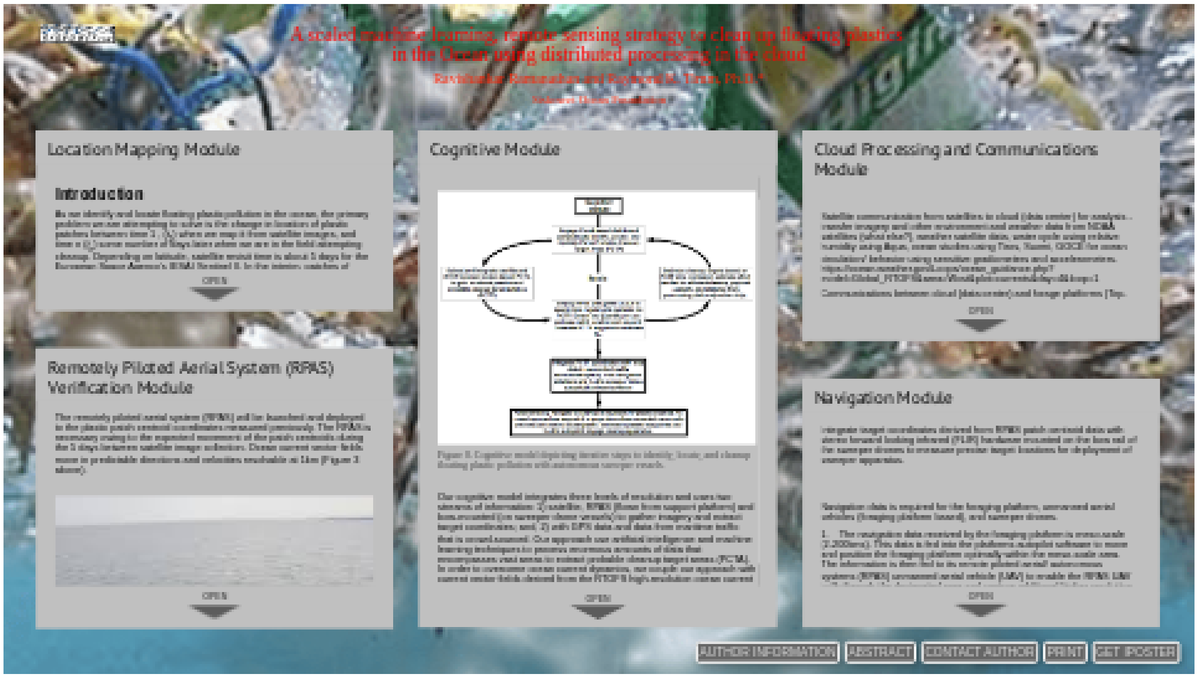
A Scaled, Machine Learning Approach to Cleaning up Floating Plastics in the Ocean



Ravishankar Ramanathan, Raymond K. Timm, Ph.D.*

Siskowet Ocean Foundation

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LOCATION MAPPING MODULE

Introduction

As we identify and locate floating plastic pollution in the ocean, the primary problem we are attempting to solve is the change in location of plastic patches between time 1 , (t_1) when we map it from satellite images, and time *n* (t_n) some number of days later when we are in the field attempting cleanup. Depending on latitude, satellite revisit time is about 5 days for the European Space Agency's (ESA) Sentinel II. In the interim, patches of plastic can move due to ocean currents and wind. They can also change configuration and composition. There are also spatial and spectral incongruencies with the floating plastic. In order to address these challenges, we take a multi-step approach

Step 1 in this process is masking any land in the scene and identifying floating plastic. In some ways, this is the most straightforward part of the process owing to work done by Biermann et al. (2020). The floating plastic index (FPI) takes advantage of ratios of red, NIR, and SWIR wavelengths (Eq. 1) to discriminate between plastic and other floating debris (Biermann et al., 2020). Image Analysis in performed in the Cloud and described in greater detail in the Cognitive Module.

$$FPI = R_{rs,NIR} - R'_{rs,NIR} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$R'_{rs,NIR} = R_{rs,RE2} - (R_{rs,SWIR1} - R_{rs,RE2})x\left(\frac{\lambda_{NIR} - \lambda_{RED}}{\lambda_{SWIR1} - \lambda_{RED}}\right)x10 \ldots\ldots (2)$$

[VIDEO] https://www.youtube.com/embed/[illegible]?rel=0&fs=1&modestbranding=1&rel=0&showinfo=0

Figure 1. Stop Animation Mockup of Floating Plastic on Ocean Currents

Mapping Patches of Floating Plastic

As mentioned above, coordinated derived from classified satellite imagery for patches of floating plastic are "stale" by the time the intial analyses are complete. Shifts in patch locations are mediated by wind and surface currents. In addition, the composition and configuration of patches changes as well.

