# Detecting marine litter on sandy beaches by using UAS-based orthophotos and machine learning methods

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# Motivation (1)

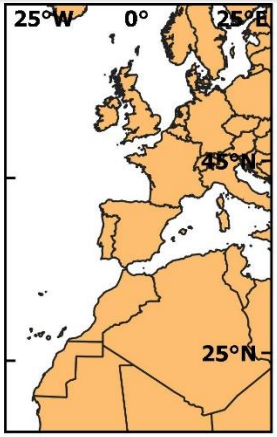
- **Marine Litter** (**MLit**) is defined as any **persistent**, **manufactured** or **processed** solid material discarded, disposed of, abandoned or lost in the marine and coastal environment (UNEP, 2005)
- The **amount of MLit** in marine and coastal environments is dramatically increasing
- MLit become a global issue of **major concern** due to its significant potential impact on coastal systems and on human health
- However, **systematic observations** of their sources, composition and distributions (detection and mapping) are still very sparse and inaccurate

# Motivation (2)

- It is **crucial** to implement a **routine** environmental **monitoring strategy** for spatial and temporal detection and **mapping** of MLit on beach-dune
- **Currently**, the common approaches for MLit monitoring along coastlines rely mainly on **in-situ visual census** methods
- **Research objectives**:
  - Develop and validate a **framework** for detecting and mapping MLit using **object oriented** machine learning methods in **orthomosaics**
  - Evaluate the **performance** of 3 commonly used machine learning methods: Random Forest (**RF**), Support Vector Machine (**SVM**), K Nearest Neighbour (**KNN**)

# Study area: Cabedelo beach

- The case study is Cabedelo Beach (40°08'N - 8°51'W), a sandy coastal stretch located on the **western Portuguese coast** facing the North Atlantic Ocean
- The beach shore is located southward Mondego River **estuary**
- It was selected since it is exposed to high potential for beaching of **anthropogenic debris** coming from the estuary



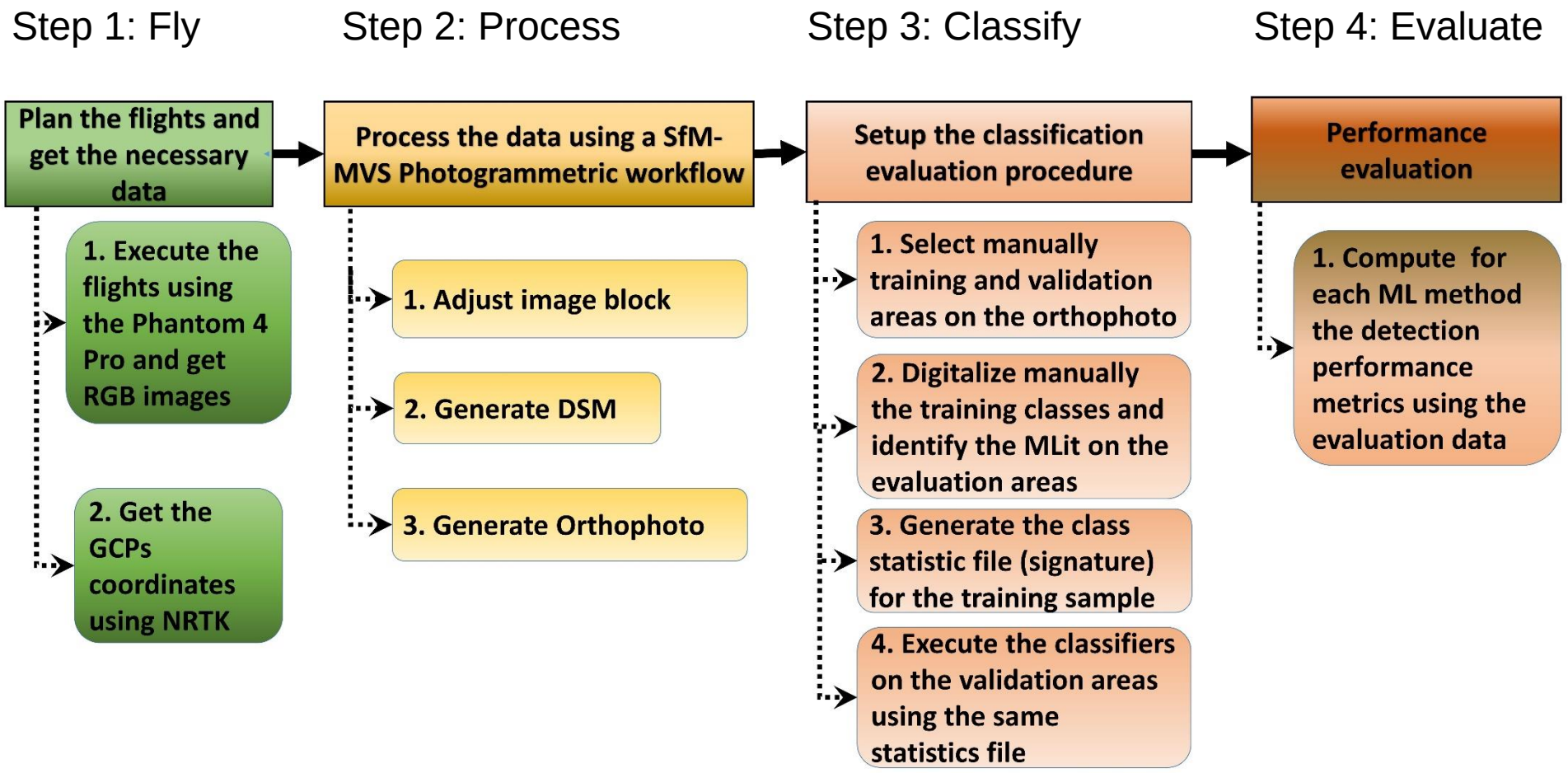
(a)


