Toward on-board plastic detection using hyperspectral imagery

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Introduction

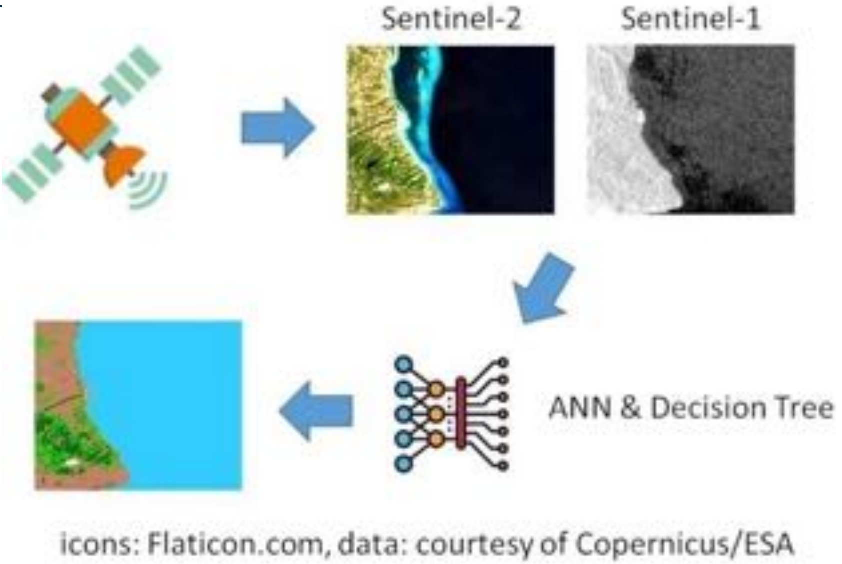
- The abundance of biodiversity and precious resources for humans and other species calls for efficient technologies to monitor marine pollution caused by plastic litter.
- Ground-based monitoring systems and field campaigns :
    - they are time-consuming,
    - expensive,
    - require great organisational effort,
    - and provide little information about the spatial and temporal dynamics of debris.
- Earth Observation (EO) using satellites can support the ground-based monitoring of marine plastic litter thanks to their global synoptic perspective.

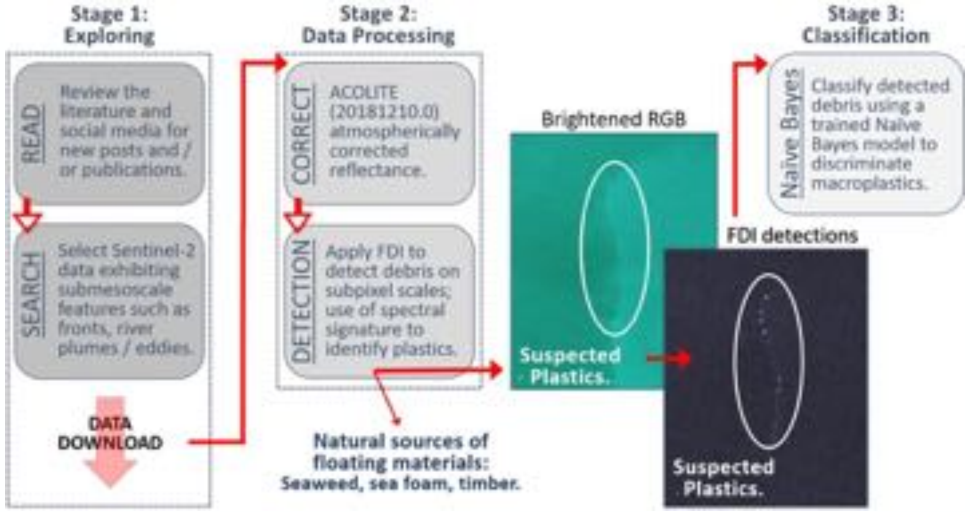
Literature review

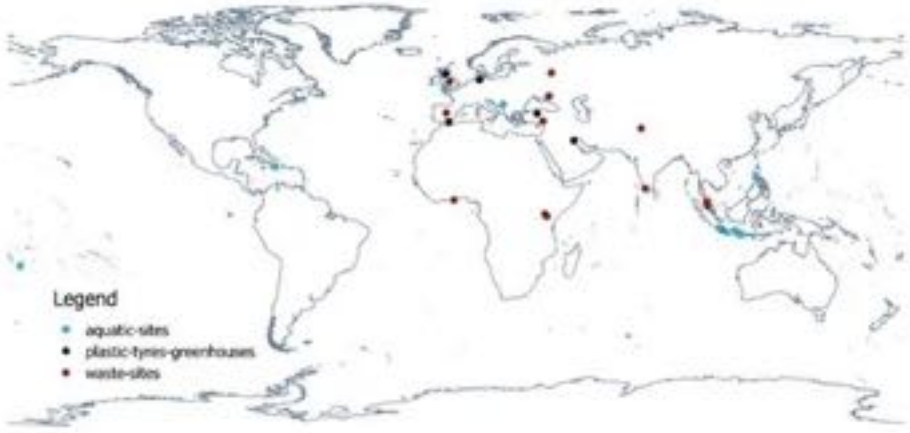
- Taking into account
  - the vastity of oceans,
  - the extension of coastal areas around the world,
  - and the effort in terms of time and human resources for processing huge numbers of remotely sensed data using traditional techniques,
- Machine Learning/artificial intelligence (ML/AI) algorithms coupled with newly available hyperspectral satellite data need to be explored.
- the adoption of ML is still in its infancy, and there is relatively little literature on the topic
- Methods used:
  - SVM
  - K-means
  - Fuzzy C-Means
  - Supervised and semi-supervised
  - CNN
  - Mostly combination of Sentine-2 and 1

