11-10-2021

Mathematically Modeling Plastic Pollution in the Great Lakes

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by

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A Dissertation Submitted in Partial Fulfillment of the Requirements

for the Degree of Doctor of Philosophy in Mathematical Modeling

School of Mathematical Sciences

College of Science

Rochester Institute of Technology

Rochester, NY

November 10, 2021

RIT | College of Science
School of
Mathematical Sciences

CERTIFICATE OF APPROVAL

Ph.D. DEGREE DISSERTATION

The Ph.D. Degree Dissertation of *Juliette Daily* has been examined and approved by the dissertation committee as satisfactory for the dissertation requirement for the Ph.D. degree in Mathematical Modeling.

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Abstract

Mass estimates of plastic pollution based on open water surface samples differ by several orders of magnitude from what is predicted based on production and input rates to the world's oceans and the Great Lakes. Researchers have proposed that this missing plastic may be located in other reservoirs, including beaches, nearshore water, the water column, or sediment. Studying plastic via sampling efforts is logistically challenging and time consuming. Models, which provide full spatial and temporal distributions, can help fill in the knowledge gaps that sampling efforts leave. Here we present the first three-dimensional modeling effort in the Great Lakes to incorporate vertical diffusion, non-neutrally buoyant particles, a functional biofouling model, and a beaching model. We focus on including mechanisms that could account for removal of plastic from open surface water. Our work suggests that plastic may be accumulating along beaches, with accumulation patterns depending on beach characteristics, current patterns, and near shore population. Additionally, we predict that plastic is accumulating in lake sediment, with the rate of deposition dependent on polymer density, lake depth, and the effects of biofouling. We estimate that there may be 381 tons of plastic in the water of Lake Erie, with the potential for another 2205-2382 tons deposited in the sediment each year in Lake Erie, and 1265-1348 tons per year deposited in Lake Ontario sediments. This work improves existing mass estimates in the water column and sediment deposition rates in Lake Erie and provides a first sediment deposition estimate for Lake Ontario. Together, the results indicate that plastic pollution is likely remaining within the Great Lakes system rather than exporting to the ocean.

Contents

Chapter 1

Introduction

I. Plastic pollution background

Plastic pollution in large bodies of water has recently come to light as a pressing environmental concern, with a great deal of public and media attention accompanying it [123, 135]. Society's attentiveness to the issue is noticeable when compared to other environmental concerns. This attention is potentially due to the dramatic visuals plastic pollution demonstrates, or the undeniable nature of it being the result of human behavior [118]. Despite the attention, there is still a great deal of uncertainty surrounding plastic pollution's transport, quantities, impacts, and ultimate fate.

Plastic production began on a wide scale in the 1950s, leading to a global shift from reusable to single use packaging. As a result, global annual plastic production had increased to about 400 million metric tons by 2015, with production growing exponentially [41]. Researchers first began discussing plastic in the world's oceans in the 1970s, and that same plastic is likely still present in the ecosystem, as plastic can take hundreds to thousands of years to decompose [58]. Unsurprisingly, this has led to an estimated 80% of the waste present on land, shorelines, the ocean surface, or seabed being plastic [9]. Adding to the urgency, as more plastic is produced and released into the water each year, it is accumulating [29].

II. Mechanisms driving plastic transport

In order to understand the scope and risks of plastic pollution, it is important to first understand the driving mechanisms. Much of the media attention on plastic pollution is devoted to floating garbage patches, where ocean gyres cause large accumulations of plastic, as it generates a more dramatic visualization of the problem. However, surface mass estimates are orders of magnitude smaller than predicted annual input, which highlights the importance of studying mechanisms that could be responsible for removing plastic from surface waters [23]. This plastic can enter the water from a variety of sources such as littering, improperly managed landfills, and discarded fishing supplies [11, 58]. However, plastic input is not the sole responsibility of coastal communities, as it can enter waterways inland and be transported to oceans or lakes, or be contained in wastewater outflow [58].

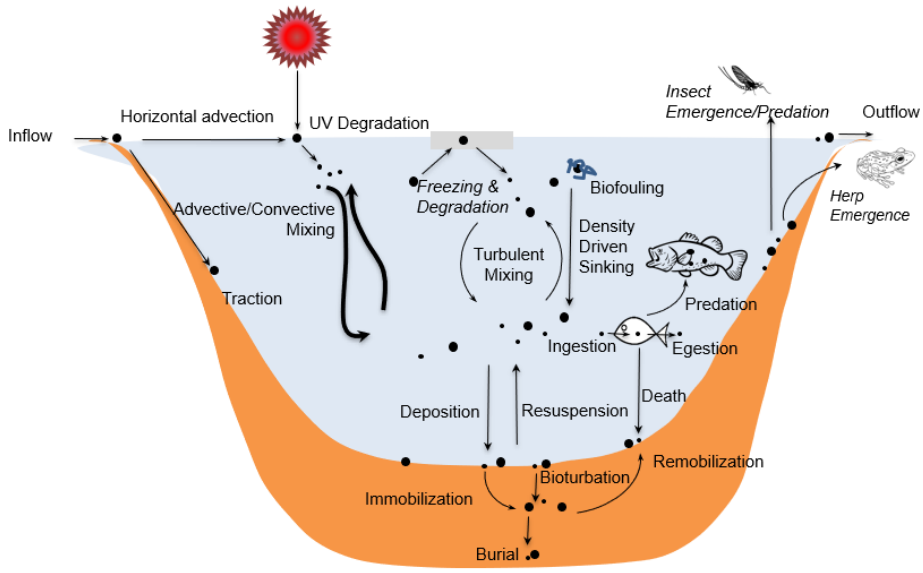

Figure 1.1: Mechanisms driving plastic transport in a lake

Once it has entered the water, plastic can be acted on by multiple mechanisms (Figure 1.1). Water currents can transport the plastic through horizontal or vertical advection. Roughly 50% (by mass) of globally produced plastic is negatively buoyant, such as polyvinyl chloride (used in pipes, flooring or

plastic wrap), or cellulose acetate (used in cigarette filters), and will immediately begin to sink after entering the water [3, 29]. Other less dense particles, such as polypropylene (used in food containers or dishes), which enter the water as positively buoyant, can be acted upon by UV degradation, freezing and degradation, or biofouling (a buildup of organic matter and organisms [139]) which can change the density of the particle and cause it to sink over time.

After the plastic has moved down in the water column, it is not guaranteed to permanently settle into the sediment, as there are more mechanisms at work in the benthos. Plastics can bounce off the lake floor, get deposited and then resuspended, or be transported along the lake floor [30, 31]. Animals can also move the plastic deeper into the sediment in a process known as bioturbation, which decreases the probability of resuspension [98]. It is also theorized that similar mechanisms can act on plastic at the shoreline, where plastic is commonly found, with the possibility of plastic being permanently beached there or temporarily deposited with the potential to reenter the water [29].

Animals can also impact the transport of plastic, as a wide size range of aquatic animals have been found to ingest plastic, even down to the size of zooplankton, invertebrates, and larvae [20]. It is theorized that these lower trophic level organisms are more likely to ingest plastics as they are typically indiscriminate feeders [92]. This plastic can then move up the food chain after ingestion of these organisms by larger predators [131].

The potential impacts of plastic pollution to the animals that ingest it are dependent on the size of the particles. Many plastics enter the water as a macroplastic, larger than 5 mm. Over time, exposure to mechanisms that degrade the plastic can reduce the particles to microplastics (smaller than 5 mm) [29]. These plastics are considered secondary microplastics, while plastics that are initially manufactured as microplastics are considered primary. Examples of primary microplastics include plastic powders or nurdles used in manufacturing or micro-beads used in cosmetics [62]. The breakdown of plastic can also result in a smaller size class, nanoplastics. The size range of nanoplastics is less agreed upon, but generally with an upper size bound of 1000 nm to 100 nm

[42].

III. Effects of plastic pollution

Macroplastics were the first plastics understood to have an impact on aquatic life [6]. Animals can become entangled in discarded fishing gear, a practice referred to as "ghost fishing," and risk becoming permanently trapped, injured, or amputating limbs [11]. A more common problem than entanglement is ingestion [131]. Macroplastics are large enough to accumulate in the digestive tracts of fish, turtles, and birds. If it is not large enough to cause a complete obstruction, which is fatal, the accumulation of plastic diminishes the hunger drive, leading to an increased risk of starvation [95].

While the impact of macroplastics on aquatic life may generate a more dramatic visual, micro and nanoplastics also pose a risk. It is thought that some animals may mistake microplastics for food and purposefully eat them [19]. Additionally, small plastic particles can form aggregates with organic matter that animals may consume [83]. Regardless of the mechanism behind ingestion, fish regularly have been found with plastics in their gastrointestinal (GI) tracts [86]. One study found a fish in Lake Ontario containing 915 ingested particles including microplastics and other anthropogenic particles, with the average number of 59 particles per fish in Lake Ontario [96].

The risk to animals and fish from microplastics is not well understood. Animals often eat these plastic particles without any immediate effects, allowing them to accumulate in the body [96]. However, these particles can contain toxins or sorb toxins from the environment, which can be transferred to the animal upon consumption, and potentially bioaccumulate [33, 105, 120]. While there is still a great deal of uncertainty about the effects these toxins may have, researchers have noted a strong inflammatory response at the cellular level in mussels after exposure to plastic [130]. Other potential risks from microplastic ingestion include mechanical stress, or changes in reproduction, behaviour, growth, and development [33]. Studies have also found evidence of plastic in fish sold for human consumption, so while the risk is still not well understood, humans are being exposed to it as well

[15, 106].

Beyond the exposure from eating fish, humans risk exposure from other sources due to plastic in large bodies of water. Plastic has been found in tap water and sea salt globally [68]. It has been found in 24 different types of German beers, which was 100% of the beer tested in that particular study [79]. Additionally, one study testing bottled water found that of 259 bottles purchased throughout 19 countries, 93% showed signs of plastic contamination [88]. Other research found that brewing one plastic tea bag can release over 11 billion microplastics and 3 billion nanoplastics into the cup [49]. Due to its ubiquitous nature, no matter what lifestyle choice someone might make, he or she is almost certainly being exposed to plastic in some way. One study even estimated that humans may ingest 0.1-5 g of microplastics per week, though the health impacts to humans from plastic ingestion remain poorly understood [115]. Beyond exposure and ingestion, plastic pollution is believed to have other implications. Globally it is thought that plastic may impact carbon and nutrient cycles, which could have implications for many animal habitats [83].

Specific to the Laurentian Great Lakes (hereinafter the Great Lakes), large amounts of pollution cause concern for several reasons. The Great Lakes are an important source of drinking water. They contain one-fifth of the world's freshwater, and about four-fifths of the available freshwater in North America [34]. Lake Ontario and Lake Erie have the first and second highest surface water concentrations of plastic in the Great Lakes, respectively [87]. This is concerning as Lake Erie supports a $1 billion sport fishing industry, which is the largest freshwater fishing industry in the world [5]. Additionally, plastic has been found in beer that was brewed from water originating in Lake Erie and Lake Ontario, and also tap water in Buffalo, NY which likely originated in Lake Erie [68].

Much of the research on plastics in the Great Lakes is based on surface samples, which have shown plastic concentrations comparable to surface samples in the oceans [87]. However, surface sampling based estimates of total floating plastic mass in the ocean and the Great Lakes differ by several orders of magnitude from what is predicted by production and input rates [23, 53]. This raises

the question of where the missing plastic has gone. While some of the unaccounted for plastic in bodies of water is theorized to be suspended in the water column [18], some plastics sink and have been found in deep sea sediment samples [136], as well as sediment samples in the Great Lakes [8, 22, 27].

As is shown in Figure 1.1 and previously explained, there are multiple vertical mechanisms impacting the movement of plastic through the water column and causing plastic to leave the water's surface, even if it was initially positively buoyant. Additionally, nearshore dynamics have the ability to trap plastic on beaches, or in nearshore waters, potentially accounting for a large share of the missing plastics in the world's oceans [46, 73, 99, 113]. Therefore, an accurate mass estimate for any body of water would need to account for plastics that have been deposited on the lake bed or beached, and would thus require understanding of behavior of plastics through the water column and along the coast. The goal of this work is to develop a more realistic three dimensional model, specifically including more vertical mechanisms impacting plastic transport and a beaching model. Ultimately, we hope to use this model for a more accurate mass estimate and sediment deposition rate for plastic in Lake Erie and Lake Ontario.

IV. Existing sampling and modeling work

Initially, scientific work on plastic pollution in large bodies of water was based on sampling. Samples are typically taken using a trawl, or net, towed from a boat, and analyzed in a lab following collection. Sampling work on marine debris has shown the accumulation of plastics in the ocean since the 1970s, but it has not been until fairly recently that samples have focused on microplastics [50]. Since the scientific community has begun to focus on microplastics, many sampling efforts have been undertaken [121]. These sampling efforts have had various target areas such as the Pacific Ocean, Atlantic Ocean, or the Mediterranean sea [24, 37, 71].

Though sampling can provide valuable information, current sampling methods are unable to collect full time series of the amount of plastic in a location, but rather samples are taken sporadically,

sometimes a year apart, and typically in different locations. Sampling is usually performed by towing a trawl from a boat (usually only about 16 cm high), but this only collects samples at a few places near the surface of the water. As the plastic is not uniformly mixed throughout the water, sampling does not provide a full spatial distribution either on the surface, or in the water column and sediment. Additionally, particles smaller than the width of the trawl are not collected, so their distribution remains unknown. Along the shore, there is sampling information from beach cleanup efforts, but this can be skewed by municipal beach grooming efforts [29]. Sediment core samples can also be taken, but these are logistically challenging to take, especially in deep areas. Due to all of this uncertainty, a mass estimate in any body of water based purely on sampling is likely to not accurately quantify the problem. Consequentially, researchers have utilized models of plastic transport to try to understand plastic pollution beyond the limits of sampling.

Much existing plastic pollution modeling work has been focused on the world's oceans. In the oceans there is a focus on large scale accumulation patterns in the surface water, commonly referred to as garbage patches. As a result of the focus on surface dynamics, and the computational cost of running a simulation on a global scale, much of the modeling of the world's oceans is two dimensional.

Maximenko et al. [89] used the trajectories from drifters released into the ocean as part of the Global Drifter Program to construct Markov transition matrices by partitioning the world's oceans into a grid with bin width and height $1/2^\circ$ longitude and latitude. Using data from the drifter trajectories, the entries $P(i, j)$ in the transition matrix correspond to probability of a particle originating in that the i^{th} grid bin traveling to the j^{th} grid bin in the predetermined time scale of the transition matrix. With this approach they were able to identify five garbage patches in the North Pacific and Atlantic, South Pacific and Atlantic, and South Indian oceans.

Further work by van Sebille et al. [127] followed a similar stochastic model approach for the oceans, but also incorporated plastic input dependent on shore population, used a bigger domain, and used a seasonally dependent transition model, which accounts for changes in ocean currents throughout the year. With these model advancements, they identified an additional sixth garbage patch, in the

Barents Sea which is north east of Scandinavia.

Stochastic models applied to plastic transport naturally lend themselves to calculating concentrations, as the state vector x_t represents the concentration in each grid bin at time t. This can be useful when predicting garbage patch formation, as was the goal of the previously mentioned work. It can also be less computationally expensive than advecting individual particles at each time step, as is done in a Lagrangian Transport (LT) model. In a LT model, individual particles are advected at each time step by the water currents in the location of the particle.

LT models have also been used in other bodies of water to model transport and accumulation such as the Mediterranean basin [85], or the Pacific Ocean, specifically focused on debris from the March 2011 tsunami [75]. Lebreton et al. [77] also used a global LT model to model 30 years of plastic input and transport, and confirmed the five accumulation zones found in previous global modeling work.

As in the oceans, early modeling work on plastic pollution in the Great Lakes was based on sampling. In 2013, Eriksen et al. [37] published the first paper confirming the presence of microplastic pollution in the Great Lakes with data from 21 samples in Lakes Superior, Huron, and Erie, with the highest concentrations in Lake Erie. They also proposed potential sources of some of the particles such as microbeads from consumer cosmetic products, helping lead public pressure on cosmetic companies and bans against microbead use [138]. Following this work, several other papers have confirmed the presence of microplastics in the Great Lakes [14, 87].

There has also been some sampling based research efforts regarding plastic in the sediment of the lakes. Two studies using sediment traps, cores, and grab sampling methods in Lake Ontario found plastic particles in near shore sediment [8, 22]. Both studies found high concentrations of plastics and Corcoran et al. [22] determined that the depths they found plastics at in the sediment implied it had been accumulating there for at least the last 38 years. Dean et al. [27] found the presence of plastic in the sediment of Lake Erie using a sediment grab sampler. They found higher concentrations in sediment near population centers, specifically the outflow region of the Detroit River, but still much

lower concentrations then was found in Lake Ontario [22]. Lenaker et al. 2019 [78] also found plastic in Lake Erie sediment, again with high concentrations of plastics near the outflow of the Detroit River.

The existing modeling work that has been done on plastic transport in the Great Lakes is based on Lagrangian Transport models. Hoffman and Hittinger 2017 [53] published the first modeling work on plastics in the Great Lakes and used a 2D LT model with flow between lakes to derive a first pass mass estimate of plastic in the surface waters of the lakes. They used population census data from zip codes bordering the lake to approximate plastic input amounts, which was the same method used for global ocean input estimates [58]. They estimated input of 2520.2 tons to Lake Erie, and 1438.7 tons to Lake Ontario. The model was ran for six years, which is likely only feasible using a 2D model due to computational cost. They compared model concentrations to sample data to derive the first mass estimates of plastic in the surface waters of the Great Lakes, with an estimated 4.41 metric tons floating in Lake Erie alone. There were no available samples at the time for Lake Ontario, so a mass estimate was not performed. The Lake Erie mass estimate is still several orders of magnitude lower than predicted input, emphasizing the need for future work to include vertical modeling. This is the only published plastic modeling work for Lake Ontario.

Cable et al. [14] also used a three dimensional LT model in Lake Erie to model the behavior of neutrally and positively buoyant particles, and compared model results to samples. Their model also showed no persistent garbage patch in the lake such as those that are present in the world's oceans. This is potentially due to cyclical currents in the lake which could cause such accumulation not being as persistent as those in the oceans [14]. Additionally, in comparing results between the neutrally and positively buoyant cases, they found that the neutrally buoyant particles have a resonance time almost five times longer than the positively buoyant particles. This means on average it takes a neutrally buoyant particle five times longer to be moved out of the lake. This is theorized to be due to currents moving slower in water below the surface, where the neutrally buoyant particles tend to accumulate. These results imply that plastic could be accumulating in the water column, which indicates that a three dimensional model is necessary for an accurate mass estimate.

Existing work modeling different types of polymers has only been done on a global scale using an Eulerian approach [94]. In an Eulerian model, the concentration fields of the particles are progressed, in this case using a partial differential equation. Mountford and Morales [94] chose this approach as their focus was global patterns of distribution and not individual particle behavior. This study modeled seven polymer types that were both positively and negatively buoyant, and also included a basic sediment deposition model. They found positively buoyant plastics tended to congregate in the previously identified ocean garbage patches, while the negatively buoyant particles gathered in the deepest areas of the sea floor. They also found that plastic tended to accumulate in the sediment primarily in shallow coastal areas.

Other global modeling work has included different transport characteristics of plastics such as beaching or biofouling [82, 99]. These modeling efforts have found both mechanisms impact the distribution of plastics, but no similar model has been developed for the Great Lakes. A model that allows for the sinking of plastics was applied to the Mediterranean Sea [59]. This work followed an inverse modeling approach, which was possible because of the high availability of sampling data for the Mediterranean. They were able to use the data to refine model parameters, develop a new surface mass estimate for the Mediterranean, and estimates for which percentages of plastic have sunk or beached.

Despite the use of an Eulerian model on the global scale to model multiple polymer types, on a smaller domain, the LT model is ideal as it is easier to provide a forecast at any point in time, and the fate of individual particles can be studied. Additionally, the problem of computational cost is not as pressing as the domain is so much smaller. We also do not follow an inverse modeling approach because there is not enough available data to validate the model in Lake Erie or Lake Ontario. Here we hope to develop more accurate mass estimates for Lake Erie and Lake Ontario, which requires expanding a 2D model to include more accurate modeling of vertical mechanisms. To do this, we model factors such as biofouling or sediment deposition which impact individual particles in varied ways. Consequentially, this work will utilize a Lagrangian transport model, which gives control over each particle, applied to Lake Erie and Lake Ontario.

Chapter 2

2D Transport Model

This work began with a 2D Lagrangian Transport model of surface plastic, expanding on the model used in [53]. Multiple physical mechanisms drive the movement of plastic in any body of water, but this is a simplified model that only accounts for advection by currents and input weighted by nearshore population. This model was compared to sampling results from 2012-2014 and used to refine the surface mass estimate for Lake Erie [87].

While this is a simplified model, several of the approaches we developed here were utilized throughout the rest of this work. These include the uniform release of plastics weighted by nearshore population, the method used for horizontal advection, and the uses of current fields from the unstructured grid Finite Volume Community Ocean Model (FVCOM). Additionally, the technique used to achieve the mass estimate by converting from model space to sample space by using the slope of the regression line was also used in our 3D mass estimate (Chapter 3).

I. 2D Transport Methods

Assuming smooth behavior of the currents below grid resolution, which allows for interpolation to finer resolution in the x-y direction, particle positions in the 2D model are progressed using the

dynamical system:

$$\frac{dx}{dt} = u(x, y, z, t)$$

$$\frac{dy}{dt} = v(x, y, z, t)$$

where u, and v, are the interpolated horizontal x-direction,and y-direction, and velocities, respectively. In the 2D model, as we are only modeling surface behavior, we fix $z = 0$. The system is solved using the Runge-Kutta 4th order numerical scheme (RK4) with timesteps of one hour. The velocities are interpolated in time using third-order Lagrange interpolation and in space, to particle locations, using cubic interpolation. The code is written in MATLAB and was previously used in [87].