(c)

(b)

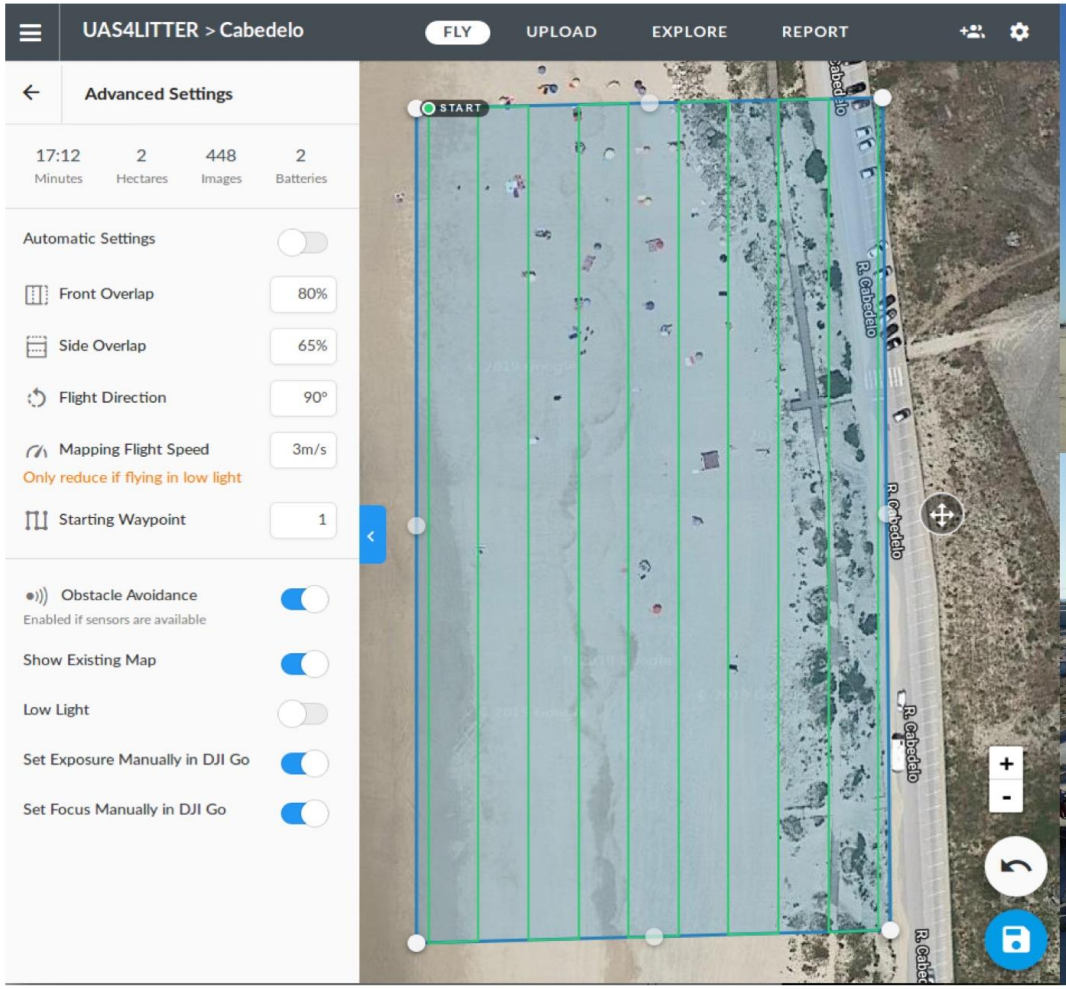

(d)