Literature Review

(a) Turnchapel Wharf (b) Millbay Marina Village (c) Cawsand bay

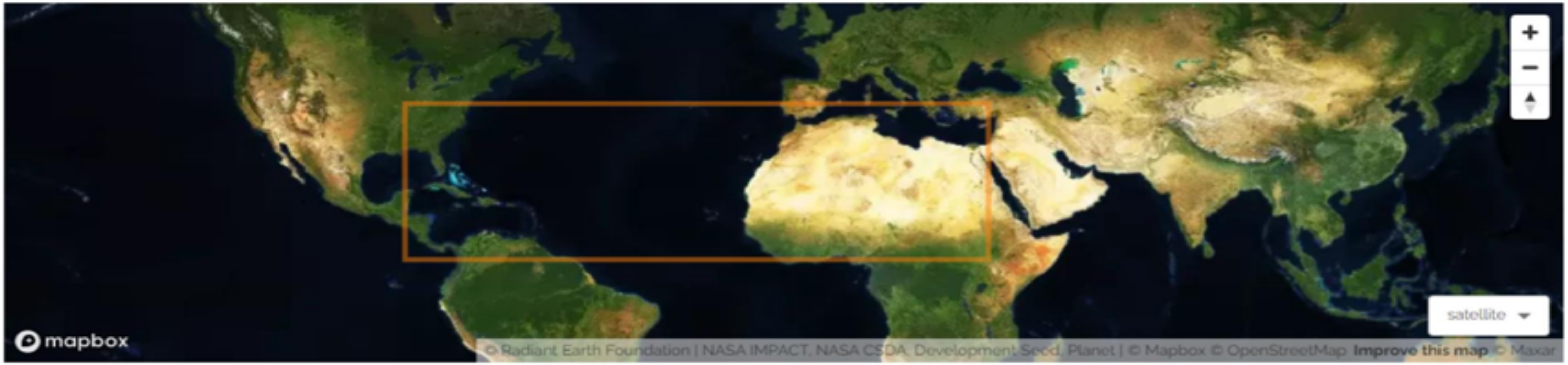




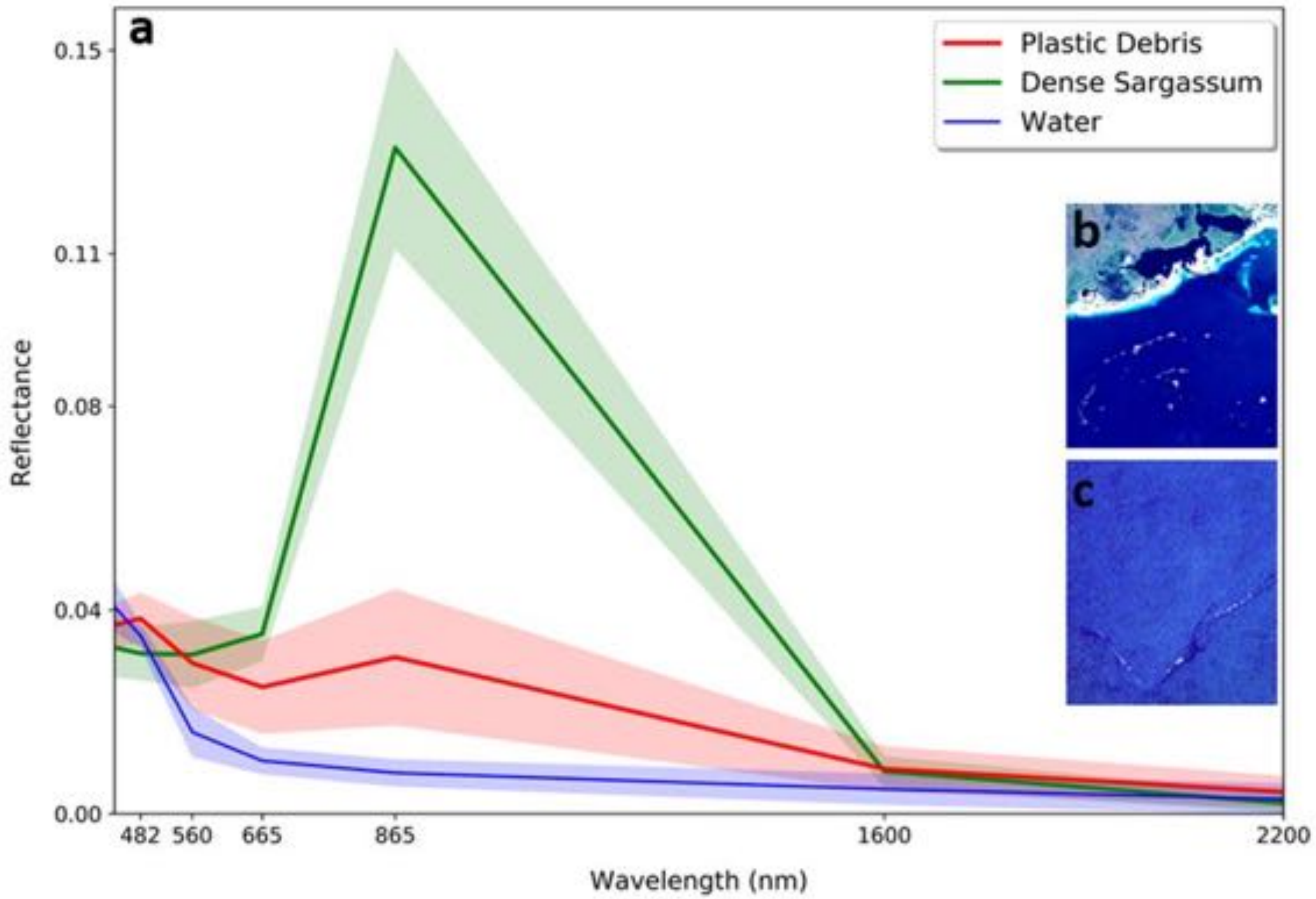


Study area and dataset

- This dataset consists of images of marine debris which are 256 by 256 pixels in size and labels which are bounding boxes with geographical coordinates gathered between 2016-2019.
    - The images were obtained from PlanetScope optical imagery
    - with 8 spectral bands (R,G,B,NIR, Coastal blue, Green I, yellow and Red Edge)
    - spatial resolution of approximately 3 meters.
