Developing a 3D trajectory modeling system to predict the aggregation of ocean floor microplastics using a voxel-based neural network approach

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Abstract

The improper disposal of plastic waste has led to an abundance of plastics in the oceans, increasing at an exponential rate, introducing a wide range of toxins along with a potential global health crisis across the entire marine and terrestrial food chain. However, the field of microplastic pollution prediction via data modeling systems is still in the early stages, and currently, there are no comprehensive, high resolution, three-dimensional trajectory modeling systems that clearly show patterns of plastic pollution distribution from the surface of the ocean, through the mid-water column, and to the ocean floor. This system was developed to simulate the 3D trajectories of individual plastic particles using a Lagrangian model, which utilizes recurrent neural networks trained with data from various prominent factors within specific regimes of ocean depths obtained from several different sources: experimentally derived data, formula-derived calculations, and peer-reviewed literature. Particle shape, size, material density, and surface characteristics were also considered and modulated to create a more extensible model. Gravitational descent rate was calculated at each vertical depth layer based on matrices determining the effect of various internal and external factors on particle downward trajectories. These matrices were informed by a sensitivity analysis, allowing the optional entry of a custom range of input values, with presets determined by a weighted median of publicly and experimentally sourced data. Recurrent neural networks were then used to post-process model output data for later use in spatial-mapping predictions. Particle density distribution maps were generated, highlighting regions of plastics aggregation, predominantly near gyres. After verifying the model using comparisons to peer-reviewed publications of surface microplastic mapping data, it was determined that this novel technique demonstrates a >90% probability of accurately predicting ocean-floor accumulation zones, with a p-value of 10^{-4}. This system lays the groundwork for future studies regarding accurate ocean floor microplastic aggregation hot-spot zone prediction.

Background Research

As recent as November 2019, MIT and Woods Hole held one of the first worldwide conferences on the concept of modeling microplastic movements within the ocean on a large scale. To date, there have been no published models that have successfully incorporated all of the key factors influencing microplastic movement with high accuracy. This is a field that requires significant attention because currently, a global pelagic and benthic microplastic distribution model does not yet exist, despite the increasing rate at which this problem is expanding.

In 2020, over 14 million metric tons of plastic pollution entered the ocean. This problem is growing at a faster rate than the global production of plastics itself. According to the American Chemistry Council, by the year 2050, it is predicted that 756 million tons of plastics will be produced. Synthetic polymers are known to cause a myriad of health effects including cancers, heart and lung defects, and more, even with exposure in trace amounts. Yet, continued exposure at ever-increasing rates is likely to affect a host of new pathologies in the years to come not only in human populations but throughout the natural living world if this problem is not remediated immediately. This is a problem of particular concern at the base of the marine food chain. As such, it is necessary to address this issue on a global scale, with a multi-pronged approach comprised of both prevention, and cleanup efforts. However, to ensure that costly, coordinated resources are used most effectively, it is essential to determine regions on the ocean floor with the highest concentrations of the most toxic microplastic particles. At present, given the lack of funding for extensive in-situ marine data collection, the only option is to create an accurate, high-resolution predictive spatial mapping model of microplastic distribution on the ocean floor, using computational resources.

The Lagrangian approach used in this simulation model tracks the predicted trajectories of individual particles from the sea surface to the ocean floor, across twenty-three years of data, considering all significant factors of influence acting upon the particle and inherent to the particle itself. One factor which has already been identified to have a large impact on the sinking rates of microplastics is the density changes that occur after binding with organic chemicals, as well as organisms, such as zooplankton or phytoplankton. The aggregation of plastic particles on the ocean floor potentially correlates with the level of insolation in a particular area. Regions that receive a large amount of sunlight are more conducive to the growth of algae. This has led to cases of microalgal blooms occurring on a fairly regular basis in marine environments around the world.

In these areas, plastics are more likely to bind to algae, and sink to the ocean floor at a faster rate than particles that are not biofilm-coated, or otherwise bound to biologicals (Khatmullina & Chubarenko, 2018). Not only would the breakdown of plastics into microplastics raise the cumulative surface area of the plastics, but the abundance of algae would also mean that biologicals are much more likely to attach to the surface of these particles. Animals on the bottom of the ocean which rely on marine 'snow' as their primary source of sustenance would consume all of these hazardous particles, which could potentially cause mass toxicity events, as well as localized extinctions of certain species in some areas. Furthermore, contamination of any kind in benthic organisms will accumulate in higher organisms through biomagnification and have the potential to spread to terrestrial environments through the fishery industry. Various satellites use image processing techniques to isolate regions where chlorophyll-associated green wavelengths are prevalent. These wavelengths will infer an abundance of plant life containing chlorophyll, such as marine algae, which is the most common phytoplankton, and among the most common life forms in the ocean.

Large amounts of algae in certain areas of the ocean will lead to the microplastics gaining density in these particular regions at a faster rate than others. The biochemical components of algae cells have, on average, higher density than most common, synthetic polymers. The composition of the dry weight of an algae cell is roughly 70% protein, 10% lipid, 10% nucleic acid, and 5% carbohydrate, and inorganics are approximately 5% of the cell weight. Protein has a density of 1.35 g/cm^3, which is a higher density than ocean water, which is 1.03 g/cm^3. The plastics that are being used in the current simulation have a range of densities from 0.92 to 1.38 g/cm^3 (PETE, HDPE, PVC, LDPE, PP, PS, TPU, PLA). This means that most plastics will gain density when binding with algae.

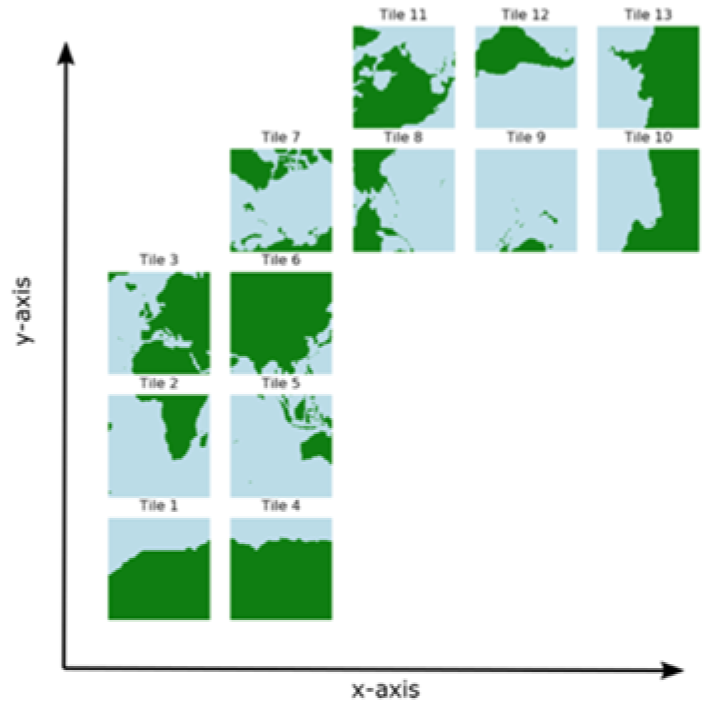
However, as the plastics with lighter densities will have a larger horizontal trajectory on and close to the surface of the ocean, it has been predicted that these particles may be deposited on beaches or areas close to continental shelves. According to some preliminary results from running the mapping simulation, most of the plastics will be deposited on continental shelves close to the shore of the ocean. These plastics would have the largest detrimental effect on human health as those areas are where many animals who have a great effect on the marine food chain reside, as opposed to plastics that have sunk to the bottom of the ocean floor and have been buried by the constant deposition of marine snow.

Methods

This is the third phase of a three-year project. Previous work involved developing an ROV to identify microplastics (plastics smaller than 5mm) using an infrared-based detection system. This system was supplemented by an AI-based unnatural color detection system and a morphology classifier. However, using an ROV to scan the ocean floor for microplastics would not be sufficiently scalable, and using a swarm of ROVs with a widely distributed network would be an overwhelmingly expensive project, unlikely to be funded any time soon. Spot verification of microplastic particles using real-world ocean floor sampling would be the only way to confirm the accuracy of the system. However, there are very few institutions with active research vessel programs, with coring and/or sediment trapping, and most don't focus on microplastics. The past year, Woods Hole has not been able to conduct this research due to the pandemic.

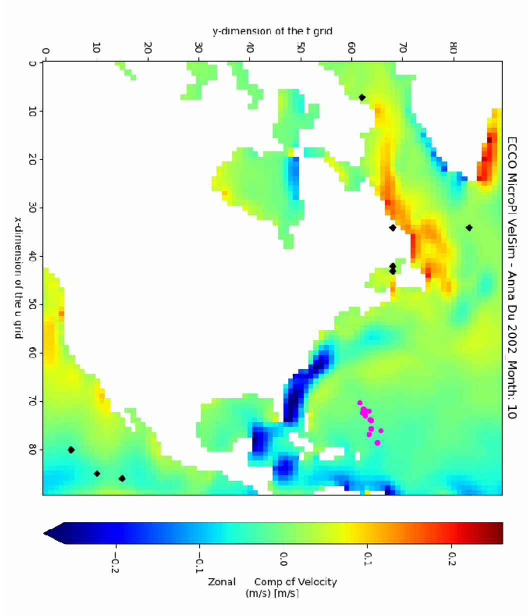
In lieu of a costly global ocean floor sampling approach to directly determine the density distribution of microplastics, a computer-simulation-based method to model and predict the location of microplastics would be absolutely necessary. To simulate how microplastic particles sink to the ocean floor, data assets from multiple sources were used to calculate particle trajectories at different layers in the ocean, under numerous environmental conditions, and in consideration of different particle material properties and physical characteristics. This included an approach that combined information from calculated values, literature reviews, and experimentally derived data. A simulation model was developed using a comprehensive matrix of potential influences on the final location of microplastics. This matrix contains factors such as biological transport mechanisms, underwater turbulence such as mesoscale eddies, changes in density due to binding with other objects, loss of mass due to abrasions, and more. New plastic particles are periodically released into the system at various scheduled times and geographic locations to simulate a real-world environment.