Patch Centroid Locations

Patch ID	Row	Column	Day
1	i_1	j_1	t_1
2	i_2	j_2	t_2
3	i_3	j_3	t_3
n	i_n	j_n	t_n

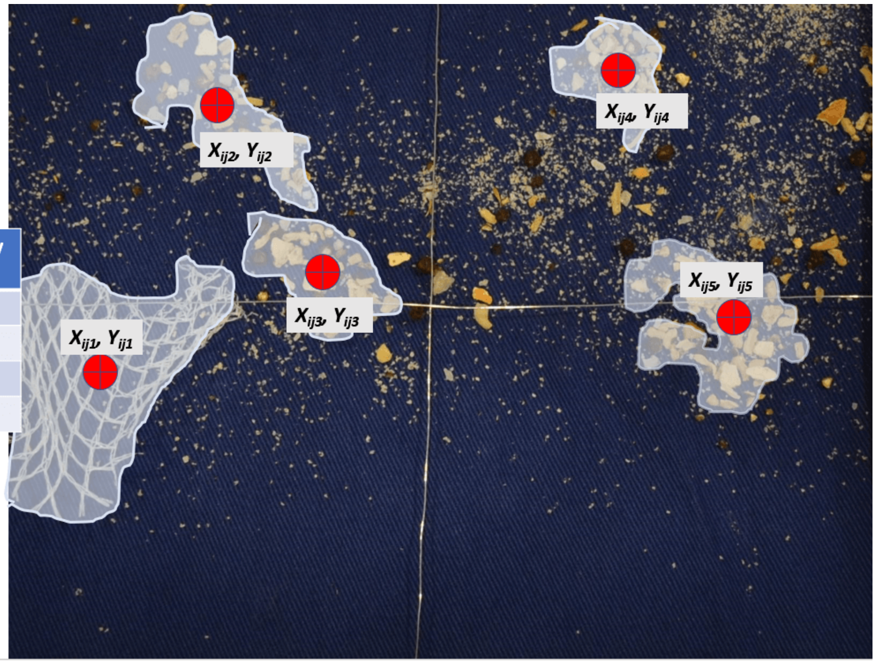

Figure 2. The centroid locations of each patch of floating plastic is added to a vector field from NOAA's RTOFS High Resolution Ocean Current Model (Figure 2).

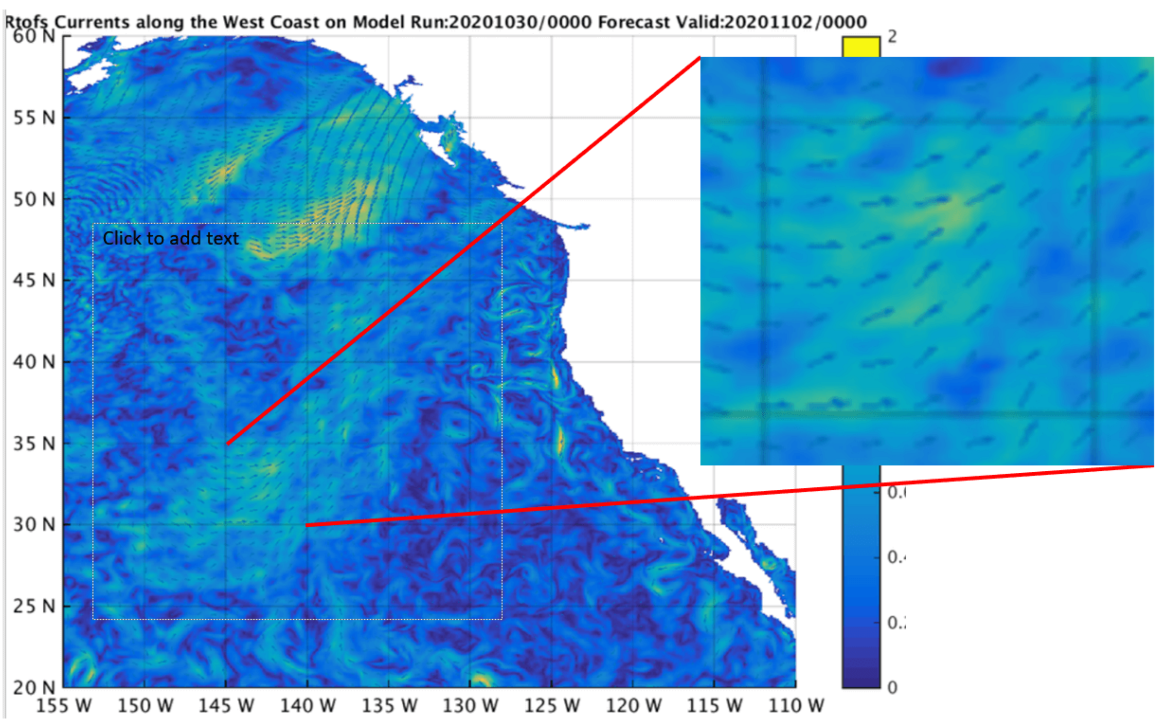

Figure 3. Global RTOFS high resolution oceanic model output for North Pacific Ocean region that encompasses the Great Pacific Garbage Patch (GPGP). The North American continent is depicted in white and is No Data in the model. Source: Ocean.weather.gov .