- In this dataset, marine debris consists of floating objects on the ocean surface which can belong to one or more classes namely plastics, algae, sargassum, wood, and other artificial items.
- Several studies were used for data collection and validation.
- While a small percentage of the dataset represents the coastlines of Ghana and Greece, most of the observations surround the Bay Islands in Honduras.



Study area and dataset

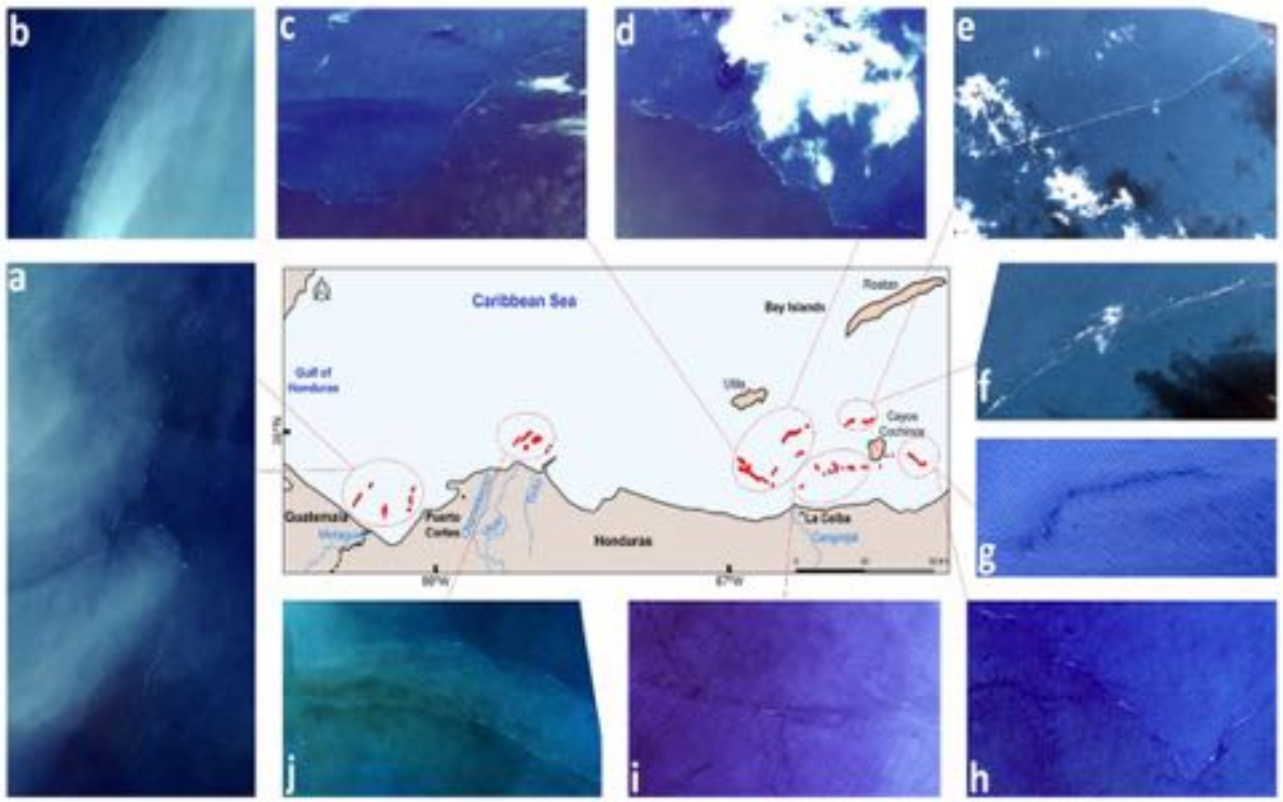


(a) Spectral signatures of plastic debris (red), dense Sargassum (green) and water (blue). (b) An indicative Planet image with dense Sargassum. (c) Indicative Planet image with plastic debris.