NASA's ECCO dataset was used as the basis for current velocities across the ocean. The dataset includes multiple buoy sensor and satellite-derived variables spanning from the year 1992 to 2015. The voxel grid system used for the model is based on NASA's ECCO tile and depth layer (ocean k-layer) system derived from the MIT GCM project. The model was initially run on k=0 (the surface of the ocean) for verification against field-collected sources including the Global Microplastics Initiative and numerous expeditions conducted by WHOI.

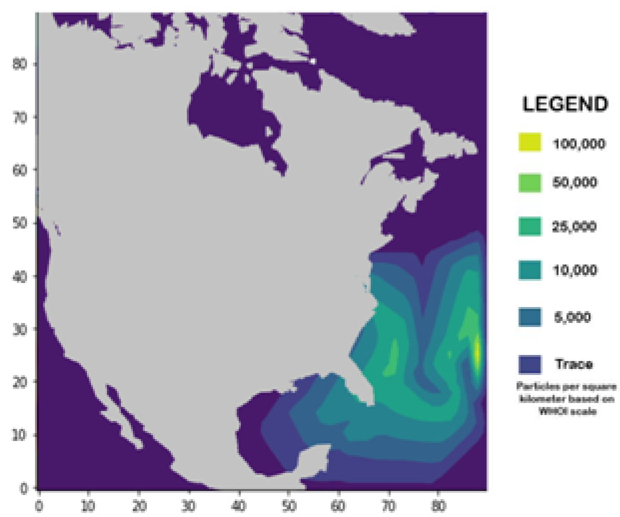


For higher resolution mapping, ECCO divides the world into 13 independent tiles

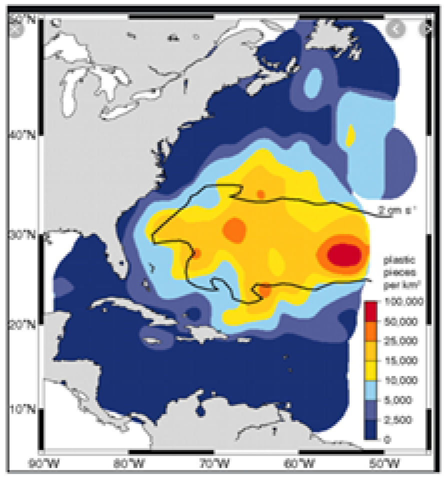
A contoured distribution map was developed from the results of the simulation model and was found to have >92% correlation to the distribution found by Woods Hole. Due to the high accuracy, this system was then used to predict potential lower-pelagic and near benthic regions of microplastic accumulation.



Preliminary tile 10 simulation model based on surface current velocities

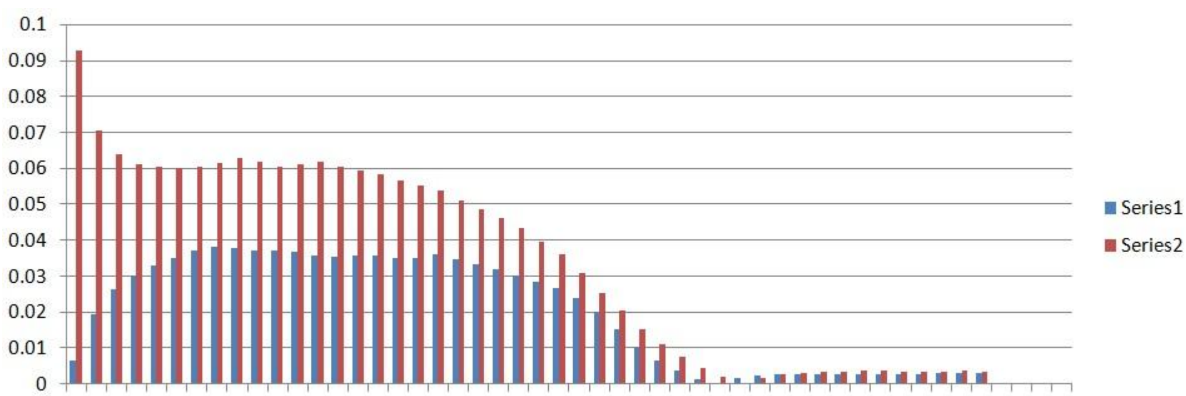


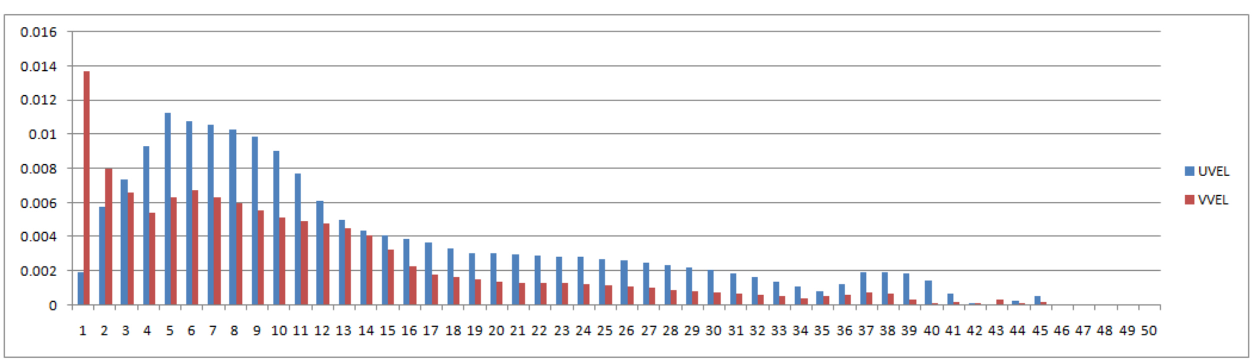
Self-generated Atlantic contoured surface particle distribution generated from the simulation model

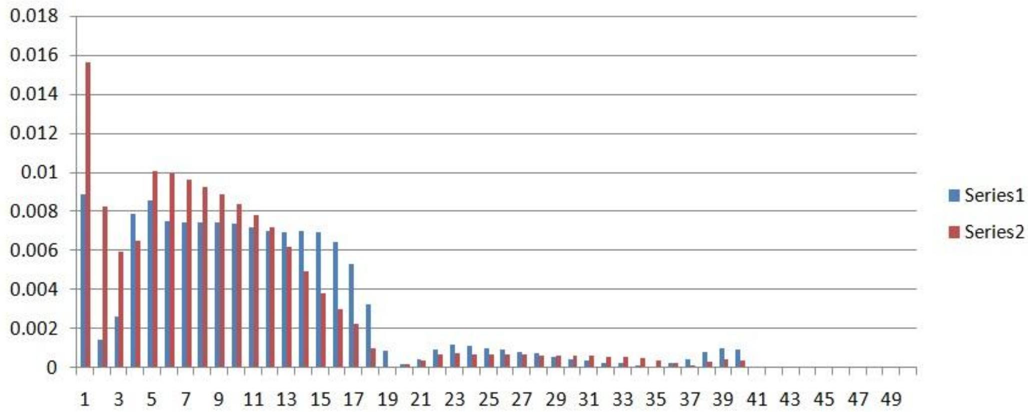


This shows WHOI and SEA foundation's distribution map based on numerous research vessels.

Voxels can be assumed to represent a one-degree slice of the earth, segmented into fifty discrete k-layers with variable heights (k-layers 0-10 are approximately 10 meters in depth, whereas k layers 10-49 are variable, and gradually increase to several hundred meters, defined within the ECCO binary files). The three-dimensional voxel units used in this simulation system can therefore be assumed to be approximately 12321 kilometers^2 (~111 kilometers in length and width) with variable k-depths.

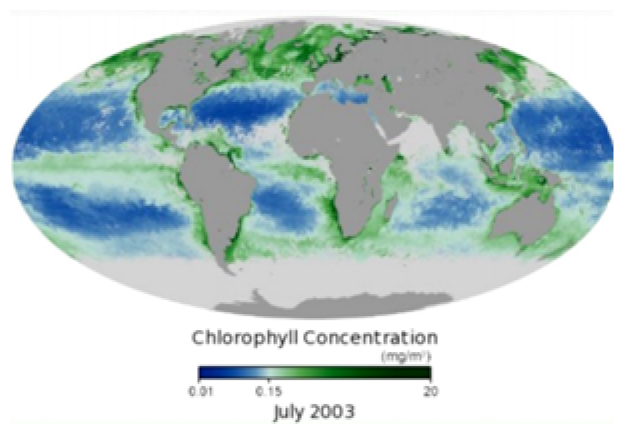




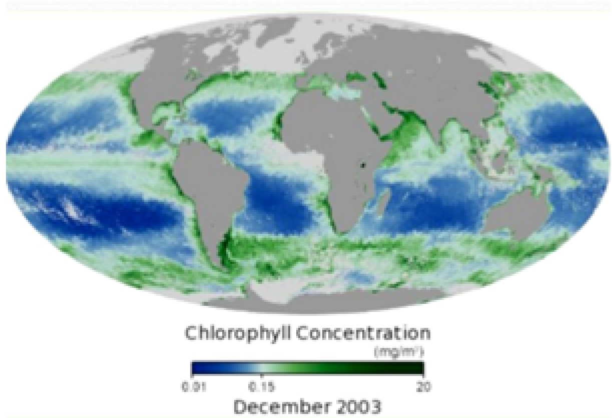


Current velocities at different k-layers, in various locations, plotted from ECCO data

The potential biological influences due to biofilm attachment or biological transport mechanisms were accounted for by tracking the abundance of chlorophyll mass (and therefore plankton mass). The Moderate Resolution Imaging Spectroradiometer (MODIS) identities wavelengths associated with chlorophyll mass, and infers regions of aggregation. As the microplastics bind with algae, the overall density of the particle increases. Thus, the regions with higher accumulations of biological organisms will correlate to an increase in particle fall velocity. The varying levels of insolation during different times of the year lead to fluctuations in chlorophyll distribution.

