

Post-doctorat



application



User-tailored machine learning IMage CLASSification for land surface mapping

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1. Context

2. Workflow

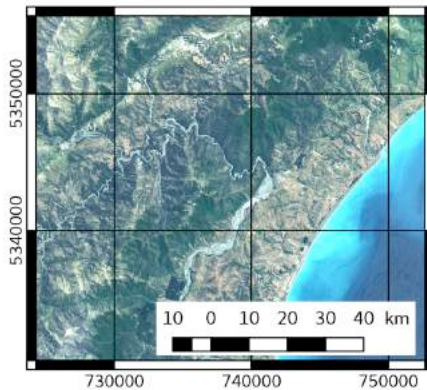
3. First
Results

4.
Perspectives

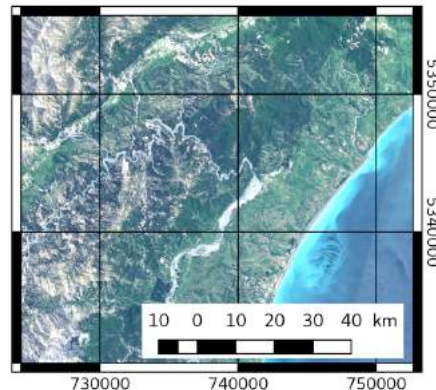
Context

Earthquakes and extreme rainfall (typhoons) can cause >1000s to 100,000s landslides.

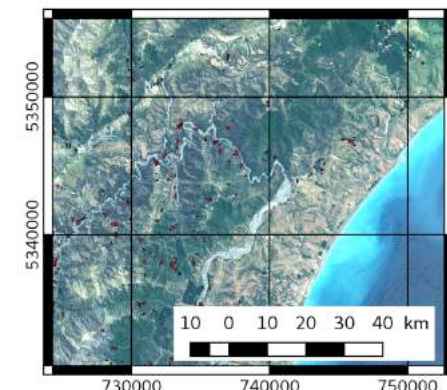
Optical imagery gives the opportunity to rapidly and efficiently detect and map landslides in very short time