The currents used in this model were obtained using the unstructured grid Finite Volume Community Ocean Model (FVCOM) with wind and boundary condition forcing files from 2014 [16]. FVCOM is the operational hydrodynamic model used by NOAA Great Lakes Environmental Research Laboratory (GLERL) for Lake Erie, Lake Michigan, and Lake Huron. It was run using the NSF funded XSEDE Comet cluster [122]. FVCOM current output has been used previously in plastic transport models [87]. FVCOM uses terrain following coordinates to account for the bathymetry in the z direction, and an unstructured, triangular grid in the x and y direction. This allows the model to smoothly fit to the shoreline, but for efficiency, our model required this output on a regular grid. This created an intermediate step of interpolating the FVCOM output to a 2 km evenly spaced rectangular grid using linear interpolation. This regular interpolated output was then used in our model.

The lake was initialized with no particles, but for the duration of the model particles were released every 12 hours from each grid point along the shore of the lake, which results in 984 particles released daily. The near shore population size at the release point of the particle was also saved, as population size serves as a proxy of the amount of pollution released from a location. Population data came from US and Canadian census data and is the same as was used in [53]. The decision was made to release particles from every grid point (as opposed with a frequency proportional to

population as was done in [53]) to allow enough particles to populate the lake to compare to samples. If there is a lack of particles active in the model, areas of zero plastic concentration can develop in the lake, which skews the conversion from model space to sample space.

II. 2D Model Results

Three year long simulations were completed for years 2012-2014, though each year was initialized with no particles. This was done so that the model plastic concentrations in later years were not biased by higher amounts of plastic in the lake. The model results were compared to samples taken in each of these three summers [87]. One benefit of the 2D model is lower computational cost, which makes it easier to perform three years worth of simulations.

To compare the model to the samples, the particles within a $r = 2$ km radius of the sample location, along with the population at their origin was saved every 3 hours. For model concentrations at the time of sampling, we average the following count $x_m^s = \sum_i^{particles \in r} P_i$, for $s = 1....n$ where n is the number of samples from that year, over the week when the sample was take.

The model demonstrated a reasonably good fit to the samples, with the exception of two points in the Eastern Basin in 2012, where the model greatly underestimates the sample concentrations. Previous work comparing to samples in 2012 also noted a particularly bad fit in this region of the lake [53]. These high sample concentrations could be caused by many factors, such a combined sewage overflow event (CSO event) or high rain event which could discharge large amount of plastic into the lake at one time which our input data does not account for.

To assess the fit of the model to the samples we perform linear regression between the model space and sample space concentrations (Figure 2.1). In this regression, the two poor fit points from 2012 were excluded, resulting in an R^2 value of 0.57. We can use the slope of the regression line, $\tau = 17,561.33$, to convert model concentrations to Lake Erie particle concentrations. By multiplying the week long averages of model particle concentrations by τ, we can achieve an abundance estimate of about 475 million floating microplastic particles in the lake. We can then multiply the abundance

estimate by a mass per particle value $1.36 * 10^{-2}$ g/particle for a total mass estimate of 6.45 tons of floating plastic. This mass estimate is on the same order as previous estimates, but still an order of magnitude lower than predicted input, which highlights the importance of modeling vertical mechanisms driving plastic movement as we do in the 3D model [53].

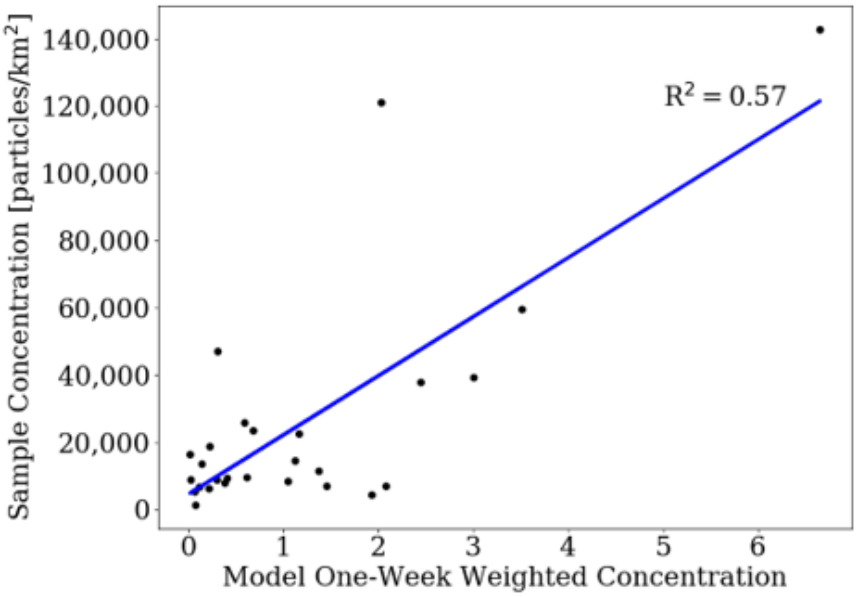

Figure 2.1: Results of linear regression for 2D model

Chapter 3

3D Transport Model With Vertical Mechanisms

I. Introduction

Plastic pollution in bodies of water has recently received much attention as a pressing environmental concern. Despite the attention [123], there is still a great deal of uncertainty surrounding the quantity and distribution of plastic litter in bodies of water. Plastic can take hundreds to thousands of years to decompose and as more is released into the water each year, it is accumulating [29]. There is potential risk to humans, wildlife, and ecosystems from plastic pollution, though this risk is still not fully quantified and is likely dependent on the size of the particles [103, 104]. Most plastic enters the water as a macroplastic, larger than 5 mm, but exposure to UV radiation, chemical breakdown, consumption by marine life, and wave mechanics can cause fragmentation [128]. Over time this reduces the particles to microplastics or nanoplastics [29, 42]. In addition to any risk from ingestion, there is potential risk from toxins either from additives leaching from the plastic or environmental chemicals that have previous sorbed to the plastic [15, 105, 106].

Current sampling methods are unable to collect full time series of the amount of plastic in a location, but rather samples are usually at the surface (by towing a net, or trawl from a boat), are sometimes

taken months to years apart, and are often collected at different places [36, 37]. As the plastic is not uniformly mixed throughout the water, surface trawls do not provide a full spatial distribution either on the surface or in the water column and sediment [70]. Additionally, particles smaller than the mesh size of the trawl are not collected, so their distribution remains unknown. Along the shore, there is sampling information from beach cleanup efforts, but this can be skewed by municipal beach grooming efforts, and lack of uniform sampling and recording standards [29]. Sediment core samples can also be taken, but these are logistically challenging, especially in deep areas, and are therefore even sparser than surface samples. Due to all of this uncertainty, a mass estimate in any body of water based purely on sampling is unlikely to accurately quantify the problem [70]. As a result, transport modeling has been used in oceans and lakes around the world [54, 77, 89, 127].

Much of the transport research is devoted to floating ocean garbage patches, where ocean gyres cause large accumulations of plastics. In these gyres, surface sampling based estimates of total floating plastic mass in the ocean differ by tens of thousands of metric tons from what is predicted by production and input rates [23, 128]. One possible explanation for this discrepancy is that the majority of the plastic litter in bodies of water is in other locations such as deeper in the water column, deposited in the sediment, or beached onto the shore [9, 136]. The same missing mass problem is also present in the Great Lakes. It has been estimated that 10,000 metric tons of plastic enter the Great Lakes each year with 4.41 metric tons residing in the surface water of Lake Erie alone [54]. Lake Erie is an important source of drinking water and an important habitat: the Great Lakes contain one-fifth of the world's freshwater and Lake Erie supports a $1 billion sport fishing industry, which is the largest freshwater fishing industry in the world [5]. Plastic has not only been found in Lake Erie itself [14, 37, 87] but has been found in beer that was brewed from water originating in Lake Erie and in tap water in Buffalo, NY which likely originated in Lake Erie [68].

While some of the unaccounted for plastic in bodies of water is theorized to be suspended in the water column [18], plastics sink and have been found in deep sea sediment samples, [136] as well sediment samples in the Great Lakes [8, 22, 27]. Therefore, an accurate mass estimate for Lake Erie would need to account for plastics that have been deposited on the lake bed, and would thus require

understanding of behavior of plastics through the water column. Understanding the deposition and buildup of plastic in the benthos is important beyond closing the mass budget as there is potential for impact on benthic ecosystems [45].

Researchers have utilized models of plastic transport to try to understand plastic pollution beyond the limits of sampling, and several of these models have been applied to the worlds oceans, to identify areas of congregation, or garbage patches, [89, 127], derive estimates of how much plastic is present [54, 65], or track the spread of plastic from a specific event [75]. However, many of these modeling efforts only focus on transport within surface water or model all particles as neutrally buoyant. The work that has been done with modeling different polymers is Eulerian based, which does not allow for following the behavior of individual particles [94]. The sinking and eventual deposition into sediment is likely for particles that are more dense than the water, meaning they are negatively buoyant. A portion of plastic pollution such as polyvinyl chloride (PVC), or cellulose acetate enters the water already more dense than water [29]. Other less dense particles, such as polypropylene (PP), may be affected by biofouling, or a buildup of organic matter and organisms [139]. Biofouling can change the density of a particle as it resides in the water, causing the particle to become negatively buoyant over time and increasing the chances of movement down the water column and potentially into the sediment [39, 67, 139]. Previous modeling has shown how positively buoyant particles have different transport properties than neutrally buoyant particles but, so far, no modeling efforts in Lake Erie have included non-neutrally buoyant particles or incorporated turbulent mixing, which are both processes that can move plastic below the surface [14, 54].

In this paper, we investigate the impact of vertical movement on transporting plastic away from the surface by modeling 3D advection and vertical diffusion. Additionally, we account for variations in plastic particle makeup and consequentially, both positively and negatively buoyant particles, which gives the basis for a first pass estimate at plastic deposition rate in the sediment and whole lake mass estimates for Lake Erie. While this model is only applied here to Lake Erie, the method and mechanisms modeled could also be applied globally to the world's oceans.

II. Methods

We expand on this 2D model to include additional physical mechanisms in the vertical direction, while still assuming that advection is the driving force of movement in the horizontal direction. In the z, or vertical direction, in addition to advection we incorporate sinking velocity and turbulent diffusion. The vertical motion also allows us to track which particles reach the lake bed and implement a basic deposition model.

The advection-diffusion partial differential equation describes the concentration field $C(z,t)$ of particles in a fluid experiencing these physical processes:

$$\frac{\partial C(z,t)}{\partial t} = \frac{\partial}{\partial z}(w_b(z,t)C(z,t) - K(z,t)\frac{\partial C(z,t)}{\partial z}),$$

where w_b is the sinking velocity of the particle, and $K(z,t)$ is the vertical turbulent diffusivity [129]. If we had defined w_b to be the sum of water velocity and sinking velocity, this equation would also describe advection. However, we will solve for movement from advection due to water velocity with RK4 as done in the x, y direction, and not within this scheme.

The advection-diffusion PDE can be considered a version of the Fokker-Planck equation in one spatial dimension if we interpret the concentration field as a probability density function of finding a particle in a certain location. The Fokker-Plank equation can then be simplified to a stochastic differential equation (SDE) for the position, z_b, due to diffusion and sinking velocity of our particle and this SDE can be approximated numerically using the Milstein scheme [90]. This gives the following expression for $z_b(t)$,

$$z_b(t+\delta t) = z(t) + w_b\delta t + \frac{1}{2}K'(z(t))[\Delta W^2 + \delta t] + \Delta W\sqrt{2K(z(t))}$$

where ΔW is a Gaussian random variable taken from a distribution with mean zero and standard deviation $\sqrt{\delta t}$ for timestep δt. The Milstein scheme is used here because of its accuracy and precision

in solving this SDE [43] as well as its previous use for Lagrangain particle tracking applications in Lake Erie (applied to algal blooms; [107]) and in the Gulf on Maine [57].

The vertical position z is then given by $z(t) = z_a(t) + z_b(t)$ where $z_b(t)$ is determined by the above scheme and $z_a(t)$ is movement due to advection from water velocity w_a. We use RK4 to solve for $z_a(t)$ which is determined by the ODE,

$$\frac{dz_a}{dt} = w_a(x, y, z, t).$$

As in the $x-y$ direction, we use timesteps of one hour for the RK4 scheme and the same interpolation methods in space and time. By considering water velocity driven advection separately, we can reduce the computational cost by using this larger timestep, whereas the SDE requires a much smaller timestep δt. We chose $\delta t = 5$ sec for a balance of computational efficiency and sufficiently small stochastic movement. This was also a timestep used with this scheme in previous work [57]. The diffusivity, $K(x, t)$, was interpolated linearly in time and cubicly in space to particle location. As with the 2D model, the currents used in the model came from FVCOM. Additionally, we used diffusivity fields from FVCOM. FVCOM's diffusivity output has been used to model algal blooms [107], and, the diffusivity values agree with the range suggested in literature [137].

The stochastic movement can cause the particle to move beyond the physical boundary of the lake, so we must implement boundary conditions. To model deposition in the sediment of the lake, if a particle moves beyond the depth, we record its deposited location and remove it from the array of actively modeled particles. If a particle moves above the surface of the lake, its position is reset to the top of the free surface. For boundary conditions on the $x - y$ plane, particles cannot move beyond the shoreline, with the exception of outflow through the Niagara River at the eastern end of the lake. This is an additional way for particles to exit the lake besides being deposited at the bottom or on shore.

In general, there is a lack of available research on microplastic sinking velocities, especially in

fresh water. We chose to use previously determined experimental results of sinking velocities for simplicity, which come from experiments using spherical particles with diameter between 1 mm and 4.75 mm [63, 69, 132]. In total, we modeled nine polymers polystyrene PS, Polyamide PA, Polymethylene Methacrylate PMMA, Polyethethylene terephthalate PET, Polyoxymethylene POM, Polyvinyl chloride PVC, Polyethylene PE, Polypropylen PP, and Expanded Polystyrene EPS.In future work this can be expanded upon to model sinking velocity for particles dependent on size and density, as more of this data is available. The values used for w_b, along with the sources, are provided in Table 3.1 .

The standard deviations included in the table are approximated from the range of plotted sinking velocity data points from the sources used. The standard deviation was used to introduce Gaussian error with mean zero and given standard deviation. This addition served two purposes. First, it allowed for natural error in the sinking velocity of the plastic which could arise from biofouling, manufacturing variation, or effects of breakdown from light or water. Additionally, it encompasses a wider range of particle sizes. The standard deviations taken from the data were chosen to include the range of sinking velocities from spherical particles with diameter between 1 mm and 4.75 mm, which correspond to the category of sizes of particles in the comparison samples.

Plastic	Common uses [29]	Sinking velocity (m/s)	Standard Deviation (m/s)
Polystyrene PS	Plates, cutlery, toys	-0.015*	0.01
Polyamide PA (nylon)	Fishing lines and net, toothbrush bristles	-0.03*	0.03
Polymethylene Methacrylate PMMA (acrylic)	Lenses, shatterproof windows, paint	-0.03*	0.02
Polyethethylene terephthalate PET (polyester)	Textiles, drink bottles	-0.05*	0.04
Polyoxymethylene POM	Automotive parts, glass frames, fasteners	-0.04*	0.04
Polyvinyl chloride PVC	Pipes, fencing, flooring, shower curtains	-0.05*	0.04
Polyethylene PE	Packaging, bags, films	0.0065†	0.005
Polypropylen PP	Straws, food containers, bottlecaps	0.01 ⋄	0.01
Expanded Polystyrene EPS	Foam plates, trays, cups	0.314 †	0.2

Table 3.1: Experimental sinking velocities and standard deviation on those velocities used for various common types of plastic polymers. Those with density higher than water (1000 kg/m^3) have negative sinking velocities, meaning they sink in the water. Sources: * [69], † [132], ⋄ [63]

III. Comparison to Samples

To evaluate the accuracy of our model, and ultimately to make total abundance and mass estimates of plastic in Lake Erie, we compared model results to previously taken samples. We used seven surface samples from Lake Erie taken using a 16 cm tall by 61 cm wide manta trawl towed in July 2014 [87], and thirteen additional samples taken using the same size trawl in May 2014 [14]. A flow meter was used to calculate the area of each trawl, and samples were normalized by trawl area to give values for plastics per square kilometer.

The model was run for six months for all nine polymer types, plus neutrally buoyant particles, both with and without vertical mixing, for a total of twenty runs. All of the runs were from January 1st to July 17th, to give a two week buffer around when the samples were taken, using forcing files and initial conditions in FVCOM from 2014.

Let x_o^s denote the observed count of particles at each sample point, where $s = 1, ..., 20$. The data for $s = 1 - 7$ come from [87] and $s = 8 - 20$ from [14]. For the approximation of model particles at the sample site, we first count all particles in the top 16 cm of the lake, within a radius $r = 1$ km of the observation location. We then take the count

$$x_m^s = \sum_{i}^{particles \in R} P_i \omega_i,$$

where P_i is the near shore population at the origin of the particle, ω_i is a scaling constant representing what percentage of estimated input to the lake is made of that polymer, and R is the set of particles within distance r from the sample location. For the model particle concentration at each sample point in particles per km^3, we divide by the volume of the region we counted particles from, here being $\pi r^2 * 0.00016$ km^3.

The values used for w_i come from the data given in Table 3.2, under the assumption that plastic input into the lake has the same distribution among polymer types as global plastic waste [41]. For PP, PS, PVC, and PET we take w_i to be their respective percent of the estimated 2015 plastic

generation. For the polymers POM, PMMA, EPS, and PA, we assumed that they made up the entirety of the "other" category, and set each to have a $\omega_i = .036/4 = 0.009$. While it is likely that there are additional polymers included in the "other" category, this was such a small percentage of the total plastic that it is unlikely that this assumption will significantly impact the results.

The categories PP&A and PUR, which make up a combined 19% of waste generation, were not modeled here as we did not have experimental sinking velocities for them. Despite this exclusion, our model still covers approximately 75% of the polymer types which comprise plastic waste.

Polymer Type	Percent of 2015 Waste Generation
PE	32.1%
PP	18.2%
PS	5.6%
PVC	4.9%
PET	10.6%
Other	3.6%

Table 3.2: Percentage of the 2015 global plastic waste generation for each polymer type [41]

To compare the model concentrations to the sample concentrations, we performed linear regression between the model space and sample space. As the two sample sets we compared to were taken a few weeks apart, we compared to model particle count averages at the time windows when the respective samples were taken. For the seven samples from [87] (taken July 8th and 10th) we used a one week average from July 6th to July 13th, of the model particle counts around sample sites. For the thirteen samples from [14] (taken June 3rd to June 30th), we used the average model particle counts of the month of June. This averaging was done to minimize the effect of small variations in concentration and was also done in [87]. We excluded five samples from [14] that were taken in a river output or at a waste water treatment plant, as these samples are likely to have concentrations more reflective of the input rather than the transport and are thus likely unaccounted for in the model.

We can see the relative agreement between sample concentrations and predicted model concentrations by comparing concentrations at each sample location (Figure 3.1). The worst fit at an individual

point is in the Central Basin along the north shore, where the model greatly over estimates the concentration. This is potentially due to the model over estimating particles at the surface, which could have then accumulated in this area. Whatever the reason, this point was treated as an outlier and excluded from the regression between sample and model space.

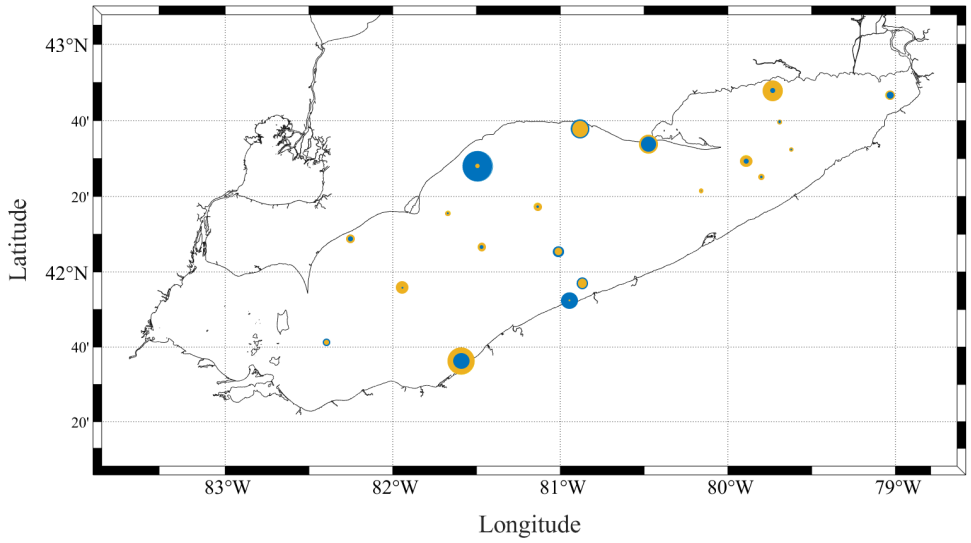

Figure 3.1: Comparison of sample concentrations (yellow) and predicted model concentrations using vertical mixing (blue)

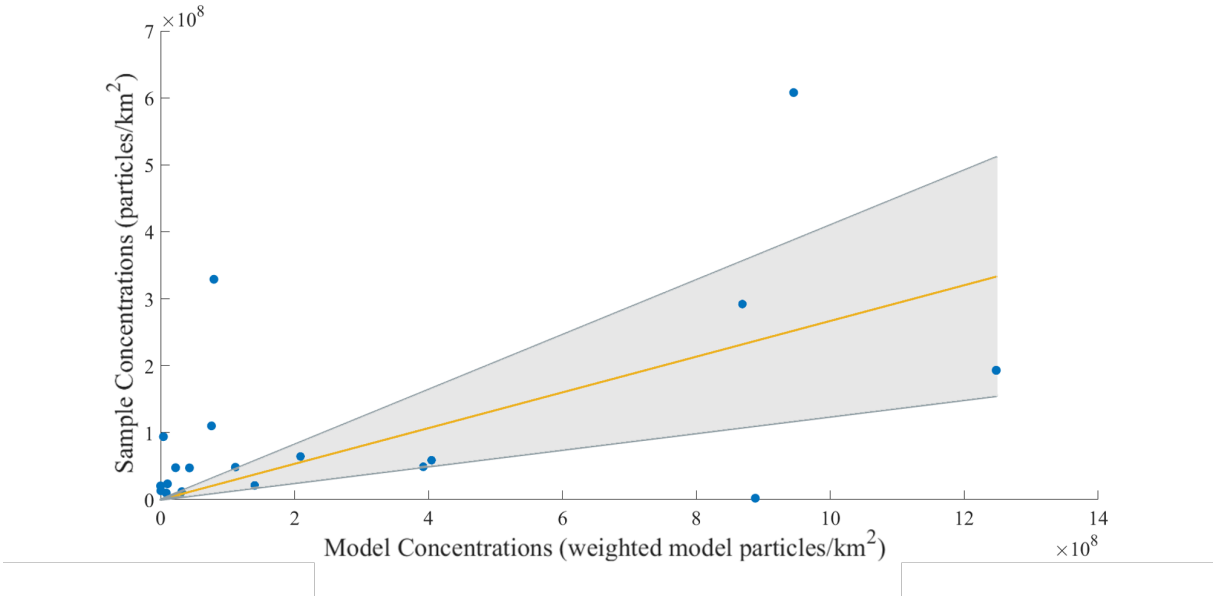

Figure 3.2: Regression between model concentrations with mixing and sample concentrations with 90% confidence intervals (in grey) on the the slope of the regression line (yellow)

To make a abundance estimate for plastic in the lake or a deposition rate, we can use the slope

of the regression line, τ, as a conversion formula from model space to sample space. This gives a abundance estimate for modeled particles of

$$A_p = \sum_{i}^{all\ particles} P_i \omega_i \tau.$$

With a 90% confidence interval we get $\tau = 0.26 \pm 0.14$ using the model that includes vertical mixing. As we only performed the regression with observed particles of diameter 1 mm and larger, we can scale up our abundance estimate to account for all size classes with $A_t = A_p/(.14 + .4)$. To convert the abundance estimate to a mass estimate, we can multiply each size class abundance by a conversion factor of mass per particle, which is a method used in ocean plastic mass estimates [128]. $M_{total} = p_1 m_1 A_t + p_2 m_2 A_t + p_3 m_3 A_t$, with p_i the percentage of particles in that size range, and m_i the average mass of particles in that size range, both given in Table 3.3.

