The MORINGA Processing Chain: Automatic Object-based Land Cover Classification of Tropical Agrosystems using Multi-Sensor Satellite Imagery

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Land Cover mapping in Tropical Agrosystems

- A growing demand for **systematic Land Cover/Land Use mapping** for the characterization and monitoring of **complex agricultural systems**:
  - Timely **productivity evaluation**, risk assessment, EWS for **food security**
  - Exploit the growing availability/variety of **satellite imagery**...
    - The "breakthrough" of ESA's **SENTINEL missions**
  - ...facing the need for automation and **operational methods**

- **Goal :** improve Land Cover mapping of **tropical agricultural landscapes**
  - Precise detection of the **annual/seasonal cropland**
  - Reliable identification of (at least) the **main crop groups/types**
  - Detection of **cropping practices**
    - *irrigated vs. rainfed*
    - *mixed/sequential crops*
    - *ecological intensification*
    - ...

A Need for Adaptation

- A set of **specific challenges** in Remote Sensing:
  - Significant **cloud coverage** (especially during cultural seasons)
  - **Small to very small (<0.5 ha) plot sizes** (**smallholder farming**)
  - Strong **landscape fragmentation**
  - **Heterogeneity of cropping practices**
  - **Limited and noisy reference data**

- Cope with the **diversity of agricultural systems**:

Burkina Faso

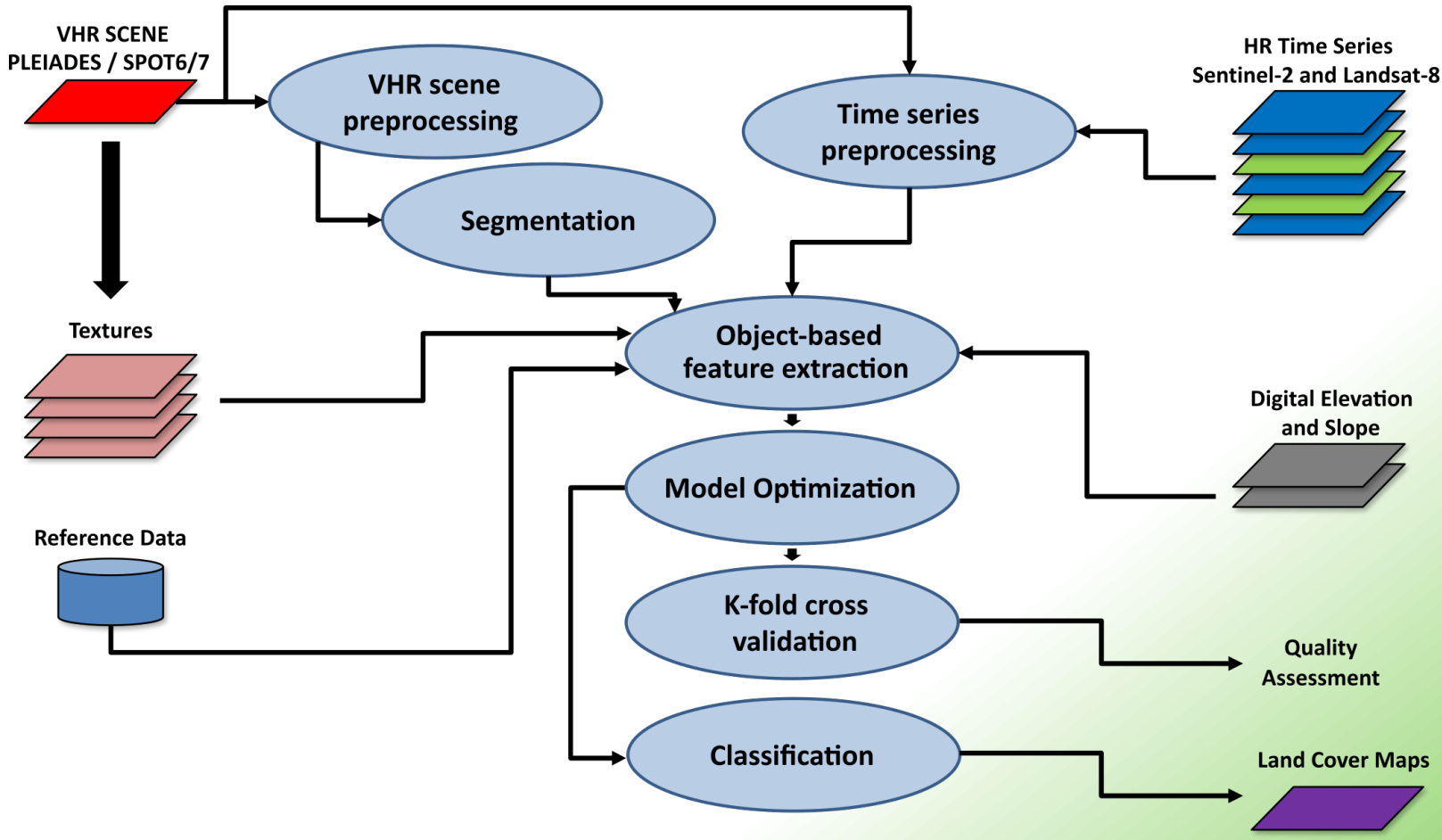
Madagascar

Brazil (Tocantins)