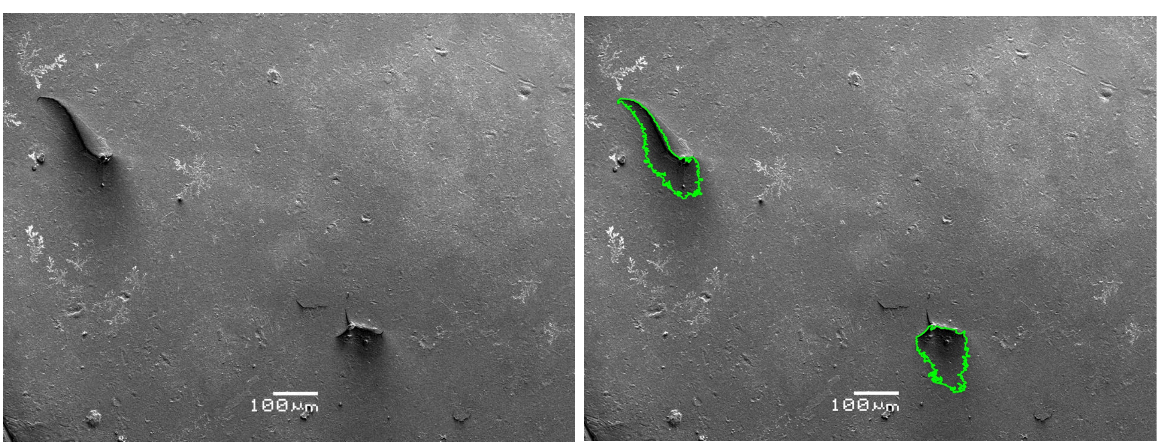


Chlorophyll mass identified using the MODIS during summer months

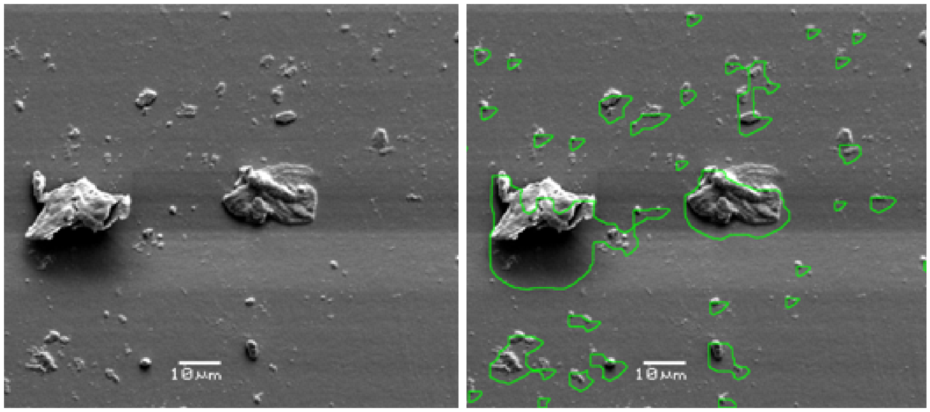


Chlorophyll mass identified using the MODIS during winter months

To establish a hydrodynamic basis for particle velocity modulation, a program using Python and OpenCV libraries for image processing and morphological feature classification was developed. Images of plastic particles from SEM micrographs were taken, and surface morphological features such as divots, bumps, crenellations, abrasions, and biologicals were identified. The program was able to obtain a total abrasion count, along with area. This allows the potential to determine the differential velocity based on plastic-type, shape, size, and density. Based on the output, a drag coefficient was able to be created, demonstrating how likely the hydrodynamic property was likely to affect microplastic movement and distribution.



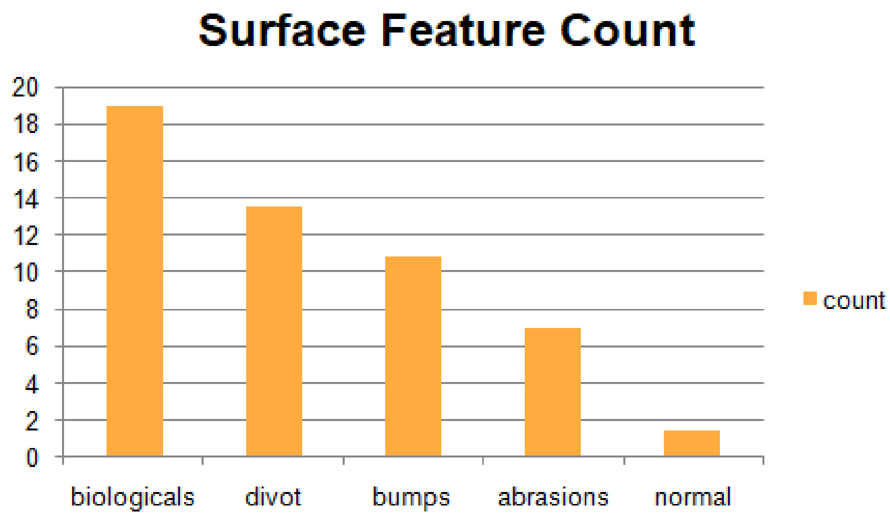
SEM Photo #1 and surface abnormality identification output



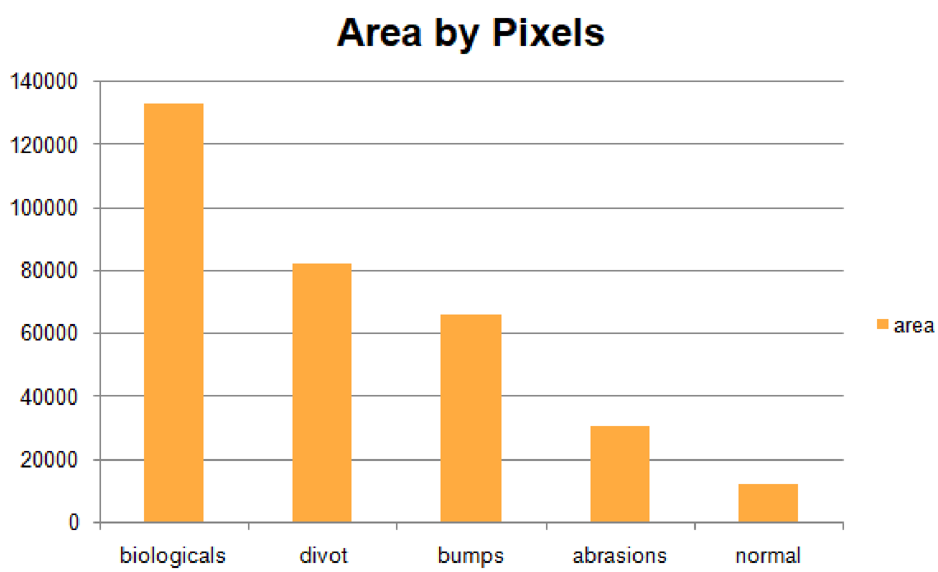
SEM Photo #2 and surface abnormality identification output

When unable to obtain SEM micrographs of samples, focus/z-stacking was used instead. Numerous images of micrographs taken at various focal depths from a polarized or a light microscope were taken and combined with a series of image processing filters and techniques, which identified the highest contrast, sharpest areas with high thresholds (aka the most focused areas), and stitches these regions together from each layer, thereby generating a blended, well-focused, high-resolution composite. The composites were then post-processed using the surface feature classification system.