Particle size (mm)	Particle mass m_i (g) [35]	Percentage of total plastic p_i [87]
0.33-1.00	0.00384	79%
1.00-4.75	0.00943	14%
>4.75	0.0803	4%

Table 3.3: Data used for mass and abundance estimate

IV. Results

At the end of the simulation, the plastic does not exhibit a uniform distribution at the surface (Figure 3.3). The accumulation pattern is driven by horizontal advection, which is the only physical process acting in the $x - y$ plane. We also do not see uniform density along the shore line (Figure 3.4), with increased accumulation on the eastern shore of the lake. This could be caused by the current moving predominantly west to east, which will push plastic into the eastern side of the lake. As this only shows abundance, and is not weighted by population at particle origin, there is a lack of expected high accumulation at some of the population centers on the lake such as Cleveland, OH or Erie, PA (Figure 3.3).

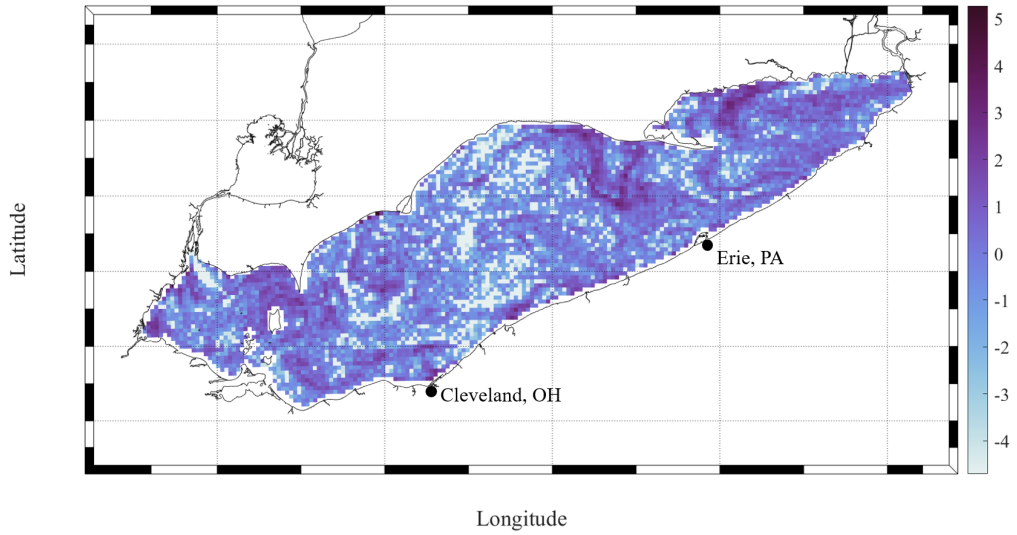

Figure 3.3: Result of half year model simulation, particle count distribution in lake open water on a log scale

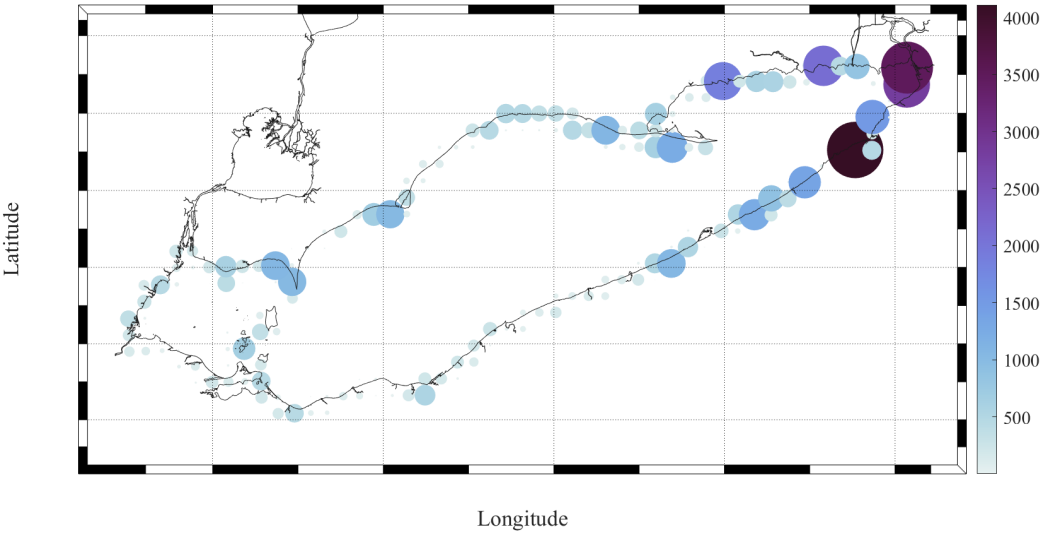

Figure 3.4: Result of half year model simulation, particle count distribution on lake shore. Marker size and color corresponds to count of modeled particles

When mixing is included in the model, the plastic is distributed slightly more evenly through the water column (Figure 3.5). Without mixing, 97% of the positively buoyant plastic in the water is in the top 2 m of the lake, compared to 88% when mixing is included. Among negatively buoyant plastics, without mixing, 81% of the particles in the water are in the top 2 m, as compared to 71% with mixing. Without mixing, it is unlikely that movement due to advection could significantly overpower movement due to the density driven sinking. For example, with no other physical

mechanisms, a particle with a sinking velocity of -0.01 m/s would sink 108.00 m in one hour, which is deeper than the 63 meter maximum depth of Lake Erie. Though vertical advection and mixing may counteract this sinking in some places, it is unlikely to completely overpower it. Still, the fact that 7% more particles are deposited in the sediment in the no mixing case, implies that more particles are moving quickly down the water column when mixing is removed. The 81% of negatively buoyant polymer particles at the surface in the no mixing case are probably plastics that have just entered the lake, or those whose noise term on the sinking velocity caused them to be positively buoyant. The same behavior happens in reverse for positively buoyant particles, in that their positive buoyancy overpowers any downward movement from advection. Even with mixing, the model does not predict much plastic distributed through the middle of the water column, but it still predicts slightly more than the model with no mixing.

We also see that in the floating case, for both the mixing and no mixing models, about 60% or 80% respectively of total plastic that entered the lake remains at the surface of the lake after a six month simulation (Figure 3.5). In both the mixing and no mixing cases, around 55% of all deposited floating plastic is in the grid boxes along shore. Because the lake is so shallow along shore, within this model it is easy for it to touch the lake floor there and be written out, which here simulates beaching. A potential model improvement could involve a more sophisticated beaching model, which would allow some of this plastic to remain active in the model for longer. We do see the amount of plastic remaining in the system is much lower for sinking polymers, at either about 7% or 14% depending on the model. This fraction is so much lower than for the floating polymers as it is much more likely for a sinking particle to be deposited and written out of the system.

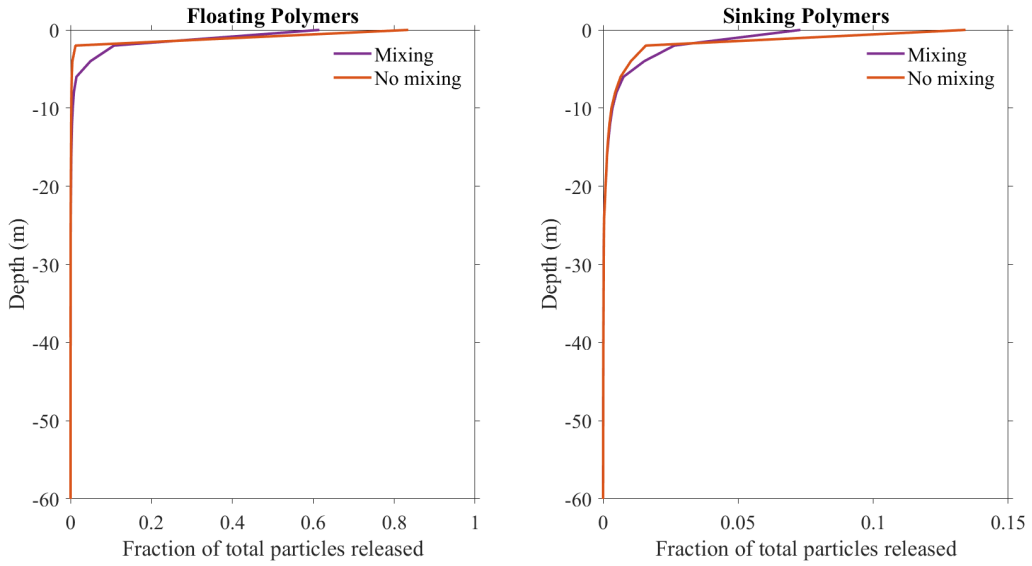

Figure 3.5: Comparison of vertical distribution across entire lake of plastic particles, as a fraction of total number of that category of released particles, with mixing and no mixing between floating polymers (PE, PP, EPS) and sinking polymers (PS, PS, PMMA, PET, POM, PVC). Distribution from end of run (July 1, 2014). Depth is binned in 2 meter increments. The remaining particles missing from the water column have being written out after being deposited along the shore or in the sediment.

Comparing the surface distributions of different polymer types, we see similar accumulation patterns depending on polymer buoyancy (Figure 3.6). The model predicts the accumulation of the three positively buoyant particles (PE, EPS, PP) at the surface. These are the three polymers most commonly found in Great Lakes samples, implying they accumulate on the surface to some extent in the actual lake [32]. For the six negatively buoyant polymers, there are much lower concentrations at the surface (Figure 3.6). We do see some presence, which is likely due to the turbulent mixing. These polymers do not accumulate at the surface though, as their sinking velocity will likely ultimately lead to deposition.

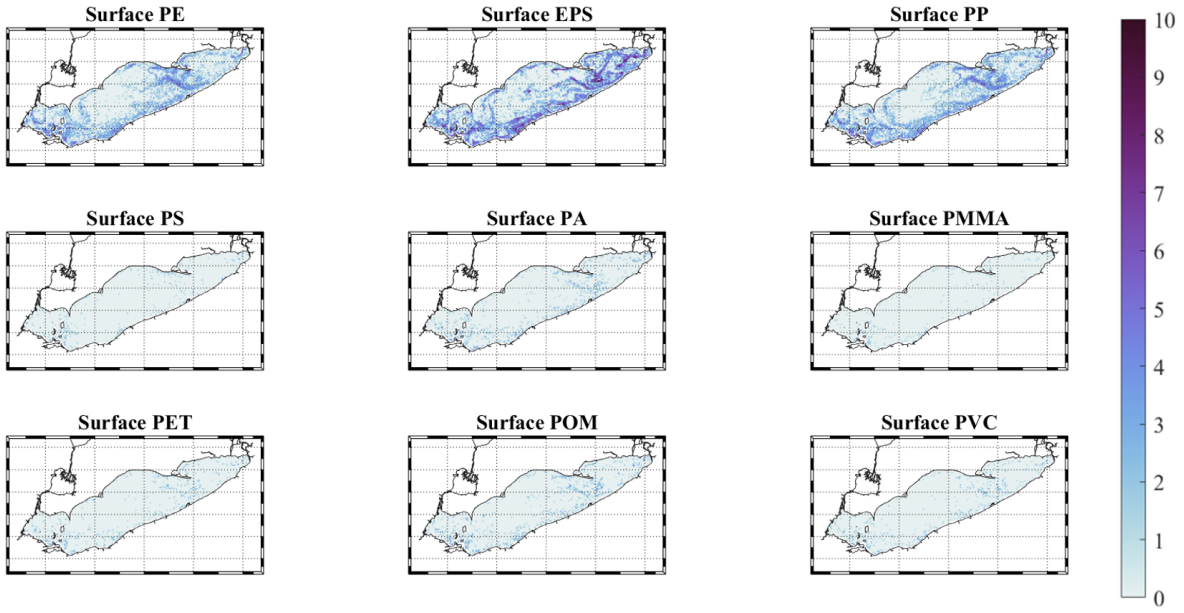

Figure 3.6: Surface distributions (all plastic within top 1 m of take) of plastic particles for all nine modeled polymers on log scale

Including mixing, and using the conversion factor range from the regression line gives an estimate of 10.4 billion ± 5.5 billion particles in the lake, with a total mass estimate of 381.1 ± 204.1 tons of plastic. Using the moderate value of τ gives an estimate of 127.9 tons of plastic in the top half meter of the lake. This surface water estimate is one to two orders of magnitude larger than previous estimates [53, 87], but is still a order of magnitude smaller than the predicted yearly input [53]. This discrepancy between mass estimates and predicted input is also seen in the oceans [23].

We can use this same method for a sediment deposition rate, but by summing over all of the particles that have hit the lake bed, rather than particles still suspended in water. This gives a sediment deposition rate of 170.8 ± 79.4 metric tons per half year. We report this as a rate and not a mass estimate because plastic accumulates in the sediment, our model does not predict concentrations but rather how much plastic reaches the lake bed in a half year period.

Sediment deposition is dependent on the buoyancy of the polymer modeled, with negatively buoyant particles most commonly deposited (Figure 3.7). Among negatively buoyant particles, the areas of high accumulation are mostly the same. Deposition is mostly near the coast, as much of the plastic

quickly sinks in the shallow water there after entering the lake. There is also more accumulation along the southern shore, where there is a higher population density. This emphasizes the importance of accurate input estimates, because the plastic sinks so quickly and is almost immediately deposited, near shore model concentration predictions are very dependent on the input data. Additionally, we do see some deposition from the generally positively buoyant polymers. This can be attributed to Gaussian noise on the sinking velocity causing it to be negatively buoyant, or the movement from vertical mixing causing the particle to reach the bottom of the lake.

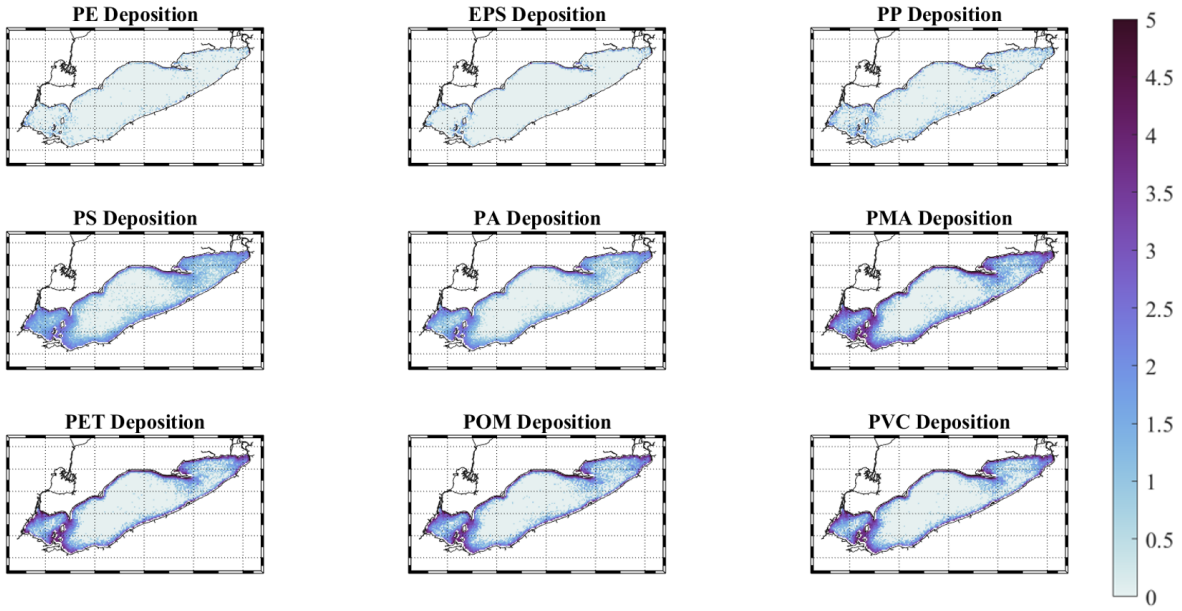

Figure 3.7: Sediment deposition concentrations for all nine modeled polymers on log scale

V. Discussion

This is the first modeling efforts in the Great Lakes that incorporates vertical diffusion and non-neutrally buoyant particles representing different polymer types as well as the first estimates of the 3D mass of plastic pollution in Lake Erie as the existing model based mass estimates were calculated using a 2D model and only gave an estimate of plastic in the surface water of the lake [54, 87]. This is also the first modeling attempt including deposition into the sediment along the entirety of the lake bed in Lake Erie. This is especially important, as sediment has been theorized as a sink for

much of the missing plastic causing the discrepancy between estimated and observed plastic masses in bodies of water [136] and plastic has been found in high concentrations in the Great Lakes [22, 27]. The sedimentation rate is especially striking when considering how long plastic has been entering the lake, and that the input rates are likely increasing.

As this is a first pass estimate, there are many improvements that could be made to the model, particularly in assumptions made about input, deposition, and sinking velocity. Along shore it is clear that because a large percentage of the plastic is negatively buoyant and therefore sinks quickly, the plastic distribution in bottom is highly dependent on the prescribed input. Particles are input uniformly around the lake in this model and this shape is evident in the areas of accumulation in deposition (Fig. 3.7). In reality, there are likely several reasons that the input is spatially and temporally heterogeneous. First, studies have indicated that rivers are a large source of plastic debris entering the Great Lakes and have a different composition than plastic types than is found in the open water [7]. Specifically, river samples contain majority of fibers whereas basin samples contain more fragments [7, 78]. Fibers tend to be denser, which is likely to lead to higher deposition rates near the outflow of rivers. Beyond rivers, points sources like wastewater treatment plants (WWTPs) have studied for releases of microplastics [91, 116]. In the Great Lakes, studies have found higher concentrations of microplastic near WWTP outflow, particularly in the size range we model in this paper [14]. Stormwater runoff has also been identified as an important source of microplastic and will have strong temporal variation [55, 80]. In large rainfall events, combined sewer overflows can discharge addition debris into the water around the Great Lakes and Lake Erie in particular. It has been speculated that CSO events could have a role in large concentrations in Lake Erie in 2012 [87]. Improving the input data to account for some or these factors would create more heterogeneous deposition patters and likely lead to higher sediment concentrations in some locations, which would potentially increase the risk for those benthic ecosystems.

Once a particle reaches the lake bed, our model assumes that is deposited in that location. In reality, plastics can bounce off the lake floor, get deposited and then resuspended, or be transported along the lake floor [30]. One potential model improvement is refining the deposition model to include

probabilities for deposition and resuspension.This would likely result in higher concentrations in offshore sediments as particles that initially hit nearshore have the opportunity to travel further into the lake. Along shore, the deposition also serves as an approximation for beaching, as particles deposited immediately along the shore (where the basin is shallow) can be interpreted to being beached. Beaching has recently been proposed as the main location of missing plastic in the ocean [73]. A more sophisticated beaching model could also provide improved results. There is no formal beaching mechanism in the model, although beaching essentially happens as bottom deposition when the depth goes to zero. In practice, similar mechanisms to deposition will also happen on shore, where plastic can be resuspended after beaching and not all plastic that hits the shore will be beached. Beaching could similarly be modeled in a probabilistic manner by defining the likelihood of being beached or resuspended. These probabilities will depend on several variables, including current and wind speed, as well as beach type and geometry.

Lastly, there are several improvements that could be made to the sinking velocity implementation in future work. As it is currently implemented, particles have the same sinking velocity no matter their placement in the lake or age. In reality, differing water densities, particle sizes, and shapes will impact sinking velocities. Additionally, the velocities will likely change over time. Currently, modeled particles with positive sinking velocities accumulate at the surface, while in reality these would likely sink over time due to biofouling [67]. As a result, the current results probably overestimate the percentage of particles that the at the surface as opposed to distributed throughout the water column and in the sediment. The sediment deposition rates predicted here, which are on the same order of predicted mass of surface plastic in the lake, especially indicate the importance of implementing a model for degradation or biofouling which would remove particles from the surface. As the model is currently implemented, when weighted by input amounts, about half of the plastics are positively buoyant and about half are negatively buoyant. Consequentially, the model predicts the fate of about half of plastic as permanently floating on the surface. In reality, these particles would likely become more dense over time and ultimately sink, meaning the model over predicts particles at the surface and under predicts amount of particles deposited in the sediment.

