MODELING OF TRANSPORT OF PLASTIC IN A NORWEGIAN FJORD

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Abstract

This thesis is a part of FACTS project. In this research, I have carried out some numerical and statistical analysis to find the places where plastic is accumulating. This work is done on a model on which simulations have already been carried out by Prithvinath Madduri using OpenDrift. I have tried to find how sinking velocity is affecting the accumulation of plastics. It was analysed that the particles with high sinking velocities sink faster close to bridge then the ones with low sinking velocities.

Problem Statement

Micro plastic pollution in our environment is becoming a global issue (Kershaw, 2016). Plastic concentration is alarmingly increasing and becoming a source of great concern. So, it is very important to identify the places where plastic is accumulating and to figure them out and do appropriate steps for its removal.

Plastic is entering waters from a number of sources. The topic on which I am doing research specifically studies the plastic that is coming from tyres of vehicles. When tyre particles move along the bridge, some micro plastics are released and enter the waters. This research basically aims at finding the the hot spots of Micro plastics accumulation in Byfjorden. The plastic that is coming from tyres of vehicles moving over the Nordhordland Bridge into the Byfjorden. I will perform some numerical and statistical calculations to look for points of accumulation.

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Chapter 1

Micro plastics in Ocean

1.1 Introduction

1.1.1 What are micro plastics?

Plastic debris is now found every where in our environment. It exists at sea coast, sea surface and even at sea bed (van Sebille et al., 2018).

This plastic debris is usually classified into four different types which include mega plastics, macro plastics, meso plastics and micro plastics (Thushari and Senevirathna, 2020). They vary in sizes. The nano plastics (1 to 100nm), micro plastics (1μm to 5mm), meso plastics (5mm to 10nm) and macro plastics($\geq 10nm$) (Frontiers, 2023).

The small pieces of plastics known as micro plastics are synthetic compound made mostly from polyethylene or polypropylene. These micro plastic are found everywhere in beaches, lakes, ocean or sea. These are extremely small pieces and large number of these are less than 5mm in size (Xu et al., 2019; Kershaw et al., 2019).

These micro plastics are a source of real concern for the marine life. These micro plastics are contaminating the ocean water and are a major polluting element in the ocean water. Lot of research has been already done to find the fate of micro plastics. This is still an unanswered question that where do these micro plastics go after they enter the ocean water.

Micro plastics have a variety depending on the size, shape and densities of particles. micro plastics are classified into two categories. Primary micro plastics and secondary micro plastics. Primary plastics are the one that usually come from cosmetic, clothing or other such products while secondary plastics are those which are formed by degradation of large plastic particles which may include water bottles or other plastic products.

These micro plastics may change their properties depending on the time they stay in ocean water. Some factors that may contribute to the change of plastic debris are bio fouling, ocean currents, winds, weathering or some other factors.

It is believed that hundred times more plastic is entering the ocean as compared to that is currently present at the surface of the ocean (Van Sebille et al., 2015). Until now, it's still unknown that the plastic that enter ocean stay on the surface of water or they settles down on the sea bed. It is in fact a very complicated problem to see what happens to the micro plastics.

1.1.2 Where are micro plastics coming from?

Micro plastics are entering sea from different sources. Large amounts of plastic debris come from polyethylene plastic that is present in medical and cosmetic products. This form of plastic enters the sea water usually by filtering methods (UNEP, 2021).

When a particle enters the sea, it experiences buoyant force as a result of which low-density plastic particles float on the ocean surface and others sink. Some studies show the presence of low-density particles on the surface of ocean. A particle sinks when the density of particle is above the density of ocean water (Amaral-Zettler et al., 2021).

However, sometimes properties of particles with low densities may change which causes sinking of these micro plastics (Amaral-Zettler et al., 2021). Research has shown that plastic remains can take thousands of years to degrade (Shahnawaz et al., 2019). Degrading of plastic depends upon treating plastic remains with ultraviolet rays but it is not easy due to presence of marine life. Moreover, there is limited oxygen and light deep down the ocean so due to non availability of favourable conditions, micro plastics decay takes hundreds and thousands of years.

Weathering is also a crucial factor that is continuously changing the large plastic pieces by breaking it into small pieces and hence contributing to plastic pollution in water. Another important factor that is responsible for accumulation of micro plastics is biological fouling which is discussed later in 1.1.3.

Plastic debris is contaminating our waters. It will not be unusual if we say that the Current Era is a Plastic Age (Thushari and Senevirathna, 2020). Plastic is now everywhere around the Earth. It is found in almost everything we humans use. Plastic has taken over the whole industry. As the time is increasing, the plastic production is increasing and so its contamination. A large amount of plastic is produced by the industries. Research shows that plastic contamination is increasing in the ocean (Kye et al., 2023).

A large amount of plastic is coming from the tyres. This plastic is coming by moving vehicles, as they move along the road, some micro plastic gets into the water by rubbing of tyres along the bridge. This research is typically dealing with plastic that is coming from tyres. The research is based on Nordhordland bridge which is located along the west coast on E39 highway. This highway joins north and south of Norway and also connects to Denmark. This is a very important source of transportation in Europe. E39 is a busy highway with a lot of traffic. On daily basis large vehicles move and in turn are a causing plastic accumulation in the fjord (Wikipedia, 2022a).

1.1.3 What is Biological fouling?

Biological fouling is the collection of biological organisms, plants and algae on the particle that is submerged (Ryan, 2015). This is basically attachment of small growth on a particle.

When plastic enters the sea water, it starts to develop bio film around the particles. Due to Wind currents, the particles mix along the water column and as the time pass by the layer around plastic particles thickens. Due to this process the densities of particles increase and hence results in eventually sinking of micro plastics.

It is also assumed that thickness over time is responsible for thickening of bio film. As the time interval increases, the layer around particle gets thicker. Plastic usually sinks within 2 weeks from as soon as it enters the ocean water (Kooi et al., 2017).

As the plastic sinks, the bio film layer around it starts to disappear due to an effect can defouling. Defouling is the dissolving of the layer that can be caused due to solving of carbon layer around particle or due to some other factors (Kye et al., 2023)

It is an important topic of for researchers and scientists to find the fate of micro plastics, but no clear results have been deduced due of lack of proper data and information.

Bio fouling not only depends on temperature of water and the availability of sunlight or nutrients, but also on the size and shape of plastic particles (Kooi et al., 2017). It is also believed that the biological process is responsible for the sinking of micro plastics together with physical factors like wind, currents, weathering etc.

1.1.4 Why are micro plastics becoming a topic of great concern?

According to National Oceanic and Atmospheric Administration (NOAA), every year **eight million** tons of plastic enters the oceans. Micro plastics are now present every where (Kosior and Crescenzi, 2020). They are present in Ocean depths, in Antarctic ice and now Japanese researchers have found micro plastics in clouds on top of two Japanese mountains **Mount Fouji** and **Mount Oyama**. This plastic accumulation in clouds can lead to weathering and increase global warming issues (Wang et al., 2023).

Micro plastics are a threat and danger for marine life and our ecological system. Since, these micro plastics cannot be degraded easily so, once they enter the ocean they remain there and cause a serious threat to life's there.

Micro plastics are consumed by the marine animals. Research has shown that micro plastics are even present inside bodies of marine creatures. Studies show that the larger sea creatures are very much affected from this plastic pollution (Wang et al., 2023).

Through sea animals this plastic can enter the food chain.The sea food like fish, shellfish, shrimp, oysters, crabs etc is then consumed by humans and are a potential threat for human health.

1.2 Physical and Dynamical properties of micro plastics

The behaviour of particles depends on the properties of the particles which include its size, shape or densities. The initial densities of particles may range from 0.05gcm^{-3} to 2.1-2.3 gcm^{-3} (Chubarenko et al., 2018).

Sometimes plastics particles change there properties due to synthetic or artificial elements used in them. On the basis of there properties like densities, plastic particles experience either positive buoyant forces or negative buoyant forces. Due to these positive or negative buoyant forces plastic particle will sink or float on the surface of ocean.

According to (Andrady, 2017), **311 million** tons of plastic was produced in 2014. 50% of particles experienced positive buoyancy while 20% negative buoyancy.

Another physical property that is very responsible for plastic accumulation in layers is size of micro plastics. Usually the size of micro plastics is less than 5mm. Micro plastics are in a variety of shapes. These are often divided into one dimensional, two dimensional and three dimensional shapes.

These physical properties of particles may change due to external conditions like Bio fouling, degradation, weathering etc. Due to these processes micro plastics may change there characteristics permanently.

Whenever we do modelling of a dynamical system, we try to study the motion of the particle on the basis of there velocities. These include the rising and settling/sinking velocities of particles. The settling velocity is the maximum velocity of particle when the particle is falling down with no acceleration whereas the rising velocity is the velocity that typically occurs due to positive buoyant forces. These velocities largely depend on the size, shape or densities of micro plastics.

The settling velocity is an important parameter as the residence time. The fate of sinking micro plastics crucially depends upon the residence time. This is the time for which the particle has stayed at a certain location along the water column. This time helps to track the path along which particle has traveled and the depth of micro plastics depend on this parameter (Khatmullina and Chubarenko, 2019)

Motion of small micro plastics is greatly influenced by the turbulence and current. Due to wind and currents the lighter plastic particles are easily blown away (Nielsen, 1993).

It is a global issue to find the micro plastics, that is getting dumped into the waters. We still have limited knowledge of where does plastic go once it enters the sea.

1.3 Some Previous Research on micro plastics

The section below gives some previous research that has been carried out for finding hot spots and accumulation areas of plastic in ocean. Some of these methods have been listed below:

1.3.1 Modeling using sinking velocities

In (Lobelle et al., 2021), the discussion is aimed at the sinking of bio-fouled plastic. They used a Lagrangian model to generate simulations using virtual particles as it is hard to do simulations on real particles in the sea. The model performed 90 days simulations on virtual particles at the sea surface.

In this model it was experimented that how long does it take for a bio fouled particle to sink. They used sea water and algae properties in his model. It was concluded that the smallest particle sink immediately as it requires small algae to let it sink. It was also noticed that the five gyres where plastic is accumulating has very rare algae growth and hence the particles remained floating during the 90 days simulation period.

They found out that the initial sizes of micro plastics have more affect on sinking timescales than the densities of micro plastics.

(Lobelle et al., 2021) is based on Kooi's Model (Kooi et al., 2017). This equation governs the befouling and sinking of micro plastics. The sinking velocity $[ms^{-1}]$ is dependent on plastic and the algae growth and its surrounding water. It is also dependent on buoyancy of virtual micro plastics. The equation is given as :

$$Vs(x,y,z,t) = \left(\frac{(\rho_{tot} - \rho_{sw}) g w_* u_{sw}}{\rho_{sw}} \right)^{1/3} \tag{1.1}$$

Here $\rho_{tot}[kgm^{-3}]$ is the total density of particle plus the algae, $\rho_{sw}[kgm^{-3}]$ is the surrounding seawater density, g $[ms^{-2}]$ is the gravitational acceleration in, $w_*[]$ is the dimensionless settling velocity. V_{sw} $[ms^{-1}]$ is the kinematic viscosity of sea water. The bio fouled particle has the algal growth that is estimated by :

$$\frac{dA}{dt} = \frac{A_A B_A}{\theta_{pl}} + \mu_A A - m_A A - Q_{10}^{\frac{T-20}{10}} R_{20} A \tag{1.2}$$

Here, A_A is the atmospheric algal concentration, $B_A[m^3s^{-1}]$ is the kernel rate. $\theta_{pl}[m^2]$ is the surface are of the plastic particle, $\mu_A[s^{-1}]$ is the growth of attached alga, m_A is the mortality rate and the last term is the respiration term (Kooi et al., 2017).

This model basically gives us idea about how sinking time depends on two things, one is the size of plastic particle and the other is the alga attached to it. If the plastic particle is big, it is more likely to bump into alga which makes it heavier and sink easily. But if it's very small, even a small alga growth will make it sink to the sea bed.

There is another model (Semcesen and Wells, 2021) which was carried on Polypropylene plastics. The researchers studied the spreading of micro plastics due to strong winds in lakes and oceans.

The study showed that the spreading of particles is largely dependent on the density of plastic particle, which may be affected by the alga growth on it. It showed that due to bio fouling, the density of polypropylene particles increases and the sinking velocities of particles becomes less effective causing particles to sink. It was also observed that small and medium sized particles sank earlier than the larger ones. According to them, smaller particle took 18 days while the bigger ones took 50 days to sink. It was observed that Bio fouling leads to increase in terminal velocities of plastic particles.

The model used by (Semcesen and Wells, 2021) was the Stokes model for calculating the terminal velocities of particles. The terminal velocity is the velocity with which particles travels down while equalizing the drag and buoyant forces. It is given by :

$$V = \frac{2(\rho_w - \rho_p)gr^2}{9\mu} \tag{1.3}$$

where $\rho_w[kgm^{-1}]$ is the density of water, $\rho_p[kgm^{-1}]$ is the density of the particle, $\mu[kgm^{-1}s^{-1}]$ is the dynamic viscosity, g$[ms^{-2}]$ is gravitational acceleration and r$[m]$ is the radius of plastic particle.

If the density of water is larger then the density of micro plastic then the particle rises and as a result terminal velocity will be positive. Whereas, if the density of water is less than the density of micro plastic particle then it will sink and have negative terminal velocity.

The Stokes theorem that is used for calculating the terminal velocity of particles has to satisfy some conditions. It assumes that the particles are smooth, spherical and move through uniform fluid that is smooth and non turbulent. There was another equation used by model for particle retention.

1.3.2 Correlation between micro plastics by PTV technique

This research by (Nguyen, 2021) is basically aimed at finding the correlation between different sized particles along the vertical direction.

The technique that was used in this model was PTV (Particle Tracking Velocimetry) and an image processing algorithm was used to figure out the geometrical features and settling velocities in still water. It was investigated that the circumscribed diameter is the best parameter to represent the size of micro plastics.

The settling velocities of the irregular micro plastics that are sized between 0.2 to 0.9 mm is usually between 0.5 to 2 mms^{-1}. The settling velocities increases twice when size changes from 0.2 to 0.9 mm. Due to size of micro plastics the sinking process of large micro plastics slow down but it has does not affect the movement of small particles less than 0.32 mm in vertical direction.