A Workflow for Automatic LULC Mapping

- Provide a **common methodology and workflow** for **fine-scale Land Cover mapping of tropical agrosystems** based on **multi-sensor data fusion** [1]
  - Use of **dense HR satellite image time series** (Sentinel-2, Landsat 8) to characterize **vegetation dynamics** and maximize non-cloudy observations
  - Integrate **VHSR imagery** (order of **1 m**) to provide information on **landscape and cropland structure** at **fine spatial scales**
  - Leverage the **OBIA paradigm** and **ensemble classification strategies** to enable multi-resolution and multi-sensor data fusion
- The **MORINGA processing chain**: an **automatic** workflow covering from **data pre-processing** to **map production and evaluation**
  - an **overall object-based methodology** and a **modular workflow** to ensure efficient improvement strategies (new sensors, advances in AI, ...)
- Our major contribution to the French ***THEIA Land Surfaces Pole***
  - Being integrated to THEIA's **Land Cover SEC *iota²*** platform [2]

Scheme of the MORINGA Processing Chain



The MORINGA chain: pre-processing modules

VHSR scene

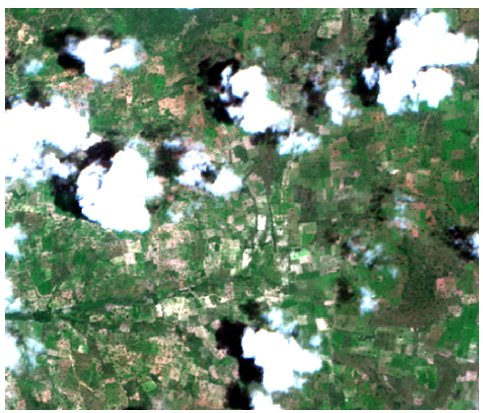
- Radiometric corrections
- Orthorectification
- Pansharpening

HR time series

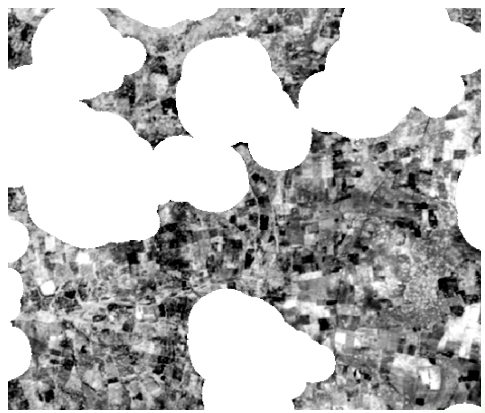
- *Sensor specific*:
  - **L8**: Conversion to TOA, cloud/shadow masking, pansharpening
  - **S2 (L2A)**: Resampling and stack of 10- and 20-meter bands
  - $\rightarrow$ Ongoing developments for **Venμs** and **Sentinel-1** imagery
- *Common time-series preprocessing*:
  - **Temporal gap-filling**
  - **VHR/HR co-registration**

Preprocessing: Temporal Gap-filling

- Using the **Orfeo Toolbox Temporal Gap-Filling** remote module as in [2]
  - **interval-weighted temporal interpolation** using closest "clear" pixels
  - resamples different tiles over a **unique temporal grid**



S2 RGB (2016/09/12)

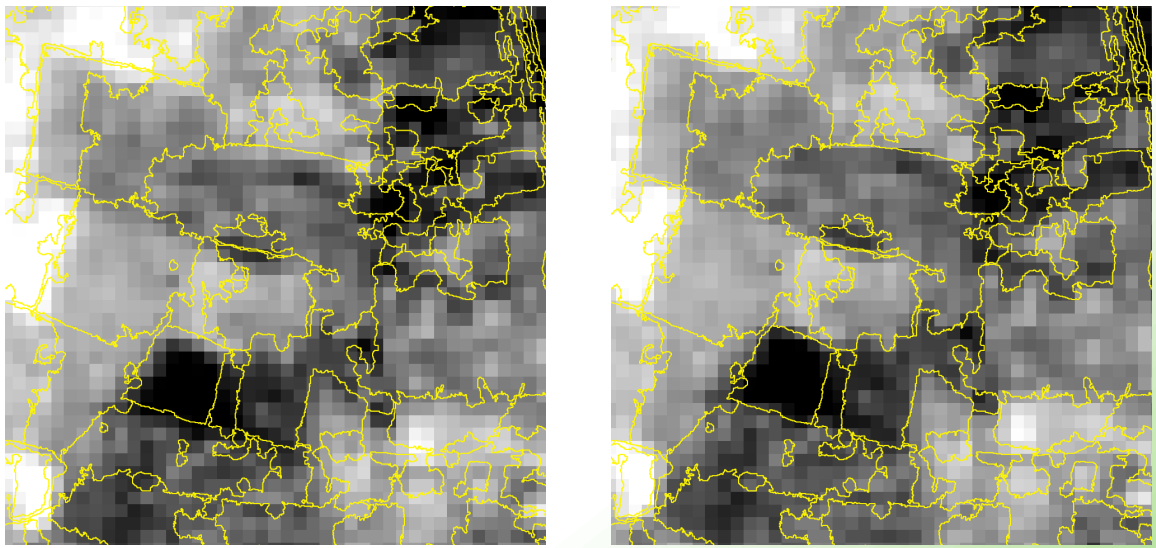


S2 NDVI (2016/09/12) (masked)