Chapter 4

Incorporating terrain specific beaching within a Lagrangian transport plastics model for Lake Erie

I. Introduction

Plastic is a ubiquitous source of pollution in various ecological compartments of the world's oceans and lakes. Historically, researchers have focused on modeling transport of plastic in the open ocean surface and lakes [53, 126]. However, mass estimates of surface plastic based on sampling efforts are orders of magnitude lower than what is predicted by input estimates [23]. Locations of this missing plastic have been proposed, such as suspended deeper in the water column, trapped in the sediment, or that it is filtered out by rivers and does not make it to large bodies of water [8, 18, 22, 27, 134]. However, one of the proposed explanations is that this missing plastic remains trapped in coastal zones for extended periods of time, potentially beaching and resuspending before eventually moving to off shore waters [17, 52, 74, 99]. Around the world, plastic has been abundantly observed on coastlines, serving as another indicator of the coastline as a proposed reservoir for plastic [47, 97, 140]. Coastal zones are also considered to be a major generator of microplastics as the mechanisms present

on shorelines are more likely to cause fragmentation [3, 117].

In the Great Lakes, much attention has been devoted to studying the presence of plastic transported in the water and deposited in sediment [22, 27, 29], and these mechanisms have been included in large-scale models for a more complete representation of plastic behavior [26, 53, 87]. Like in the global oceans, plastic has been found on the beaches of the Great Lakes, but specific beaching mechanisms have not been included in any large-scale hydrodynamic models for the lake [29, 140]. Previous modelling efforts in Lake Erie, which include sediment deposition, have shown significant accumulation of particles in the shallow nearshore sediment. This underlines the need to include near-shore processes, such as beaching, in these models for a more accurate understanding of nearshore plastic accumulation [26].

Surface samples taken in the Great Lakes have shown high plastic concentrations, which are even higher than average concentrations in North Atlantic and South Pacific [33, 37, 71]. Of the Great Lakes systems, Lake Erie often reports some of the highest surface plastic concentrations [14, 33, 37, 87]. Lake Erie is also an important source of fresh water for the region, and plastic has been found in tap water originating from the lake [68].

The existing work on the beaching of plastic is difficult to compare because of the variety of approaches taken. Beaching research began with a focus on sampling to understand concentrations with methods ranging from detailed surveys within specified regions of the beach to compiling data from community clean up efforts. [47, 97, 140].

Hinata et al. [52] expanded on this work to estimated residence times of plastic items on a beach. While the study only considered one beach, it showed various types of plastic items have beach residence times of 69 - 273 days by marking and tracking beached items on the beach over the course of 1 - 2 years.

Preliminary modeling work of beached plastics has not accounted for resuspension [25, 124]. Recently, Onink et al. [99] systematically tested parameterizations for plastic beaching and resuspension on a global scale, identifying coastlines and nearshore water as significant oceanic plastic reservoirs.

Currently, there is no modeled plastic beaching work in the Great Lakes. While beaching modeling work specific to plastics is not extensive, we can draw from other fields of particle modeling such as oil beaching [44]. Some observations indicate that different beach types have an impact on beaching and retention of various particles, where areas of more sediment accumulation are more likely to trap particles compared to steep rocky beaches which are less likely to retain plastic [47, 108]. Samaras et al. [109] modeled the behavior of beaching oil droplets and quantified the retention behavior of nine different beach types. However, no similar work has been done to date for microplastic resuspension.

We include our beaching model within a large-scale hydrodynamic model to capture the combined effect of the beaching and open water mechanisms. In this work we incorporate a beaching model from [99] to a previously used hydrodynamic model for Lake Erie [26, 87]. The existing Lake Erie model accounts for three-dimensional advection, diffusion, polymer density and size, and sediment deposition. Additionally, we use a high resolution shoreline classification for the lake to assign terrain specific beaching probabilities. Together this allows us to predict areas of plastic accumulation along the coastline and derive a first pass estimate for the amount of plastic on the beaches of Lake Erie.

II. Model

The hydrodynamic model was previously used in [26], and a two dimensional version was used in [87]. We apply to model to Lake Erie. Lake Erie is the shallowest of the Great Lakes, with an average depth of 19 m [1]. The persistent current in Lake Erie flows west to east with inflow in the west from the Detroit River and outflow in the east to the Niagara River [110]. In the $x-y$ direction, particle positions are advected given the dynamical system:

$$\frac{dx}{dt} = u(x, y, z, t)$$

$$\frac{dy}{dt} = v(x, y, z, t)$$

where u, and v, are the interpolated horizontal x-direction, and y-direction velocities, respectively. We assume smooth behavior of currents below grid resolution, which allow for interpolation to the particle location. Here we use cubic interpolation in space, and third-order Lagrange interpolation in time. We solve the system using a Runge-Kutta 4th order numerical scheme (RK4) with timesteps of one hour, and the code is implemented in Matlab.

In the vertical, or z, dimension we also model diffusion and density driven sinking in addition to advection. In the z-direction, the surface is set to $z = 0$ and greater depths have negative values. The vertical position is given by the Milstein solution [90] to an advection diffusion PDE model [129]. This gives z as

$$z(t + \delta t) = z(t) + (w_a + w_b)\delta t + \frac{1}{2}K'(z(t))[\Delta W^2 + \delta t] + \Delta W\sqrt{2K(z(t))}$$

where w_b is the rise velocity of the particle, w_a is vertical water velocity, $K(z, t)$ is is the vertical turbulent diffusivity, and ΔW is a Gaussian random variable taken from a distribution with mean zero and standard deviation $\sqrt{\delta t}$ for timestep $\delta t = 5$ sec. If a particle moves below the depth of the lake, we consider it deposited and remove it from the system after recording the location.

The rise velocities, w_b, were calculated using a modified version of Stokes' Law to allow for particles of irregular size [28]. With this method, we have a way to calculate sinking velocities for a range of particle sizes, densities, and shapes and also account for changes in sinking velocity due to temperature variations in lake. This method has also been previously used to model microplastics sinking velocities by [67]. Implementing sinking velocity using Stokes' Equation for particles of irregular shape [28], the velocity is given by

$$w_b = \Big(\frac{\rho_p - \rho_w}{\rho_w} g w_* \nu\Big)^{1/3},$$

where ρ_p is the density of the particle, ρ_f is the density of the water, ν is the kinematic viscosity of

the water, and w_*, the dimensionless sinking velocity, is given by

$$w_* = 1.71 \times 10^{-4} D_*^2$$

with

$$D_* = \frac{(\rho_p - \rho_w)}{\rho_w \nu^2} g D_n^3.$$

Here D_n is the equivalent spherical diameter, or the diameter of a sphere of the same volume as the particle of irregular shape. To set bounds for D_n, we first define the Corey Shape Factor (CSF) as

$$\phi = \frac{c}{\sqrt{ab}}$$

where a, b, c are the longest, intermediate, and shortest lengths of the particle respectively. We assume $b = c$, implying it is symmetric in size along two of its axes. With this assumption,

$$\phi = \sqrt{\frac{c}{a}} \tag{II.1}$$

Assuming the irregular particle is an ellipsoid with dimensions a, b, c, and recalling D_n is the diameter of a sphere with the same volume as the particle of irregular shape:

$$\frac{4}{3}\pi\left(\frac{D_n}{2}\right)^3 = \frac{4}{3}\pi\frac{a}{2}\frac{b}{2}\frac{c}{2},$$

or again assuming $b = c$ and solving for D_n.

$$D_n = \sqrt[3]{ac^2}$$

Lastly, substituting Equation II.1 into the above, we have $D_n = a\phi^{4/3}$.

An irregular particle presents a worst case scenario for D_n, as for a perfectly spherical particle D_n is simply the diameter, so we assume an irregularly shaped particle to calculate a lower bound on D_n. To find this lower bound, we use values for CSF from literature, specifically $\phi = 0.6$ which was estimated as the mean CSF for a fragment [66]. Fragments make up 31% of microplastics found in water sampling, the second most common shape after fibers, which represent 48.5% of sampled shapes by count [13]. We do not model fibers because the shape is too irregular to calculate sinking velocity or model as a passive tracer. Additionally, while fibers are common by count, they have a low mass compared to particles are are unlikely to account for a significant portion of missing plastic mass [66].

Plastic sample sizes are typically reported as the length of the longest dimension, which here is equivalent to a. To generate a range of values for D_n, we randomly generate numbers uniformly distributed between $D_{n(min)} = a_{min}(.6)^{4/3}$ and $D_{n(max)} = a_{max}$ for whatever range particle size (a_{min} to a_{max}) we wish to model. Here we model particles with longest dimension from 1.00 mm to 4.75 mm. It is possible that uniform may not be the best distribution for particle size, as sampling efforts tend to find higher quantities of particles at smaller sizes [66]. Investigating different distributions for size could be a potential improvement in future work.

To include beaching, we follow the approach of [99]. We first identify all particles within a 2x2 km grid cell that borders the coastline of the lake as nearshore. The probability of beaching for any nearshore particle is given as

$$P_b^i = 1 - \exp\left(-dt/T_b^i\right),$$

where dt is the time step and T_b^i is the characteristic beaching time at that shore point i. Once a particle is beached, the probability of resuspension is given by

$$P_r^i = 1 - \exp\left(-dt/T_r^i\right),$$

where T_r^i is the characteristic residence time for plastic on the beach for that beach type.

We expand the beaching model to include beach type dependence. To classify beach types, we interpolate a beach type data set to our model grid (Figure 4.1).We classify seven different beach types of sand beach, artificial, coarse grain flat coast, coastal wetland/riparian zone, N/A – mixed beach, rocky cliffs/bluffs, and sediment scarp (Table 4.1). These beach types were selected because they were the classification types in the data set, taken from [133]. To include the beach type dependence in the model, we choose T_b^i and T_r^i values based on that beach type at shore point i. The beaching probability does not depend on changes in the local hydrodynamics, but the stochastic nature of the parametrization is intended to account for this.

There is a lack of research on beaching behavior for plastics specifically, so we use ratios, γ_r^i, of the residence time of oil droplets on sand beaches to the residence times for other beach types in the Mediterranean Sea [109]. The beach types in this paper do not directly correspond to the classifications in our data set, so they were paired as accurately as possible, in some cases using satellite images of shorelines to identify characteristics (Table 4.1). We then use the characteristic residence time, T_r^{sand} for plastics on a sand beach from [52] to predict residence times, $T_r^i = \gamma_r^i * T_r^{sand}$, for all other shore types. We make the assumption for all beach types that the characteristic beaching time is dependent on the reciprocal of the residence time ratio, where $T_b^i = \gamma_b^i * T_b^{sand}$ with $\gamma_b^i = 1/\gamma_r^i$. This assumption is made because if a certain beach type has a high probability of beaching, it is also likely to trap the plastic leading to a long residence time. Conversely, beach types with a low probability of beaching are expected to have a low residence time. This is similar to the approach by [99], where resuspension times were varied using a ratio for the sandiness of a coastline.

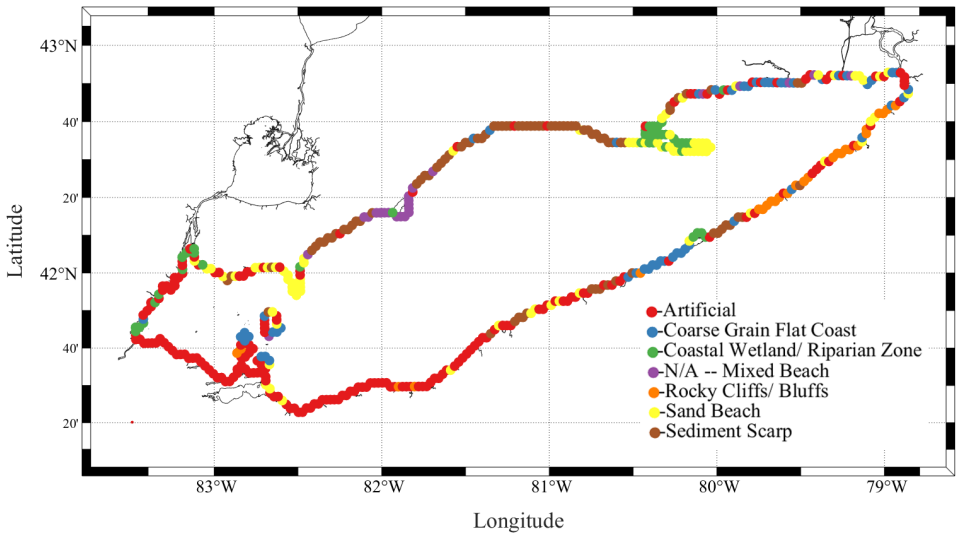

Figure 4.1: Beach type classifications interpolated to model grid for Lake Erie

Table 4.1: Beaching time and residence time ratios to sand beach for beach type classifications.

Erie Classification [133]	Samaras Classification [109]	Beaching time ratio to sand beach γ_b^i	Residence time ratio to sand beach γ_r^i
Sand beach	Sand beach	1	1
Artificial	Rocky shore	4/3	3/4
Coarse grain flat coast	Sand and gravel	1	1
Coastal wetland/ riparian zone	Sheltered marsh/ mudflat	1/5	5
N/A – Mixed beach	Sand and gravel	1	1
Rocky cliffs/ bluffs	Seawall, concrete, ect.	Inf	0
Sediment scarp	Exposed headland	24	1/24

To examine the sensitivity of the model we also run a version with no beach type dependence (NBD), meaning a particle has the same probability of beaching or resuspending at any shore point. In the NBD model, the values for T_b and T_r are fixed for the entire lake, so T_b^i is either 1, 2, or 5 days depending on the run, and $T_r^i = 69$ days. These values are constant for all i. This was the lower range of observed residence time for plastics on a beach based on field observations [52], and was also a value used in previous modeling work [99]. The choices for T_b^i are the lower range of values used in modeling work in the worlds oceans [99]. They were chosen to reflect the lower overall time scales in the smaller system of the lake, as compared to the ocean.

For all models, we prevent nearshore particles from being deposited. This is done to isolate the effect

of beaching because as depth goes to zero, we cannot differentiate between beaching and deposition, and deposition is permanent in the model. If model dynamics cause particles to move below the depth in a nearshore cell, they are reset to above the lake floor by a distance of 5% of the lake depth in that location. We do not anticipate near shore deposition would dramatically impact results, because we model floating polymers that are less likely to sink in the lake.

In order to further understand the impact of beach type dependence on accumulated particles, we also use a reduced model without transport and compare full model results to expected number of particles for each beaching probability. In the reduced model without transport, we only model beaching and resuspension. We release particles along the shore in the water and only give them the mechanisms of beaching and resuspending. This allows us to independently analyze the beaching behavior with no impact from the other model mechanisms. To calculate the expected number of beached particles, we set up a system of differential equations for the number of beached particles, B, and nearshore particles in the water, W, at any shore point experiencing only beaching:

$$\frac{dB}{dt} = P_b W - P_R B$$
$$\frac{dW}{dt} = P_R B - P_B W$$

where P_B is the chance of beaching at the shore point and P_R is the chance of resuspension. To find the steady state, we set them equal and see

$$B = \frac{P_B}{P_R} W,$$

but W is still unknown. As beaching is the only mechanism here, we know $B + W = n$ where n is the number of particles released at this shore point. So we have

$$B + \frac{P_R}{P_B} B = n, \text{ or } B = \frac{n}{1 + \frac{P_R}{P_B}}.$$

To input plastic into the model, we release a particle from every nearshore grid point, for a total of 492 particles, and assign each particle a weight representative of the nearshore population at the release point. Nearshore population data comes from [53], and this was also the same method used in [26, 87]. The nearshore population is calculated using US and Canadian census data of postal regions along the lake. We release particles every 12 hours for the first two months of each run. This is done because the modeled distribution of coastal and beached plastic is sensitive to input, and this way we can track the evolution of the distribution without the influence of continuously released plastic. This was also the same approach taken by [99]. These simulations are run with particles of polyethylene (PE) which is positively buoyant, with initial densities, ρ_p, randomly sampled from a uniform distribution from 917 to 965 kg/m^3 [51]. We choose to model polyethylene because it is positively buoyant, meaning unlike a negatively buoyant particle, it will not sink shortly after entering the lake. Floating particles have the opportunity to experience beaching and nearshore dynamics. Polyethylene is also very common; it makes up about 32% of all produced plastic, more than any other single polymer [41].

We use interpolated temperature, diffusivity, and current output from NOAA's Lake Erie FVCOM hydrodynamic model ran using forcing files from 2012-2014 [16]. FVCOM uses an unstructured grid to fit smoothly to shoreline. For our use, the FVCOM output was linearly interpolated to a regular 2 km spaced grid to reduce computational cost of interpolation within the model. A 2 km grid has been previously used for plastic transport mesh size in Lake Erie [26, 87]. FVCOM is the operational hydrodynamic model used by NOAA Great Lakes Environmental Research Laboratory (GLERL). The density and viscosity of the water, ρ_w and ν, are calculated using the state equations for water with salinity zero and temperature output from FVCOM [40].

III. Results

We first ran model simulations with no beach type dependence (NBD) for a year each, over three runs comparing different parameters. The simulation length was chosen to balance long term model

behavior and computational cost while comparing parameter choice. The three choices of 1 day, 2 days, and 5 days for the parameter T_b in the NBD model had a significant effect on the number of beached particles (Figure 4.2). With each choice of beaching parameter, the beached fraction increased linearly over the first two months, and then after the particle input ended the beached fraction slowly decreased over time. Lower T_b values reduce the total beached fraction, but the general qualitative behavior remained the same. Because the general behavior is the same for all values of T_b, we choose $T_b^{sand} = 2$ days for the beach type dependence model runs as it is a intermediate choice. The model with beach type dependence is run for three years to capture more long term beaching behavior. We chose three years for the run length because Lake Erie has a hydraulic residence time of 2.7 years [102]. One choice was used for T_b^{sand} in the three year run to limit computational cost.

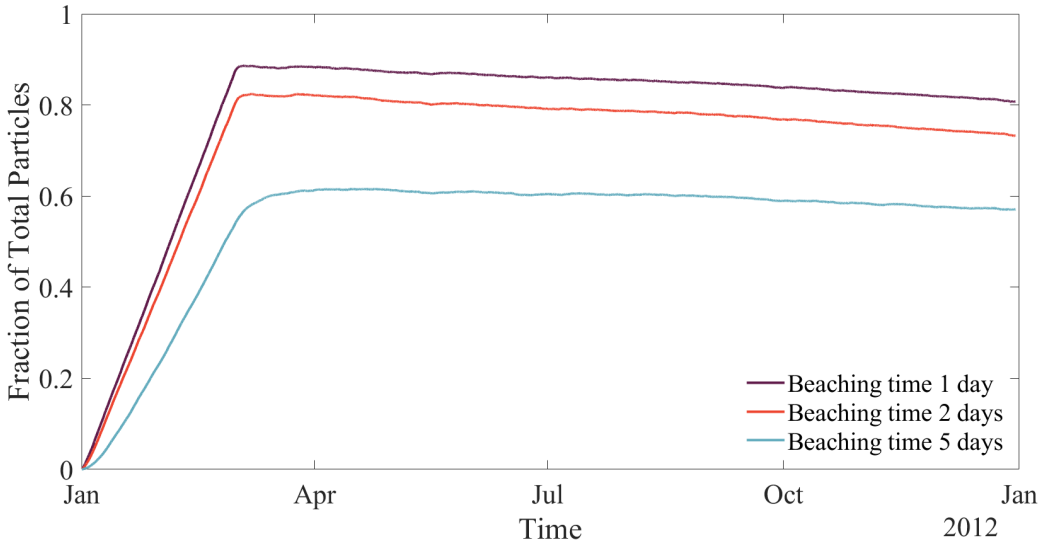

Figure 4.2: Comparison of three values for expected beaching time, T_b, for the model run with no beach type dependence (NBD). Residence time for plastic on the beach was fixed at $T_b = 69$ days for all three runs.

We define four reservoirs particles can be in. These reservoirs are beached, deposited, offshore, and nearshore, where nearshore are particles in the adjacent 2 km x 2 km grid cell to shore (Figure 4.3). Beached particles make up a majority of all particles after a year long simulation, 62.7% for the model with beach type dependence and 71.9% without beach type dependence. As for differences between the two models, there are slightly fewer beached particles in the beach dependence model

because there is, on average, a lower probability of beaching across the lake of .058 versus .061 per three-hour timestep. There is no accumulation of nearshore deposited particles that has been seen in other modeling work because there is no deposition in nearshore grid cells [26]. However, of the reservoirs, the number of deposited particles is the only one with monotonic growth, as it is the only reservoir particles cannot move out of. In this model, deposition is permanent, while in reality particles may have the chance to resuspend. This is a deficiency of the model both as it does not reflect lake dynamics, and if the model were to run indefinitely, all the particles would eventually be in this reservoir.