Study area and dataset

The detected plastic debris (red dots in the map) and snapshots of the corresponding satellite images at the Gulf of Honduras and Bay Islands during late September–October 2017.

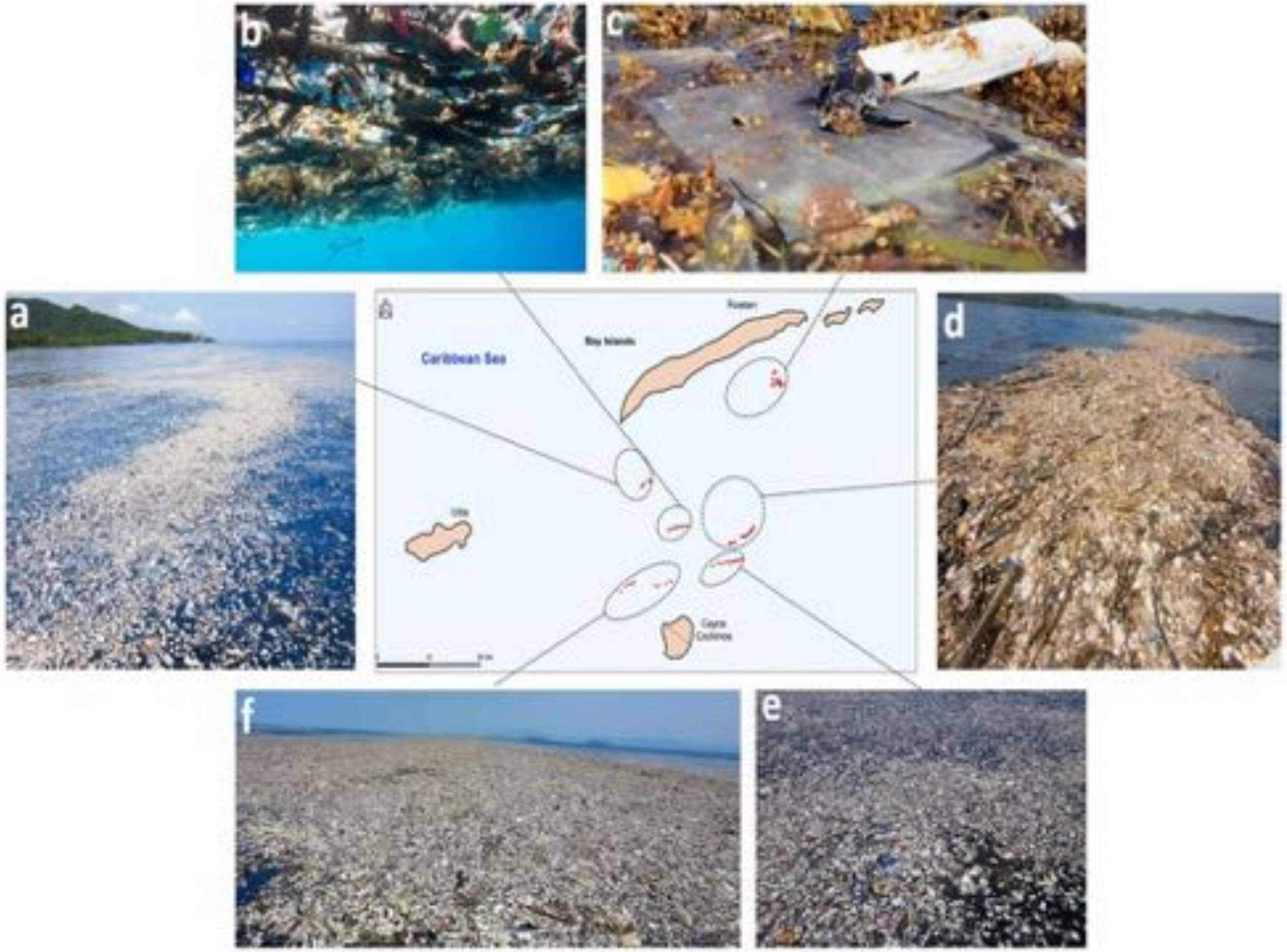
- (a,b) Planet images with the detected plastic debris from the Motagua River on 27/9/2017.
- (c,d) The location of the detected debris on 15/10/2017.
- (e,f) Two days afterwards (17/10/2017), debris reached Cayos Cochinos island.
- (g) Debris trails were detected (9/10/2017) on a Sentinel-2 image.
- (h) Same as (g) but on a Planet image.
- Debris detected on 7/10/2017 indicating that River Cangrejal also contributes to plastic pollution.
- (j) Planet data (27/9/2017) with the detected plastics originating from the Chamelecon, Ulua and Tinto rivers.