Patch ID	Row	Column	Day
1	i_1	j_1	t_1
2	i_2	j_2	t_2
3	i_3	j_3	t_3
n	i_n	j_n	t_n

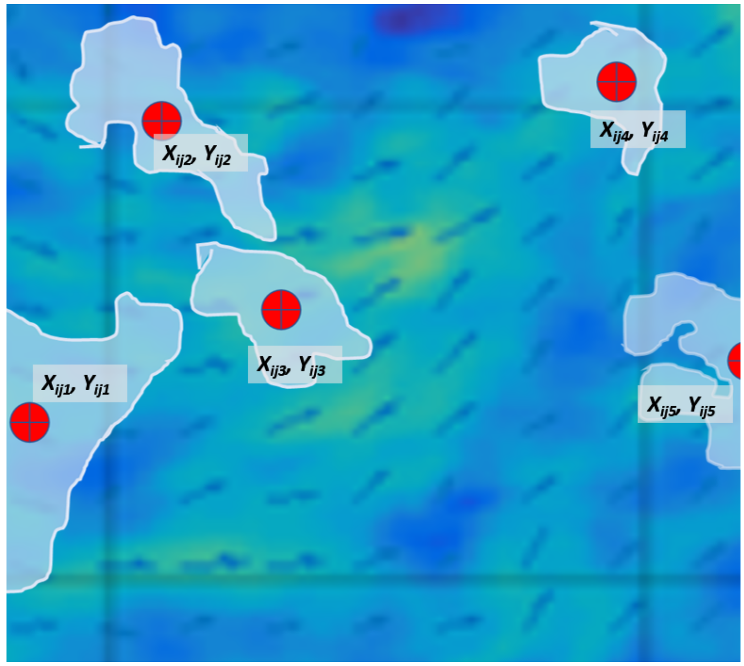

Figure 4. Simulated plastic patch coordinates superimposed on RTOFS current vector field.

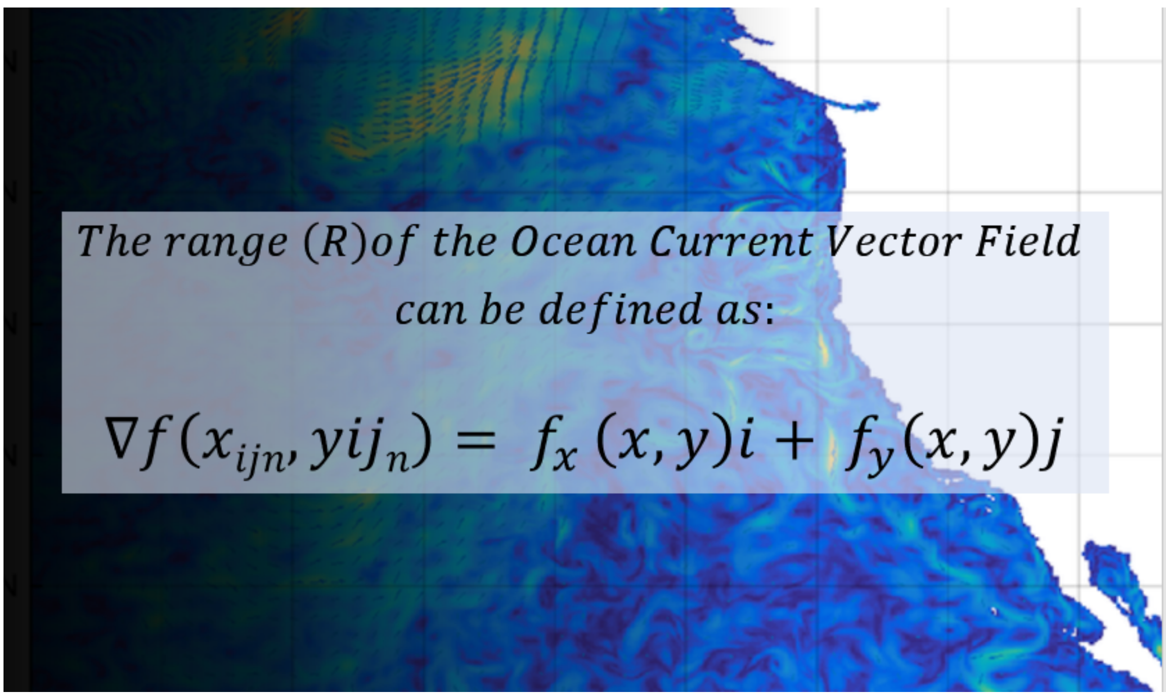

Figure 5. Vector field model with equation. Larson et al. 1990.

Our Machine Learning (ML) Model incorporates Plastic Patch Locations Mapped from Satellites Coupled with Current Model Vector Field Ranges

•For: Each Plastic Patch Centroid (PPC) mapped at Time t_1, add the Ocean Current Vector across the range (R) for the number of days (*1* through *n*) between Satellite and RPAS observations.

•The sum of those quantities is used to estimate new PPC locations. The RPAS is programmed to fly a 5km regular grid with 10% sidelap, centered on these new PPC.

•RPAS flights verify and map updated PPC locations. This file becomes navigation waypoints for sweeper drone boats.

REMOTELY PILOTED AERIAL SYSTEM (RPAS) VERIFICATION MODULE

The remotely piloted aerial system (RPAS) will be launched and deployed to the plastic patch centroid coordinates measured previously. The RPAS is necessary owing to the expected movement of the patch centroids during the 5 days between satellite image collection. Ocean current vector fields move in predictable directions and velocities resolvable at 1km (Figure 3 above).

Figure 6. Launcing remotely piloted aerial system (RPAS) from boat deck. Image Source: Grace-oil-project.eu

We couple plastic patch locations with current predictions (NOAA 2020) to estimate plastic movement during that interim. For each meso-scale region, we then deploy the RPAS with a green LiDAR to fly a regular 5 km grid with10% sidelap of each path, centered on the predicted locations of plastic patches. The location of floating plastic aggregations determined from the RPAS become navigation targets for the sweeper drones. In addition, these targets are used to calculate the optimal position the mother ship to maximize foraging effectiveness for the entire fleet of sweeper drones. Target optimization and prioritization is accomplished by evaluating descriptive spatial statistics of floating plastic patches. These include things statistics such as contagion, clumpiness, dominance, and nearness. If, for example, a group of patches exceed a certain clumpiness or contagion threshold, they are virtually aggregated into a single patch and then compared against dominance metrics for all other patches.