Pre-event image



Post-event image



Landslide inventory

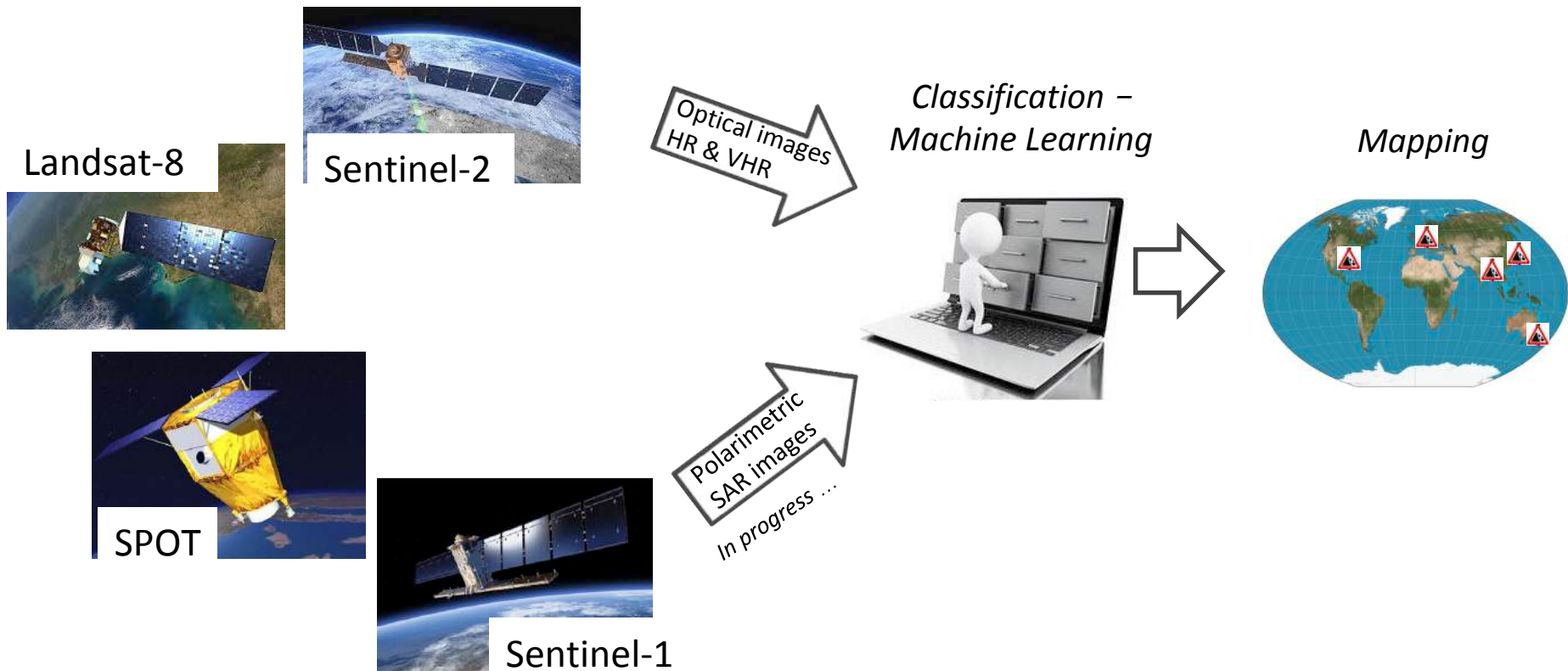
1. Context

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Results

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Perspectives

Context: input data



1. Context

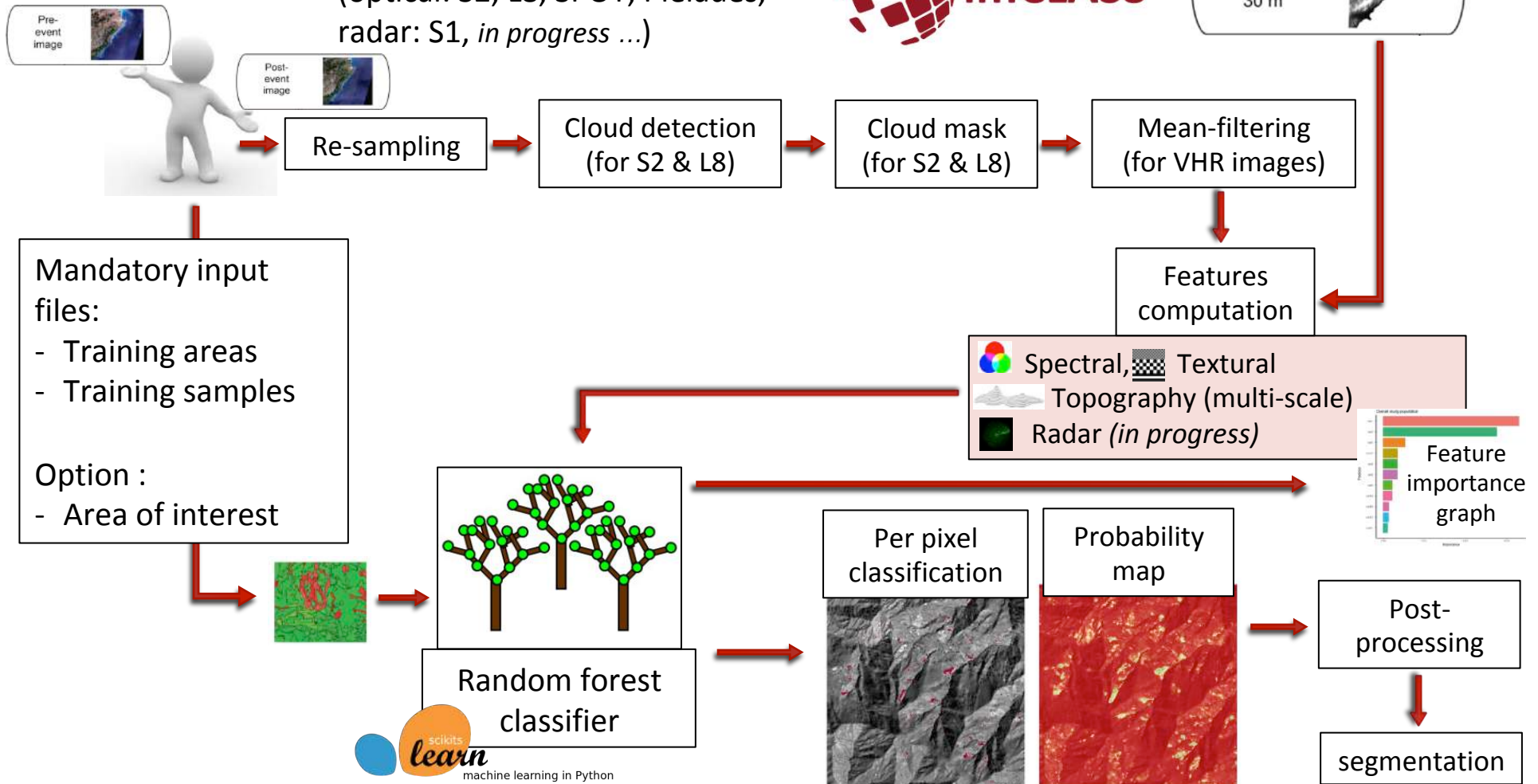
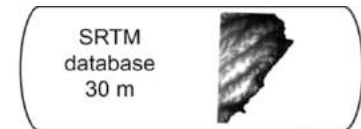
2. Workflow

3. First Results

4. Perspectives

Workflow

Image selection
(optical: S2, L8, SPOT, Pleiades,
radar: S1, *in progress* ...)