Study area and dataset

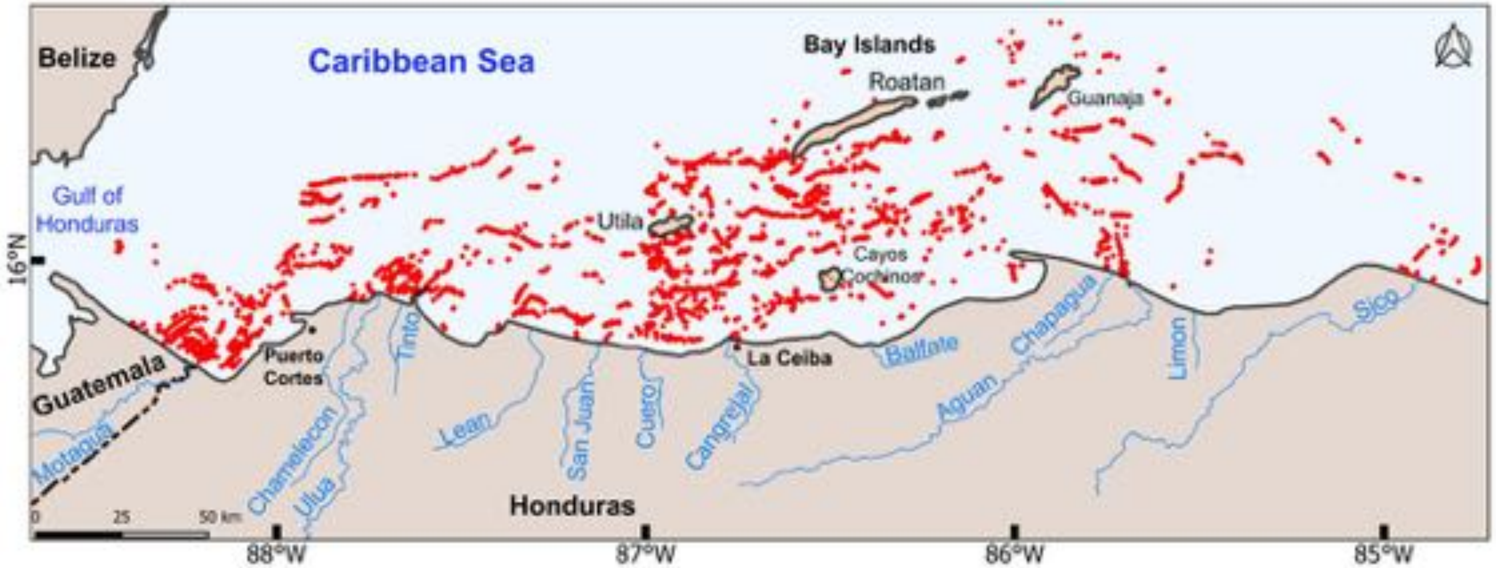
Detected plastic debris in satellite data (red dots in the map) and the corresponding in situ verification during the years of 2014–2018 around Bay Islands.

- Collected in situ data southwest of Roatan island in September 2014.
- (b) In situ observations and underwater capture in November 2016.
- (c) Collected plastics in Roatan area. Sargassum macroalgae and a dead juvenile turtle were also recorded (October 2018).
- (d) Observed plastics during October 2016. Organic material (i.e., wood) was also recorded.
- (e) Observed plastic masses during November 2015.
- (f) Large plastic masses recorded in October 2017.



Methodology

Total satellite-detected marine plastic debris from 2014 to 2019 in the southeast Gulf of Honduras and Bay Islands in the Caribbean Sea (red dots in the map). Plastics debris enters Caribbean Sea through river discharges. Plastic debris travels long distances dispersed in the entire study area.