It was also discovered that size of micro plastic inside the water to the projection on a circle gives us a 2D image of the particle (Nguyen, 2021). He used the Particle Tracking Velocimetry technique to calculate the terminal velocities by the total time travelled along the vertical direction. The curve fitting technique was used to fit the settling velocity as a function of time. After that image processing technique was also used . The settling velocities of the particles was then calculated by taking the ratio of vertical distance of micro plastics δy and the time difference δt which is given by:

$$V = \frac{\delta y}{\delta t} \tag{1.4}$$

In order to analyse the shape they used 2D assumptions. The projected area is $D_A[m^2]$ is the measure of the 2D shape that was assumed :

$$D_A = \sqrt{\frac{4A_{MP}}{\pi}} \tag{1.5}$$

A_{MP} is the projected area of micro plastic. During this research the dimensionless factors were also considered and the projection sphericity ψ that compares the circumscribed and the inscribed circle of a micro plastic is given as:

$$\psi = \sqrt{\frac{D_o}{D_i}} \tag{1.6}$$

Here D_o[mm] is the diameter of smallest circumscribed circle and D_i[mm] is the diameter of largest inscribed circle . Most of the micro plastic do not have the shape of the sphere. The maximum sphericity found was 0.92 and minimum is 0.42. It was also investigated that the micro plastics which have high value of D_o have less sphericity value whereas those who have low value of D_o have high sphericity. Similarly, same was the case with D_i. c[] is the circularity which is the ratio between the perimeter of projected area and the perimeter of micro plastic P_{MP}.

$$c = \frac{\pi D_A}{P_{MP}} \tag{1.7}$$

and c_o[] is the operational circularity which is the ratio between projected area A_{MP} and the smallest circumscribed circle A_o.

$$c_o = \frac{A_{MP}}{A_o} \tag{1.8}$$

The average value of settling velocity was calculated as follows:

$$v = 2.44 \log D_o + 2.23, \qquad \text{if } 0.34 \le c_o < 0.51 \tag{1.9}$$
$$v = 1.58 \log D_o + 2.01, \qquad \text{if } 0.51 \le c_o < 0.69 \tag{1.10}$$
$$v = 2.80 \log D_o + 2.70, \qquad \text{if } 0.69 \le c_o < 0.86 \tag{1.11}$$

This is very usual technique in calculating the settling velocities of differently sized micro plastics in water. This technique can help the future researchers to find the shapes of the irregular or uneven micro plastic particles (Nguyen, 2021).

1.3.3 A Lagrangian model for transport

(Herzke et al., 2021) investigated the distribution and movement of micro fibers released from the untreated waste water into the Adventfjorden on the Arctic Svalbard. A high resolution hydrodynamic model together with a finite volume ocean model was used to study the dispersion and spreading of micro fibres in Adventfjorden. Large emissions of micro fibers were discovered which showed how important is to treat this waste water. The researchers used a Lagrangian model framework to track the movement and the distribution of micro fibers in the fjord.

It was also noticed that the distribution and spreading was dependent on densities of micro fibers. Light fibers remained on the surface and transported rapidly as compared to the heavy ones. Due to the tidal currents the small particles were transported out of the fjord while the heavy particles sank at bottom of the sea bed and mostly along the northern shore. It was also noted that the southern shore was not much affected and had less micro fibres accumulation. This study basically indicated the hot spots of micro fibers accumulation and dispersion in the fjord (Herzke et al., 2021).

The researchers studied the distribution of micro fibers by distributing them into four density classes. It was observed that micro fibres that had high or very high density were **heavy** and **very heavy**. While the micro fibers with low density and neutral buoyant were **light** and **neutral** (Herzke et al., 2021).

This study suggested that that the light particles remain on the surface and can leave the fjord in short time. While the heavy ones, settle at the bottom and can accumulate in the water column. The researchers also carried out a non parametric test to check the emissions of micro fibers on daily basis. During there study they found that there was not much statistical difference.

1.3.4 A 3D Lagrangian model

(He et al., 2021) modeled the dispersion and transportation processes of micro plastics that are present in the river sediments. They used a 3D hydrodynamic model and a particle tracking model in the research. Their study showed that the micro plastics that have low density are less movable as compared to the ones that have heavy density.

It was also shown that PE (Polyethylene) and PP (Polypropylene) mostly move away at a large distance while PA (Poly amide) and PET (Polyethylene terephthalate) remain close to the source locations. The model used was a three dimensional Lagrangian model to track the motion of particles. In this research a three dimensional numerical hydrodynamic model was used for solving non linear shallow water waves. The horizontal and vertical random walk velocity component was scaled was scaled by the horizontal and vertical diffusivity (nu) (He et al., 2021) given as:

$$[u', v'] = \frac{R\sqrt{2nu^{*}dt}}{dt} \tag{1.12}$$

Here nu$[m^2 s^{-1}]$ is the horizontal diffusivity. dt[s] is the Lagrangian time step and R is a random number from Gaussian distribution.

$$[w'] = \frac{dnu}{dz} + \frac{R\sqrt{2nu'^{*}dt}}{dt} \tag{1.13}$$

Here dnu/dz is the vertical diffusivity gradient at current location z_o. nu' is the vertical diffusivity at z'. Where z' is:

$$z' = z_o + 0.5\frac{dnu}{dz} * dt \tag{1.14}$$

It was observed that due to high flow more particles are transported away from source. It also discussed the retention of micro plastics in river sediments (He et al., 2021).

(Berezina et al., 2021) modeled the transport of plastic along with the effects of biota and organic matter. It was based on a two dimensional benthic-pelagic transport model, biogeochemical model OxyDep and micro plastics transformation model Bioplast.

A hydrodynamic model was used to track the effect of changes in the ecological system and the transport of micro plastic. They compared the properties based on different seasons. There are four different types of plastics used in this study that are free, bio-fouled, Zoo plankton and fecal based were used for experimentation.

The results proved that the particles with high densities are not much affected by the biological process and accumulate in sediments.

There were some limitations in this model. In this research only some specific sized fiber was used while ignoring the structure, porosity and some other features. The biological and mechanical degradation was also ignored.

In short, it was investigated that the micro plastics with neutral buoyant forces can move to a smaller distance as compared to that in winters. It was found that biogeochemical are typically responsible for the transport of light weighted micro plastics into deep waters. While, the high density particles are not much affected by these biogeochemical processes.

In recent days, there is much work being done in finding the micro plastics found in waters. Researchers are using different numerical models to check the transport of plastics by estimating there sinking velocities and studying there pathways. Research is being carried out using latest machine learning and computer visualization techniques to identify the plastic pollution and monitoring the increasing plastic concentrations (Phan and Luscombe, 2023).

Chapter 2

Modeling of Plastic in Ocean

2.1 Ocean Modeling

Ocean models help us to identify different complex physical systems in the ocean. Ocean circulation models helps us to study ocean circulations, wind, currents and other physical or chemical process being carried out in the ocean.

These models that are governed by conservation laws and cannot be solved easily by analytically reasoning. Therefore, different numerical methods are used that simplify the equations and help to do the calculations numerically. These calculations are usually carried out on high efficiency computers (Kämpf, 2009).

Researchers can used the information they get through the ocean model simulation to predict weather and climate changes. Ocean models are also very much helpful in figuring out the pollutants and there impacts on our ecosystem. These models help to protect and secure the marine life. They can also warn about natural threats and guide us to make enough preparation before there happening.

An ocean model basically needs the initial conditions. It includes all the physical variables. Using the given initial conditions, the ocean models undergo numerical computations, usually under the effect of external forces which may be wind, heat or currents. The equations are solved by the ocean model are then calculated forward in time.

Ocean Waves are a very important factor while studying the ocean models. Tides are also subjected to some boundary conditions. These boundary conditions very much affect the performance of models. The results of ocean models varies largely on the basis of the ocean tides, external forces and the boundary conditions.

To get the best results, data should be complete and accurate. When working on an ocean model, the choice of model is very crucial. Every parameter has different effect and has different impact on final results.

As ocean models undergo powerful simulations, they can help scientists and researchers in studying ocean. How they behave and climate effects and the connections between them. These models are very crucial as they can help to study the changes in weather and there relevant affect on the climate change. Ocean models are very much used in predicting natural disasters like thunderstorms, hurricanes or tsunamis. To show ocean models on a fine resolution grid they need a finer resolution grid. This also means that they require more grid points to cover the same area as compared to atmosphere models. These models are usually defined on a smaller time step taking into account the size of grid. In order to get the accurate numerical stability along with CFL condition, smaller time steps are taken. But when smaller time steps are taken it means we need more time to do our computations. When using implicit or semi implicit finite difference schemes it can also raise some stability concerns in the given model (Martin et al., 1998).

One drawback in using these models is that when doing computations of model with finer grids they need more time, high memory and efficient computers. The model is also very much affected by the numerical method under study. Now a days researchers are using large and complex methods to study ocean models.

There are different types of models being used to carry out simulations in oceans. Some of them (Martin et al., 1998) are listed below:

- General Circulation models(GCMs)
- Regional Ocean models
- Coupled-Ocean Atmosphere models
- Biogeochemical models

General Ocean models GCMs are very powerful and high resolution models that can help researchers to understand and predict ocean currents and waves. This model typically focuses on ocean currents, waves and temperature.

This general circulation model can help the researchers and scientist to figure out that how climate can change over a period of long time. These models help to study the changes and patterns in oceans. These General circulation models assist in predicting the ocean waves. General circulation model predict changes over decades or centuries.

Regional Ocean models are models that focus on a particular part of the ocean which may include coastal areas or any specific area. These models predict what is going on in a specific region and how the ocean currents, wind, temperature and other factors affect a particular region.

These models are very convenient to use because they can help us to study a specific region and to study the properties of that specific region. The approach can be very useful in predicting natural disasters and the formation of hurricanes or tsunamis. General circulation models help us to study the whole ocean and its features whereas these Regional ocean models help in predicting the behaviour of particular region and help to make improvement in that specific area and to study its impact on ecosystem.

Coupled-Ocean Atmosphere models are the models that study both the ocean and the atmosphere at the same time. These models help us to study the relation between ocean and the atmosphere and how they both interact and influence each other. These are useful in predicting the weather and understanding the climate change over a period of long time.

Scientists and researchers use these models to study the effect of global warming on ocean and our ecosystem. So, in short these coupled ocean atmosphere models are typically weather and climate detectors and help to study and figure out the planets environment and climate. These models are computationally costly.

Biogeochemical Models are quite helpful in studying the relation between ocean life and the nutrients present in the ocean.

Biogeochemical models help to study how nutrients move in ocean. These models also predict how tiny plants in ocean commonly known as plankton’s grow.They assist the researchers in studying ocean’s chemistry and life associated with them. These models also help up understand how marine animals get there food and other nutrients from the ocean water and how they respond to the environment changes.

Biogeochemical models largely study connection between ocean and the ecosystem and also assist in taking necessary steps in preserving our ecosystem (Martin et al., 1998).

Ocean models and Atmosphere models look although much similar by they typically exhibit distinct features. Both these models undergo a lot of computational analysis which involve solving large complex equations but they may have different characteristics. One clear difference is that ocean models undergo far more computational calculations then the atmosphere models. Ocean models generally require more CPU time, memory and storage because they are defined on small or finer patterns/grids.

In contrast, if we do not take such method that involves time stepping. This model may still work but we need to do a lot more calculations and have to be much careful while doing computations. So in short, ocean models involve more complex calculations due to the variations of ocean and its characteristics (Martin et al., 1998).

2.2 What is Numerical Modelling of plastic and why it is important?

Numerical modelling is an important method to see the distribution and spreading of plastics (Shynybayeva and Rojas-Solórzano, 2020). These numerical models typically work with dealing with currents, winds, algae growth, degradation and similar features and showing there affects .

There are two main key ideas in modeling of marine debris. The main goal is to understand why and from where the plastic residues are entering or leaving by understanding the economic and geophysical features of that area. One main goal is to model the plastic by understanding it and and the other one is to understand its impact on the ecological system (Shynybayeva and Rojas-Solórzano, 2020).

The three main important fluxes in the study of ocean plastics are supposed to have the most amount of plastic contamination in them. These include the fluxes that are between ocean and the seashore, between seashore and the ocean and the fluxes that occur between the oceans that may also include surface, water column or sea bed and the biota. The first two fluxes are supposed to be most important zones and have the highest amount of biodiversity in them (Shynybayeva and Rojas-Solórzano, 2020).

There are normally two ways to study the motion of particles in Fluid dynamics. One method uses the tracers to study the pathway and they are usually categorized as Eulerian approach. Where as, the second one is the Lagrangian to track the particles motion (Van Sebille et al., 2018).

The detail of these models is listed below :

- Eulerian modeling
- Lagrangian modeling

In **Eulerian method**, the flow of fluid is considered as continuous field and we try to study the properties such as velocity, pressure, density or others on a fixed point or on a grid in space .

In this approach, the domain is then distributed on a grid and try to do computations by some governing equations like Navier-Stokes equations and try to solve the equations. This model is typically used in pipes, channels or large bodies of fluid (Wikipedia, 2023).

These computations are used quite a lot for scientific and engineering purposes. In this method, we usually study a particle at each point on a fixed grid and find the properties of the particles (Subramaniam, 2013).

2.3 Lagrangian modelling

In **Lagrangian modelling**, the flow of fluid is usually represented by tracking the motion of particle in both space and time.

Lagrangian analysis is a very efficient way to study the ocean circulation models. Lagrangian modeling helps us to understand the motion and transport of individual particles.This Lagrangian model analysis helps us to figure out the pathway and the transport of particles. They help us to study the pathways of ocean drifts. These involve the use of velocity fields on there native grids.

2.3.1 The OpenDrift Lagrangian Model

OpenDrift is use to track the location of particles. This model is an open source model and works in python. OpenDrift model is developed by the Norwegian Meteorological department (Dagestad et al., 2018). The basic purpose of this model is to calculate drifts of particles in ocean or atmosphere. OpenDrift model is used in oil-drift models, search and rescue models. This is a very flexible model. It is used by Norwegian Meteorological department on daily basis (Institute, 2021).

OpenDrift Lagrangian model uses a mechanism known as backtracking. This mechanism is used to calculate the trajectory of particle in opposite direction from there recent position so, it track the location back to previous position. In this backtracking model the sign of displacement vector is reversed. This helps to calculate the motion of particle and negative time step. This negative time step is that the particles are moved backward in time to estimate the previous locations (Dagestad et al., 2018).