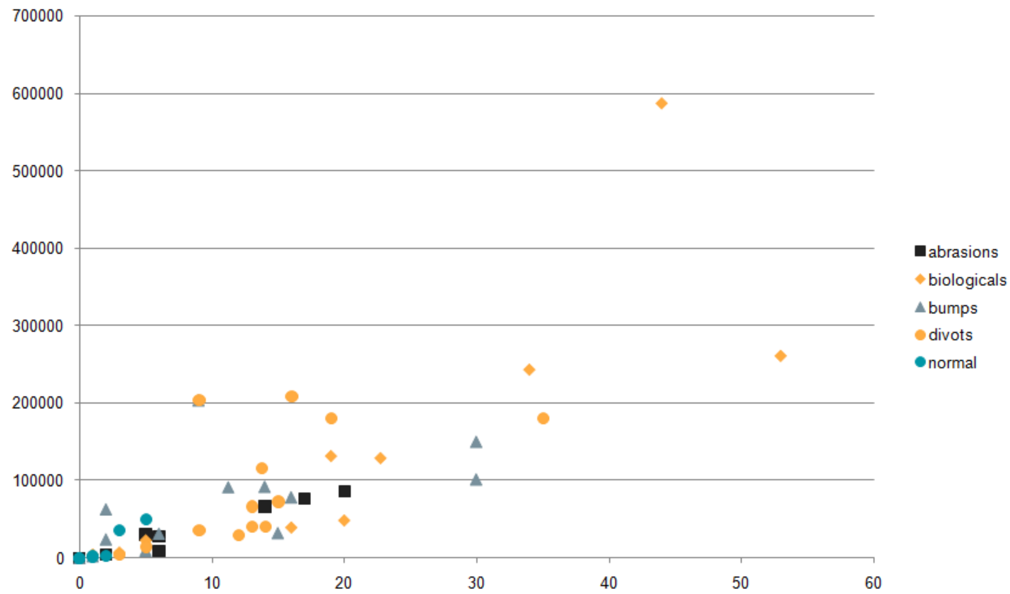
An example of a focused composite of a microplastic particle



The number of each type of surface features that were identified



Comparing each type of surface features by area



Surface area versus feature count comparison: *Comparing area of surface features present on plastic particles by pixels^2, versus the number of surface features identified (1 pixel ~ 100 nm)*

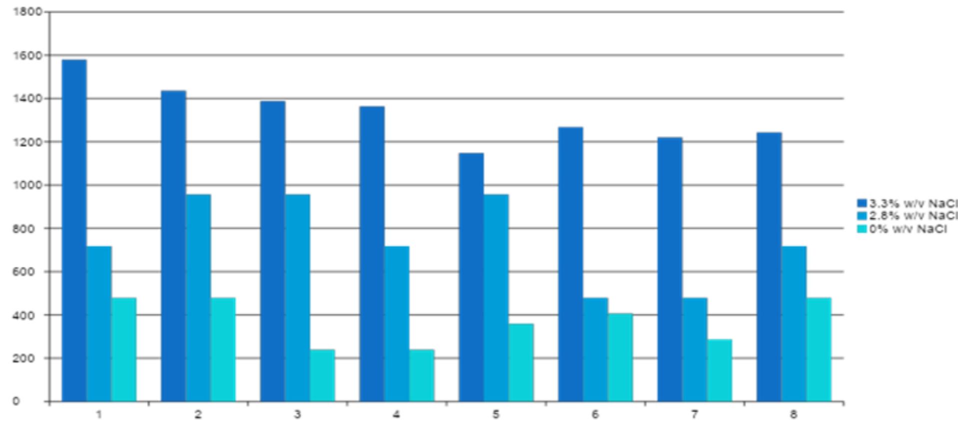
Three experiments were conducted to observe how microplastics reacted to various environmental factors with homemade marine environment emulation tanks. A long-term experiment was run over the course of several months to observe how abrasive actions alter the morphologies of microplastics, forming abrasions, crenellations, and other surface features, which cause micro-turbulence effects that have the potential to influence the particle downward trajectories through various densities of saltwater. Differences in microplastic particles were observed before and after being exposed to an abrasive environment with materials commonly found in the ocean, such as sand and glass, within a saline environment. A medium-term, two-month experiment to identify the accumulation of biologicals on microplastics was conducted, along with a final, one-month-long experiment which observed the differences in the morphology of microplastics, with various particle types, shapes, and sizes.

The key metric was the delta in the mass of the particles before and after experimental treatment with both abrasive and biological factors. Because a microscale measurement tool was not available, and local labs had been closed, an alternate approach was taken. A method to repurpose materials at home had to be utilized to create a suitable replacement for a microgram level scale. The idea of measuring the differences in electrical output on a meter movement/galvanometer/ammeter to be used as a makeshift microgram scale has been around since 2000, from an article originally published in Scientific American. A more recently updated version has been developed using pulse width modulation.

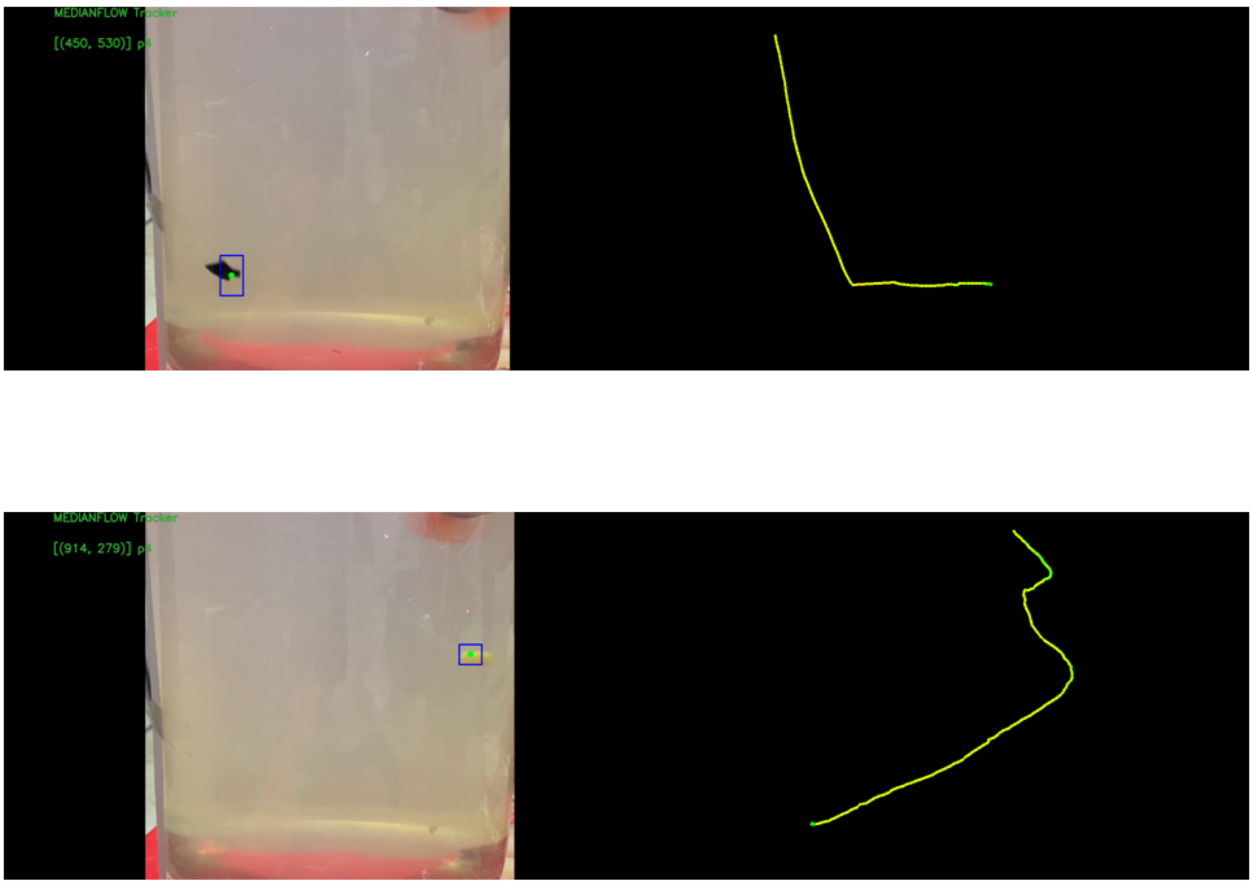
Using this galvanometer-based system, a certain amount of electricity is required to maintain a tare point, inclusive of the sample holder. After trial and error with the Arduino software to scale the width of the gaps between current pulses, a suitable range was found that would allow for accurate measurements of the weights needed for the sample set of emulated microplastic particles. When weight is added to the needle of a galvanometer, the needle is drawn down due to gravity, and more current or pulse width must be added to return the needle to the original position. The delta in pulse frequency and/or pulse length is linearly proportional to the mass of the item and can be measured in comparison to objects with known weights to calibrate the system and obtain an accurate measure of the weight. Aluminum foil was taped to the needle as a way to hold the plastics. The tare weight from the aluminum foil was taken into consideration as well, by measuring the amount of current based on the pulse-width modulation (PWM) at a steady state for stabilization. The same was done with the plastics, and after subtracting the PWM deltas, I extrapolated a set of weights, and then I subtracted the final weight from the tare weight, and what remains is the mass of the object inferred from the difference in PWM values.

Using the microgram scale made from a repurposed galvanometer to measure the weights of various plastic particles

The vertical trajectories of microplastic particles were tracked using a marine environment emulation tank. A large glass cylinder was utilized to simulate the mid-water column of an ocean, with motors attached to propellers connected to a microcontroller (Arduino) to modulate simulated ocean currents. Photoresistors were placed in various ‘layers’ of the cylinder, along with an array of LEDs arranged in a circular pattern. Plastics of different polymer types (PETE, HDPE, PVC, LDPE, PP, PS, TPU, PLA) were prepared to represent a wide range of shapes and sizes. As particles pass through the layer of LEDs, the slight change in light intensity would be identifiable by the photoresistor and could be measured. Such a set-up on multiple different layers could be used to determine how fast the microplastics are sinking between a predetermined length, and could thus be scaled up to fit the entire ocean. Multiple salinities were tested to obtain an accurate range that could be applied across the entire ocean.