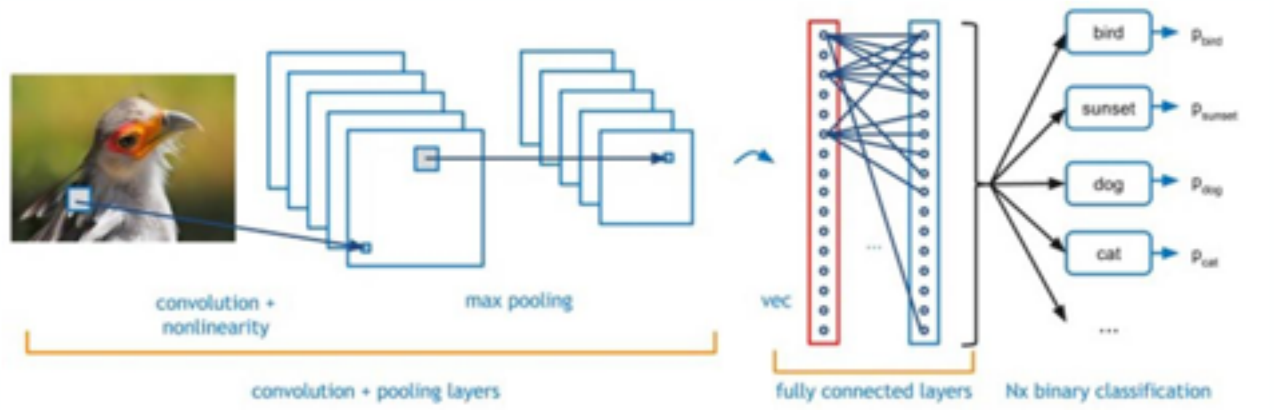
Methodology

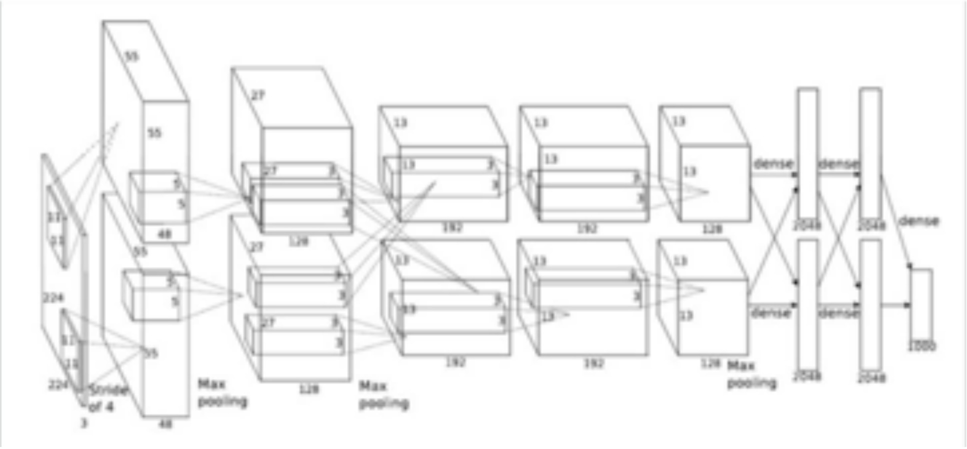
focus on deep learning techniques

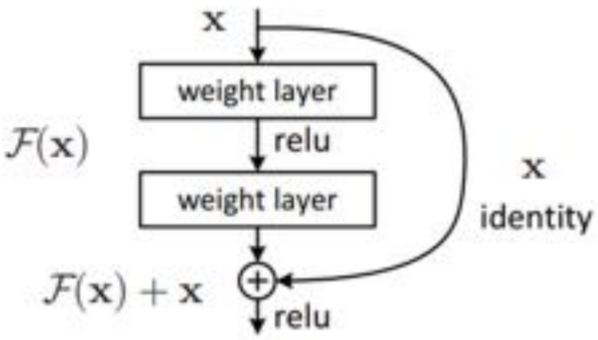
Specifically: CNNs(LeNet, AlexNet, ResNet,etc.,)

they are currently available and heavily optimized in the available development platforms for efficient inference

