0)
if Distance__value_or_field_ == '#' or not Distance__value_or_field_:
    Distance__value_or_field_ = "20 Kilometers" # provide a default value if unspecified

# Input final layer that will contain model results
final_layer = arcpy.GetParameterAsText(1)
if final_layer == '#' or not final_layer:
    final_layer = "\\final_layer" # provide a default value if unspecified

# Local variables:
```

```
# List of variables defined by ArcGIS removed for publication
# Variables used in following code may include the following:
#    CY = 2-digit Current Year
#    PY = 2-digit Previous Year
#    YYYY = 4-digit Current Year
#    PREV = 4-digit Previous Year


### PRE-2003: BEGIN INVASION FROM MONTREAL ###

# Process: Buffer
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(montreal_testsite__2_, ship_py_g0, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_g0, spread1_g0, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_g0, "pred", "SHORT", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_g0__2_, "pred", "1", "VB", "")


### 2003-2009: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Identity
# Identify source locations that fall within the infected boundary
arcpy.Identity_analysis(gl_discharge_source_red, spread1_PY__3_, source_inf_PY, "ALL", "",
"NO_RELATIONSHIPS")
```

```
# Process: Join Field
# Join infected sources with table containing source-to-discharge trip information
arcpy.JoinField_management(sourcedis_freq_PREV, "Source_Location", source_inf_PY, "Location", "pred")

# Process: Table Select
# Select discharge locations that have received ballast water from an infected source
arcpy.TableSelect_analysis(sourcedis_freq_PREV__4_, sourcedis_inf_PY, "\"pred\" = 1")

# Process: Summary Statistics
# Calculate the number of visits discharge locations received from infected sources
arcpy.Statistics_analysis(sourcedis_inf_PY, dis_inf_PY, "FREQUENCY SUM", "Discharge_Location")

# Process: Join Field
# Join the table from Summary Statistics to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red__28_, "Location", dis_inf_PY, "Discharge_Location",
"SUM_FREQUENCY")

# Process: Add Field
# Create a field to hold the number of visits each location received from an infected source
arcpy.AddField_management(gl_discharge_loc_red__2_, "inf_visits", "LONG", "", "", "", "", "NULLABLE",
"NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the field with the number of visits each location received from an infected source
arcpy.CalculateField_management(gl_discharge_loc_red__29_, "inf_visits", "[SUM_FREQUENCY]", "VB", "")

# Process: Delete Field
# Delete the field added to the discharge feature class from Join Field (14)
arcpy.DeleteField_management(gl_discharge_loc_red__30_, "SUM_FREQUENCY")

# Process: Add Field
# Add a field to calculate the number of visits resulting in infection
arcpy.AddField_management(gl_discharge_loc_red__31_, "infPY", "DOUBLE", "", "", "", "", "NULLABLE",
"NON_REQUIRED", "")
```

```
# Process: Calculate Field (27)
# Calculate the number of visits that resulted in infection by drawing from a binomial distribution
# n = number of visits, p = p(VLP)
arcpy.CalculateField_management(gl_discharge_loc_red__32_, "infPY", "numpy.random.binomial(n= !inf_visits!,
p= !decay_per! )", "PYTHON_9.3", "import numpy.random\\nfrom numpy.random import binomial")

# Process: Buffer
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(gl_discharge_loc_red__33_, dis_inf_py_CY, "2 Kilometers", "FULL", "ROUND", "LIST",
"infg0")

# Process: Select
# Select areas that were newly infected
arcpy.Select_analysis(dis_inf_py_CY, dis_inf_yes_CY, "infg0 >= 1")

# Process: Union
# Combine the current year's newly infected areas to the previous year's infected areas
arcpy.Union_analysis("\\spread1_PY #;\\dis_inf_yes_CY #", ship_py_CY, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_CY, spread1_CY, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_CY, "pred", "SHORT", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_CY__2_, "pred", "1", "VB", "")

# Process: Delete Field
# Delete prediction files from tables that contain source-to-discharge trip information
```

```
arcpy.DeleteField_management(sourcedis_freq_YYYY__4_, "pred;pred")


### 2003-2009: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###

# Process: Identity
# Overlay the actual VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_YYYY, spread1_CY__3_, ship_pred_CY, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field
# Add a field to hold the model iteration count
arcpy.AddField_management(ship_pred_CY, "iter", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(ship_pred_CY__2_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity to the final layer
arcpy.Append_management("\\ship_pred_CY", final_layer, "NO_TEST", "Location \"Location\" true true false
100 Text 0 0 ,First,#,\\ship_pred_CY,Location,-1,-1;Year \"Year\" true true false 2 Short 0 0
,First,#,\\ship_pred_CY,Year,-1,-1;actual \"actual\" true true false 2 Short 0 0
,First,#,\\ship_pred_CY,actual,-1,-1;pred \"pred\" true true false 2 Short 0 0
,First,#,\\ship_pred_CY,pred,-1,-1;iter \"iter\" true true false 4 Long 0 0 ,First,#,\\ship_pred_CY,iter,-
1,-1;a \"a\" true true false 4 Long 0 0 ,First,#;b \"b\" true true false 4 Long 0 0 ,First,#;c \"c\" true
true false 4 Long 0 0 ,First,#;d \"d\" true true false 4 Long 0 0 ,First,#", "")
```

Propagule Pressure Model: Lake St. Clair and Montreal

```
# ---------------------------------------------------------------------------
# vhs_pplscmon_model.py
# Created on: 2013-07-03 14:47:41.00000
#   (generated by ArcGIS/ModelBuilder)
# Usage: vhs_pplscmon_model <Distance__value_or_field_> <final_layer>
# Description:
# ---------------------------------------------------------------------------

# Set the necessary product code
# import arcinfo


# Import arcpy module
import arcpy

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "\\base"

# Script arguments

# Input natural spread distance and units
Distance__value_or_field_ = arcpy.GetParameterAsText(0)
if Distance__value_or_field_ == '#' or not Distance__value_or_field_:
    Distance__value_or_field_ = "10 Kilometers" # provide a default value if unspecified

# Input final layer that will contain model results
final_layer = arcpy.GetParameterAsText(1)
if final_layer == '#' or not final_layer:
    final_layer = "\\final_layer" # provide a default value if unspecified

# Local variables:
```

```
# List of variables defined by ArcGIS removed for publication
# Variables used in following code may include the following:
#    CY = 2-digit Current Year
#    PY = 2-digit Previous Year
#    YYYY = 4-digit Current Year
#    PREV = 4-digit Previous Year
```

2003: BEGIN INVASION FROM 1st LAKE ST. CLAIR OCCURRENCE AND MONTREAL

```
# Process: Merge
# Merge 2003 presence/absence feature class and Montreal initial infection location into one feature class
arcpy.Merge_management("\\vhs_pasites_2003;\\montreal_testsite", vhs_pasites_2003_lscmon, "Location
\"Location\" true true false 100 Text 0 0 ,First,#,\\vhs_pasites_2003,Location,-1,-1;Year \"Year\" true
true false 2 Short 0 0 ,First,#,\\vhs_pasites_2003,Year,-1,-1;Source \"Source\" true true false 250 Text 0
0 ,First,#,\\vhs_pasites_2003,Source,-1,-1;actual \"actual\" true true false 2 Short 0 0
,First,#,\\vhs_pasites_2003,actual,-1,-1;RECTYPE \"RECTYPE\" true true false 1 Text 0 0
,First,#,\\montreal_testsite,RECTYPE,-1,-1;VERSION \"VERSION\" true true false 2 Text 0 0
,First,#,\\montreal_testsite,VERSION,-1,-1;REVISION \"REVISION\" true true false 2 Text 0 0
,First,#,\\montreal_testsite,REVISION,-1,-1;MODDATE \"MODDATE\" true true false 4 Long 0 0
,First,#,\\montreal_testsite,MODDATE,-1,-1;POINTID \"POINTID\" true true false 8 Double 0 0
,First,#,\\montreal_testsite,POINTID,-1,-1;FEATUREID \"FEATUREID\" true true false 10 Text 0 0
,First,#,\\montreal_testsite,FEATUREID,-1,-1;LONGITUDE \"LONGITUDE\" true true false 8 Double 0 0
,First,#,\\montreal_testsite,LONGITUDE,-1,-1;LATITUDE \"LATITUDE\" true true false 8 Double 0 0
,First,#,\\montreal_testsite,LATITUDE,-1,-1;DESCRIP \"DESCRIP\" true true false 35 Text 0 0
,First,#,\\montreal_testsite,DESCRIP,-1,-1;STFIPS \"STFIPS\" true true false 2 Short 0 0
,First,#,\\montreal_testsite,STFIPS,-1,-1")

# Process: Select
# Select Lake St. Clair and Montreal presence locations to create initial infection feature class
arcpy.Select_analysis(vhs_pasites_2003_lscmon, vhs_possites_2003, "\"actual\" = 1")

# Process: Buffer
```

```
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(vhs_possites_2003, ship_py_03, "2 Kilometers", "FULL", "ROUND", "ALL", "")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_03, spread1_03, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a “prediction” field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_03, "pred", "SHORT", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute “prediction” filed to identify infected areas
arcpy.CalculateField_management(spread1_03__2_, "pred", "1", "VB", "")


### 2004: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Identity
# Identify source locations that fall within the infected boundary
arcpy.Identity_analysis(gl_discharge_source_red, spread1_03__3_, source_inf_03, "ALL", "",
"NO_RELATIONSHIPS")

# Process: Join Field
# Join infected sources with table containing source-to-discharge trip information
arcpy.JoinField_management(sourcedis_freq_2003, "Source_Location", source_inf_03, "Location", "pred")

# Process: Table Select
# Select discharge locations that have received ballast water from an infected source
arcpy.TableSelect_analysis(sourcedis_freq_2003__2_, sourcedis_inf_2003, "\"pred\" = 1")

# Process: Summary Statistics
# Calculate the number of visits discharge locations received from infected sources
arcpy.Statistics_analysis(sourcedis_inf_2003, dis_inf_2003, "FREQUENCY SUM", "Discharge_Location")
```

```
# Process: Join Field
# Join the table from Summary Statistics to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red__18_, "Location", dis_inf_2003, "Discharge_Location",
"SUM_FREQUENCY")

# Process: Add Field
# Create a field to hold the number of visits each location received from an infected source
arcpy.AddField_management(gl_discharge_loc_red, "inf_visits", "LONG", "", "", "", "", "NULLABLE",
"NON_REQUIRED", "")

# Process: Calculate Field
# Attribute the field with the number of visits each location received from an infected source
arcpy.CalculateField_management(gl_discharge_loc_red__3_, "inf_visits", "[SUM_FREQUENCY]", "VB", "")

# Process: Delete Field
# Delete the field added to the discharge feature class from Join Field (2)
arcpy.DeleteField_management(gl_discharge_loc_red__4_, "SUM_FREQUENCY")

# Process: Calculate Field
# Calculate the number of visits that resulted in infection for 2004 by drawing from binomial distribution
# n = number of visits, p = p(VLP)
arcpy.CalculateField_management(gl_discharge_loc_red__5_, "inf03", "numpy.random.binomial(n= !inf_visits!,
p= !decay_per!  )", "PYTHON_9.3", "import numpy.random\\nfrom numpy.random import binomial")

# Process: Buffer
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(gl_discharge_loc_red__14_, dis_inf_py_04, "2 Kilometers", "FULL", "ROUND", "LIST",
"inf03")

# Process: Select
# Select areas that were newly infected for 2004
arcpy.Select_analysis(dis_inf_py_04, dis_inf_yes_04, "inf03 >= 1")
```

```
# Process: Union
# Combine the 2004 newly infected areas to the previous years infected areas
arcpy.Union_analysis("\\spread1_03 #;\\dis_inf_yes_04 #", ship_py_04, "ALL", "", "GAPS")

# Process: Buffer
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_04, spread1_04, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field
# Add a "prediction" field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_04, "pred", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
# Attribute "prediction" filed to identify infected areas
arcpy.CalculateField_management(spread1_04__2_, "pred", "1", "VB", "")


### 2005-2009: IDENTIFY NEW AND CONTINUING INFECTIONS ###

# Process: Identity
# Identify source locations that fall within the infected boundary
arcpy.Identity_analysis(gl_discharge_source_red, spread1_PY__3_, source_inf_PY, "ALL", "",
"NO_RELATIONSHIPS")

# Process: Join Field
# Join infected sources with table containing source-to-discharge trip information
arcpy.JoinField_management(sourcedis_freq_PREV__2_, "Source_Location", source_inf_PY, "Location", "pred")

# Process: Table Select
# Select discharge locations that have received ballast water from an infected source
arcpy.TableSelect_analysis(sourcedis_freq_PREV, sourcedis_inf_PREV, "\"pred\" = 1")

# Process: Summary Statistics (2)
# Calculate the number of visits discharge locations received from infected sources
```

```
arcpy.Statistics_analysis(sourcedis_inf_PREV, dis_inf_PREV, "FREQUENCY SUM", "Discharge_Location")

# Process: Join Field (4)
# Join the table from Summary Statistics to the discharge feature class
arcpy.JoinField_management(gl_discharge_loc_red__14_, "Location", dis_inf_PREV, "Discharge_Location",
"SUM_FREQUENCY")

# Process: Calculate Field (5)
# Attribute the field with the number of visits each location received from an infected source
arcpy.CalculateField_management(gl_discharge_loc_red__7_, "inf_visits", "[SUM_FREQUENCY]", "VB", "")

# Process: Delete Field (2)
# Delete the field added to the discharge feature class from Join Field (4)
arcpy.DeleteField_management(gl_discharge_loc_red__8_, "SUM_FREQUENCY")

# Process: Calculate Field (6)
# Calculate the number of visits that resulted in infection for 2005 by drawing from binomial distribution
# n = number of visits, p = p(VLP)
arcpy.CalculateField_management(gl_discharge_loc_red__27_, "inf0PY", "numpy.random.binomial(n=
!inf_visits!, p= !decay_per! )", "PYTHON_9.3", "import numpy.random\\nfrom numpy.random import binomial")

# Process: Buffer (5)
# Apply the 2-km spread distance to discharge locations
arcpy.Buffer_analysis(gl_discharge_loc_red__2_, dis_inf_py_CY, "2 Kilometers", "FULL", "ROUND", "LIST",
"infPY")

# Process: Select (3)
# Select areas that were newly infected for 2005
arcpy.Select_analysis(dis_inf_py_CY, dis_inf_yes_CY, "infPY >= 1")

# Process: Union (2)
# Combine the 2005 newly infected areas to the previous years infected areas
arcpy.Union_analysis("\\spread1_PY #;\\dis_inf_yes_CY #", ship_py_CY, "ALL", "", "GAPS")
```

```
# Process: Buffer (6)
# Apply the natural spread distance to infected areas
arcpy.Buffer_analysis(ship_py_CY, spread1_CY, Distance__value_or_field_, "FULL", "ROUND", "ALL", "")

# Process: Add Field (4)
# Add a “prediction” field to the attribute table to identify infected areas
arcpy.AddField_management(spread1_CY, "pred", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field (7)
# Attribute “prediction” filed to identify infected areas
arcpy.CalculateField_management(spread1_CY__2_, "pred", "1", "VB", "")


### 2005-2009: COMPARE PREDICTIONS TO ACTUAL OCCURRENCES ###

# Process: Select (4)
# Create feature class with all presence/absence locations except Lake St. Clair
arcpy.Select_analysis(vhs_pasites_YYYY, vhs_pasites_ship_YYYY, "\"Location\" <> 'Lake St. Clair-1'")

# Process: Identity (3)
# Overlay the actual 2005 VHSV presence/absence data with the predicted data
# Resulting feature class contains the actual status of the location and predicted status
arcpy.Identity_analysis(vhs_pasites_ship_YYYY, spread1_CY__3_, ship_pred_CY, "ALL", "", "NO_RELATIONSHIPS")

# Process: Add Field (5)
# Add a field to hold the model iteration count
arcpy.AddField_management(ship_pred_CY, "iter", "LONG", "", "", "", "", "NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field (8)
# Attribute the iteration field with the iteration count
arcpy.CalculateField_management(ship_pred_CY__2_, "iter", "%n%", "VB", "")

# Process: Append
# Append the data resulting from Identity (3) to the final layer
```

```
arcpy.Append_management("\\ship_pred_CY", final_layer, "NO_TEST", "", "")
```

Appendix C

Chapter 3 Model Code

Following is the Python code for the models used to backcast the spread of Eurasian Ruffe and zebra mussel and to forecast the spread of Eurasian Ruffe, killer shrimp, and golden mussel. The code has been modified so as to include generic file names. The random and location models both include code from a random selection tool (RandomSelection.tbx) that was downloaded from the ESRI website: http://arcscripts.esri.com/details.asp?dbid=15441 (last accessed: 3/29/2011) and modified.

Table of Contents

BACKCASTING MODELS

Random Model

```
# Import the arcpy module
import arcpy, os, sys, traceback, subprocess
import random
import numpy.random
from numpy.random import poisson

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "in_memory"
arcpy.env.overwriteOutput = True

# Script arguments
Spreaddistance = arcpy.GetParameterAsText(0)
Spreadunits = arcpy.GetParameterAsText(1)
stStartyear = arcpy.GetParameterAsText(2)
stEndyear = arcpy.GetParameterAsText(3)
Finallayer = arcpy.GetParameterAsText(4)

#Local Variables
v_scratchworkspace = "%scratchworkspace%"
randinfpoints = "\\rand_inf_points"
speciesboundary = "\\species_boundary"
iStartyear = int(stStartyear)
iEndyear = int(stEndyear)
global iyear
iyear = iStartyear
global styear
styear = str(iyear)
global inewyear
inewyear = iyear + 1
global stnewyear
stnewyear = str(inewyear)
global iyear2
iyear2 = int(stStartyear)
global styear2
```

```
styear2 = str(iyear2)
global iPreviousyear
iPreviousyear = iyear2 - 1
global stPreviousyear
stPreviousyear = str(iPreviousyear)
Bufdist = Spreaddistance + " " + Spreadunits


#Process: Clip--clip randomly generated points to species boundary
arcpy.Clip_analysis(randinfpoints, speciesboundary, "in_memory\memSpeciesRand_" + styear)

#Create a layer of random points that have not been previously selected for next year
while int(iyear) <= int(iEndyear):

    #Block of code that selects and maps random points.
    #Created from RandomSelection.py by Leah Saunders, ESRI Inc.
    #With major modification by Stephen Lead.
    ranct = numpy.random.poisson(lam=4)
    desc = arcpy.Describe("in_memory\memSpeciesRand_" + styear)
    recct = int(arcpy.GetCount_management("in_memory\memSpeciesRand_" + styear).getOutput(0))
    if ranct <= recct:
        numValues = (ranct)
    else:
        numValues = (recct)
    arcpy.AddMessage("Selecting " + str(numValues) + " random features")

    if numValues > 0:

        inList = []
        randomList = []
        fldname = desc.OIDFieldName
        rows = arcpy.SearchCursor("in_memory\memSpeciesRand_" + styear)
        row = rows.next()
        arcpy.AddMessage ("Loading all IDs into a list")
        while row:
            id = row.getValue(fldname)
            inList.append(id)
            row = rows.next()

        selpnts = 0
```

```
        arcpy.AddMessage("Creating the list of randomly selected features")
        while len(randomList) < numValues:
            selpnts += 1
            selItem = random.choice(inList)
            randomList.append(selItem)
            inList.remove(selItem)

        theLen = len(str(randomList))
        sqlexp = '"' + fldname + '"' + " in " + "(" + str(randomList)[1:theLen - 1] + ")"
        arcpy.MakeFeatureLayer_management("in_memory\memSpeciesRand_" + styear, "\\SpeciesRand_" +
styear
        + "_selection.lyr", sqlexp)
        arcpy.SaveToLayerFile_management("\\SpeciesRand_" + styear + "_selection.lyr",
"\\SpeciesInf_"
        + styear + ".lyr")
    else:
        arcpy.MakeFeatureLayer_management("\\false_point", "\\SpeciesInf_" + styear + ".lyr")

    #Process: Merge--merge layer of randomly selected points with fake point in case of empty layer
    arcpy.Merge_management(["\\SpeciesInf_" + styear + ".lyr", "\\false_point"],
"in_memory\memSpeciesInf_"
    + styear)

    #Process: Add field--add prediction field
    arcpy.AddField_management("in_memory\memSpeciesInf_" + styear, "pred", "SHORT")

    #Process: Calculate field--calculate prediction field
    arcpy.CalculateField_management("in_memory\memSpeciesInf_" + styear, "pred", "1")

    #Process: Select--select predicted points
    arcpy.Select_analysis("in_memory\memSpeciesInf_" + styear, "in_memory\memSpeciesInf_" + styear +
"_2",
    "\"pred\" = 1")

    #Process: Buffer--Buffer infested locations so they will not be re-selected
    arcpy.Buffer_analysis("in_memory\memSpeciesInf_" + styear + "_2", "in_memory\memSpeciesInf_" +
styear +
    "_3", "1 Feet", "FULL", "ROUND", "ALL")

    #Process: Erase--Erase infested areas from random points layer to prevent re-selection
```

```
    arcpy.Erase_analysis("in_memory\memSpeciesRand_" + styear, "in_memory\memSpeciesInf_" + styear +
"_3",
    "in_memory\memSpeciesRand_" + stnewyear)

    #Process: Delete prediction field
    arcpy.DeleteField_management("in_memory\memSpeciesRand_" + stnewyear, "pred")

    global iyear
    iyear += 1

    global styear
    styear = str(iyear)

    global inewyear
    inewyear = int(iyear + 1)

    global stnewyear
    stnewyear = str(inewyear)

fc_list = arcpy.ListFeatureClasses("memSpeciesRand*")

arcpy.AddMessage("List of Feature Classes:" + str(fc_list))

for fc in fc_list:

    #Process: Merge--merge infested points with random point in case of empty layer
    arcpy.Merge_management(["in_memory\memSpeciesInf_" + styear2 + "_2", "\\false_point"],
    "in_memory\memSpeciesInfPtAll_" + styear2)

    #Process: Buffer--buffer to create infested area
    arcpy.Buffer_analysis("in_memory\memSpeciesInfPtAll_" + styear2, "in_memory\memSpeciesPy_" +
styear2,
    "1.4 Kilometers", "FULL", "ROUND", "ALL")

    if iyear2 > iStartyear:

        #Process: Union--union previous years' infestations
        arcpy.Union_analysis(["in_memory\memSpeciesPy_" + styear2, "in_memory\memSpeciesInfYes_" +
        stPreviousyear], "in_memory\memSpeciesPyAll_" + styear2, "All", "", "GAPS")
```

```
    else:

        #Process: Copy Features--create feature class to be buffered when iyear = iStartyear
        arcpy.CopyFeatures_management("in_memory\memSpeciesPy_" + styear2,
"in_memory\memSpeciesPyAll_" +
        styear2)

    #Process: Buffer--buffer to simulate natural spread
    arcpy.Buffer_analysis("in_memory\memSpeciesPyAll_" + styear2, "in_memory\memSpeciesInf_" +
styear2,
    Bufdist, "FULL", "ROUND", "ALL")

    #Process: Clip--clip to species boundary
    arcpy.Clip_analysis("in_memory\memSpeciesInf_" + styear2, speciesboundary,
    "in_memory\memSpeciesInfYes_" + styear2)

    #Process: Add field--Add prediction field
    arcpy.AddField_management("in_memory\memSpeciesInfYes_" + styear2, "pred", "SHORT")

    #Process: Calculate field--Calculate prediction field
    arcpy.CalculateField_management("in_memory\memSpeciesInfYes_" + styear2, "pred", "1")

    #Process: Identity--Combine prediction results and actual data
    arcpy.Identity_analysis("\\species_" + styear2, "in_memory\memSpeciesInfYes_" + styear2,
    "in_memory\memSpeciesPred_" + styear2, "ALL")

    #Process: Add field--Add iteration count field
    arcpy.AddField_management("in_memory\memSpeciesPred_" + styear2, "Iter", "LONG")

    #Process: Calculate field--Calculate iteration count
    arcpy.CalculateField_management("in_memory\memSpeciesPred_" + styear2, "Iter", "%n%")

    #Process: Append--Append results to final layer
    arcpy.Append_management("in_memory\memSpeciesPred_" + styear2, Finallayer, "NO_TEST")

    global iyear2
    iyear2 += 1
    iyear2 = int(iyear2)

    global styear2
```

```
styear2 = str(iyear2)

global iPreviousyear
iPreviousyear = int(iyear2 - 1)

global stPreviousyear
stPreviousyear = str(iPreviousyear)
```

Location Model

```
# Import the arcpy module
import arcpy, os, sys, traceback, subprocess
import random
import numpy.random
from numpy.random import poisson

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "in_memory"
arcpy.env.overwriteOutput = True

# Script arguments
Spreaddistance = arcpy.GetParameterAsText(0)
Spreadunits = arcpy.GetParameterAsText(1)
stStartyear = arcpy.GetParameterAsText(2)
stEndyear = arcpy.GetParameterAsText(3)
Finallayer = arcpy.GetParameterAsText(4)

# Local Variables
gldischarge = "\\gl_discharge"
speciesboundary = "\\species_boundary"
iStartyear = int(stStartyear)
iEndyear = int(stEndyear)
global iyear
iyear = iStartyear
global styear
styear = str(iyear)
global inewyear
inewyear = iyear + 1
global stnewyear
stnewyear = str(inewyear)
global iyear2
iyear2 = int(stStartyear)
global styear2
styear2 = str(iyear2)
rand_point = "\\rand_point"
global iPreviousyear
iPreviousyear = iyear2 - 1
```

```
global stPreviousyear
stPreviousyear = str(iPreviousyear)
Bufdist = Spreaddistance + " " + Spreadunits

#Process: Clip--clip discharge data to species boundary
arcpy.Clip_analysis(gldischarge, speciesboundary, "in_memory\memSpeciesDischarge_" + styear)

#Create a discharge location of points that have not been previously selected for next year
while int(iyear) <= int(iEndyear):

    #Block of code that selects and maps random points.
    #Created from RandomSelection.py by Leah Saunders, ESRI Inc.
    #With major modification by Stephen Lead.
    ranct = numpy.random.poisson(lam=4)
    desc = arcpy.Describe("in_memory\memSpeciesDischarge_" + styear)
    recct = int(arcpy.GetCount_management("in_memory\memSpeciesDischarge_" + styear).getOutput(0))
    if ranct <= recct:
        numValues = (ranct)
    else:
        numValues = (recct)
    arcpy.AddMessage("Selecting " + str(numValues) + " random features")

    if numValues > 0:

        inList = []
        randomList = []
        fldname = desc.OIDFieldName
        rows = arcpy.SearchCursor("in_memory\memSpeciesDischarge_" + styear)
        row = rows.next()
        arcpy.AddMessage ("Loading all IDs into a list")
        while row:
            id = row.getValue(fldname)
            inList.append(id)
            row = rows.next()

        selpnts = 0
        arcpy.AddMessage("Creating the list of randomly selected features")
        while len(randomList) < numValues:
            selpnts += 1
            selItem = random.choice(inList)
```

```
        randomList.append(selItem)
        inList.remove(selItem)

    theLen = len(str(randomList))
    sqlexp = '"' + fldname + '"' + " in " + "(" + str(randomList)[1:theLen - 1] + ")"
    arcpy.MakeFeatureLayer_management("in_memory\memSpeciesDischarge_" + styear,
    "\\species_discharge_" + styear + "_selection.lyr", sqlexp)
    arcpy.SaveToLayerFile_management("\\species_discharge_" + styear + "_selection.lyr",
    "\\species_inf_" + styear + ".lyr")
else:
    arcpy.MakeFeatureLayer_management("\\false_point", "\\species_inf_" + styear + ".lyr")

#Process: Merge--merge with fake point in case of empty layer
arcpy.Merge_management(["\\species_inf_" + styear + ".lyr", "\\false_point.lyr"],
"in_memory\memSpeciesInf_" + styear)

#Process: Add field--add prediction field
arcpy.AddField_management("in_memory\memSpeciesInf_" + styear, "pred", "SHORT")

#Process: Calculate field--calculate prediction field
arcpy.CalculateField_management("in_memory\memSpeciesInf_" + styear, "pred", "1")

#Process: Join field--Join infected locations with the discharge locations
arcpy.JoinField_management("in_memory\memSpeciesDischarge_" + styear, "Location",
"in_memory\memSpeciesInf_" + styear, "Location", "pred")

#Process: Select--Select locations that have not been infested yet
arcpy.Select_analysis("in_memory\memSpeciesDischarge_" + styear, "in_memory\memSpeciesDischarge_"
+
stnewyear, "\"pred\" IS NULL")

#Process: Delete prediction field
arcpy.DeleteField_management("in_memory\memSpeciesDischarge_" + styear, "pred")
arcpy.DeleteField_management("in_memory\memSpeciesDischarge_" + stnewyear, "pred")

global iyear
iyear += 1

global styear
styear = str(iyear)
```

```
    global inewyear
    inewyear = int(iyear + 1)

    global stnewyear
    stnewyear = str(inewyear)

 fc_list = arcpy.ListFeatureClasses("memSpeciesDischarge*")

 arcpy.AddMessage("List of Feature Classes:" + str(fc_list))

 for fc in fc_list:

    #Process: Merge--merge with random point in case of empty layer
    arcpy.Merge_management(["in_memory\memSpeciesInf_" + styear2, "\\false_point"],
    "in_memory\memSpeciesInfPtAll_" + styear2)

    #Process: Buffer--buffer to create infestation area
    arcpy.Buffer_analysis("in_memory\memSpeciesInfPtAll_" + styear2, "in_memory\memSpeciesPy_" +
    styear2, "1.4 Kilometers", "FULL", "ROUND", "ALL")

    if iyear2 > iStartyear:

        #Process: Union--union previous years' infestations
        arcpy.Union_analysis(["in_memory\memSpeciesPy_" + styear2, "in_memory\memSpeciesInfYes_" +
        stPreviousyear], "in_memory\memSpeciesPyAll_" + styear2, "All", "", "GAPS")

    else:

        #Process: Copy Features--create feature class to be buffered when iyear = iStartyear
        arcpy.CopyFeatures_management("in_memory\memSpeciesPy_" + styear2,
"in_memory\memSpeciesPyAll_"
        + styear2)

    #Process: Buffer--buffer to simulate natural spread
    arcpy.Buffer_analysis("in_memory\memSpeciesPyAll_" + styear2, "in_memory\memSpeciesInf_" +
styear2,
    Bufdist, "FULL", "ROUND", "ALL")

    #Process: Clip--clip to species boundary
```

```
    arcpy.Clip_analysis("in_memory\memSpeciesInf_" + styear2,
speciesboundary,"in_memory\memSpeciesInfYes_"
    + styear2)

    #Process: Add field--Add prediction field
    arcpy.AddField_management("in_memory\memSpeciesInfYes_" + styear2, "pred", "SHORT")

    #Process: Calculate field--Calculate prediction field
    arcpy.CalculateField_management("in_memory\memSpeciesInfYes_" + styear2, "pred", "1")

    #Process: Identity--Combine prediction and actual data
    arcpy.Identity_analysis("\\species_" + styear2, "in_memory\memSpeciesInfYes_" + styear2,
    "in_memory\memSpeciesPred_" + styear2, "ALL")

    #Process: Add field--Add iteration count field
    arcpy.AddField_management("in_memory\memSpeciesPred_" + styear2, "Iter", "LONG")

    #Process: Calculate field--Calculate iteration count
    arcpy.CalculateField_management("in_memory\memSpeciesPred_" + styear2, "Iter", "%n%")

    #Process: Append--Append results to final layer
    arcpy.Append_management("in_memory\memSpeciesPred_" + styear2, Finallayer, "NO_TEST")

    global iyear2
    iyear2 += 1
    iyear2 = int(iyear2)

    global styear2
    styear2 = str(iyear2)

    global iPreviousyear
    iPreviousyear = int(iyear2 - 1)

    global stPreviousyear
    stPreviousyear = str(iPreviousyear)
```

Propagule Pressure Model

```
# Import the arcpy module
import arcpy, os, sys, traceback

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "in_memory"
arcpy.env.overwriteOutput = True

# Script arguments
Spread_distance = arcpy.GetParameterAsText(0)
Spread_units = arcpy.GetParameterAsText(1)
stStart_year = arcpy.GetParameterAsText(2)
stEnd_year = arcpy.GetParameterAsText(3)
Survival = arcpy.GetParameterAsText(4)
Final_layer = arcpy.GetParameterAsText(5)

#Local Variables
v_scratchworkspace = "%scratchworkspace%"
istartyear = int(stStart_year)
iendyear = int(stEnd_year)
fsurvival = float(Survival)
discharge = "\\gl_discharge"
speciesboundary = "\\species_boundary"
speciesdischarge = "\\species_discharge"
Bufdist = Spread_distance + " " + Spread_units
speciesstartyear = "\\species_" + stStart_year
global iyear
iyear = istartyear
global styear
styear = str(iyear)
pred = "Pred"
glsource = "\\gl_discharge_source"
sourcedischargetrips= "\\source_discharge_trips"
falsepoint = "\\tb_ppfalse_point"
infvisits = "inf_visits"
global iyear
inewyear = iyear + 1
```

```
global stnewyear
stnewyear = str(inewyear)
itera = "iter"


#Process: Copy Features--Copy feature classes into memory
arcpy.CopyFeatures_management(discharge, "in_memory\memDischarge")
arcpy.CopyFeatures_management(speciesboundary, "in_memory\memSpeciesBoundary")

#Process: Clip--Clip discharge locations to species boundary
arcpy.Clip_analysis("in_memory\memDischarge", "in_memory\memSpeciesBoundary",
"in_memory\memSpeciesDischarge")

#Process: Select--Select initial species locations
arcpy.Select_analysis(speciesstartyear, "in_memory\memSpeciesInitial", "\"Actual\" = 1")

#Process: Buffer--Buffer initial infestation area
arcpy.Buffer_analysis("in_memory\memSpeciesInitial", "in_memory\memSpeciesInit_" + styear, "1.4
Kilometers", "FULL", "ROUND", "ALL")

#Process: Buffer--Buffer to simulate natural spread
arcpy.Buffer_analysis("in_memory\memSpeciesInit_" + styear, "in_memory\memSpeciesPy_" + styear,
Bufdist, "FULL", "ROUND", "ALL")

#Process: Clip--Clip to species boundary
arcpy.Clip_analysis("in_memory\memSpeciesPy_" + styear, speciesboundary, "in_memory\memSpeciesInf_" +
styear)

#Process: Add field--Add prediction field
arcpy.AddField_management("in_memory\memSpeciesInf_" + styear, "Pred", "SHORT")

#Process: Calculate field--Calculate prediction field
arcpy.CalculateField_management("in_memory\memSpeciesInf_" + styear, "Pred", "1")

global iyear
iyear = istartyear

while iyear <= iendyear:

    #Process: Identity—Identify source locations within infestation areas
```

```
    arcpy.Identity_analysis(glsource, "in_memory\memSpeciesInf_" + styear, "in_memory\memSourceInf_"
+
    styear)