1. Context

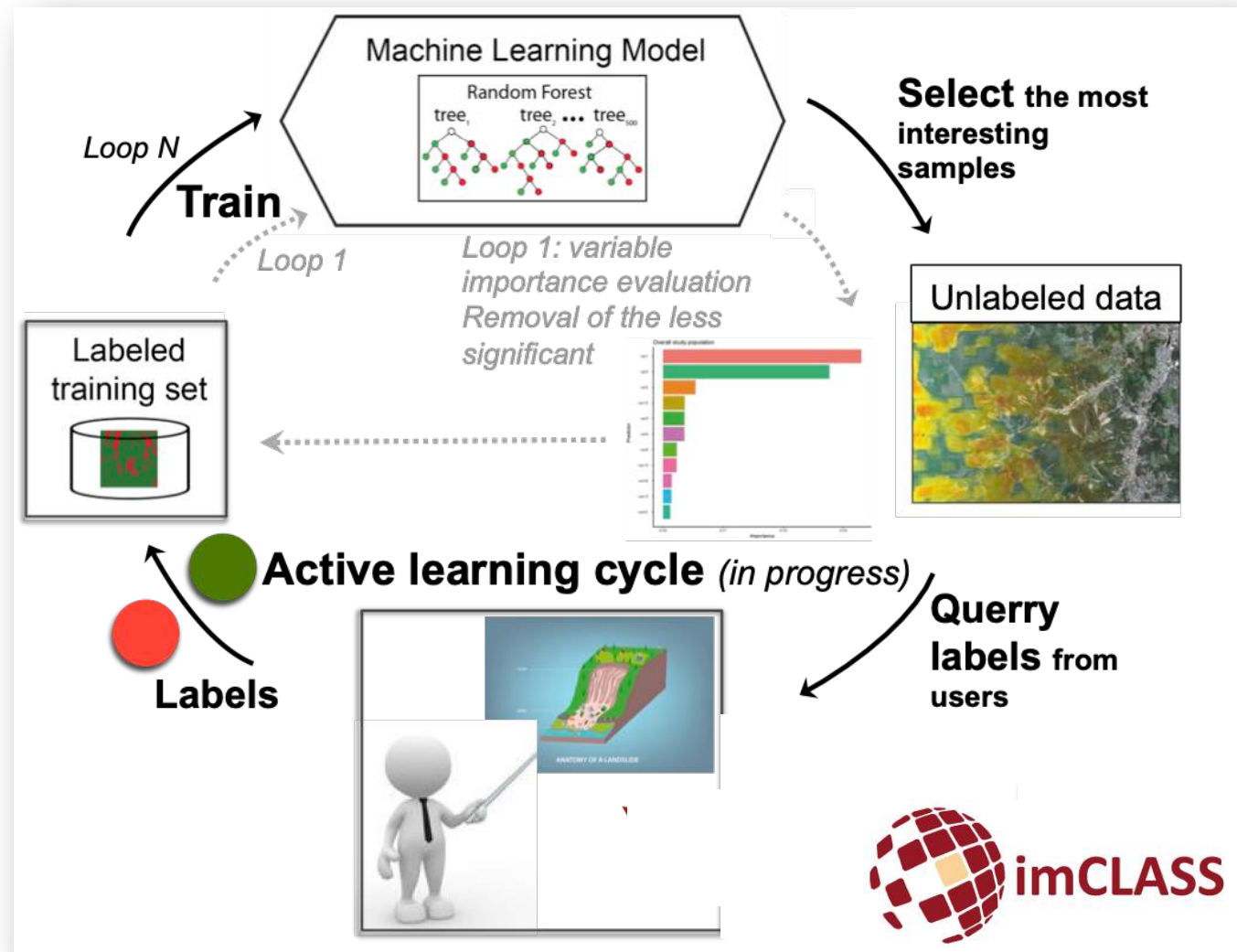
2. Workflow

3. First Results

4. Perspectives

Workflow

- Variables selection with respect to their relative importance
- Selection of the most reliable pixels to add in the training sample
- Active learning cycle



1. Context

2. Workflow

3. First
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Perspectives

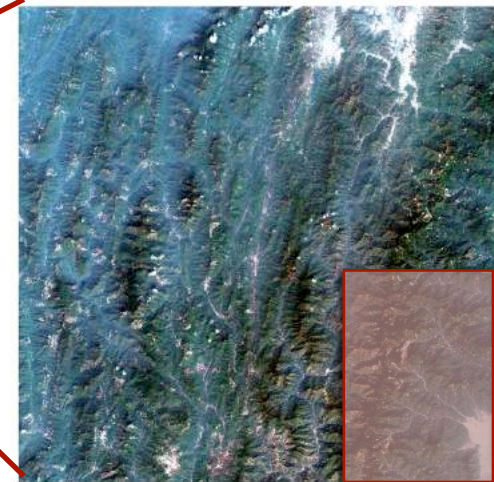
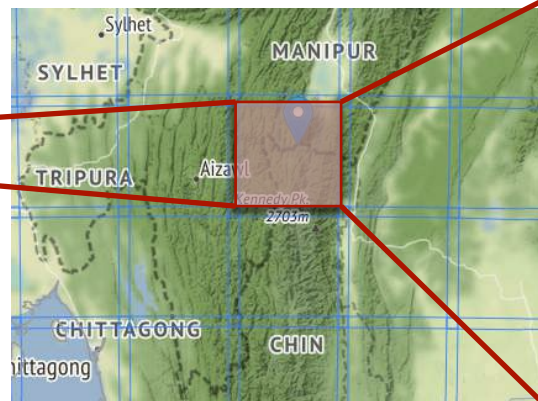
First Results