1. The navigation module is then informed by the nearness of these ordered patches.

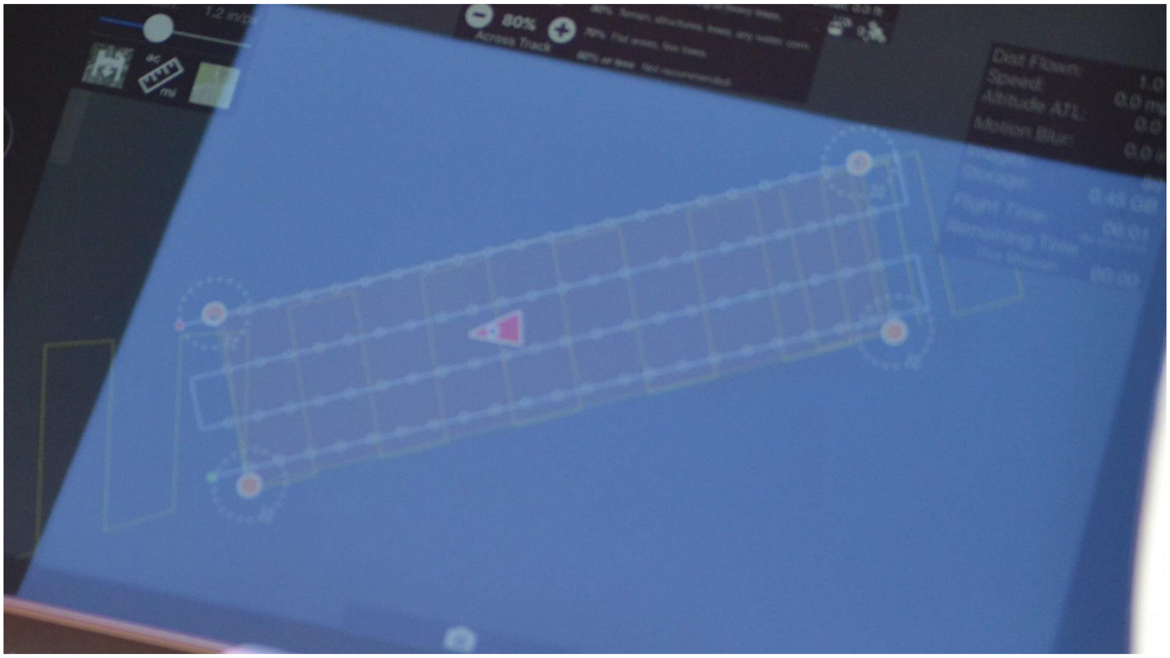

Figure 7. RPAS flight plan in regular grid depicting flight lines with 10% sidelap.

COGNITIVE MODULE

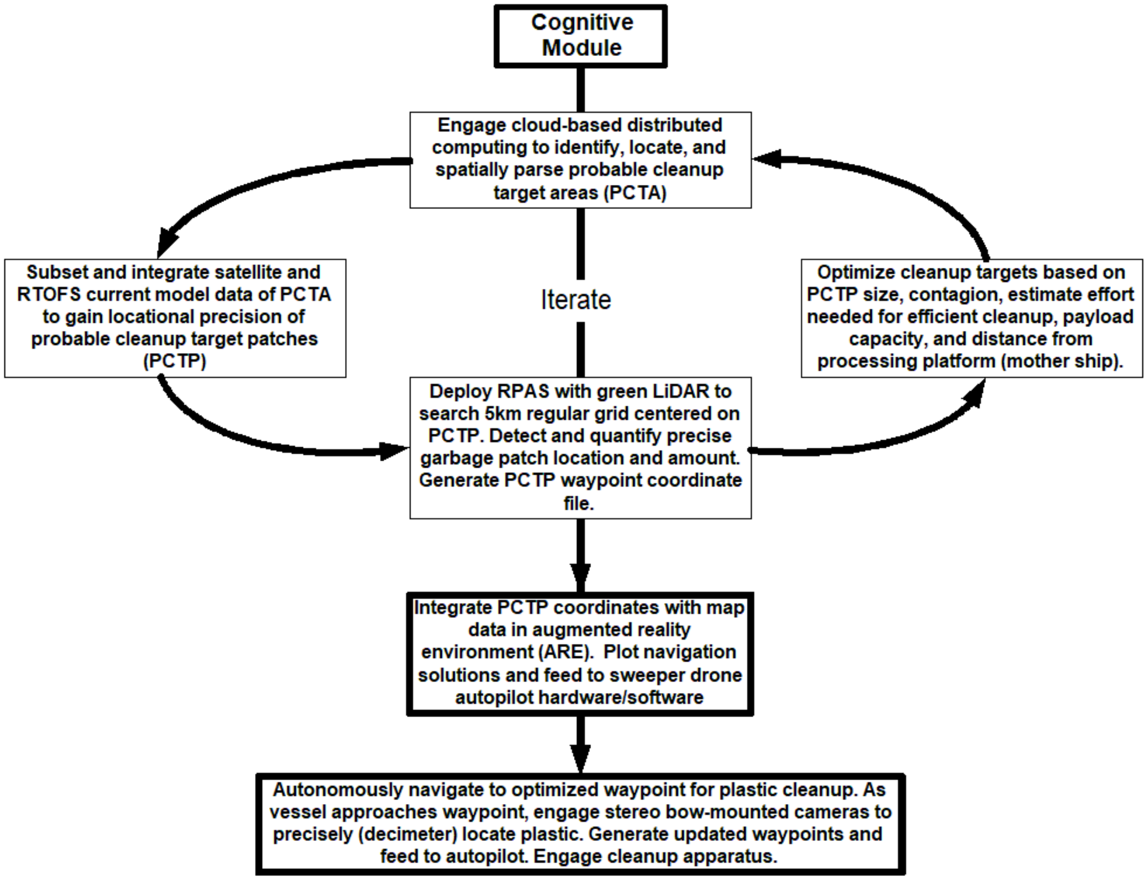

Figure 8. Cognitive model depicting iterative steps to identify, locate, and cleanup floating plastic pollution with autonomous sweeper vessels.