S2 NDVI (2016/09/12) (gapfilled)

Preprocessing steps: VHR/HR co-registration

- An independent module implemented using the **Orfeo Toolbox**
  - downsample the reference VHR band to the target resolution (e.g. S2)
  - automatically search for **homologous points** (using SIFT features)
  - build a new **RPC-based sensor model** for the HR image
  - perform a new **orthorectification**

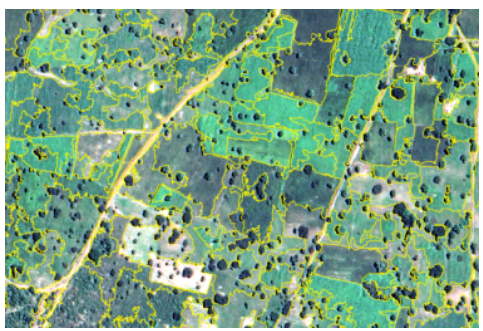


Before co-registration

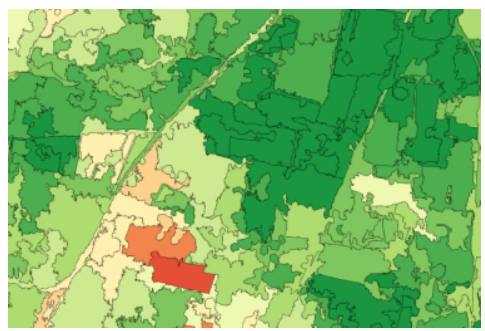
After co-registration

Preprocessing steps: co-registration effects

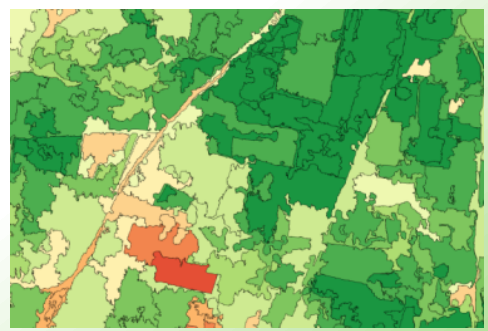
- **NDVI object means** on a **small sample area**:
  - 6,5% mean difference w.r.t. the full NDVI dynamic
  - 8,5% mean difference w.r.t. the 2% NDVI dynamic
  - **15,5% mean difference w.r.t. the "crop" dynamic**
  - Obviously, **the smaller the object, the bigger the difference**



Sample area
(detail)



NDVI means
without co-reg.



NDVI means
with co-reg.

The MORINGA workflow

- **VHSR scene segmentation**
  - **Baatz and Schaepe** technique (Large-scale Generic Region Merging [3])
  - segmentation parameter **to be assessed manually** beforehand but...
  - ...for a fixed VHR sensor, **low sensitivity to parameter selection**

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  - original polygons are **intersected with the segmentation**
  - "multiplies" training samples and **addresses intra-plot variability**

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- **Optimized computation of object statistics**
  - an accurate **multi-resolution zonal statistics tool** has also been developed
  - **scans HR images using the VHR grid** - no resampling needed

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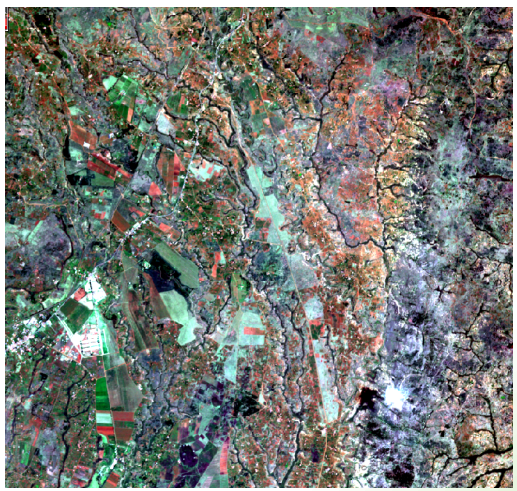
  - **scans HR images using the VHR grid** - no resampling needed
- **Object-based classification**
  - **direct classification** of the vector layer using **Random Forest** (OTB)
  - automatic validation using **k-fold cross validation**, **rasterized output**