Also, testing hybrid setups i.e., LSTM for segmentation of HS imagery

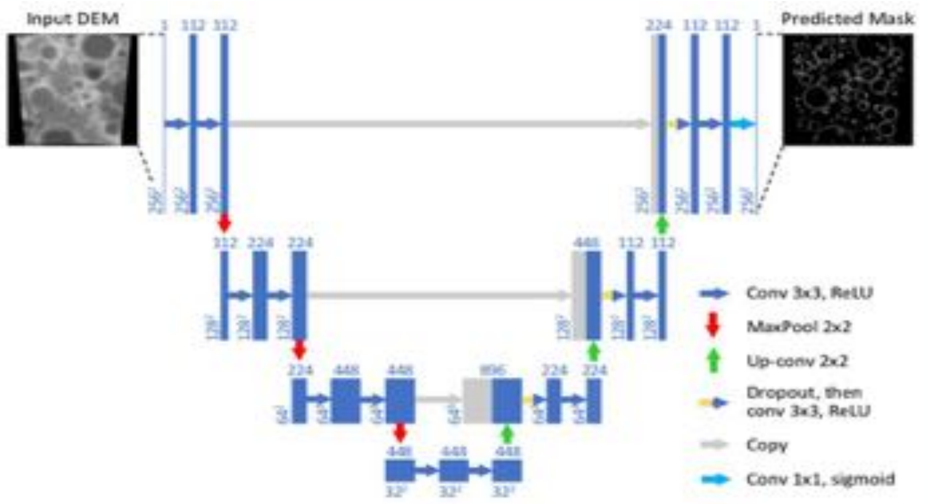


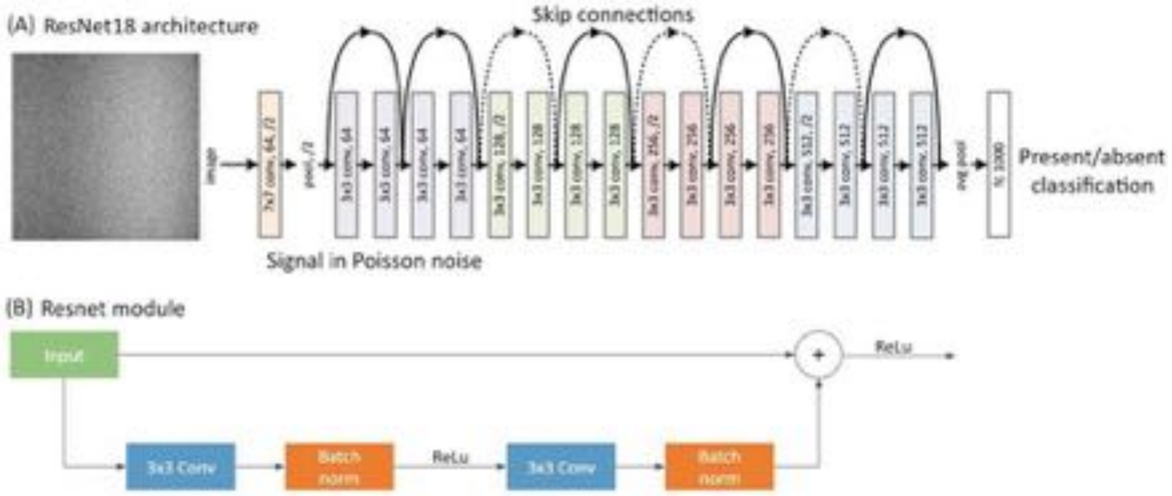




Methodology

- dataset of visible marine debris using the ImageLabeler on scenes from the Planetscope satellite.
- This dataset consists of 1370 bounding boxes of marine debris which were validated using peer-reviewed studies.
- An object detection deep learning model was trained on our curated dataset and initial results on Planetscope's optical imagery were obtained.
- Network architecture: CNN (Unet, ResNet)
- 1D, 2D and 3D layers
- Spectral and spatial-spectral
- Use the architectures of the investigated deep models—the spectral network (1D-CNN), alongside two spectral-spatial CNNs (2.5D-CNN and 3D-CNN, with 2.5D-CNN).
- Although both spectral-spatial models operate on image patches, 2.5D-CNN convolutional kernels span the entire spectrum of B bands.
- On the other hand, we utilize small $(3 \times 3 \times 3)$ kernels in 3D-CNN to effectively capture local features that may be manifested in specific (often tiny) parts of the spectrum.



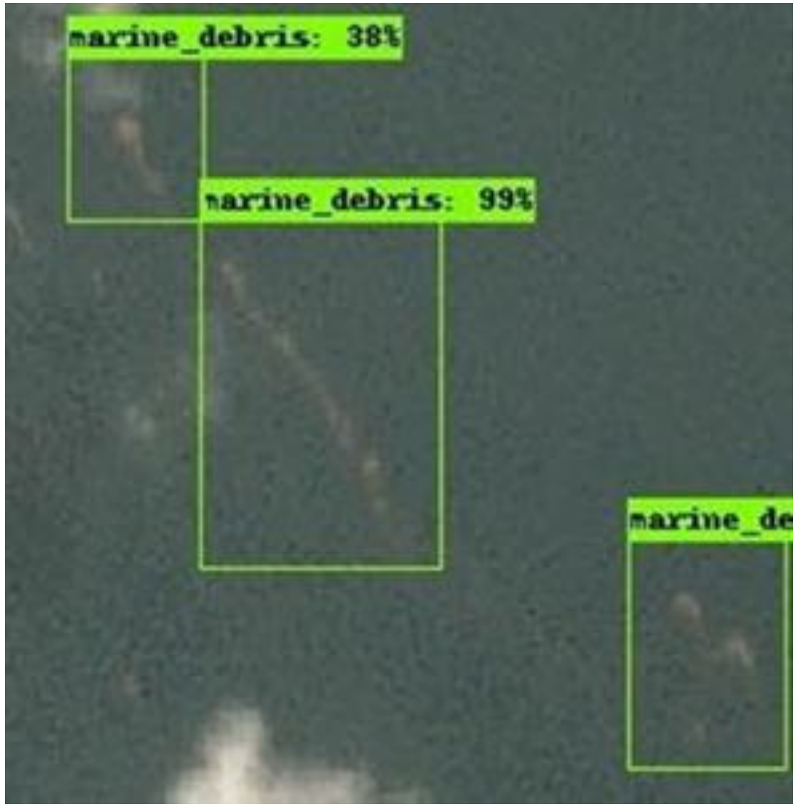


Results

The images below display two examples of the detections from the model. The percentage represents a likelihood accuracy of the detection belonging to the class of marine debris.