Our cognitive model integrates three levels of spatial resolution and variable temporal resolution (ca. 10 days to <1 day) and employs two streams of information (Table 1). Data sources are integrated across all scales to provide navigation target coordinates that guide the ACV in cleaning up floating plastic debris. In order from coarsest spatial resolution to finest, 1) RTOFS current model (103 m); satellite imagery (101 m); RPAS LiDAR that is guided from the support platform (10-1 m); and bow-mounted stereo cameras that are used to precisely guide autonomous cleanup vessels (10-1 m) to gather imagery and extract target coordinates; and, 2) with augmented reality environment (ARE) using GPS data and data from maritime traffic that is crowd-sourced.

Table 1. Data source, spatial and temporal resolution, and data stream in the cognitive module.

Data Source	Resolution	Data Stream
Sentinel II Satellite Imagery[1]	10^1 m; ca. 10 days to < 1 day	1
RTOFS Current Model[2]	1/12° ; 3 hours	1
RPAS LiDAR	10^{-1} m; instantaneous	1, 2
ACV Stereo Cameras	10^{-1} m; instantaneous	1, 2

[1] European Space Agency, Copernicus Earth Observation Programme. ESA - Copernicus

[2] National Oceanic and Atmospheric Administration, Real Time Ocean Forecast System (RTOFS), High Resolution Oceanic Model Global RTOFS High Resolution Oceanic Model (weather.gov)

Our approach uses supervised machine learning (ML) techniques to process enormous amounts of data that encompass vast areas to extract probable cleanup target areas (PCTA). In order to overcome ocean current dynamics, we couple our approach with ocean current vector fields derived from the RTOFS high-resolution ocean current model (NOAA 2020). This allows us to estimate cleanup target range, angle, and velocity relative to initial locations as mapped from satellites to generate X,Y coordinates for probable cleanup target patches (PCTP). These are further refined as described in the RPAS Verification Module to provide precise cleanup targets for autonomous cleanup vessels (ACV).

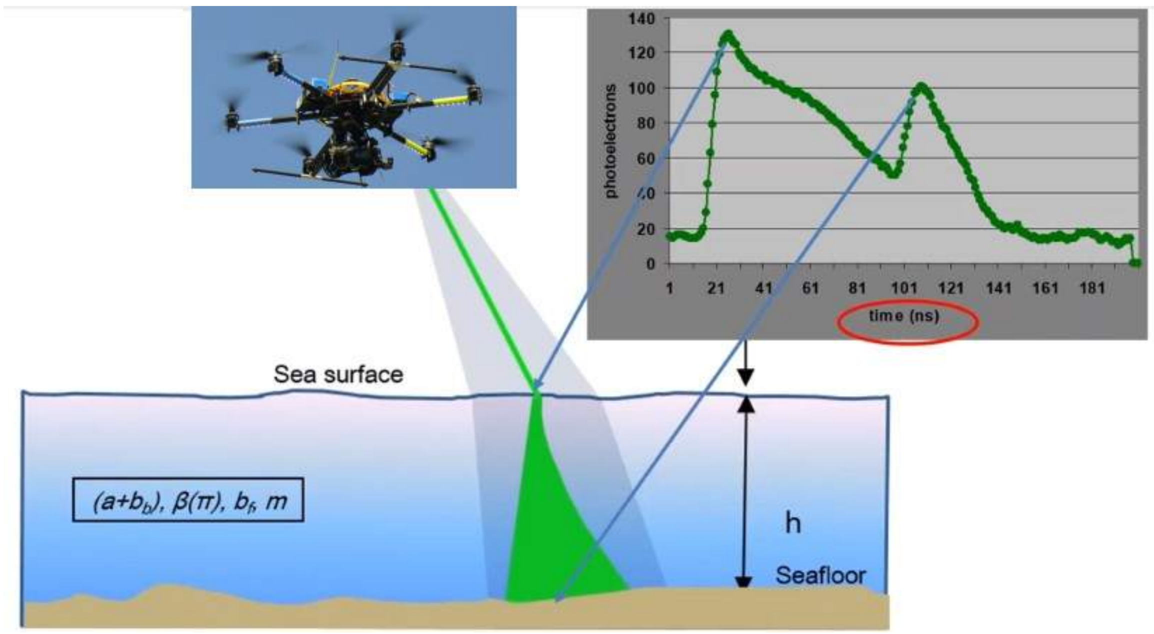

Figure 9. RPAS surveying PCTA for floating plastic with Green LiDAR (Image Source: Teledyne Optech 2020).