Benchmarking: a cross-site approach

- Tests on **several contrasted study sites** in tropical countries
  - **Koumbia***, *Hauts Bassins*, Burkina Faso, 2016
  - **Antsirabe***, *Hautes Terres*, Madagascar, 2016-17
  - **Botucatu***, *São Paulo*, Brasil, 2017
  - **Kandal** province, Cambodia, 2017
  - **Reunion Island**, *French Overseas Region*, 2016-17

Koumbia



Antsirabe

Botucatu

* ***JECAM*** **site**

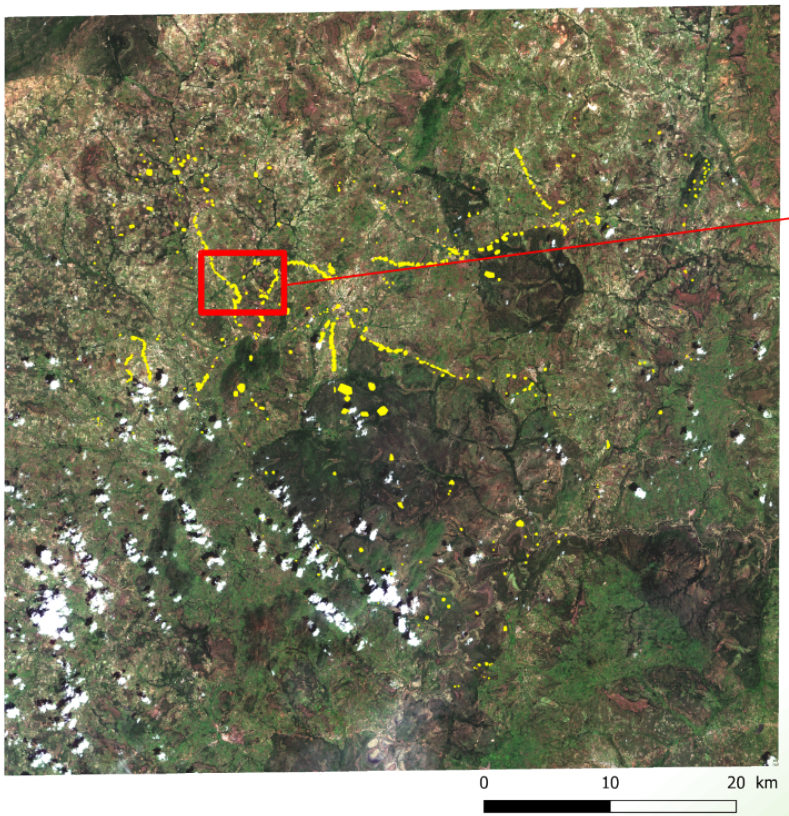
Benchmarking: a cross-site approach

- A **common dataset specification** for each study site
  - A **single VHSR (SPOT6/7) scene** at the **peak of the growing season**
  - **S2 (L2A)**[1] **and L8 (L1) time series** covering at least the **growing season**
  - **Comparable agrosystem nomenclatures** at multiple levels
    - *Crop/Non-crop, Land Cover, Crop groups, Crop types*
  - A **suitable reference dataset** (field + photointerpretation) with a **minimum required surface** per class (around 30ha).
- A **common set of features** extracted from each image (VHR/TS)
  - **OLI reflectances** (L8), **10- and 20-meter bands** (S2)
  - **NDVI, NDWI, BRI, MNDVI, MNDWI, Red-edge NDVI** (S2 only)
  - **Textural indices (Haralick)** extracted from VHR panchromatic band at two relevant scales (intra and inter-plot)
  - *Digital Elevation Model (SRTM-30m), Slopes*

[1] Provided by **CNES** via the **THEIA Pôle**, precessed using the **MAJA** processor [4]

Study sites: Koumbia (Burkina Faso)

- **1650 Km^2, 1190 reference polygons**
- *#classes over levels*: **2, 6, 12, 20**
- *Issues* : **fragmented landscape, trees in crops, scattered rainfalls**



Images SPOT6 du 29 septembre 2016
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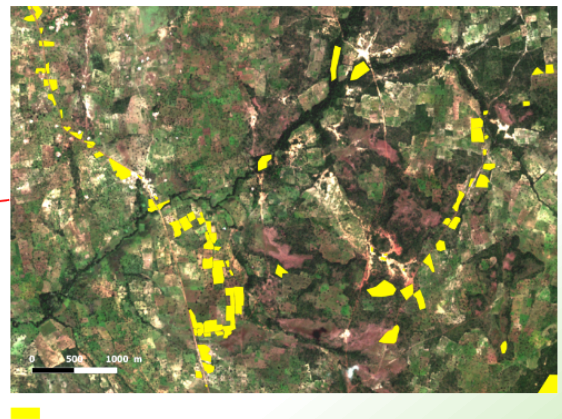