# General workflow



# UAS flight planning: DroneDeploy

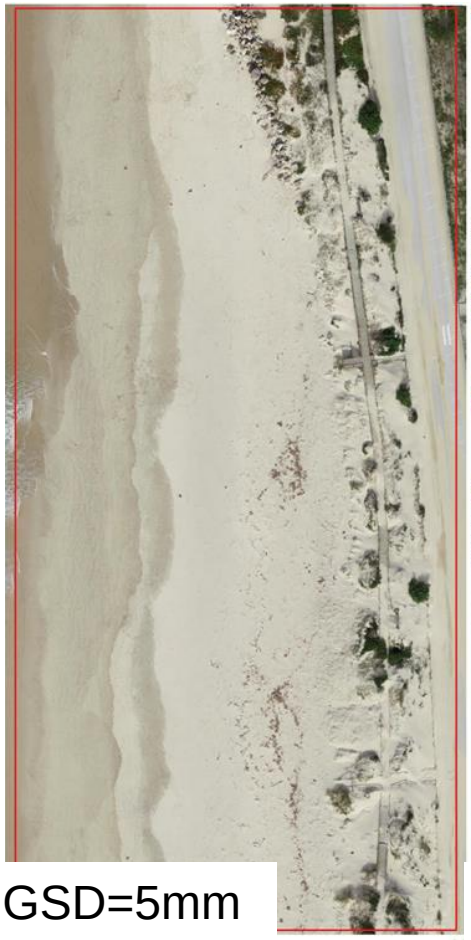
3 Flights are planed with front 80% and side overlap 65%, mapping speed 3m/s and flight heights 20 m, 40 m and 60 m




# SfM-MVS processing

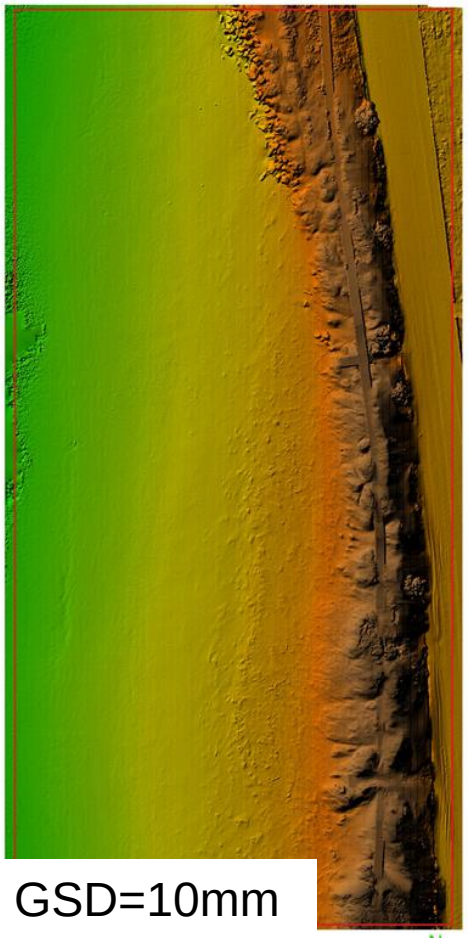
- For this work only the **20 m flight** was used
- **6 GCPs** are used in the image block adjustment
- **Autocalibration** approach was used for computing the internal camera orientation parameters (f, cx,cy, k1.k2,p1,p2)
- Agisoft **MetaShape** software was used to generate the DSM and Orthophoto