Particle velocity in seconds, in water with various salinities



Tracking the trajectory of the microplastics as they descend through a vertical water column

To estimate the microplastic particle descent velocity, a finite element analysis was run to attempt to model the plastics' sinking rates and to see what the process of developing a model like this would be like. The potential velocities of plastic particles were predicted using the

Dietrich formula. Previous research papers had also been reviewed to observe the most common rate of descents for various types of plastics. Then, experimental data was collected and compared to the Dietrich formula. The experimental results were normalized as a result, and standard deviation along with linear interpolation was used where needed. This all came together to develop an appropriate consensus model.

$$W_* = \frac{v}{d} d_*^3 \left[\left(\frac{3A}{4} \right)^{2/n} + \left(\frac{3B}{4} d_*^3 \right)^{1/n} \right]^{-n/2}$$

W_S = settling velocity

v = kinematic viscosity of fluid

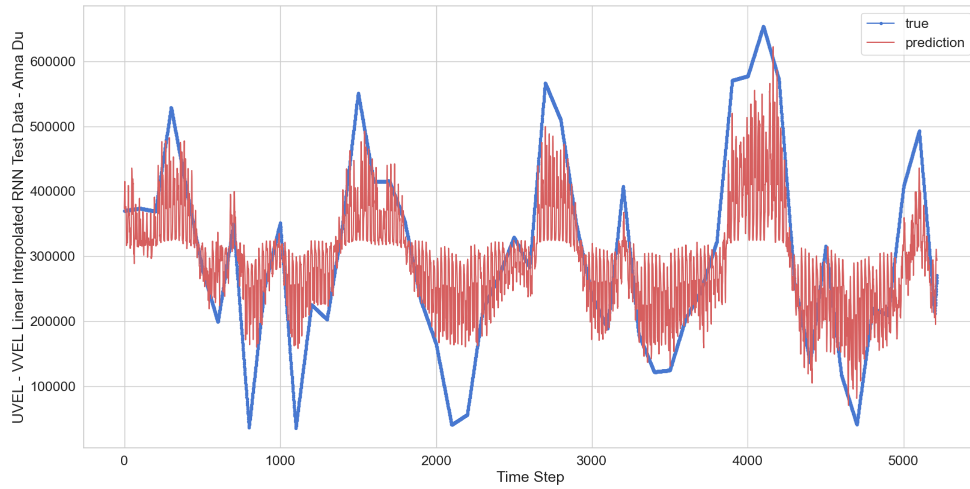
d = particle diameter

$d*$ = dimensionless particle diameter

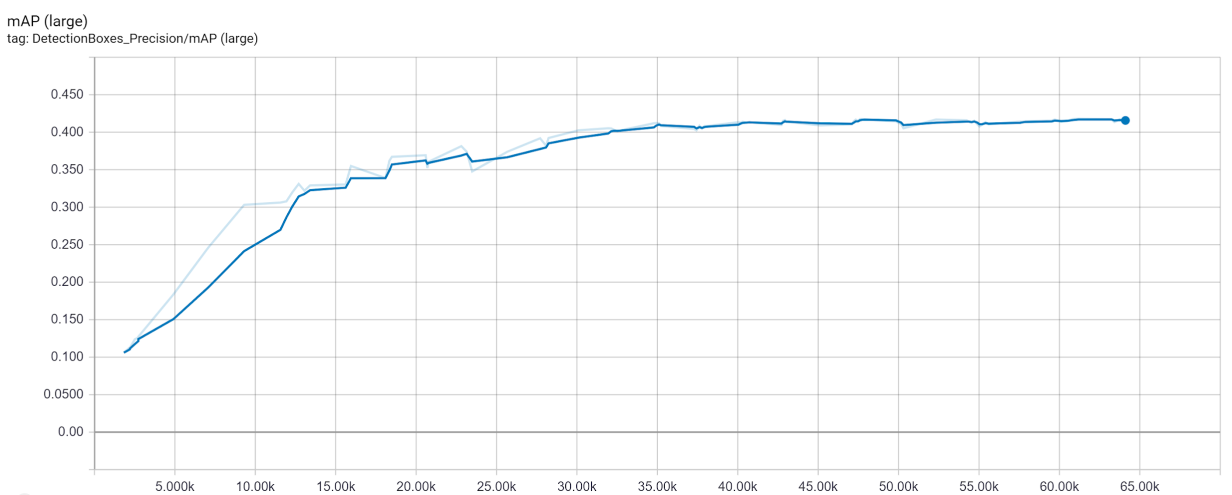
A, B, n = calibration coefficients

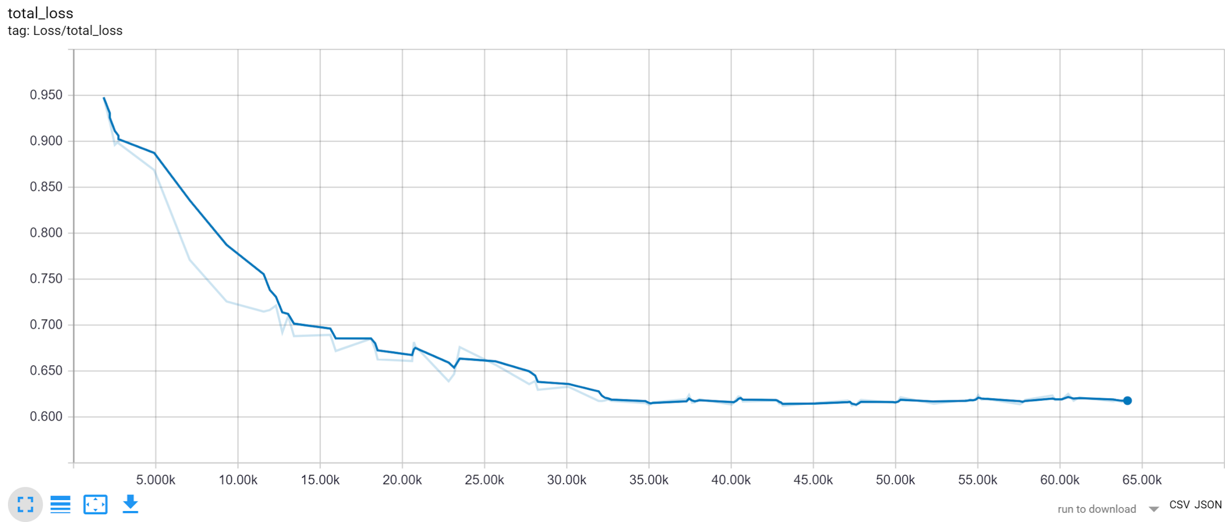
A simplified version of the Dietrich formula used to calculate particle fall trajectories in the simulation model

Recurrent neural networks have been used in this project, as it excels with processing temporal sequences such as videos and blocks of text. The RNN (recurrent neural network) based model split the data into two categories -- 80% of the data went into the training category and 20% into the testing category. The learning optimizer utilized in this model was Adam with a gradual decay of the learning rate over time. To minimize the total loss, additional data inputs were added, and outliers were removed.



Example comparison of RNN value predictions with the true future for UVEL and VVEL

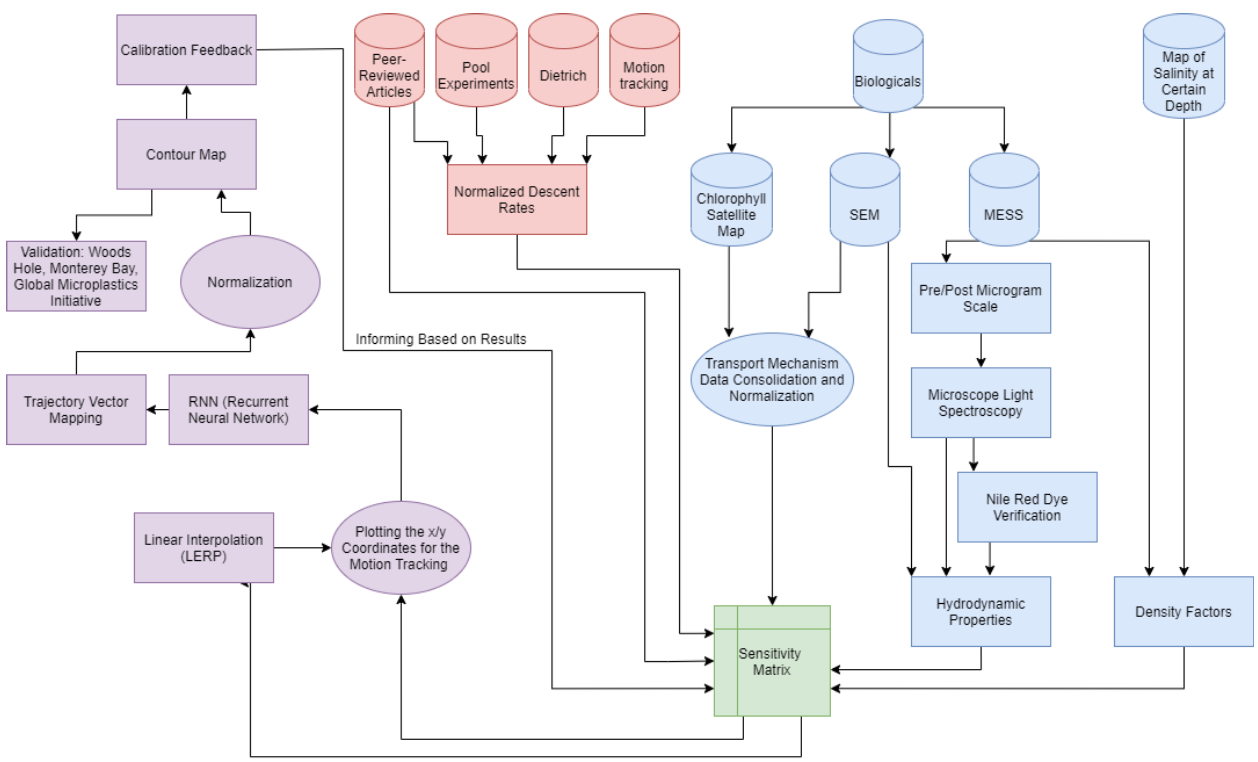




Example accuracy and loss of an RNN that ran using a GPU over the course of a few hours.