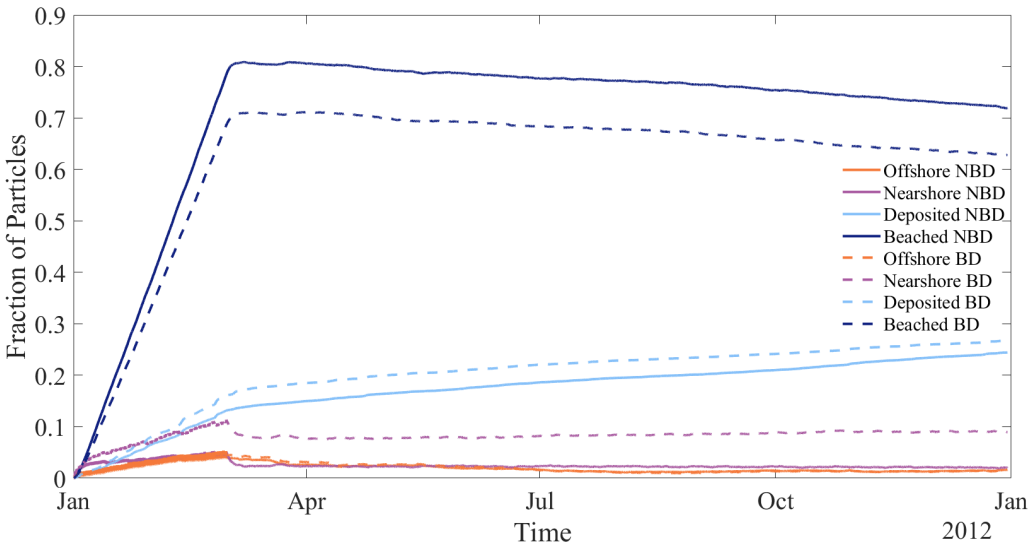

Figure 4.3: Particle locations over one year for both beach type dependence (BD) and no dependence (NBD) with $T_b = 2$ days

Additional motivation for a more sophisticated sediment resuspension model comes from examining the distribution of particle sizes remaining in the system. Particle density and size begin with uniform distributions. When considering floating, non-beached particles, we see after the three-year run a distinct preference for larger particles to remain in the system (Figure 4.4). This is likely due to smaller particles being closer to neutrally buoyant, and thus more likely to move down the water column and ultimately be deposited. This is also consistent with observations by [35], who found fewer smaller microplastics than expected in surface samples, which could be due to increased susceptibility to vertical transport mechanisms. This skew towards larger particles is less noticeable

among the beached particles, where the distribution of the diameters is closer to uniform. This is likely because particles can accumulate on the beach where their size and rise velocity becomes meaningless in the scope of our model, and they can not be deposited. Within our model, being beached protects particles from the mechanisms that can introduce a bias towards larger particles. It is possible that if deposition was not an ultimate fate, the size distribution would not be as skewed at the end of the run.

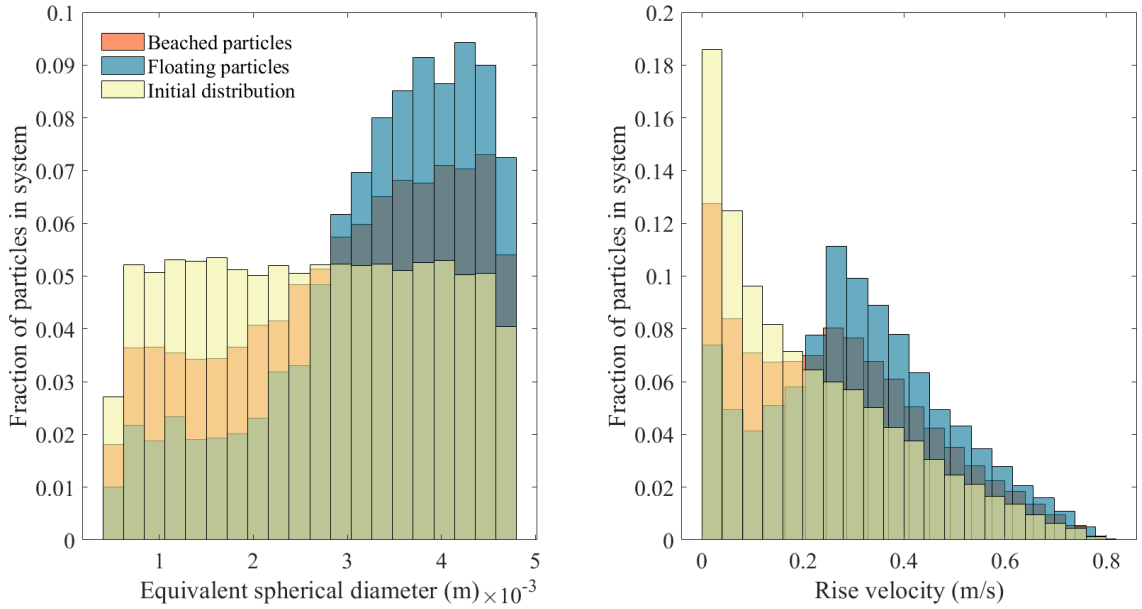

Figure 4.4: Distributions of particle equivalent spherical diameter, or the diameter of a sphere of the same volume as the particle of irregular shape (left) and calculated rise velocities (right) in the system for beached and floating particles after a three year run. A floating particle has a positive sinking velocity.

In nearshore water we have removed deposition and replaced it with beaching. However, in the rest of the lake as it is currently implemented, particles are permanently deposited if they hit the lake bed. We also do not account for resuspension from the sediment, which causes the number of deposited particles to increase monotonically. This reduces the number of particles active in the system over time. In a real lake, plastic may resuspend, or move along the lake floor. A more sophisticated model for deposition would ideally incorporate strategies used in this beaching model such as lake bed type specific chances of deposition and resuspension, or consider near-bed velocities and particle transport along the lake bed [30, 61]. However, such data is currently not available and would require additional laboratory and field experiments.

Our model does not account for mechanisms that can remove positively buoyant plastic from the surface, but these mechanisms would also increase depositions. In our model, this would likely have the effect of increasing deposition and reducing the amount of beached plastic. Positively buoyant plastics have been found in samples in both nearshore and deep sea sediment [38]. This is potentially because of biofouling, or the buildup of organic matter and organisms [139]. Biofouling can increase the density of a particle, causing it to sink over time [39, 67, 139]. The role of biofouling could be studied in a future model iteration by combining the current hydrodynamic model with a marine ecosystem model, such as with [82]. The amount of beached plastic could also be influenced by fragmentation, which we do not account for in our model. Fragmentation is the breakdown of the size of plastic particles, often caused by photo-degradation and abrasion [9]. The mechanisms that cause fragmentation can be stronger in shallow, nearshore water, potentially causing fragmentation to have an increased impact on beached plastic [74].

Initially when implementing the beach type dependent model, we hypothesized that beach type would be the predominant factor impacting plastic accumulation. It does have an undeniable impact, especially in regions with a high probability of beaching, such as wetlands. However, we still see many similarities between accumulation patterns for both the beach dependence and no dependence models (Figure 4.5). These similarities can likely be explained by shore geometry and advection patterns, which are constant through both models. Additionally, some impact from beach type may indirectly be included in the no dependence model. Regions of high sediment accumulation (i.e. sandy beaches or wetlands) have high probabilities of beaching in the model, but also the lake has the physical properties that made this specific beach type in the first place over a much longer timescale, which could also allow for plastic accumulation.

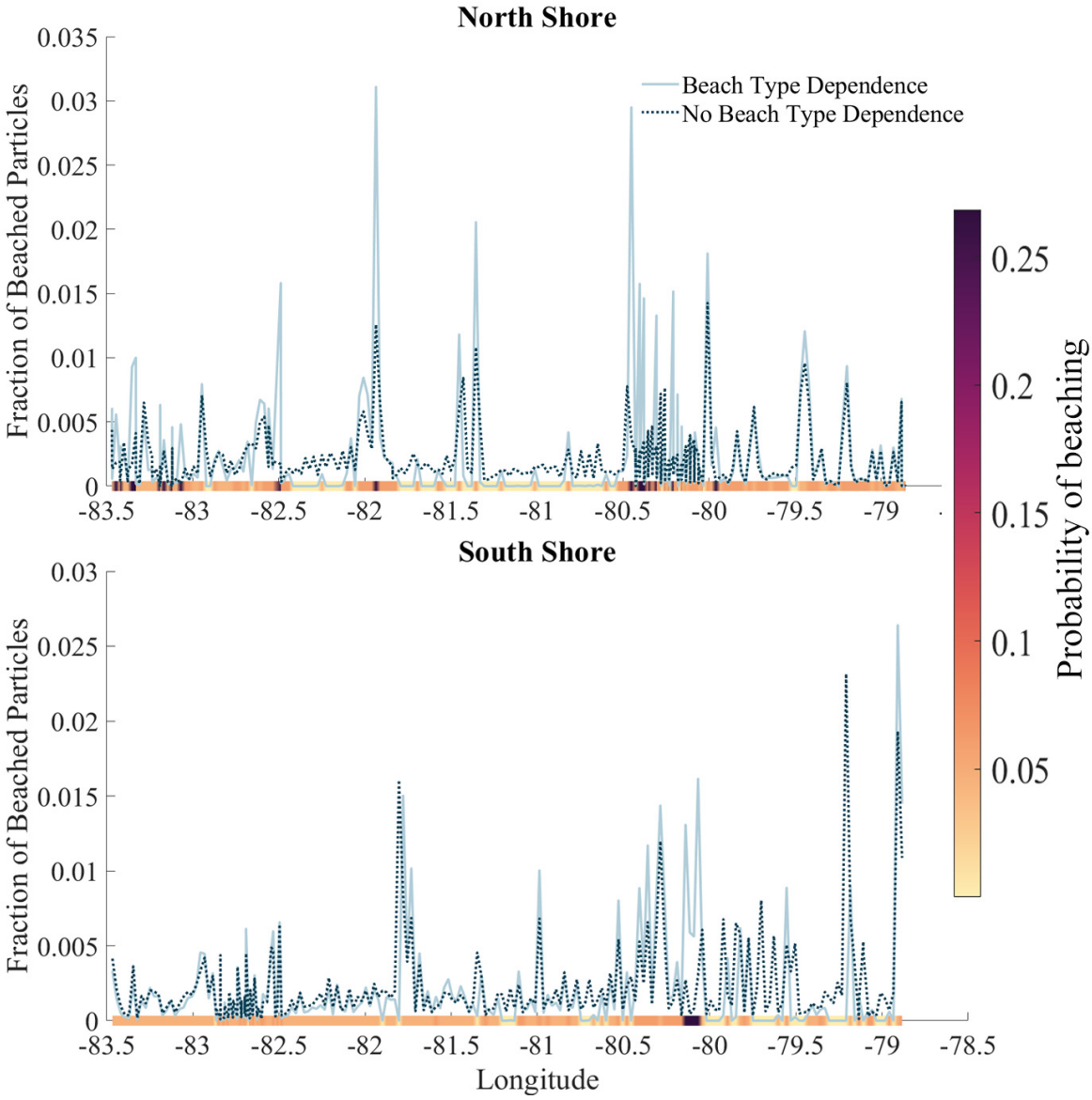

Figure 4.5: Number of particles beached on the North and South shores for the model with and without beach type dependence. For the model with beach type dependence, chance of beaching is shown on the x-axis.

If we perform regression between expected number and observed number of particles in the model beached for a reduced model without transport, we see $R^2 = 1$, but when performed for the full model with beach type dependence, we see $R^2 = .50$. This correlation value implies that beach type and corresponding beaching probability is not necessarily the leading mechanism behind beach accumulation patterns. Rather, other mechanisms at work in the lake such as advection or deposition have a large impact, as we also observed when comparing the model with beach type dependence and no dependence (Figure 4.5).

We also see the influence of other mechanisms when we consider average particle counts of the full model with beach type dependence compared to the reduced model without transport (Figure 4.6). When beaching is the only mechanism acting, all the particles in the system will likely become beached if there is any significant probability of it happening. This is because they can not be transported away from the shore, and remaining in a nearshore cell gives enough repeated chances for beaching that it is almost certain to happen. For the beaching timescales we studied, resuspension does not seem to impact this accumulation too greatly because the characteristic timescale is so long compared to beaching. However, when advection is also present and able to move particles through the water, chance of beaching at a location is more influential as a particle does not have as many chances to beach. This leads to less particles being beached where there is a lower chance of beaching, and more being beached where there is a higher chance. This is especially apparent at the highest beaching probability, where the full model has an average more than double the average of the reduced model without transport.

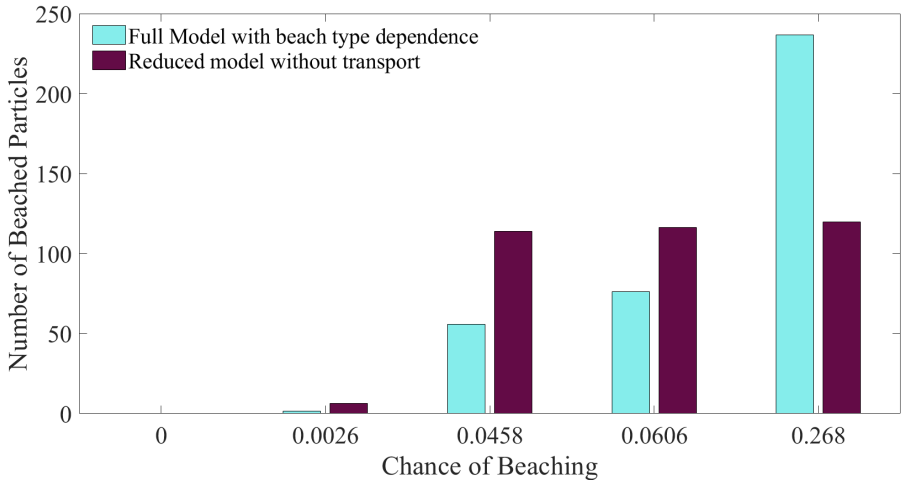

Figure 4.6: Comparison of average number of beached particles for different beaching probabilities for the full model with beach type dependence and a simplified model that only simulates beach type specific beaching and does not include any of the transport mechanisms.

The predominantly west to east currents, caused by the prevailing wind and outflow on the east side of the lake, have a large impact on patterns of accumulation and areas with the highest concentrations of beached plastic in the lake. Plastic tends to be pulled towards the eastern side of the lake, which causes plastic in this region to come from all over the lake. Plastic beached at the western side of

the lake tends to originate almost entirely from within that region of the lake. When we consider the amount of particles beached by count, this behavior is fairly uniform across the lake, i.e. as we move east, the percentage of beached plastic that originated within that same region drops (Figure 4.7). Specifically, in the western most region of the lake (Region 1 in Figure 4.7), 100% of beached plastic comes from within that region. Contrasting with this, the eastern most region containing Buffalo, NY (Region 10 in Figure 4.7) produced only 41% of the plastic by particle count beached there.

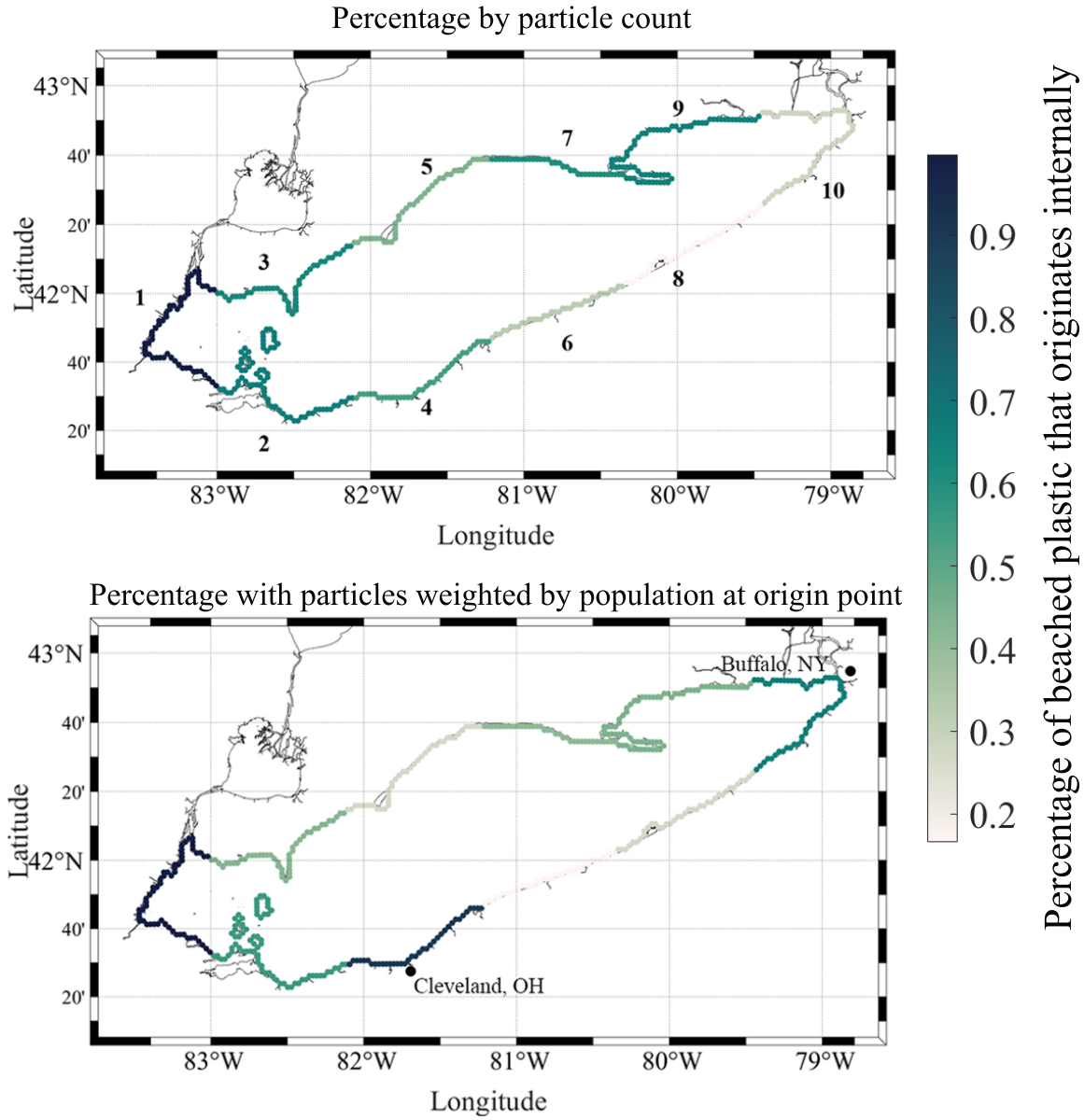

Figure 4.7: Percentage of beached plastic in a region that originated internally. Top: percentage by particle count, bottom: percentage with particles weighted by population at origin point. Numbers in top figure correspond to region number.

However, the impact of population centers on the lake can disrupt this trend. If we weight the particles by the nearshore population where they originated, the percentage of plastic in the Buffalo, NY (Population 1.1 million) area that originated internally rises to 74% (Figure 4.8) [12]. Additionally, after weighting particles by population, the percentage of plastic in the Buffalo region originating from Cleveland, OH (Population 2.0 million) rises from 2% to 8%. Within the Cleveland region itself (Region 4 in Figure 4.7), the percentage of internally produced plastic rises from 63% to 91% after weighting by population. The effect of population centers and prevailing currents can work together to impact regions down current from population centers. In the region immediately to the east of Cleveland (Region 6 in Figure 4.7), 54% of the beached plastic originated in the Cleveland region when weighted by population. It is also possible that the beach types across these regions could impact accumulation patterns (Table 4.2). The coastal wetland beach type only account for 8% of the shoreline in the lake, but holds 29% of beached plastic. These regions likely trap plastic that would otherwise be transported out of that region, and may drive accumulation in the regions they are located such as the western end of the lake (Region 1) or the north east coast (Region 9). Conversely, sediment scarp makes up 17% of the shoreline, but only holds .4% of beached plastic. This may prevent regions with sediment scarp from accumulating self produced plastic, and instead offload it to other regions.

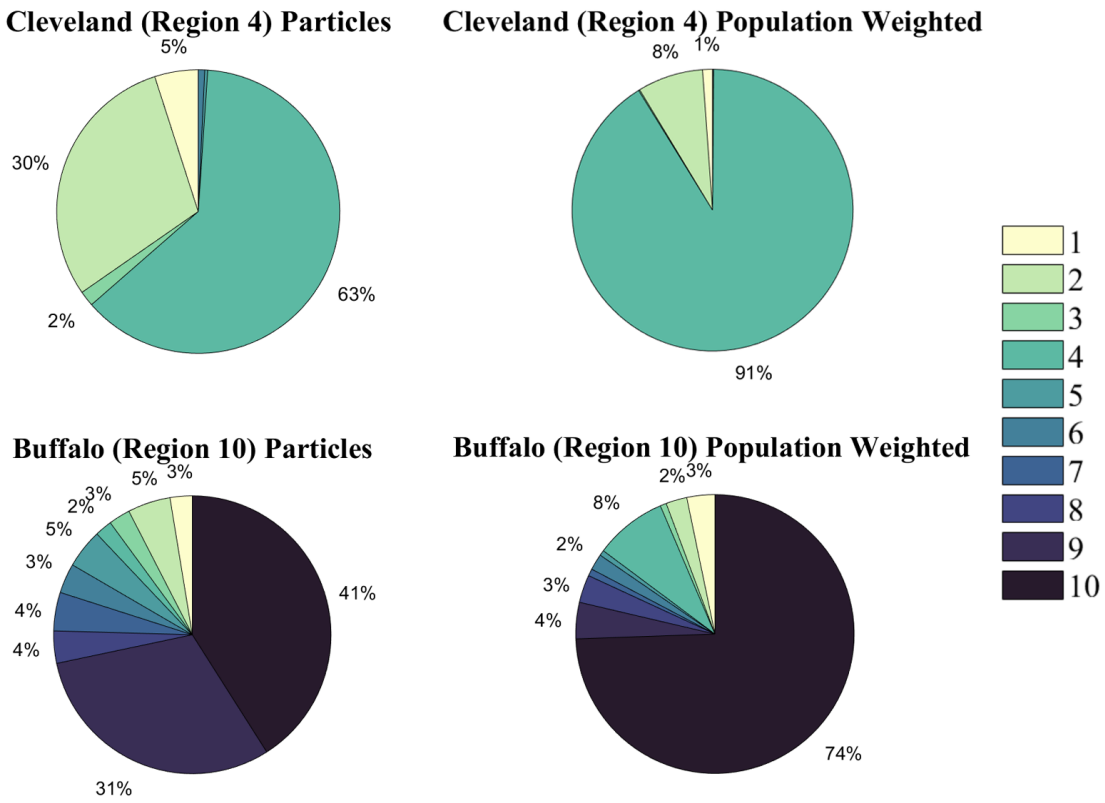

Figure 4.8: Origins of beached particles in Cleveland (Region 4) and Buffalo (Region 10). Left: percentages by particle count, Right: percentages weighted by population at particle origin point

Table 4.2: Portion of the shoreline each classification makes up and what portion of beached plastic is beached in that type across the lake after 3 years with BD model.