    #Process: Merge--Merge false point in case of empty feature class
    arcpy.Merge_management(["in_memory\memSourceInf_" + styear, "\\false_point"],
    "in_memory\memSourceInf2_" + styear)

    #Process: Select--Select infested sources
    arcpy.Select_analysis("in_memory\memSourceInf2_" + styear, "in_memory\memSourceYes_" + styear,
    '\"Pred\" = 1')

    #Process: Join field--Join frequency fields
    arcpy.JoinField_management(sourcedischargetrips, "Source_Location", "in_memory\memSourceYes_" +
styear,
    "Location", ["Location", "Pred"])

    #Process: Table Select--Select source locations that are infested
    arcpy.TableSelect_analysis(sourcedischargetrips, "in_memory\memSpeciesInfSource_" + styear,
    '\"Location\" Is Not NULL')

    #Process: Delete Field--Delete prediction field
    arcpy.DeleteField_management(sourcedischargetrips, ["Location", "Pred"])

    #Process: Add field--Add survival field
    arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "surv_rate", "DOUBLE")

    #Process: Calculate field--Calculate survival field
    arcpy.CalculateField_management("in_memory\memSpeciesInfSource_" + styear, "surv_rate",
fsurvival)

    #Process: Add field--Add trip survival field
    arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "trip_surv", "DOUBLE")

    #Process: Calculate field--Calculate trip survival
    arcpy.CalculateField_management("in_memory\memSpeciesInfSource_" + styear, "trip_surv",
    "[surv_rate]^[trip_med]")

    #Process: Add field--Add infestation field to discharge locations
    arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "inf_discharge", "LONG")
```

```
    #Process: Table Select--Select discharge locations that received visits
    arcpy.TableSelect_analysis("in_memory\memSpeciesInfSource_" + styear,
    "in_memory\memSpeciesInfDischarge_" + styear, '"trip_countperyear" > 0')

    #Process: Calculate field--Determine infestation status for each trip
    arcpy.CalculateField_management("in_memory\memSpeciesInfDischarge_" + styear, "inf_discharge",
    "numpy.random.binomial(n=!trip_countperyear!, p=!trip_surv!)", "PYTHON_9.3",
    "import numpy.random\nfrom numpy.random import binomial")

    #Process: Table Select--Select infested discharge locations
    arcpy.TableSelect_analysis("in_memory\memSpeciesInfDischarge_" + styear,
    "in_memory\memSpeciesInfNewDis_" + styear, '"inf_discharge" > 0')

    #Process: Add field--Add prediction field
    arcpy.AddField_management("in_memory\memSpeciesInfNewDis_" + styear, "Pred", "SHORT")

    #Process: Calculate field--Calculate prediction field
    arcpy.CalculateField_management("in_memory\memSpeciesInfNewDis_" + styear, "Pred", "1")

    #Process: Join field--Join source and discharge locations
    arcpy.JoinField_management("in_memory\memSpeciesDischarge", "Location",
    "in_memory\memSpeciesInfNewDis_" + styear, "Discharge_Location", ["Discharge_Location", "Pred"])

    #Process: Select--Select infested points
    arcpy.Select_analysis("in_memory\memSpeciesDischarge", "in_memory\memSpeciesDischargeYes_" +
styear,
    '\"Discharge_Location\" Is Not NULL')

    #Process: Delete field--Delete fields from join above
    arcpy.DeleteField_management("in_memory\memSpeciesDischarge", ["Discharge_Location", "Pred"])

    #Process: Buffer--Buffer to create infestation area
    arcpy.Buffer_analysis("in_memory\memSpeciesDischargeYes_" + styear, "in_memory\memSpeciesInit_" +
    stnewyear, "1.4 Kilometers", "FULL", "ROUND", "LIST", "Pred")

    #Process: Select--Select infested areas
    arcpy.Select_analysis("in_memory\memSpeciesInit_" + stnewyear, "in_memory\memSpeciesPred_" +
stnewyear,
    '\"Pred\" = 1')
```

```
    #Process: Union--Union to previous year of infestation
    arcpy.Union_analysis(["in_memory\memSpeciesPred_" + stnewyear, "in_memory\memSpeciesInf_" +
styear],
    "in_memory\memSpeciesPredYes_" + stnewyear, "ALL", "", "GAPS")

    #Process: Buffer--Buffer with spread distance
    arcpy.Buffer_analysis("in_memory\memSpeciesPredYes_" + stnewyear, "in_memory\memSpeciesPy_" +
    stnewyear, Bufdist, "FULL", "ROUND", "ALL")

    #Process: Clip--Clip to species boundary
    arcpy.Clip_analysis("in_memory\memSpeciesPy_" + stnewyear, "in_memory\memSpeciesBoundary",
    "in_memory\memSpeciesInf_" + stnewyear)

    #Process: Add field--Add prediction field
    arcpy.AddField_management("in_memory\memSpeciesInf_" + stnewyear, "Pred", "SHORT")

    #Process: Calculate field--Calculate prediction field
    arcpy.CalculateField_management("in_memory\memSpeciesInf_" + stnewyear, "Pred", "1")

    #Process: Identity--Combine prediction results with actual data
    arcpy.Identity_analysis("\\species_" + stnewyear, "in_memory\memSpeciesInf_" + stnewyear,
    "in_memory\memSpeciesPred_" + stnewyear)

    #Process: Add field--Add iteration count field
    arcpy.AddField_management("in_memory\memSpeciesPred_" + stnewyear, itera, "LONG")

    #Process: Calculate field--Calculate iteration count
    arcpy.CalculateField_management("in_memory\memSpeciesPred_" + stnewyear, itera, "%n% + 99")

    #Process: Append--Append to final layer
    arcpy.Append_management("in_memory\memSpeciesPred_" + stnewyear, Final_layer, "NO_TEST")

    global iyear
    iyear += 1

    global styear
    styear = str(iyear)

    global inewyear
```

```
inewyear = iyear + 1

global stnewyear
stnewyear = str(inewyear)
```

FORECASTING MODEL

Prediction Model

```
# Import the arcpy module
import arcpy, os, sys, traceback

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "\\scratch_data"
arcpy.env.workspace = "in_memory"

# Script arguments
Spread_distance = arcpy.GetParameterAsText(0)
Spread_units = arcpy.GetParameterAsText(1)
stStart_year = arcpy.GetParameterAsText(2)
stEnd_year = arcpy.GetParameterAsText(3)
Survival = arcpy.GetParameterAsText(4)
Final_layer = arcpy.GetParameterAsText(5)

#Local Variables
v_scratchworkspace = "%scratchworkspace%"
istartyear = int(stStart_year)
iendyear = int(stEnd_year)
fsurvival = float(Survival)
speciesinitial = "\\species_initial"
discharge = "\\gl_discharge"
speciesboundary = "\\species_boundary"
speciesdischarge = "\\species_discharge"
Bufdist = Spread_distance + " " + Spread_units
global iyear
iyear = istartyear
global styear
styear = str(iyear)
pred = "Pred"
glsource = "\\gl_discharge_source"
sourcedischargetrips= "\\source_discharge_trips"
```

```
falsepoint = "\\tb_ppfalse_point"
infvisits = "inf_visits"
global iyear
inewyear = iyear + 1
global stnewyear
stnewyear = str(inewyear)
itera = "iter"
predyear = "predyear"


#Process: Copy Features--Copy feature classes into memory
arcpy.CopyFeatures_management(discharge, "in_memory\memDischarge")
arcpy.CopyFeatures_management(speciesboundary, "in_memory\memSpeciesBoundary")

#Process: Clip--Clip discharge locations to species boundary
arcpy.Clip_analysis("in_memory\memDischarge", "in_memory\memSpeciesBoundary",
"in_memory\memSpeciesDischarge")

#Process: Buffer--Buffer initial infestation area
arcpy.Buffer_analysis(speciesinitial, "in_memory\memSpeciesInit_" + styear, "1.4 Kilometers", "FULL",
"ROUND", "ALL")

#Process: Buffer--Buffer to simulate natural spread
arcpy.Buffer_analysis("in_memory\memSpeciesInit_" + styear, "in_memory\memSpeciesPy_" + styear, Bufdist,
"FULL", "ROUND", "ALL")

#Process: Clip--Clip to species boundary
arcpy.Clip_analysis("in_memory\memSpeciesPy_" + styear, "in_memory\memSpeciesBoundary",
"in_memory\memSpeciesInf_" + styear)

#Process: Add field--Add prediction field
arcpy.AddField_management("in_memory\memSpeciesInf_" + styear, "Pred", "SHORT")

#Process: Calculate field--Calculate prediction field
arcpy.CalculateField_management("in_memory\memSpeciesInf_" + styear, "Pred", "1")

global iyear
```

```
iyear = istartyear

while iyear <= iendyear:

    #Process: Identity--Combine infestation area with ballast sources
    arcpy.Identity_analysis(glsource, "in_memory\memSpeciesInf_" + styear, "in_memory\memSourceInf_" +
    styear)

    #Process: Merge--Merge false point in case of empty feature class
    arcpy.Merge_management(["in_memory\memSourceInf_" + styear, "\\false_point"],
    "in_memory\memSourceInf2_" + styear)

    #Process: Select--Select infested sources
    arcpy.Select_analysis("in_memory\memSourceInf2_" + styear, "in_memory\memSourceYes_" + styear,
    '\"Pred\" = 1')

    #Process: Join field--Join frequency fields
    arcpy.JoinField_management(sourcedischargetrips, "Source_Location", "in_memory\memSourceYes_" + styear,
    "Location", ["Location", "Pred"])

    #Process: Table Select--Select source locations that are infested
    arcpy.TableSelect_analysis(sourcedischargetrips, "in_memory\memSpeciesInfSource_" + styear,
    '\"Location\" Is Not NULL')

    #Process: Delete Field--Delete prediction field
    arcpy.DeleteField_management(sourcedischargetrips, ["Location", "Pred"])

    #Process: Add field--Add survival field
    arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "surv_rate", "DOUBLE")

    #Process: Calculate field--Calculate trip survival field
    arcpy.CalculateField_management("in_memory\memSpeciesInfSource_" + styear, "surv_rate", fsurvival)

    #Process: Add field--Add survival field
    arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "trip_surv", "DOUBLE")

    #Process: Calculate field--Calculate trip survival
```

```
arcpy.CalculateField_management("in_memory\memSpeciesInfSource_" + styear, "trip_surv",
"[surv_rate]^[trip_med]")

#Process: Add field--Add discharge infestation field
arcpy.AddField_management("in_memory\memSpeciesInfSource_" + styear, "inf_discharge", "LONG")

#Process: Table Select--Select discharge locations that received visits
arcpy.TableSelect_analysis("in_memory\memSpeciesInfSource_" + styear,
"in_memory\memSpeciesInfDischarge_" + styear, '"trip_countperyear" > 0')

#Process: Calculate field--Calculate infestation status for each trip
arcpy.CalculateField_management("in_memory\memSpeciesInfDischarge_" + styear, "inf_discharge",
"numpy.random.binomial(n=!trip_countperyear!, p=!trip_surv!)", "PYTHON_9.3",
"import numpy.random\nfrom numpy.random import binomial")

#Process: Table Select--Select infested discharge locations
arcpy.TableSelect_analysis("in_memory\memSpeciesInfDischarge_" + styear,
"in_memory\memSpeciesInfNewDis_" + styear, '"inf_discharge" > 0')

#Process: Add field--Add prediction field
arcpy.AddField_management("in_memory\memSpeciesInfNewDis_" + styear, "Pred", "SHORT")

#Process: Calculate field--Calculate prediction field
arcpy.CalculateField_management("in_memory\memSpeciesInfNewDis_" + styear, "Pred", "1")

#Process: Join field--Join source and discharge locations
arcpy.JoinField_management("in_memory\memSpeciesDischarge", "Location",
"in_memory\memSpeciesInfNewDis_" + styear, "Discharge_Location", ["Discharge_Location", "Pred"])

#Process: Select--Select infested points
arcpy.Select_analysis("in_memory\memSpeciesDischarge", "in_memory\memSpeciesDischargeYes_" + styear,
'\"Discharge_Location\" Is Not NULL')

#Process: Delete field--Delete fields from above
arcpy.DeleteField_management("in_memory\memSpeciesDischarge", ["Discharge_Location", "Pred"])

#Process: Buffer--Buffer to create infestation area
```

```
arcpy.Buffer_analysis("in_memory\memSpeciesDischargeYes_" + styear, "in_memory\memSpeciesInit_" +
stnewyear, "1.4 Kilometers", "FULL", "ROUND", "LIST", "Pred")

#Process: Select--Select infected areas
arcpy.Select_analysis("in_memory\memSpeciesInit_" + stnewyear, "in_memory\memSpeciesPred_" + stnewyear,
'\"Pred\" = 1')

#Process: Union--Union to previous year of infestation
arcpy.Union_analysis(["in_memory\memSpeciesPred_" + stnewyear, "in_memory\memSpeciesInf_" + styear],
"in_memory\memSpeciesPredYes_" + stnewyear, "ALL", "", "GAPS")

#Process: Buffer--Buffer with spread distance
arcpy.Buffer_analysis("in_memory\memSpeciesPredYes_" + stnewyear, "in_memory\memSpeciesPy_" +
stnewyear, Bufdist, "FULL", "ROUND", "ALL")

#Process: Clip--Clip to species boundary
arcpy.Clip_analysis("in_memory\memSpeciesPy_" + stnewyear, "in_memory\memSpeciesBoundary",
"in_memory\memSpeciesInf_" + stnewyear)

#Process: Add field--Add prediction field
arcpy.AddField_management("in_memory\memSpeciesInf_" + stnewyear, "Pred", "SHORT")

#Process: Calculate field--Calculate prediction field
arcpy.CalculateField_management("in_memory\memSpeciesInf_" + stnewyear, "Pred", "1")

#Process: Identity--Combine with prediction results with actual data
arcpy.Identity_analysis("in_memory\memSpeciesDischarge", "in_memory\memSpeciesInf_" + stnewyear,
"in_memory\memSpeciesPred_" + stnewyear)

#Process: Add field--Add iteration count field
arcpy.AddField_management("in_memory\memSpeciesPred_" + stnewyear, itera, "LONG")

#Process: Calculate field--Calculate iteration count
arcpy.CalculateField_management("in_memory\memSpeciesPred_" + stnewyear, itera, "%n%")

#Process: Add field--Add year field
arcpy.AddField_management ("in_memory\memSpeciesPred_" + stnewyear, predyear, "LONG")
```

```
    #Process: Calculate field--Calculate year
    arcpy.CalculateField_management ("in_memory\memSpeciesPred_" + stnewyear, predyear, iyear)

    #Process: Append--Append to final layer
    arcpy.Append_management("in_memory\memSpeciesPred_" + stnewyear, Final_layer, "NO_TEST")

    global iyear
    iyear += 1

    global styear
    styear = str(iyear)

    global inewyear
    inewyear = iyear + 1

    global stnewyear
    stnewyear = str(inewyear)

else:

    print iendyear
```

Appendix D

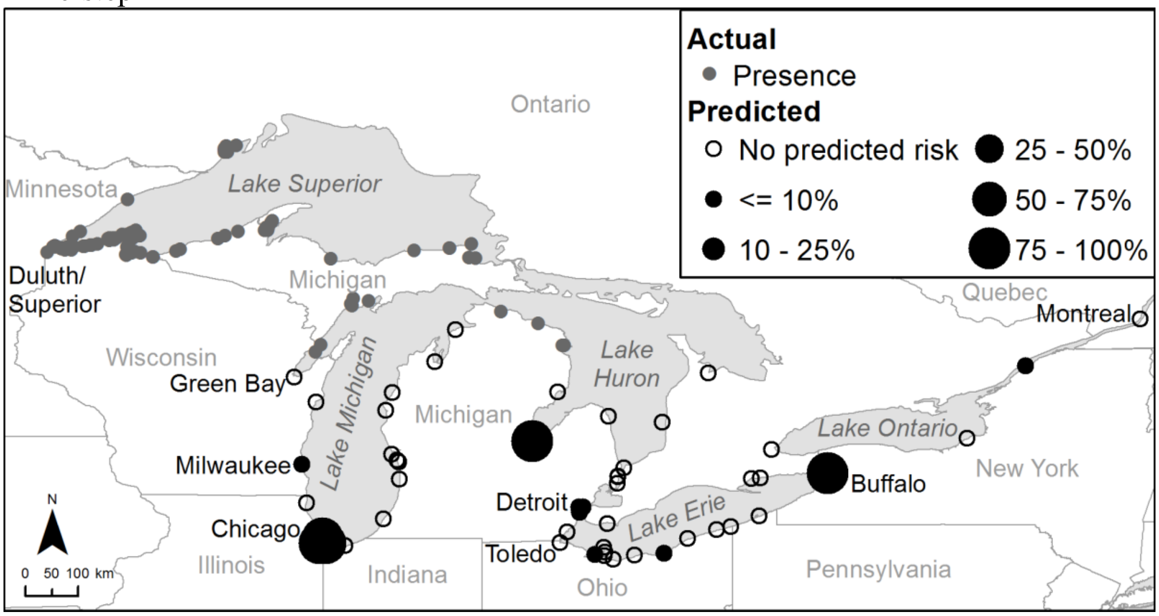
Chapter 3 Prediction Maps

Following are the resulting predictions modeled for Eurasian Ruffe, killer shrimp, and golden mussel. Ten time-steps were modeled from each of the invasion start locations for each species. Results are also included for both sets of parameter values used to predict the future spread of Eurasian Ruffe. Killer shrimp spread predictions were not modeled from Superior, Wisconsin due to its proximity to Duluth, Minnesota.

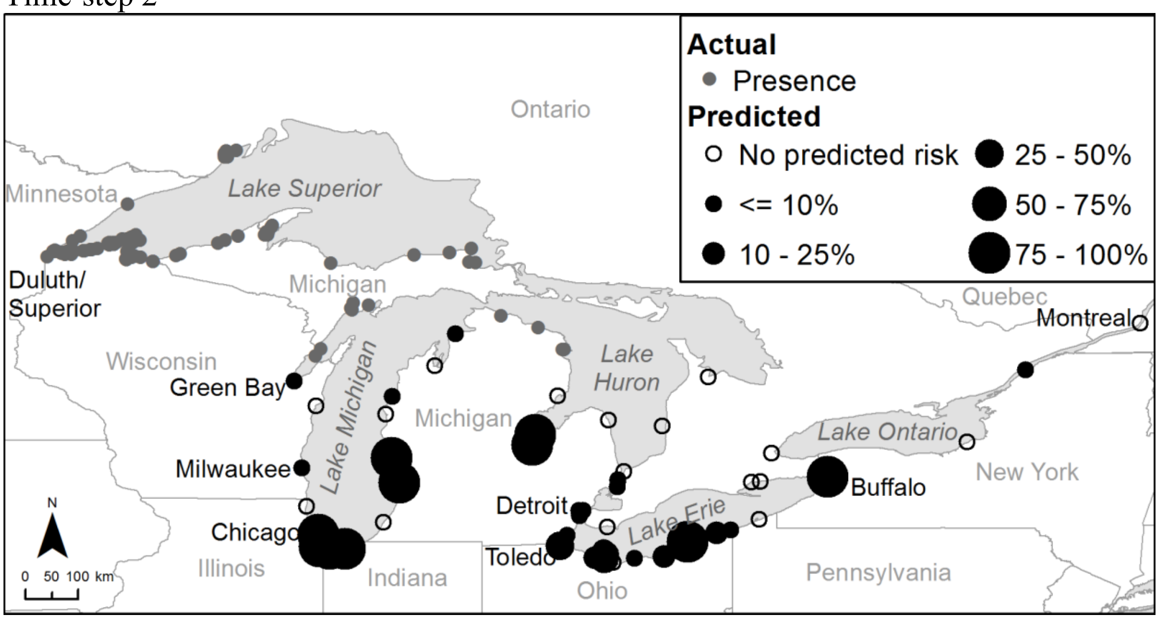
Table of Contents

Eurasian Ruffe
Dispersal Distance = 10-km and Probability of Infestation = 0.01

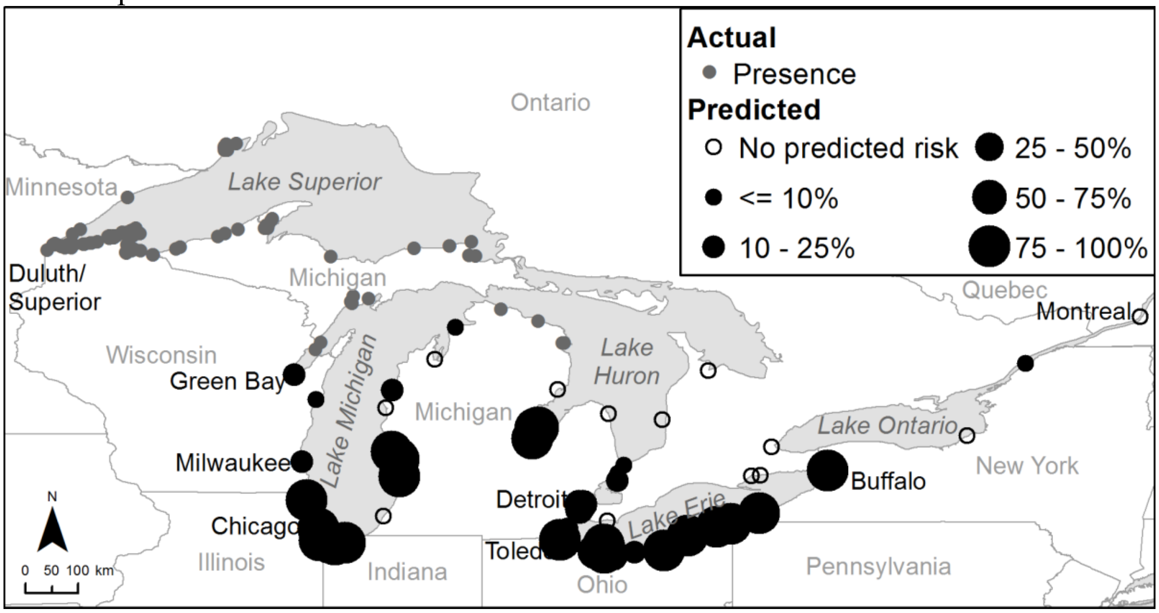
Time-step 1



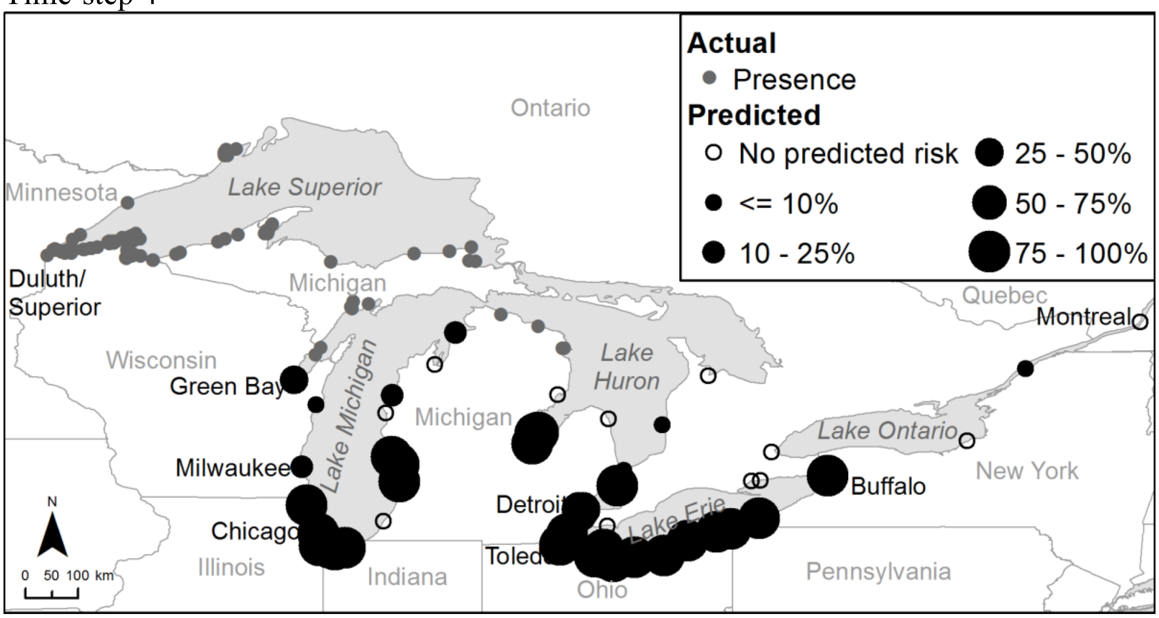
Time-step 2



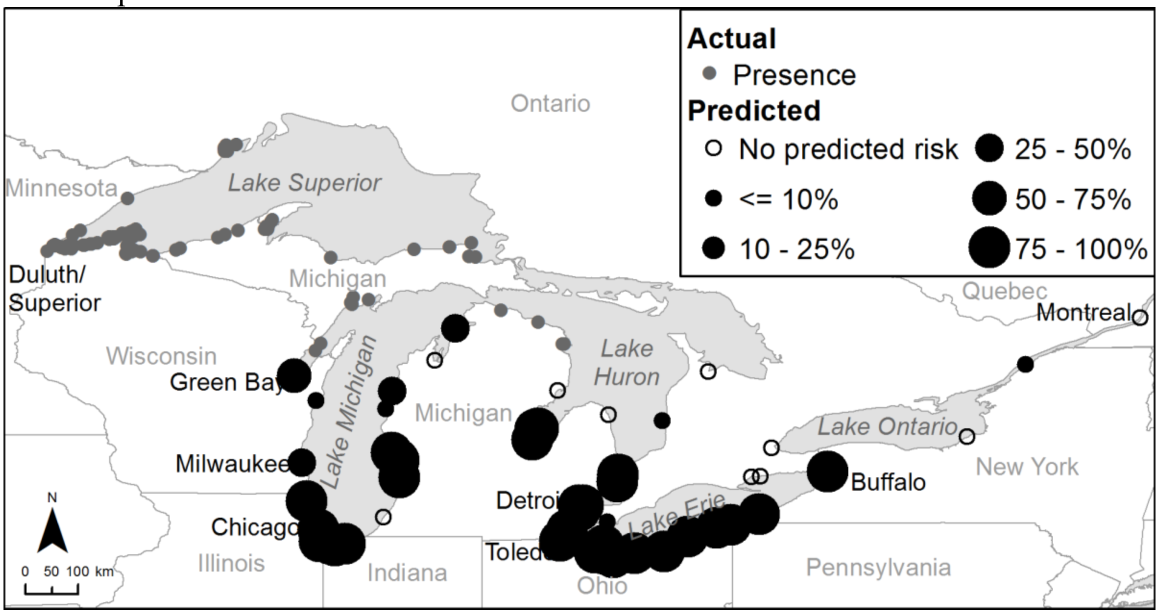
Time-step 3



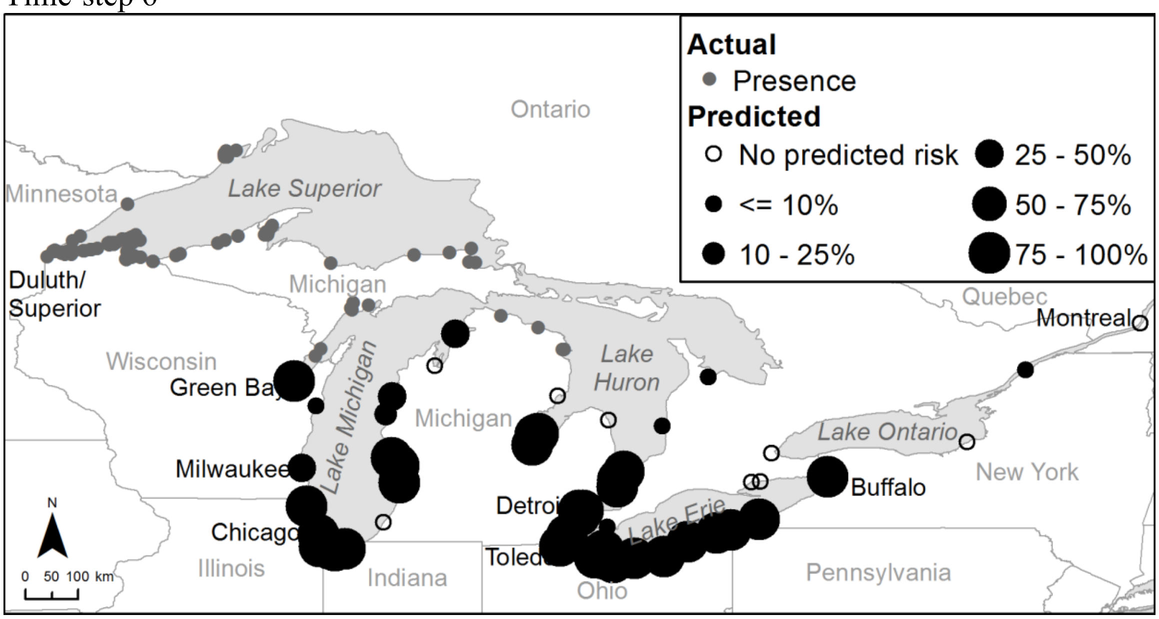
Time-step 4



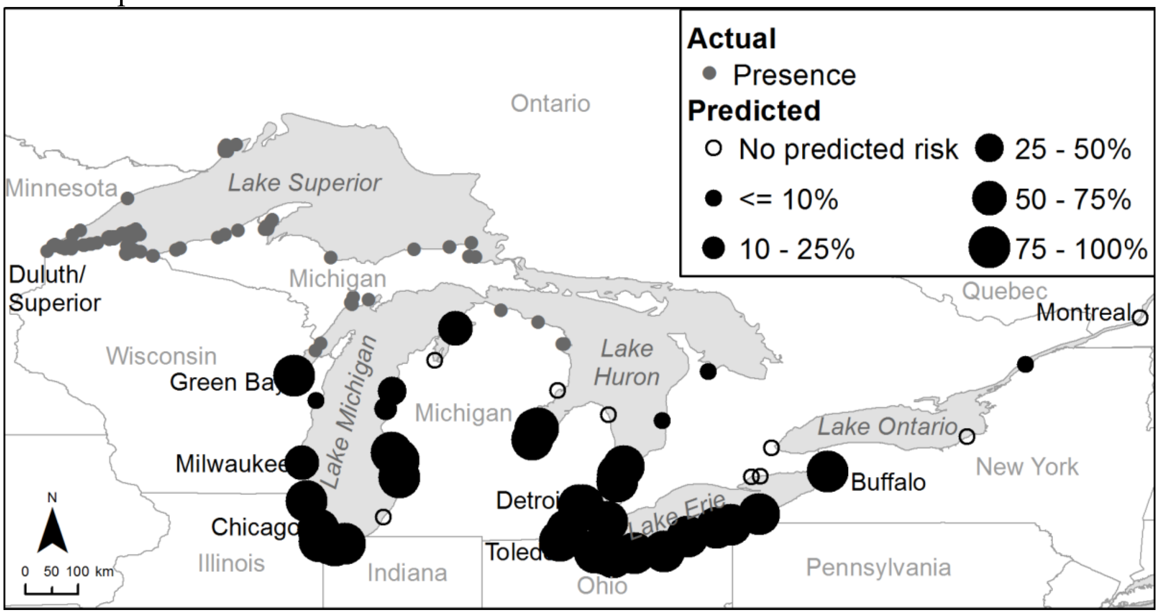
Time-step 5



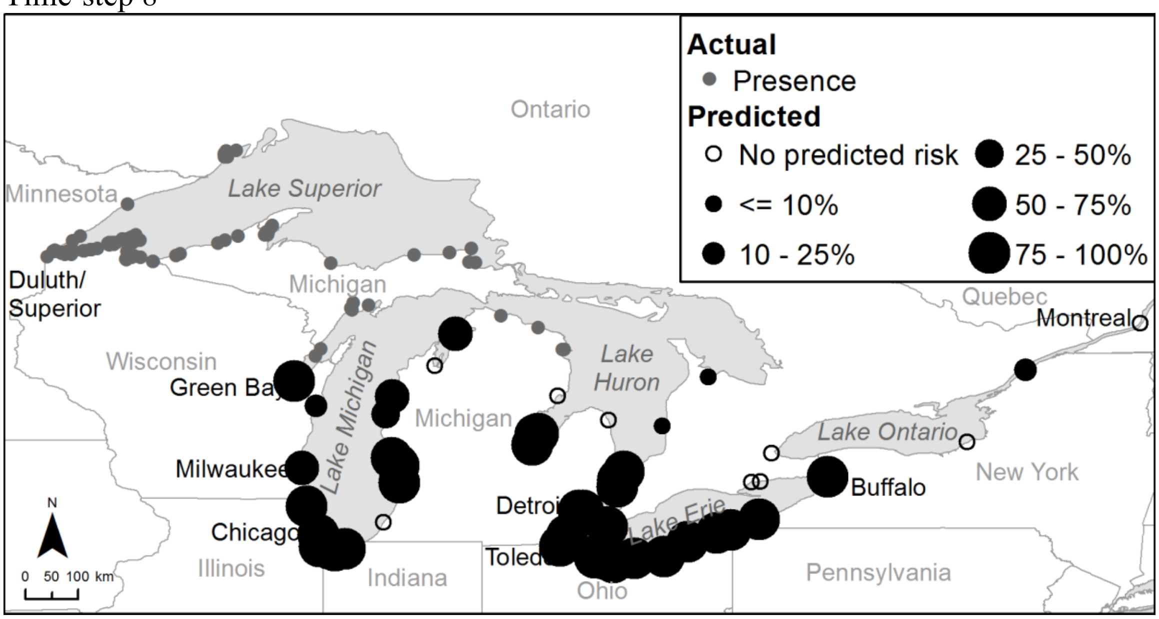
Time-step 6



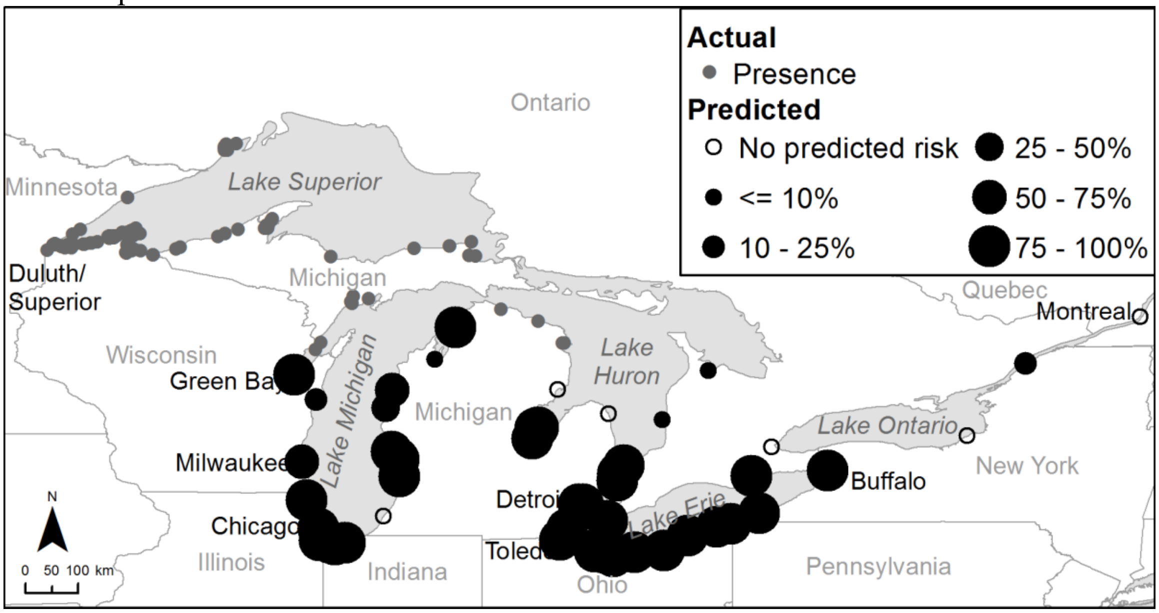
Time-step 7



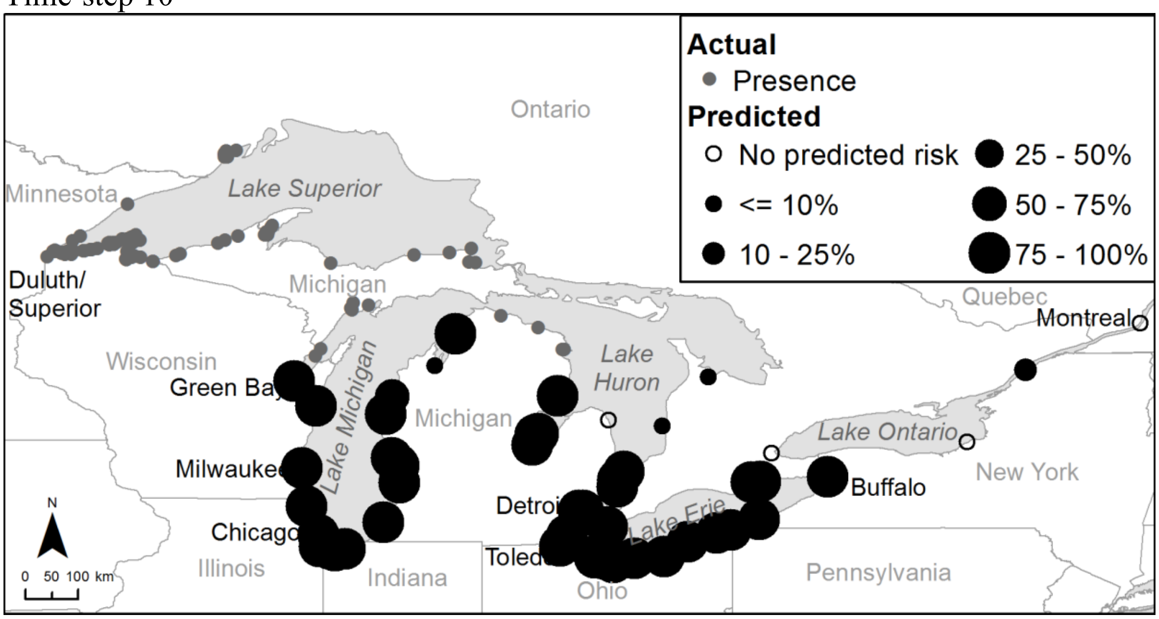
Time-step 8



Time-step 9

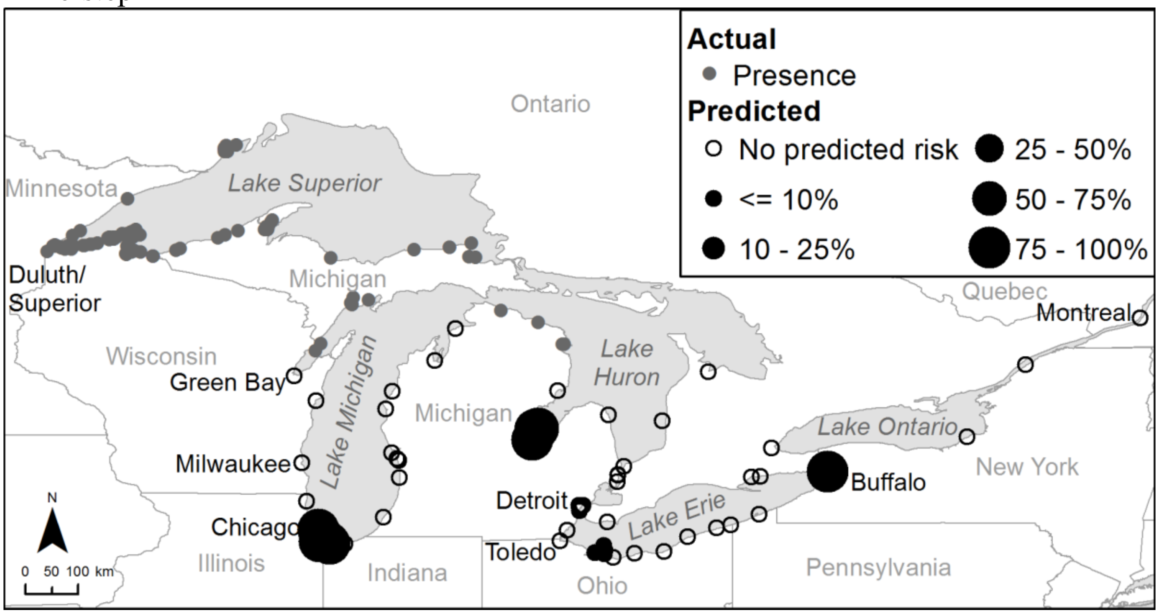