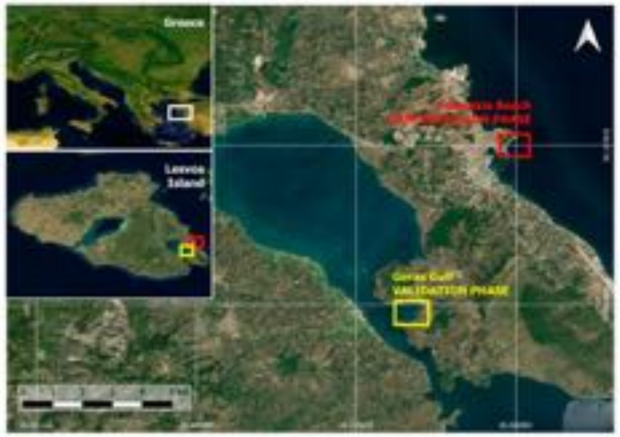
ResNet

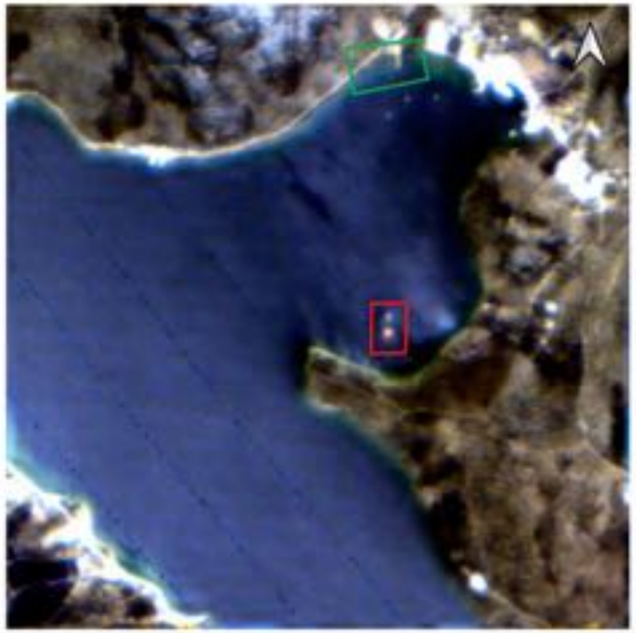
Unet



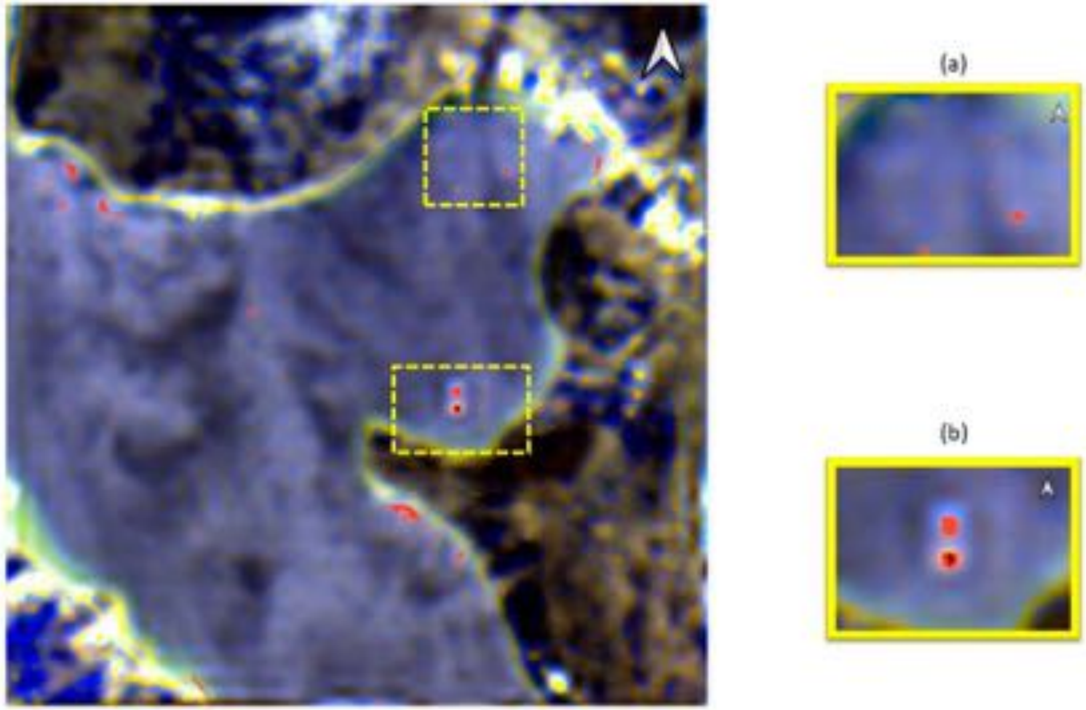
Results (extra test on PRISMA data)

pan-sharpened PRISMA data collected over the Geras Gulf 23 June 2021





(a) A zoom of floating objects. (b) shows the two targets that were detected with high probability.



Conclusion and following steps:

- The in situ detection of plastic accumulation for monitoring large surfaces raises certain difficult issues.
- The availability of satellite imagery to detect actual plastic accumulation with the proper spatial and spectral resolutions, which are cloud-free and collected under good sea weather conditions, are the main drawbacks of remotely sensed optical data.
- The availability of new hyperspectral satellites (PRISMA, future CHIME) that collect data at high spectral resolution (i.e., 239 hyperspectral bands plus a panchromatic band) and medium spatial resolution (i.e., 30 m for the hyperspectral cube and 5 m for the panchromatic band) together with ML algorithms creates room for improvement.
- Our work aimed to develop a new method, based on AI to detect plastic targets offshore. RESNET and UNET detected possible floating plastic with accuracy of more than 90%. We also observed false positive with probability of 30% which should be removed in after processing steps. The results show the capability of the proposed method to detect floating objects offshore.
- Despite the small number of satellite training data , the study showed that the new approach can effectively identify plastic floating marine objects larger than 2.4 m.
- Furthermore, the study suggests that using more training samples can help reducing false positives such as boats or those caused by sun light.
- Increasing the satellite dataset with floating plastic material would also allow the exploration of more Deep Learning methodologies, i.e. Generative Adversarial Networks.

Following steps

- Training CNN networks on zero-level data or simulated TOA condition to detect desired target (the ability of image segmentation prior to do atmospheric correction)
- Training hybrid networks
- Generate different types of noise (Gaussian, impulsive, and Poisson noise) and inject it into hyperspectral imagery and test the network under noisy condition
- benchmark the algorithm on well-known hyperspectral scenes, and to quantify the robustness and generalization abilities of spectral and spectral-spatial CNNs against varying-quality data.