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Campaign on Remote Sensing of Plastic Marine Litter

MARLISAT

Executive Summary

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1 Introduction

1.1 Overview

The objective of the MARLISAT project was to further develop Marine Plastic Monitoring through the use of multiple satellite technologies. In effect, the intention was to use satellite technology to detect Marine litter, track it and forecast it pathways. The project had a initial duration of 18 months but had to be extended due to delays caused by the COVID-19 pandemic and the electronic components shortages:

In effect, 4 satellite technologies were combined:

- **Satellite Optical Earth Observation** analysis for plastic detection on the coast through the use of Machine Learning

- **Satellite telemetry** and **Satellite positioning** for the tracking of the marine plastic debris

- **Satellite Radar altimetry** to derive surface currents.

- **During Phase 1**, the focus was on finding the right manufacturer for the tag casing and preliminary work on the plastic detection by satellite. Satellite data was also used to improve estimates of ocean surface currents derived from observations and in situ data.

- **During Phase 2**, the consortium built and deployed the tags at the mouths rivers in Indonesia known to be polluted. The consortium also produced a specific dataset of near surface ocean currents derived from Earth Observatories which can be used in a drift modelling studies. The trajectories of the new tags was used to adjust the parameters of the drift model and helped in providing plastic beaching locations over which the plastic detection algorithm was run

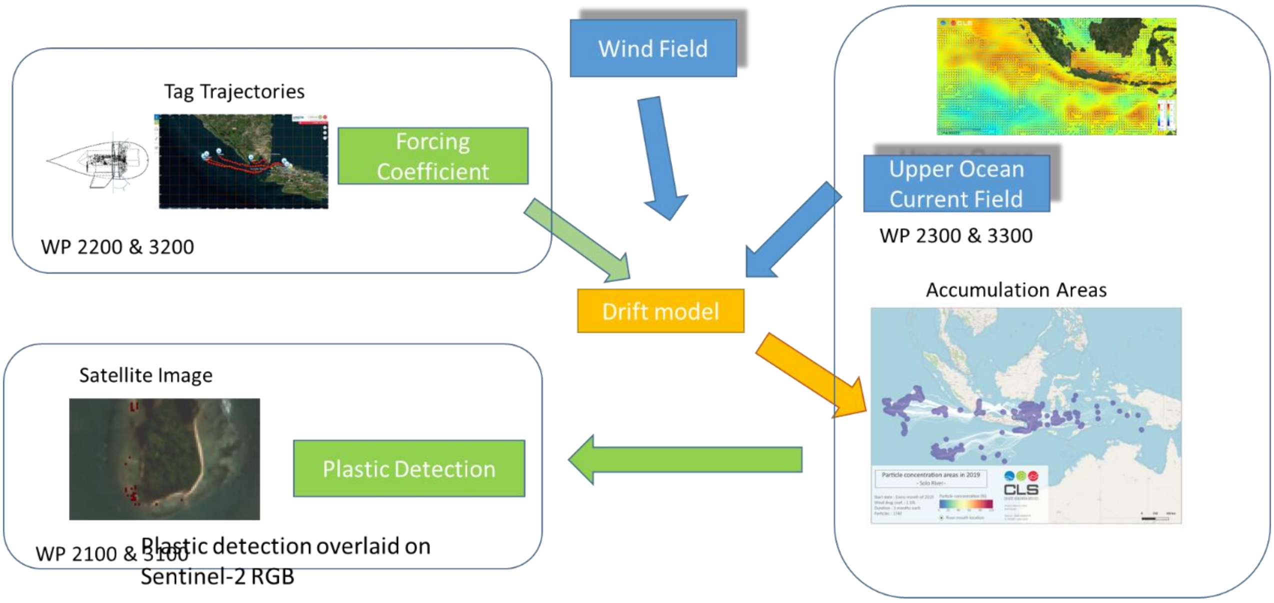

Figure 1: Marlisat Concept

1.2 Project Highlights

The project led the successful deployment of 4 Marine Plastic litter tags in Indonesia enabling the derivation of wind and current forcing coefficients of the drift model.