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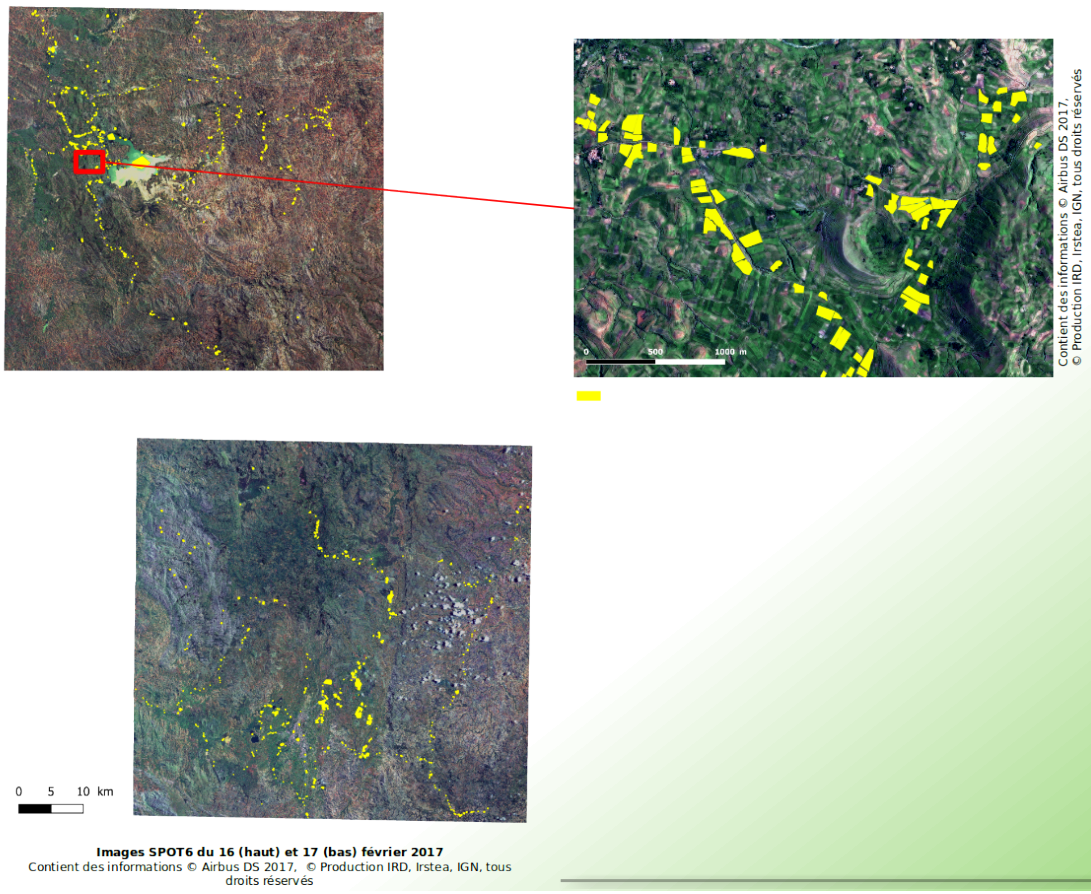
Study sites: Antsirabe (Madagascar)

- **7200 Km^2, 1178 reference polygons**
- *#classes over levels*: **2, 6, 16, 18**
- *Issues* : **fragmented landscape, very small plots**



Images SPOT6 du 16 (haut) et 17 (bas) février 2017
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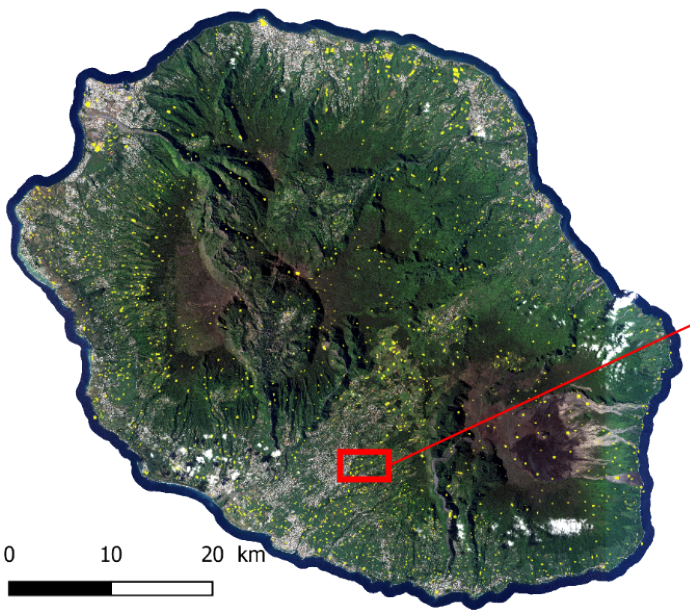
Study sites: Reunion Island

- **2512 Km^2, 2650 reference polygons**
- *#classes over levels*: **2, 8, 14, 24**
- *Issues* : **strong reliefs, large majority of sugar cane**