Orthophoto



GSD=5mm

DSM

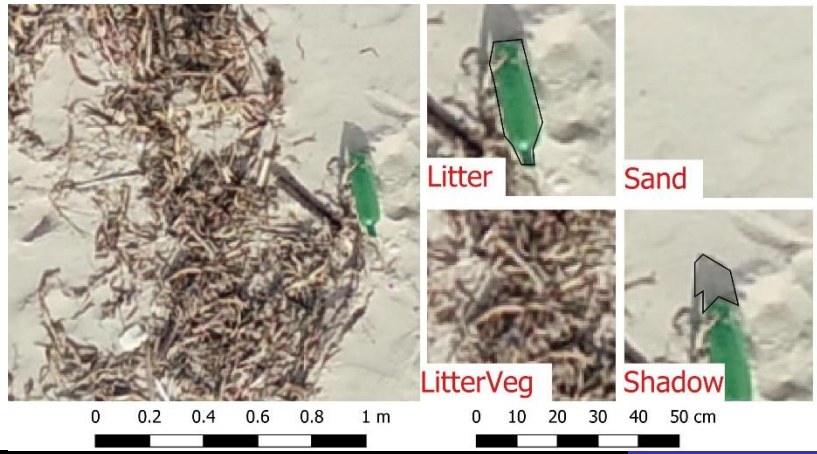


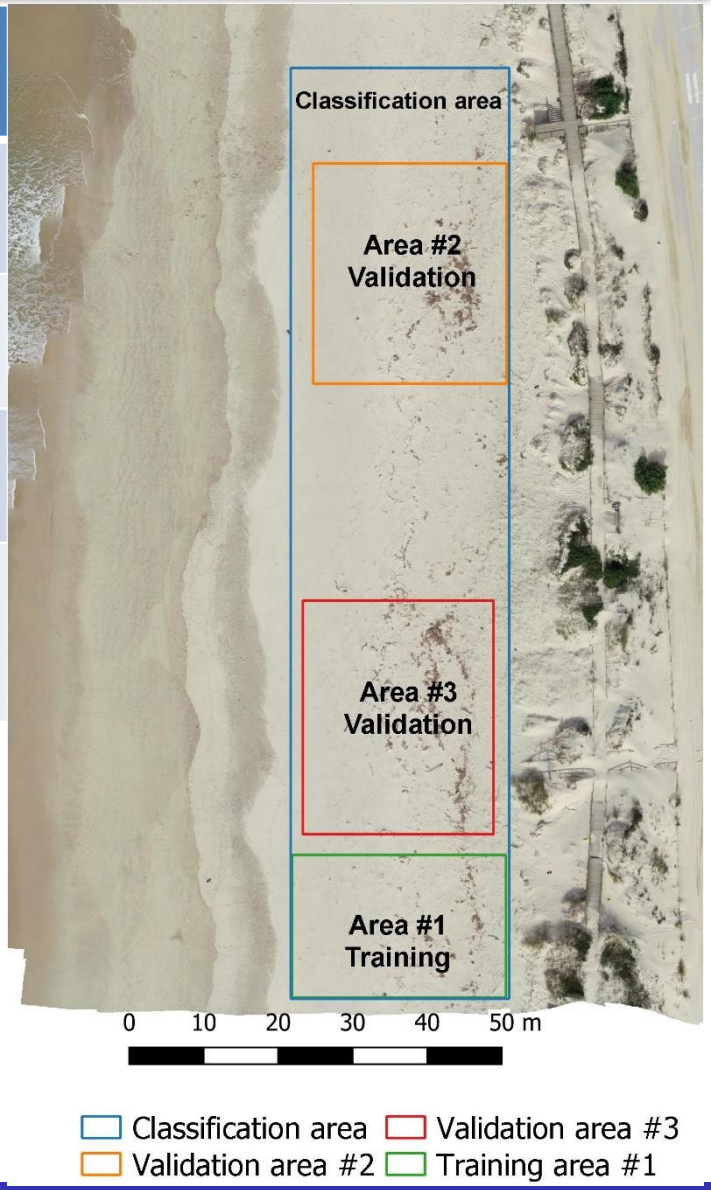
GSD=10mm

# Working areas and nomenclature

| Class ID | Class Name | Description |
|---|---|---|
| **Litter** | Litter | Persistent, manufactured or processed solid material |
| **LitterVeg** | Vegetated litter | Non-anthropogenic (vegetated) debris |
| **Sand** | Dry Sand | All kind of dry sand located in the back shore |
| **Shadow** | Cast shadows | Shadows of all kind of elevated objects and footprints |

Examples:



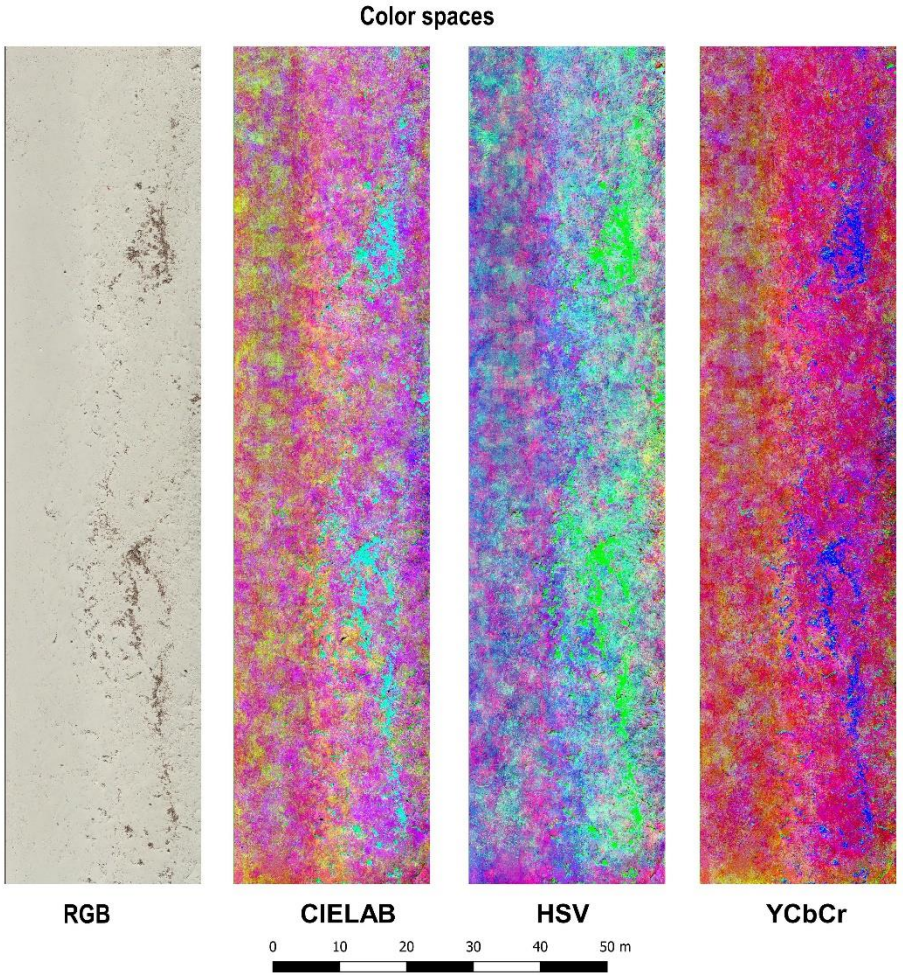
# Colour spaces in MLit detection

Rationale:

- MLit is generally characterized by their strong **manufactured colours**
- For detection objects based on colour the RGB is **not enough** because of its non uniform characteristics and mixing of colour and intensity information