The results of the drift simulation performing using the coefficient inferred from the tag tracks let to the identification of 3 accumulation areas in the vicinity of the mouth of the Cisadane river that flows through Jakarta, one of the most polluted rivers in the world.

PIxalytics was then able to run the machine learning plastic detection algorithm that had been improved during the project over those location and identified plastic accumulation in all 3 locations, highlighting the usefulness of ground truthing data for the development of plastic detection methods using current satellite sensors.

Finally, the new set of surface currents data developed within the project showed great promise with very good validation results when compared to similar products.

1.3 Next steps

The project results showed the ability of small wooden tags to provide useful information on the behavior of macro plastics in the marine environment. An interesting next step would be the deployment of a significant number of similar tags in order to gather more data on the surface dynamics that drive the movement of plastics. Such data would help validate ocean current models and drift model tools and provide some insights on the beaching and remobilization of debris in coastal areas. Ideally, the region would have fewer island than the Indonesian seas to facilitate the collection data over longer time periods.

The plastic detection machine learning algorithm that successfully detected plastics could be further improved with additional training data and once it is deemed sufficiently mature, be deployed in an operational set-up to automatically detect and report plastic accumulation sites in areas of particular concern. In the long term, this would provide useful understanding of the dynamics of such accumulations, how they respond to extreme events (floods & storms) and also the effectiveness of policy set up to limit the amount of plastic waste reaching the marine environment.

The near surface current derivation method needs to be implemented in a less challenging area, in other words not so close to the equator as this is where the geostrophic approximation breaks down and in an area with a greater number of drogue less surface floats. Indeed, the Indonesian region is known for being under sampled in terms of surface drifters. A good candidate is the Mediterranean Sea, which is extensively studied and instrumented, and which faces significant challenges in terms of solid and oil pollution. These two issues could greatly benefit from a near surface current database derived from satellite observations. A further possible improvement would be the use of wind data from Satellite Scatterometer observations in the computation of the surface currents rather than those coming from a numerical model. This was not possible in the MARLISAT project as the Metop Ascat data had some spatial inconsistencies.

2 Plastic detection by satellite

Plastic detection using satellite data is particularly challenging because of the size of the plastic debris, which is often very small when compared to the optical satellite resolution and because, in the marine and coastal environment it is often combined with other material such as wood and other type of vegetation. Furthermore, the chemical composition of plastics is very heterogeneous and varies as it decays. As a result, the optical signature of plastic debris is very diverse and none of the current sensors flown on satellite can detect plastic debris in a straightforward manner.

In MARLISAT, the choice was made to focus on large plastic items, namely macro plastics. Rather than identify individual items, the effort was put into looking at larger targets such as accumulation areas and apply Machine learning methods to that end.

Based on previous work, Pixalytics investigated two different approach: one based on a Random Forest (RF) implementation and one based on a Neural Network (NN) approach. In the end, the Neural Network approach was preferred as it enable the training of the algorithm to be performed over multiple images whereas the Random Forest training focuses on a single image.

2.1 Neural Network Improvements:

The NN models are iteratively improved through both the addition of more training data and the testing of different input parameters. In Marlisat, the following data sets were used to train the Neural Network and improve its detection capabilities

2.1.1 Kuta beach, Bali, Indonesia

Figure 2.1 shows the results for Kuta beach, in Bali, after a storm littered plastic debris along the shoreline in February 2019. During the clean-up process, the rubbish was initially placed in piles along the beach; piles of debris that can clearly be seen on Google Earth on the 17th February 2019 (**Erreur ! Source du renvoi introuvable.**, left). Some of these piles are large enough to be identified on Sentinel-2 images, and hence we were able to create a ground truth data set, where we could be relatively confident that plastic was present in 40 pixels.

Figure 2: Kuta beach, Bali – Google Earth image 17th February 2019 where plastic debris is clearly visible both as small piles along the beach and as a "scum line" running along the shore (left). A slightly wider view of the same

Google Earth image (middle) which includes the area shown on the left. The RGB Sentinel-2 image taken around the same time(right), with the predicted plastic from our model overlaid (in yellow)

2.1.2 Bosnia and Herzegovina, Višegrad with a dam

Figure 2 shows the results for the Višegrad that has a hydroelectric dam that accumulates plastic waste.