The mechanism of backtracking helps a lot to find the drifts in sea water. OpenDrift model can also help some times to calculate different geophysical parameters for example it can help to calculate the Stokes drift or some other variable that are based on wind or currents (Dagestad et al., 2018).

2.3.2 How an OpenDrift model works?

The purpose of an OpenDrift model is to study the pollution in water or air or for some other reasons. It involves two classes one is Reader Class and the other Base model class. The **Reader class** helps to find the data and gather the related information for the simulations to run using the external sources. These sources can include ocean data, wave models or atmospheric data (Dagestad et al., 2018).

The **Base model class** is where actual calculations are carried out. Base model contains the main loop for doing the time steps in correct order. The OpenDrift model involves different steps to get to the results. The first step involves the initilizations of parameters and variable involved in it. The method involves the time integration of equations. We time integrate the numerical equations in time to calculate there velocities and positions. The model mostly deals with advention diffusion equations. The advention is a very crucial factor as it models the transport of particle in the fluid flow.

This can be based on fluid dynamics models or any oceanographic data.

The next step involves adding the readers which involve creating and adding readers which can provide variables like ocean currents or winds. After this, we do the seeding of elements that initialize the process at a specific time and position. The OpenDrift modules usually need to set the configuration setting before the start of simulation.

After the running of the OpenDrift model using the initialization, configuration, adding of Readers and seeding of elements the model is then started.

The source or forcing term is very important term in this model. These may include wind, temperature gradients or heat change or some other factors. These terms very much affect the flow of fluid in water or atmosphere.

Boundary conditions are also very important as they restrict some area of research or study and they define the edge our system in the specific domain that we are focusing on in our simulation. After carrying out our simulations the models tracks the location and trajectory of particles that can help us to identify different characteristics to classify the data.

Another step that is very crucial is validation of data. When analyzing the results, the output is compared with the actual measurements and if there are chances of improvement, the data is then validated and changes are made in model accordingly.

After running of simulations, we get the output of the model. The output is then stored in files. This data can be then visualized with using libraries in Python like Seaborn, Plotly or Matplotlib or others like them.

One main advantage of using this open drift model that it can tackle a large data set without converting the data into different formats. Scientists and researchers can very easily use this data to draw some useful conclusions and can also visualize them using some data tools. There are many different methods that are working today but they need data to be first converted into some special format. This process may take a lot time and and a large number of computations. This becomes very expensive. In short, OpenDrift model is very efficient and effective to carry out simulations.

The framework involved in OpenDrift model involves scalar as well as vector data that can be collected from a large number of sources which may include data collected from observations or calculated from experiments carried out in ocean or atmosphere. It has its applications not only in research fields but also in every day life (Dagestad et al., 2018).

Chapter 3

Data and Methods

This study focuses on the Nordhordland Bridge which is located in the North of Norway. The tyre plastics that is entering the Byfjorden from the vehicles moving over the bridge. Figure 3.1 shows the location of our study.

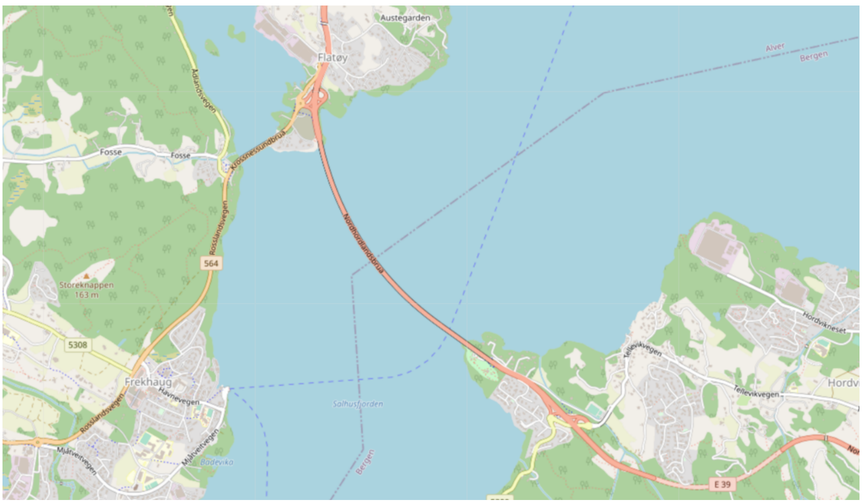


Figure 3.1: The Nordhordland Bridge ref: Maps (2023)

This model on which I am doing visualizations and statistical analysis of has already been run by Prithvinath Madduri. He has used the OpenDrift Lagrangian model on the data of available velocity fields using Bergen Ocean Model BOM to find the trajectories of particles released from the bridge.

The model used in this data was read by BOM using the data of velocity fields. The shape of particle was assumed to be spherical and have constant sinking /terminal velocities that were calculated using Stokes's law which has been discussed in 1.3.1.

In this model, a reflecting boundary condition is used at the sea shore where particles are brought back to the previous position when they hit the boundary of land and take there path based on there time steps. The ocean model data was read by the reader and with external conditions added to it.

Seeding elements, properties of particles and boundary conditions were used to run the simulation. The particles were seeded using the Monte Carlo release approach. The sinking velocity are named here as terminal velocity. In Open drift the terminal velocities were also added to start the simulations.

The simulation were made to run from start time to end time using the change of time which is fixed to be Δt which was 1 hour. After initiating, the next step is to do the propagation which is also known as "Drift Scheme" through Euler's method. The Euler method is used to calculate the propagation of particle in space and time. This method helps to solve the current velocities using a method that takes the previous and next time to find the trajectories of particles.

Current velocities of particles are then multiplied by the time step Δt to find the displacement of particles. These displacements are added to the original location of particles to calculate the new location of particles.

Simulations are made to run until the end of cycle and then the output is obtained. These simulations results in start and end locations of the particles specifying there longitude and latitude values.

This output is stored in NetCDF4 and Pickle files. These files contains the data of 200,000 plastic particles coming from tyres. These particles are assumed to be spherical in shape.

These data files contain the path line of particles and its location at each time step. Here, each time step is one hour. It means that the first column is at t_0 the next is at t_1 and similarly the last entry shows the t_{end}. Location of particles are defined using latitude and longitude with corresponding start and end locations of particles. This NetCDF4 file also contains the sinking velocities of particles in ms^{-1}.The sinking velocity is here termed as terminal velocity. This velocity shows the speed with which particles are sinking into the fjord.

The coordinates of the bridge are in form of latitude and longitude are in data set. Locations are given in form of degrees. The data contains "longitude start","latitude start","longitude end", "latitude end","time start","time end" ,"residence time" and "terminal velocity" of 200,000 particles. The sinking velocities are modeled in a uniform distribution. They are constant and uni-directional towards the sea bed. There are 20 discrete sinking/terminal velocities.

3.1 Distance along the Bridge

This step involves the visualization's of particles on Bridge before the start of simulation as figure 3.2. There is uniform distribution of 100 random points on the bridge. This visualization is shown below:

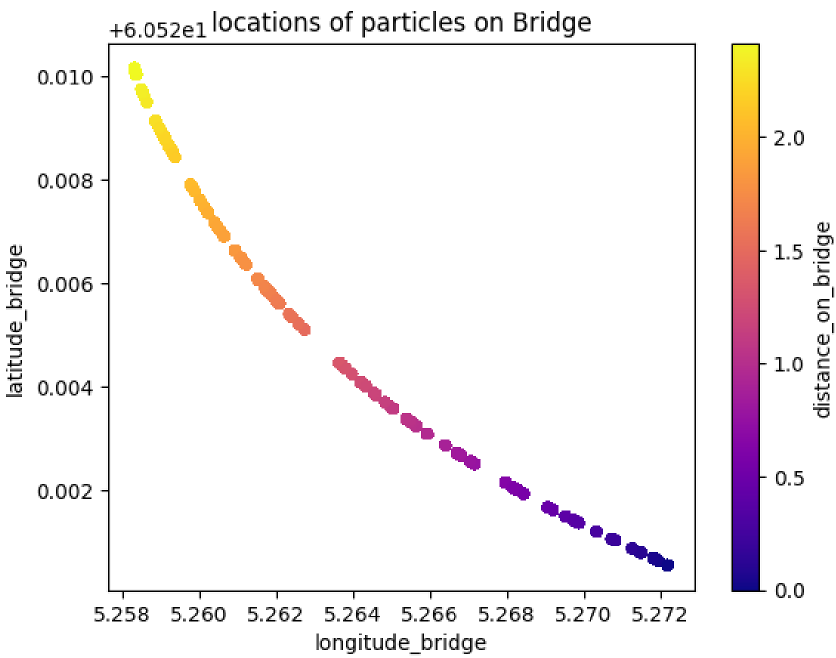


Figure 3.2: Locations of particles on bridge

In this visualization, I calculated distance d in meters along the bridge with coordinates *(x,y)* with respect to a reference coordinates *(xmax,ymin)*. d is calculated as:

$$d = \sqrt{(x - x_{\max})^2 + (y - y_{\min})^2} \tag{3.1}$$

For calculating this distance d, I first converted the coordinates with longitude and latitude into UTM-x and UTM-y coordinates using a UTM-converter which is an open source python library.

UTM is Universal Transverse Mercator Wikipedia (2022b) shows the locations on Earth's surface in meters. It converts the longitude and latitude to meters. This Nordhordland Bridge is in UTM-zone=33 and ellipsoid =WGS84. The corresponding longitude and latitude are represented with coordinates utm x and y respectively.

UTM is a system of projection that assigns location on Earth surface. It typically treats Earth as a perfect Ellipsoid and hence neglecting the altitudes. On the basis of UTM coordinate system there are 60 zones in which the Earth is divided into (Wikipedia, 2023). The utm coordinates can be accessed from pyproj 3.6.1.I have used pyproj to convert the coordinates. This is a package that converts does the coordinate transformation. These can also be referred to as UTM-Easting and UTM-Northing. The corresponding longitude and latitude are represented with coordinates UTM x and y respectively. UTM coordinates make the computations easy by converting degrees into meters. After converting them to UTM , I then calculated the distance along the bridge using a reference coordinate ($xmax$,$ymin$) on the bridge where $xmax$ here is the maximum value along the x axis , here it refers to utm-x and similarly $ymin$ is the minimum value along the y axis , here it refers to utm-y. The maximum value of x is 84893.8360 m and the minimum value of y is 6743200.1324 m.

3.2 Release of particles

The particles are released from the bridge using a wind model and then after getting locations of particles on surface they are run using OpenDrift. After running the simulation using OpenDrift on the bridge coordinates, we get the start locations of the particles. The start locations with the color code as the distance along the bridge is shown in figure 3.3.

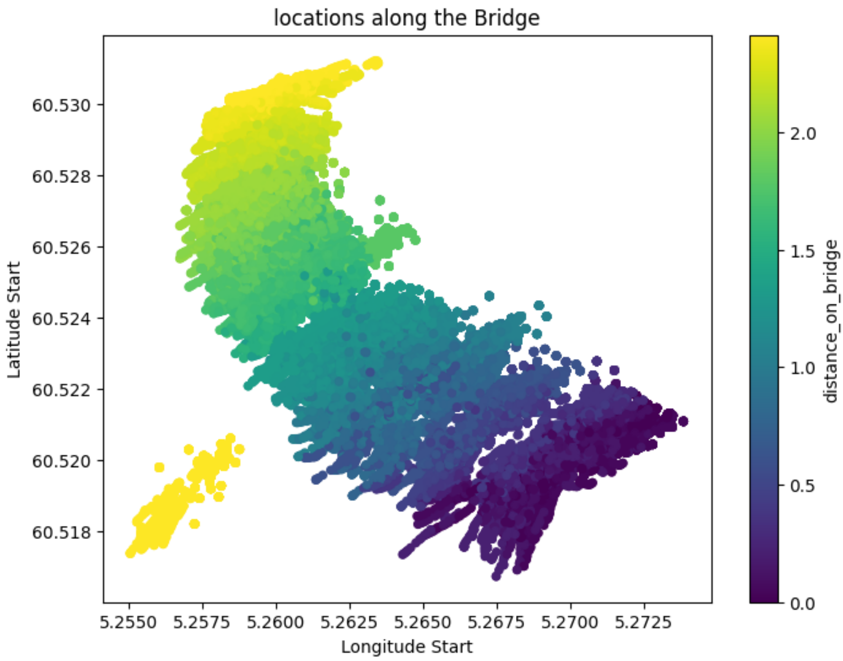


Figure 3.3: Start locations of particles

Visualizing the figure 3.3 we can see that the particles that are on the top North of the Bridge are spreading and they are moving far from the bridge due to seeding effect of OpenDrift. We can see that the yellow ones are coming from a single point in the Northern top of the bridge and are spreading farther away from the bridge. This is due to OpenDrift model.

The reason is that if the OpenDrift finds that a point is on the land, based on the ocean model data provided, then it moves it to the nearest point in the ocean by perturbation by a small value.

So, in short these points are a type of defect of the OpenDrift and we can remove these from our data set and get a new filtered data set .These were 2000 particles so they are removed from the our data set and now we have a filtered data set with 198,000 particles.

The visualization of the filtered data set can be shown in figure 3.4. This shows now the start locations of our particles after filtering.