Mapping of landslides after heavy rains and cyclone Komen.
Myanmar, 2015

Input data:

- Landsat 8 image pre-event (resolution : 15m for panchromatic band, 30m for the RGB + NIR bands)
- Sentinel 2 image post-event (resolution : 10m for RGB + NIR bands)

Location:



1. Context

2. Workflow

3. First Results

4. Perspectives

First Results: Mapping of landslides after heavy rains and cyclone Komen. Myanmar, 2015

Training set size influence

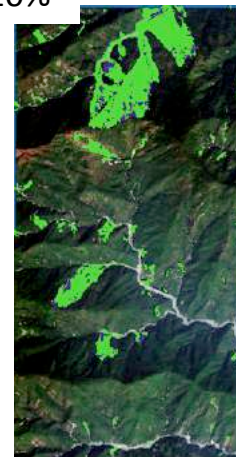
Pixels to classify	50 048 209	52 257 598	53 831 443
Training pixels	5 361 685 (10%) (-:5 180 228, +:181 457)	3 152 296 (6%) (-: 3 030 935, +: 121 361)	1 578 451 (3%) (-: 1 540 660, +:37 791)

(x%) : ratio
(nb pixels in training set) /
(nb total of pixels)
+ : landslide pixel
- : no-landslide pixel

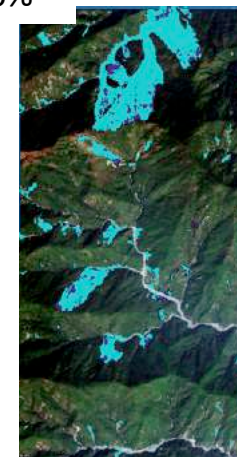


Manual digitalisation

10%



6%



3%



Per pixel classification

1. Context

2. Workflow

3. First Results

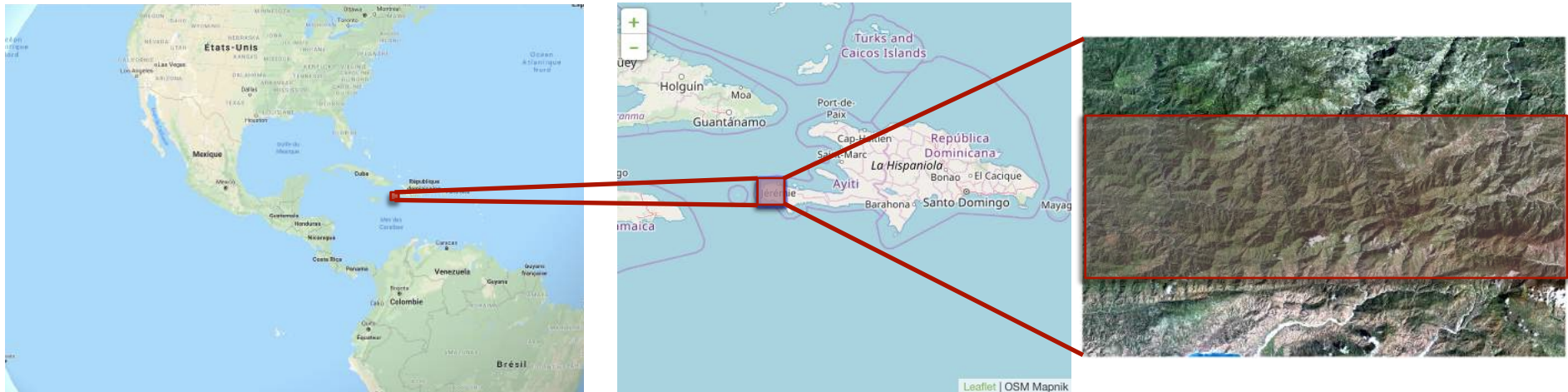
4. Perspectives

First Results: Mapping of landslides after Hurricane Matthew. Haïti, 2016

Input data:

- SPOT6 images (resolution : 1.5m for panchromatic images, 6m for the RGB + NIR images)
- SPOT7 images (resolution : 1.5m for panchromatic images, 6m for the RGB + NIR images)

Location:



1. Context

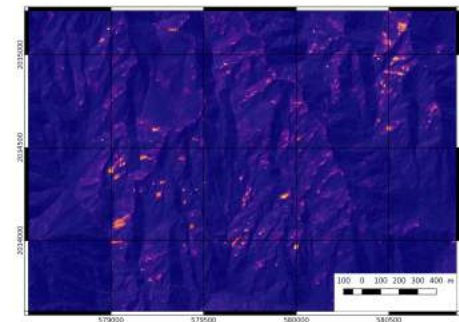
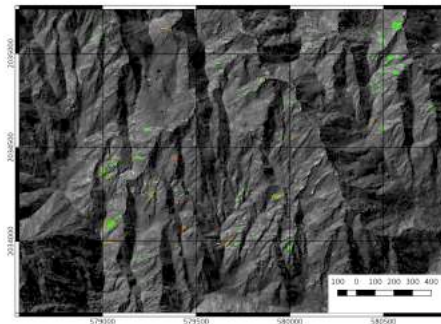
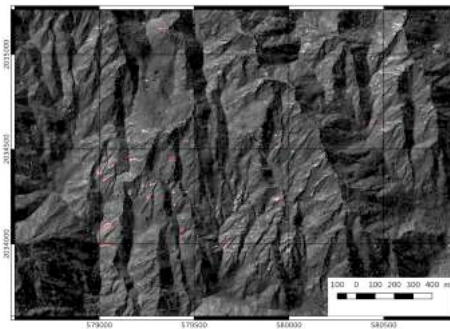
2. Workflow