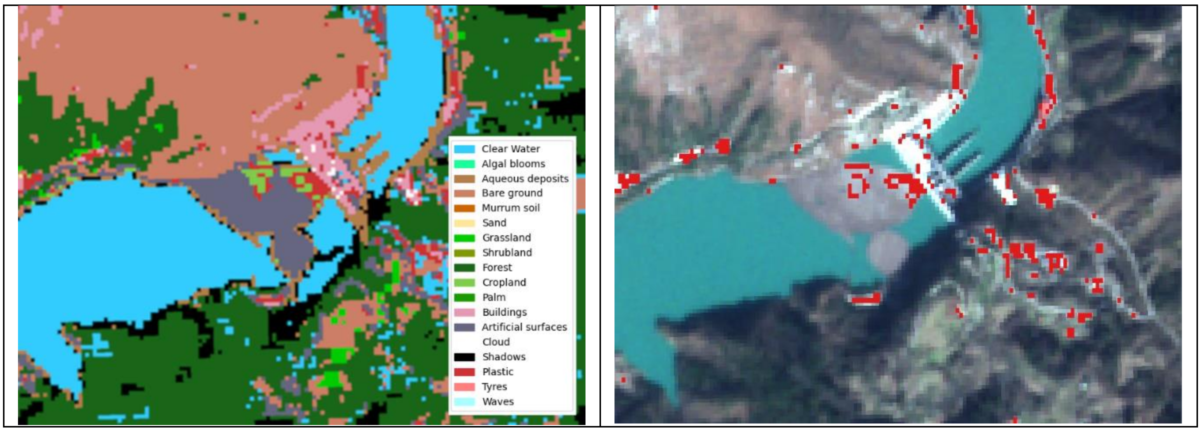

Figure 3: Višegrad, Bosnia and Herzegovina – Google Earth (top left), 19 June 2021 Sentinel-2 RGB image (top right), with the new results as (bottom left) the full classification result and (bottom right) plastic pixels overlaid on the Google Earth.

2.1.3 Chemor landfill, Malaysia

Erreur ! Source du renvoi introuvable. shows the results for the Chemor landfill that had a temporary accumulation of plastic waste.

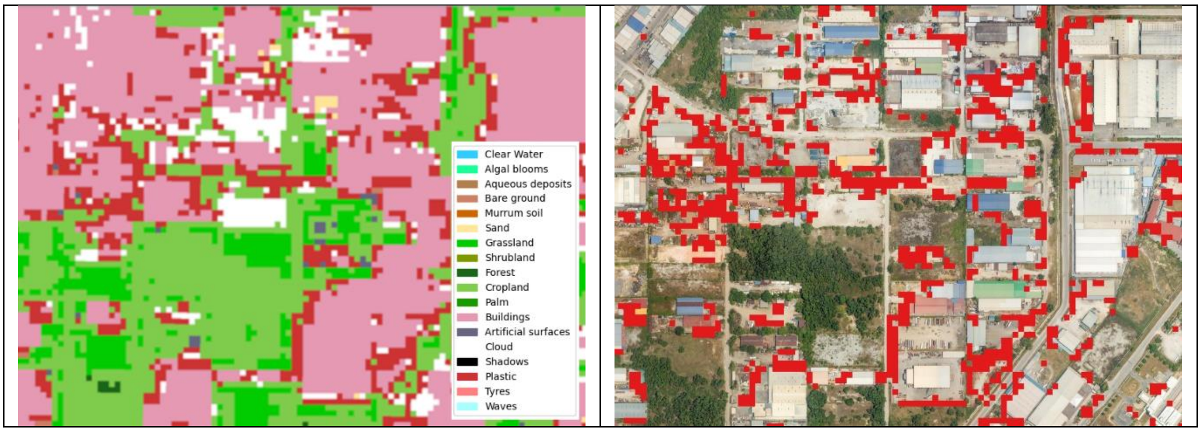

Figure 4: Chemor landfill, Malaysia– Google Earth with a pink point to show location (top left), 01 September 2018 Sentinel-2 RGB image (top right), with the new results as (bottom left) the full classification result and (bottom right) plastic pixels overlaid on the Google Earth.