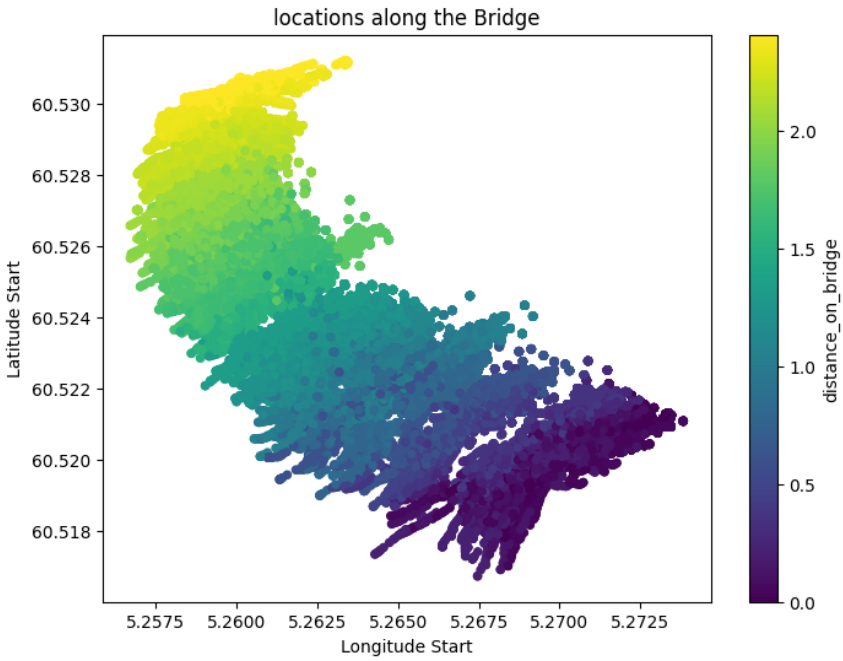
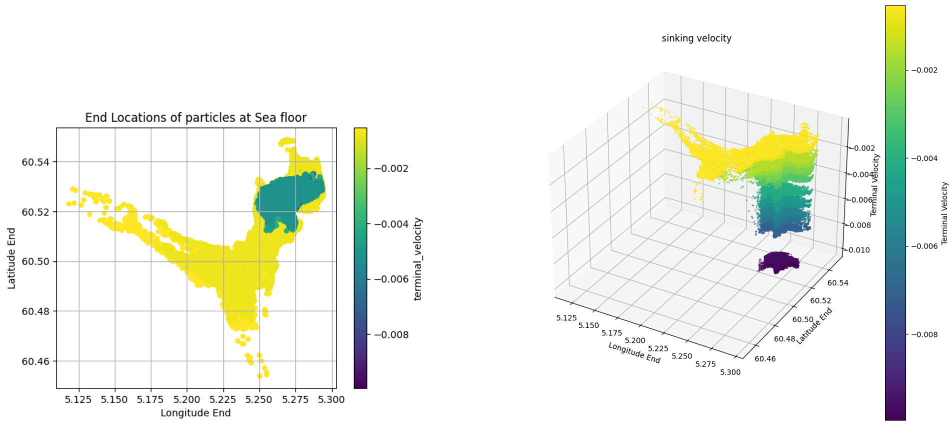


Figure 3.4: locations at the sea surface

The figure 4.1b shows the 3D Distribution of terminal velocities with the end locations of particles at the sea floor.The figure 4.1a shows how velocities are distributed along the fjord. There are 20 discrete sinking velocities that are uniformly distributed such that first 10,000 have one sinking velocity, next 10,000 have other and soon.



(a) End locations of particles with terminal velocity

(b) 3D visualizations of terminal velocity

After getting the end locations of particles I have calculated different distance to see variation in data.

3.2.1 Calculating the distance of the particles from the bridge to the start locations(d1)

This step involves the initialization of particles. It involves calculating distance of the particles from bridge to the start locations.

To calculate this distance, I have used the Haversine formula that helps to calculate the shortest distance on Earth surface between any two geodesic locations using open source python software Haversine. This is also an open source software that is python based. It can be accessed through haversine 2.8.0.

The reason for using this formula is that it measures the shortest and accurate distance between two points in different locations on Earth. Euclidean distance could also be used but since, we have to measure distance that was not on a flat surface. This distance was far and so haversine was best method to be used. This calculates the distance in less time and is very fast as compared to Euclidean. Euclidean is best to use where we have a surface that is flat.

The figure 3.6 shows the location of particles when they started with color code as the distance of particles from bridge to start locations.

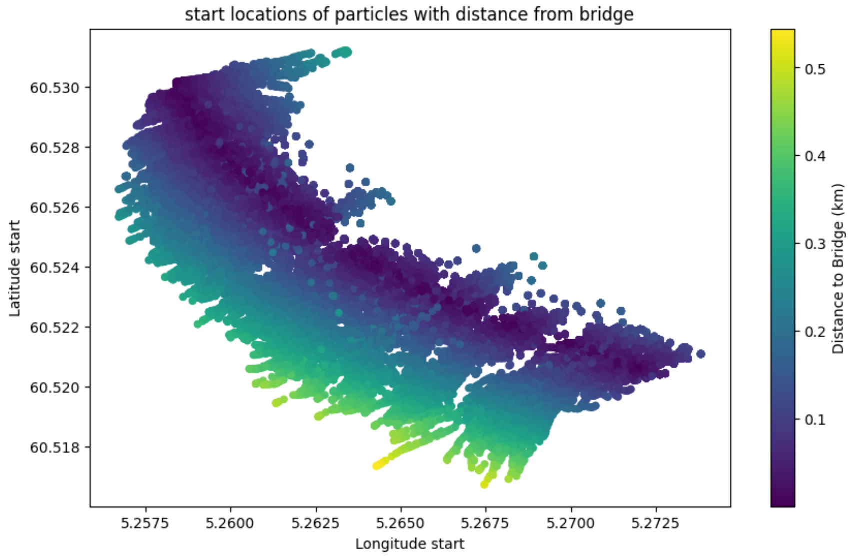


Figure 3.6: Distance from Bridge to start locations of particles

This can be seen in figure 3.6 that the particles are mostly in a area close to bridge. Yellow ones can be seen to be farther away from the bridge. This may be due to shape of bridge. The south of bridge is taller so particles some particles have moved far away from the bridge.

The maximum distance a particle moved from bridge to start location is 0.5443km or 544m from the bridge locations.

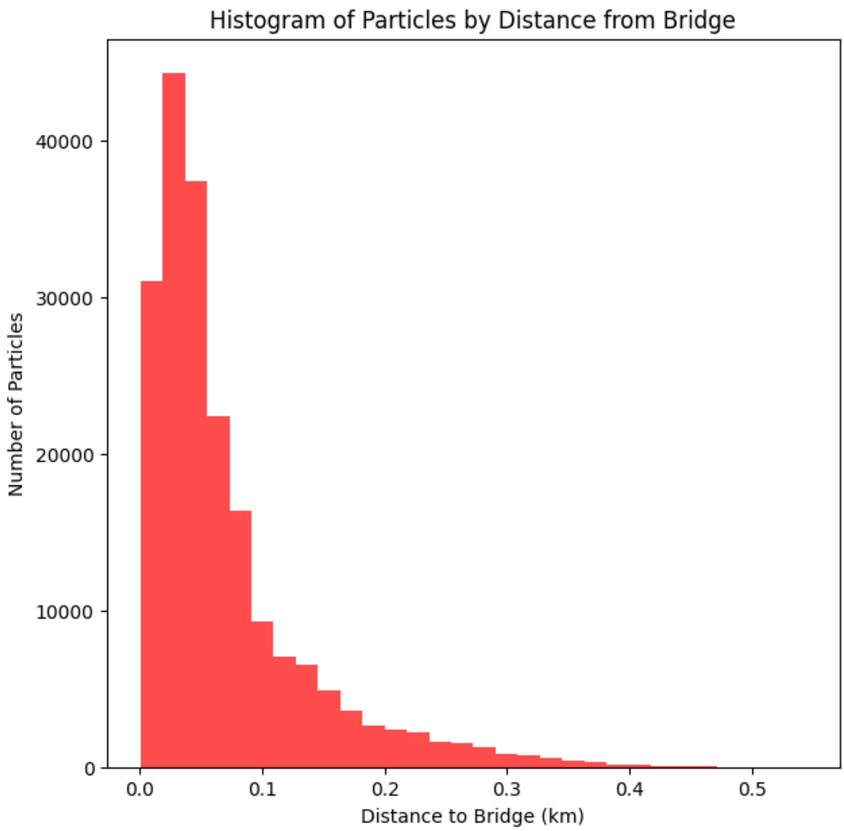


Figure 3.7: Distribution of Distance from the bridge to start locations

The frequency distribution of distance of particles from the bridge to start locations is given as figure 4.3. This histogram shows how particles are spread when they initially started. This shows the distance of bridge coordinates to the start locations of particles in km. Most of the particles are within the range of 0 to 0.2km.

3.3 Depth of particles at sea floor

The data provided to me did not had the topography so, I also calculated the depth of particles at the sea floor. Here, it shows how deep the particle have reached.

The figure 3.8 shows the end locations of particles with respect to the water depth. The yellow ones are the deeper ones and the blue ones are shallower ones.

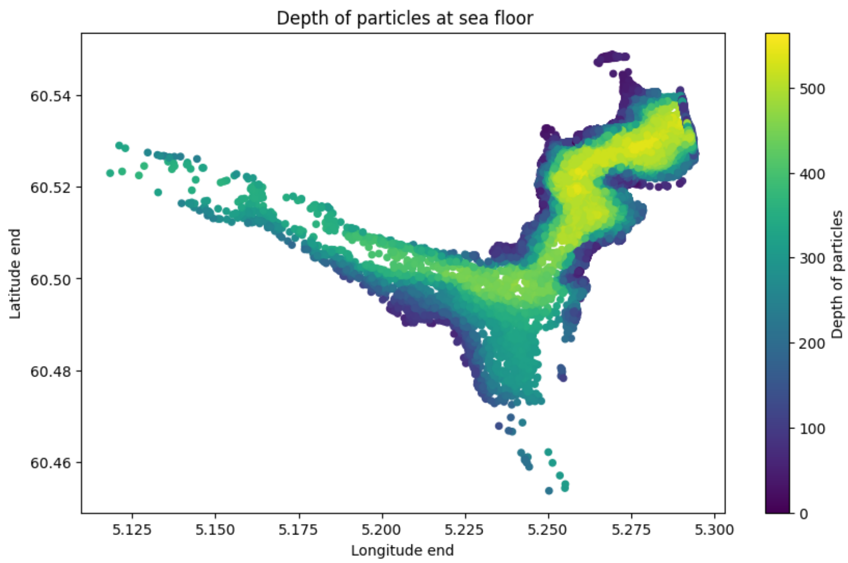


Figure 3.8: Depth of particles at end locations

It is calculated by taking the product of sinking velocity and the residence time and taking the absolute value. Residence time is the time for which the particle has stayed in water column during its movement from start to end location. This means it is difference between end time and start time.

The figure 3.9 shows the frequency distribution of the depth. This distribution shows the spread of depth of particles in the fjord.

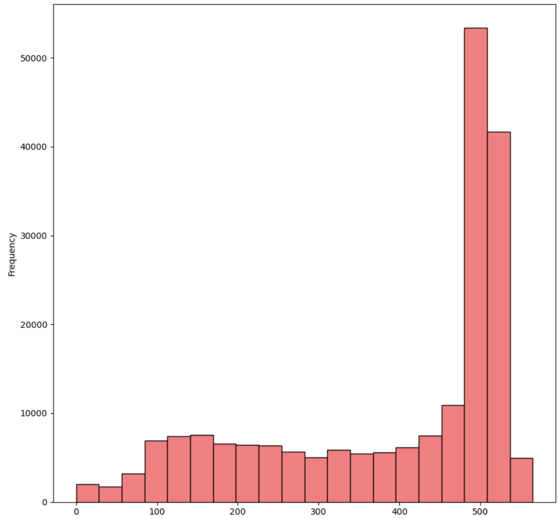


Figure 3.9: frequency distribution of depth

This shows much particles have landed deeper. The shows the range of depth and particles depth in fjord.

The next step is to calculate the distance traveled by the particles. Total distance traveled by the particles is measured by particles over each time step. It involves calculating distance for each particle through the whole path as it moves through the trajectory back and forth several times till it reaches the end locations. This means calculating distance at each time step. Time step is fixed to be one hour. Starting from the point where particle motion started and calculating the distance in between when it has moved back and forth and then summing the distance over each Particle Index and calculating a column in data named as ”TotalDistance”. I have used the Euclidean distance to calculate the Distance traveled by each particle along the path. The units are ”meters”.

After calculating the different quantities, we try to find the relation of the sinking velocities with the above calculated distance traveled, depth, distance of particles from bridge and residence time using different libraries in python like seaborn and matplotlib. Finding the variations of these quantities using box plots.

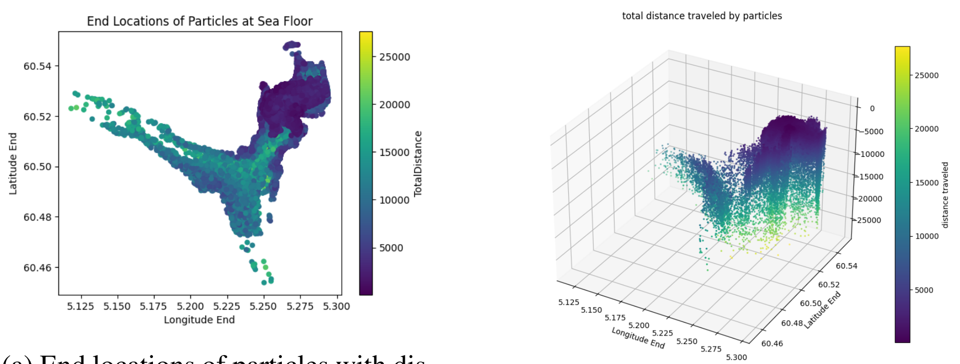
I have also used k-means clustering technique to look for some hot spots of plastic accumulation in fjord. For this I have used sklearn.cluster library to get k-means cluster.

All calculations and results obtained in this project using different libraries in python including seaborn, matplotlib, pandas, numpy ,UTM, pyproj, haversine and other similar ones.

Chapter 4

Results

4.1 Distance Traveled by the particles



(a) End locations of particles with distance traveled

(b) 3D visualizations

This figure 4.1a shows the Total distance traveled by the particles. The is the distance that particle has traveled from start to end location during its trajectory. This distance is calculated by converting to UTM coordinates and then using Euclidean distance formula to calculate distance over each time step. Time step here is one hour that is same for each particle. This visualization figure 4.1b shows 3D visualization showing distribution of distance traveled in meters. The table 4.1 shows the distance range for different particles. This table shows the spread of particles with different ranges in distances.