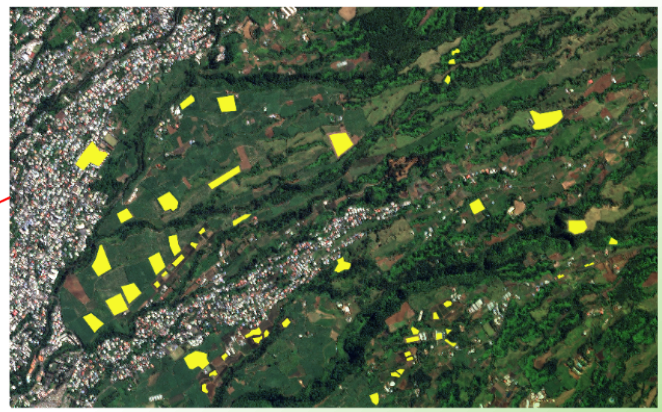
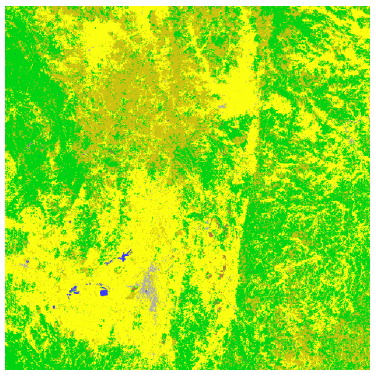


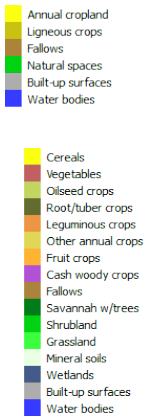
Image Spot6 du 8 avril 2016 (Le Tampon)

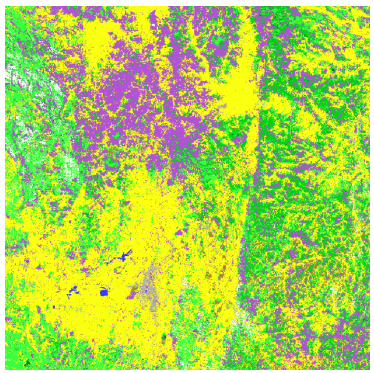
0 1000 2000 m

Results : Cross-site overall

Antsirabe (Madagascar)



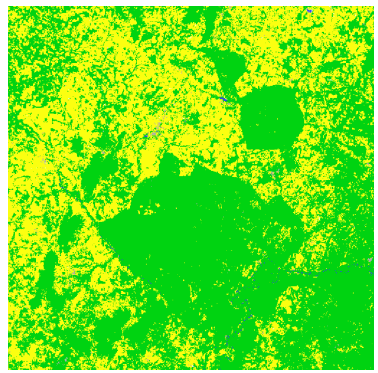


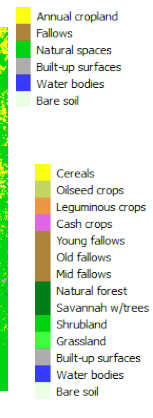


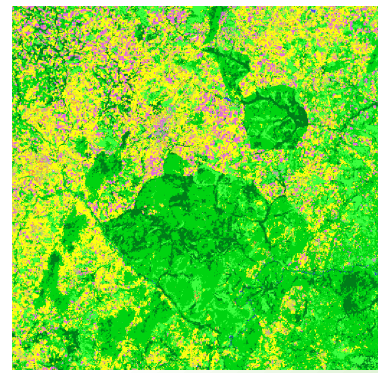
Land Cover (6 classes)
OA : 84.71% - κ : 0.79

Crop Groups (16 classes)
OA : 74.38% - κ : 0.70

Koumbia (Burkina Faso)



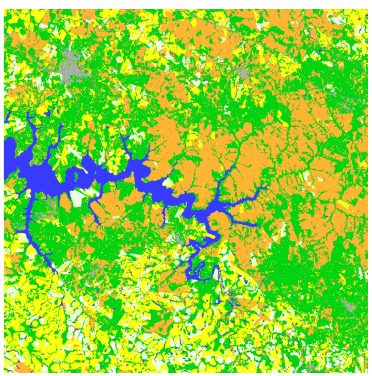


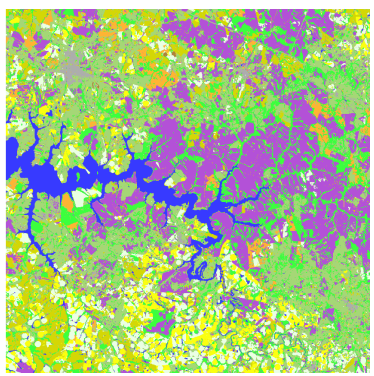


Land Cover (6 classes)
OA : 93.67% - κ : 0.87

Crop Groups (12 classes)
OA : 76.20% - κ : 0.71

Botucatu (Brasil)