The result for all land cover types shows a reasonable classification, e.g. vegetated areas are green while housing is predominately buildings (pink) with some misclassification as cloud pixels (white) due to the brightness (Figure 4)

2.1.4 Greenhouses in Almeria, Spain

The greenhouses in Almeria, Spain, have been further analysed as they are plastic plus result in large amounts of agricultural plastic waste.

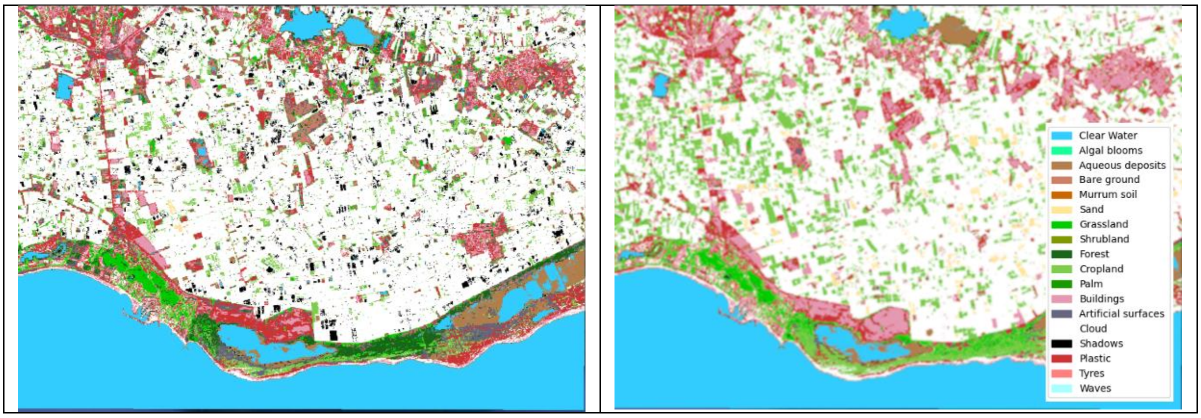

Figure 5 Almeria, Spain , 15 January 2021 NNet classification for all categories (bottom left) and 05 May 2021 NNet classification for all categories (bottom right).

2.2 Detecting Plastic in Indonesia

The Neural Network Machine Learning algorithm was run over the locations identified through the drifter release campaign and the subsequent drift modelling activities. The classification code was run on Sentinel-1/-2 data from July and August 2021. The location of the drifter beaching showed plastic along the coast and there is plastic inland due to aquaculture ponds (Figure 6)