We evaluate classified satellite imagery to locate floating patches of plastic debris within 100km2 moving window AOI. Once located, we add the PCTP coordinates to RTOFS vector fields to predict their movement during the time between when the satellite image is collected and when we can get to the field for cleanup. This process accurately provides locational data to the support platform (mothership) and ACV. Machine learning improves the prediction of PCTP waypoint coordinates for autonomous drones as they navigate to cleanup patches of floating plastic. At each scale shift (i.e., satellite and RTOFS to RPAS to ACV), empirical measurements of plastic patch centroid coordinates will teach the ML algorithm by quantifying the difference between expected and observed locations. In addition, the ML algorithms optimize the waypoint priority based on spatial composition and configuration (Turner et al. 2001) of plastic patches. For example, we evaluate the size, contagion and nearness (McGarigal and Marks 1995) to prioritize the order in which the ACV navigate to and collect the floating plastic debris.

Specific Steps to Cognitive Integration

1.

· A cloud-service based cognitive processing unit for synoptic scale data (i.e., satellite imagery; ESA and ROTFS current model; NOAA 2020) is downloaded.

· By using extract transform load (ETL) process, that information is loaded onto our cloud-based service which classifies satellite imagery to extract the floating plastic index (FPI) following Biermann et al (2020) to identify potential patches of floating plastic in ocean.

· Using ML, the data is processed to generate and deliver highly accurate coordinates in a text file that facilitates navigation to floating patches of plastic for cleanup.

2.

· A dual system (cloud/ forage platform) meso-scale cognition processing detects and quantifies floating plastic location and size, estimate amount of floating plastic (Biermann et al. 2020)

· Generate general cleanup target coordinates for ACV from FPI patch centroid coordinates. Refine with data onboard (forage platform) and from RPAS (green LiDAR) to produce updated navigation waypoints.

· Convert to X,Y text file for transmission to ACV.

3.

· The ACV have limited local processing capabilities. Most onboard computing is limited to that necessary for communication, precise navigation, and direct cleanup activities. Estimates of cleanup effort, payload capacity, and distance from processing platform (mothership) are undertaken on the mothership. Communication with the mothership is accomplished via VHF radio and limits file size.

CLOUD PROCESSING AND COMMUNICATIONS MODULE

Satellite imagery, current models, RPAS LiDAR and crowd sourced data result in huge amounts of data that are difficult to process by humans efficiently. Machine learning enables data driven modeling systems to bridge the gaps and lessen demands on human experts as. It is also critical to producing parsimonious instruction sets. This is important because our ACV have liminted processing capabilities. Our ML algorithms are used to improve on predictions of PCTP by ground-truthing PCTP locations at time t_{1+n}. where PCTP are added to the ROTFS vector field for n days following satellite imagery date. All these data are retrieved, analyzed, and stored in the cloud. The primary data product from the analyses (see Cognitive Module) are text files containing X, Y coordinates that are transmitted among various platforms deployed in the field, and the cloud (Figure 10). The advantage to this approach is that we can limit the computing power to that necessary for navigation and cleanup in the ACV. In that way we maximize cleanup effectiveness.

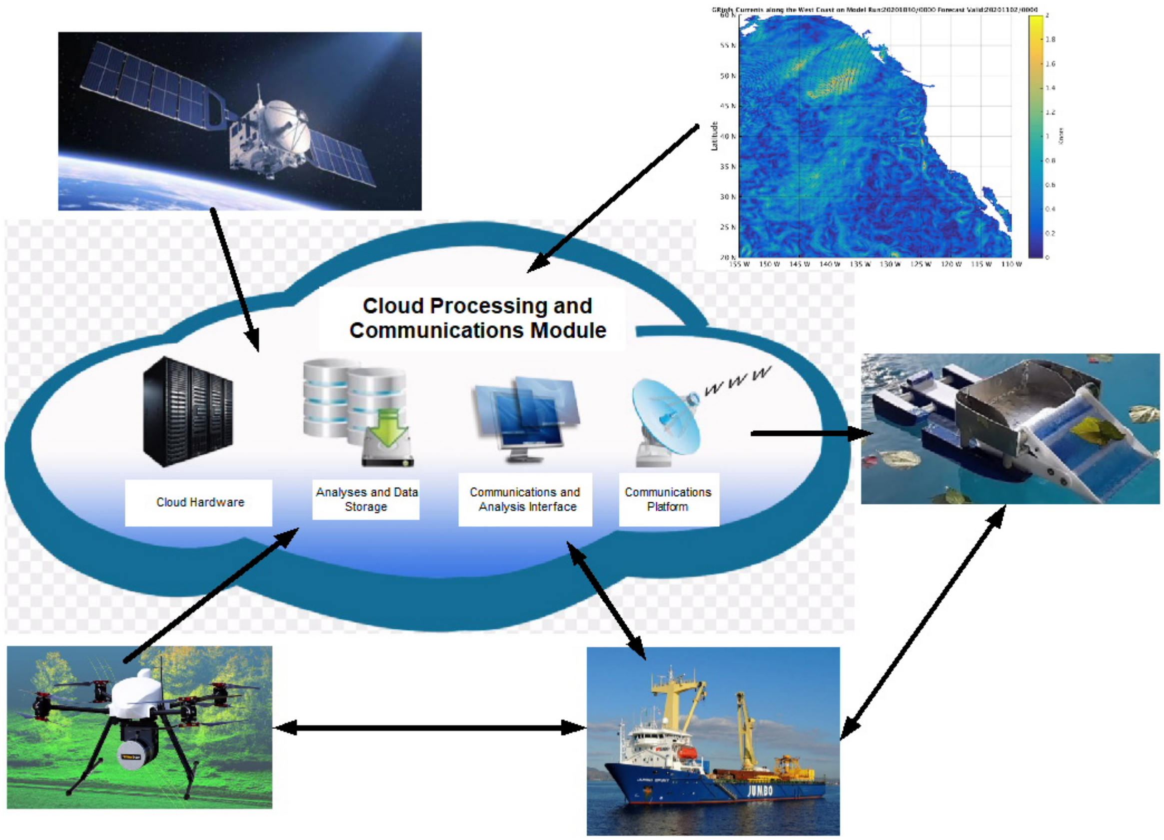

Figure 10. Depiction of communication pathways and directions between data sources, the cloud, and data users in the Cloud Processing and Communications Module.