Time-step 10

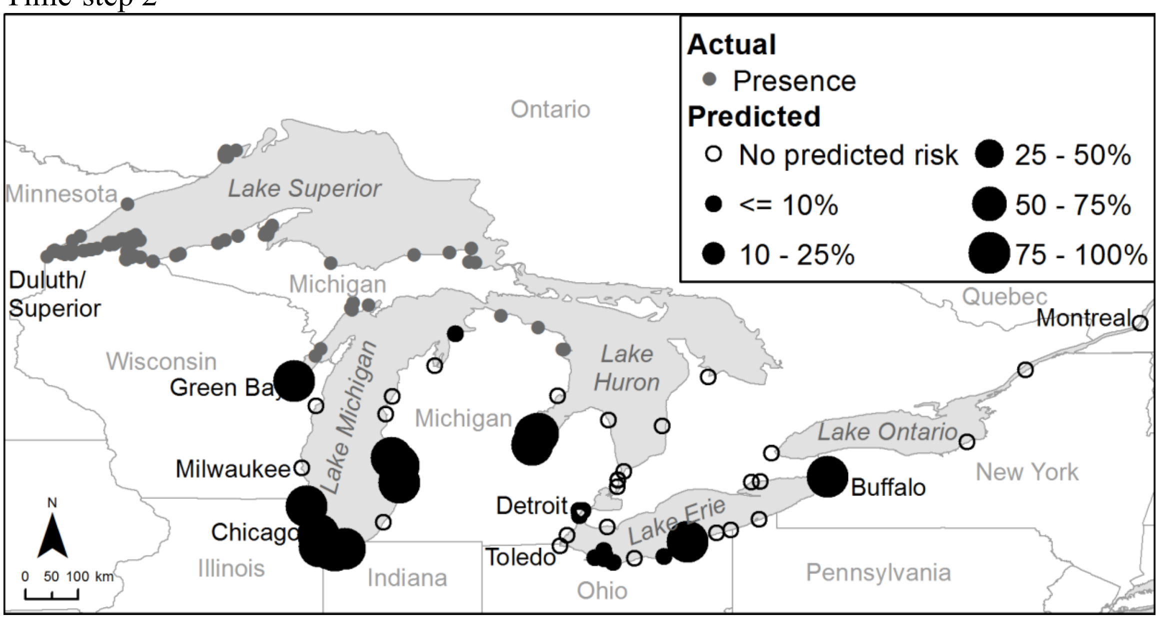


Eurasian Ruffe
Dispersal Distance = 25-km and Probability of Infestation = 0.0001

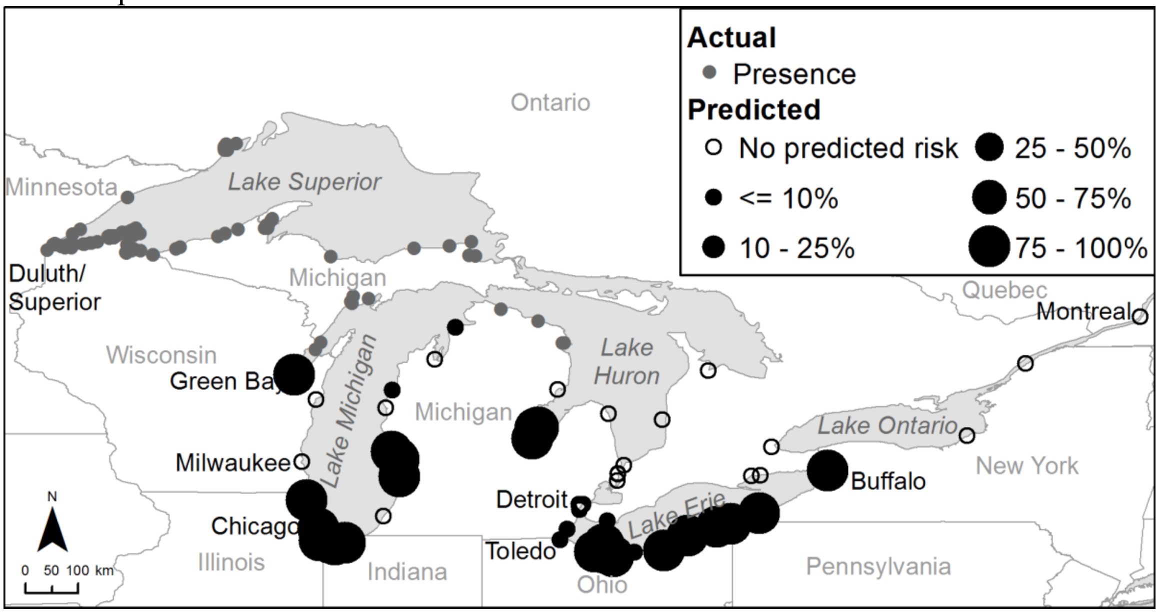
Time-step 1



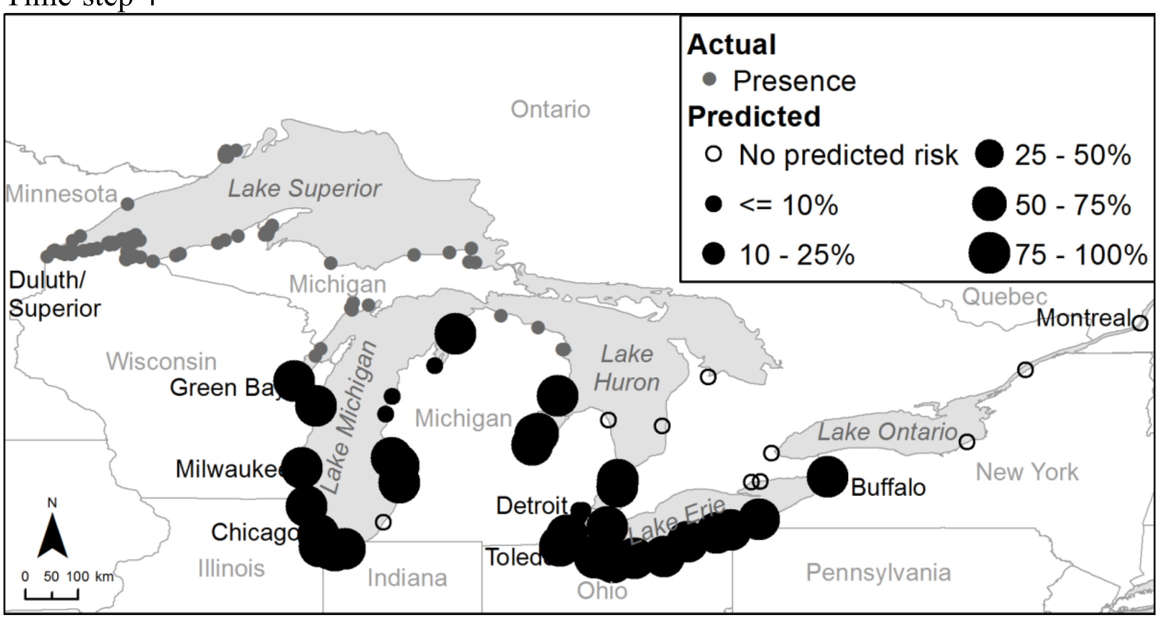
Time-step 2



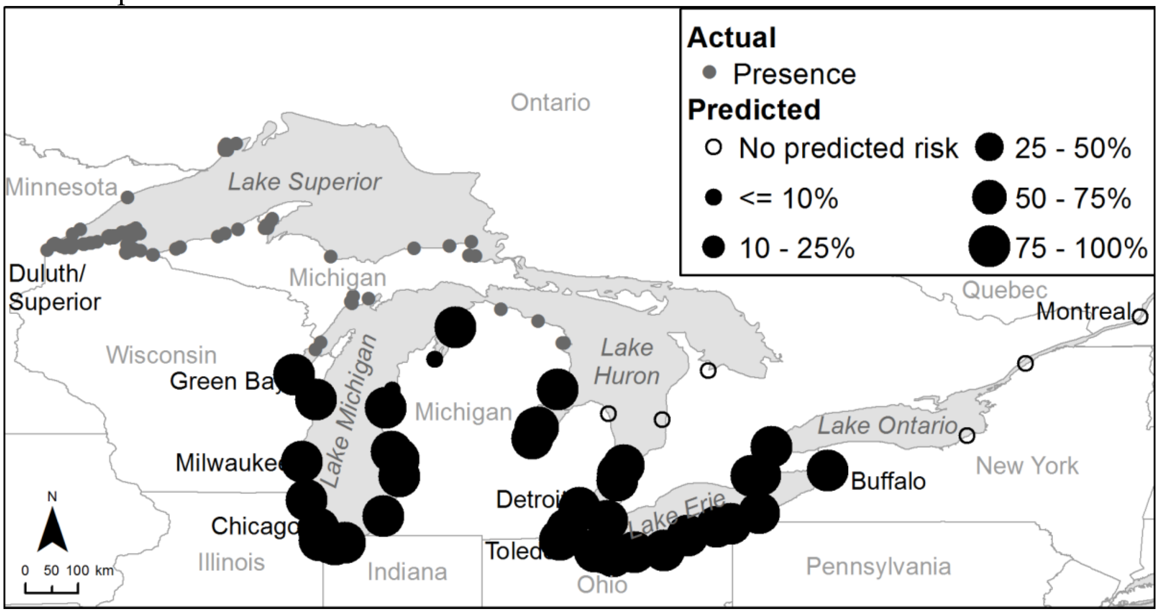
Time-step 3



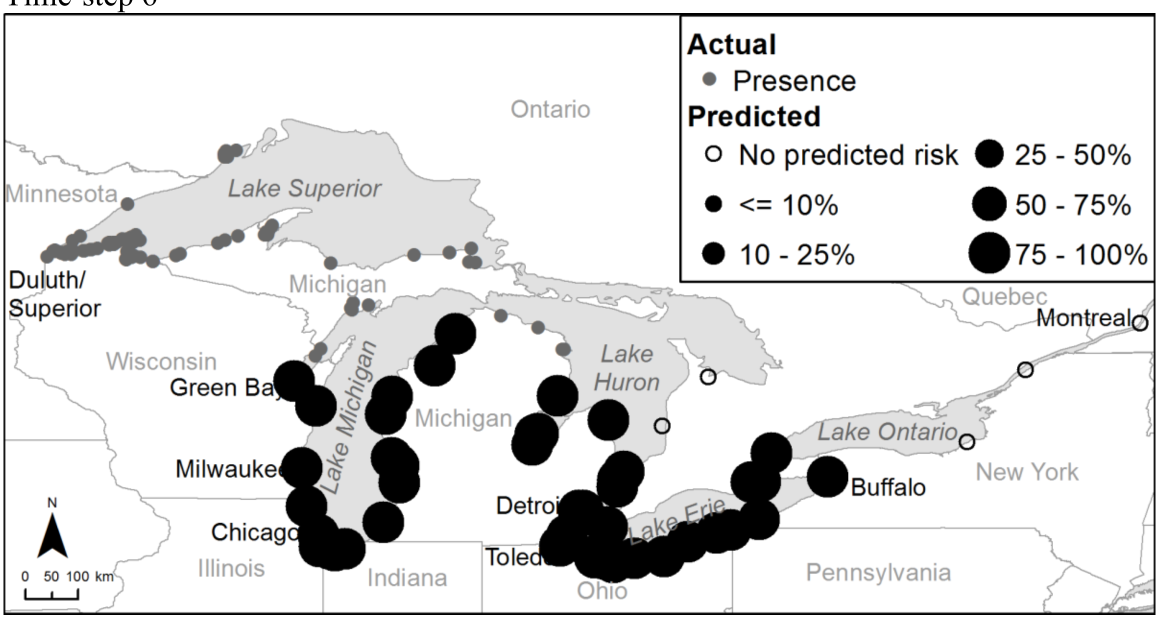
Time-step 4



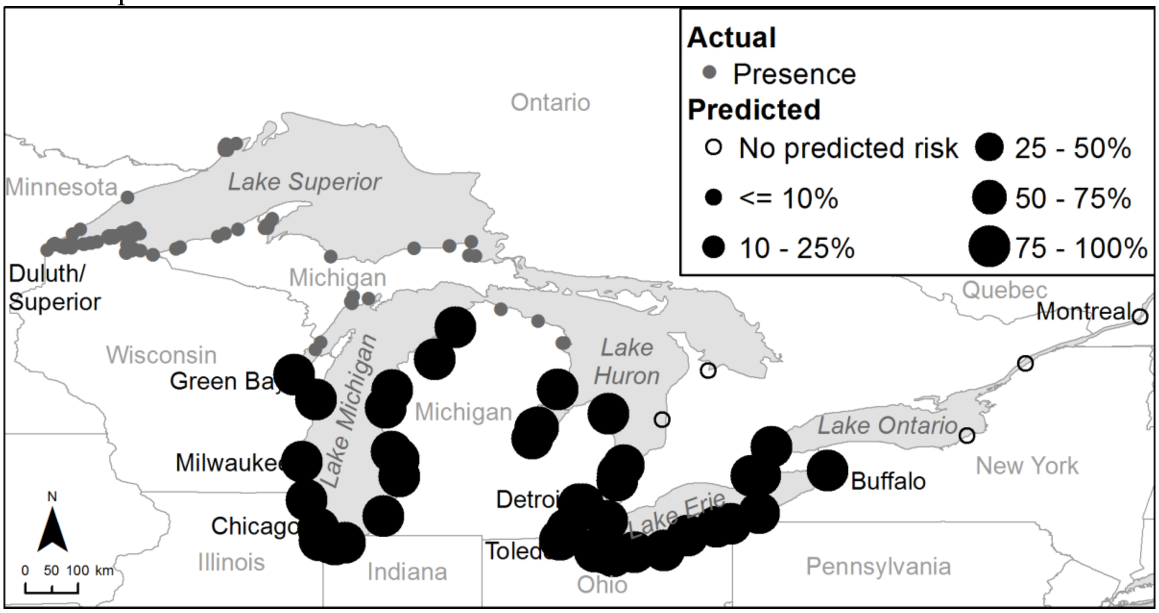
Time-step 5



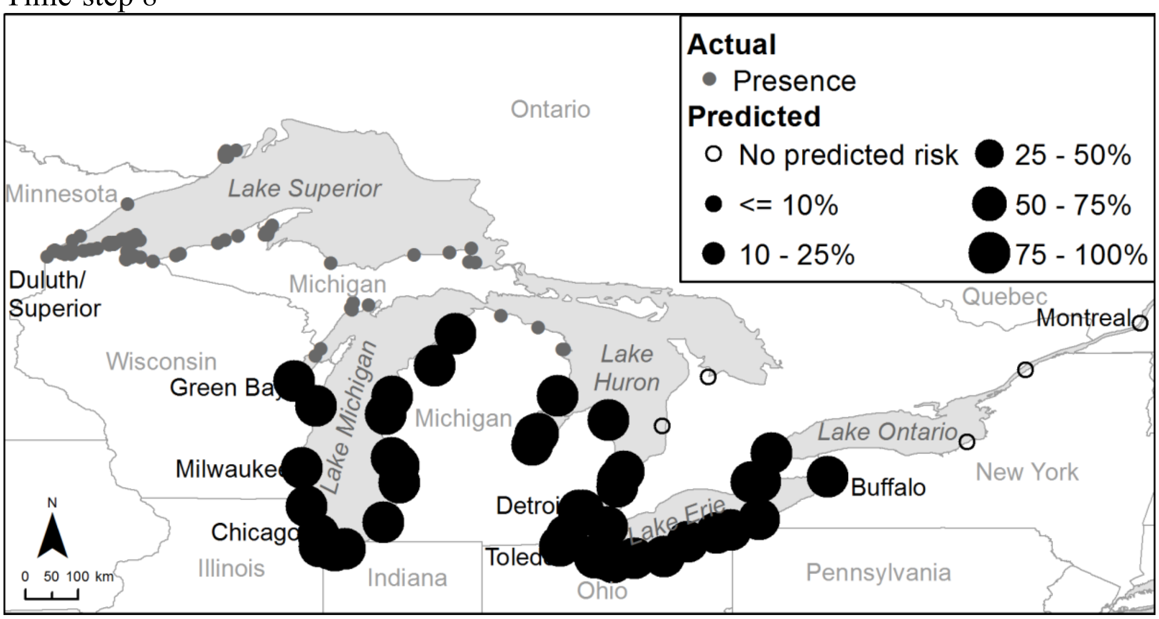
Time-step 6



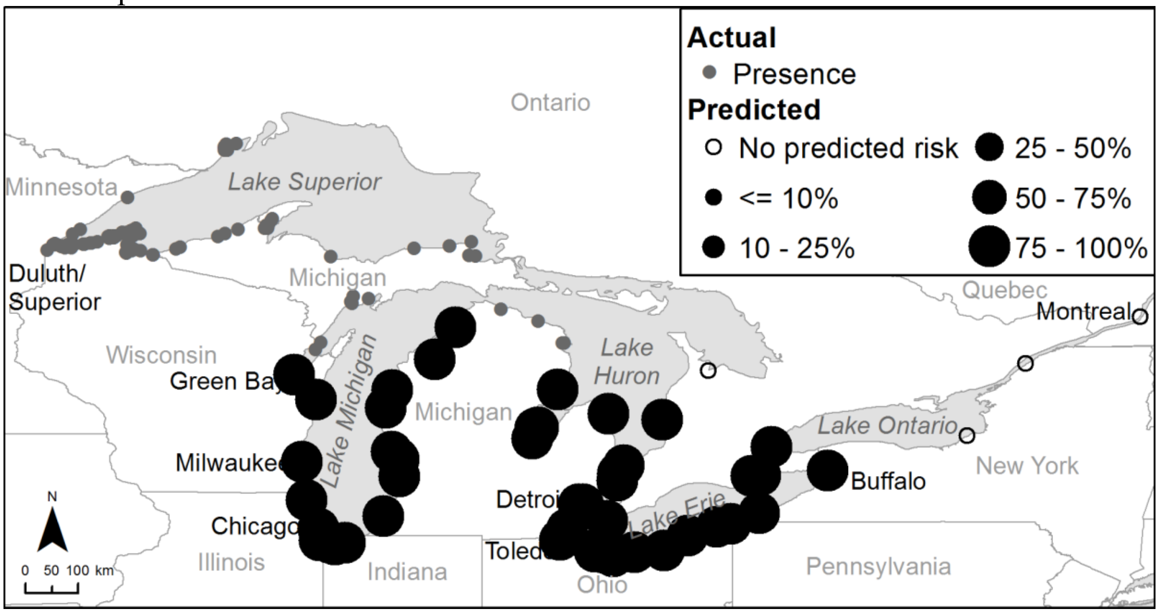
Time-step 7



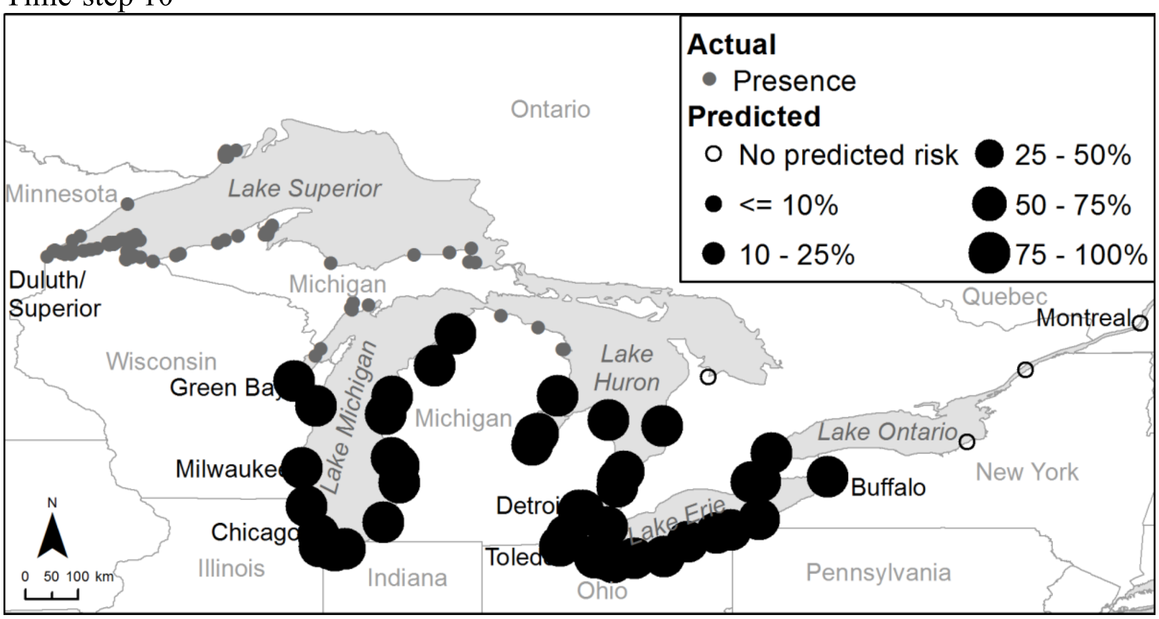
Time-step 8



Time-step 9

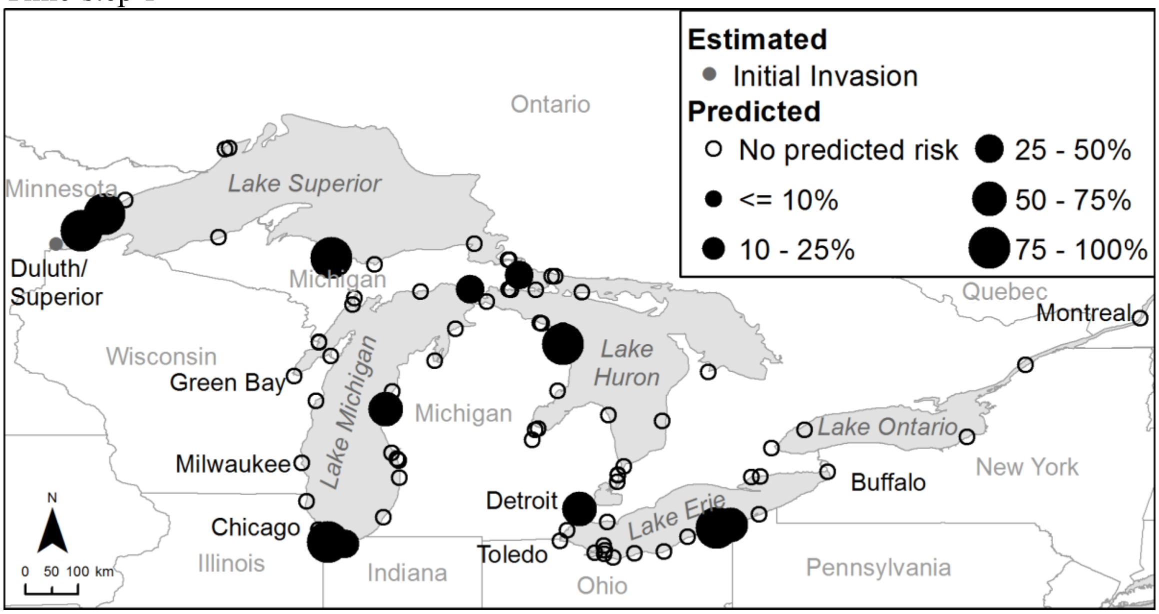


Time-step 10

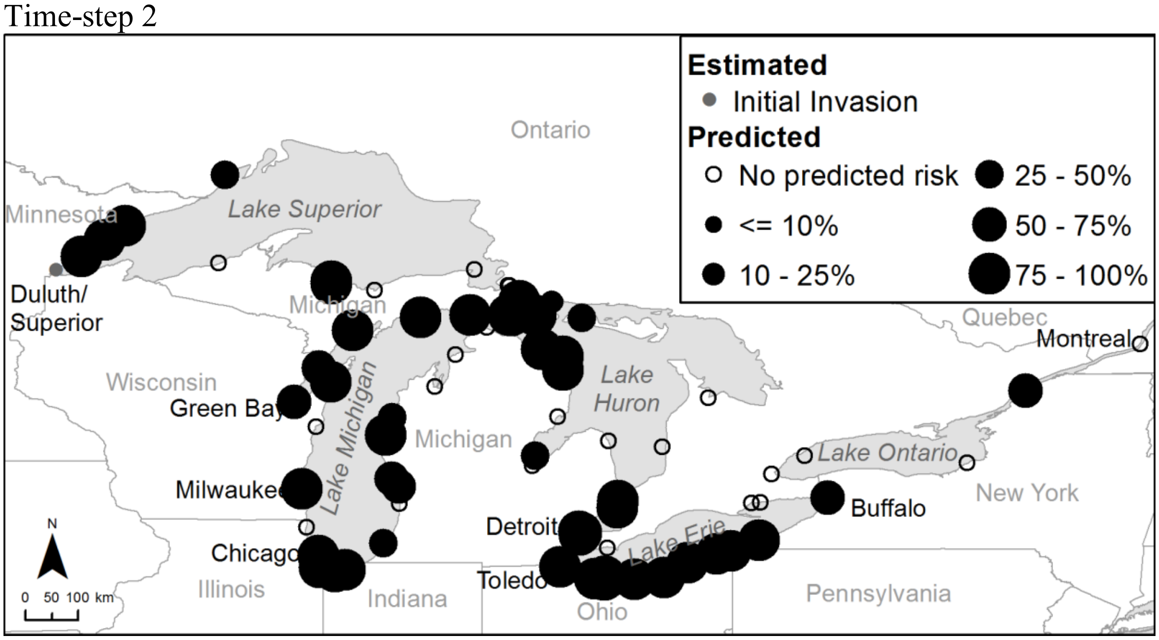


Killer Shrimp
Duluth, Minnesota
Dispersal Distance = 0-km and Probability of Infestation = 0.75

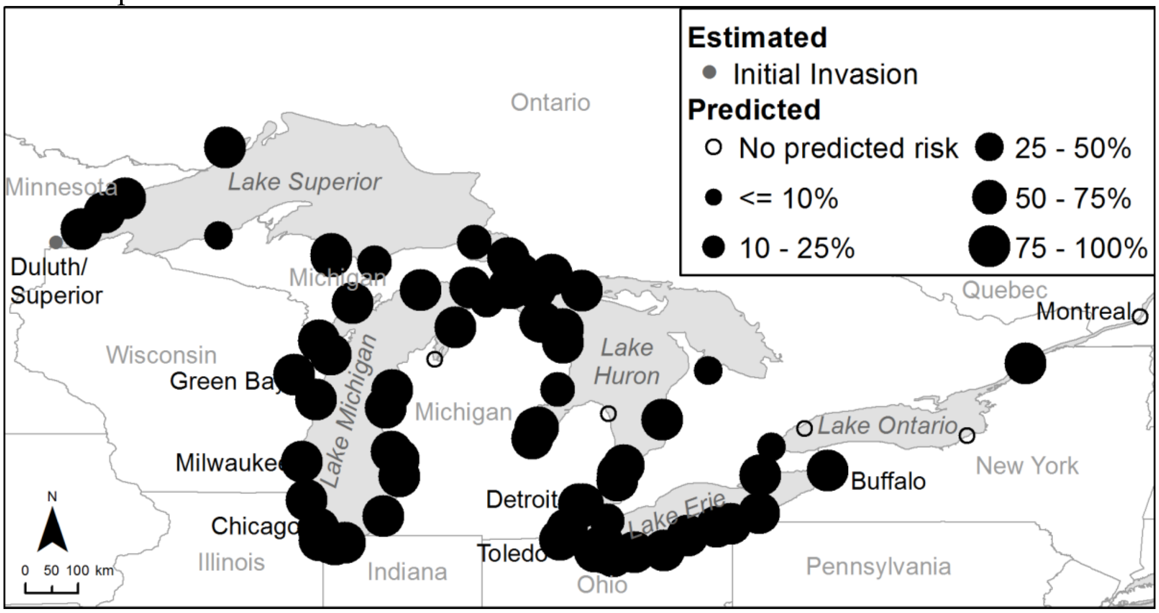
Time-step 1



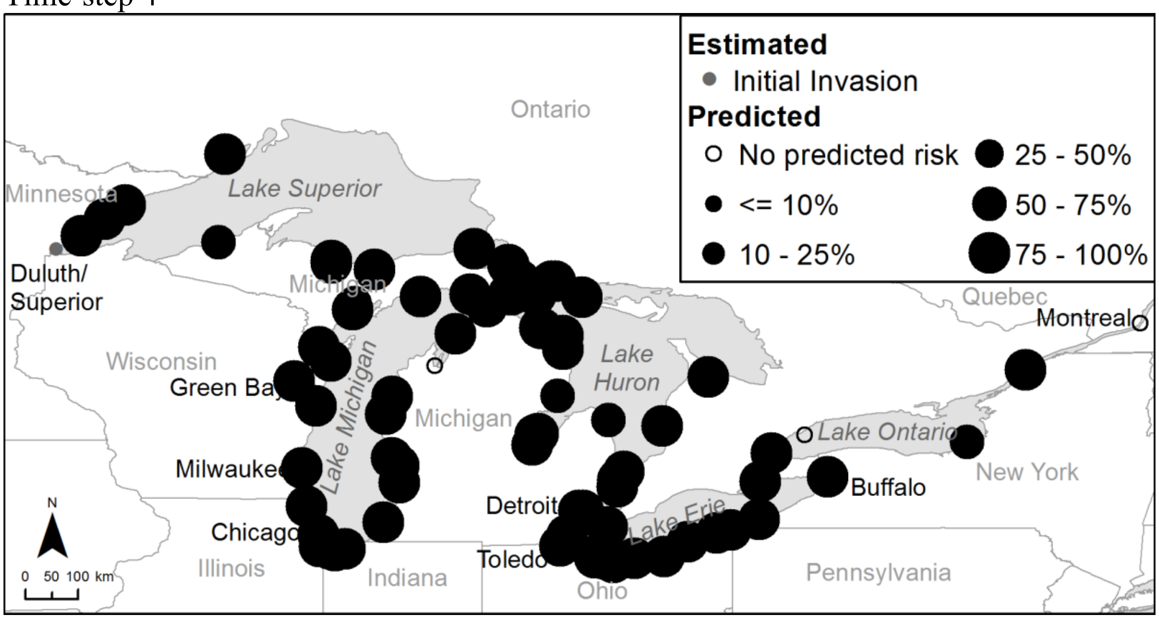
Time-step 2



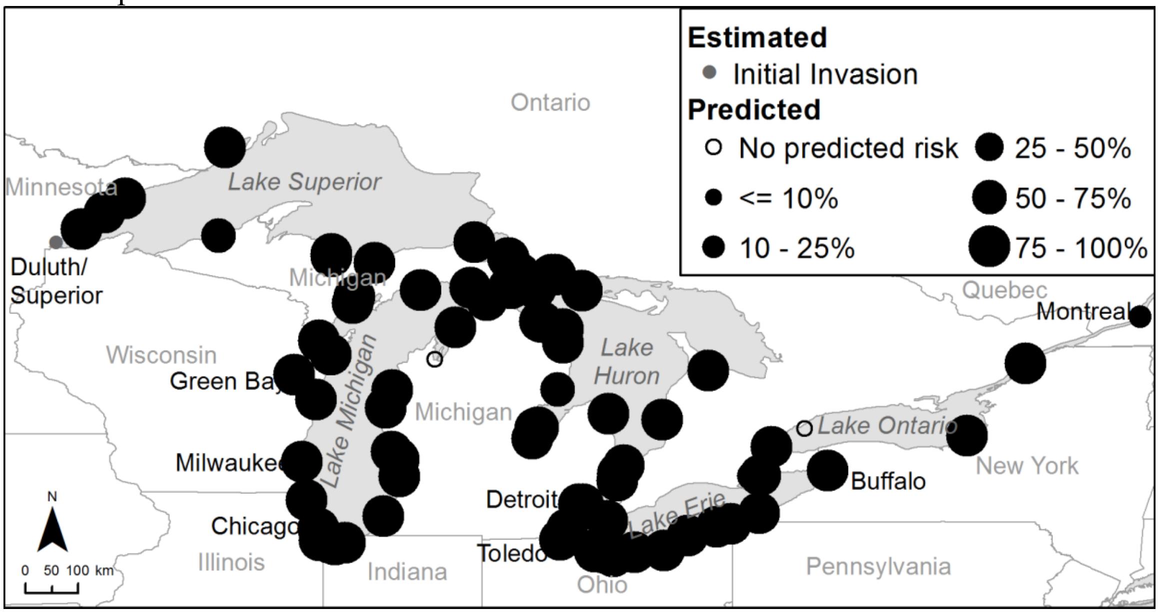
Time-step 3



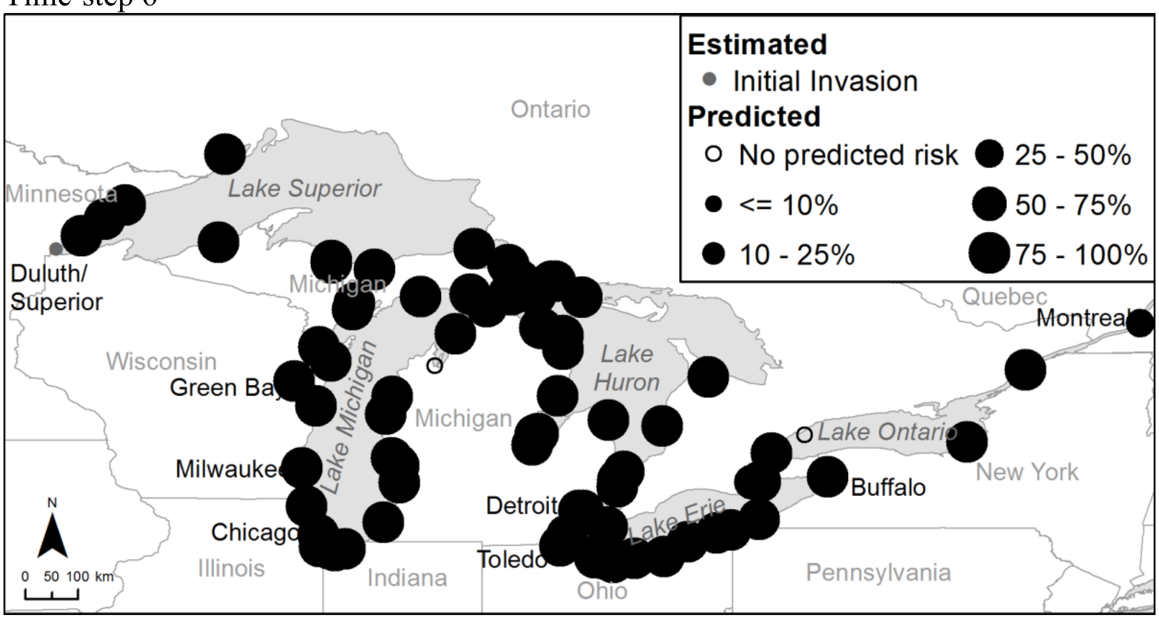
Time-step 4



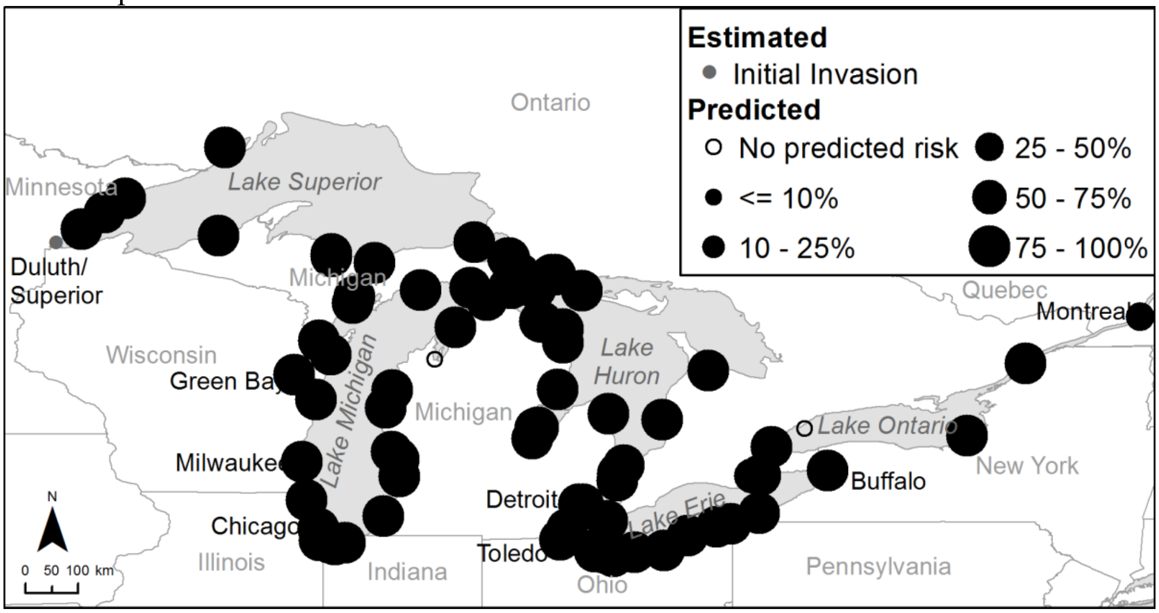
Time-step 5



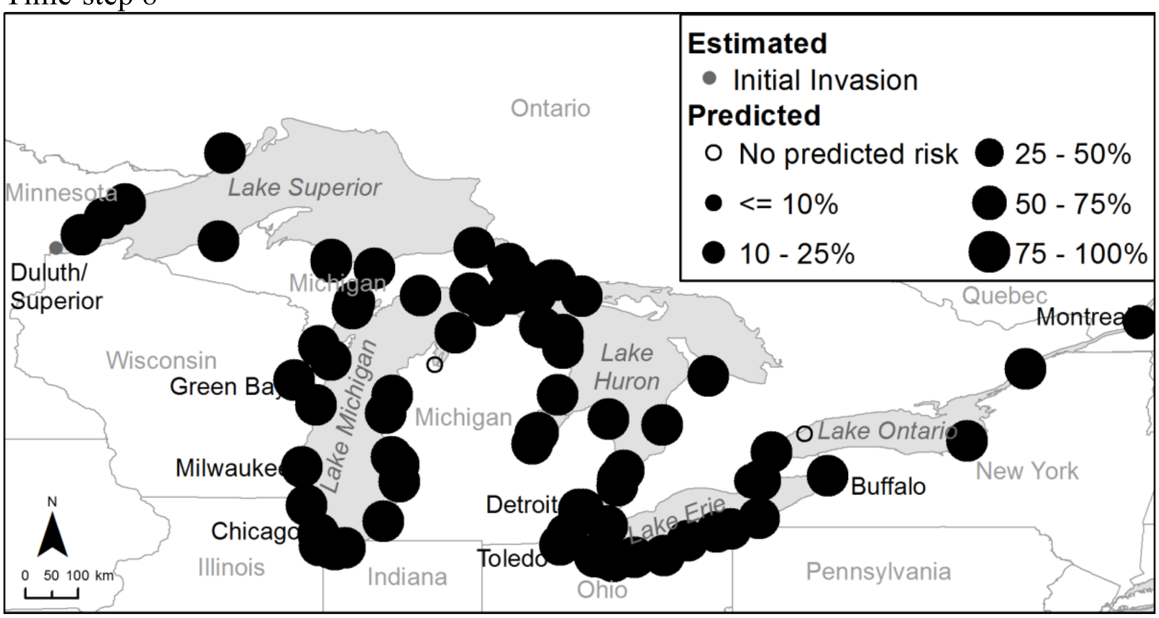
Time-step 6



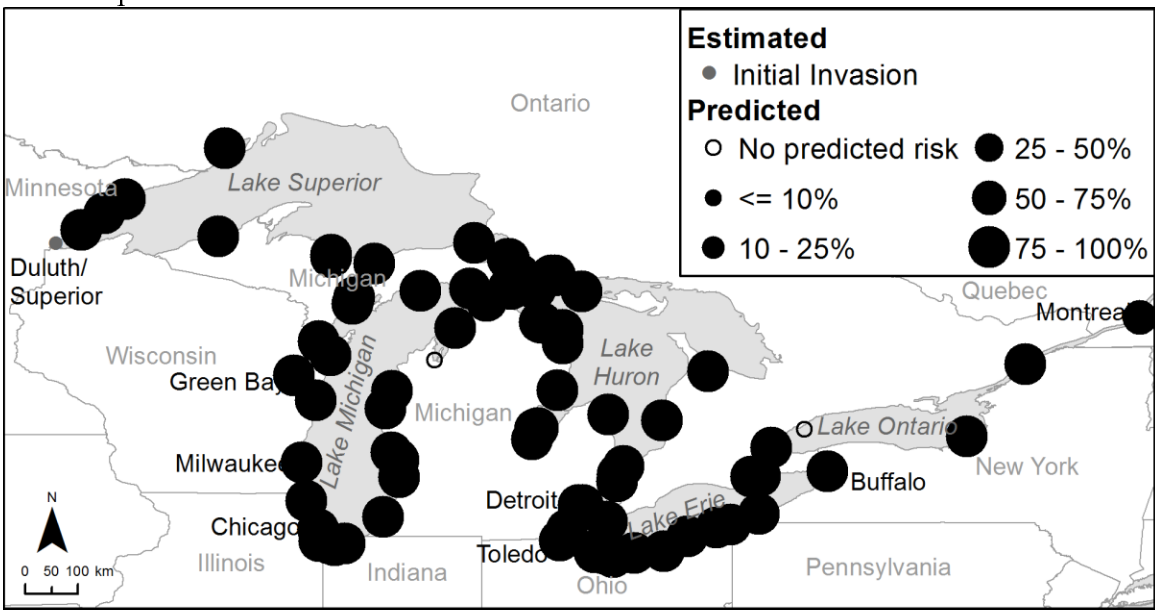