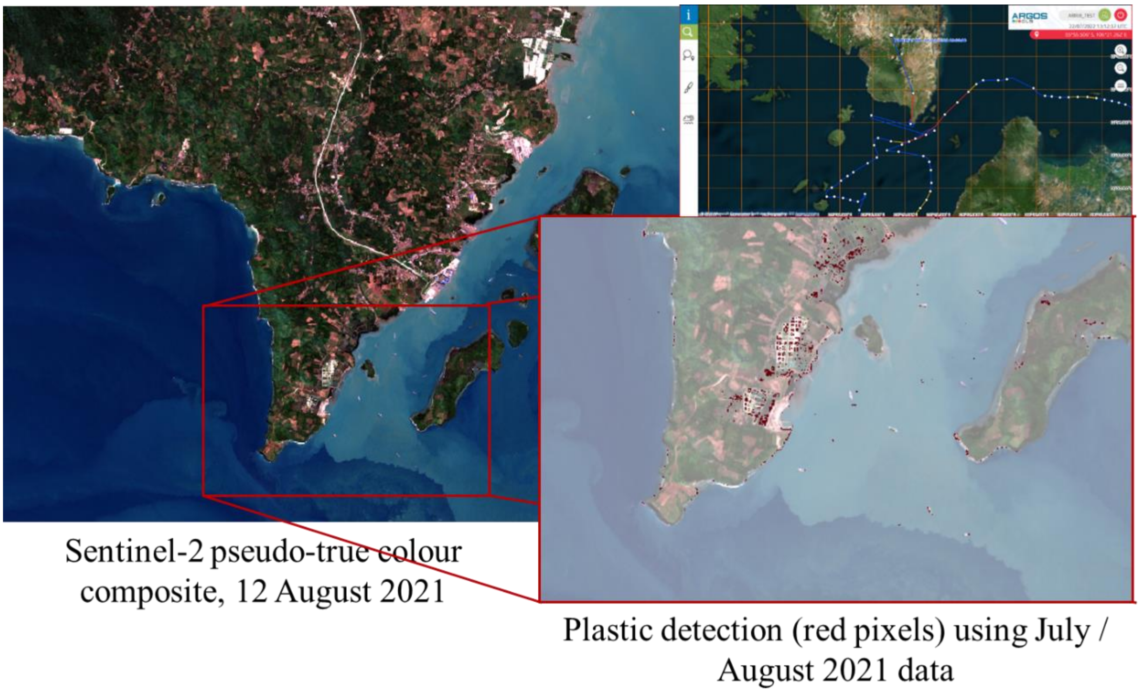

Figure 6 Plastic detection for drifter beaching location

In terms of the drift modelling outputs, plastic was similarly detected along the coast; see **Erreur ! Source du renvoi introuvable.** and figure 8:

- Plastic is being detected around Tidung Barat that is the centre of one of the large patches in the model

- Plastic is being detected around Pulau Laki that is the centre of a smaller patch in the model
- There are multiple detections off Pulau Opak Besar Timur that appear to be aquaculture cages, with the strong detection on the right of the island being an eco-tourism resort.

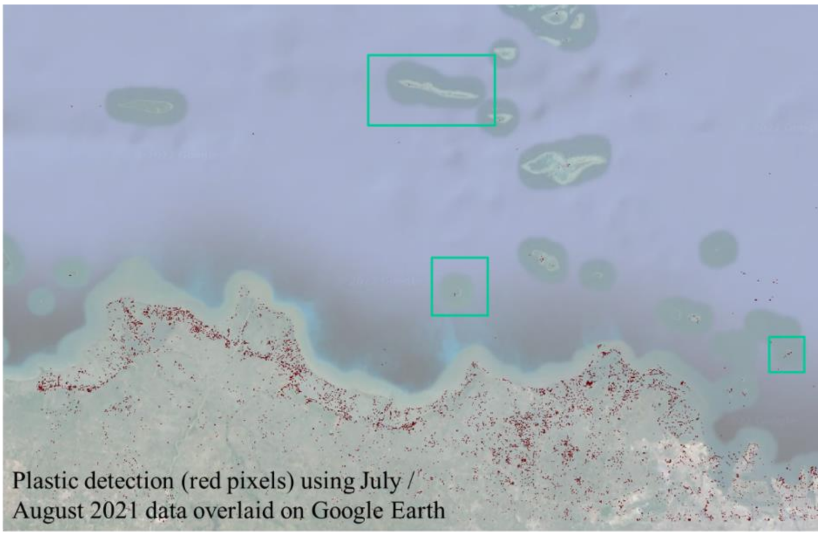

Figure 7: Detection of plastic linked to modelling outputs; the three blue squares represent zoomed-in areas shown figure 8.