Satellite imagery are identified from a moving area of interest (AOI) that is 100km on a side. Images in the AOI are classified in the cloud following Biermann et al. (2020). Data are extracted from Euorpean Space Agency servers via an API, classified to identify patches of floating plastic, and patch centroids determined and downloaded as text files. These coordinates are then uploaded to the cloud and added to vector fields derived from NOAA's RTOF ocean current model and run for the number of days between satellite image collection and field work. From this step we produce X, Y coordinate predictions of where the plastic is likely to be which are then downloaded as text files. These predicted coordinates become the geographic basis for RPAS grid serches. RPAS-verified patches of plastic are optimized and prioritized in the cloud, converted to X,Y coordinates and transmitted to the mothership and ACV as text files containing navigation waypoints. Lastly, when the ACV approach the navigation waypoints (within 10m), stereo bow-mounted cameras are engaged to determine the precise locations of floating plastic. These precise X, Y coordinates instantaneously update the waypoint files in the autopilot to ensure that the cleanup aparatus engages the floating plastic. This last communication step is accomplished on board the ACV via local network hardware.

Communications between the cloud (data center) and ACV forage platforms are "Top-Down", and inter-platform "Lateral" communications. ACV platforms communicate their location, trajectory and instantaneous exploitation (plastic cleanup) rates with each other. Identification of garbage concentration another attribute that is up for communication as well - it can determine intelligence "Bottom Up" that we can build into individual platforms. Using VHF radio transmissions.

Communications between individual ACV, its ACV group and the mothership occur via VHF and are monitored by the mothership computers to continuously re-optimize clearnup targets. Updated and reprioritized waypoints are transmitted to ACV as they are generated. Again, this is "Lateral", "Top-Down" and "Bottom-Up" communication at the micro-scale level.

NAVIGATION MODULE

RPAS Navigation

Centroids of confirmed patches of floating plastic are converted into navigation data, and passed from the mothership to RPAS and the ACV. As mentioned previously, the RPAS navigates in a regular grid that is 5 km on a side and centered on known accumulations of floating plastic –termed Probable Cleanup Target Area (PCTA; Figure 7). The RPAS flies complete coverage of the grid with 10% sidelap between each flight path. Mounted on the RPAS is a green LiDAR that maps the extent, shape, and centroid coordinates of each patch of floating plastic in the PCTA (Figure 9). When the RPAS returns to the mothership, the LiDAR data are classified in a binary way as “plastic” or “non-plastic”. Patches classified as plastic are quantified in terms of their size, contagion, and proximity to the mothership and to ACV engaged in cleanup. All these variables are run through an optimization algorithm to generate a prioritized cleanup target list which in turn, becomes the waypoint file of X, Y coordinates that the ACV navigate to for cleanup activities.

ACV Navigation

A text file containing sub-meter X, Y coordinates are transmitted to the ACV via VHF radio signals from the mothership. This text file contains the prioritized list of waypoints that are entered into the ACV autopilot. The ACV autopilot software guides the ACV to within 10m of known cleanup targets. As the ACV moves to within proximity of known plastic accumulations, stereo bow-mounted cameras are engaged to discriminate floating plastic from clean water and to compute highly precise (decimeter) coordinates of plastic patches. These new coordinates are continuously computed and supersede previous coordinates in the waypoint file if they are within 10m of the new coordinates. This is a critical step in the navigation process because it allows the ACV to position the foraging cleanup apparatus so that it effectively collects the floating plastic.

All the while, aboard the mothership, the navigation computer platform is monitoring the location of all ACV in the fleet, other ships that may be in the area, land, shallow water and other potential navigation or collision hazards. This augmented reality environment (ARE) is layered on top of the navigation waypoints of each ACV (Raymarine 2020). The ARE considerations are continuously computed and updated. If updates cause changes to the order of ACV waypoints, they are transmitted via VHF radio. The ACV is also continuously updating the mothership with information regarding cleanup efficiency, onboard battery capacities, and payload capacity. The waypoint optimization algorithm integrates that information with data received from the ACV fleet in real-time to improve the effectiveness and performance of the sweeper drones. For example, if an ACV is achieving unusually high cleanup efficiency, the optimization algorithm calculates the distance to nearby ACV and compares the same list of variables to determine if given ACV should move to improve their exploitation rates.

Figure 11. Autonomous cleanup vessels (ACV) working in proximity to Mothership 1.

The ACV fleet communicates continuously with the mothership, transmitting location, payload capacity, and battery power reserves. When the ACV reaches payload goals or calculated battery reserves necessary to return to the mothership, it switches from cleanup mode to navigation. Upon reaching the mothership, the ACV is emptied and fresh batteries installed. It is then assigned a new, optimized set of cleanup coordinates and returned to cleanup mode. In this way, the ACV fleet can maximize effective cleanup of the floating plastic pollution.

AUTHOR INFORMATION

Raymond Timm, Ph.D.