Time-step 7



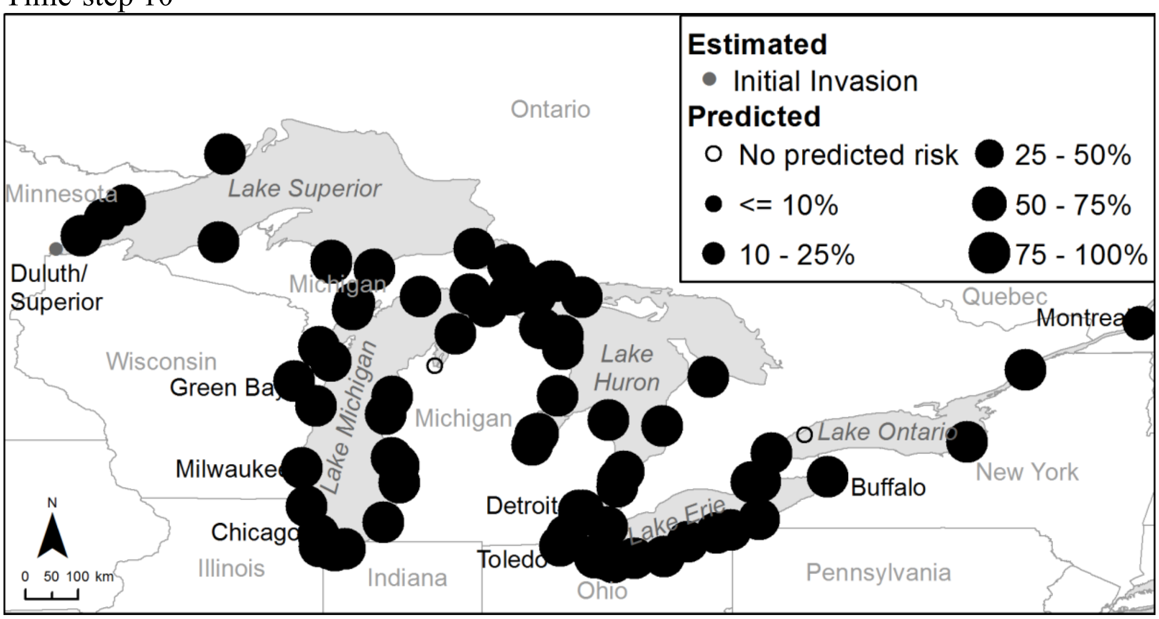
Time-step 8



Time-step 9

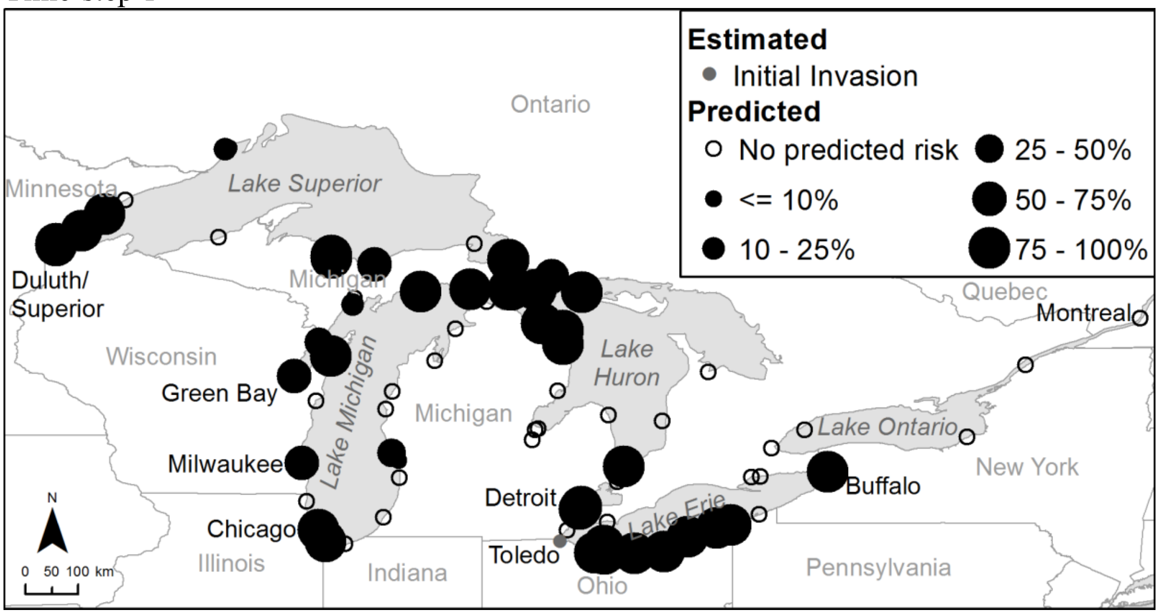


Time-step 10

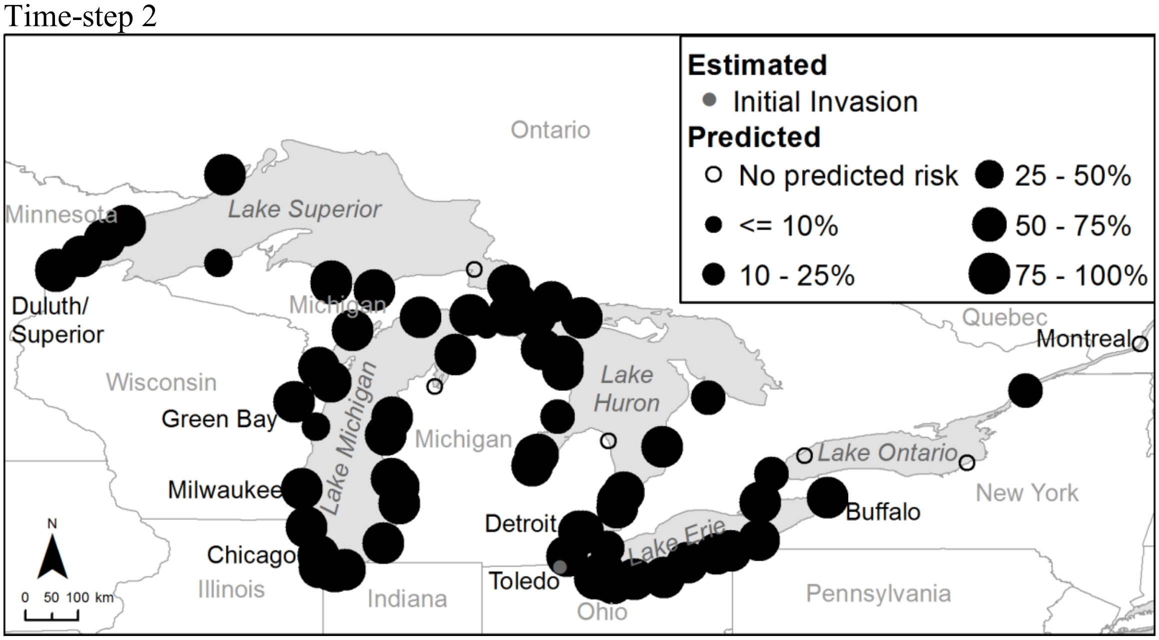


Killer Shrimp
Toledo, Ohio
Dispersal Distance = 0-km and Probability of Infestation = 0.75

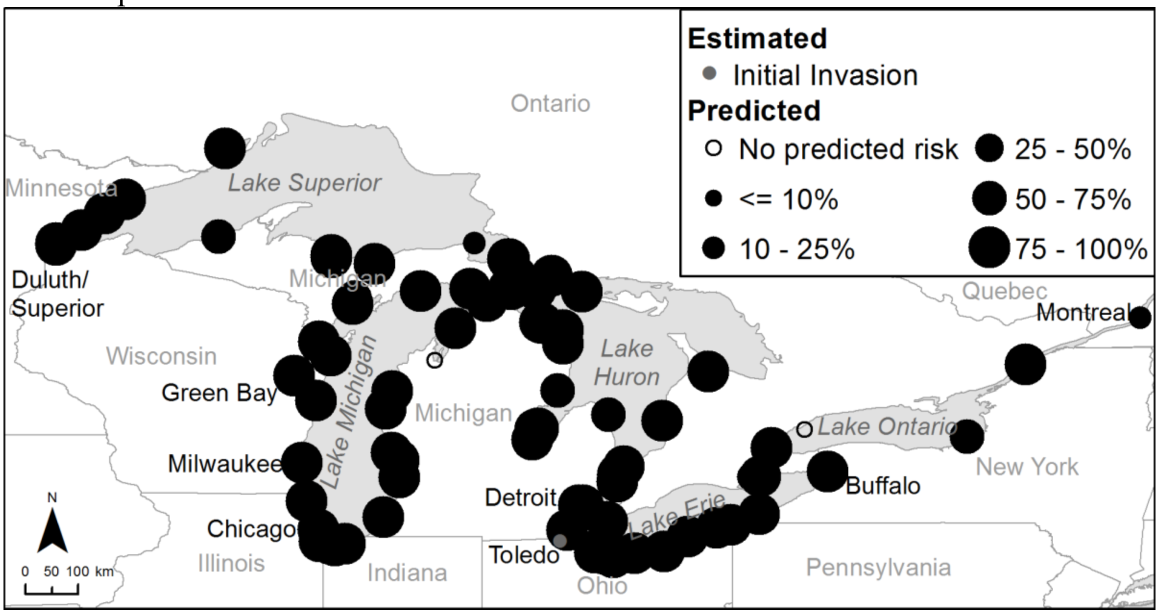
Time-step 1



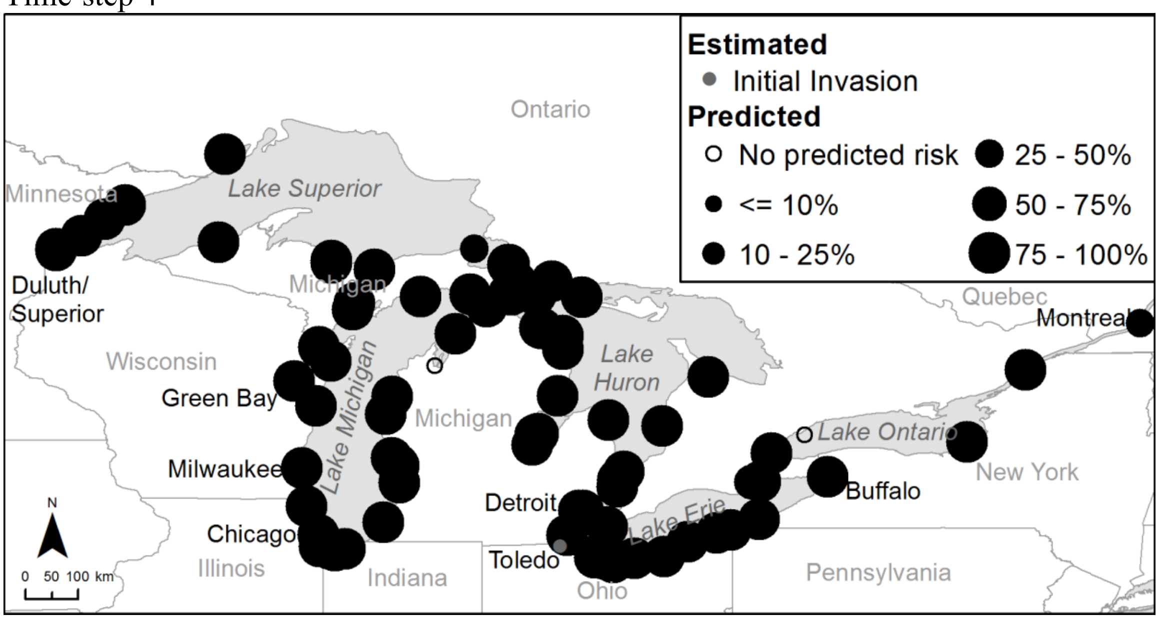
Time-step 2



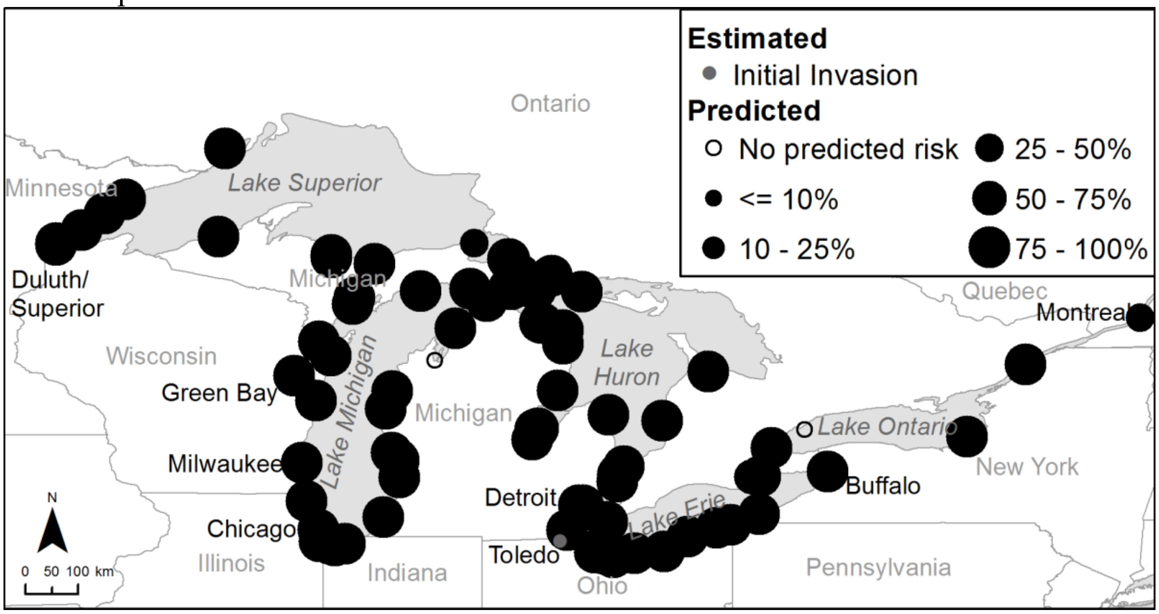
Time-step 3



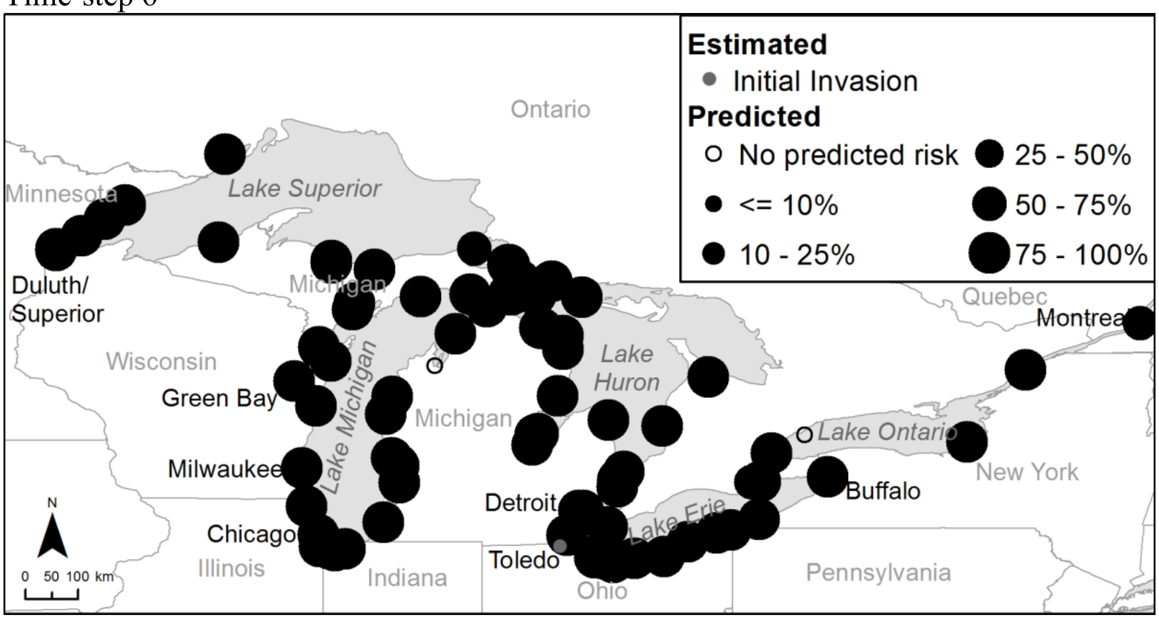
Time-step 4



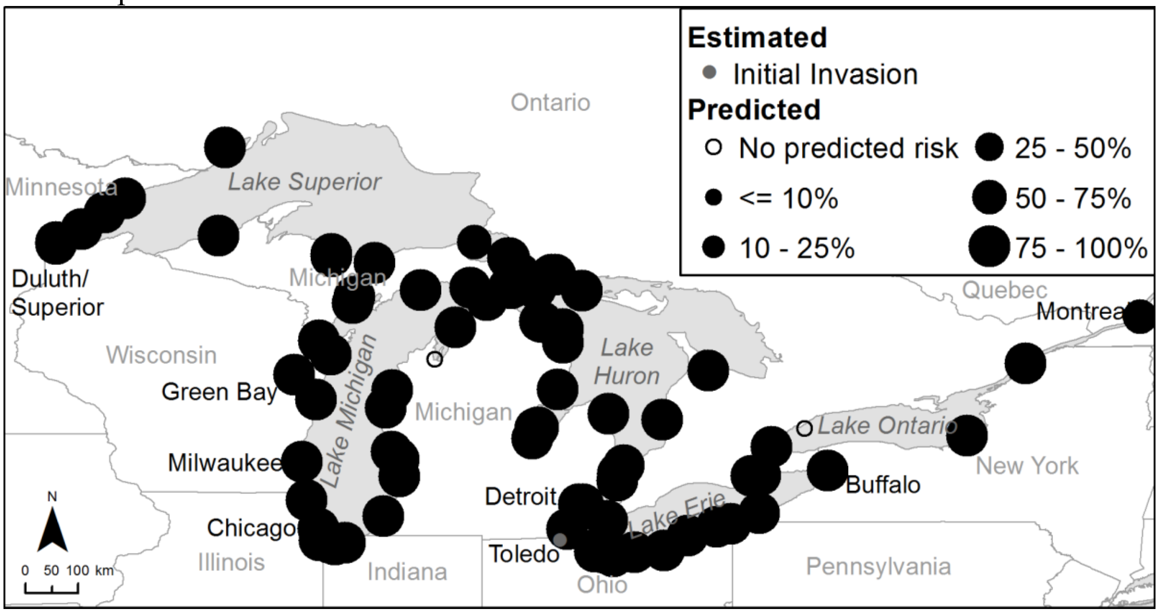
Time-step 5



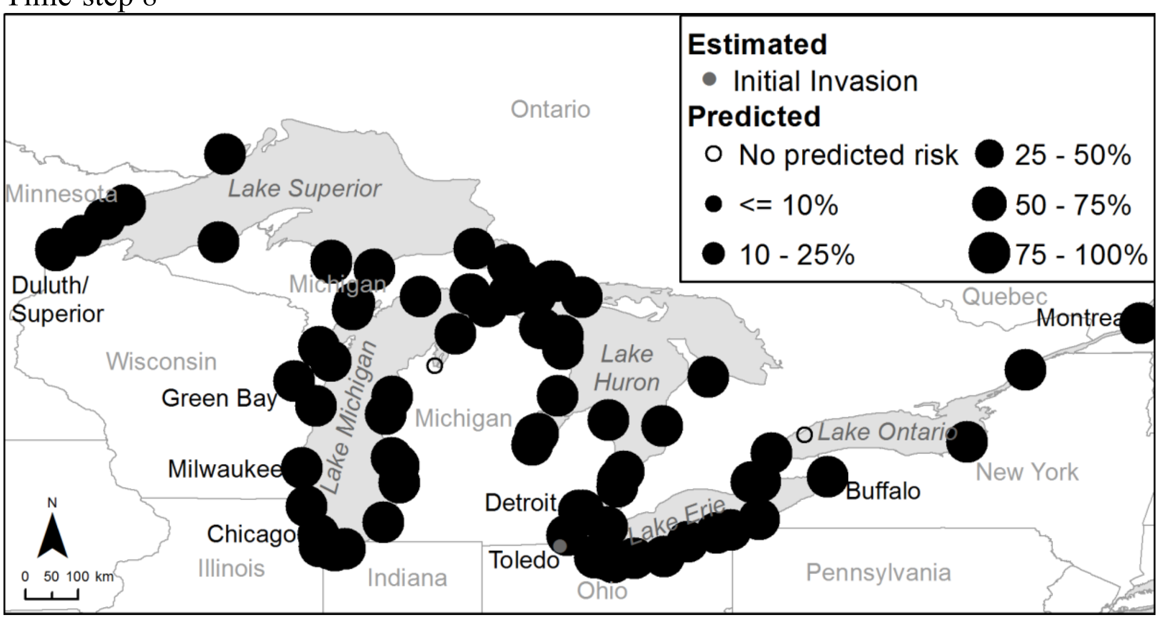
Time-step 6



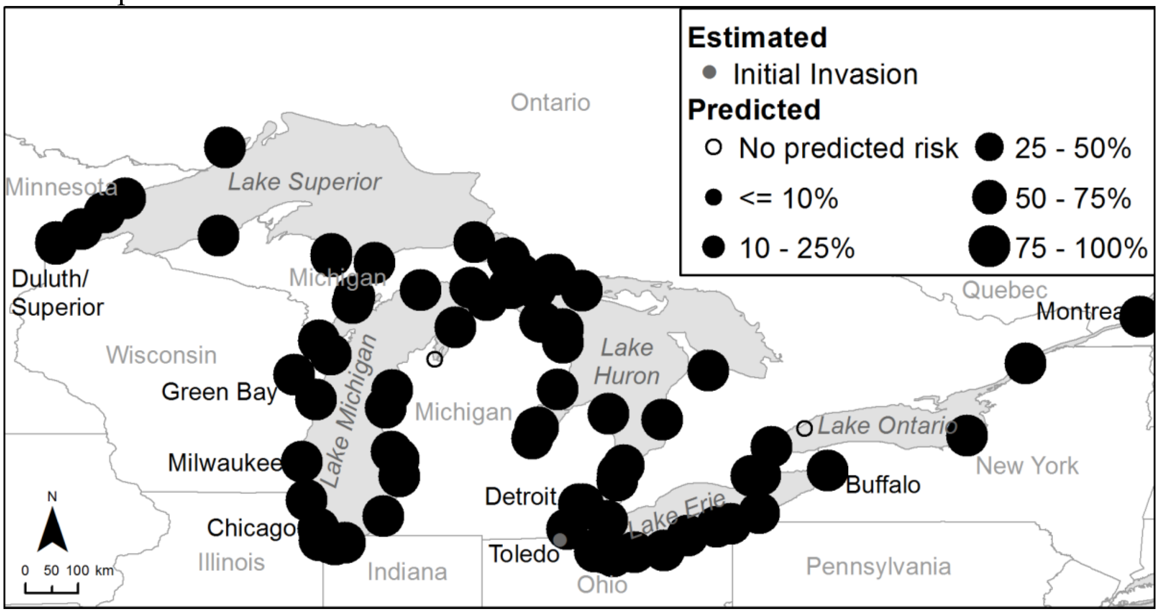
Time-step 7



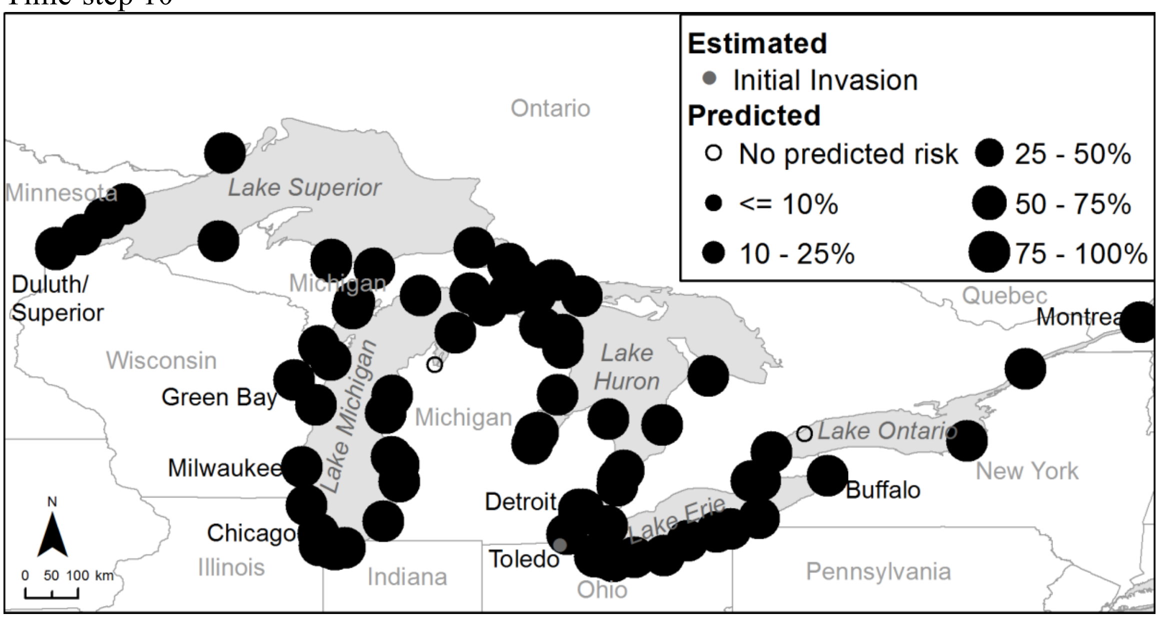
Time-step 8



Time-step 9

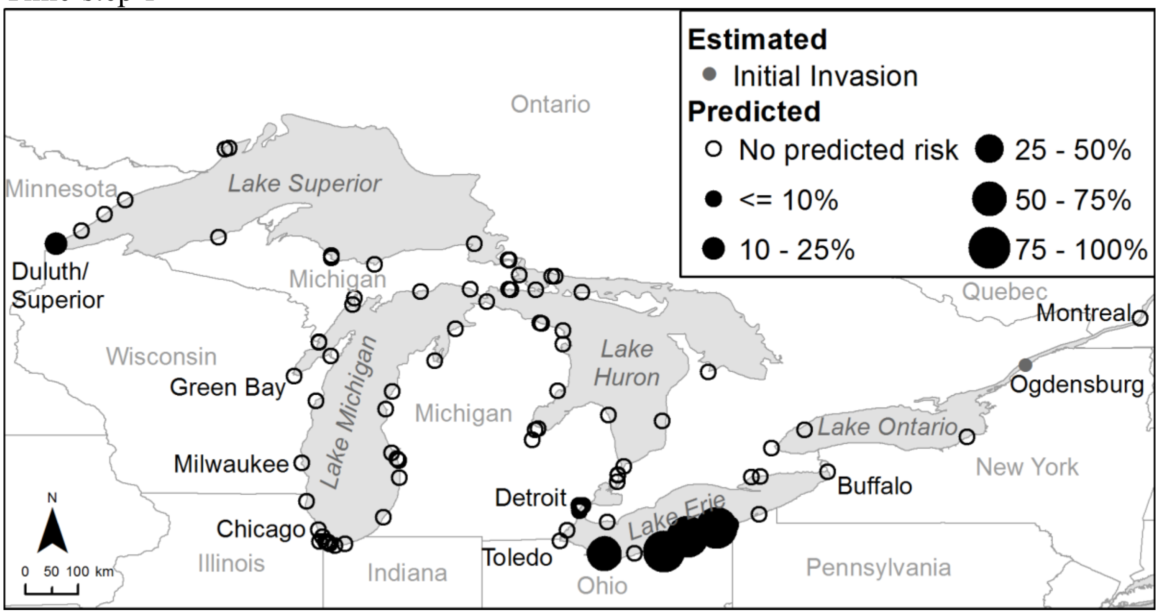


Time-step 10

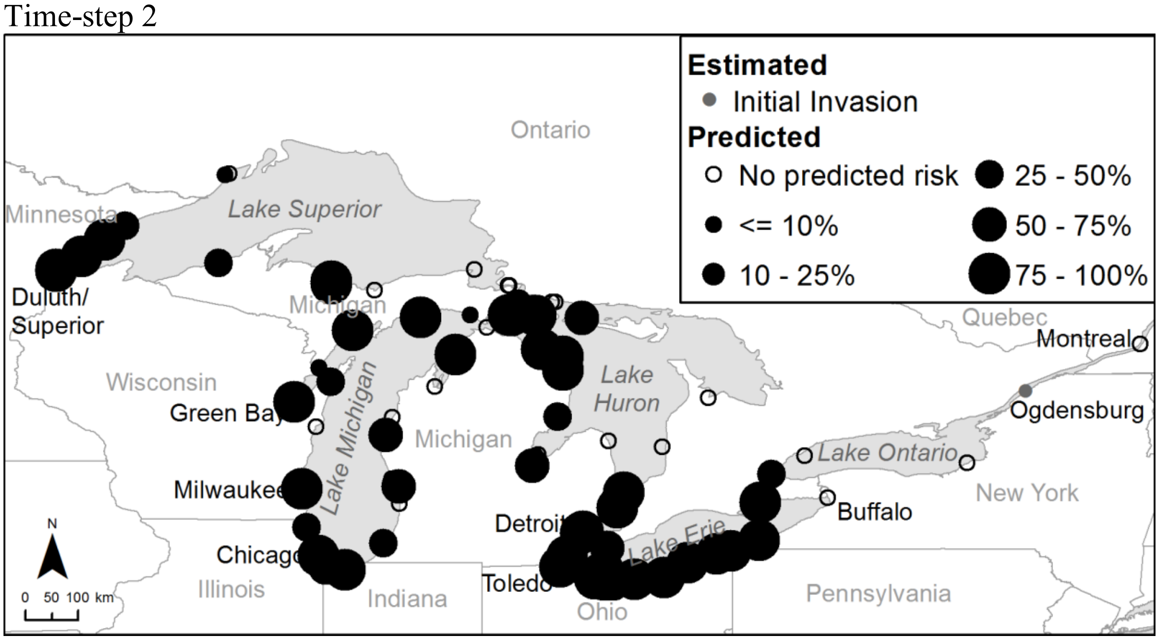


Killer Shrimp
Ogdensburg, New York
Dispersal Distance = 0-km and Probability of Infestation = 0.75

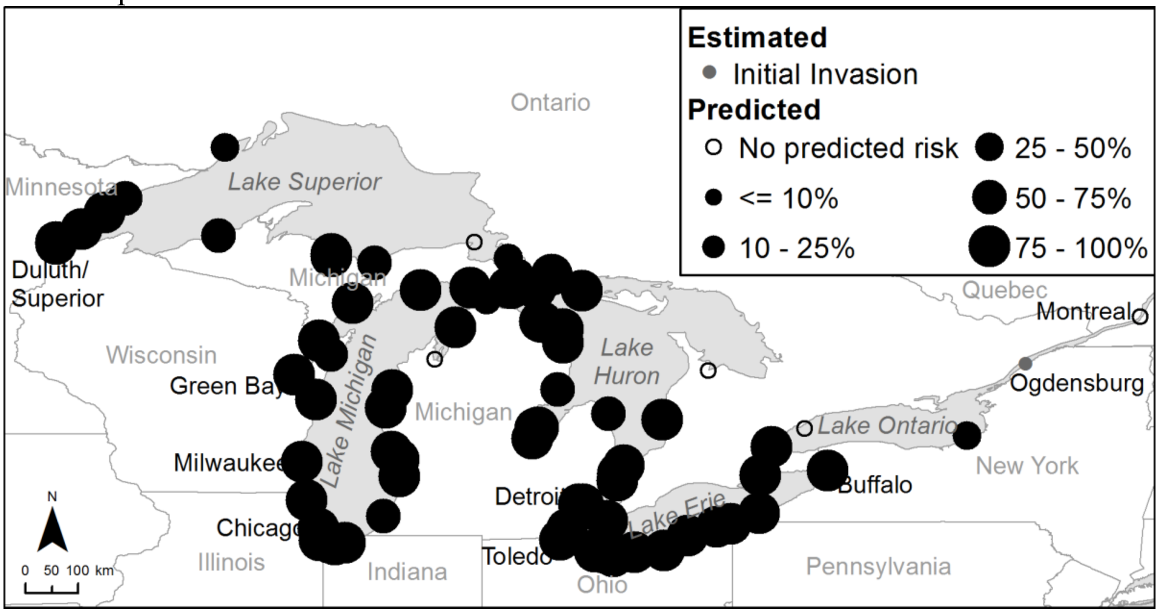
Time-step 1



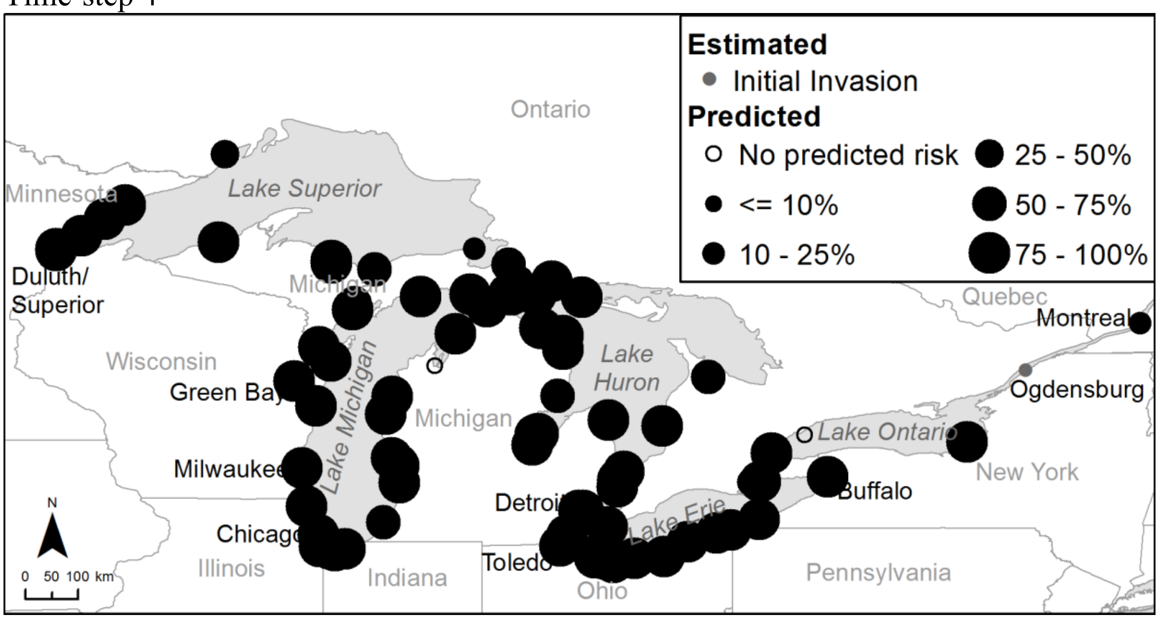
Time-step 2



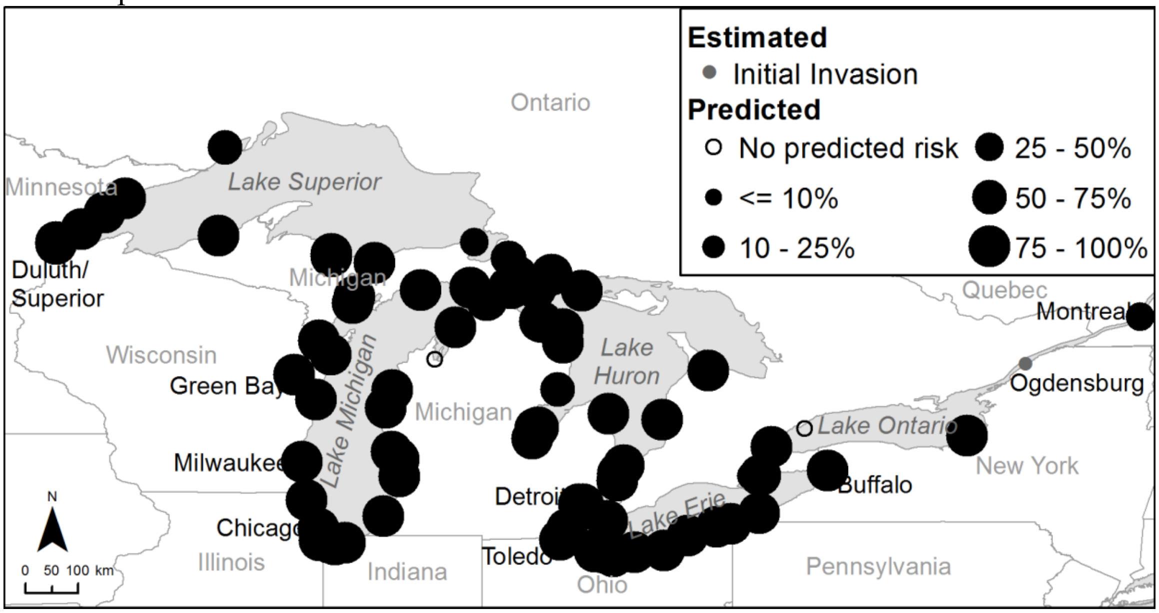
Time-step 3



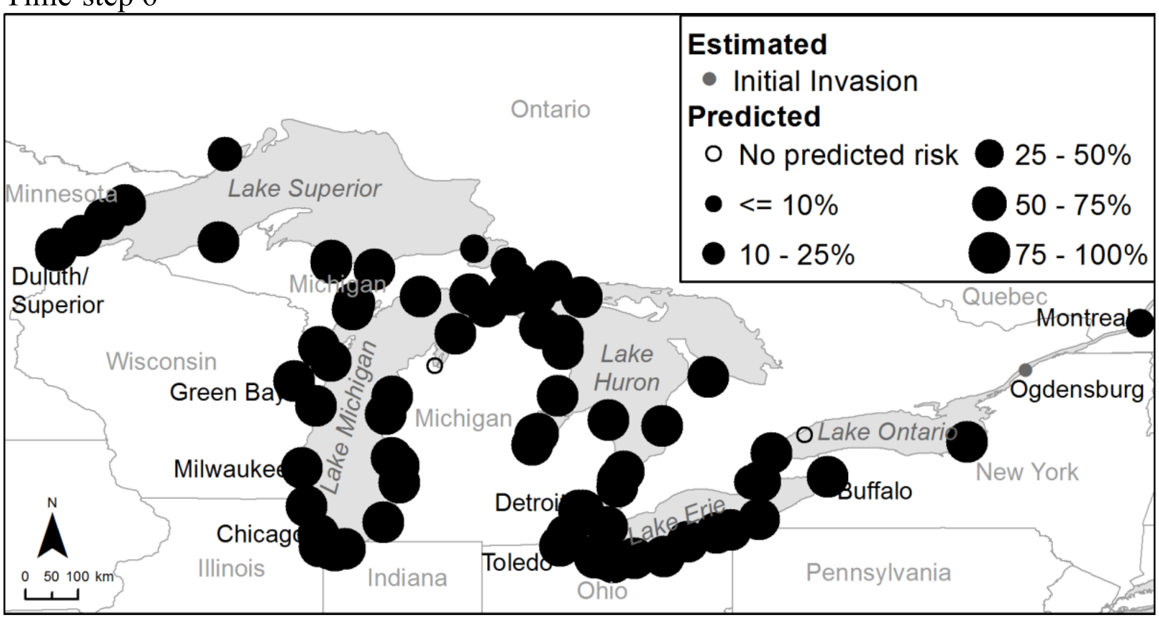
Time-step 4