Beach type	Portion of shoreline	Portion of beached plastic
Sand beach	.15	.09
Artificial	.38	.33
Coarse grain flat coast	.11	.21
Coastal wetland/ riparian zone	.08	.29
N/A – Mixed beach	.04	.06
Rocky cliffs/ bluffs	.05	0
Sediment scarp	.17	.004

We compare our three year run results, ending in 2013, to the one published beach sample data for Lake Erie that is available in the literature with samples from 2008 [140]. To compare, we normalize our model concentrations and sample concentrations by dividing each by the sum of concentrations of that type (Figure 3.1). When considering our model ran with beach type dependence, we see

both the highest sample concentration (Presque Isle) and the lowest sample concentration (Port Stanley) agree with the locations of the highest and lowest model concentrations. However, there are some faults with this comparison. The sample locations were all classified as sandy when reported, however the model only classifies shore type down to the grid cell, which is 2 km by 2 km, and does not allow for high enough resolution to capture the full shore complexity. Thus, we see that our model only classifies two of the sample locations as sandy. Additionally, it is especially difficult to compare beached plastic sample data to model results. The beach samples used here, and in general, are normally only taken on sandy beaches. As this is only one beach type, we do not receive data on concentrations for other types to examine model behavior compared to samples in other terrain. Additionally, sand beaches are most likely to be used for recreation, and consequentially more likely to be the site of grooming or trash pickup efforts, which can skew samples collected there. Ideally, the model could be improved by validating with more current beach samples, taken at regular spacial intervals around the lake to account for all beach types, rather than just sandy. In addition, regularly revisiting beach sites would provide greater insight into the temporal variability of samples concentrations.

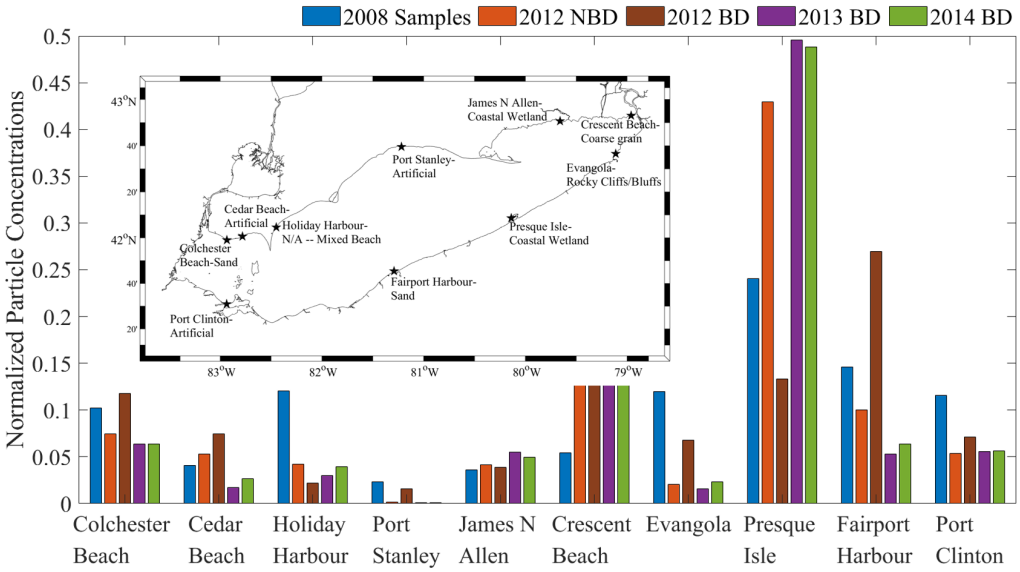

Figure 4.9: Comparison to 2008 samples [140] for 2012 with no beach type dependence (NBD) and 2012-2014 with beach type dependence (BD). Model classifications of beach type and sample locations shown on the inlaid map.

IV. Conclusions

In the world's lakes and oceans plastic mass estimates based off surface sampling differ by multiple orders of magnitude from what is predicted by input estimates, indicating large quantities of missing plastic that are not present at the surface. In the oceans, it has recently been proposed that nearshore beaching plastic is the predominant location of this missing plastic [46, 73, 93, 99, 113]. Additionally, previous modeling modeling work for Lake Erie has shown high accumulation of plastic in the sediment in grid cells along the coast, further motivating the inclusion of beaching in the model [26].

Here we model particle beaching within the scope of a three dimensional hydrodynamic model, as the first work for the Great Lakes to do so. Additionally, this is the first large-scale beaching model to include specific plastic beaching probabilities for multiple beach types from broad morphological typologies. The total amount of beached plastic is sensitive to parameter choice for characteristic beaching time, T_b, so it is difficult to draw any definitive conclusions about what percentage of plastic litter we expect to be beached in the lake. However, the general accumulation behavior did not show a high dependency on parameters, at least for the parameters tested here. For all the parameter choices we considered, the majority of plastic in the system is beached. We also found that besides shore type, other factors such as advection and shoreline geometry impact accumulation patterns in the lake. We also found that as one moves east across the lake, there is more impact from input from all over the lake, while at the western most side of the lake, 100% of beached plastic is internally produced. We did find that population centers disrupt this general west to east accumulation pattern by causing higher accumulation in their regions, or regions downstream. We would expect comparable results for a similar body of water such as Lake Ontario which has similar size, shape, and prevailing currents as Lake Erie [1]. However, local flow and beach characteristics along with the distribution of population centers can influence beached plastic accumulation.

The parameters used in our model could be improved by additional experimental research on plastic beaching. Additionally, model beaching results are difficult to validate because beach samples often

do not reflect the true amount of plastic that is likely to have accumulated. As is the case for Lake Erie, beach samples tend to be taken on sandy beaches [140]. In addition to being unable to compare across beach types, sandy beaches are often used for recreation, and litter is typically routinely removed by grooming or pickup efforts, skewing down the amount of plastic reported in these locations [29]. A sampling effort that took regularly spaced samples around the lake, regardless of beach type, could provide better data for model validation [47].

Beaching plastic results are also heavily dependent on input data, as compared to other plastic modeling, because land-based plastic enters the system directly at the beaching location. In the worlds oceans, land-based plastic is considered the dominant source of plastic pollution [62]. Additionally, while we include population based plastic input from around rivers, we do not specifically model river input as a point source, but rather distribute this input along the coastline near the river mouth. This has the potential to impact accumulation patterns near the river mouth. Wastewater treatment plants (WWTP) are also understood to be a source of microplastics [91, 116]. Additionally, we do not account for plastic released within the lake from fishing or shipping [29]. With a more encompassing input data set, we could likely improve our beaching model and further understand the most impacted areas.

While future work can expand on our findings here, this serves as preliminary model of beached microplastics in Lake Erie. We find that while our parameter choices were uncertain, for the parameters we tested the general behavior of the plastic was similar, with a majority of plastic being beached. The model used here indicates that accumulation in the lake is very dependent on advection patterns, with some impact from shoreline geometry and population centers. In future work we hope to be able to refine parameter choices and include a more complex deposition model.

Chapter 5

Modeling the three-dimensional transport of and impacts of biofouling in Lake Erie and Lake Ontario

I. Introduction

Plastic pollution in large bodies of water is a growing research field, in part because of the huge quantities that enter the water and the potential harm to humans and ecosystems it poses [15, 58, 103, 104, 105]. Despite this attention, there is still a great deal of uncertainty regarding the transport and fate of plastic. Sampling efforts in the Great Lakes have shown that plastic is a ubiquitous pollutant in water, sediment, and along shorelines [21, 36, 37, 87, 140]. However, sampling efforts can be time consuming and logistically challenging to take, and it is not possible to use samples to achieve a full spatial or temporal distribution of plastic as a pollutant [70]. Plastic modeling studies are important because they can fill in the gaps in knowledge left by sampling efforts, which helps identify which regions of the lake are most impacted, and therefore risk can be predicted.

Surface mass estimates derived from empirical studies differ by orders of magnitude from what is predicted by production and input rates in the worlds oceans [23]. This is also true for the Great

Lakes, which have plastic concentrations comparable to surface samples in the oceans [87]. Annual plastic input to Lake Erie is estimated to be 2520 tons [53], but there is only an estimated 6.45 tons floating in the surface waters [87]. There has been an increase in plastic hydrodynamic modeling studies in both the worlds oceans and lakes in recognition of the growing concern about plastic pollution and in an effort to reconcile input estimates with empirical measurements [53, 77, 89, 127]. While the existing plastic modeling efforts provide valuable insight, the fate of plastic in large waterbodies, especially freshwater systems, is largely unknown.

Although the fate of the "missing" plastic is uncertain, empirical estimates suggest that plastic takes hundreds to thousands of years to fully decompose, so it must still be located in other reservoirs [58]. Some of these potential reservoirs or exit pathways include plastic beached on shore, transported out of the lake, or broken down to smaller than detectable size [53, 119]. Plastic can also be located deeper in the water column, or deposited in the sediment[9, 136]. Plastic has been found in deep sea sediment samples,[136] and in sediment samples in the Great Lakes [8, 22, 27, 78]. [22] determined that the pattern of plastic concentration with depth in the sediments in Lake Ontario implied it had been accumulating there for at least the last 38 years. Some of the presence of plastic in sediment can be explained by the nature of the polymers entering the water. Roughly 40% of globally produced plastic is negatively buoyant, such as polyvinyl chloride (used in pipes, flooring or plastic wrap), or cellulose acetate (used in cigarette filters), and will immediately begin to sink after entering the water [3, 29, 58]. However, even normally positively buoyant polymers, such as polyethylene (used in packaging, bags, or films) or polypropylene (used in food containers or dishes), have been found in sediment samples [38].

One proposed reason for the presence of these positively buoyant polymers in the sediment is biofouling, or the buildup of organisms and organic matter on the surface of plastic particles [139]. Biofouling may change the net density of the particle, causing it to sink over time [39, 67, 139]. During the fouling process, initially just a biofilm forms on the particle, but this film allows for the attachment of invertebrates and algae, which along with the film, can further increase the net density of the particle [81]. It is not well understood how long this process takes. There have been

laboratory studies on the timescale of fouling in salt and freshwater [39, 60, 114]. There is still a lack of understanding of how the fouling process occurs for different particles, especially in freshwater, and how exactly a particle's density or settling velocity will change once it begins to foul.

Early experimental work suggested that plastic would foul and sink in the water, but could then "defoul" when light reaching the particle was limited at greater depths, which would cause the density of the particle to decrease [139]. This could theoretically result in oscillating behavior, with repeated fouling and sinking followed by defouling and rising. This oscillating behavior was also shown in a later theoretical model of biofouling [67]. However, other experimental work has shown both a linear and logistic increase in the sinking velocity of polystyrene and polyethylene, respectively [60, 114]. Previous work in the world's oceans has included a biofouling model within a transport model, but no similar work has been done in the Great Lakes [82], in spite of the high concentration of plastic found in the Lakes and their clear economic and ecological importance. While more experimental work is needed to fully understand the biofouling process, modeling the potential for biofouling to influence sinking behavior will advance our understanding of the potential fate of plastic in freshwater systems. The focus of this work is not to develop a model for the specific underlying mechanism for the colonization and fouling of particles, but to explore the implications of and differences between the predicted fate and plastic distributions given by the two most commonly proposed functional models describing biofouling.

We compare these two potential biofouling behaviors, logistic and sinusoidal, in an effort to understand the sensitivity of the plastic distribution within the lakes to not only the models themselves, but also to parameterizations within each model. Both the logistic and sinusoidal models assume biofilm growth increases the density of a particle, which causes fouling to be a mechanism that remove plastic from surface water. The first model is a logistic model, which assumes simple biological growth on the surface of the particle, and is based on previously observed behavior, which does not always show defouling [39, 114]. The logistic model is also influenced by population modeling concepts, and is the standard model for a population with a carrying capacity [64]. Here the population is the growth of the biofilm on the surface of the particle, which is limited by available surface. The

logistic model does not allow for defouling of the particle.

The second model is a sinusoidal fouling model. This model expands on the logistic model by including a fouling period followed by a defouling period, and surface area to volume ratio dependence. It is based off of experimental and modeling results [67, 139]. The defouling periods allow for times where the particle becomes less dense, as the growth dies off. This models assumes that the biofilm is made up primarily of photosynthetic organisms, which would be impacted by changes in light availability [60].

Biofouling is thought to impact particles of different sizes differently, as it is believed that smaller particles may foul faster because, unless the particles are flat, smaller particles have a larger ratio of surface area to volume [67]. Supporting this idea, it has been observed that smaller fouled particles begin sinking faster than larger particles [39, 114]. This is consistent with empirical field measurements, where researchers have found fewer smaller particles than expected in ocean surface samples, with size-dependent biofouling as one proposed explanation [35]. Because of this, following the comparison of the two functional models, we explore the impacts of a surface area to volume ratio dependence on the sinusoidal fouling model. This allows us to investigate some of the influence size may have on the behavior of fouled particles.

Previous three dimensional modeling work for Lake Erie has shown an accumulation of positively buoyant particles in the water's surface [26]. Biofouling would reduce this behavior and increase the deposition rate into the sediment. Here we incorporate functional models for biofouling into a large scale hydrodynamic transport model. The transport model includes advection, vertical diffusion, particle size and density, and deposition into the sediment. We investigate the effects of biofouling in Lake Erie and Lake Ontario, two of the five Laurentian Great Lakes. We have performed previous modeling work with Lake Erie, and choose to compare it to Lake Ontario because they are similar in size, shape, and retention time [1]. However, Lake Ontario is much deeper, with an average depth of 86 m compared to 19 m in Lake Erie. Because biofouling has a direct impact on particle depth, the increased vertical space in Lake Ontario will impact results. Additionally, this is the first plastic

transport modeling effort for Lake Ontario.

II. Model

We use the same transport model equations for both Lake Erie and Lake Ontario, but the simulations are run separately. The hydrodynamic model was previously used in [26] for Lake Erie and includes three-dimensional advection, vertical diffusion, and density driven sinking/rising. A two dimensional version was used in [87] including only advection. Mathematically, particle positions in the $x-y$ direction, are given by the dynamical system:

$$\frac{dx}{dt} = u(x, y, z, t)$$

$$\frac{dy}{dt} = v(x, y, z, t)$$

where u, and v, are the interpolated horizontal x-direction, and y-direction velocities, respectively. We interpolate to the particle location based on the assumption of smooth behavior of currents below grid resolution and solve the system using the Runge-Kutta 4th order numerical scheme (RK4) with timesteps of one hour. The interpolation used is cubic interpolation in space and third-order Lagrange interpolation in time.

In the vertical z-dimension we model diffusion and density driven sinking in addition to advection. The vertical (z) position is then given by the Milstein solution [90] to an advection diffusion PDE [129] as

$$z(t+\delta t) = z(t) + (w_a + w_b)\delta t + \frac{1}{2}K'(z(t))[\Delta W^2 + \delta t] + \Delta W\sqrt{2K(z(t))}$$

where w_b is the sinking velocity of the particle, w_a is vertical water velocity, $K(z,t)$ is is the vertical turbulent diffusivity, and ΔW is a Gaussian random variable taken from a distribution with mean

zero and standard deviation $\sqrt{\delta t}$. In this work a timestep $\delta t = 5$ sec was used. We include deposition by finding particles which have a z position below the model grid bathymetry at the end of a time step. These particles are considered deposited and removed from the system after recording the deposited position.

The currents, diffusivity, and temperature fields used to calculate water density and viscosity, came from the unstructured grid Finite Volume Community Ocean Model (FVCOM) with wind and boundary condition forcing files from 2014 in Lake Erie and 2018 in Lake Ontario [16]. FVCOM is the operational forecast model used by NOAA Great Lakes Environmental Research Laboratory (GLERL) for Lake Erie, Lake Michigan, and Lake Huron and is being developed for use in Lake Ontario. In Lake Erie, the model code was provided for us by GLERL and was run on the NSF funded XSEDE Comet cluster [122]. For Lake Ontario, the output fields were provided for us by Eric Anderson at GLERL. FVCOM current output has been used previously for plastic modeling by [87], and [26] also uses current output in addition to diffusivity fields for plastic modeling. FVCOM uses an unstructured, triangular grid in the x and y direction to fit smoothly to shoreline. For our use, the output was linearly interpolated to a regular 2 km spaced grid to reduce computational cost of interpolation within the model. To limit the computational cost of parameter comparisons, the run length was set to 6 months (January to July) in both lakes, which gives sufficient time for particles to disperse through the lake.

The sinking velocity, w_b, of a particle was calculated at each time step using a modified version of Stokes' Law to allow for particles of irregular shape [28]. This allows us to model particles of different sizes, densities, and shapes and also account for changes in sinking velocity due to temperature variations in lake. This method has been previously used to model microplastic sinking velocities [67].

According to Stokes' Equation for the sinking velocity of particles of irregular shape [28], the velocity is given by

$$w_b = \left(\frac{\rho_p - \rho_w}{\rho_w} g w_* \nu\right)^{1/3},$$

where ρ_p is the density of the particle, ρ_f is the density of the water, ν is the kinematic viscosity of the water, and w_*, is a dimensionless sinking velocity,

$$w_* = 1.71 \times 10^{-4} \Big(\frac{(\rho_p - \rho_w)}{\rho_w \nu^2} g D_n^3 \Big)^2.$$

Here D_n is the equivalent spherical diameter, or the diameter of a sphere of the same volume as the particle of irregular shape. We set a bound on D_n using the Corey Shape Factor (CSF), ϕ, which is a measure of how spherical a particle is, where a perfect sphere would have a CSF of 1. We use the mean CSF for a fragment, $\phi = 0.6$, to form a lower size bound on modeled particles which accounts for those of irregular shape [66]. We chose to model fragments because it is the second most common microplastic shape after fibers [13]. We do not model fibers or films because their shape is too non-spherical to calculate sinking velocity using this method. A full explanation of this derivation is available in Chapter 4. Our values for D_n are distributed between $D_{n(min)} = a_{min}(0.6)^{4/3}$ and $D_{n(max)} = a_{max}$. Here a_{min} to a_{max} is the range of particle sizes we wish to model, given as the length of the longest dimension which here is 1.00 mm to 4.75 mm. [66] suggested microplastic size ranges would follow a power law, so our initial distribution of particle sizes is given as $y = D^{-a}$, where $a = 1.6$ was taken from [66]. D is a random uniformly distributed variable between $\frac{1}{D_{n(min)}}^{1/a}$ and $\frac{1}{D_{n(max)}}^{1/a}$ which gives us the desired range of particle sizes. The initial distribution of sizes is shown in Figure 5.1.

For input in the model, a particle was released from every nearshore grid point every twelve hours, for a total of 984 particles daily in Lake Erie or 1,294 particles daily in Lake Ontario. The nearshore population at the particle's origin point was saved, to approximate the amount of plastic released at that location. The nearshore population was calculated using the method in [53], and this method for input quantification was the same as used in [26]. These simulations are run with particles of polyethylene (PE), which is positively buoyant in its pristine form with initial densities, ρ_p, uniformly randomly distributed between 917 and 965 kg/m^3 [51]. We choose to model polyethylene because it is positively buoyant in lake water and will float initially after entering the lake, and would require a

biofouling-like mechanism to sink. Polyethylene is also very common; it makes up about 32% of all produced plastic, more than any other single polymer [41].

II.1 Biofouling

To account for fouling in the model, we develop expressions for the density of a particle as a function of time. In the first fouling model, or the logistic fouling (LF) model, the expression for density is the solution to the logistic differential equation. The density of the particle, ρ_p, is given by

$$\rho_p(t) = \rho_0 + \frac{b_0 k e^{rt}}{b_0(e^{rt} - 1) + k} \tag{II.1}$$

where r is a growth rate of the material on the particle, k is a carrying capacity of additional density to the particle, b_0 is an initial added density, and ρ_0 is the initial particle density.

The second fouling model, sinusoidal fouling (SF), assumes repeated fouling and defouling of the particle. This give the expression for the density of any particle, $\rho_p(t)$, as:

$$\rho_p(t) = \begin{cases} \rho_0 + \frac{\rho_w - \rho_0}{\tau} t & \text{if } t < \tau * \eta_\tau \\ \rho_w + A * \eta_A * \sin(\omega t) & \text{if } t > \tau * \eta_\tau \end{cases} \tag{II.2}$$

A particle will enter the water with initial density ρ_0, and will linearly increase to the density of the water over a time delay $\tau * \eta_\tau$. After the time delay, the particle's density will fluctuate with amplitude $A * \eta_A$ and frequency ω. We calculate η_τ and η_A in the same way, but differentiate so that we can compare the results of including the ratio on each parameter independently. For some runs, we fix $\eta_\tau = 1$ or $\eta_A = 1$ for each particle to turn off the effects of the surface area to volume ratio. In this case, all particles will begin to oscillate after the same time delay or oscillate with the same amplitude.

To account for surface area dependent fouling, we scale certain parameters by the ratio of surface area to volume. The ratio of surface area to volume for any sphere is $\frac{3}{d}$, where d is the diameter of

the sphere. To scale the ratio between 0 and 1, we normalized by the maximum possible ratio in our model, which would be from the minimum particle size, $\frac{3}{D_{n(min)}}$. So, our scaled ratio is given by:

$$\eta = \frac{D_{n(min)}}{d}, \tag{II.3}$$

for any particle with dimension d. The dependence on surface area was tested only on the sinusoidal model.

In both fouling cases, model parameters are adjusted based upon available data. Previous fouling work noted that 50% of PE particles became negatively buoyant between 17 and 66 days in ocean water [39]. Additionally, experimental work with fouling of polypropylene, with density slightly less than our modeled range for polyethylene, found that they typically sink after 18 to 50 days in simulated Great Lakes conditions [114]. We chose the model parameters that control time till negative buoyancy, τ for SF and r for LF, based on these estimates. These parameters are shown in Tables 5.1, 5.2.

For all runs with LF, $b_0 = 1$ kg/m^3 and $k = 120$ kg/m^3. These parameters were fixed to limit variations between runs, and their impact could be controlled for by varying r. Additionally, it is unlikely for a particle to remain in the system long enough to approach k, meaning a max particle density of 1037 to 1085, without being deposited. The specific values used were chosen because when paired with different r values, they were able to provide a time till neutral buoyancy that agreed with the literature.