Distance range	No.of particles
70.89 - 1905.66 m	93569
1905.66 - 3740.43 m	63338
3740.43 - 5575.20 m	20827
5575.20 - 7409.97 m	8414
7409.97 - 9244.74 m	3772
9244.74 - 11079.51 m	2493
11079.51 - 12914.28	2064
12914.28 - 14749.05 m	1410
14749.05 - 16583.82 m	960
16583.82 - 18418.60 m	556
18418.60 - 20253.37 m	318
20253.37 - 22088.14 m	161
22088.14 - 23922.91 m	78
23922.91 - 25757.68 m	29
25757.68 - 27592.45 m	11

Table 4.1: Number of particles in different Distance range

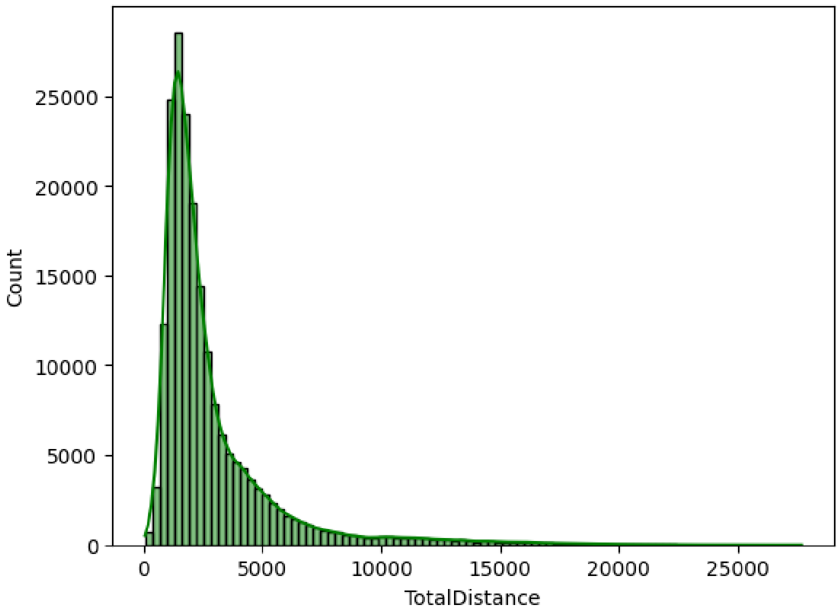


Figure 4.2: Distribution of distance traveled(m)

This figure 4.7 shows the distribution of particles with respect to the distance traveled. This distribution shows that most particles are in the range of 0 to 5000m. The peak value shows that most of the particles have traveled less distance before eventually settling at the bottom of fjord.

4.2 Calculating the distance of the particles from the bridge to the End locations(d2)

This denotes the distance the particle has traveled from Bridge to the end locations. This distance is also calculated by using the Haversine distance formula as calculated distance of particles from bridge to start locations(d1) in previous chapter 3.2.1.

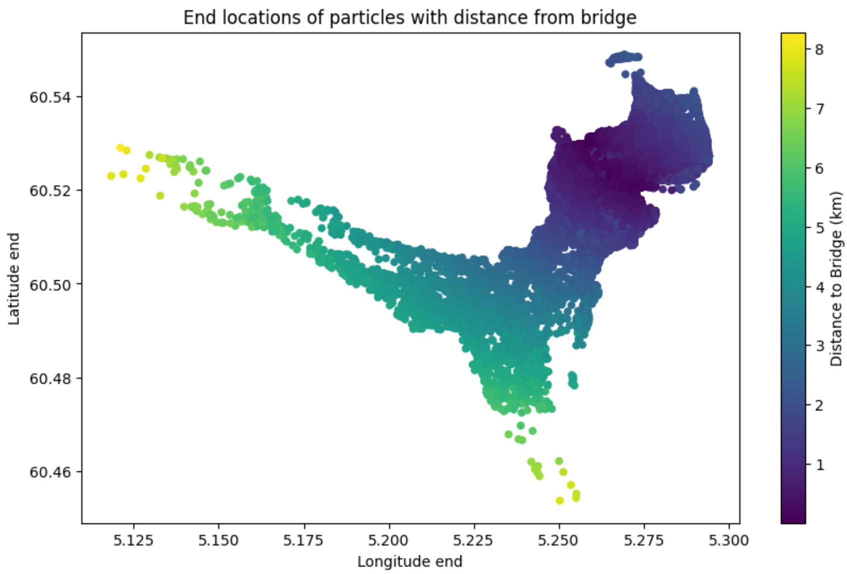


Figure 4.3: Distance of particles from bridge to end location

This figure 4.3 shows how far the particles have landed from the bridge locations.This basically tells us the final locations of particles. The frequency distribution of the distance of particle from bridge to end locations is also given below. This frequency distribution figure 4.4 shows the range with different distance and where most particles fall. The maximum distance that a particle has travelled from bridge to end location is 8.278km or 8278m.

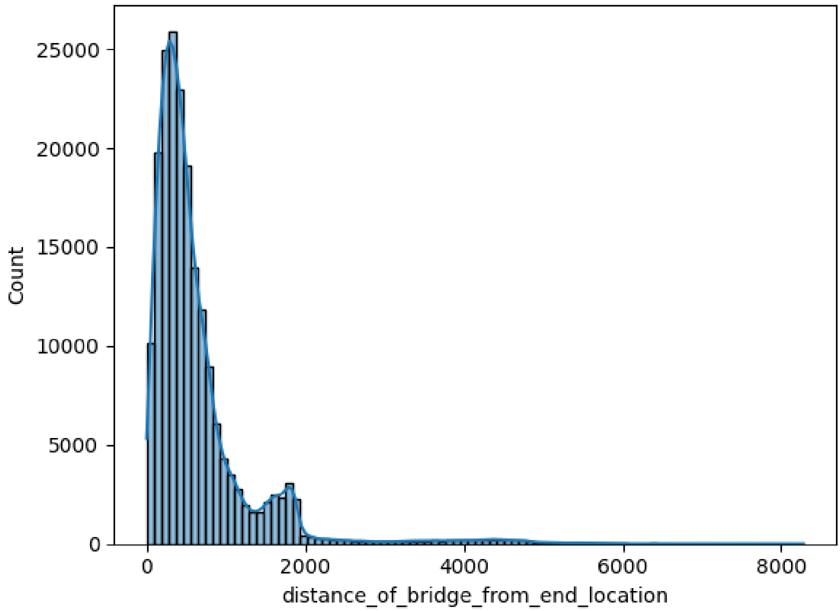


Figure 4.4: Frequency Distribution

In the figure 4.4 we can see the range where the particles have landed. In this figure we can see a small top after a peak value. This second top or peak shows the particles that are leaving the system through the North East boundary.

Now, we are interested to see how distance traveled, residence time, distance of particles from bridge to end locations and depth changes with different terminal velocities. Before that we are going to have a look at correlation heat map to check how different quantities are correlated.

4.2.1 Correlation Heat map

The correlation heat map is very important in statistical analysis. It help us to understand the relation between different quantities. It tells how one quantity is affected by the change in another quantity. In this heat map each square box shows the relation between any two variables. Correlation map has usually a range from -1 to 1. The values that fall close to positive 1 are strongly correlated and the values that fall close to negative 1 are weakly correlated. When the correlation is zero it means they are not correlated. Diagonal entries are 1 and show the relation of each variable with itself.

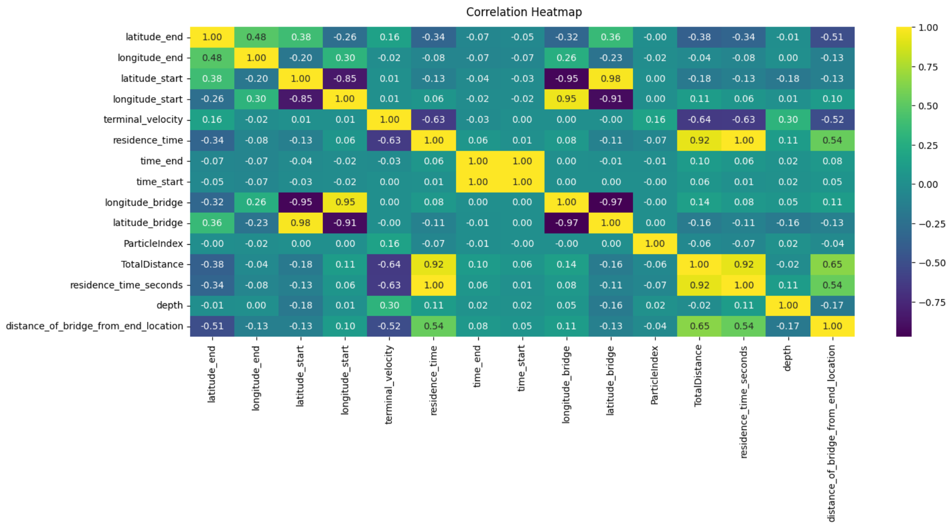


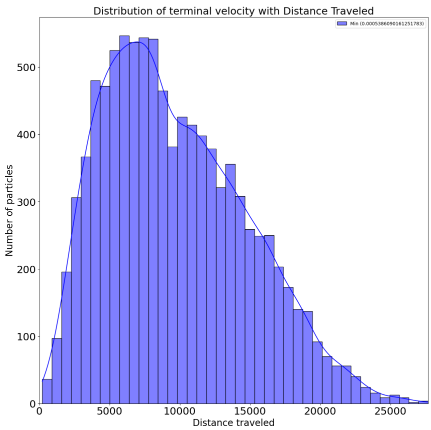
Figure 4.5: Heat map

In this heat map figure 4.5, we can analyse that the darker ones are negatively correlated and the yellow ones (lighter) are positively correlated. Positively correlated means that means when one quantity increases so does the other and negative correlation means when increase of one quantity decreases other and vice versa.

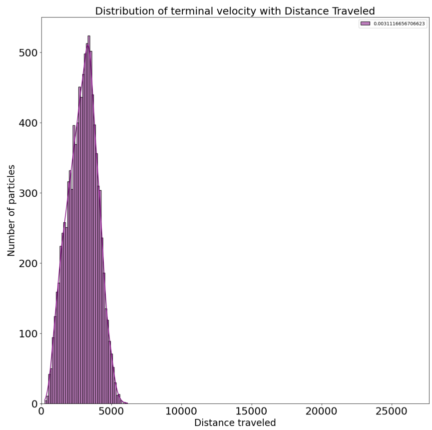
Residence time, distance of particles and distance traveled by particles have a weak correlation with respect to terminal velocities whereas, the depth has a positive correlation. It doesn't have a strong correlation but has a positive correlation.

4.2.2 Terminal velocity and distance traveled

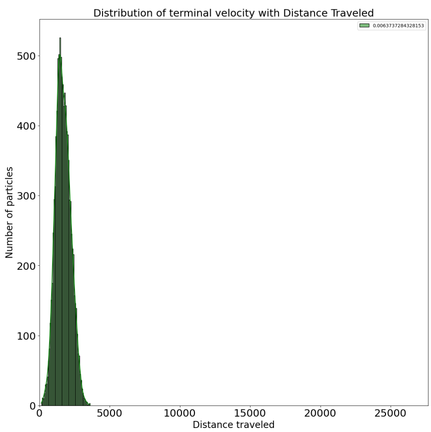
This section shows the relation between the distance traveled and the terminal velocity. There is a weak correlation between distance traveled and the sinking velocity. This means that by increasing the sinking velocity the distance traveled decreases and similarly, if the sinking velocity decreases the distance traveled increases. The correlation coefficient between these two is -0.639.



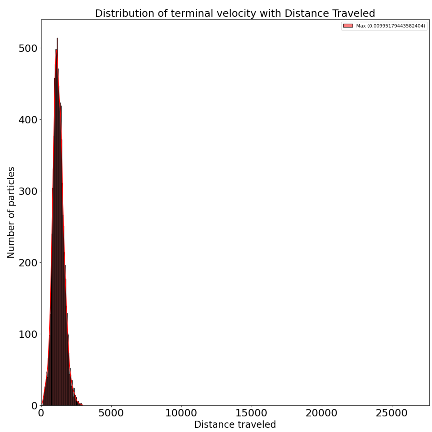
(a) v1(0.000538)



(b) v2(0.003111)



(c) v3(0.006373)



(d) v4(0.009951)

Figure 4.6: Distribution of four sinking velocities with Distance Traveled

In the figure 4.6 above the figure 4.6a is minimum velocity, 4.6b and 4.6c are two velocities in between minimum and maximum value and 4.6d is the maximum value of sinking velocity. It can be seen that 0.000538 ms^{-1} has the broader curve where as as we move towards the maximum the curve becomes narrower. In figure 4.15d the curve is very narrow. This shows that the distance traveled by maximum velocity is very little and hence narrow curve. On the contrary, it can be seen that the figure 4.15a has broader curve with more distance traveled. Showing that particles have stayed and traveled more distance before sinking into the bottom of fjord. This figure 4.8 shows the distribution of sinking velocity with distance traveled. It can be seen that the maximum velocity has a peak value showing that distance traveled between the range of 0 to 2500m. But the minimum velocity has traveled the more distance. Maximum velocity has traveled much less distance as compared to the minimum velocity. As, the velocity increases the curve becomes narrow showing least distance traveled. On this basis of this relation between terminal velocity and the distance traveled we can say that the particles with less sinking velocities have stayed in the water column for a long time than the ones with the higher sinking velocity.

This is because the particles that have less sinking velocity are lighter and less dense so they take more time until they settle. While the particles with large sinking velocities are more dense and heavy so, they travel faster and sink to the bottom of the fjord speedily. The particle that have stayed in water column for long time till it finally settled down is of velocity 0.000538 ms^{-1} and the total distance traveled by this particle is 27674m. This is the maximum distance traveled by all the particles.

In figure 4.7 we try to analyze these four velocities together with minimum and maximum velocity value. In this figure 4.8 below we can see the velocity distribution of all the 20 sinking velocities with distance traveled. This shows the analysis of four velocities together with the distance traveled by them.