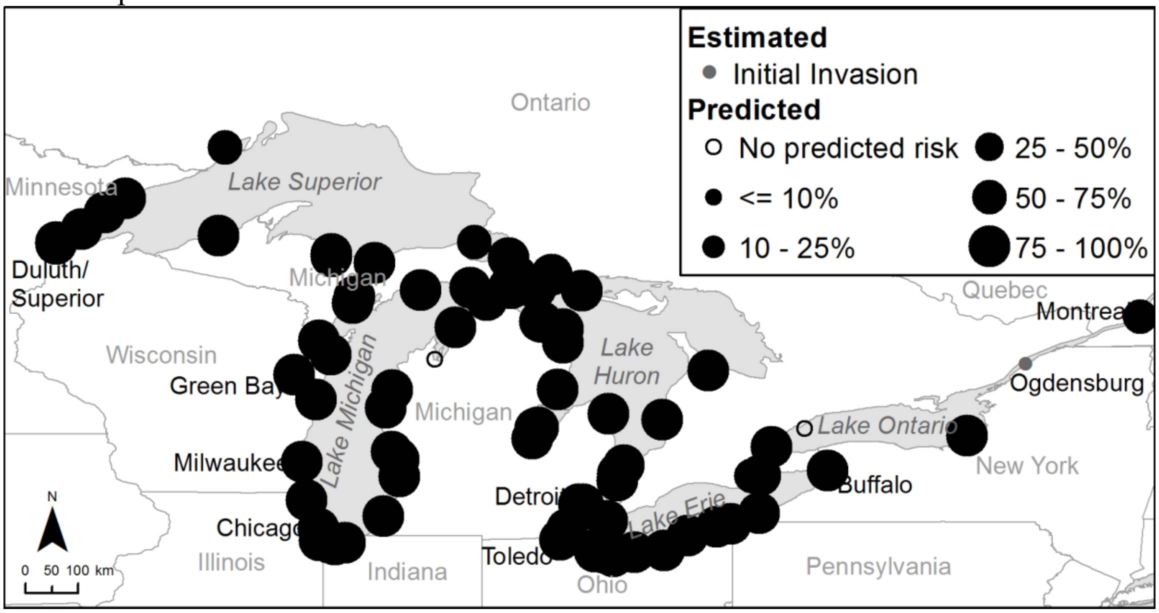
Time-step 5



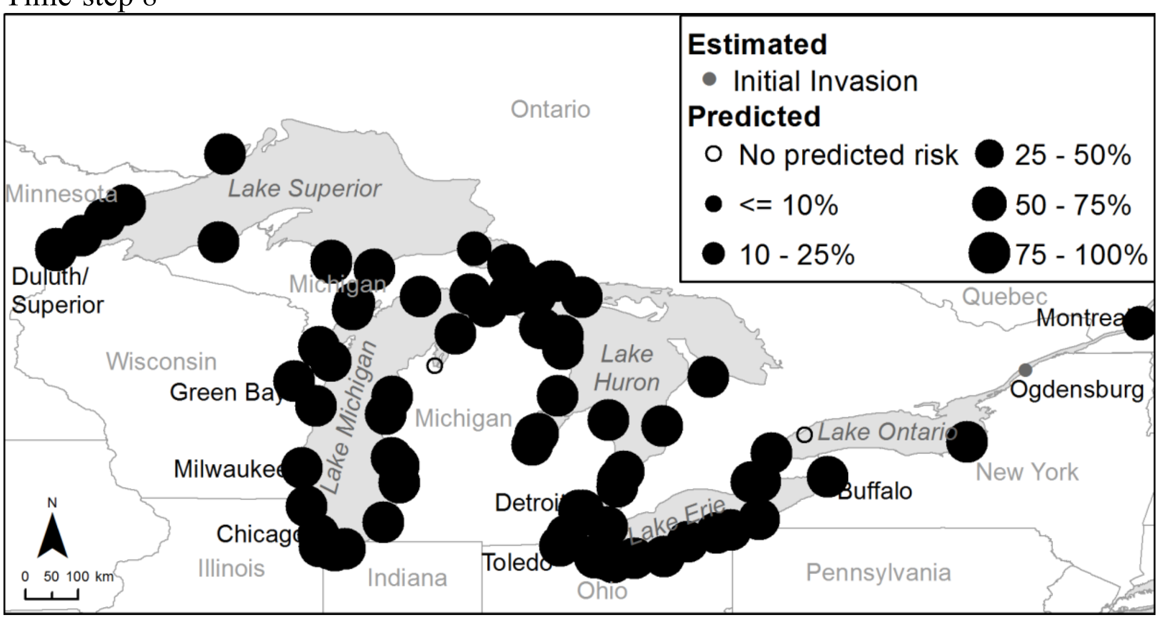
Time-step 6



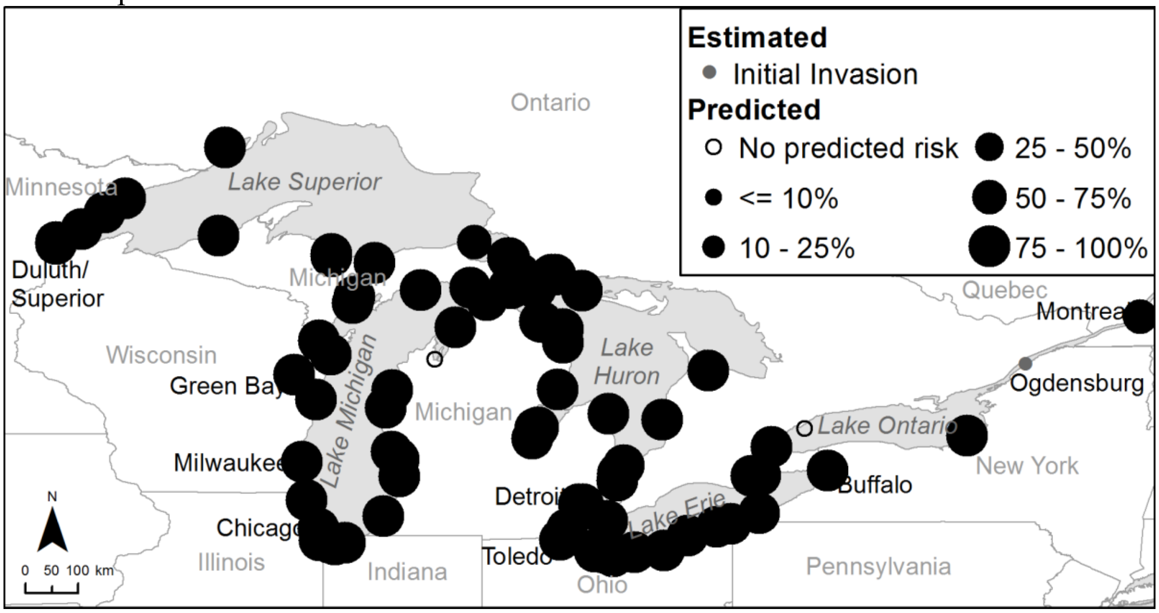
Time-step 7



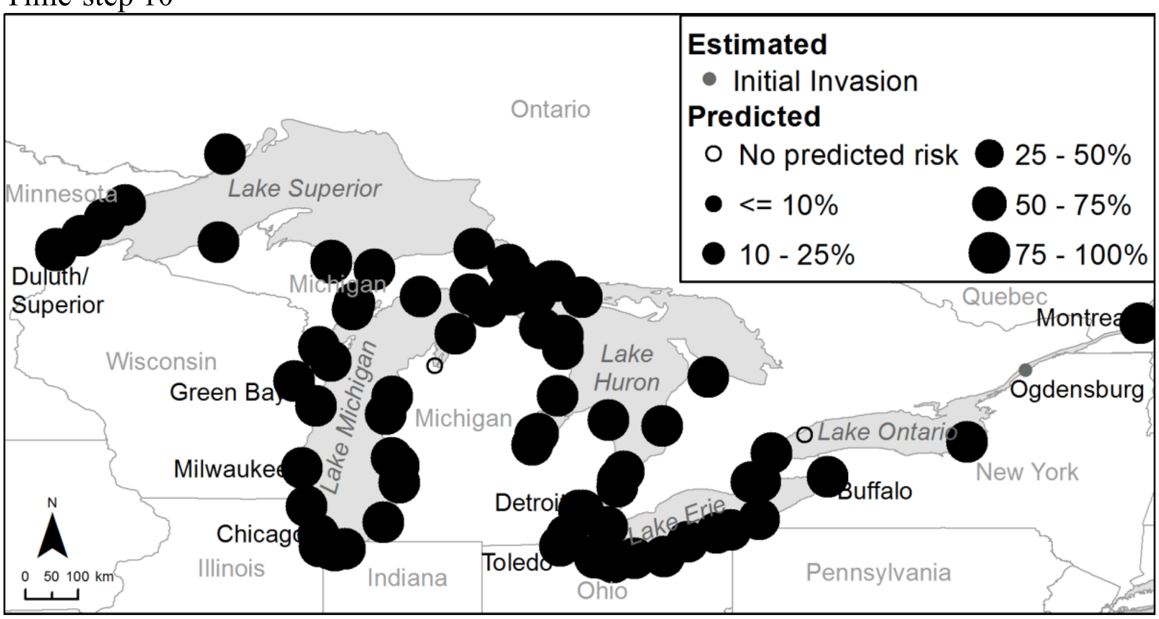
Time-step 8



Time-step 9

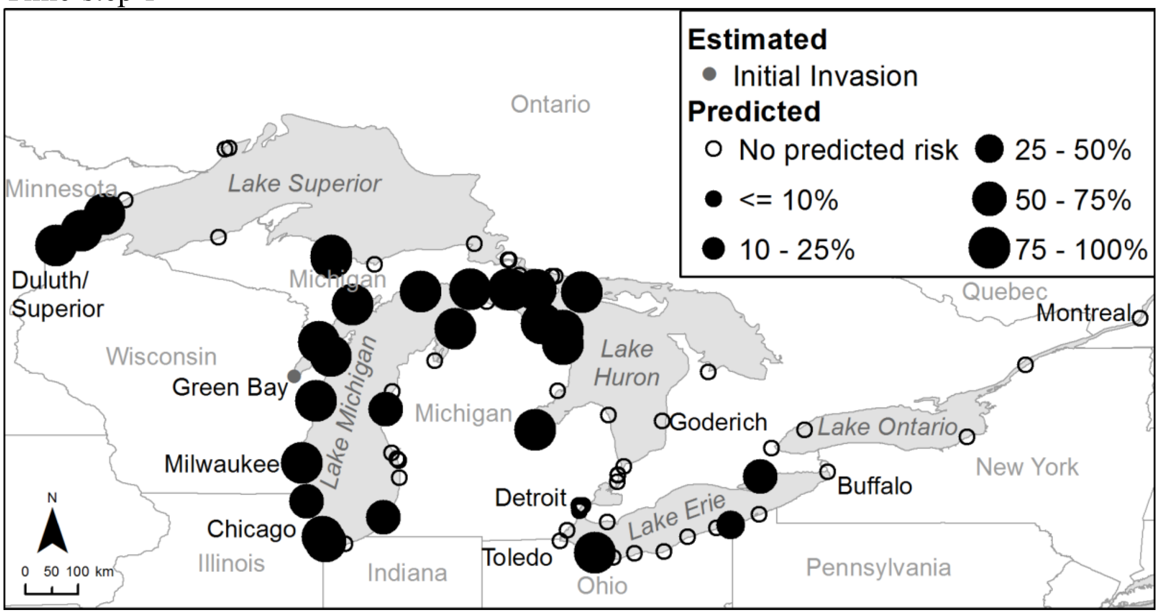


Time-step 10

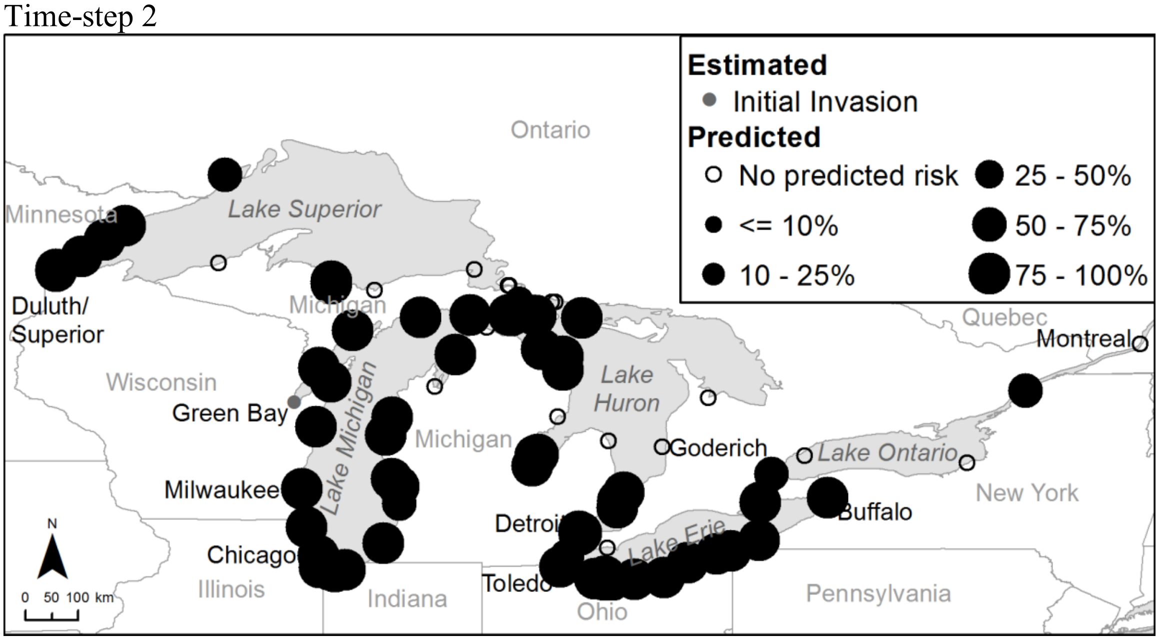


Killer Shrimp
Green Bay, Wisconsin
Dispersal Distance = 0-km and Probability of Infestation = 0.75

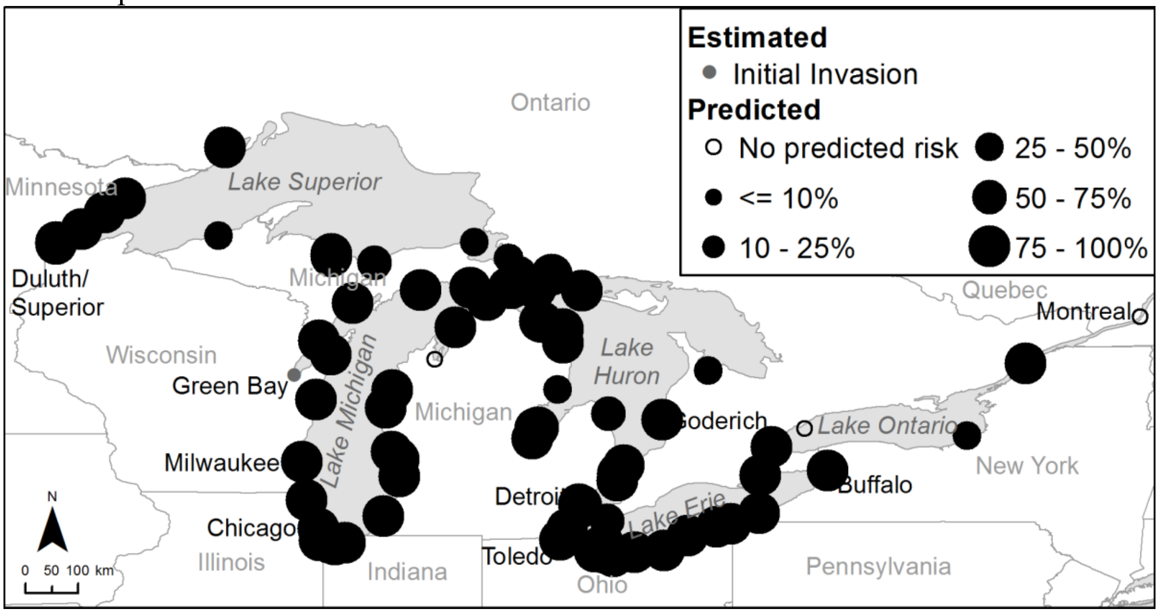
Time-step 1



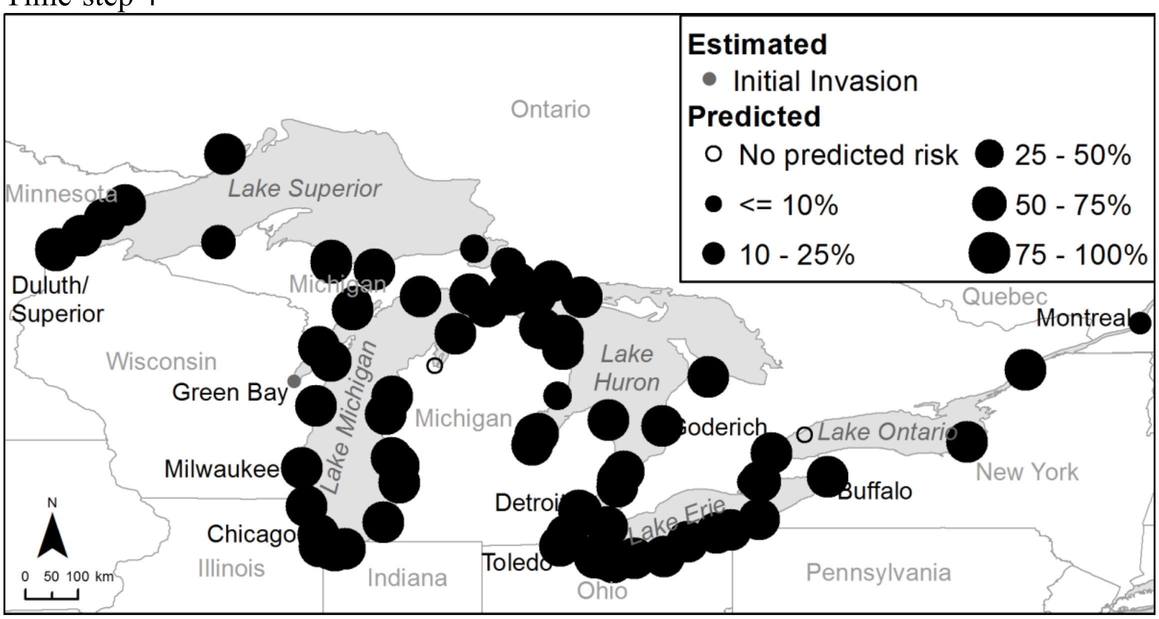
Time-step 2



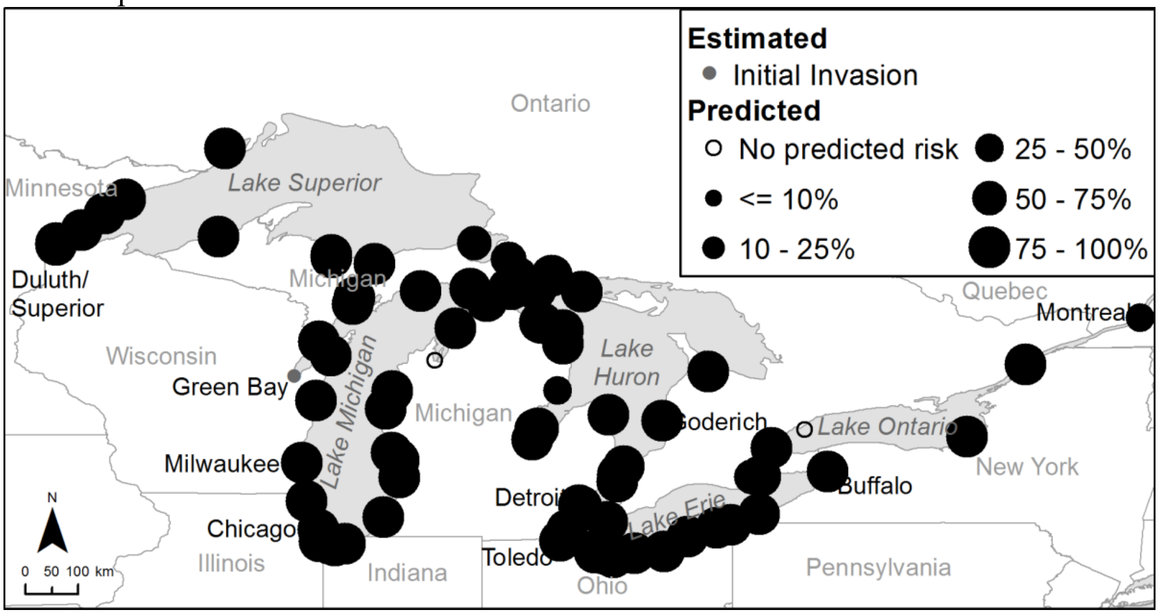
Time-step 3



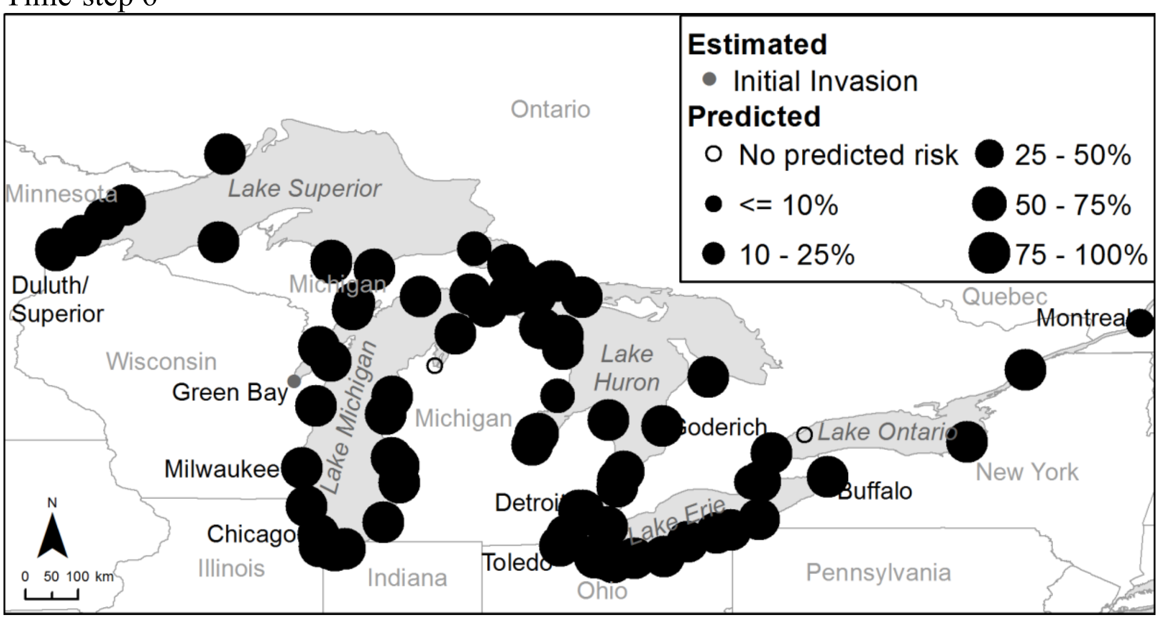
Time-step 4



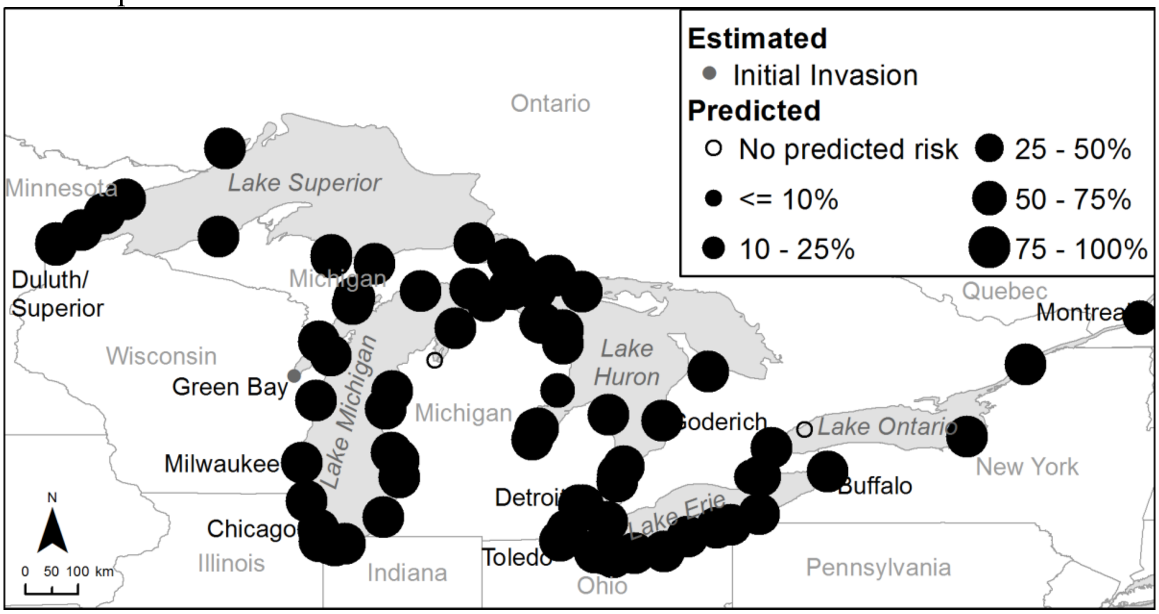
Time-step 5



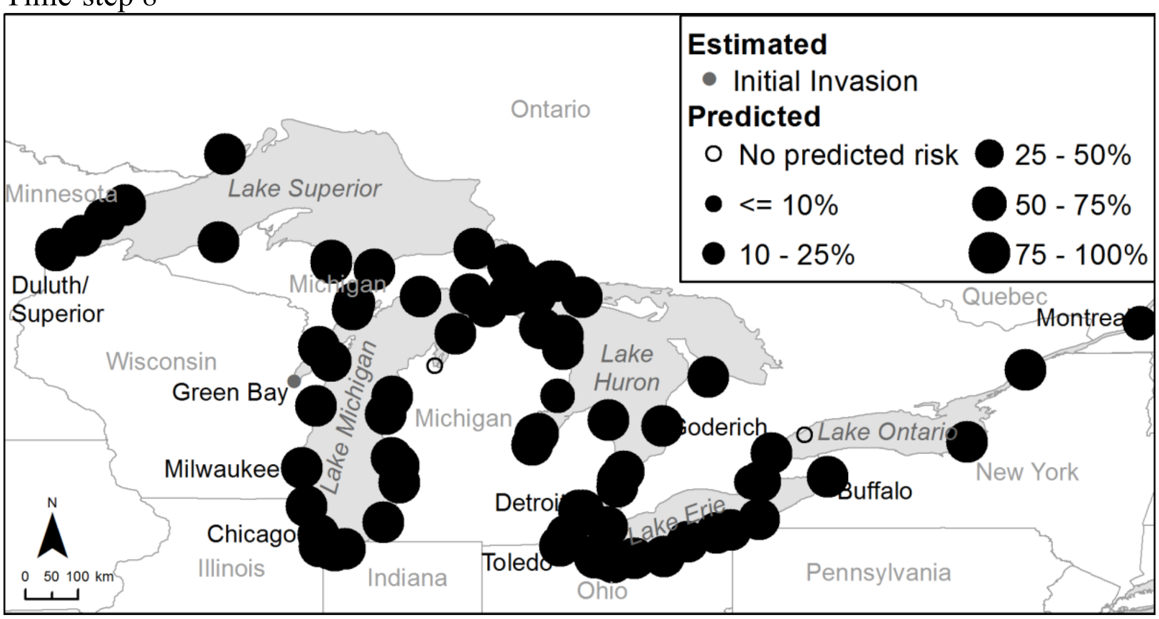
Time-step 6



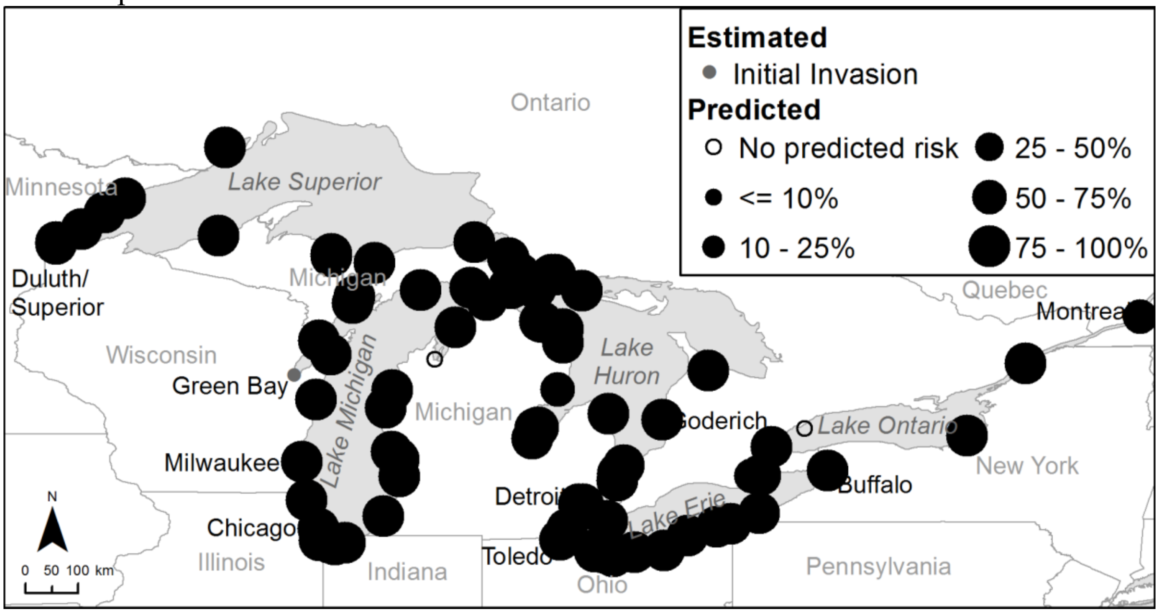
Time-step 7



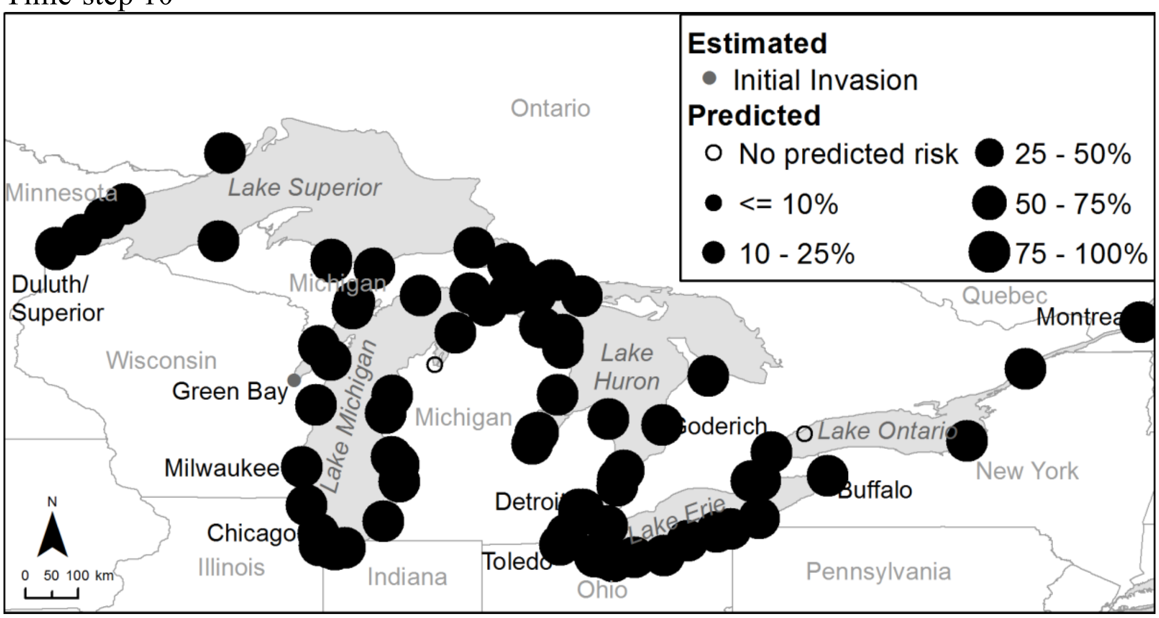
Time-step 8



Time-step 9

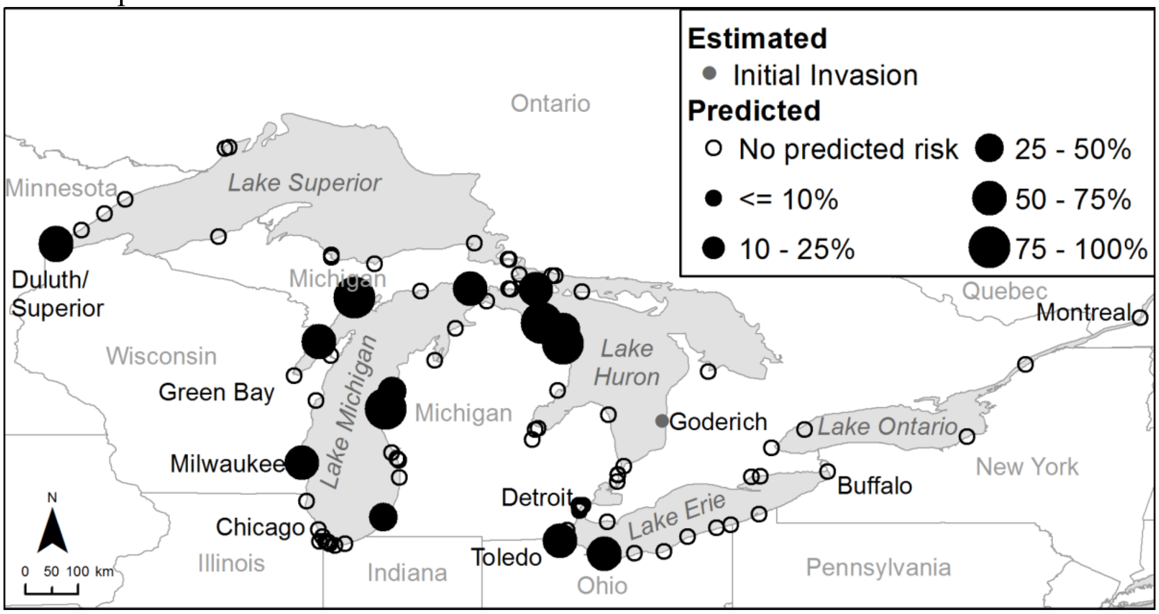


Time-step 10

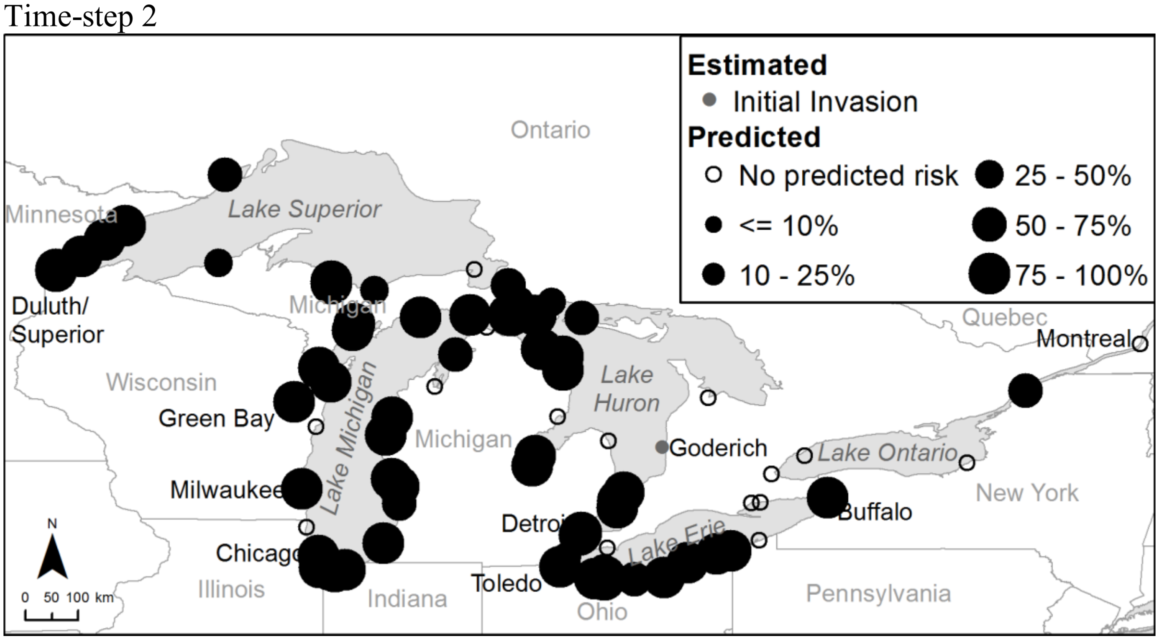


Killer Shrimp
Goderich, Ontario
Dispersal Distance = 0-km and Probability of Infestation = 0.75

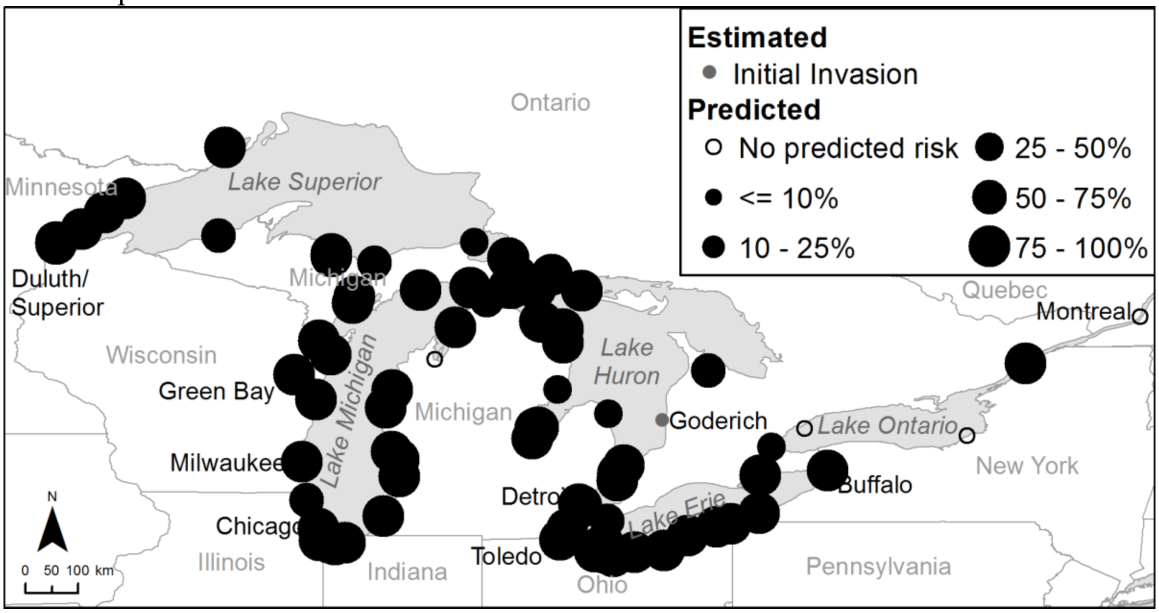
Time-step 1