The amplitudes, A, for the density oscillations in the SF model were chosen so the maximum depth of the particle position corresponded to the depth of the euphotic zone in the lake, 12 to 26 meters deep for Lake Erie and 12 to 29 meters deep for Lake Ontario (Table 5.2). The range for the depth of corresponding particles is approximate because very large particles close to the upper end of our size range, 4.75 mm, will sink much further than this upper bound. However, because of the initial distribution of particle sizes these larger particles are uncommon in the model. For all runs with sinusoidal fouling, we fixed $\omega = \frac{2\pi}{24}h^{-1}$ to limit variation between runs, and as this was the frequency

of oscillation observed in previous modeling work [67]. We also fix $\tau = 30$ days for all runs. The value for τ was not found to have a significant impact on results, besides impacting which fraction of particles had begun to foul. Additionally, we account for variation in τ when we scale it by η_τ.

Growth rate r (h^{-1})	**Approx. time to neutral buoyancy (days)**
0.025	20-27
0.015	34-45
0.011	50-60

Table 5.1: Parameters used for growth rate for runs with logistic fouling

Amplitude of density oscillation A (kg/m^3)	**Approx. corresponding amplitude of particle oscillations (m)**
1.5	6-14+
3	12-20+
6	24-30+

Table 5.2: Parameters used for runs with sinusoidal fouling

Because parameter choice is constant across the lake and time, both fouling models do not account for spatial or temporal factors that could impact biofilm growth. Nutrient availability is not constant across the lake, and is higher in certain locations such as in nearshore water, or at warmer times of the year [4, 84]. Variations in nutrient availability would likely impact the rate of film growth and could impact our biofouling models. This model also does not account for potential differences in fouling between particles of different polymers, which may not have uniform fouling behavior [4]. Addressing these assumptions is an opportunity for future work on refining these models.

II.2 Metrics and output

One metric we use to study the effects of biofouling is percent retention of particles in the lake water column, or the percent of particles that have not been deposited. This is calculated as the number of particles still in the water column over the total number of particles that have been input into the lake. We differentiate percent retention between all particles in the system, and those that have reached negative buoyancy, at least once. Because SF particles oscillate, they will have times of positive buoyancy even after reaching negative buoyancy, so we make this distinction. The number

of SF particles that have reached negative buoyancy is calculated as the number that have been in the lake longer than the time delay τ. The number of LF particles that have reached negative buoyancy is calculated as the number that have a density greater than the approximate density of the lake water, 1000 kg/m^3.

We also use reconstructed three-dimensional trajectories of particles in Lake Ontario to observe the effects of biofouling. These trajectories were constructed by saving model output every 3 hours for the duration of a 6 month run. If a particle was deposited, its is removed from the simulation (i.e. set to NaN in the code). After the run, the particle locations at each time point were spliced together, giving us a full time series of each particles location over 6 months.

We can use the percent of plastic retained in the system to make a rough estimate for a sediment deposition rate in the lake. Assuming all initially negatively buoyant plastic sinks, we see

$$\text{mass deposition rate= [Annual mass entering]*}$$

$$\big[\text{(Percent that enters negatively buoyant)(100\% rate of sinking)+}$$

$$\text{(Percent that enters positively buoyant)(Rate of sinking) }\big],$$

where the rate of sinking is not yet known. We use values for annual mass entering the lake from [53] (1438.5 tons/year for Ontario and 2520.2 tons/year for Erie). The estimated portions of buoyant plastic from [3, 58], assuming the portion of buoyant plastic is the same in the Great Lakes as ocean input:

$$\text{mass deposition rate=[Annual mass entering]} * \big[(0.4)(1.0) + (0.6)(\text{Rate of sinking})\big],$$

leaving an unknown value for rate of mass sinking. We use the modeled results of particles not deposited to define a range for this term, and we use the minimum and maximum values for each

fouling method to define our range (Table 5.4). Rate of the mass that sinks is defined as:

$$\text{rate of sinking} = 1 - \frac{\sum_{i}^{particles\ not\ deposited} \rho_i V_i}{\sum_{i}^{all\ particles} \rho_i V_i}$$

where ρ_i is the initial density of each particle, without fouling changes, and V_i is the volume of each particle. The numerator of the above equation sums over the particles that have not been deposited, and the denominator sums over all particles, those that have been deposited and those still in the water column.

III. Results and Discussion

We see significant differences between the percent retention in the water column in Lake Ontario and Lake Erie after 6 month runs (Table 5.3). Even with no biofouling, Ontario has almost two times higher retention compared to Erie. This is likely because Erie is shallower than Ontario, especially in nearshore waters. This shallow water makes it easier for particles that are mixed below the surface to be deposited into the sediment, even without fouling. In Ontario's deeper water, particles have more space to move vertically without being deposited. We also see these differences if we compare the distributions of particle sizes remaining in the water column in both lakes. In Lake Erie, there are more smaller particles, or particles less than 2 mm, missing across different runs when compared to Lake Ontario (Figure 5.1). This is consistent with ocean studies, where smaller, less buoyant particles are mixed away from the surface more than larger particles [100].

The differences between retention in the water column are also apparent when considering the runs with biofouling. Particles with sinusoidal fouling (SF) have more room to oscillate in Lake Ontario without being deposited, which likely causes a higher retention rate as compared to Lake Erie. There is also higher retention in the water column of logistic fouled (LF) particles in Lake Ontario. Even though LF particles will likely ultimately be deposited, it takes more time to reach the sediment

because of the greater depth in Lake Ontario. This leads to higher retention as particles will likely take less time to reach the lake floor in Lake Erie.

We also see with SF particles that there is more dependence on parameter values as compared to the LF particles. Considering the logistic runs, the percent retention in the water column of particles that have reached negatively buoyancy (NB) is very similar for all three r values in both lakes. There is variation in the overall percent retention in the water column for LF, because a larger value for r causes particles to reach negative buoyancy faster. However, for the SF particles, there are more differences in retention in the water column for negatively buoyant particles between the three scenarios for A, especially in Lake Ontario. This is likely because a LF particle will continue to increase in density until it is deposited, and this results in almost certain deposition. Because the sinusoidal particles can oscillate, they are not guaranteed to deposit. This causes more dependence on the depth of their oscillations, which is controlled with A.

	Lake Ontario		**Lake Erie**	
	Percent retention	**Percent retention NB particles**	**Percent retention**	**Percent retention NB particles**
No fouling	51.1	N/A	18.5	N/A
Logistic: r=.011	25.8	0.28	6.6	0.01
Logistic: r=.015	21.4	0.23	5.2	0.01
Logistic: r=.025	15.7	0.16	3.7	0.005
Sin: A=1.5, $\eta_a = \eta_\tau = 1$	20.6	1.6	4.0	0.54
Sin: A=3, $\eta_a = \eta_\tau = 1$	19.7	1.1	3.8	0.35
Sin: A=6, $\eta_a = \eta_\tau = 1$	19.0	0.73	3.59	0.13

Table 5.3: Percent of particles retained in water column, or not deposited, in both lakes. This shows a comparison or percent retention in the water column of all particles, and particles that have fouled to the point of being negatively buoyant (NB).

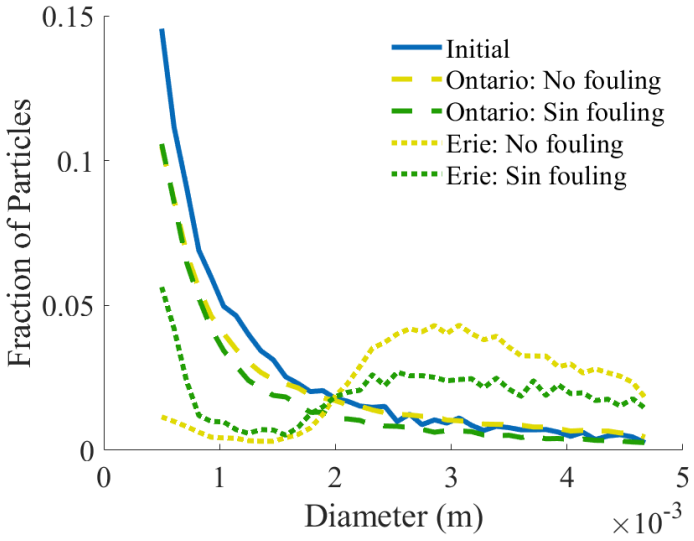

Figure 5.1: Distribution of particles left in the water column for both lakes. Bin width: 0.1 mm

Particles that are not fouled stay relatively close to the surface and travel further distances. For example, if we consider the potential trajectories of a selection of particles that originated in Toronto, Canada, we see that many of them reach the Eastern Basin of the lake, about 240 km away (Figure 5.2). Even though many of these particles traveled along the Southern shore, where the water is shallower, they were not deposited because they stayed at the top of the water column, with an average particle depth overall of less than 1 m. From the vertical positions, we can see that sometimes diffusion or advection will cause downward motion of a few meters. However, the positive buoyancy quickly makes up for this and moves the particle back to the surface.

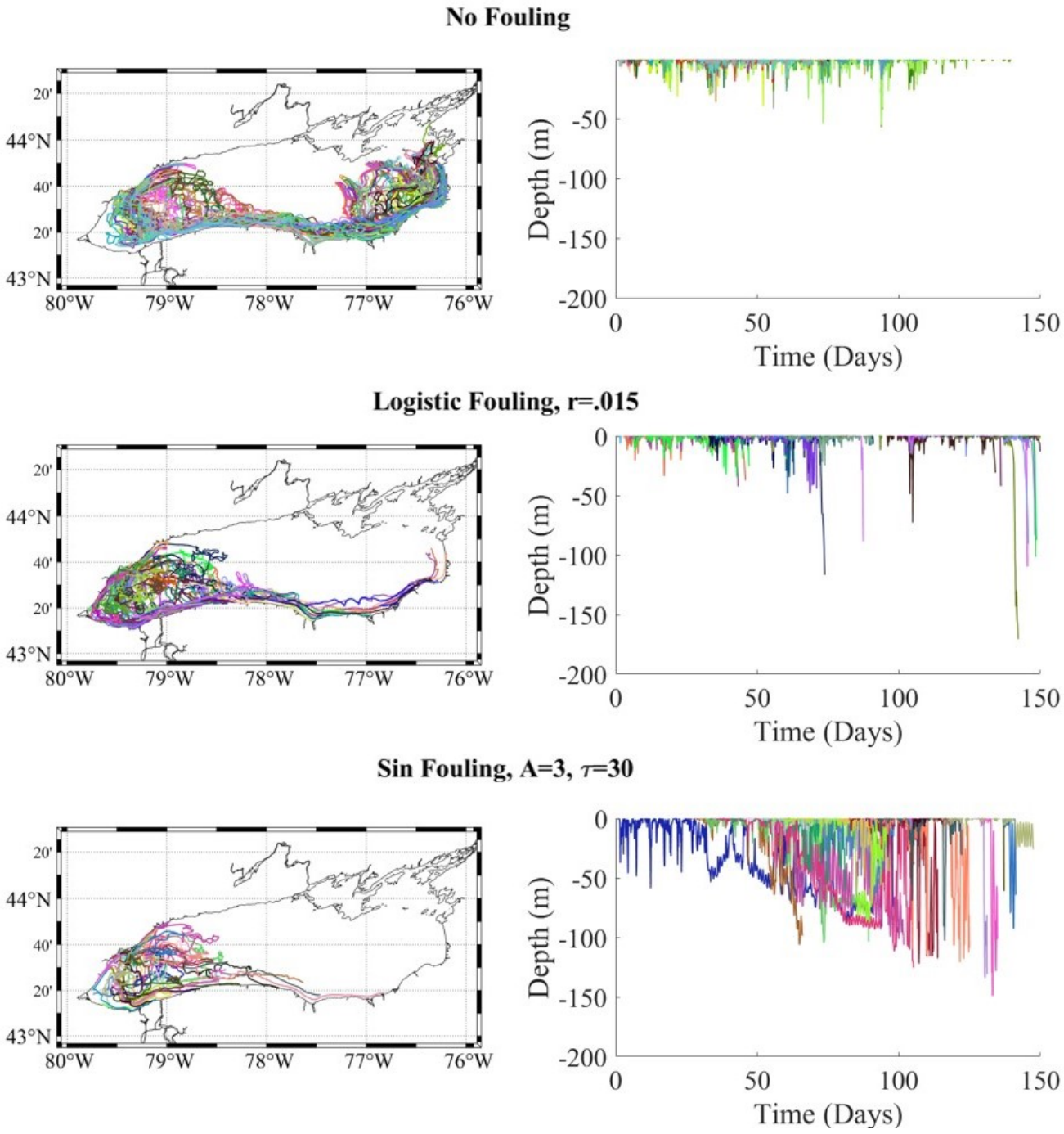

Figure 5.2: Horizontal and vertical trajectories of a selection of particles leaving Toronto, Canada over 6 months. Colors in both views correspond to the same particles.

When we include biofouling in the model, the vertical and horizontal movement of the particles changes. LF particles move deeper in the water column than with no fouling. However, they do not spend much time deeper in the water column, and once fouling begins, sink very quickly and are deposited (Figure 5.2). They do not travel as far horizontally as particles with no fouling. This is

because once these particles reach negative buoyancy, they quickly start to become very heavy, and are more likely to be deposited, and thus do not reach the Western Basin.

With SF where A=3 and $\eta_A = \eta_\tau = 1$ (no surface area dependence) the particles have less horizontal movement, but more vertical movement (Figure 5.2). Unlike the LF particles, SF particles do spend more time deeper in the water column. SF particles have shorter vertical trajectories on average because they reach negative buoyancy faster than LF particles. If we consider the trajectories of SF particles leaving Toronto, most of them do not exit the Western Basin before being deposited. LF particles with $r = .015$ take longer to reach the density of water than sinusoidal particles, which allows them to travel further before being deposited. This is evidenced by the presence of Toronto derived particles in the Eastern Basin not seen with SF. Specifically, the LF particles take 34-45 days to reach the density of water, while the SF particles take 30 days, as determined by τ.

In Lake Ontario, with no biofouling, any deposited particles gather along the shoreline where the water is shallow enough for them to be mixed below the surface and reach the bottom (Figure 5.3). After including any form of fouling, we see much higher deposition in the middle of the lake. There are differences between the LF and SF deposition patterns, due to the differences between the two fouling mechanisms. As mentioned previously, when $r = .015$, logistic particles have more time before becoming negatively buoyant than sinusoidal particles. This allows them to travel further through the lake towards the eastern side, following the predominant currents in the lake. This is noticeable in the Eastern Basin, where there are higher accumulations of LF particles.

The SF deposition accumulation also show more dependence on the lake bathymetry. This is especially noticeable along the southern lake shore, where the dark band of accumulated particles corresponds very closely to the coastal shelf. There is also a higher presence of sinusoidal particles along the shallow western side of the Northern Shore, as compared to the logistic particles. This depth dependence arises because LF particles tend to deposit close to where they begin to foul, regardless of depth. However, SF particles in deeper water can oscillate and move throughout the lake without being deposited. Once they move into shallower regions, they are more likely to be

deposited, causing the accumulation not seen in the logistic case.

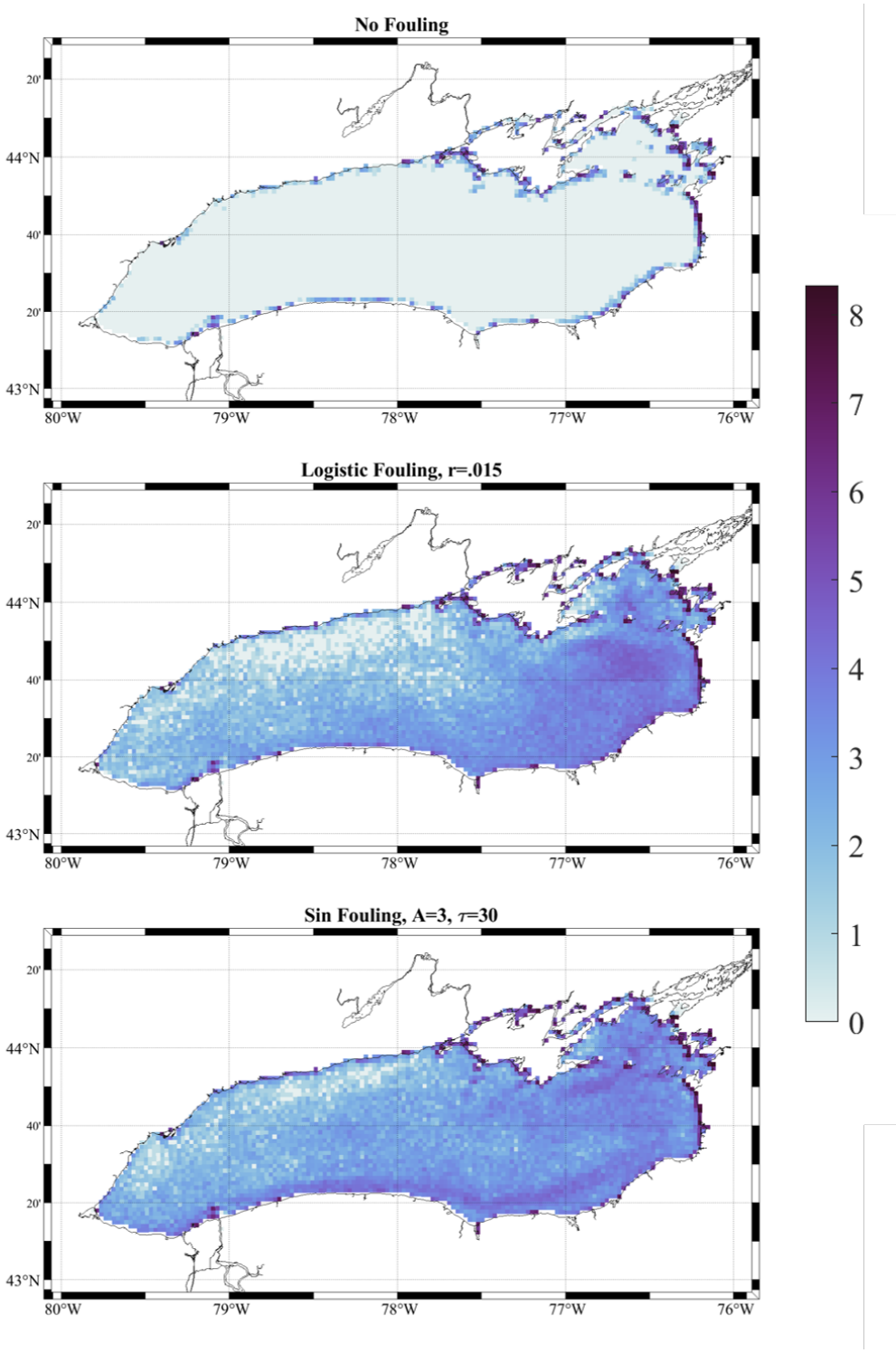

Figure 5.3: Concentrations of deposited particles in Lake Ontario (Particles per 2km x 2km grid cell). Shown on a log scale.

We introduced a ratio, η, that describes the ratio of surface area to volume for all particles (Equation

II.3). We scale model parameters by η to investigate the impact of surface area on the size distribution of particles at the surface in Lake Ontario (Figure 5.4), which could impact smaller particles in two ways. First, it could cause them to become negatively buoyant faster than larger particles. Second, the surface area to volume ratio could cause smaller particles to become relatively more fouled when compared to larger particles, which would make them heavier and more negatively buoyant.

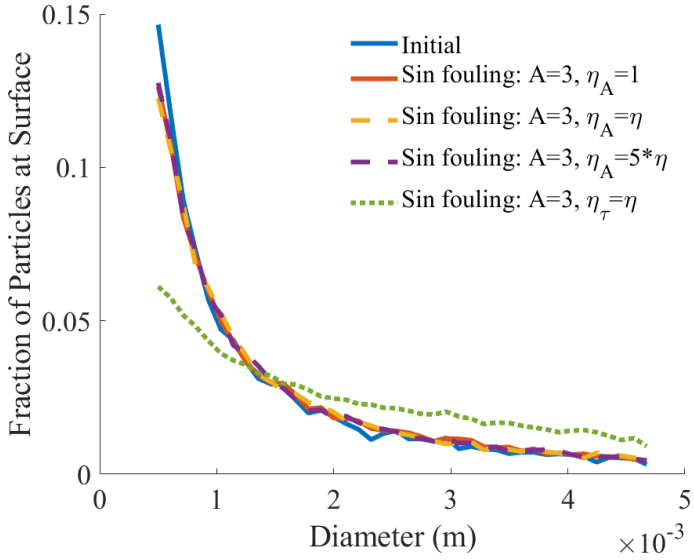

Figure 5.4: Size distribution of particles at the surface (top half meter) in Lake Ontario

Smaller particles experience more fouling when $\eta_A = \eta$, which gives smaller particles larger amplitude oscillations in density relative to larger particles. When considering this case, we do not see noticeable differences in size distributions at the surface. Even if we scale oscillations by 5 with $\eta_A = 5 * \eta$, the size distribution of particles at the surface is almost identical to the initial distribution, or SF with $\eta_A = 1$. This is because almost all of the particles at the surface have not reached negative buoyancy yet. Even with the density oscillations, SF particles are unlikely to return fully to the surface. This means changes to oscillation amplitude are unlikely to impact surface distribution, because these particles have not begun oscillating.

However, when we set $\eta_\tau = \eta$, which gives smaller particles a shorter time delay on fouling, we do see a difference in surface size distribution. When $\eta_\tau = \eta$ there are fewer smaller particles present at the surface, because they have reached negative buoyancy faster and moved away from the surface.

So within our model, making smaller plastics reach neutral density quicker has a larger impact on surface distribution.

Additionally, the indifference to changes in η_A for small particles is likely caused because in our model, size has a more significant contribution to sinking velocity than density. We see that the smallest modeled particles require significantly higher densities to be as negatively buoyant as the largest particles (Figure 5.5). Even taking $\eta_A = 5 * \eta$ does not give smaller particles a high enough density to rival the sinking velocities of larger particles. It is possible that the formation of biofilm may increase the total size of the particle, which may in turn could also impact its sinking velocity. This effect would possibly have a disproportionate impact on smaller particles, where even small increases in size are more significant in relation to the size of the overall particle. This is not accounted for in our model, but could impact this behavior by causing more smaller particles to sink, and bears future study.