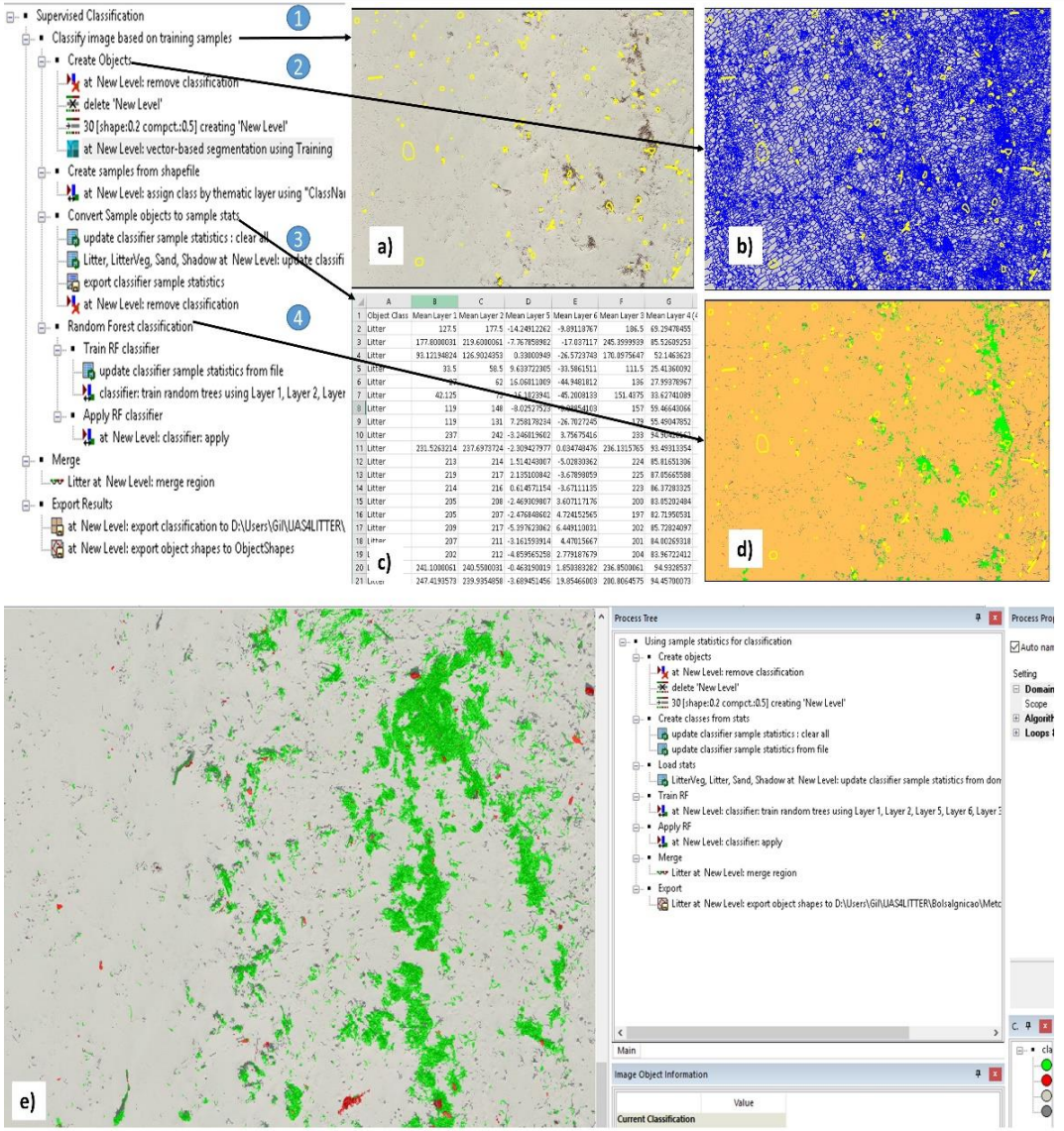
Additional colour spaces

- **CIELAB** = CIE L*,a*,b*
- **HSV** = Huge, Saturation, Value
- **YCbCr** = Y, Cb, Cr