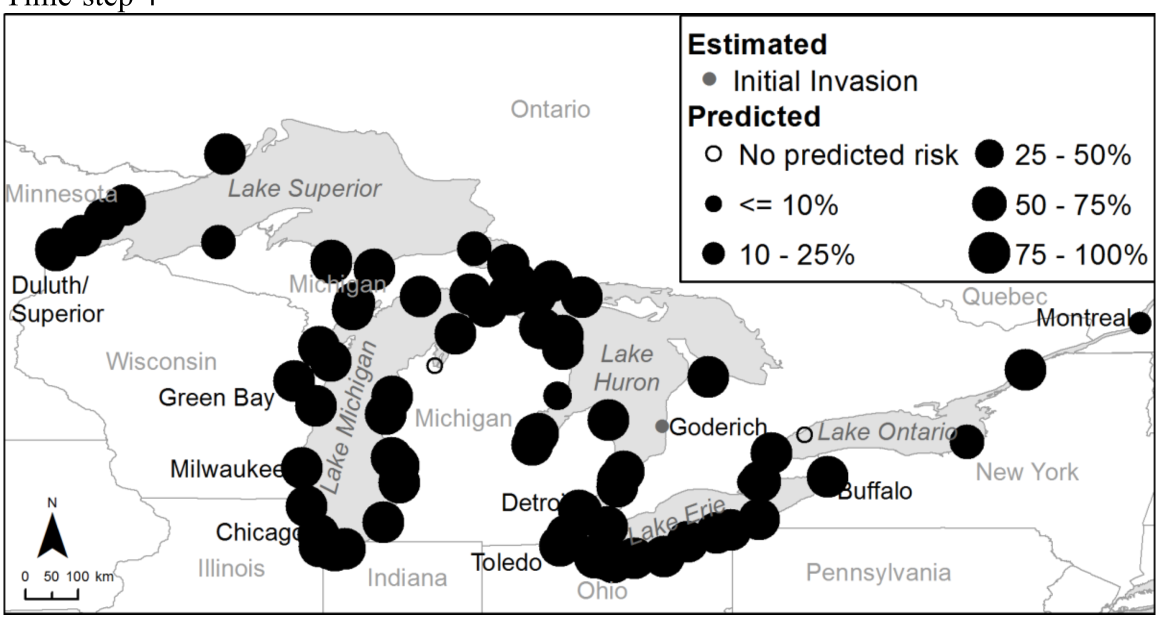
Time-step 2



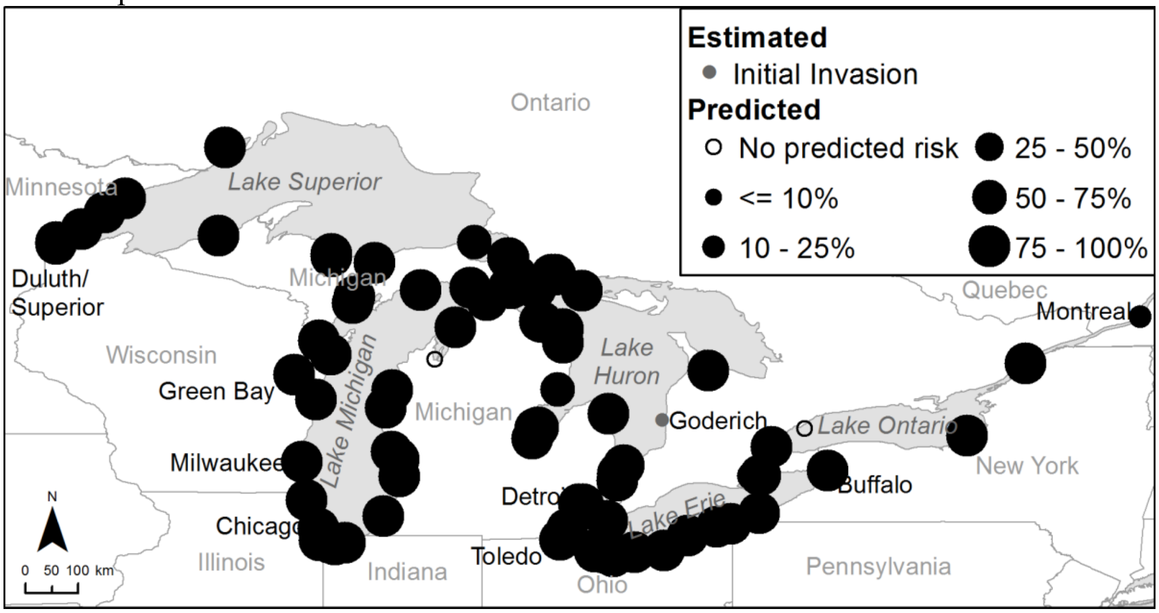
Time-step 3



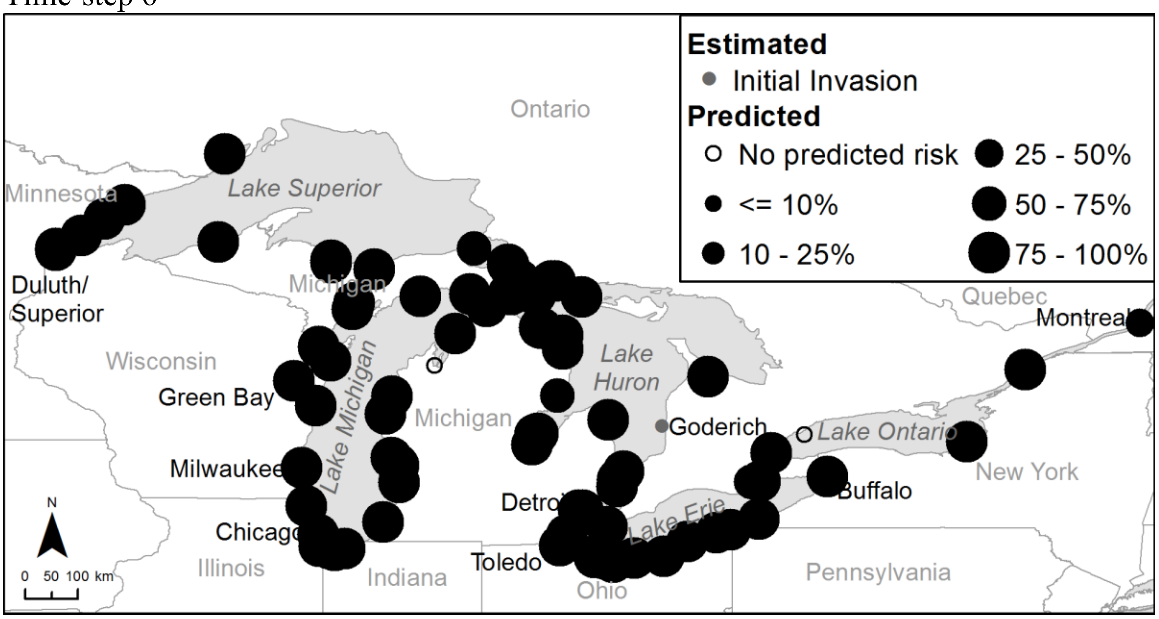
Time-step 4



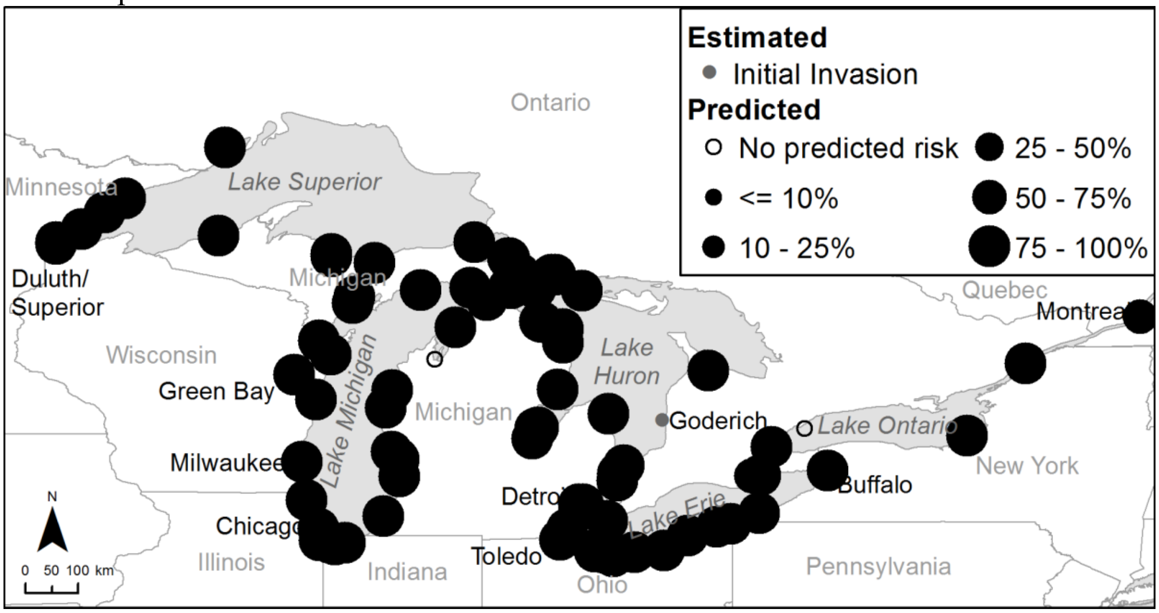
Time-step 5



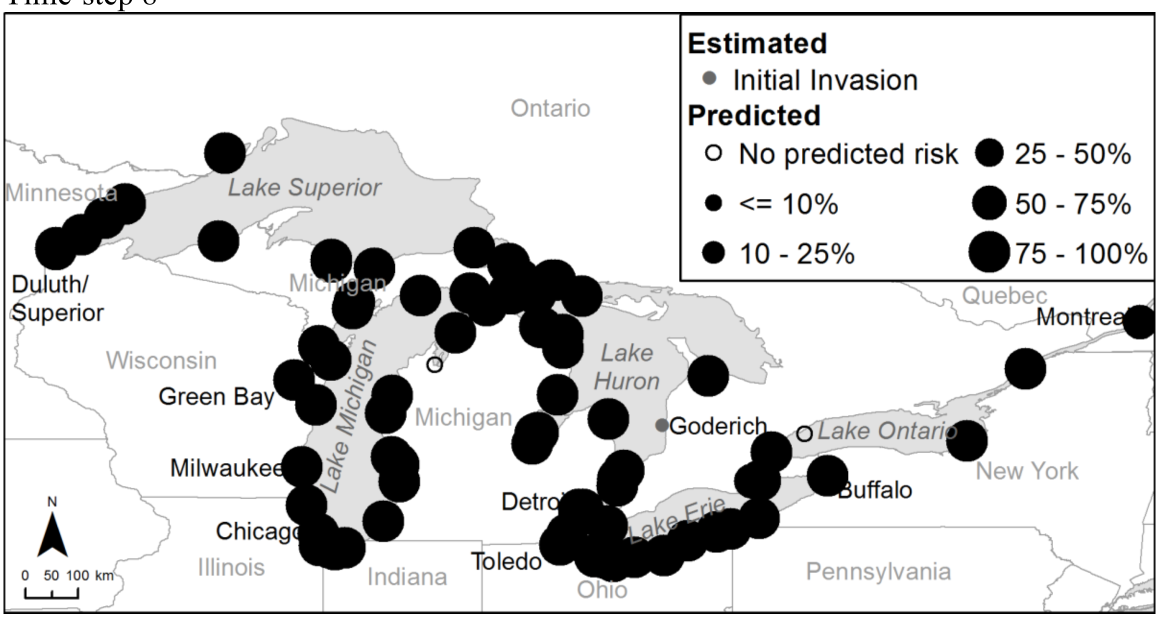
Time-step 6



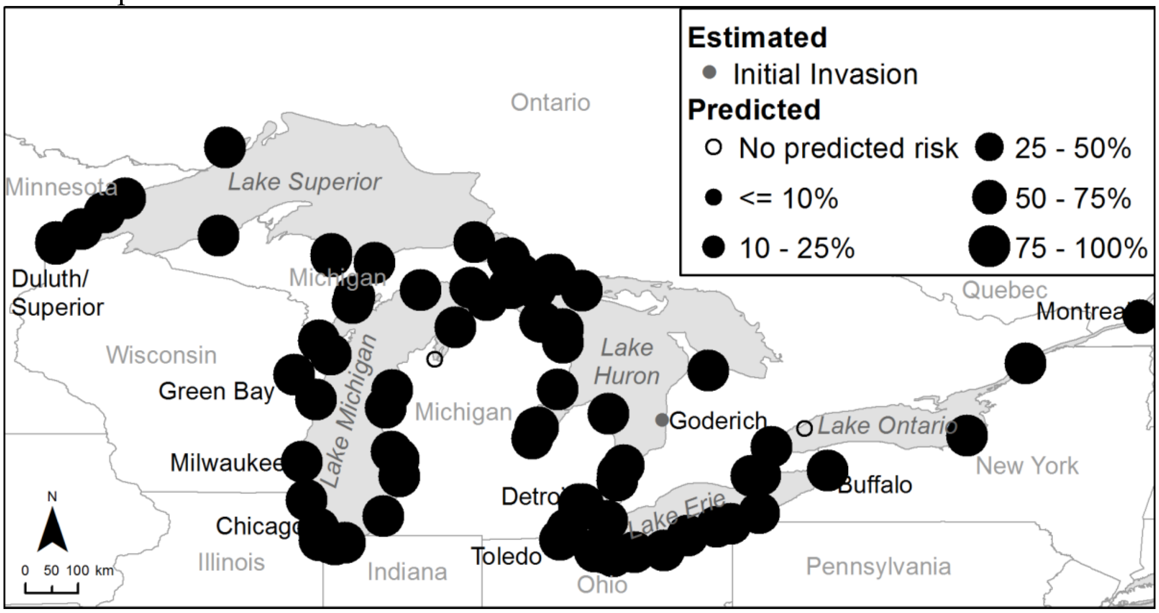
Time-step 7



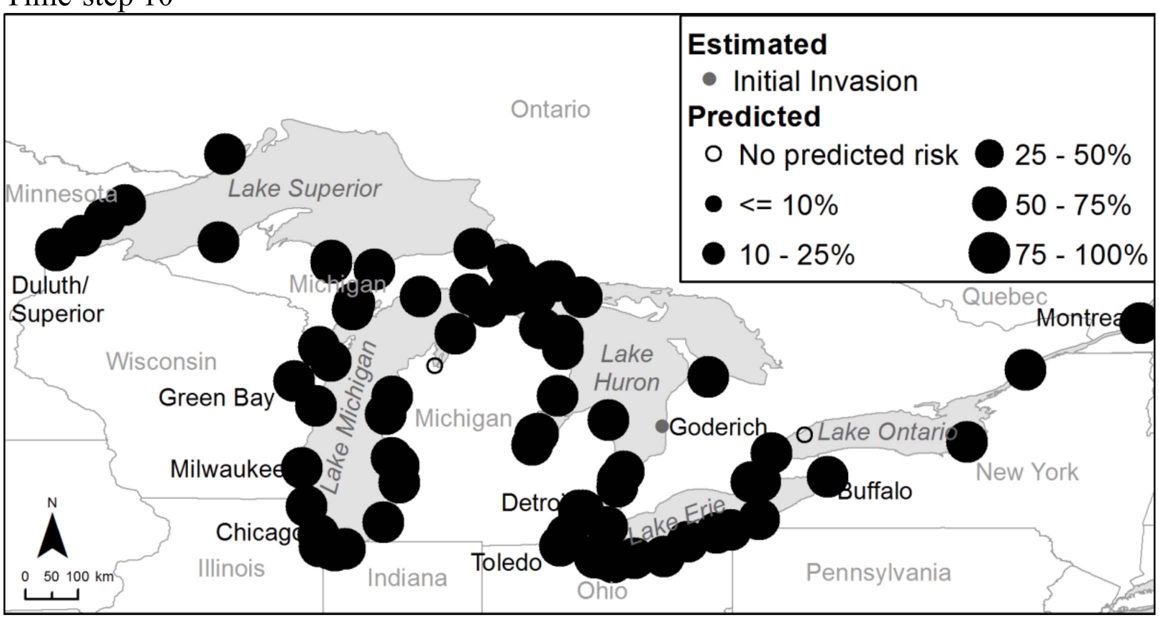
Time-step 8



Time-step 9

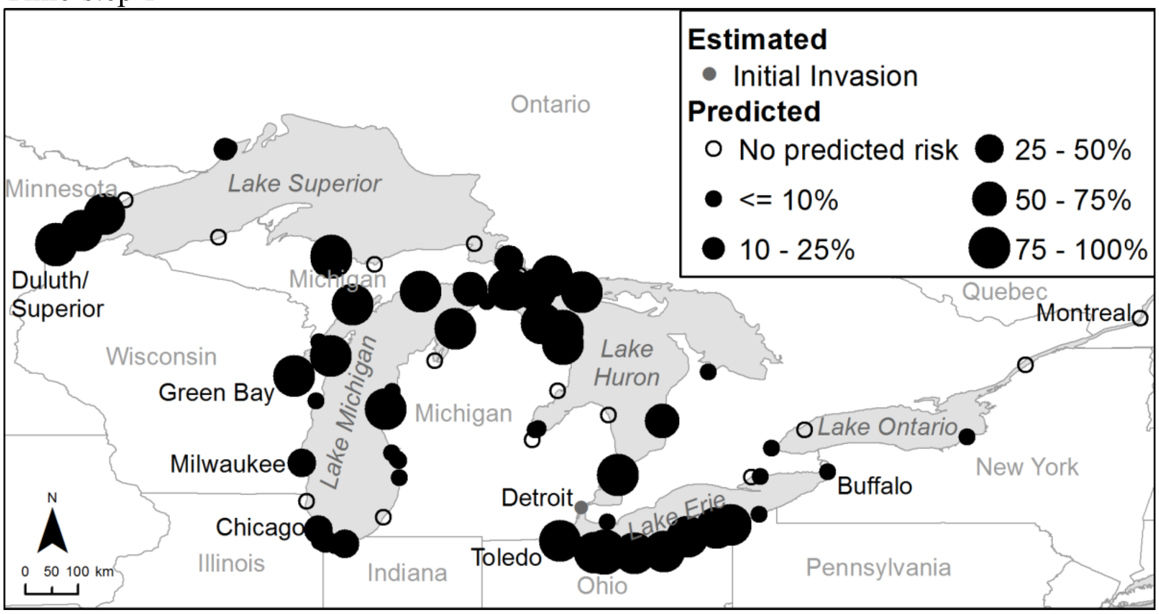


Time-step 10

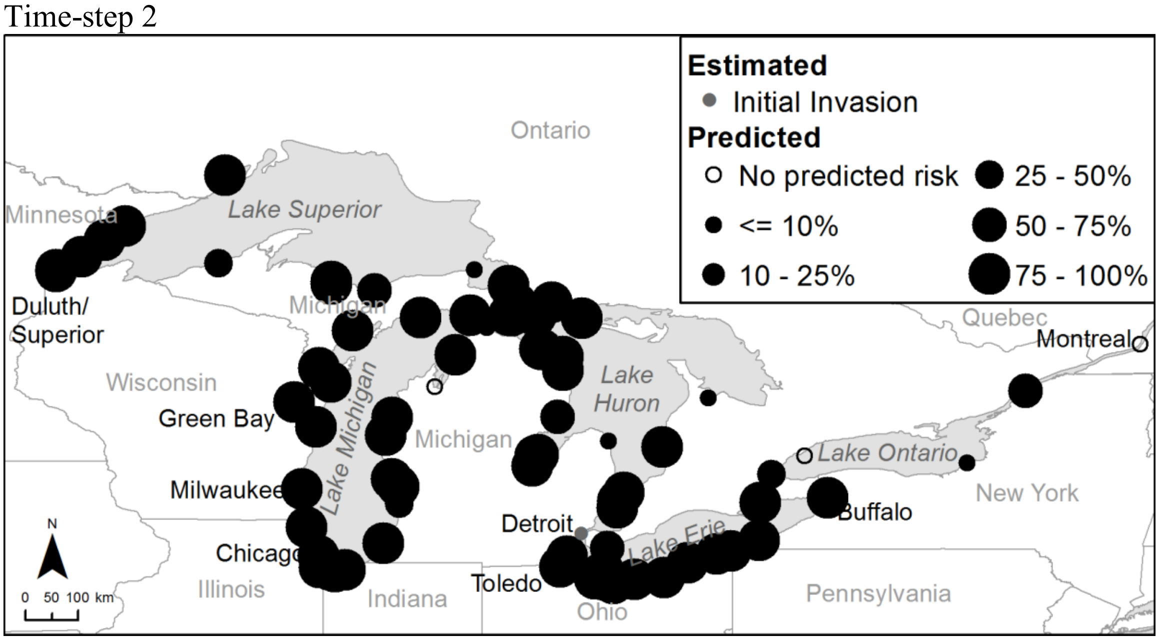


Killer Shrimp
Detroit, Michigan
Dispersal Distance = 0-km and Probability of Infestation = 0.75

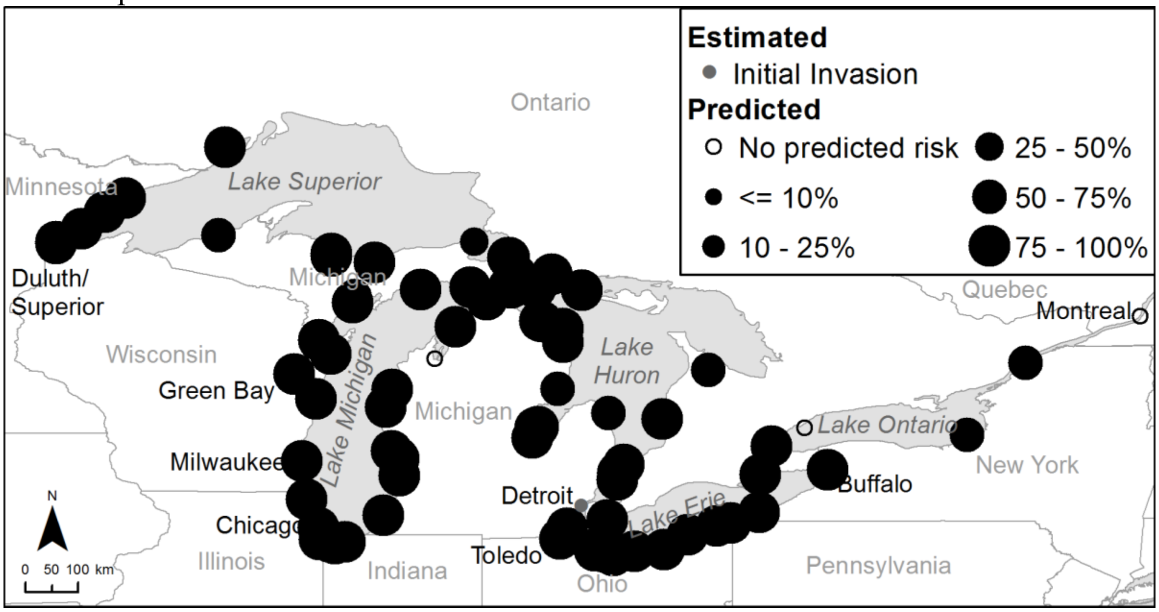
Time-step 1



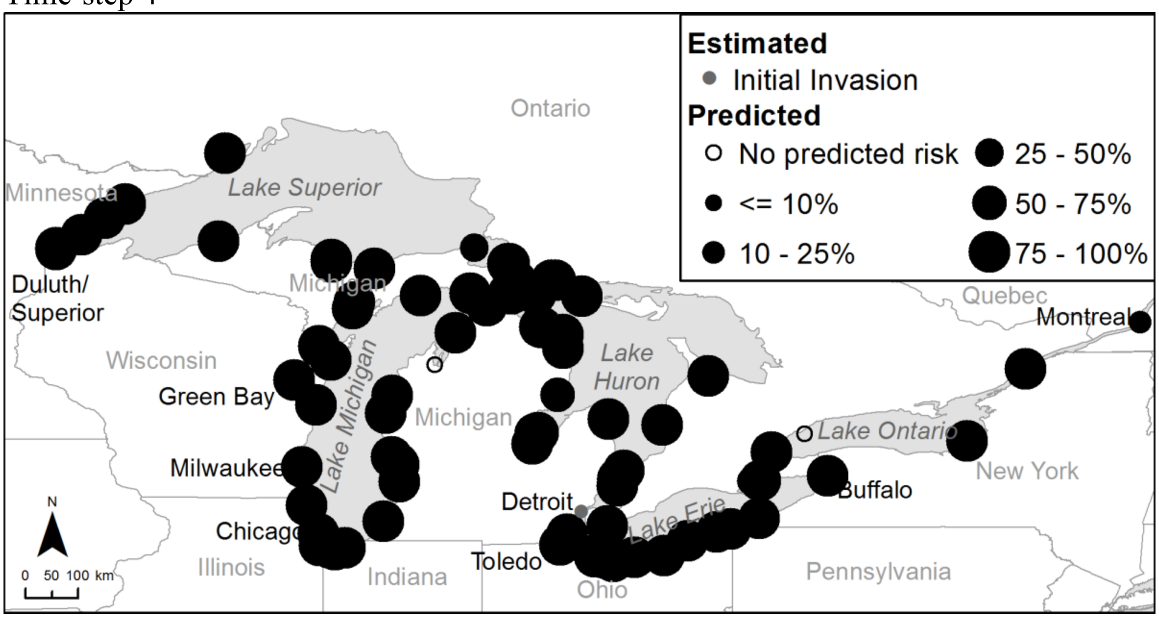
Time-step 2



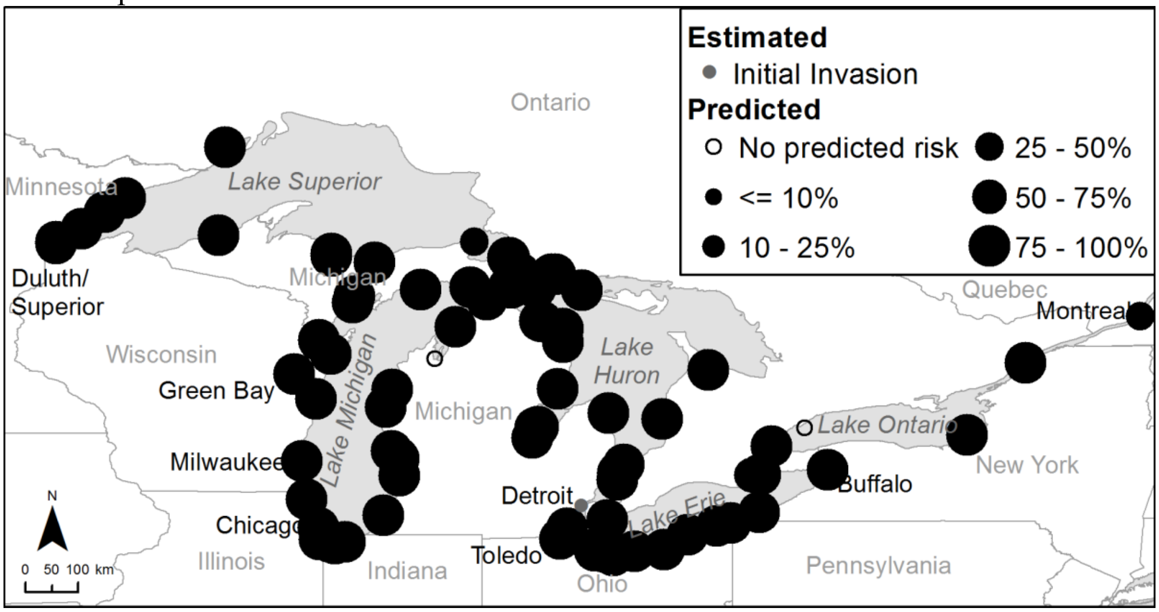
Time-step 3



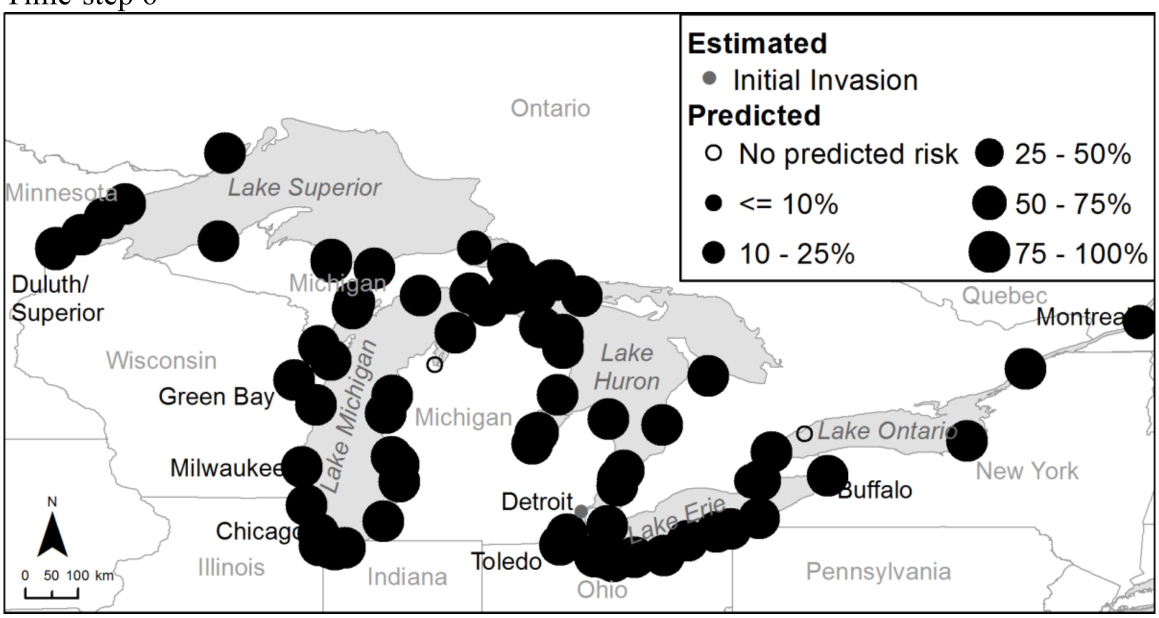
Time-step 4



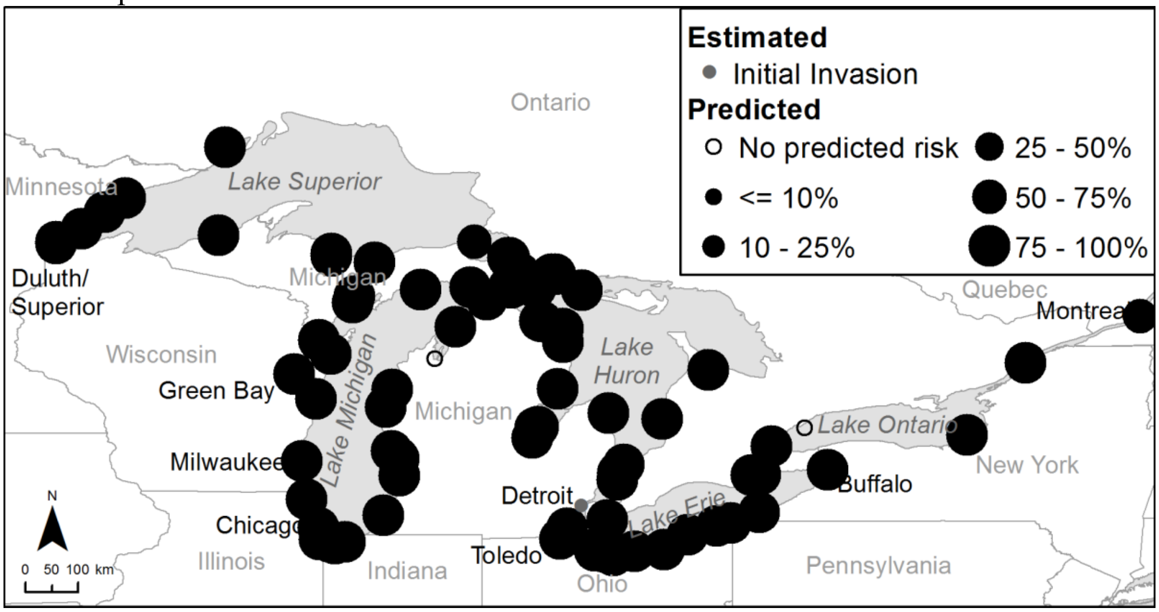
Time-step 5



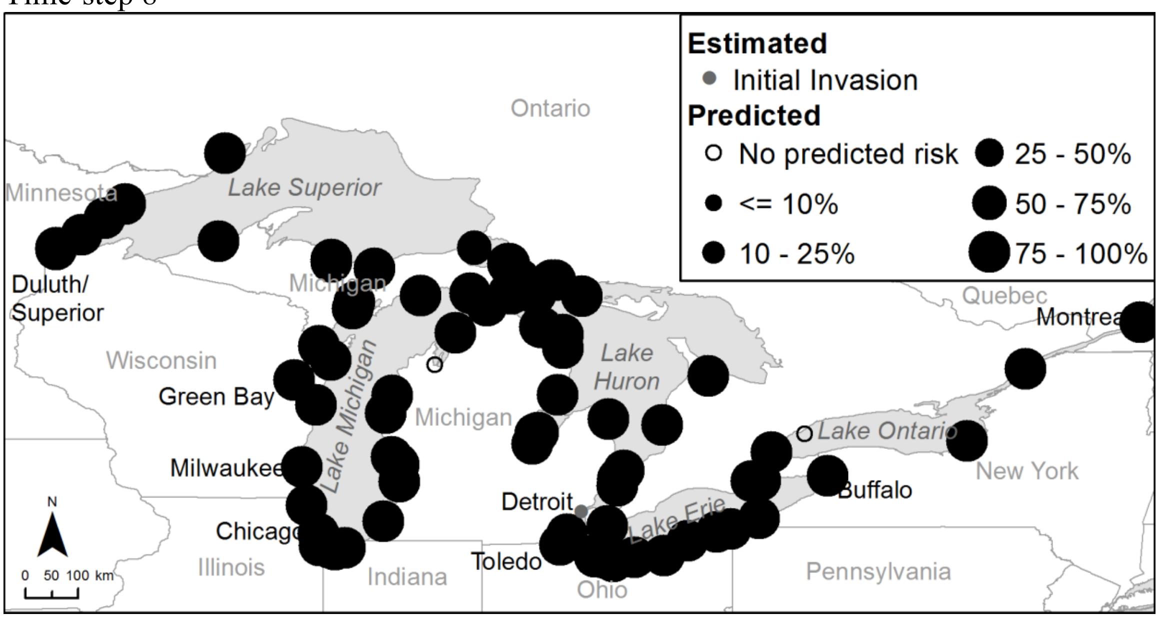
Time-step 6



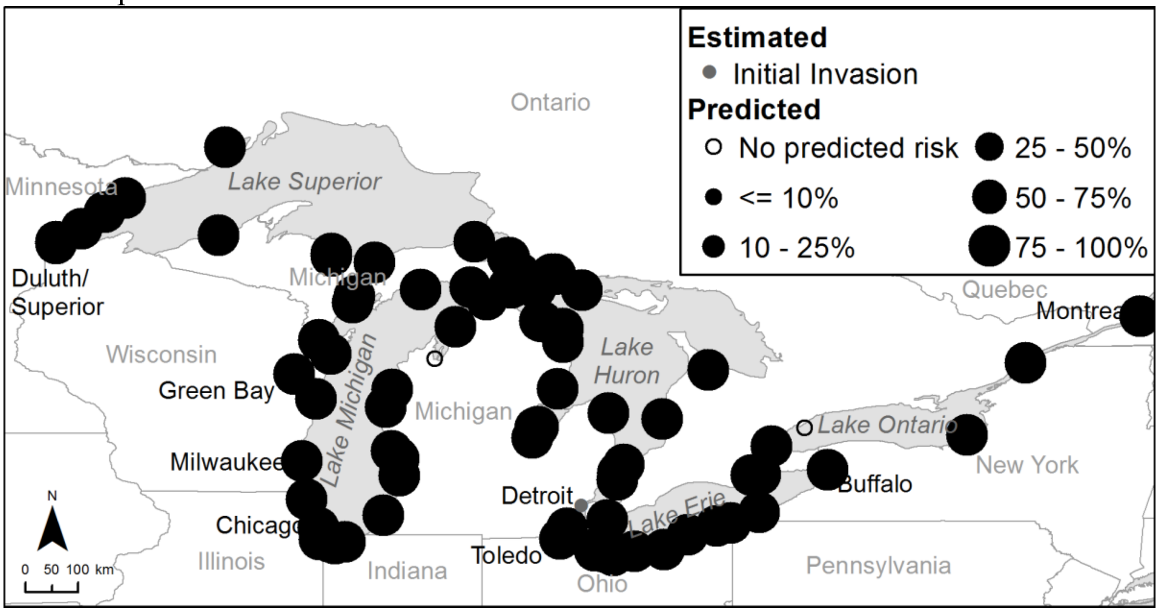
Time-step 7



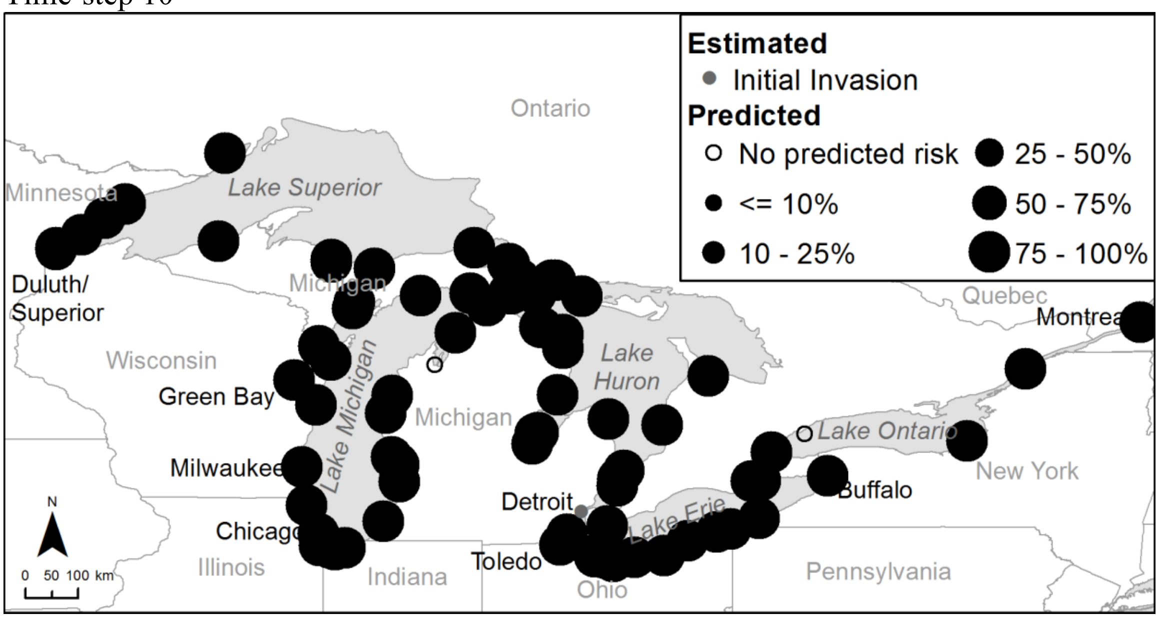
Time-step 8



Time-step 9

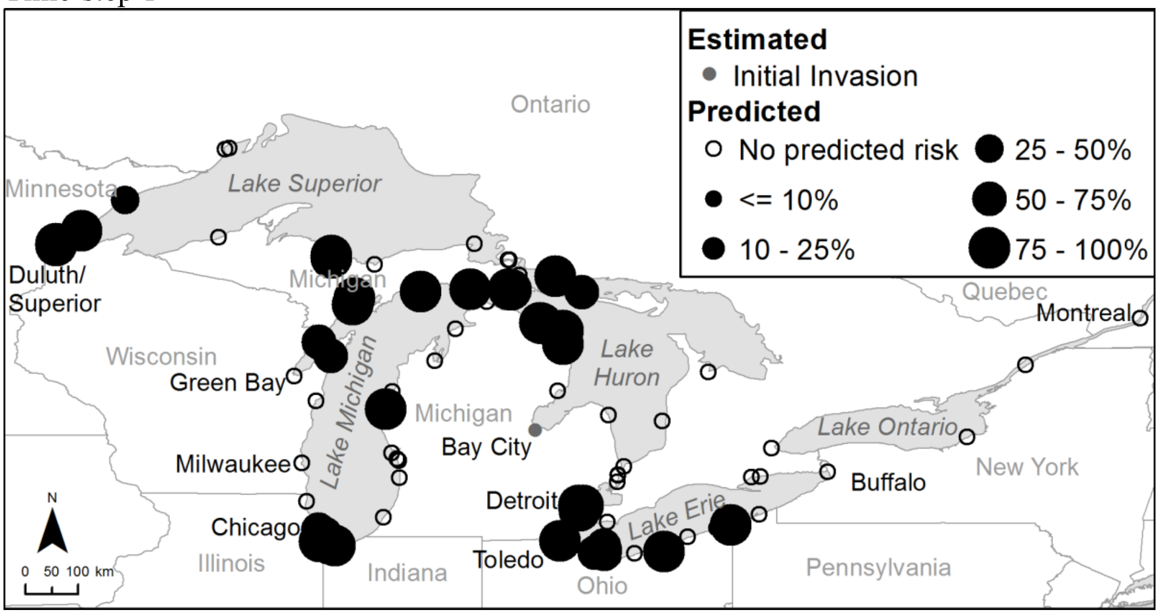


Time-step 10

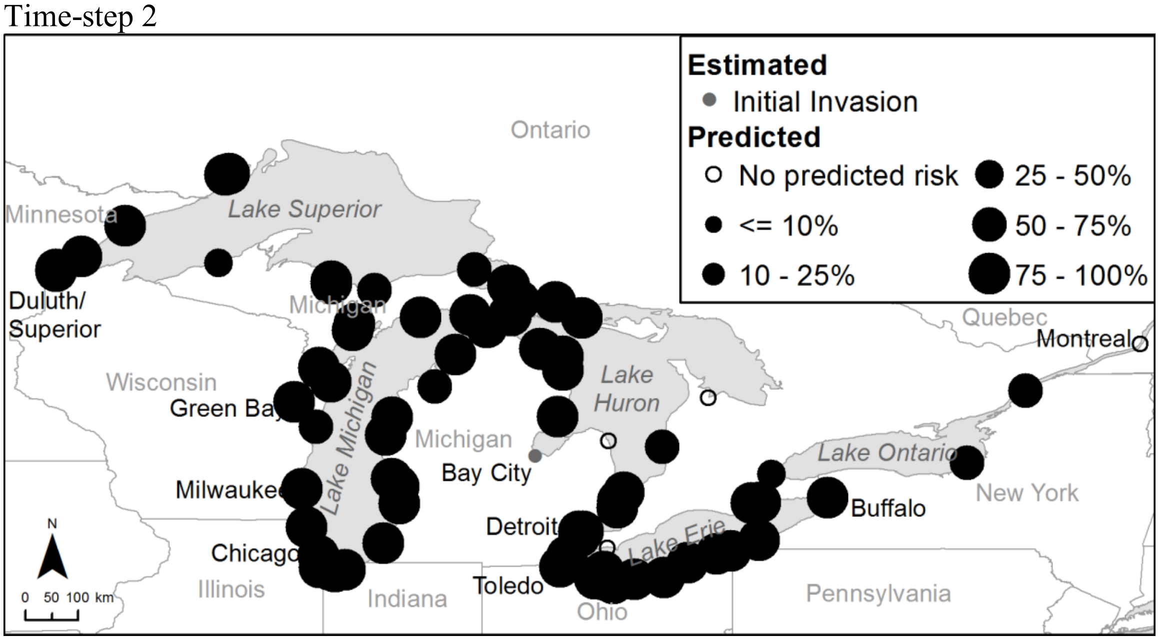


Golden Mussel