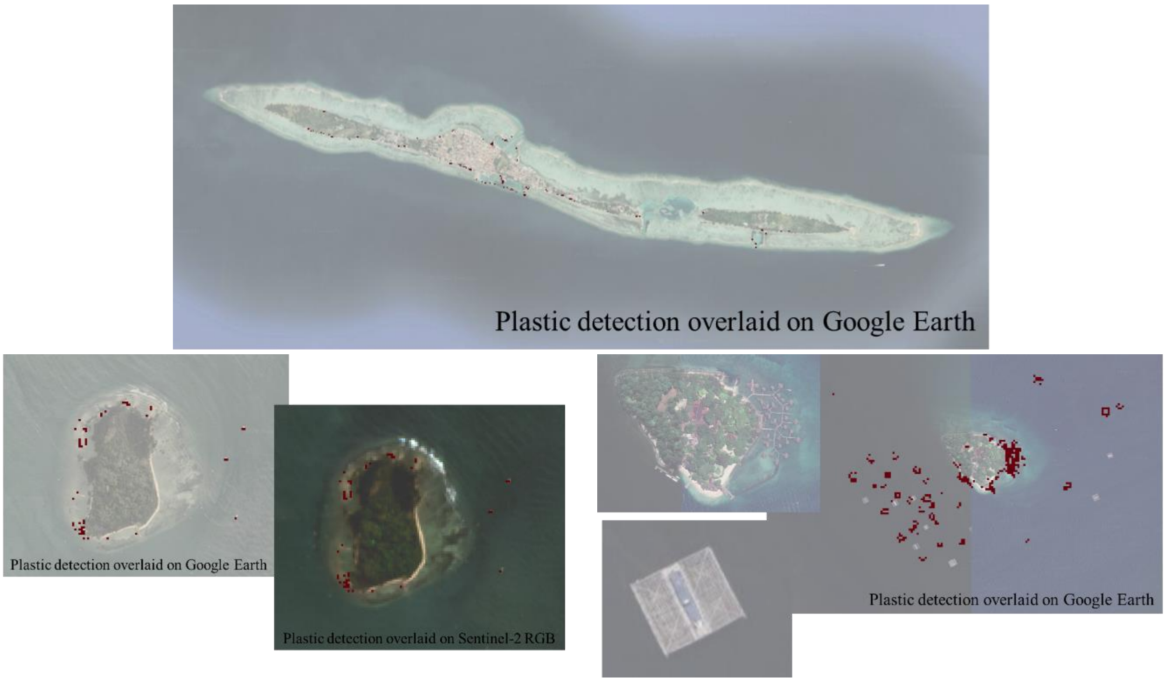

Figure 8: Zoomed-in regions showing plastic detection for the (top) Tidung Barat (bottom left) Pulau Laki and (bottom right) Pulau Opak Besar Timur islands.

3 Marlisat Tag Development

3.1 Tag predesign

The initial work focused on the shape of the tag to minimize drag, the choice of electronics and identifying a manufacturer to produce the tag casing.

Based on the work by Hurley et al, 2008, a tear drop shape was chosen as it reduces the drag ration to 40% of that of a sphere.

The manufacturing was entrusted to the CETELOR laboratory of the Université de Loraine in France which specializes in wood research and development.

For the electronics, after tests and discussion, the team settle on a CLS linkit Core board, an Ansmann 3.6V Lithium-Ion 2.6Ah 18650 (rechargeable) and an SMA whip antenna

3.2 Tag manufacture

The tag manufacturing started with the building of a 3D plastic model using a 3Dprinter in order to prepare the manufacturing process.

Figure 9:3D model of the tag with the electronics.:

Once this was done, the wood cutting machines could be programmed to produce the casing, first by cutting the external shape and then by drilling out the interior cavity that holds the electronics.

Stability tests showed that a small keel was needed in order to limit the oscillations in water and improve the transmission quality.

3.3 Tag assembly

The Tags were assembled by CLS by fixing the antennas to the hull and adding the battery and Linkit electronic board. During assembly, one electronic board was lost.

Figure 10: Tags prior to final assembly

Test were performed to check the water tightness and adjust the transmission setting. One tag was deployed off the coast of Barcelona, attached to a moored buoy for test at sea

3.4 Tag deployment

The Tags were deployed in Indonesia on the 25th May 2022, in the Bay of Jakarta, one the major sources of pollution the region

After test ensuring that they were working properly, 3 the tags were attached to plastic bottles with a small rope, and one was left untethered as a control. The tags were then deployed from a small boat almost simultaneously at 12.15 local time

Figure 11: Tag tracks after 24 hours

The 3 tethered tag move rapidly to the west while the control tag has a much smaller velocity, in keeping with a lesser exposure to the wind forcing.