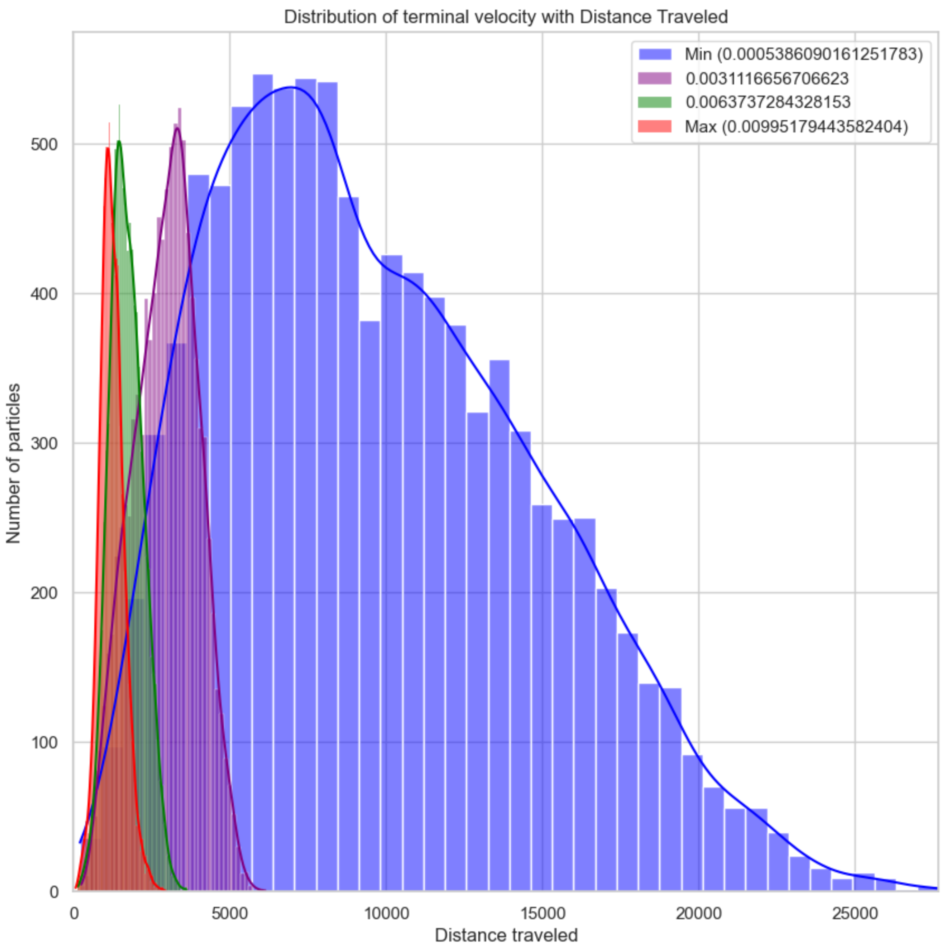


Figure 4.7: Distribution of distance traveled(m)

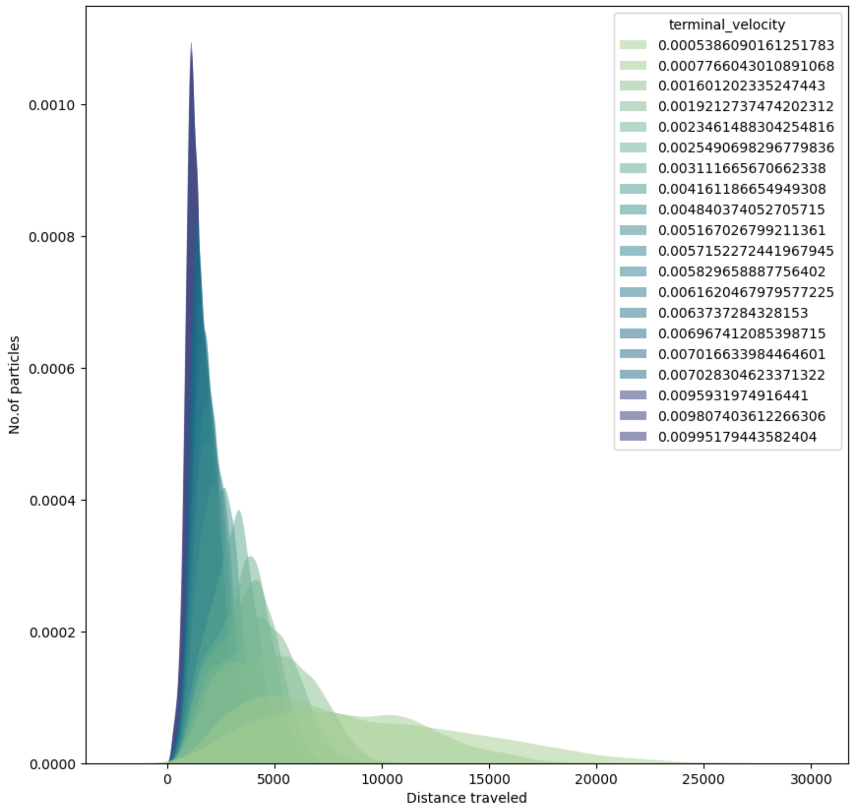
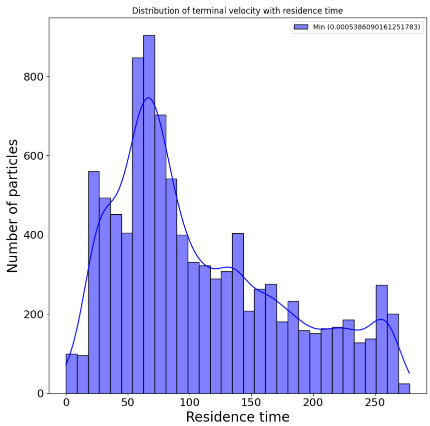
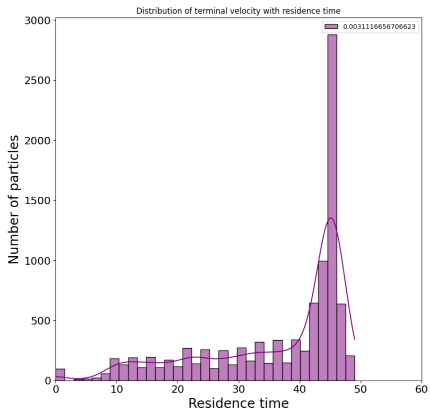


Figure 4.8: Terminal velocity with distance traveled

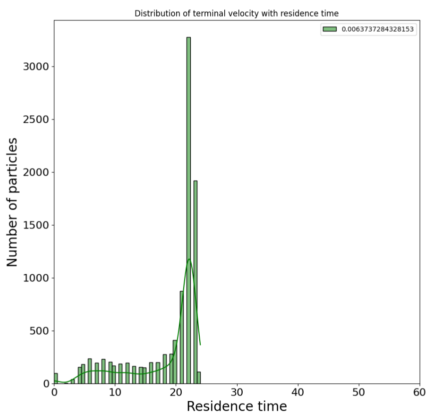
4.2.3 Terminal velocity and the residence time



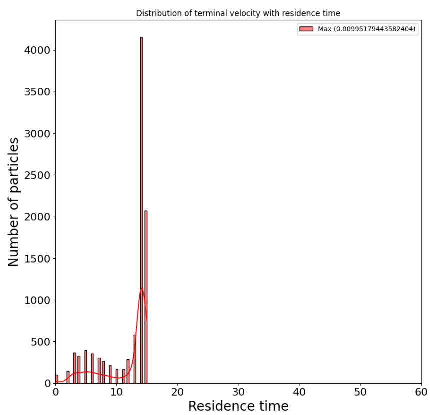
(a) t1(0.000538)



(b) t2(0.003111)



(c) t3(0.006373)



(d) t4(0.009951)

Figure 4.9: Distribution of four sinking velocities with Residence time

Overall distribution of these four velocities:

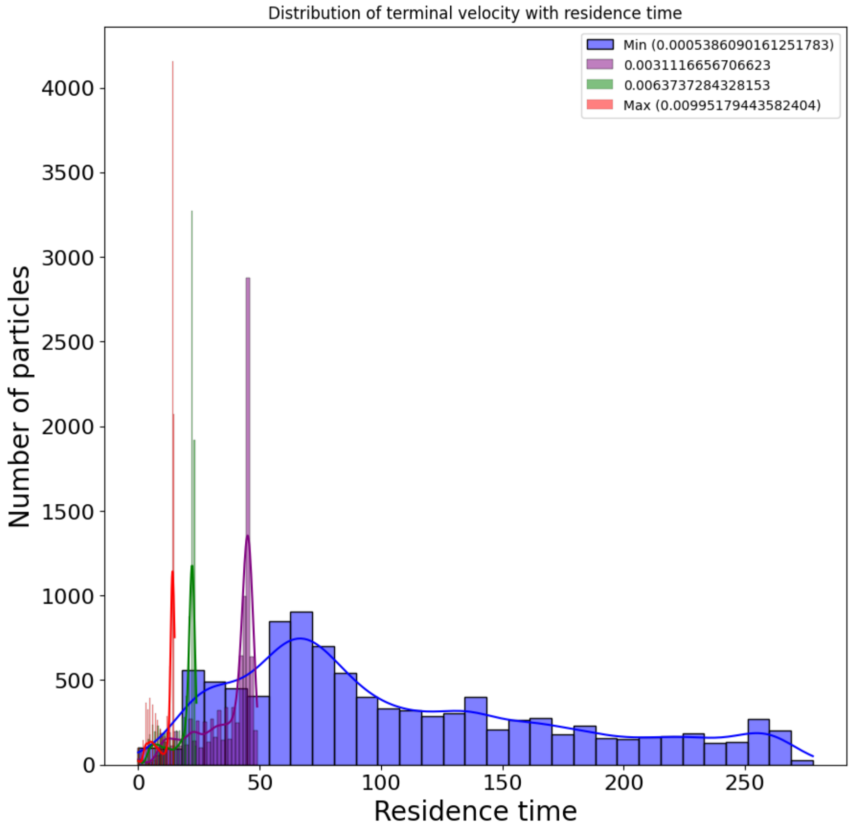


Figure 4.10: Terminal velocity with residence time (hours)

If we now try to analyse the velocities on the basis of the time the particles have stayed in the water column. It can be seen that the particles that have stayed in water column for a long time are the ones that have least sinking velocities. More the sinking velocity is less time they will take to settle while the ones with small sinking velocity have stayed in for a long time.

In the subplots shown above, we can see that as the velocity is increasing the time of residence in the water column is decreasing. The curve is becoming narrow as we move towards the high velocity from low velocities. In 4.9 we can see that minimum velocity 4.9a has a broad curve with residence time is widely distributed while in figure 4.9b and 4.9c we get a narrow curve and for the maximum velocity 4.12d we have a very narrow curve. This shows the way the terminal velocities are distributed with respect to the residence time.

In short, the minimum velocity has stayed in the water column for a long time before eventually settling. Where as, the maximum velocity has much less residence time. As the velocity is increasing, particles are more rapidly settling down thus residence time and the sinking velocity have are weakly correlated.

There is a negative correlation between the terminal velocity and the residence time. The correlation coefficient is -0.63. This means by increasing the sinking velocity the residence time decreases and vice versa.

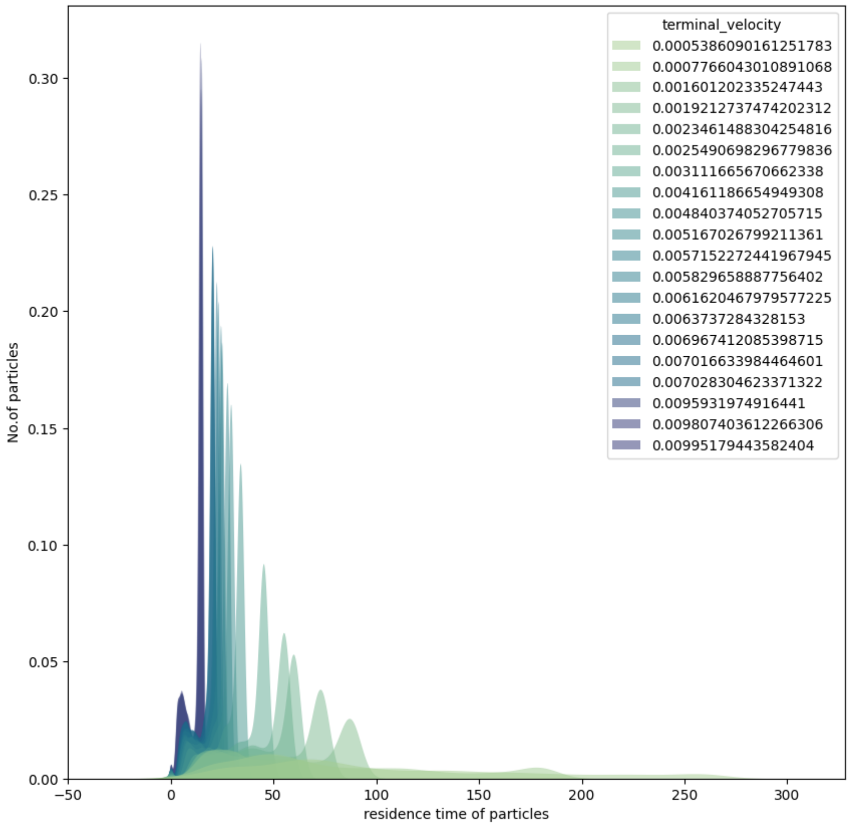
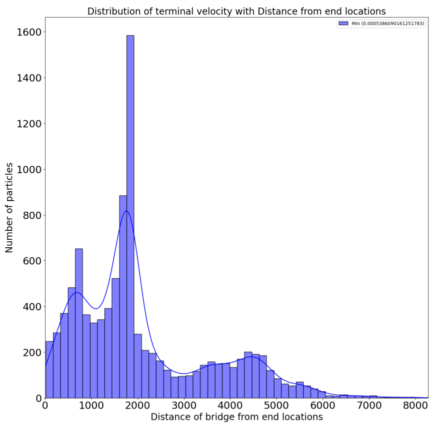
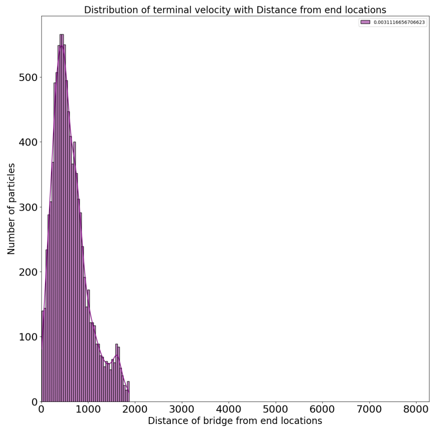