3. First
Results

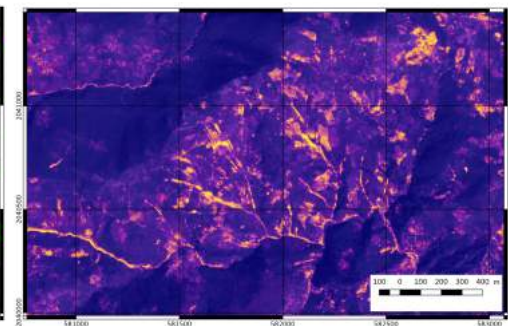
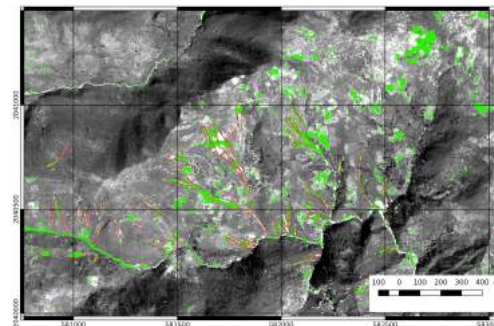
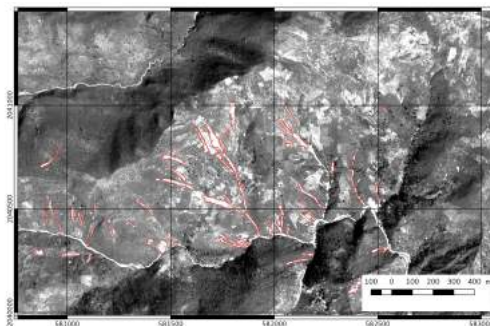
4.
Perspectives

First Results: Mapping of landslides after Hurricane Matthew. Haïti, 2016

A lot of small
landslides well
identified



But some zones
are more
difficult to
classified ...



Rivers &
agricultural
plots
erroneously
mapped

Panchromatic image +
manual digitalization

Pixels mapped as
landslide



1. Context

2. Workflow

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Results

4.
Perspectives

First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

Input data:

- Sentinel2 images (resolution : 10m- 60m)



1. Context

2. Workflow

3. First
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First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

Sentinel 2 **pre-event**: 23 Feb. 2019

Zone 1



1. Context

2. Workflow

3. First
Results

4.
Perspectives

First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

Sentinel 2 **post-event**: 25 March 2019

Training area: 100 landslides interpreted for the training sample, eg. ca. 30 min of labour work

Zone 1



1. Context

2. Workflow

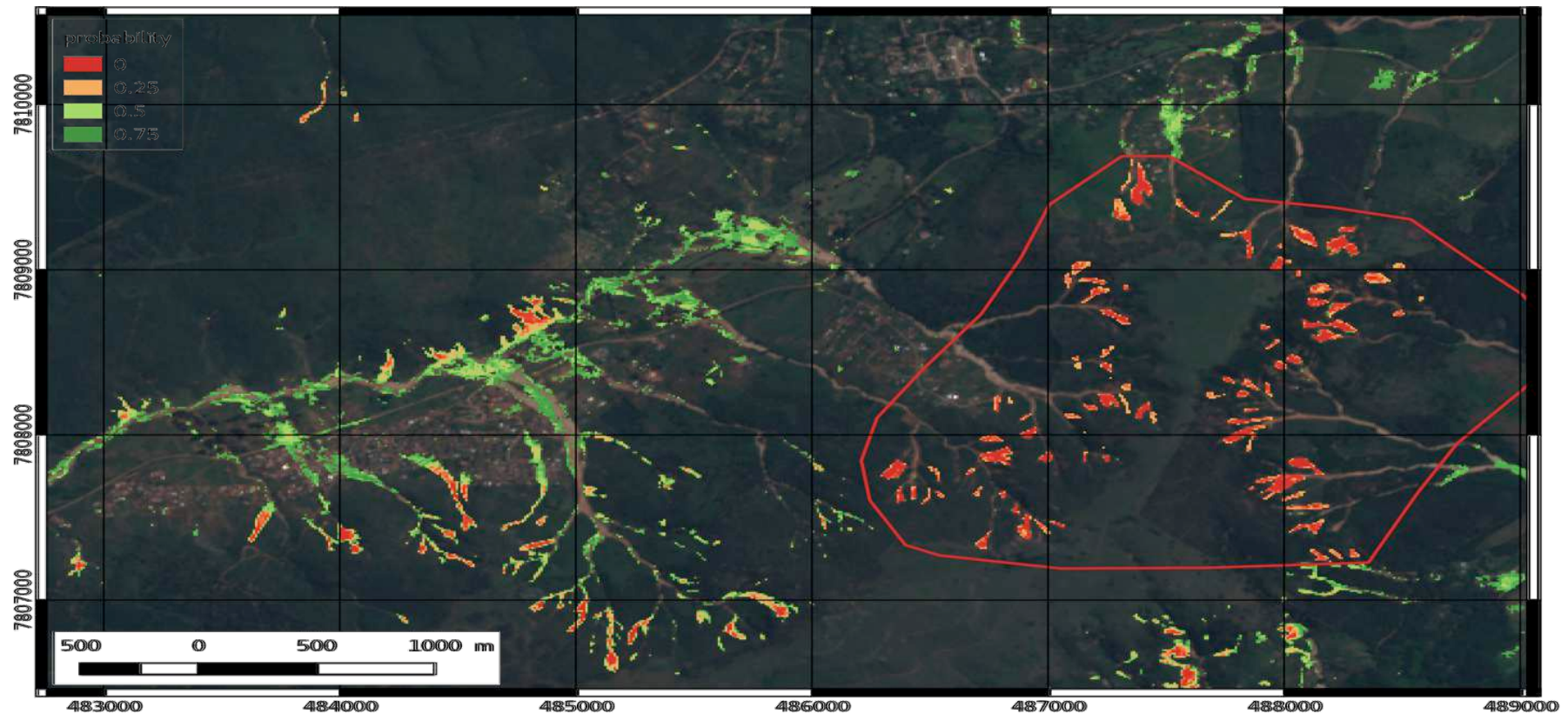
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Results