The RNN models predicted future particle trajectories based on the data assets that were input into the sensitivity matrix, including the hydrodynamic properties of microplastics. To quantify the extent to which microplastic particles would be affected by the surface microstructural characteristics, convolutional neural networks were used in conjunction with image processing. Initially, training the CNN models took several hours to run 2000 iterations. When the surface characteristics of the particles were classified using Keras/TensorFlow, the results were somewhat mixed. Supplementing the object detection with an image processing program using OpenCV had substantially better results, as well as comparative data in terms of the number of surface features versus the area of those features. This allowed for a much better job quantifying the likely hydrodynamic drag coefficients. The GPU version of TensorFlow 1.14 was used, as using the CPU version for a simple two-class classifier took a few days to complete, and the accuracy did not exceed 70%. However, with the GPU version, it took 12 hours to complete almost 200,000 iterations. The more surface features that can be classified as erosions/abrasions, the greater the drag is. However, if the features appear to be biological in nature, it's likely that this is adding to the density of the particle, and while it does add to drag, certainly, it is also likely the case that the additional density of the microorganisms cause the particles to sink faster, despite the additional drag. In that sense, it is believed that the density has a greater impact on the gravitational descent, as opposed to the surface characteristics, in the pelagic/mid-water column region of the ocean.

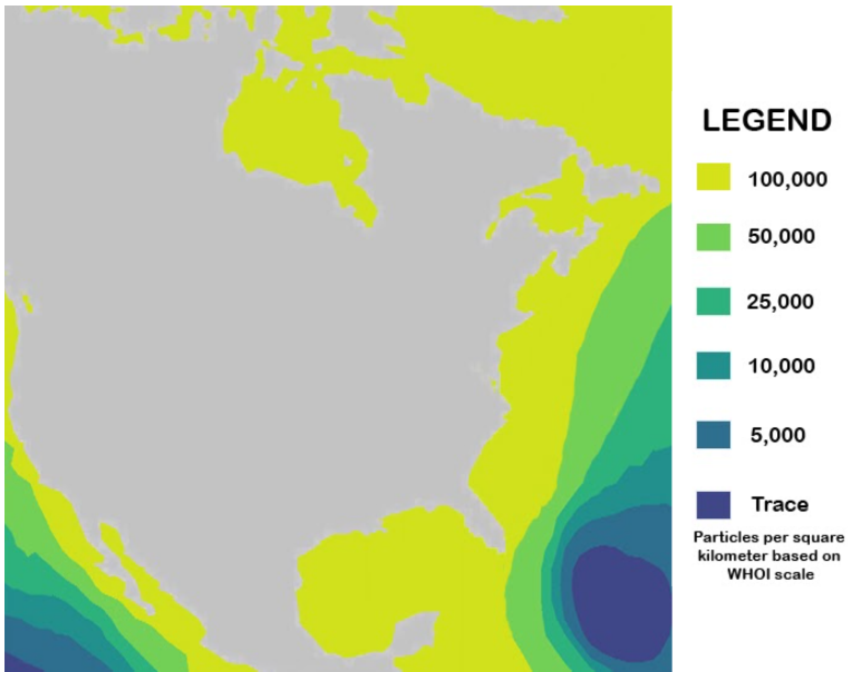
Sensitivity analysis models had to be established, due to the limited literature availability, and the oversimplification of ocean dynamics in single-variable experiments. This allowed the modulation of combinations of factors, to create numerous simulation model outputs. An effective range of parameters was determined, including the amount of time a certain type of plastic will remain at one k-layer, along with other environmental factors. Chubarenko placed this value at six months, and Kvale estimated this value to be around two years. A review of other literature yields values within this range. These parameters were modulated to determine a scale that is realistic for plastic distribution. The Python module matplotlib is used to process CSV outputs from the simulation model to generate high-resolution spatial maps of all plotted data points at each specified time frame. This data can then be visualized as still images, or as full-motion video, using FFmpeg.



Core model system architecture

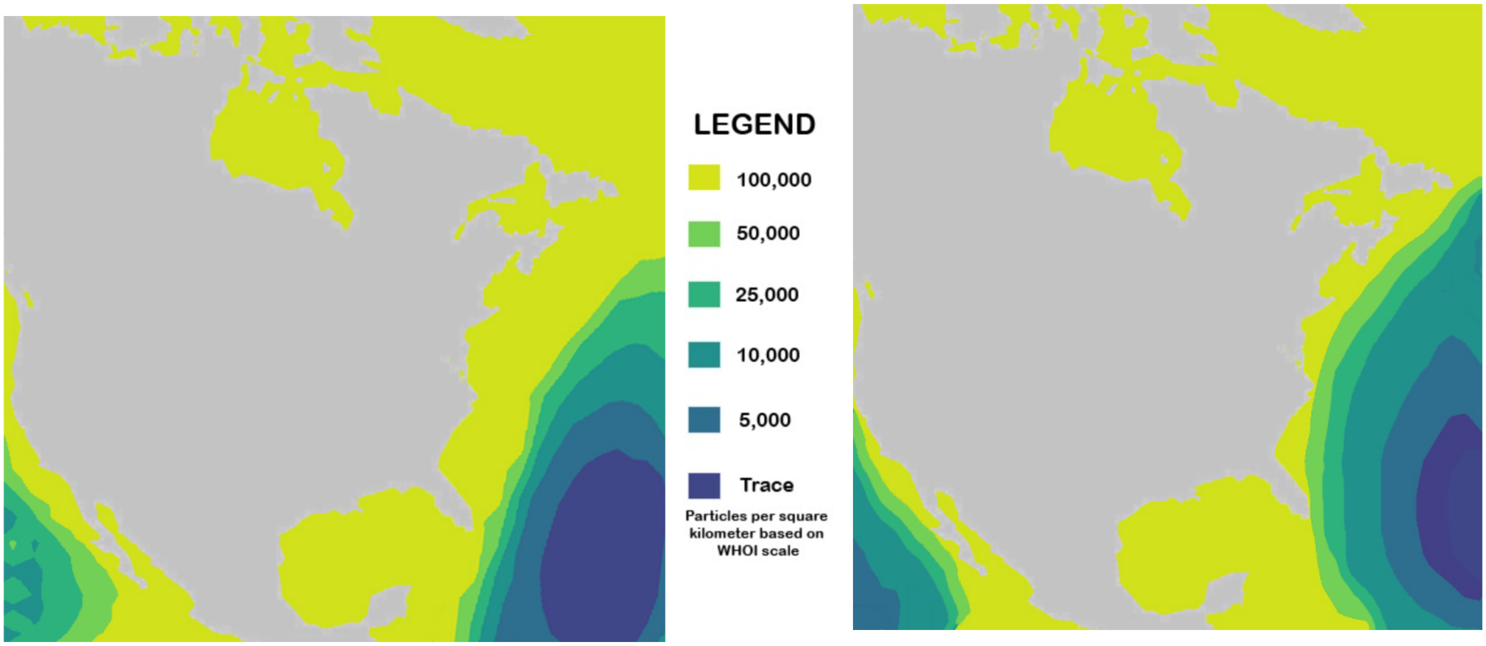
Results

The results of this simulation model are output as a series of distribution maps. After running this model 100 times, the p-value was calculated to be around 10^{-4}. This demonstrates that my model is highly statistically significant.



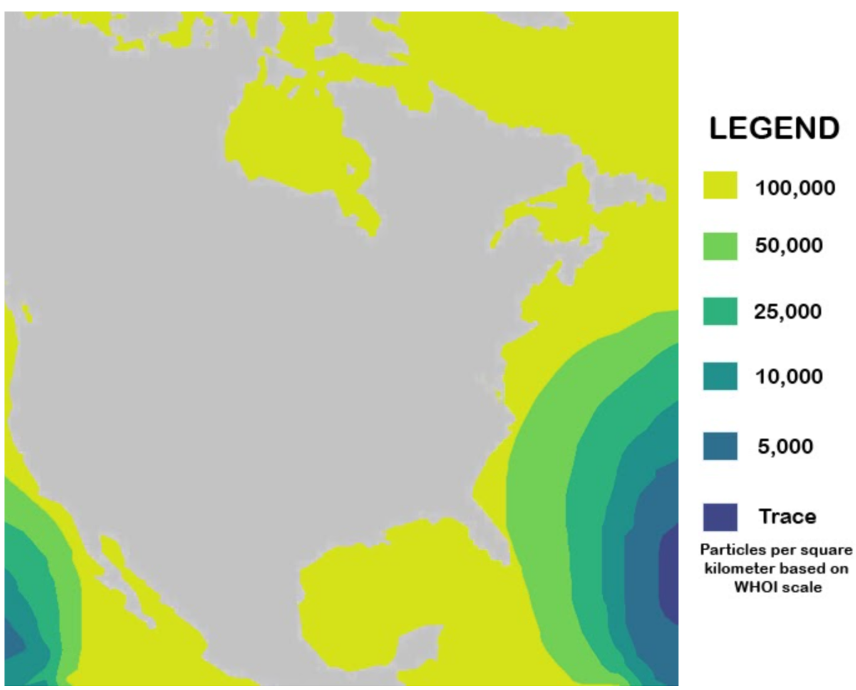
Probability of Distribution of Microplastic Particles Based on Plastic Type/Material Density

This map shows the distribution of plastics which have been affected primarily by their material densities.