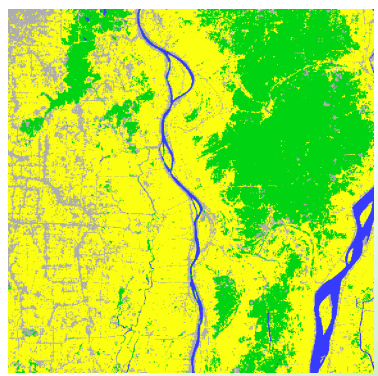


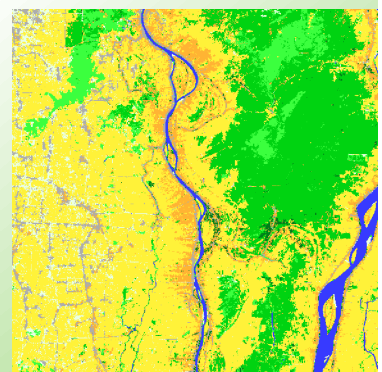


Land Cover (7 classes)
OA : 89.49% - κ : 0.87

Crop Groups (11 classes)
OA : 88.83% - κ : 0.87

Kandal (Cambodia)





Land Cover (4 classes)
OA : 89.97% - κ : 0.86

Crop Groups (8 classes)
OA : 85.56% - κ : 0.83

Results : Antsirabe (Madagascar)

Crop vs. Non-crop

Class	F-Score
Crop	0.8984±0.0329
Non-crop	0.8865±0.0356
Overall Acc.	**89.66% ± 3.05%**
Kappa	**0.7853 ± 0.0563**

Land Cover

Class	F-Score
Annual cropland	0.8741±0.0396
Ligneous crops	0.8132±0.0580
Fallows	0.4786±0.2193
Natural spaces	0.8221±0.0398
Built-up surfaces	0.8977±0.0859
Water bodies	0.9713±0.0374
Overall Acc.	**84.71% ± 4.38%**
Kappa	**0.7932 ± 0.0549**

@Crop Type : OA 71.12% - κ 0.67

Crop Groups

Class	F-Score
Cereals	0.7850±0.0295
Vegetables	0.5443±0.2003
Oilseed crops	0.5566±0.1367
Root/tuber crops	0.4401±0.1143
Leguminous crops	0.0000±0.0000
Other annual crops	0.4769±0.1500
Fruit crops	0.4171±0.0687
Cash woody crops	0.8333±0.0296
Fallows	0.6830±0.1214
Savannah w/trees	0.2109±0.0888
Shrubland	0.5524±0.1657
Grassland	0.6221±0.0938
Mineral soils	0.8077±0.1090
Wetlands	0.7491±0.1508
Built-up surfaces	0.9201±0.0577
Water bodies	0.9713±0.0374
Overall Acc.	**74.38% ± 5.06%**
Kappa	**0.6959 ± 0.0479**

Results : Koumbia (Burkina Faso)

Crop vs. Non-crop

Class	F-Score
Crop	0.9235±0.0144
Non-crop	0.9578±0.0074
Overall Acc.	**94.56% ± 0.98%**
Kappa	**0.8815 ± 0.0215**

Land Cover

Class	F-Score
Annual cropland	0.9182±0.0130
Fallows	0.0765±0.1122
Natural spaces	0.9667±0.0086
Built-up surfaces	0.8070±0.0825
Water bodies	0.9913±0.0174
Bare soil	0.5419±0.2014
Overall Acc.	**93.67% ± 0.98%**
Kappa	**0.8759 ± 0.0200**

Crop Groups

Class	F-Score
Cereals	0.7555±0.0362
Oilseed crops	0.4996±0.0410
Leguminous crops	0.3998±0.0762
Cash crops	0.7636±0.0418
Fallows	0.1915±0.1510
Natural forest	0.8030±0.1528
Savannah w/trees	0.2523±0.2066
Shrubland	0.7953±0.1173
Grassland	0.8137±0.0618
Built-up surfaces	0.8269±0.0597
Water bodies	0.9913±0.0174
Bare soil	0.5829±0.1928
Overall Acc.	**76.20% ± 5.01%**
Kappa	**0.7096 ± 0.0610**

@Crop Type : OA 72.02% - κ 0.66

Results : Botucatu (Brasil)

Crop vs. Non-crop

Class	F-Score
Crop	0.9264±0.0174
Non-crop	0.9225±0.0101
Overall Acc.	**92.52% ± 1.25%**
Kappa	**0.8489 ± 0.0244**

Land Cover

Class	F-Score
Cropland	0.8411±0.0604
Tree crops	0.9575±0.0268
Fallows	0.2338±0.2826
Natural spaces	0.9176±0.0316
Built-up surfaces	0.9421±0.0349
Water bodies	0.9979±0.0033
Bare soil	0.6468±0.0688
Overall Acc.	**89.49% ± 2.21%**
Kappa	**0.8663 ± 0.0263**

Crop Groups

Class	F-Score
Millet	0.7310±0.0470
Soy beans	0.0000±0.0000
Sugar cane	0.8981±0.0273
Fruit crops	0.9371±0.0371
Cash woody crops	0.9530±0.0268
Fallows	0.2179±0.2950
Grassland	0.9464±0.0209
Pastures	0.8548±0.0514
Built-up surfaces	0.9333±0.0364
Water bodies	0.9979±0.0033
Bare soil	0.6808±0.0459
Overall Acc.	**88.83% ± 1.29%**
Kappa	**0.8694 ± 0.0138**