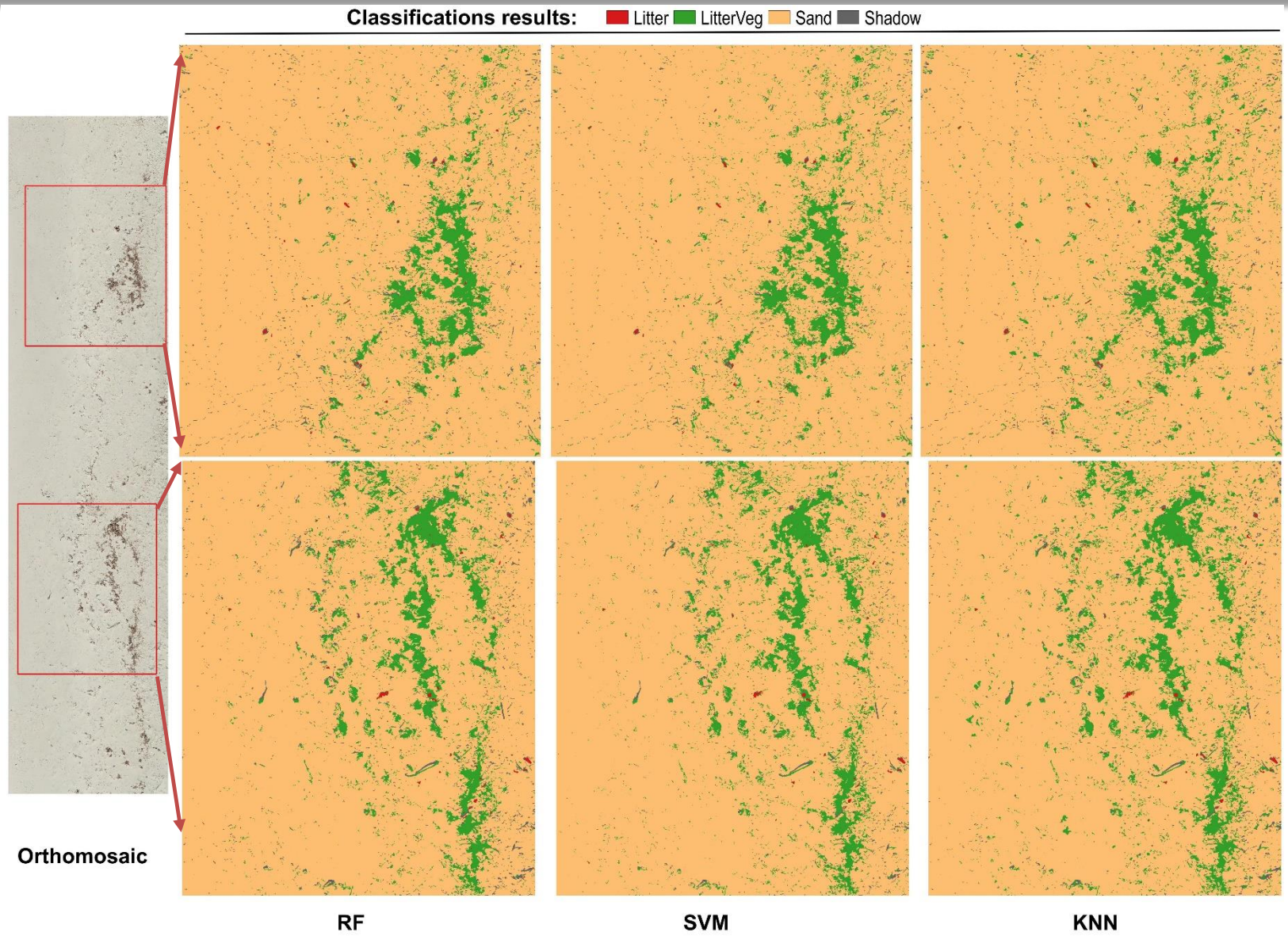


# Object Based Image Analysis (OBIA)

- The OBIA classification in **Ecognition Developer** can be carried out in four steps
  - **Manually** delineate the training areas (a)
  - **Segment** the image and integrate the manual training areas (b)
  - Generating the objects **statistics file** using the training data sample (c-d)
  - Using the statistics file to **train the classifier**
  - **Applying** the classifier to a new image or area (e)



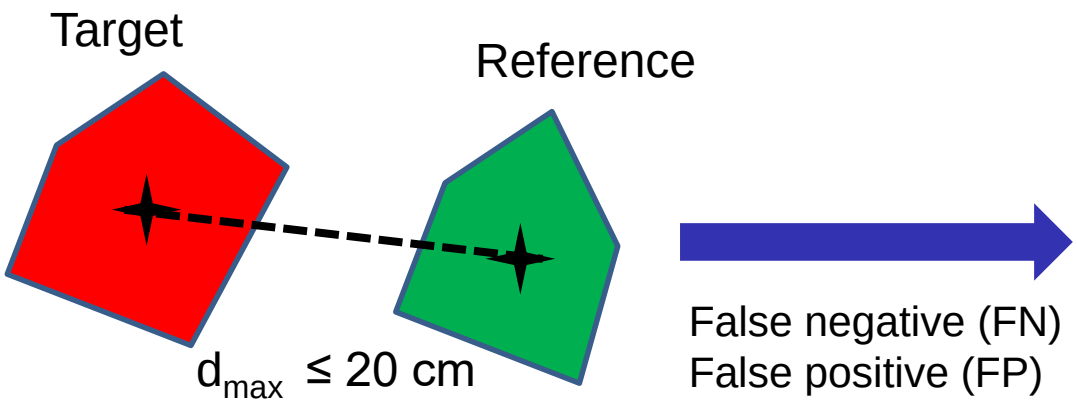
# Results: classifications



# Results: ML detection accuracy

| Val Area # | Classif | TP | FN | FP | P | R | F |
|---|---|---|---|---|---|---|---|
| 2 | RF | 81 | 37 | 44 | 0.65 | 0.69 | 0.67 |
| | SVM | 69 | 49 | 20 | 0.78 | 0.58 | 0.67 |
| | KNN | 71 | 47 | 35 | 0.67 | 0.60 | 0.63 |
| 3 | RF | 91 | 33 | 62 | 0.59 | 0.73 | 0.66 |
| | SVM | 75 | 49 | 25 | 0.75 | 0.60 | 0.67 |
| | KNN | 83 | 41 | 37 | 0.69 | 0.67 | 0.68 |

True positive (TP):




False negative (FN)
False positive (FP)