3.5 Derivation of wind and current forcing coefficients

The trajectory information provided by the trackers deployed allow for derivation of the coefficients that represent the effect of the wind, tide, and the currents on the macro plastic litter.

To do this, a series of 27 drift experiments using the drift model Mobidrift with varying wind and current coefficients were performed, with an initial starting point located on the deployed buoy trajectory.

The analysis of the results shows that to get a model trajectory as close as possible to that of the buoy, a wind coefficient of 10%, a tidal coefficient of 75% and a current coefficient of 75% must be used.

This is indicative of a highly buoyant object very sensitive to the wind forcing, which is unsurprising when one considers that the object tracked are light weight plastic bottles.

3.6 Large scale plastic drift simulations

In order to have a better appreciation of the potential beaching and accumulation sites of lightweight plastics that was tag with the trackers within the Indonesian archipelago, the CLS drift model Mobidrift was used to perform a series of simulations. The simulation period was chosen in concertation with Pixalytics in order to provide them with locations of plastic accumulations when satellite imagery was available, in effect June and July.

9 weekly simulations with 250 particles were performed and the results plotted on a map to visualize the main accumulation areas (Figure 6)

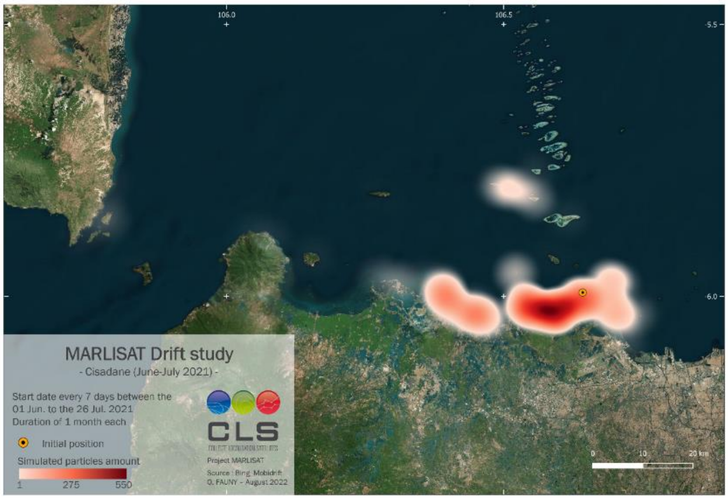

Figure 12: Heat maps showing the dominant accumulation areas

As shown in Figure 13, most of the particles accumulate close to the source, with a large patch along the Bay of Jakarta shore and a couple of less pronounced patches centered on island to the North.

These locations were passed on to the Pixalytic team.

4 Satellite derived currents

In first steps of the project, different methods to estimate wind-driven current were tested:

- the methods of Poulain et al (2009)
- the CLS method (Mulet et al; 2021).

The CLS method uses wind driven parameters estimated from YoMaHa drifters and shows better results than the Poulain et al (2009) estimation. Hence, the CLS method is chosen. Moreover, latest tests carried out to evaluate the contribution of the Stokes drift are inconclusive overall on both methods. For the CLS method, the addition of the CMEMS Stokes drift improves the zonal component but degrades too much the meridian component. A possible explanation is that part of the Stokes drift is probably already included in the Ekman currents estimated with this method. For the final method of calculating currents, it seems more reasonable not to add this component.

Concerning wind fields, some spatial inconsistencies in the 6-hourly resolution of CERSAT (observed products) wind stress, together with the wind fields, lead to choose ERA5 wind fields for the final surface product.

Finally, the large-scale bias reduction method based, on a linear regression presents an improvement of the results in terms of bias (Figure 13) and squared error (Figure 14) using surface drifters as reference field. This correction is therefore kept in the final method (called MARLISAT currents method).