Figure 4.11: Residence time with terminal velocity

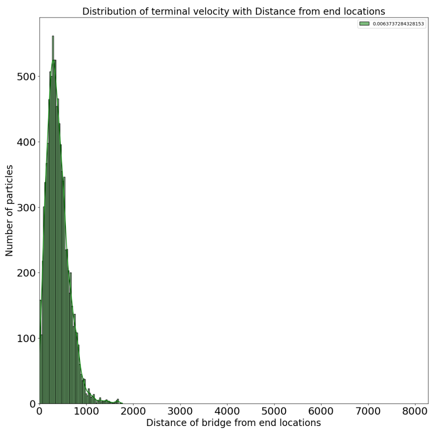
4.2.4 Terminal velocity and the Distance of particles from bridge to End locations(d2)



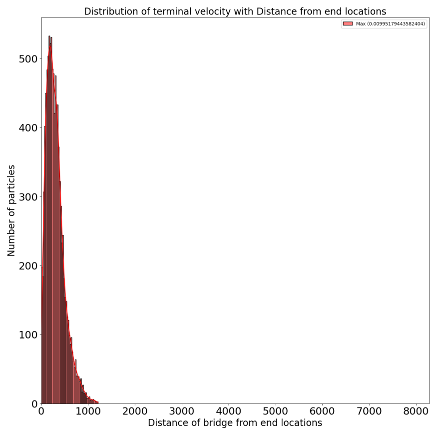
(a) T1(0.000538)



(b) T2(0.003111)



(c) T3(0.006373)



(d) T4(0.009951)

Figure 4.12: Distribution of four sinking velocities with Distance from end location

overall distribution of these four velocities:

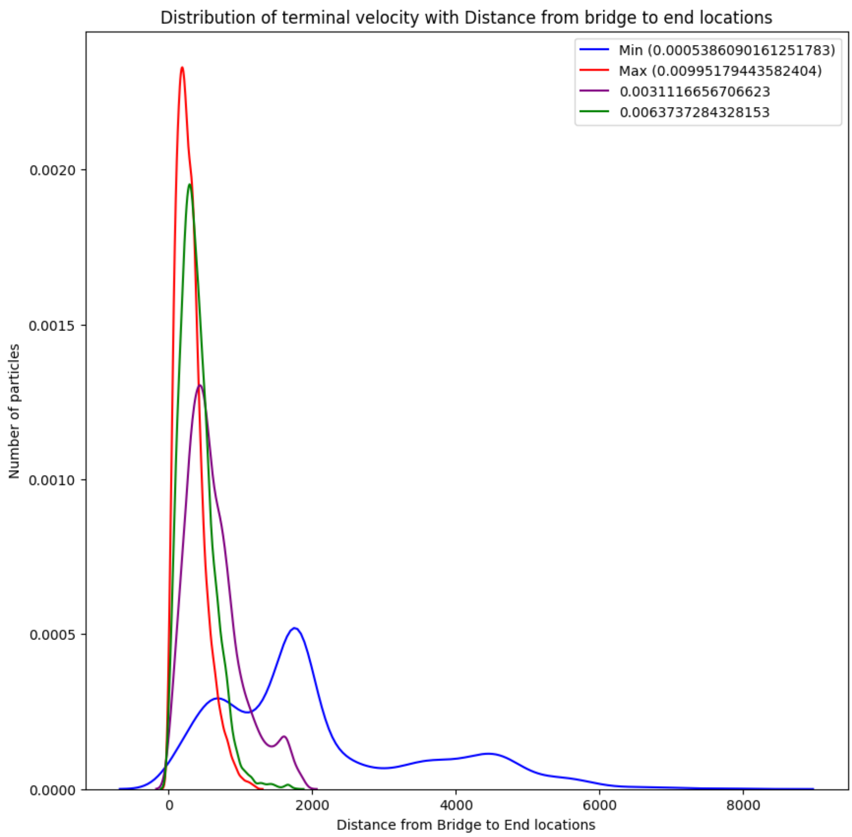


Figure 4.13: Terminal velocity with the distance from bridge(m)

If we now study the behaviour of terminal velocity with the distance of the bridge from the end locations. It is quite evident that maximum sinking velocity has much smaller distance from the bridge where as, the minimum velocity has the more distance from the bridge and landed far from the bridge. In this case we have the same behaviour of terminal velocity as seen before in case of distance traveled and the residence time. It can be visualized that the curve of minimum velocity with distance of particles from bridge to end location is broader with more distance traveled by minimum velocity. By increasing the sinking velocity, the curve is becoming narrow with less distance from the bridge to the end locations of particles and at last we get a very narrow curve with least distance of particles from bridge .

We can see that as the particles with the fastest sinking velocity landed very close to bridge and as we decrease the sinking velocity the distance of particles from bridge increases.

So,in short there also a weak correlation between terminal velocity and the distance of the particle from bridge to the end locations. The correlation between them is -0.52.

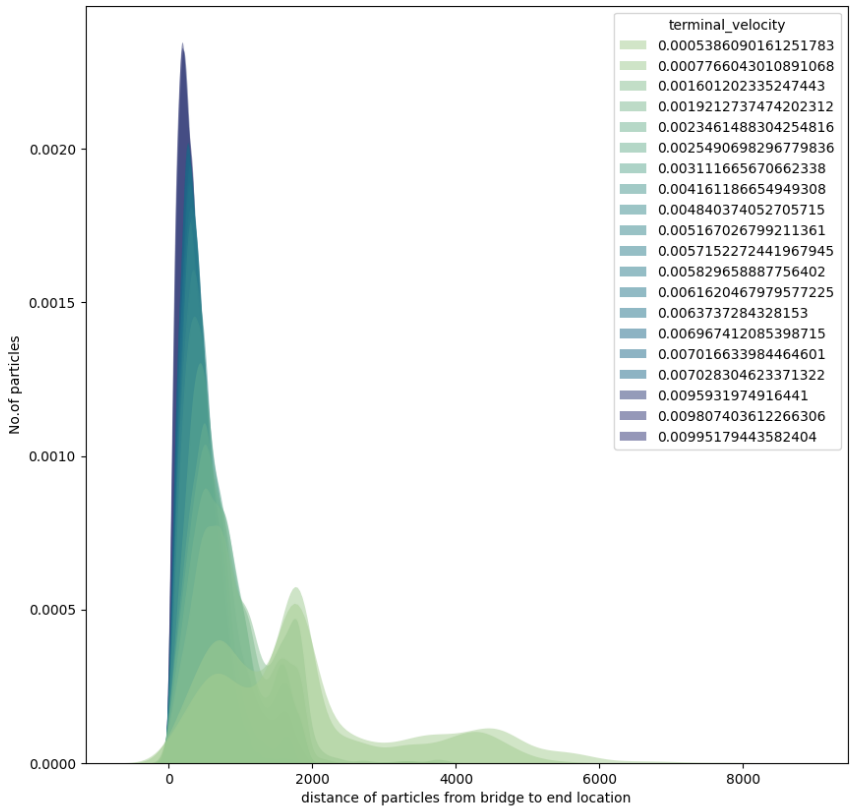
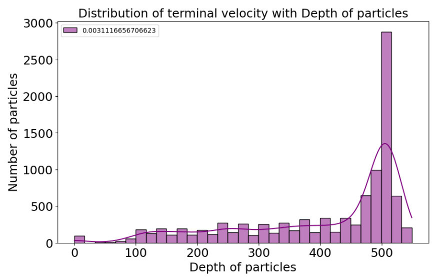


Figure 4.14: Terminal velocity with the distance

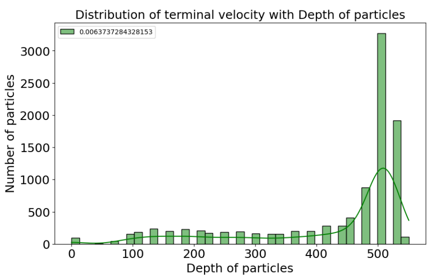
4.2.5 Terminal velocity and the depth

figures/depth1.png

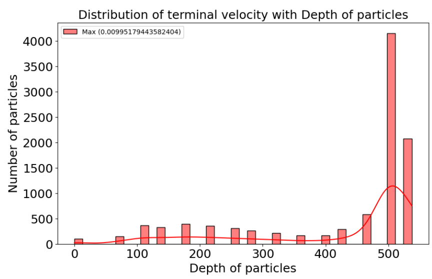
(a) D1(0.000538)



(b) D2(0.003111)



(c) D3(0.006373)



(d) D4(0.009951)

Figure 4.15: Distribution of four sinking velocities with Depth of particles

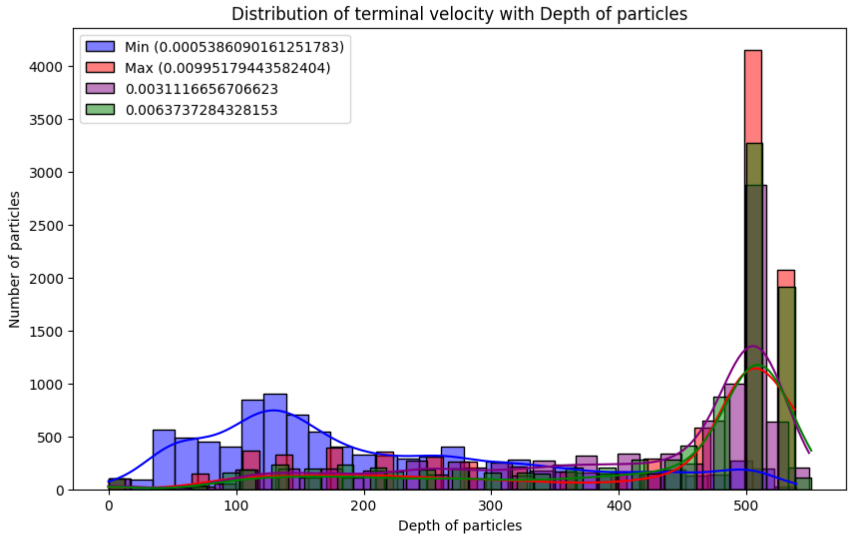


Figure 4.16: Terminal velocity and the depth(m)

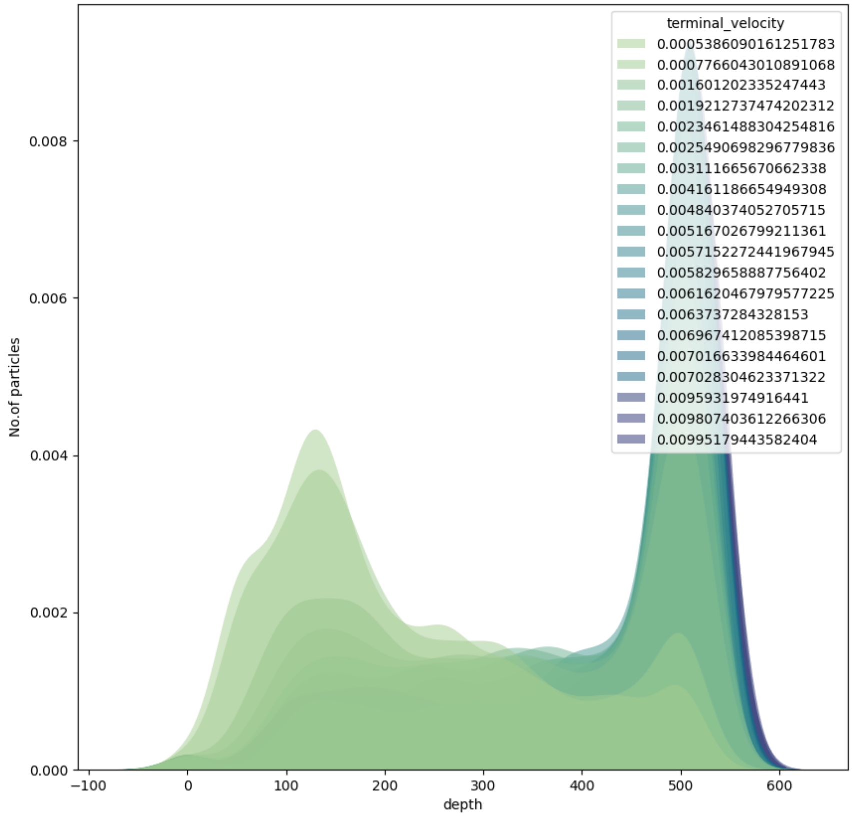


Figure 4.17: Terminal velocity and depth

To study the relation of the sinking velocity with depth. The depth of the particles have little different behaviour as we had in the last three cases. In this case, depth and sinking velocity are correlated with correlation coefficient 0.30. The shows that by increasing one quantity we see a slight increase in order quantity and vice versa. We do not have a strong correlation between these two quantities but still they are correlated.

The figure 4.15 shows that 0.000538 ms^{-1} is minimum velocity with much broader curve and 0.003111 ms^{-1} and 0.006373 ms^{-1} do not show much different behaviour. They has almost the same behaviour and the one with maximum velocity 0.009951 ms^{-1} are seen to be much deeper ones.

In figure 4.16 small the blue top are the ones that are leaving the system through the boundaries because these are shallow ones and are not much deep. This depth shows the yellow are deep particles while as the color gets dark it moves to shallower area. Blue ones are the shallow ones. Close to bridge we have deep ones and as we move far it gets shallow.

The unit of depth is meters and it shows how longer the particles a has stayed in water. The visualization shows close to bridge particles are more deep and have stayed longer compared to the ones that are far from the bridge. These are the ones that have landed far from the bridge and eventually leaving from the boundary. Figure 4.17 shows the overall behaviour of all the 20 sinking velocity with the distance traveled.

From this behaviour, it can be understood that the ones with minimum velocity are the shallow ones and the as velocity is increasing and becoming maximum we get the deeper ones. These deep particles landed close to bridge with much faster speed then the ones with slow velocities.

It can be concluded, that the maximum velocity are deeper ones while the ones with minimum velocity are the shallow ones. The particles with less sinking velocity are less deep because they are less dense and light and are less deep where as, the particles with large sinking velocities are faster and settle more deep into the fjord. The depth and sinking velocities have a positive correlation.