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Perspectives

First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

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Zone 1



1. Context

2. Workflow

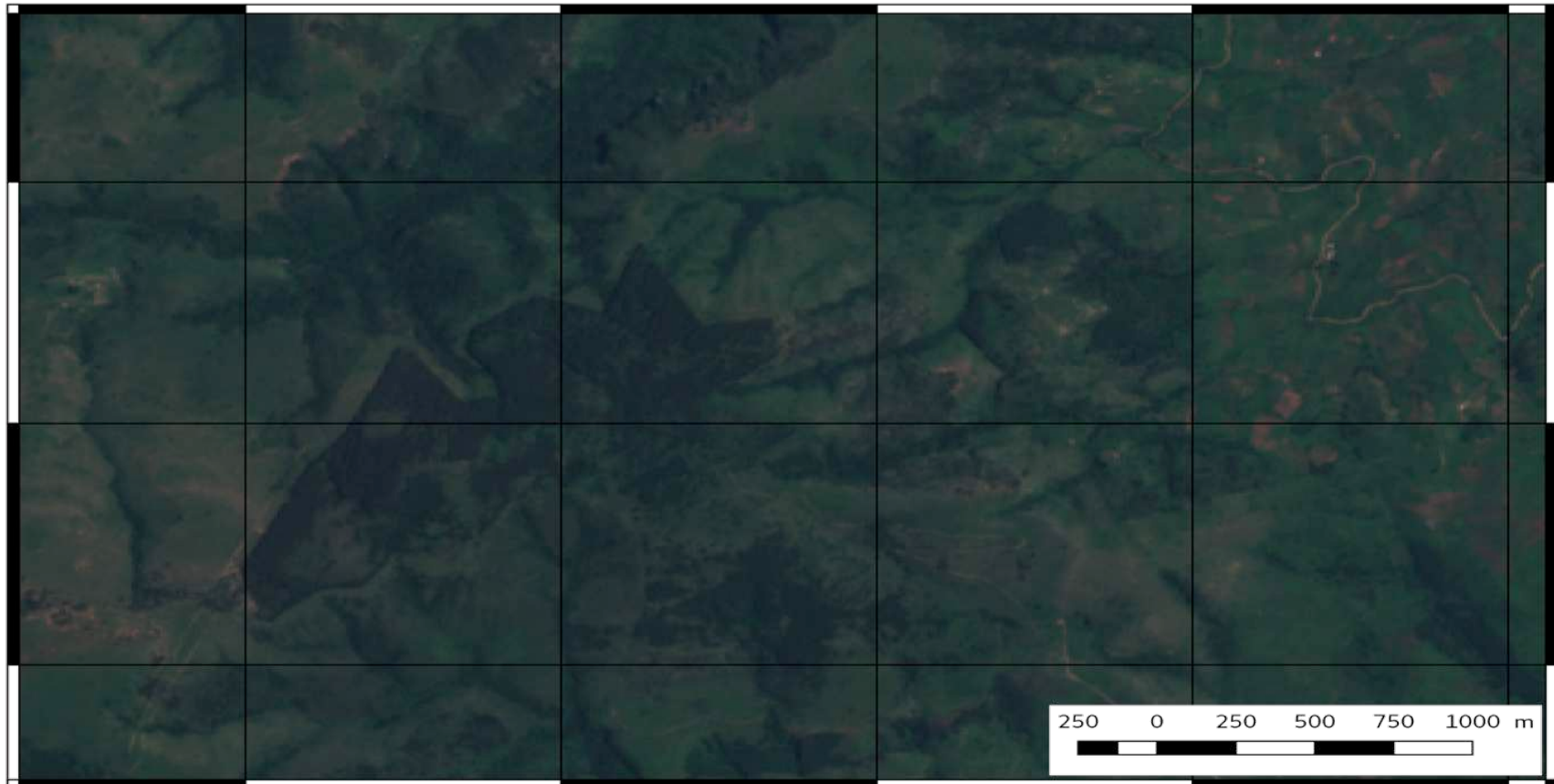
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Perspectives