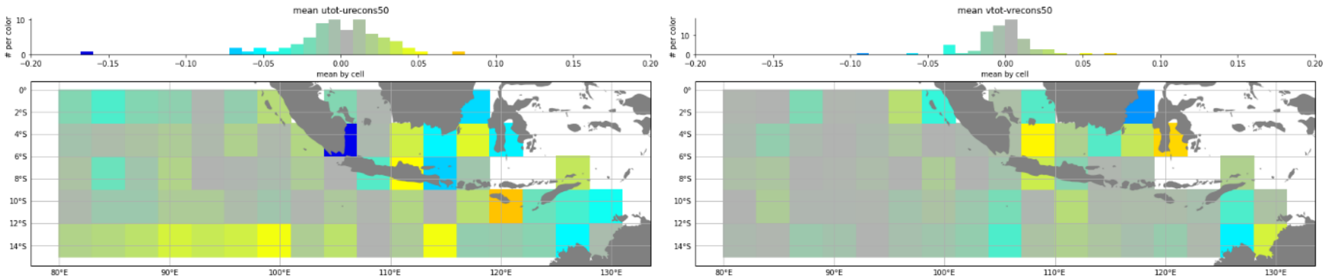

Figure 13 : Bias between reconstructed currents and total currents from drifters for the zonal component on the left and the meridional component on the right for the model 50.

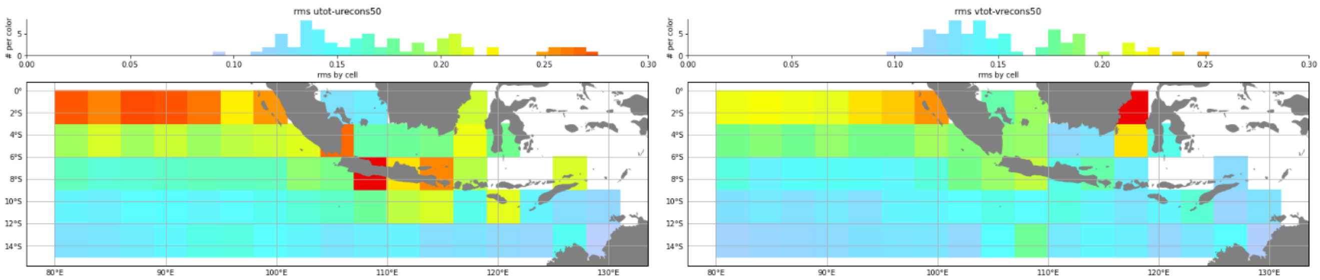

Figure 14 : RMS of the differences between reconstructed currents and total currents from drifters for the zonal component on the left and the meridional component on the right for the model 50.

Further drift experiments, using Surface Velocity Program undrogued drifters (Lumpkin and Centurioni, 2019) shows that the MARLISAT currents compare fairly well to more complex and heavier systems like SMOC (Surface and Merged Ocean Currents, Lellouche et al. 2019) in open ocean away from the equator (few degrees.) Hence, the Java Sea and to some extends the MARLISAT domain is not the most favorable area for this methodology.

But results are promising and promote the continuation of this kind of study in more favorable areas, such as the Mediterranean Sea with the use of recently tested Machine Learning methods to get more benefits from the observations.

5 Conclusion

The Marlisat project has shown the way in which a combination of space borne solutions, namely Earth Observation and Telemetry can support research on the behavior and fate of Macro sized Marine Plastic. This is particularly relevant as they are one of the main sources of micro and nano plastics as they break up, often helped by shoreline dynamics and waves.

Although single items cannot be easily detected by EO means, the deployment of trackers allows the identification of potential accumulation sites. EO data combined with machine learning algorithm can then confirm the presence of plastic.

Combining EO and drifter track data acquired via satellite telemetry allows for the computation of a new type of shallow surface ocean currents that can help in providing more accurate information on the drifting patterns of plastics in the near surface.

Marlisat is obviously part of a much wider effort and synergies need to be looked at to continue investigating how Satellite data can support the fight against plastic pollution, a major societal challenge for the coming decades and recently identified as a priority at the UN Ocean conference in Lisbon.

6 Reference

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