Founder, Siskowet Ocean Foundation.

ray.timm@siskowet.com

206/963-1098

Dr. Timm is a disturbance ecologist who has been engaged in ecosystem restoration since the mid 1990s. He has studied or otherwise worked on issues that range from the incipient North American invasion of the zebra mussel in Lake St. Clair, to salmon recovery in the Pacific Northwest.

He has more than 25 years of experience in project management, habitat restoration, ecosystem modeling, remote sensing, and spatial modeling with geographic information systems (GIS). He uses highly quantitative spatially explicit analyses and models to identify, prioritize, and implement restoration actions. He has led watershed assessment and restoration planning efforts involving scientists, managers, tribes, ranchers, and other interested parties.

In 2018, in response to the conservation emergency posed by floating plastic in the oceans, he started Siskowet Enterprises. The name was inspired by the lake trout encountered by early commercial fishers in Lake Superior. When dragging their nets, they would encounter two races of lake trout - the siskowets and the leans. The legend has it that a siskowet was so fatty, that lucky anglers could toss them in the boiler to run the boat because they burned as hot as white pine. Not only did the legend of the siskowet inspire the name of our foundation, it is the basis of our economic model. We collect plastic garbage floating in the ocean and convert it to electricity to fuel our cleanup operation.

When his young daughter, armed with photos of sea turtles entangled in plastic, asked him to fix this problem his ecological concern became conflated with parental concern. From that moment, he started thinking about the problem and the barriers to successfully addressing it. This presentation is an overview of how Siskowet integrates various technologies across scales as broad as the open ocean to smaller, manageable cleanup targets. Because the collected plastic fuels our generators, our process is continuous and self-sustaining.

ABSTRACT

It took less than two decades for plastics to become notable marine contaminants following their initial commercial introductions. In the ensuing five decades, global plastics production has increased 500% each year. Currently, 300 million metric tons of plastic are produced every year - much of this ends up in the ocean. In the mid-1970s it was thought that most of this plastic derived from discarded trash by ocean-going vessels. Now, we know that plastic debris in the oceans is exported by nearly all the major rivers of the world, as well as from fishing, aquaculture, petrochemical, and shipping industrial sources. These plastics are long-chain polymers that are extremely durable in the environment, which is in part, why they become troublesome pollution. One practical difficulty is that in addition to the massive geographic extent of the plastic debris, the distribution is patchy in 4 dimensions (i.e., length, width, depth, time). Our approach takes advantage of the unique spectral signatures of floating plastic that can be identified in freely available Sentinel-2 imagery from the European Space Agency (ESA). Recent analytical developments identified a floating plastic index (FPI; Biermann et al. 2020) that takes a ratio of red, red edge, NIR, and SWIR bands (4, 6, 8, and 11 respectively) to discriminate between floating plastic and other floating materials such as foam, wood and vegetation. Here we present a scaled approach to identify patches of floating plastic and generate coordinates to guide cleanup efforts. The initial area of interest is 100 km on a side and is passed through hierarchical loops that 1.) separate land from water; 2.) interrogate the image files for pixels with reflectance values consistent with FPI; and, 3.) generate pixel centroid coordinates for image pixels that contain suspected floating plastic pollution. To overcome the coarse spatial (20m, bands 6 and 11) and temporal (ca. 5 days) resolution, and dynamic nearshore environment, remotely piloted aerial systems (RPAS) navigate to pixel centroids to confirm plastic accumulations. Once identified and located, updated coordinates guide navigation via autopilot in autonomous sweeper drone vessels. These sweeper drones are equipped with stereo bow-mounted hyperspectral cameras that scan the proximal waters to identify precise locations of floating plastic, plot a navigation solution, and engage the drone's sweeper apparatus to collect the plastic. The approach integrates, distributed processing of satellite imagery in the cloud, RPAS verification of plastic locations, communication with navigation software and hardware of cleanup vessels to plot navigation solutions at the 20m scale. Finally, onboard hyperspectral cameras collect and process stereo imagery to identify precise targets which are layered on the navigation software and hardware system to direct cleanup actions. The approach is comprised of five hierarchically integrated modules that include: Coarse Location Mapping Module, RPAS Verification Module, Cloud Processing and Communications Module, Cognitive Module, and Navigation Module.

REFERENCES

Biermann, Lauren; Clewley, Daniel; Martinez-Vicente, Victor; Topouzelis, Konstantinos. 2020. Finding Plastic Patches in Coastal Waters using Optical Satellite Data. Scientific Reports (2020) 10: 5364. DOI 10.1038s441598-020-62298-z.

Daniels II, Joel; Anderson, Erik W.; Nonato, Luis G.; Silva,Claudio T. 2010. Interactive Vector Field Feature Identification. IEEE Transactions on Visualization and Computer Graphios, Vol. 16, No. 6

Larson, Roland E.; Hostetler, Robert P.; Edwards, Bruce H. 1990. Calculus with Analytic Geometry. 4th Ed. D. C. Heath and Company, Lexington, Massachusetts. 1093 p.

McGarigal, Kevin; Marks, Barbara J. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 122 p.

National Oceanographic and Atmospheric Administration (NOAA); National Centers for Environmental Information. 2020. Real Time Ocean Forecast System (RTOFS). Global RTOFS High Resolution Oceanic Model (weather.gov).

Raymarine, Inc. 2020. Augmented Reality Environment (ARE). Raymarine | Marine Electronics by Raymarine.

Turner, Monica G.; Gardner, Robert H.; O'Neill, Robert V. 2001. Landscape Ecology in Theory and Practice: Pattern and Process. Springer-Verlag New York, Inc. New York. 332 p.