Bay City, Michigan
Dispersal Distance = 20-km and Probability of Infestation = 0.75

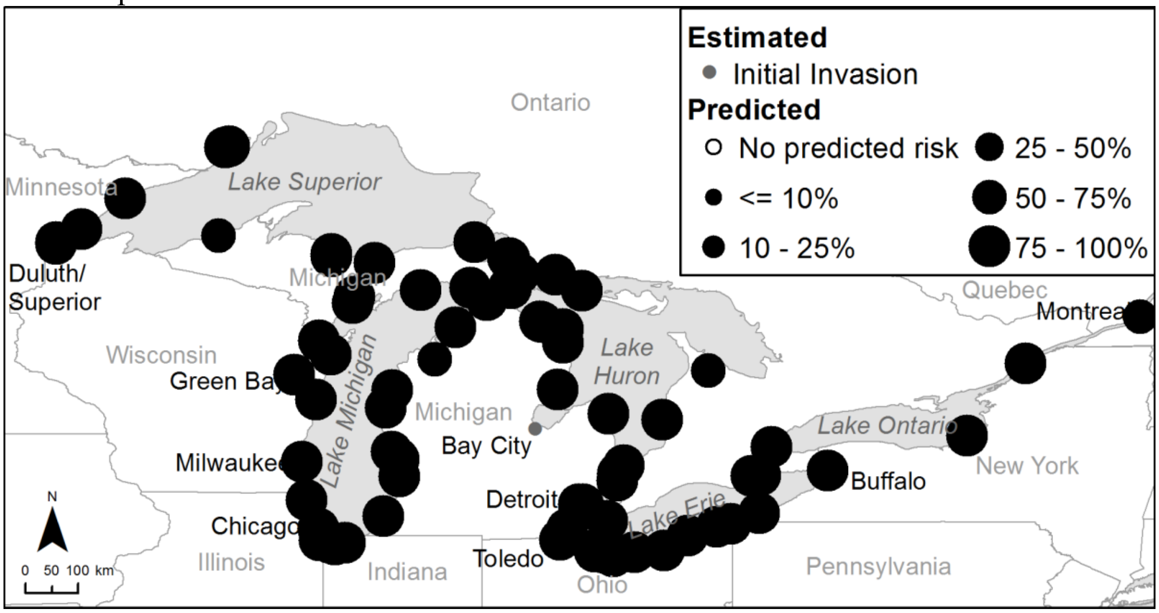
Time-step 1



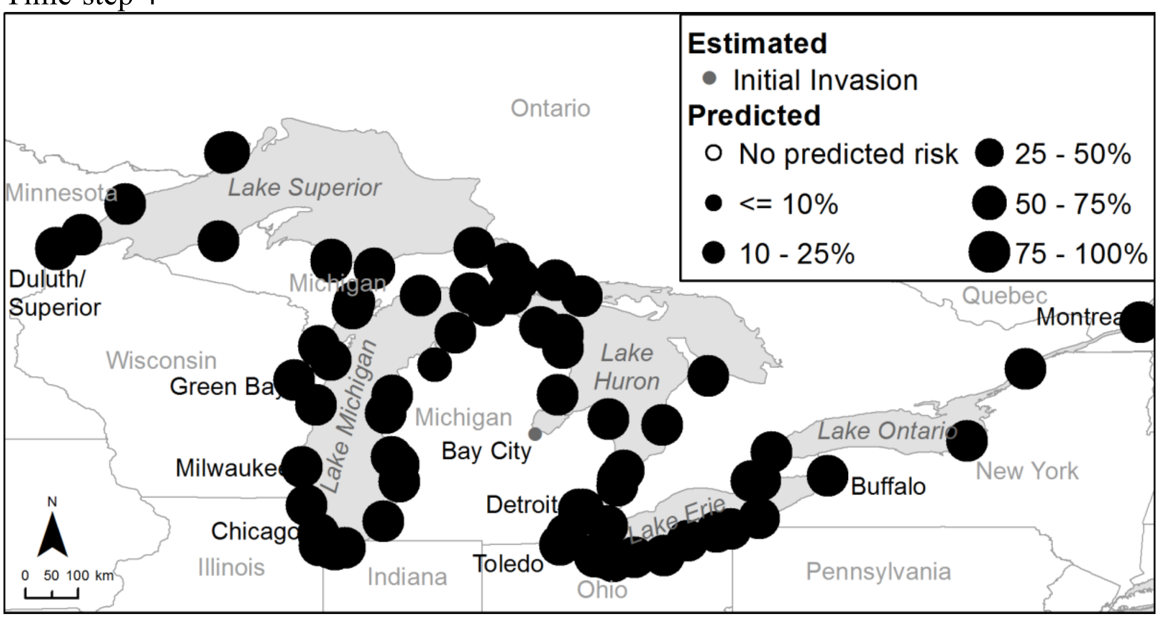
Time-step 2



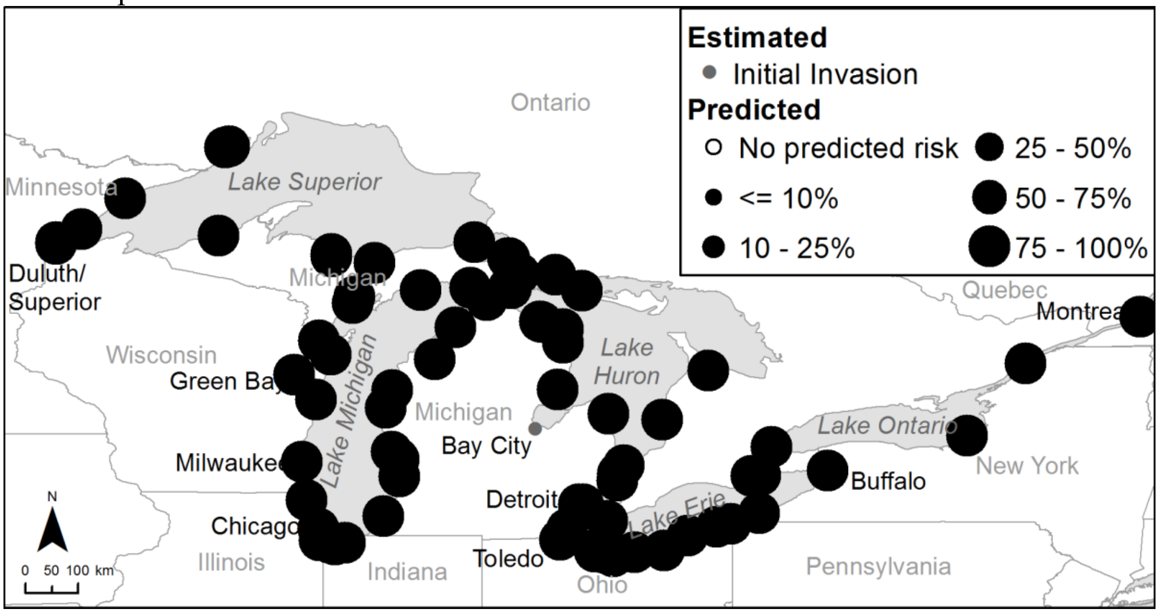
Time-step 3



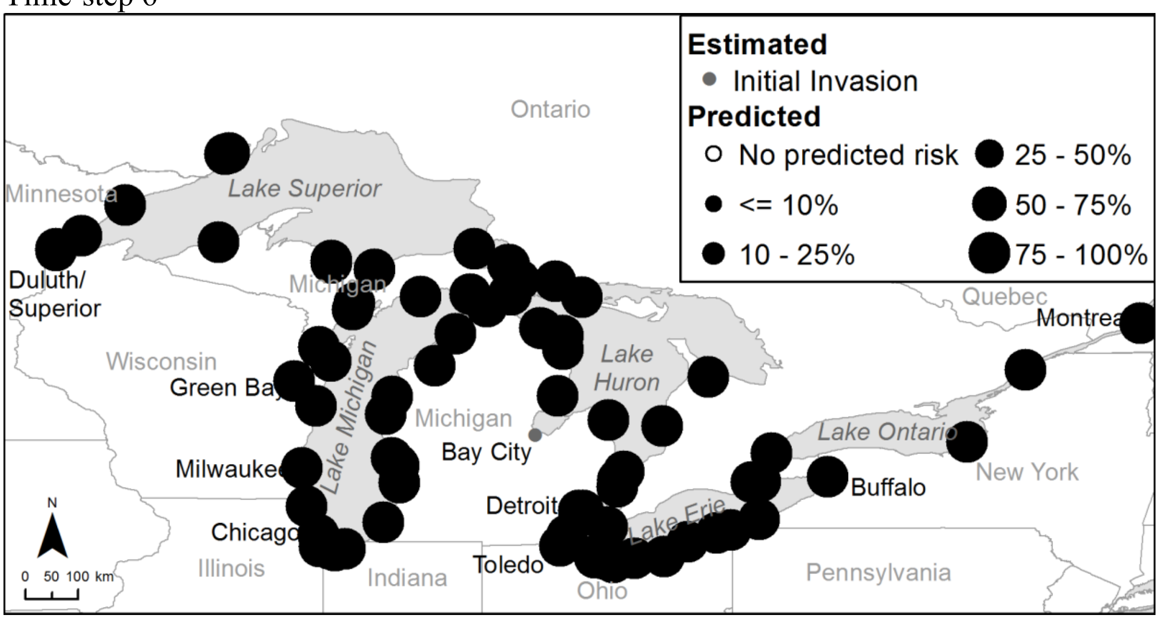
Time-step 4



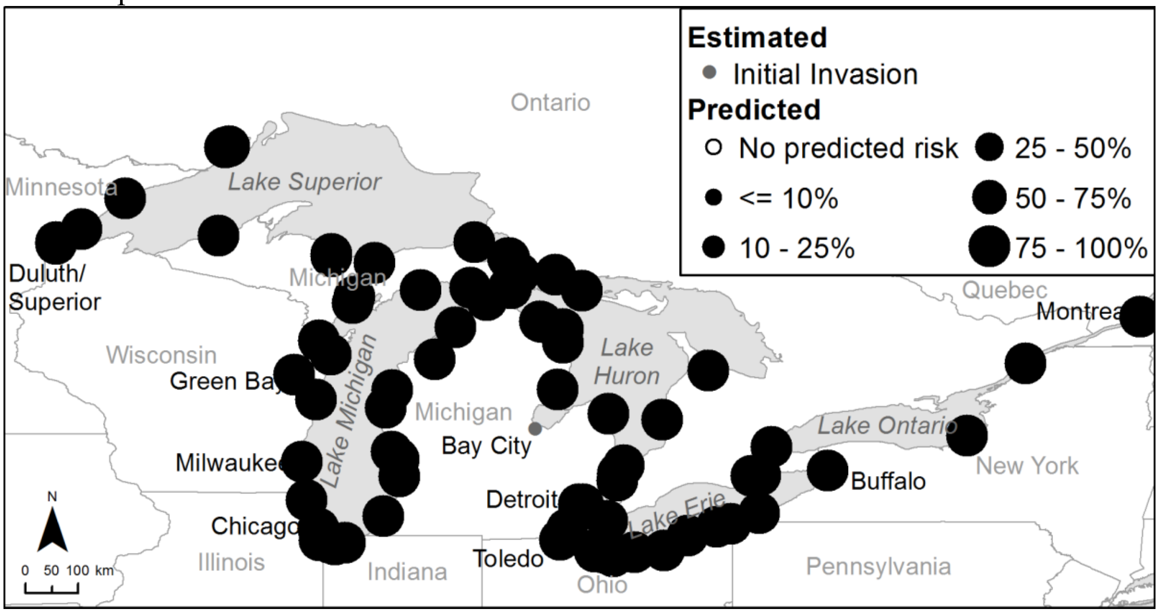
Time-step 5



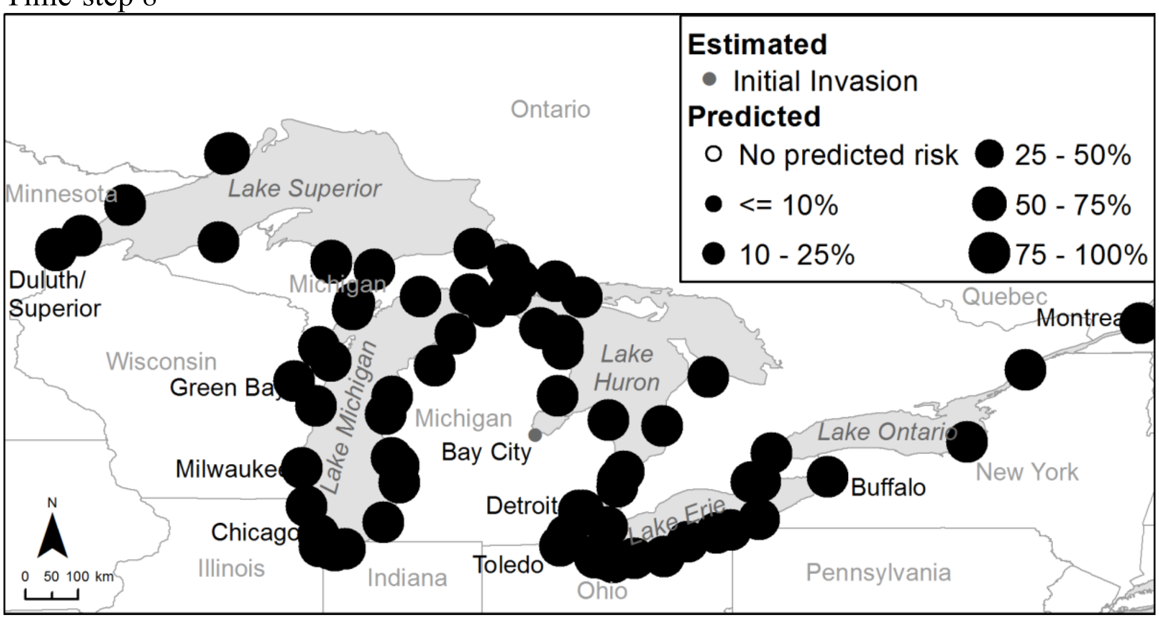
Time-step 6



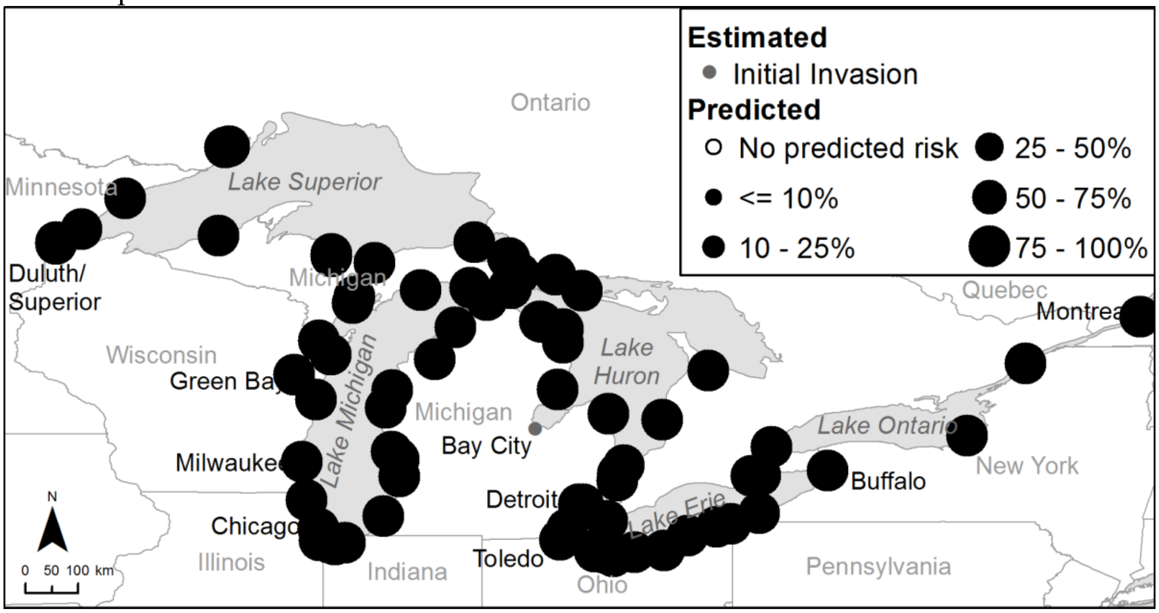
Time-step 7



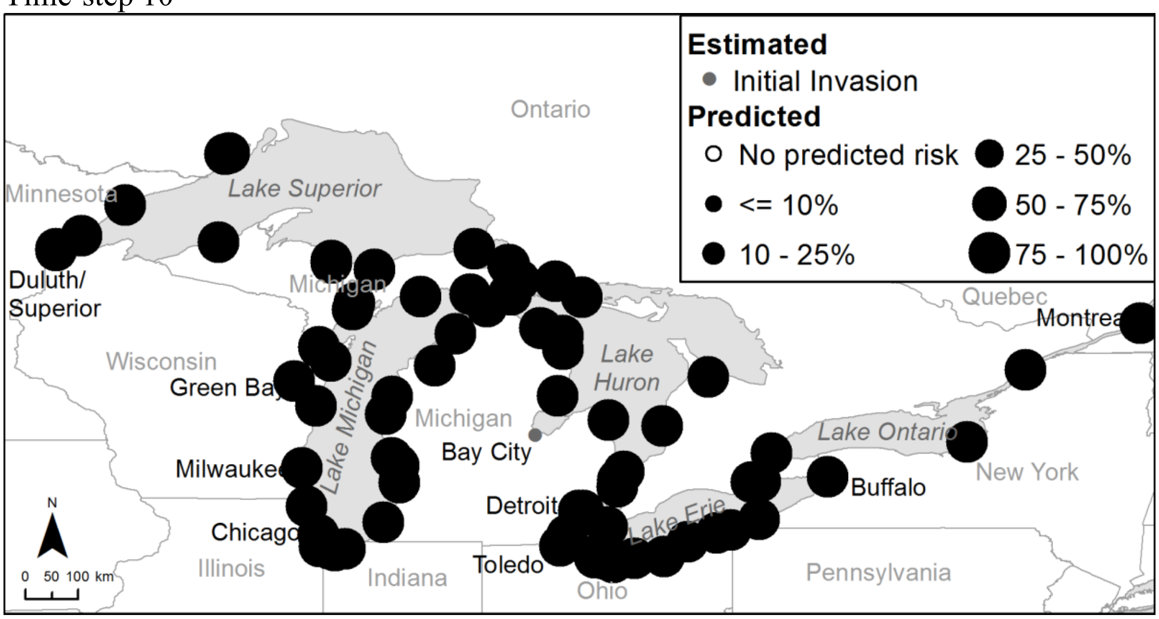
Time-step 8



Time-step 9

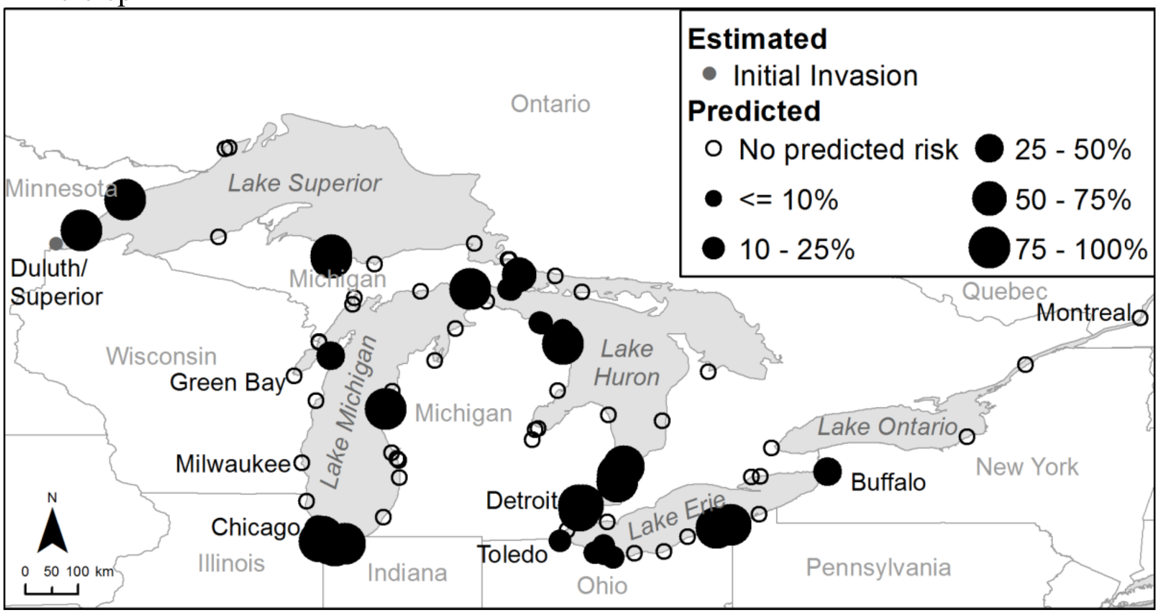


Time-step 10

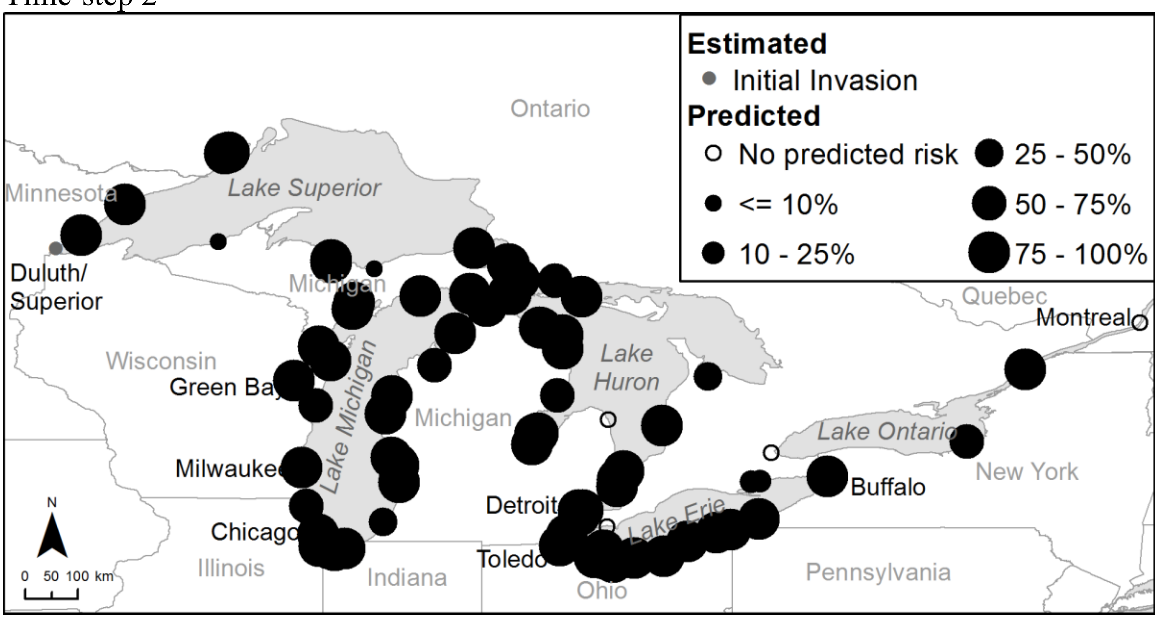


Golden Mussel
Duluth, Minnesota
Dispersal Distance = 20-km and Probability of Infestation = 0.75

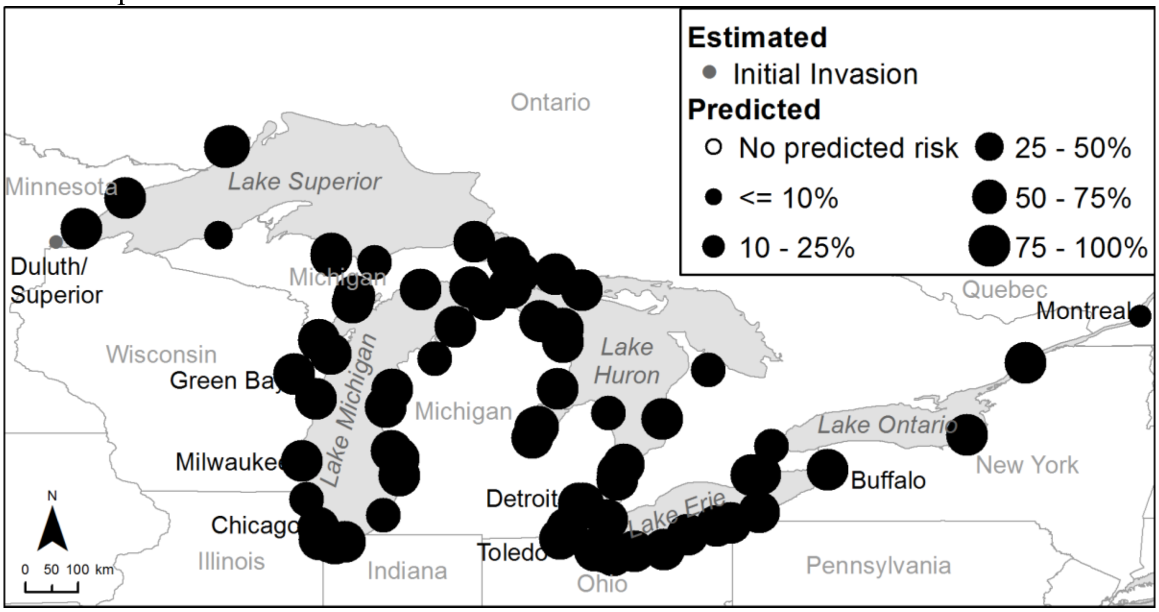
Time-step 1



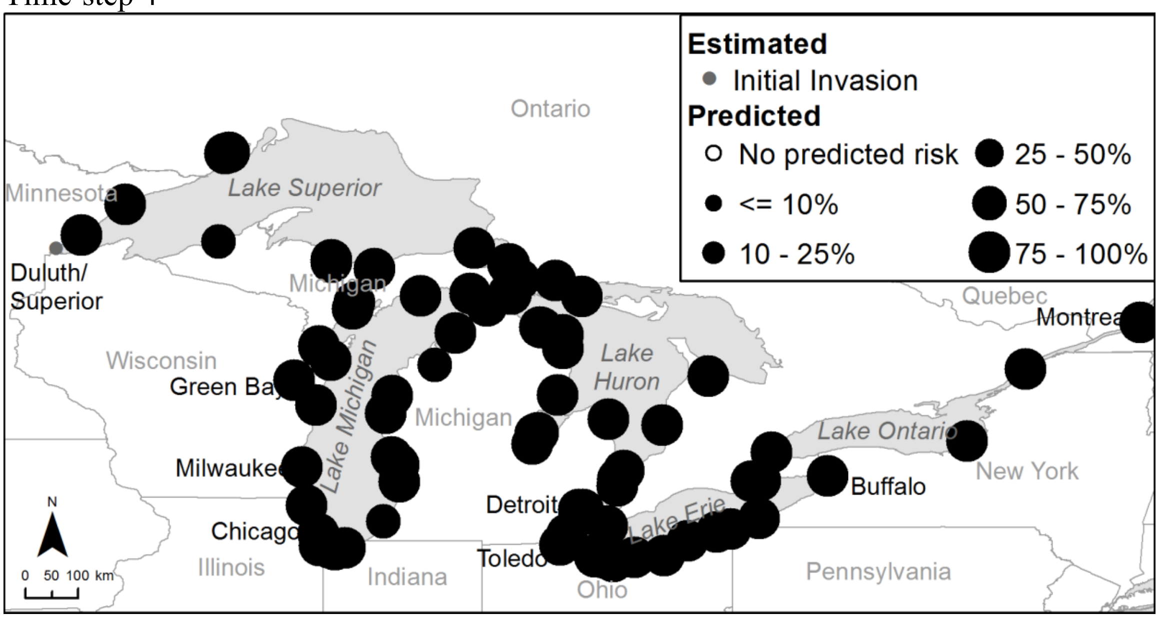
Time-step 2



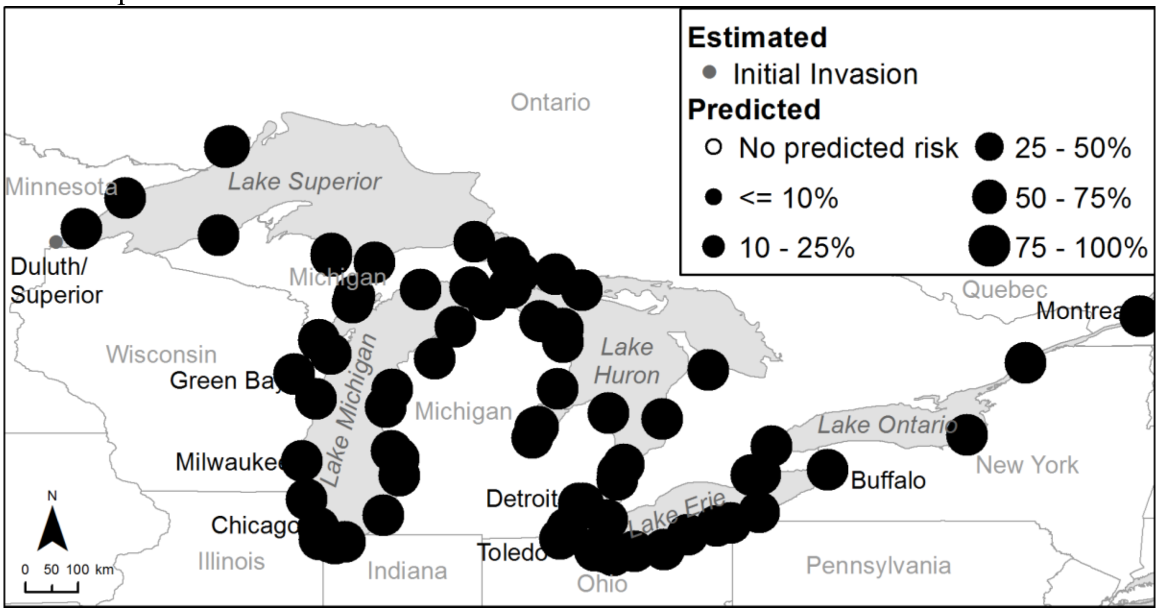
Time-step 3



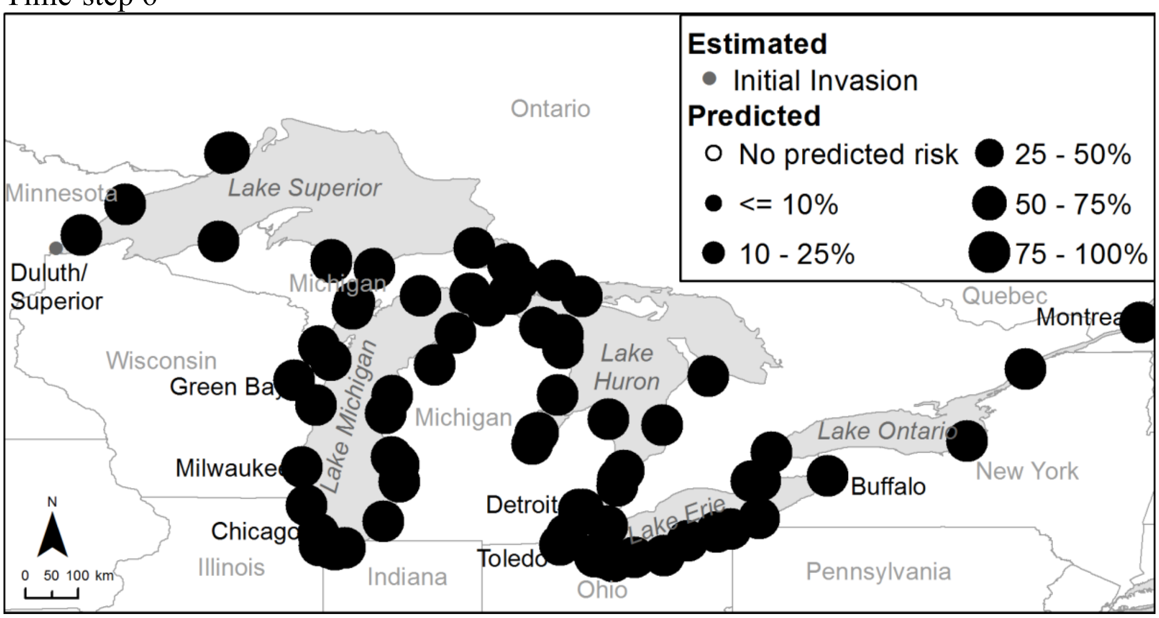
Time-step 4



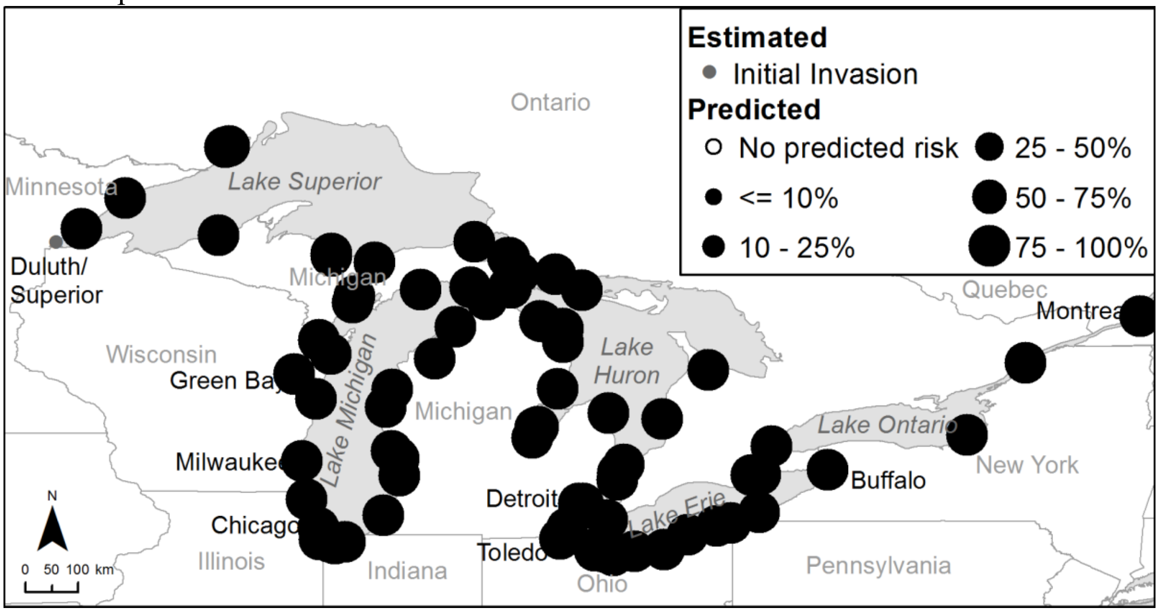
Time-step 5



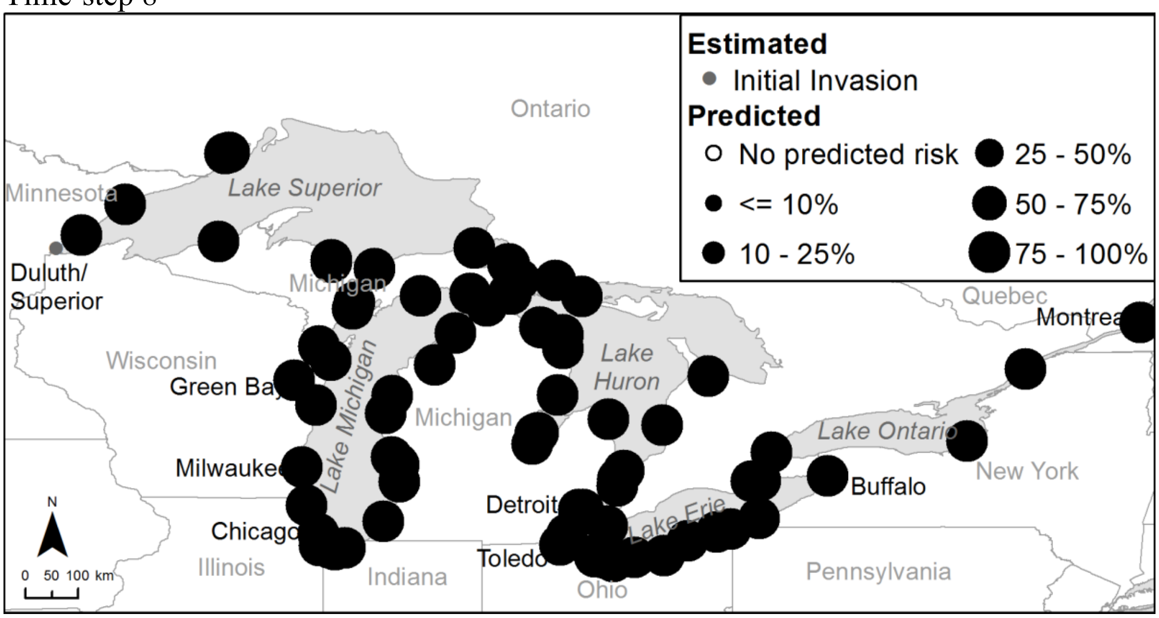
Time-step 6



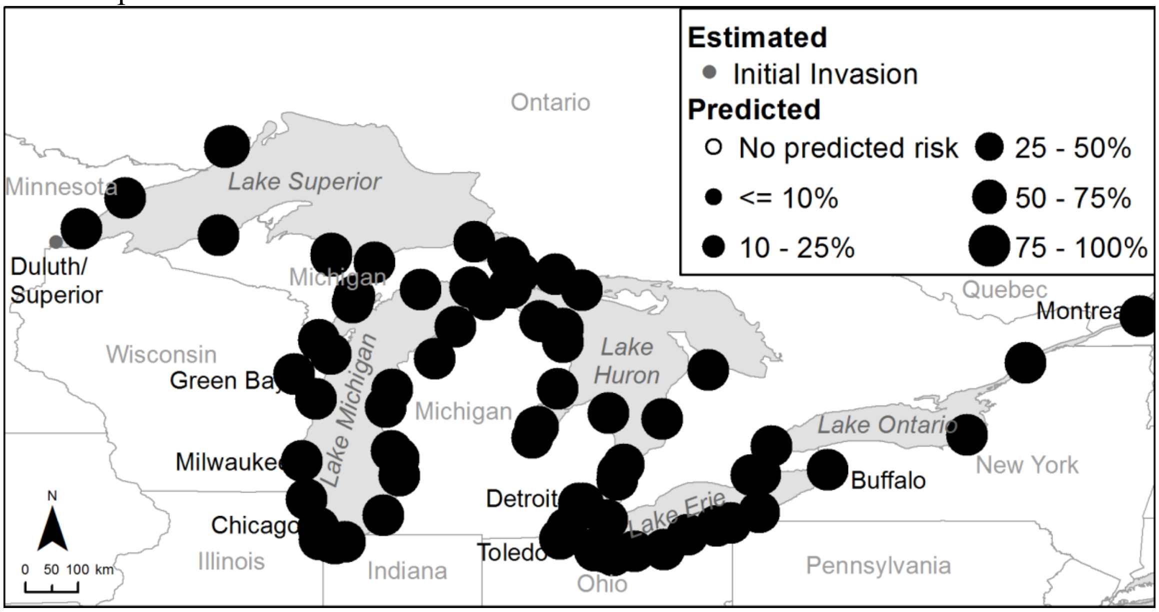
Time-step 7



Time-step 8



Time-step 9



Time-step 10