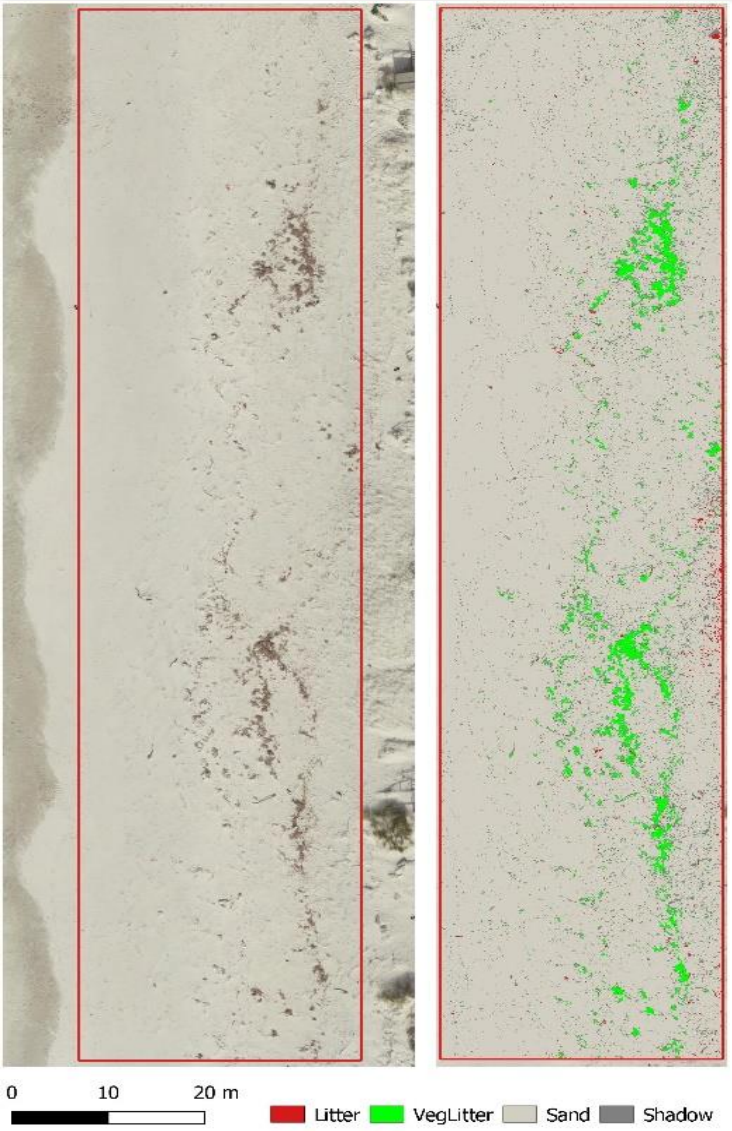
Metrics:

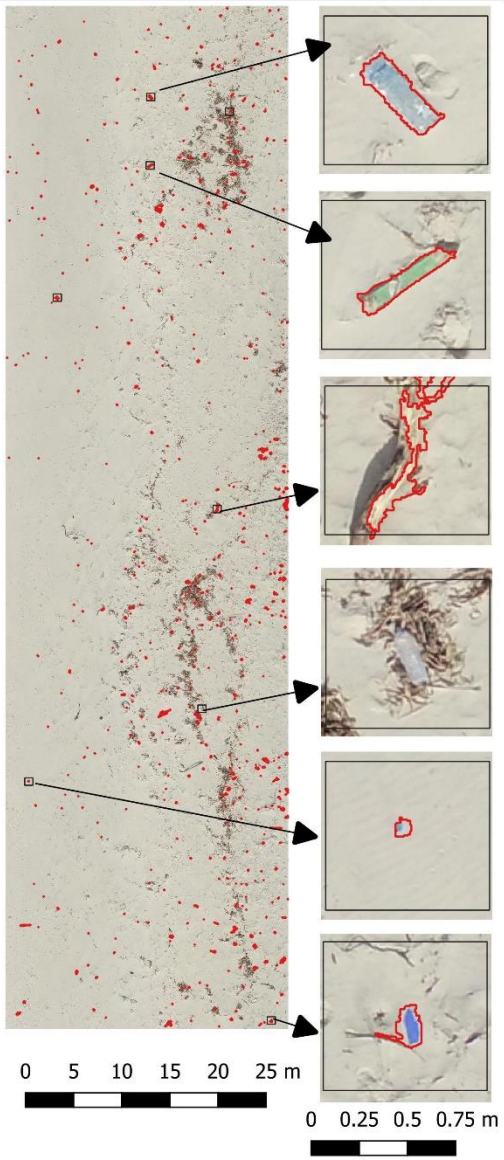
Precision: $P = \frac{TP}{TP + FP}$

Recall: $R = \frac{TP}{TP + FN}$

F-score: $F = 2 \times \frac{P \times R}{P + R}$

# Results: ML detection accuracy




# Conclusions

- The proposed approach is **a cost-effective solution** for mapping Marine Litter (MLit)
- The 3 ML classifiers (RF, SVM and KNN) have about the **same MLit detection performance**.
  - **KNN is more simple** to tune (only one parameter)
  - **RF is more complex** to tune (8 parameters)
- A Litter map (including density map) can also be used to **optimize the clean-up operations**.
- The use of **multispectral images** (and multi-camera systems) for detecting persistent marine on the dune zone is **currently underway**.

# Thanks

Any question?