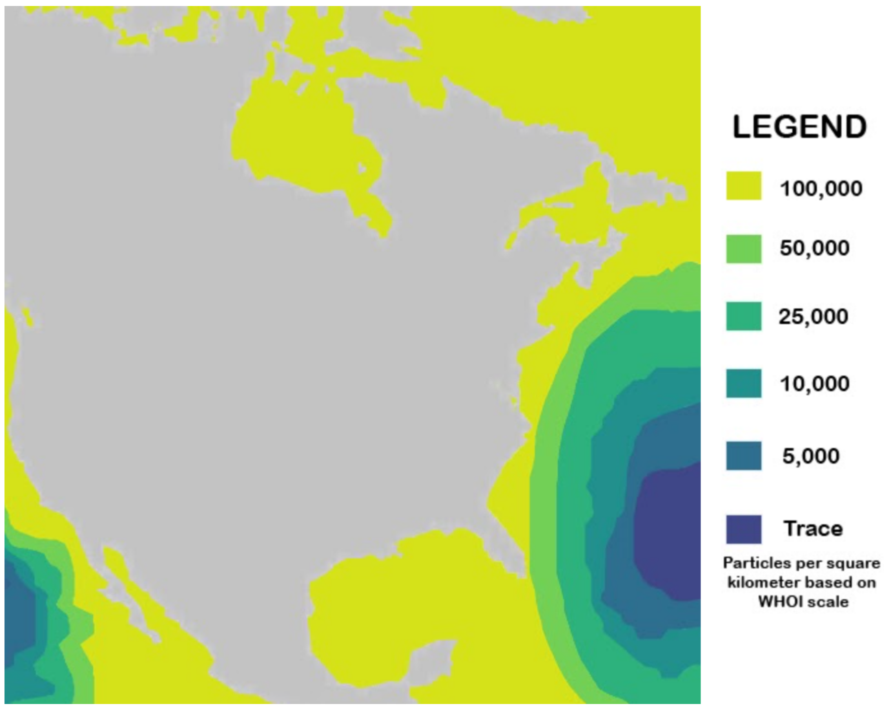
Probability of Distribution of Microplastic Particles Based on Biological Influences (Biofilms and Biological Transport Mechanisms) in Summer and Winter Respectively

The two maps above display the distribution of microplastic particles based on the movement of biological organisms during the summer and winter months, showing that seasonal differences in distribution are substantial.



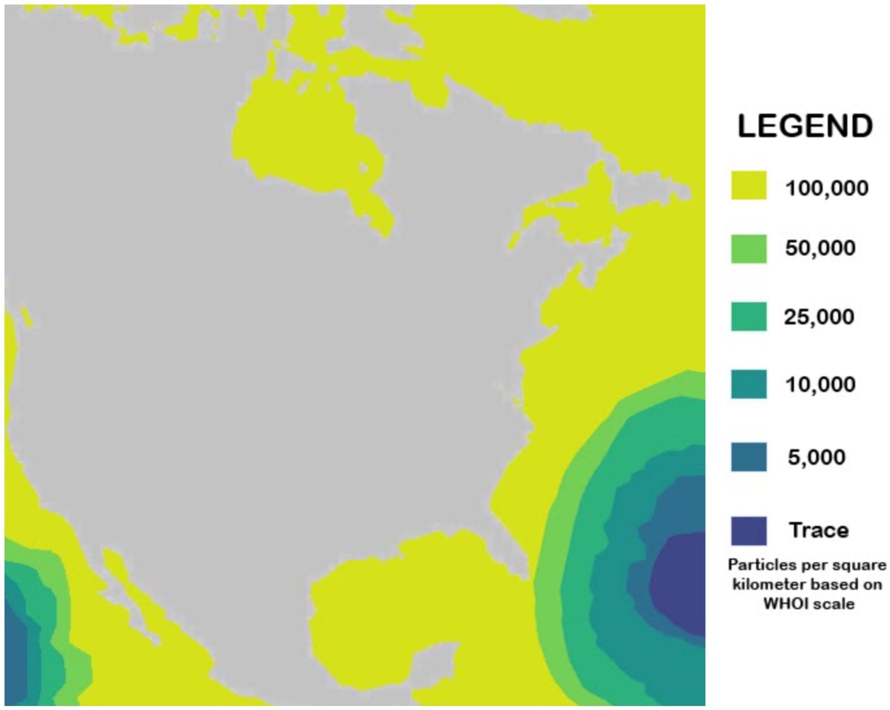
Probability of Distribution of Microplastic Particles Based on Hydrodynamic Influences

The hydrodynamic property of a piece of plastic has the most influence on the plastic movement in the lower half of the mid-water column, near the benthic layer of the ocean.



Probability of Distribution of Microplastic Particles Based on Particle Shape

While the shape of a particle does not have as much of an effect on the eventual location as material density or the hydrodynamic property (which, due to the numerous surface features present, can often show orders of magnitude differences in surface area), the simulation model was still able to account for changes in the bulk shape of the particle.

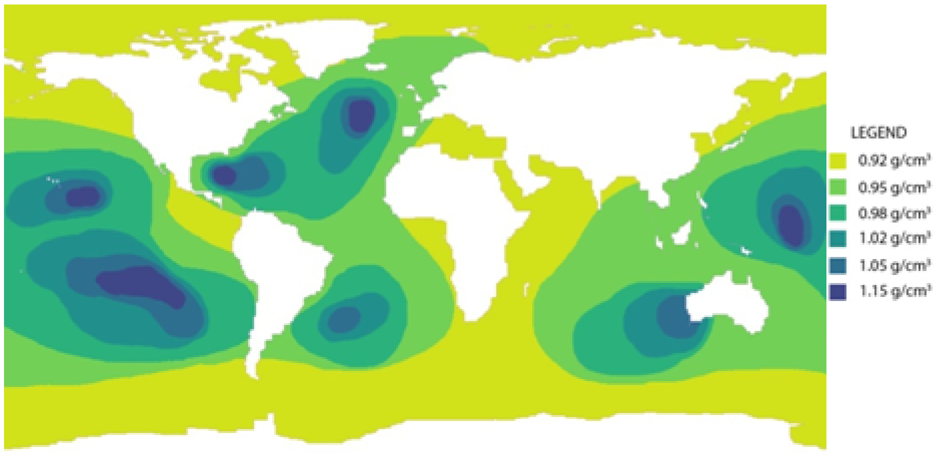


Probability of Distribution of Microplastic Particles Based on Particle Size

The size of the particle, when all other factors are considered equal, had the least effect on microplastic distribution for a similar reason as the shape of the particle.

	Wind	UVEL/VVEL	Biological Transport	Hydrodynamics	Density Changes	Turbulent Forces
k=0	30	50	10	5	3	2
k=1-5	0	65	15	10	7	3
k=5-10	0	60	20	10	10	10
k=10-20	0	50	15	15	15	5
k=20-30	0	40	15	30	10	5
k=30-40	0	10	3	70	5	2
k=40=50	0	5	10	75	5	5

This is a sample sensitivity matrix for an average particle, of medium abrasion, with relatively low maturity

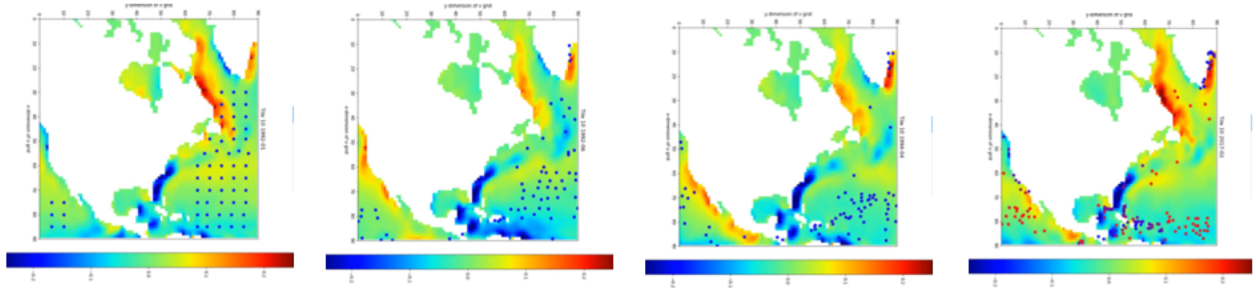


This is a sample global distribution map that displays microplastic aggregation based on the material density of the particle, based on the sensitivity matrix above

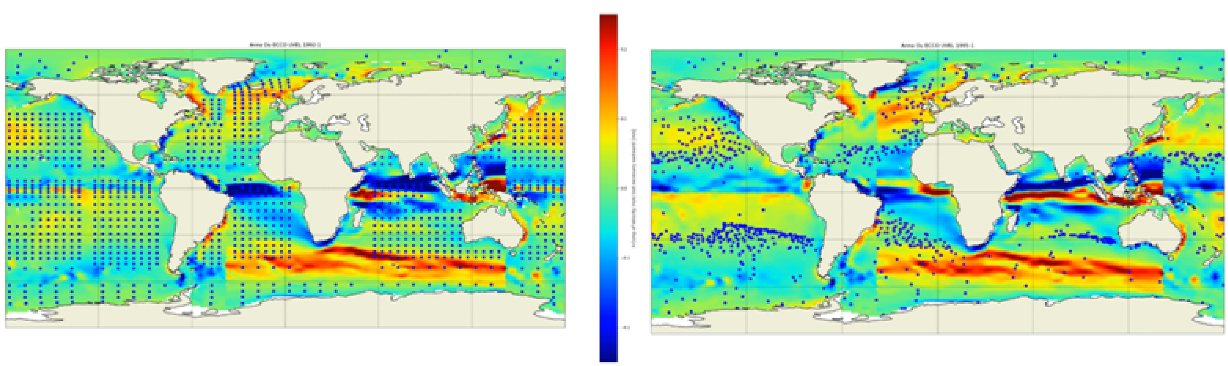
A global distribution map was created based on a sensitivity matrix of a particle with medium abrasion, an initial material density close to seawater, and a combination of spherical and sheet-like particles when descending through the mid-water column. In the initial simulation outputs, it was proven that the material density of the particle had the largest effect on microplastic distribution. Thus, the global distribution maps are based on the material density of the particle.