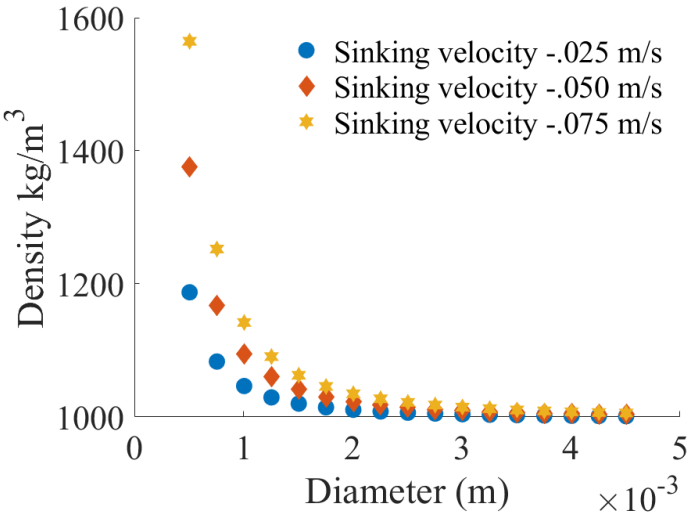

Figure 5.5: Modeled density per particle needed for particles of varying sizes to have equivalent sinking velocity for three potential sinking velocities

We use the percent retention in the water column in both lakes to estimate an annual sedimentation rate for each fouling model (Table 5.3). In both lakes, the estimates for both fouling methods are relatively close. However, the estimates between lakes are very different. Lake Erie has a significantly higher deposition estimate than Ontario because Lake Erie has a much higher estimation for annual

mass entering, due to higher population around the lake [53]. Even though Lake Erie has lower percent retention in the water column than Lake Ontario (Table 5.3), the values for percent of mass that sinks is comparable to Lake Ontario. This is because the majority, by count, of the particle that sink in Lake Erie are smaller, and contribute less to the overall mass that sinks. The larger particles that are more likely to remain in the water column skew the rate of mass sinking to be lower than expected when just considering count. The range in rate of sinking for SF particles is fairly low, especially compared to the LF particles. This is because of the dependence on r for the LF particles. As r roughly controls the time it takes particles to begin sinking, there is a significant dependence between it and of the number of particles remaining in the water column, and consequently the deposition rate estimate. Within the SF runs there is not as much variation in the overall amount of particles remaining in the water column.

	Lake Ontario		**Lake Erie**	
	Rate of sinking	**Deposition rate (tons/year)**	**Rate of Sinking**	**Deposition rate (tons/year)**
Logistic Fouling	79-89	1265-1348	79-90	2205-2376
Sinusoidal Fouling	86-87	1325-1327	90-91	2378-2382

Table 5.4: Rate of mass sinking and corresponding sediment deposition rate for both lakes and fouling models.

It should be noted that these relatively small mass ranges, especially for SF, do not imply we are certain in this value. It is small because we only account for uncertainty in the rate of sinking value, and changes in rate of sinking, which has low variance, do not carry through to give large changes in the overall estimate. There is still uncertainty in each of the other parameters used in the deposition estimate that we did not account for in our confidence interval. However, the focus of this work was the effects of biofouling, so we consider that uncertainty here.

Additionally, both deposition rates for Erie are more than three times higher than the previously published sediment deposition rate for Lake Erie of 762 tons per year [26]. There are several reasons for this increase. The previous model did not include biofouling, which increases deposition. Additionally, different methodologies were used for this and the previous deposition estimate, which can impact results. It is also important to note that a great deal of this deposited plastic is deposited

along the coastline, and would potentially be beached instead of deposited, if beaching was included in this model.

IV. Conclusion

We developed the first large scale Lagrangian Transport model of plastic in the Great Lakes to include a functional biofouling model. The inclusion of the biofouling model was motivated by both a previous model showing plastic accumulation in surface waters which does not align with measured values, and the possibility that missing plastic in large bodies of water is removed from the surface by biofouling [26, 67]. This is also the first three dimensional plastic transport model implemented in Lake Ontario. The model allows us to derive a first pass rough estimate for a sediment deposition rate in Lake Ontario and a new deposition rate for Lake Erie.

Here we present two functional models; a sinusoidal fouled model with oscillations, and a logistic fouled model with constantly increasing particle density. We found that for both fouling models, in both lakes, the majority of particles are deposited into the sediment after becoming fouled. This is especially true in the shallower Lake Erie where particles do not have as much vertical space to move through. In Lake Ontario, we saw that without biofouling, deposited plastic accumulated primarily along the shoreline. Including either fouling model spread plastic throughout the lake floor, though it was more likely to accumulate in shallower regions of the lake in the sinusoidal fouling model. When investigating the impact of size dependent fouling, we found that a time delay dependent on size caused the greatest impact to the surface distribution.

While this work serves as a first pass quantification of the effects of biofouling in the Great Lakes, there are many improvements that could be made. Here we only included a functional biofouling model, meant to capture impact on a particle's density. Our model did not account for differences in fouling between different polymers, or spatial and temporal variation in factors that could impact fouling like temperature, season, or nutrient availability. A potentially more realistic approach would be a mechanistic biofouling model, such as [67, 82], that directly models organic growth on the

particle, and could account for other factors impacted by biofouling such as changes to the particle's size.

Our biofouling model could also be refined with more experimental work which could better inform parameter choices. Ideally, temporal data on density changes in fouled particles exposed to lake conditions would help inform modeling efforts. Additionally, more detailed information on plastic input, specifically the makeup of different polymers, could improve the model and deposition estimate. Understanding the initial distributions of the densities of particles that enter the lake would ensure more accurate model predictions.

Another area for improvement in the model is the deposition implementation. We currently have an 100% chance of permanent deposition for particles that hit the bottom of the lake. In reality, particles likely can resuspend, bounce off the bottom, or move along the lake floor [30]. Additionally, while we account for particles of a range of sizes in our model, we do not include fragmentation, which is a mechanism that creates more smaller particles [9]. Our deposited plastic is sensitive to changes in input because it tends to accumulate along shore, especially in the model with no fouling. The model could be improved with better input estimates along shore. For example, output from waste water treatment plants (WWTP) is known to be a source of microplastics in the lakes, but in our model we do not account for them [91, 116]. We also do not include any sources of plastic input into the lake from locations besides the coast. It is possible that fishing or shipping could be a source of plastic pollution that enters in the center of the lakes [29].

More research is needed to fully understand biofouling, but this work serves as a first effort on modeling its effects in the Great Lakes. We found that including biofouling causes a majority of particles to become deposited. Including biofouling also spreads plastic accumulation across the lake floor, instead of concentrated at the shorelines. By investigating the impact of biofouling on particles of different sizes, we found that allowing smaller particles to foul faster recreates the absence of them at the surface which has been observed in samples. In the future, we hope to be able to refine this model and better understand the accumulation rates of plastic in the sediment and the risk it

may pose for benthic organisms and ecosystems.

Chapter 6

Conclusion

I. Conclusion

There are still many unknowns in the field of plastic transport in any large body of water. At this time, it is likely impossible to achieve a full and complete understanding of plastic transport in water. However, the goal of this work was to investigate the impacts that different physical mechanisms might have on the transport and fate of plastics in the Great Lakes. This helps inform mass estimates, and indicates where plastic may be accumulating, and consequentially which communities may be impacted most.

Initially, we focused on including vertical mechanisms that could transport plastic beyond surface waters in Lake Erie. Specifically, we included vertical advection, turbulent mixing, and density driven sinking. This model also served as the base for all future models in Lake Erie and Lake Ontario. This work showed a significant dependence of fate on polymer density, where we saw positively buoyant particles accumulating in surface waters, and negatively buoyant polymers mostly accumulating in near shore sediments. We used this work for a first pass 3D mass estimate and sediment deposition rate in Lake Erie. This accumulation of plastics in surface waters illustrated the need to investigate mechanisms that may be responsible for removing plastics from the surface. These findings impacted the future stages of this project where we implemented two such mechanisms:

biofouling and beaching.

In the plastics field, biofouling is commonly proposed as the primary mechanism that may cause the movement of positively buoyant plastics away from surface waters [67, 114, 139]. Though there are still many uncertainties, it is thought that the growth of the film of organic matter on a floating particle can cause it to become dense enough to sink [39, 60]. In this work we considered two potential fouling models, a sinusoidal and logistic model, and applied both to transport models in Lake Ontario and Lake Erie. We also investigated the impacts of size dependent fouling. We determined that accumulation of deposited plastic are dependent on lake depth and fouling method. There is a behavior dependence on parameter choice, but overall the inclusion of fouling prevents the accumulation of plastics in surface waters. We also used the model to provide a rough estimate of sediment deposition in the presence of biofouling in both lakes. This work would benefit from more experimental results to validate our model and parameter choices.

Lastly, we implemented a model that allowed for beaching of plastic onto the shore in Lake Erie. It has been proposed in the oceans that nearshore water and beaches hold a significant amount of plastics trapped in a cycle of beaching and resuspending [17, 52, 74, 99]. Our model utilized a high resolution data set of beach types for the lake to allow for terrain specific beaching behavior. We found that the accumulation patterns of beached plastic was driven by the general west to east currents in the lake, and population centers. Certain beach types also led to regions of very high beached plastic concentrations. This model could be improved or validated with experimental data on beaching behavior of plastics in the Great Lakes. Additionally, we were only able to compare to one sampling result from 2008 with limited data on plastic collected from sandy beaches in Lake Erie [140]. Sandy beaches are also known to be biased by cleanup or grooming efforts, which can additionally bias data on plastic amounts. If we had a more complete or recent data set it is possible we could improve the accuracy of our model.

II. Future Work

There are a significant number of things that could likely improve our transport model. Two that may be particularly helpful to this work are improvements to input estimates and refining the biofouling model with experimental results.

II.1 Input estimates

One of the greatest uncertainties in any plastic modeling effort is the approximation of input amounts. Here we followed the method used in [53], where input was estimated based on the populations in the zip codes surrounding the lakes. We use these input estimates to evaluate if our mass estimates seem valid. However, there is no proof that these input estimates are fully accurate. The methods we follow were based on early work on estimating global plastic input [58]. This method relied on the assumption that wealthy countries, like the United States and Canada, have 0% inadequately disposed waste, meaning all waste that is disposed of ends up properly recycled or in a landfill, with no plastic leaking out to the environment. All released plastic from wealthy countries comes from an estimated 2% littering rate applied to waste generation by coastal populations [58]. However, since the original publication these input parameters have been questioned [72]. Many researchers have attempted to improve or expand on this first pass global input estimate. Our work would also be improved by adopting more sophisticated input estimate methods.

One improvement to input estimates would be including river input. Rivers, which may carry plastic from inland to open water, are thought to be an important source of plastic input [76, 111]. However, the impact of rivers may be more complicated than only a source of plastic. One work found that improving input estimates by including the effect of rivers as a sink determined that there was no missing plastic in the oceans [134]. Other work has even proposed that the using population as the main predictor of input estimates is not reliable [112].

Our input estimates also do not include other potentially important sources of plastic. Beyond

rivers, point sources like wastewater treatment plants (WWTPs) have been studied as sources of microplastics [91, 116]. In the Great Lakes, higher concentrations of microplastic have been found near WWTP outflow [14]. Stormwater runoff has also been identified as an important source of microplastics [55, 80]. Additionally, we do not account for plastic released within the lake. This can come from fishing or shipping, which are both common activities in the Great Lakes [29]. Our model would likely be improved by including more sophisticated input estimates that take these factors into account. The beaching model would likely see the most improvement, as beached plastic results are especially sensitive to input data from land. These improvements would likely have the greatest impacts on beached plastic around population centers, or areas down current from population centers. Additionally, areas around the outflow of major rivers would likely see noticeable differences in predicted plastic, especially rivers transporting water from the other Great Lakes such as the Niagara River in Lake Ontario or the Detroit River in Lake Erie.

II.2 Experimental work

As previously mentioned, it is thought that biofouling, or the buildup of organisms and organic matter, which can increase the density of particles, causes plastic to sink below the surface [39, 67, 139]. This can cause buoyant plastic to accumulate in the sediment or lower in the water column. In this modeling work, we examined the effects of two functional biofouling models: an oscillating sinusoidal fouling model and a standard population model which we called the logistic fouling model. We aimed to base our biofouling models and parameters on the limited research that is available. Unfortunately at the time of the work, there was not a great deal of experiments, especially in freshwater, that we could draw from. Additionally, our model assumes a 100% chance of deposition and no ability for resuspension. This behavior could be validated or improved by experimental work. Future improvements for our transport model would include refining it based upon the experimental results from aging experiments conducted locally in the Rochester area.

There is limited work on the impact of biofouling on settling velocity with plastics of any size category. Early work exposing macroplastics to marine conditions found that biofouling could

increase the density of positively buoyant polymers to the point of sinking, with different polymers impacted by fouling in different ways, though the plastic may defoul in deeper water [139]. Studies of biofouling of microplastics in marine environments have also shown increases in sinking velocities, but we cannot be certain how these trends carry over to freshwater environments [39, 60]. Research indicates there are differences in biofilm formation between freshwater and marine environments, and on different polymer types yet there is limited work investigating the impact of biofouling on sinking velocity in freshwater environments [48, 56]. Work with microplastics exposed in a Great Lakes freshwater environments did find increases in particle density, and examined the impact these results could have on microplastic retention between lakes, but failed to address potential changes in fouling between multiple polymer types or different water conditions [114].

Different bodies of water will likely lead to different characteristics of biofilm growth and different changes to settling velocity, as factors such as temperatures, nutrient availability, light availability, oxygen, or the presence of other pollutants can impact biological growth [48]. These differences likely can impact the overall distribution in large bodies of water, but also the transport of plastics through smaller tributaries, and their ultimate fate. Dense plastics or fouled plastic that has begun to sink are less likely to be transported through rivers and ultimately output to large lakes or the ocean [125]. Changes in sinking velocity of particles in tributaries impact the chances of particles being transported through waterways and ultimately released, helping to inform input estimates from rivers, which are a significant source of plastic [76]. Yet thus far, there has been limited investigation into differences in biofouling between different bodies of water or smaller tributary sources in fresh water.

Once plastic sinks to the lake bed, sinking either from its original settling velocity or changes due to biofouling, its final fate is not well understood. Plastic can resuspend and be transported along the lake bottom by erosion and bottom currents. [61]. However, plastic with a larger net sinking velocity is less likely to resuspend [61]. The behavior of particle resuspension can impact where plastic accumulates in the lake and the overall plastic retention in the lake [114]. This work attempts to clarify the fate of plastics that do reach the sediment by analyzing changes to sinking velocity

after exposure to sediment conditions.

To address these uncertainties, year long experimental aging experiments were started in July 2020. Six different post consumer polymer types were purchased at or ground to microplastic size:

- Polyethylene terephthalate fibers (PET-F)
- Polyethylene terephthalate bottles (PET-B)
- Polystyrene cups (PS)
- High-density polyethylene bottle caps (HDPE)
- Styrene-butadiene crumb rubber(SBR)
- Polyvinyl chloride particles (PVC)

Eight rafts were constructed with housing for the particles that had mesh ends to allow water to pass through, but could contain the particles. The rafts were deployed at four locations, with one raft floating at the surface and one anchored to the bottom. The locations were Lake Ontario, Conesus Lake, a rural pond, and a storm water retention pond on RIT's campus (J-lot pond). These locations are significant as the rural pond and J-Lot pond are representative of downstream water sources for Conesus Lake and Lake Ontario respectively. So, the fates of plastic in the pond have implications for the ultimate transport of plastics through the watershed and towards larger bodies of water. Plastic samples were retrieved at 1, 4, and 12 months. At each time point, and for the pristine samples, the sinking velocity of about 20 particles was measured using a camera and a long, clear, acrylic chamber filled with water.

This experimental work studied the relationship between biofouling driven changes in settling velocity for microplastics across polymer type, season, and location. These results will allow us to investigate how these factors impact settling velocity and ultimate fate of plastics. We hope these results will be able to inform our modeling efforts in multiple ways, primarily by improving understanding of biofouling driven changes to settling velocity, but also clarifying the impact biofouling has on resuspension and transport through smaller tributaries. A full understanding of the distribution of

microplastics and affected communities in freshwater likely depends on improved parameterization of fouling across multiple polymer types.

III. Mitigation

Research can often be guilty of creating more questions than it answers, especially in a field as new as plastic pollution. While the work we do may be able to provide some insight on how much plastic might reside in the Great Lakes, or which regions and systems of the lakes are most effected, this is not usually the answers people are looking for. People overwhelmingly want to know what can be done to fix the problem. Unfortunately, this is another complex issue, and it is difficult to present solutions.

Cleanup efforts are expensive and ineffective when compared to the quantity of plastic entering the environment. Ultimately, the best solution is reducing input of plastic pollution through increased recycling, reduced use, and pursuing alternative materials [101]. Only about 9% of United States plastic waste is destined to be recycled, though a large portion of that amount is exported to other countries. It is unknown exactly how much of the plastic that is exported as recycling is ultimately properly recycled, and not disposed of improperly [72]. Many companies now offer various types of bioplastic packaging, but these can often be chemically equivalent to the original polymer and do not actually biodegrade [2]. Unfortunately, if current plastic production trends continue, the amount of plastic that enters aquatic ecosystems will continue to grow exponentially, even with current mitigation efforts [10]. This indicates the need for a more aggressive approach to the issue of mitigating plastic emissions into the environment.

Ultimately, educating the public through outreach is one of the most influential ways scientists can make a difference. Researchers have found that consumers may be willing to alter their behavior if they are informed on an issue [101]. To address that point with this work, we developed an interactive web model to give the general public an additional outlet of education about the issue of plastic pollution, especially as it pertains to Lake Ontario. The eventual goal for this website is that

it will serve as an educational tool for users about the potential impacts of plastic pollution in Lake Ontario.

III.1 Markov Model

Because of the computational cost of the original Lagrangian Transport Model and the memory required to store several months of current, temperature, or diffusivity fields it was not practical to convert this model to a web based version. Instead we implemented a 2D Markov model which is less costly to store and implement. This is also similar to the approach used for a global web model [127].

For the Markov model the area of the lake and surrounding region was discretized into 5km by 5km evenly spaced grid cells. Each grid cell containing the lake was identified and made up the entries in the state vector, X. Each entry in the state vector was defined as the probability of finding plastic within that cell. To release plastic in a location, the value of the entry in the corresponding cell was set to 1 with all other entries being 0.

The state vector was progressed at each time point using a probability transition matrix P with rows that summed to 1. It follows that the state vector at any time step t is given by:

$$X_{t+\Delta t} = X_t P = X_0 P^{t+\Delta t},$$

where the timestep $\Delta t = 2$ days. Each entry in the probability matrix, $P_{i,j}$ is defined as the probability of moving from the i^{th} grid cell to the j^{th} cell.

Four different probability matrices, or one for each season, were calculated for the model. This was done to account for the seasonal changes in lake transport behavior. The probability matrices were calculated based on 2 day long model runs using a 2-D version of the Lagrangian Transport model for Lake Ontario modeling only advection. Each run the lake was initialized with evenly spaced particles every 500 m. This corresponds to 100 particles in each grid cell. After 2 days, the final

locations of each particle were saved and the initial and final location of each particle were binned into the 5 km by 5 km grid cells.

Initial and final locations for each particle were used to calculate the probability of moving from one grid cell to any other cell in the lake. To avoid an overly sparse probability matrix, three separate 2 day runs were averaged to calculate the probability matrix. Dates for these runs are shown in Table 6.1.

Season	**Transport Model Dates (Year is 2018)**
Winter	January 1 to 3
	January 4 to 6
	January 7 to 9
Spring	April 1 to 3
	April 4 to 6
	April 7 to 9
Summer	July 1 to 3
	July 4 to 6
	July 7 to 9
Fall	October 1 to 3
	October 4 to 6
	October 7 to 9

Table 6.1: Dates for 2-D Lagrangian transport model runs used to calculate the probability transport matrix.

III.2 Website

The lower computational and data storage cost of the Markov model allows it to be easily run on a web server. The user can select a grid cell in the lake, a season for the transport, and watch the updated plastic probability field at each time step. To limit computational cost and time, the matrix powers are precalculated and stored on the web server. Because of storage limits, each season is limited to 19 stored matrices, or the ability to propagate the matrix for 38 days in each season.

Figure 6.1: Screen display for plastics website available at *www.http://www.lakeontarioplastic.org/*

Figure 6.2: QR Code to access *www.http://www.lakeontarioplastic.org/*

We hope that providing an easily accessible model of plastic transport can help those that live near the Great Lakes understand potential impacts of their actions and output into the lake. There is much more work that needs to be done to address the problem of plastic pollution, but this work

will likely not be successful without the support of the public. The goal of this website is to provide an educational source that will hopefully help to educate and inspire the public to care about the issues related to plastic pollution.

Chapter 7

Acknowledgments

This research is a product resulting from project NYSG: 80794/1160707/1 funded under award NA18OAR4170096 from the National Sea Grant College Program of the U.S. Department of Commerce's National Oceanic and Atmospheric Administration, to the Research Foundation for State University of New York on behalf of New York Sea Grant. The statements, findings, conclusions, views and recommendations are those of the author(s) and do not necessarily reflect the views of any of those organizations. Additionally, this work used the Extreme Science and Engineering Discovery Environment (XSEDE), which is supported by National Science Foundation grant number ACI-1548562, through allocation TG-OCE150006. Additionally, I would like to thank Dr. Matthew Hoffman for advising, my committee, and the RIT plastics team, especially Christy Tyler for her help with the biofouling manuscript. I am also grateful to Victor Onink, Cleo E. Jongedijk, Charlotte Laufkötter for their help with the beaching model and manuscript. Lastly, I would also like to thank my family and friends for their support. Special thanks to Alex for helping build the plastics site. I dedicate this thesis to my mom, for first introducing me to the problem with many mornings on the beach together spent walking and picking up plastic.

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