4.3 Statistics of Different Distances

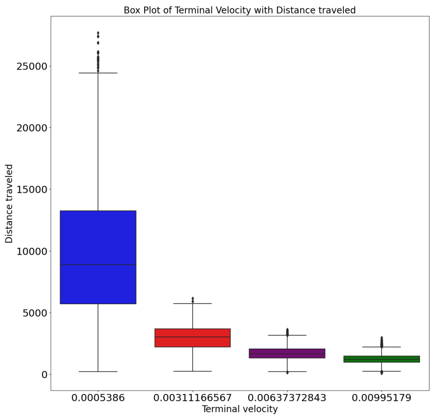
The table 4.2 shows some statistics of different distance calculated. Here distance d1 refers to the distance of particles from bridge to the start locations 3.2.1 and the distance d2 refers to the distance of particles from bridge to end locations 4.2. The table below shows the mean value, standard deviation, variance, maximum values, minimum values, 25% , 50%, 75% of different distance calculated above. The statistics shows the behaviour of data .

	Depth(m)	Distance d1(m)	Distance d2(m)	Distance traveled(m)
mean	389.47	70.1	637.744	2895.132
std	153.19	67.57	695.2957	2723.69
min	0	0.44	0.79	70.89
max	564.906	544.35	8278	27592
25%	265.59	26.22	257.8	1383
50%	479.93	47.9	440.45	1986
75%	506.037	87.7	734.9836	3262

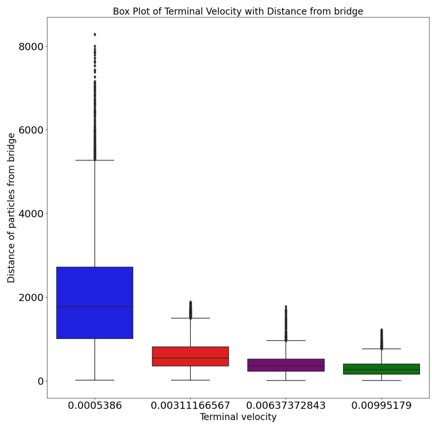
Table 4.2: Statistics of distances

This statistics is quite helpful in statistical analysis to study the behaviour and variations in the data.

4.3.1 Variation in data with respect to terminal velocities:



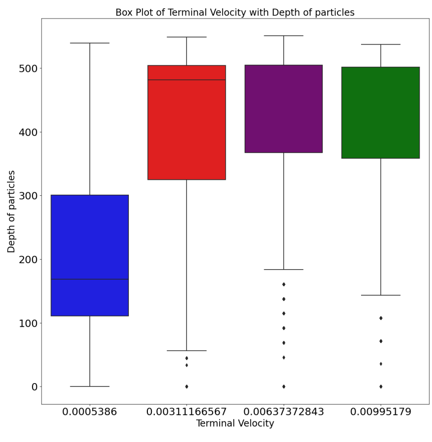
(a) Distance traveled



(b) Distance from End locations

figures/3.png

(c) Residence time



(d) Depth of particles

Figure 4.18: Box plot of data

These four box plots shows the variability of different variables of data. These include Distance traveled, Distance of particles from bridge to end locations, residence time and depth of particles. We can see that the larger terminal velocity has less variability as compared to the the ones with less sinking velocity.

The minimum velocity has a large variability in data. The data has more variation when we have small velocity but when the velocity increases the variation of data is very less. It can be viewed that the maximum velocity doesn't vary much and except for the depth of particles. Since, depth has a positive correlation with the sinking velocity so, the maximum terminal velocities varies with depth. The faster ones have less variability as compared to the slower ones.

4.4 Particles leaving the system

This step involves to look for particles that are leaving the system. The tyre particles that are leaving the system through the boundaries of the system.

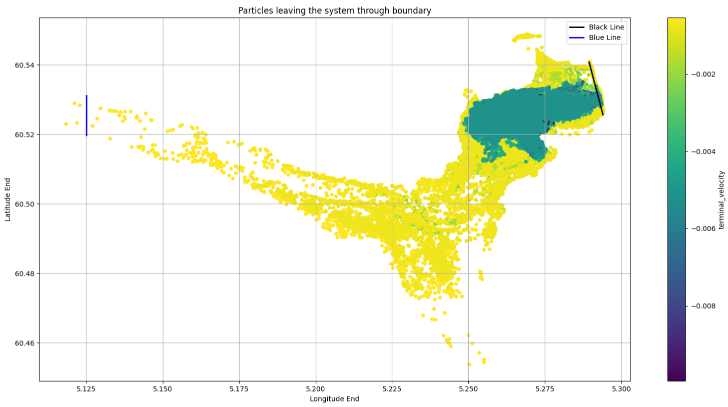


Figure 4.19: Particles leaving the system

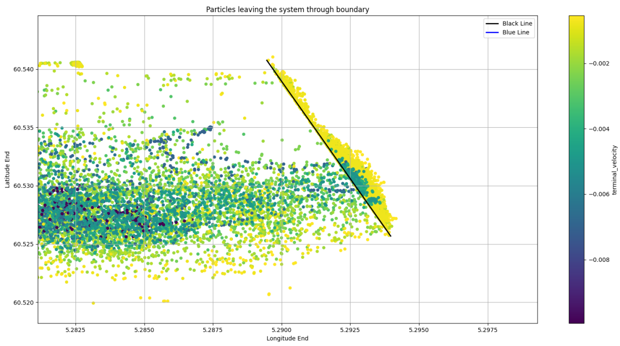
There are two main boundaries in this domain from where the particles are leaving the system. One is at the North west and other one at the North East of the figure 4.19. The particles that are leaving from the top North west are quite a few. They are four in number. The figure 4.20 shows the ones leaving from the North East boundary. There are nearly 9489 particles that are leaving from the North East. There are 7240 leaving particles that have the sinking velocity of 0.0007766 ms^{-1}. There are nearly 5% particles that are leaving through boundaries.

Due to low sinking velocity, these particles have fallen far from the bridge and are leaving the system from the boundaries.

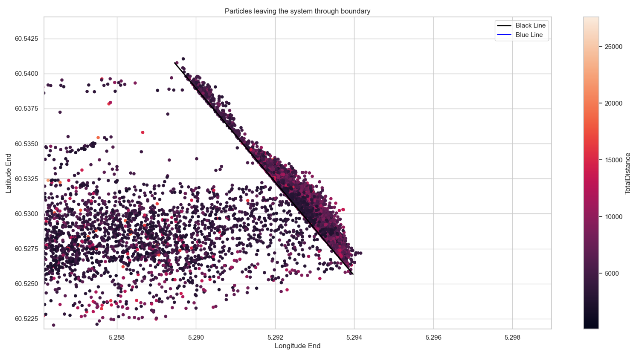
In short, due to less sinking, they landed far away from the source of origin(bridge) and are leaving the system from the boundary as shown4.20.

If we now try to analyse the particles leaving the system by the distance traveled and the depth. It can be visualized that most particles that are leaving from the boundaries are those that have not traveled much distance.

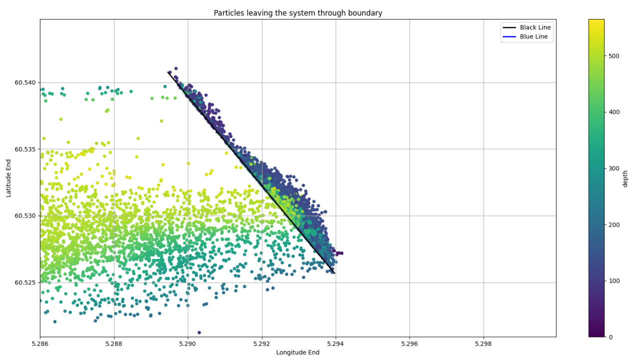
These are the particles that are shallower ones. Close to bridge the particles are quite deep . On the basis of distance traveled, the results are almost the same and these particles leaving the system have not traveled much of distance .



(a) Terminal velocity



(b) Distance Traveled



(c) Depth

Figure 4.20: Particles leaving the system from North East

4.5 Clustering techniques to figure out hot spots

Clustering is a very effective technique used in machine learning. As, the name indicates it helps us to identify data and cluster a big data into small groups so it becomes easy to identify and study the characteristics of typical cluster.In this data I have used K-means clustering algorithm to see and identify different clusters.The clustering is done on the data with different raw variables and newly calculated distances and depth. After applying clustering, K-means clustered the data into different clusters and assign different labels to each clusters.

The figure 4.21 shows how it has distributed the clusters based on end locations of particles. The table 4.3 shows the particles which have fallen in each of the seven clusters. Most of these particles 65857 have fallen in cluster 3 which is in range between 0 to 3000 m . This shows that most particles have not traveled much distance before eventually settling down. It also shows that very small number of particles nearly 2691 have traveled most distance. The figure 4.22 shows the clusters on the basis of distance traveled by the particles.

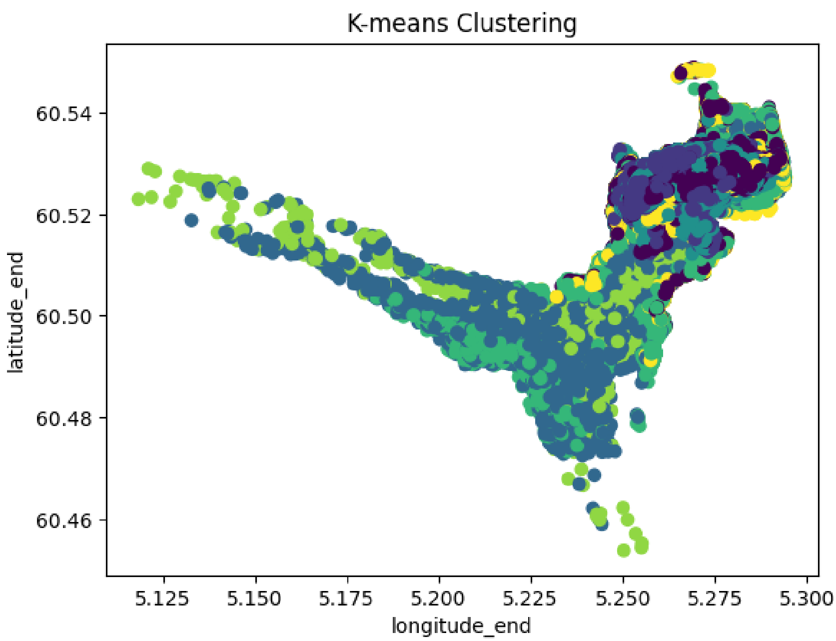


Figure 4.21: K-means Algorithm

Cluster	No.of particles
0	28818
1	6370
2	19649
3	65857
4	15908
5	2691
6	58707

Table 4.3: Particles in each cluster

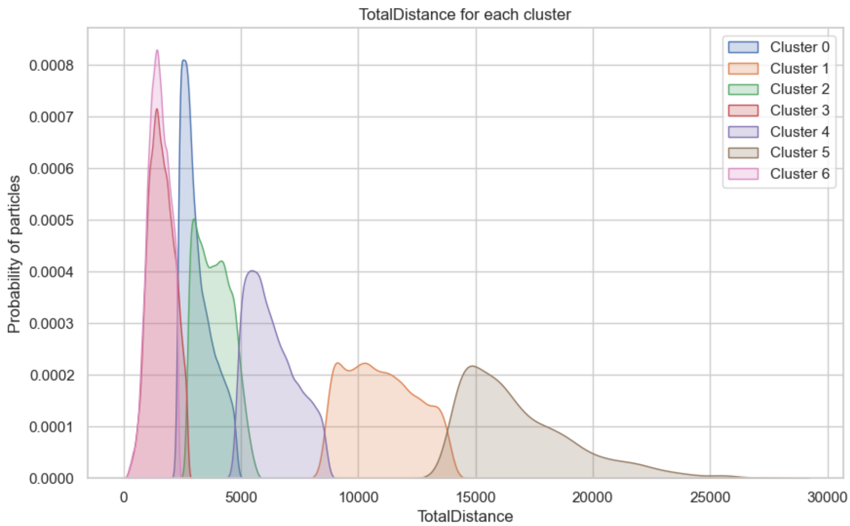


Figure 4.22: Cluster on the Distance traveled(m)

Chapter 5

Discussions and Conclusions

Analysing and compiling the results derived in previous chapter the relation of terminal velocities with different parameters is studied.

It can be concluded that the tyre particles when falling from bridge into the fjord, the particles that had the high sinking velocity stayed in the water column for a short time and hence, sank rapidly and quickly near the bridge. These particles have traveled much less distance. These particles have settle deeper and are supposed to be accumulated at the sea floor.

On the other hand, the particles with lower sinking velocity stayed in water column for a long time. These particle took a long time before sinking. These particles have traveled a large distance before eventually settling at the bottom or leaving through boundary of the fjord. Most of these particles are not much deep and have settled at lower depths. These ones are much shallower than the ones with higher sinking velocities.

In short, tyre particles with low sinking velocities are not much deeper and have landed far from the bridge due being less dense and light. Very few particles, nearly 5% are leaving the system through the boundaries. These particles that are leaving have a small sinking velocity. Since, these had small velocity due to which they landed far from the bridge, eventually a small number from them leave the system.

5.1 Limitations of OpenDrift

OpenDrift is a model that is run by a system. It reads the data that is feed to it. One drawback of this model is that, if it does not find a value at a certain point then it may give some improper information which can be seen in our data shown earlier in figure 3.3.

Since, it is read and accessed by machine so, the chances of error in computations increases a lot. We can encounter error while carrying simulations like we dealt in our data. In our data, it did not find a point in the ocean data model so it perturb the some points data by a factor and give some results of its own. Another real limitation is in our sinking model that is the Stokes's model being used here. Stokes law assumes the shapes of particles to be spherical but in case of tyre particles it can be differently shaped. So using here Stokes's law for tyre particles with varying shapes and sizes may not give the actual sinking velocities.

5.2 Future Work

We have studied the tyre plastic without taking into account the bio fouling effects. In future, this topic can be studied by considering the bio fouling effects. How much bio fouling has effect on the accumulation of plastics? How does bio fouling effect on particles with less sinking velocities of change? Do the Bio fouling change the velocities of sinking plastic particles. Moreover, I had access to limited data. If I had access to more simulations I could look more into the data. In future, seasonal effects could be taken into account with more BOM(Bergen Ocean Model) runs. In future, sinking velocities could be computed using different models that yield more accurate velocities and results could be analyzed. I have not done much on Clustering due to lack of time. In future, different Clustering techniques can be applied to the data.

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