First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

Sentinel 2 **pre-event**: 23 Feb. 2019

Zone 2, with no reference inventory



1. Context

2. Workflow

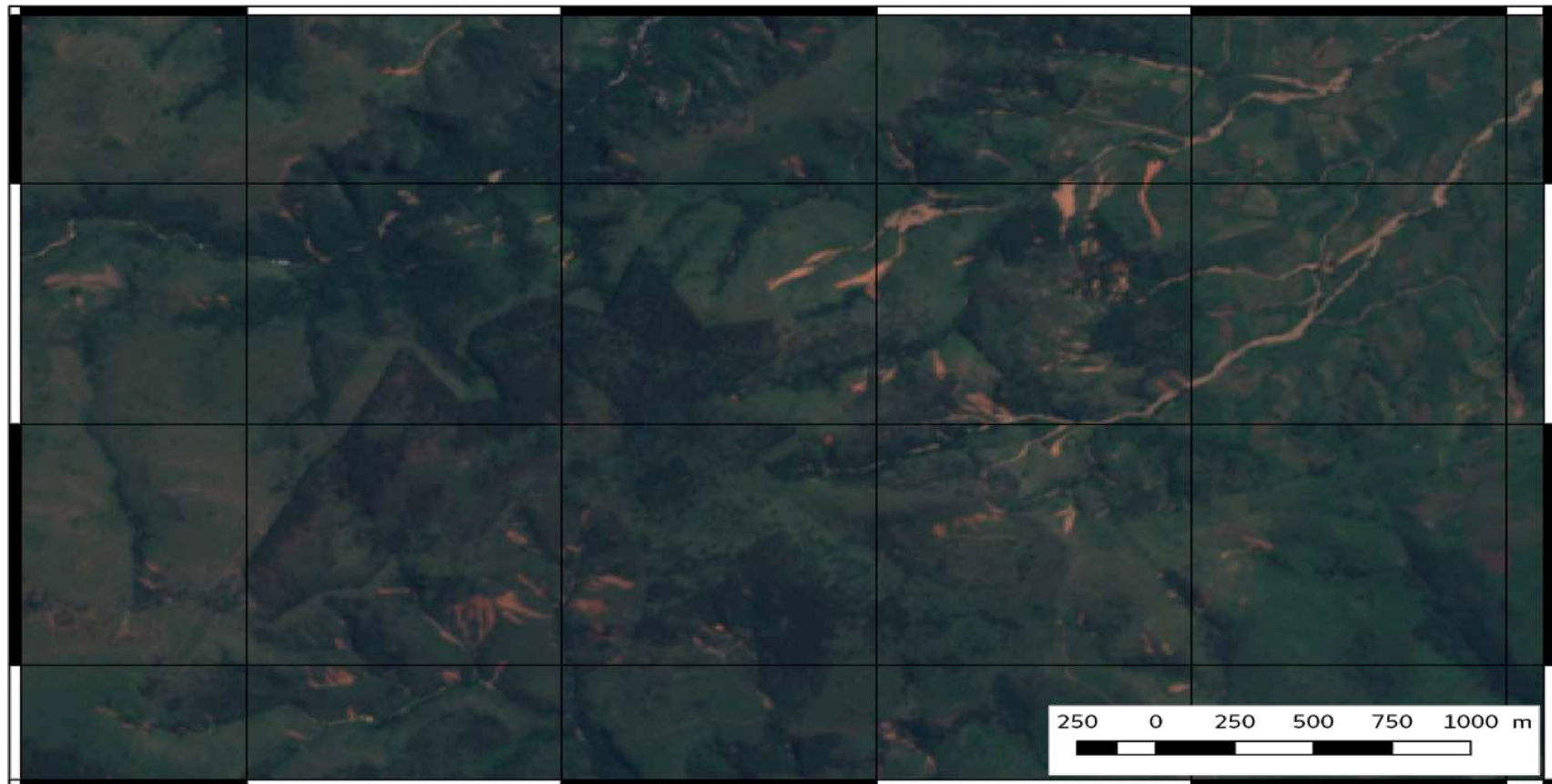
3. First
Results

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Perspectives

First Results: Mapping of landslides after cyclone Idai. Mozambique, 03/2019

Sentinel 2 **post-event**: 25 March 2019

Zone 2, with no reference inventory



1. Context

2. Workflow

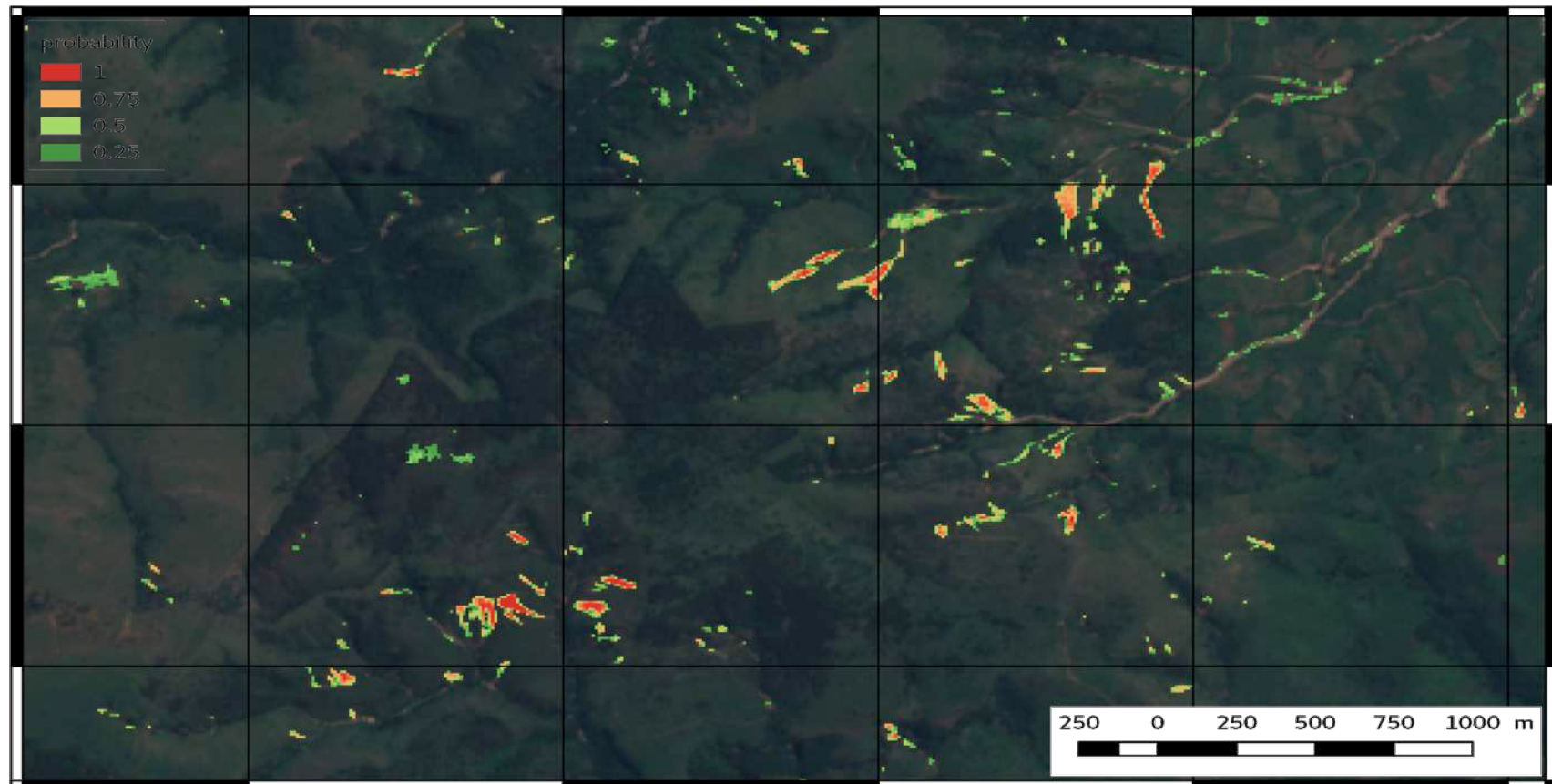
3. First
Results

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Perspectives

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Zone 2, with no reference inventory



1. Context

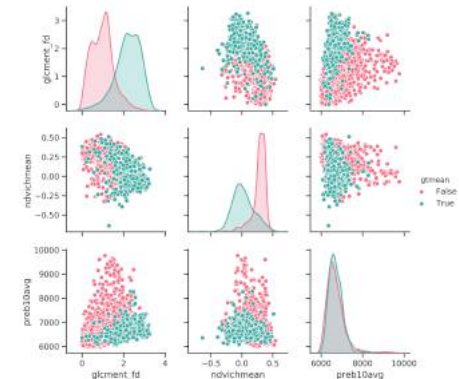
2. Workflow

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Results

4.
Perspectives

Optimizations & Perspectives:

- **Training set optimization:**
 - Active learning implementation
- **Best selection of the attributes**
 - Adding radar attributes (use of S1tiling (Koleck et al., CNES/Cesbio))
 - Adding height information (from de DSM Pléiades, (S2P CNES))
- **Classifier generalisation**
 - Algorithm able to classify any kind of objects, based on a reliable training sample
- **Upscaling**
 - Porting the code on an high performance computer



1. Context

2. Workflow

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Optimizations & Perspectives:

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