Summary Average Data						
	Density	Biologicals - Summer	Biologicals - Winter	Hydrodynamics	Shape	Size
Total Area	46925	52407	60333	43258	44255	35663
Highest Aggregation	6675	15395	7863	1181	3961	2876
Percent	14.22%	29.38%	13.03%	2.73%	8.95%	8.06%

The ratio between the areas of the densest region of distribution of particles was compared against the total amount of distribution of plastics according to the particle data that was entered into the model. This ratio was then normalized across trial runs, and a median predictor was used as the value to compare the output of the simulation, and every trial run was compared against the expected ideal value for each particular category of simulation.



Sample tile 10 particle distribution output from the simulation model inclusive of all factors which influence microplastic accumulation



Sample global particle distribution output from the simulation model inclusive of all factors which influence microplastic accumulation

The global simulation model was run, with randomized size, shape, material density, hydrodynamic property, and biological influences. The surface microplastic distribution data predicted by my model were compared to the published data collected over the course of decades by WHOI (Woods Hole Oceanographic Institution) and SEA (Sea Education Association), and seemed to be highly correlated both in terms of relative density of aggregation, and also the total area of the particle distribution. The predicted vertical profiles based on the trajectory simulation model outputs of mid-water column microplastic distribution data were compared to the biological transport data from MBARI (Monterey Bay Aquarium Research Institute), which demonstrated that most of the plastics (in this case, especially the ones that are affected by biological transport mechanisms) are located predominantly around k-layer 17, or around 300 meters deep. A mathematical comparison between the two models and the simulation outputs was completed, and the statistical significance of overlap of existing data and alignment of maps was found. However, none of these methods would give a reliable method for verifying that the locations on the ocean floor are accurate. To do this, an ROV/AUV that automatically collects samples could be used. These underwater vehicles can traverse the ocean floor to identify hot spots of microplastics. However, this could only be used as a spot verification method, as using ROVs or AUVs to search the entire ocean floor would be extremely inefficient. Another method for identifying microplastics on the ocean floor is by using a sediment trap. This method is much more passive than the other verification techniques, but it would give an accurate representation of how microplastics accumulate over time.

Conclusions

The distribution maps created from the simulation model output data demonstrate multiple key findings. Of the major factors which were studied, including material density, particle shape and size, biological transport mechanisms, and the hydrodynamic properties of the particle, there were two that yielded conclusive correlations to significant ocean floor distribution patterns -- material density and seasonal biological influences. In addition, it was found that hydrodynamic surface properties play a substantial role in particle trajectories at lower k-levels of the ocean mid-water column.

It was shown that the material density of a plastic particle appears to have the largest effect on plastic distribution. This is due to the fact that current velocities in near-surface pelagic regions of the ocean play the single greatest role in oceanic transport. This is evident from current velocity range charts. Particles that have a lower material density will remain near the surface of the ocean for a longer period of time and will be highly affected by the current and wind, especially when compared to particles with a higher density, which will more rapidly descend to the ocean floor, either from within gyres, or near sources of pollution, including fluvial outputs, landfill barges, and nearshore factories.

One of the major findings from the biological influences simulation output distribution was seasonal variation in plastic accumulation. The insolation in a given region plays a large role in algae growth, and satellite imagery and sensor data of areas containing known chlorophyll abundance. These regions are correlated to greater quantities of zooplankton/phytoplankton, and other marine life, that consume these organisms (as well as microplastics). The combined effect of algae binding and biofilming of microplastic surfaces and the ingestion and excretion of microplastic particles by a multitude of base trophic feeders will tend to increase the bulk density of microplastic particles. In addition, regions with greater biological activity tend to be associated with a greater incidence of particle aggregation due to binding through an abundance of organic compounds present in marine snow. As such, according to the model, the seasonal shifts in biological activity are strongly associated with massive amounts of rapid microplastic accumulation on the ocean floor, as can be seen in the biological influences distribution map above. The winter vs summer clearly shows distinct differences between the particle area of distribution that can only be explained by the seasonal effect of biological influences on particles.

Another key finding from this study is that hydrodynamics of the microplastic particle surfaces due to microstructural characteristics are a significant factor affecting particle trajectory. The primary domain of ocean current velocity influences resides in the upper portion of the water column. The velocity difference between k-layer 5 and k-layer 20, can be an order of magnitude. Generally speaking throughout the ocean, k-layers 20 and lower, tend to have limited ocean currents. Yet it is at these depths, that microplastic particles which have passed through the photic zone, would presumably contain a combination of biofilms, UV radiation effects, and other chemical and mechanical weathering. These surface features play a substantial role in bulk material density changes and the drag coefficient of the particle. According to the surface area versus feature count comparison chart, it was possible to classify the types of surface features found commonly on microplastic particles using both SEM and light microscopes, along with an image processing and CNN-based system, with a system identification/localization accuracy exceeding 92%. Statistical analysis was performed on this dataset and was able to obtain a p-value of 10^{-4}. This can be correlated to the extent of the features presence, therefore, this can be used as a highly quantitative means of assigning and classifying particle surface morphologies, even when the surfaces contain evidence of a combination of erosion and biological effects. In combination with calibration experiments, this can be used to infer a drag coefficient that can be applied to all microplastic particle types. The drag coefficient of each particle does not play a substantial role as compared to particle shape, size, or density, where current velocity is high. However, in the mid-water column to the benthic zone of the ocean, hydrodynamics could potentially be the most significant factor in particle movement.

This demonstrated my hypothesis, and clearly shows a high correlation to the areas of particle accumulation as shown in the distribution maps created by WHOI and SEA Foundation's decade-long study. The fact that the surface data output from my study matches with the WHOI data with a 90% overlap accuracy, and a statistical significance of 10^{-4}, shows that this model could be highly accurate in predicting ocean floor microplastics as well. Future sampling studies will confirm the assumptions and conclusions of this report based on the model output density distribution spatial maps. In the near future, the simulation model will be confirmed by WHOI research sediment trap data, and in conclusion, if this model is verified to be highly accurate, it could be used for a higher resolution study, and could also be widely used in other applications as well. Specifically for microplastics research, the level of resolution obtained from the ECCO dataset is not very high but does provide an indication of where, on a granular level, microplastic accumulation is most egregious, and should be addressed according to various priorities, including impending danger to the benthic ecosystem, ability to be addressed with low-cost cleanup efforts, the likelihood of association with other toxins such as POPs, heavy metals, radioactivity, etc, and the general possibility of causing harm to humans and the environment at large.

Future Considerations

Within the next year, it is expected that these various simulation model output distribution maps will be verified using experimentally derived real-world data from sediment trapping and sediment column collection via oceanographic research vessels. In addition, a software interface will be created to simplify the process of modulating inputs into the probability matrix and sensitivity analysis, to provide a service to the oceanographic community, to collaborate on this effort. An API would also be created to share the information with outside oceanographers and data scientists, on applications such as GitHub and Kaggle, and/or others, such as in conjunction with NASA's ECCO dataset. According to a WHOI conference regarding the topic of microplastics, more data is becoming available, so further research in the peer-reviewed journal space will be used, including the surface distribution from WHOI's SEA Foundation, the volunteer-collected data from the Global Microplastics Initiative, the simulated data from JPL's HTC laboratories, as well as MBARI's study regarding the abundance of microplastics across the mid-water column by microorganisms. Furthermore, once a sediment trap plan is in place, and other systems are in place to verify the data in specific locations, it would be possible to do some spot verifications on the ocean floor. Additional verification can also be done in areas where there are sediment core samples. Another major factor to consider is the re-suspension of plastics from the ocean floor. Neutrally buoyant particles may sink down the vertical water column until a current or a movement causes the particle to float to the surface again.

I have already begun the process of filing a provisional patent. I have also created two systems for collecting data from a modular automated sensor-based buoy platform, that is capable of accurately measuring microplastic trajectories based on the emulation of particle buoyancy in a real-world environment. This system is a more robust and advanced version of the ROV/AUV work I had done in phase one. However, this proposed system is capable of accurate measurements at depths of 8,000 meters. In addition, another newly invented system concept for surface microplastic and mid-water column microplastic detection has been invented, involving the concept of infrared light, combined with automated detection sensors, as well as cam based, AI-enhanced image processing in a vehicle capable of being towed by research vessels as a low-cost approach to automated microplastic collection. Intellectual property is currently being formulated regarding both of these inventions, and it is planned that this will be the focus of additional phases of my research. This high-resolution real-world data will not only verify my simulation model approach but will also demonstrate significant improvements over the status quo of sensor/equipment-based microplastic detection and quantification.

It is imperative that systems like my highly accurate particle trajectory simulation model as well as new forms of automated sensor-based data collection systems are adopted by the research community, and supported by governments and non-profit organizations as quickly as possible, to take initial steps toward curbing the microplastic pollution problem. Furthermore, the predictive and spatial mapping capabilities could be extended for mapping trajectories of other materials, including different types of environmental pollutants such as cargo spillage and radioactive particulates. Through my outreach work in creating the non-profit Deep Plastics Initiative (http://deepplastics.org/), it is my hope to continue to reach out, not only to the general public to inform them about this grave concern, but to educate others about the latest research in this field, and to share information and resources with the scientific community, and other aspiring young scientists and engineers.

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