@Crop Type : OA 87.72% - κ 0.86

Results : Kandal province (Cambodia)

Crop vs. Non-crop

Class	F-Score
Crop	0.8618±0.0591
Non-crop	0.9475±0.0177
Overall Acc.	**92.44% ± 2.72%**
Kappa	**0.8097 ± 0.0755**

Land Cover

Class	F-Score
Cropland	0.8849±0.0490
Natural spaces	0.9211±0.0494
Built-up surfaces	0.8208±0.1142
Water bodies	0.9807±0.0201
Overall Acc.	**89.97% ± 5.05%**
Kappa	**0.8653 ± 0.0669**

Crop Groups

Class	F-Score
Rice	0.8585±0.1000
Fruit crops	0.8683±0.0622
Shrubland	0.8525±0.0780
Grassland	0.8208±0.1400
Mixed trees	0.6529±0.1163
Bare soil	0.7107±0.1848
Built-up surfaces	0.8695±0.0868
Water bodies	0.9807±0.0201
Overall Acc.	**85.56% ± 6.20%**
Kappa	**0.8310 ± 0.0732**

Results : Reunion Island (France)

Crop vs. Non-crop

Class	F-Score
Crop	0.9726±0.0042
Non-crop	0.9690±0.0039
Overall Acc.	**97.10% ± 0.37%**
Kappa	**0.9416 ± 0.0074**

Land Cover

Class	F-Score
Cropland	0.9491±0.0059
Tree crops	0.8553±0.0156
Grassland	0.9060±0.0227
Natural spaces	0.9456±0.0084
Bare Soil	0.9424±0.0329
Built-up surfaces	0.9697±0.0167
Water	0.9779±0.0222
Shadows	0.9562±0.0430
Overall Acc.	**93.79% ± 0.47%**
Kappa	**0.9217 ± 0.0055**

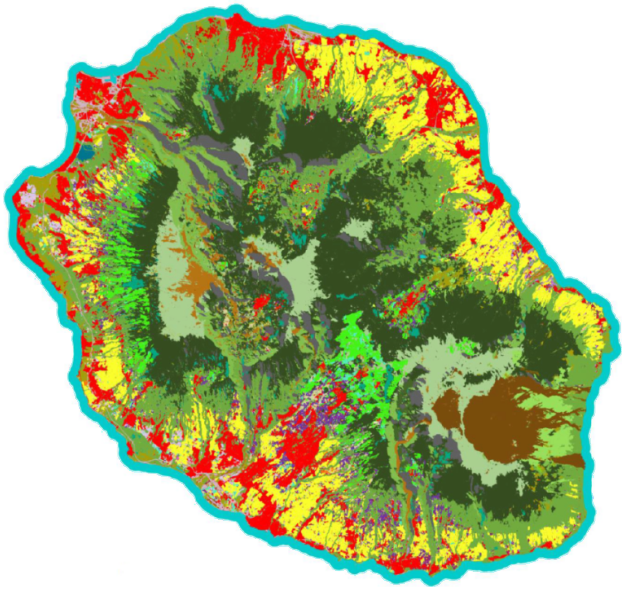
Crop Groups

Class	F-Score
Vegetables	0.7159±0.0368
Sugar cane	0.9595±0.0127
Geranium	0.2050±0.0876
Fruit crops	0.8382±0.0234
Planted forest	0.8630±0.0386
Meadows	0.9065±0.0212
Natural forest	0.9313±0.0098
Shrubland	0.8452±0.0315
Herbaceous savannah	0.7332±0.0963
Bare soil	0.9460±0.0359
Built-up surfaces	0.9527±0.0119
Greenhouses	0.5263±0.1251
Water	0.9772±0.0225
Shadows	0.9541±0.0432
Overall Acc.	**91.47% ± 0.70%**
Kappa	**0.8995 ± 0.0080**

@Crop Type : OA 90.22% - κ 0.88

Results : Reunion Island (France)

- A set of **"delivered" products** in *Open Access*



Reunion Island 2017 LC Map **34 classes @CropGroups, OA 86.28%**

- Available via THEIA at `https://www.theia-land.fr`
- Other finalized products have been delivered in specific projects (Antananarivo Metropolitan Area, Haiti - Cayes, ...)

Conclusions and perspectives

- **The MORINGA processing chain** : from the JECAM Experience to a ***hands-on* tool for land cover mapping of tropical agrosystems**
  - **Fully automatic**, developed in *Python*, using the *Orfeo Toolbox*
  - **Open source**, code publicly available : `https://gitlab.irstea.fr/raffaele.gaetano/moringa.git`
  - Being integrated as a specific workflow of the ***iota*^{2} platform**
- **Conceived to evolve** : many ongoing developments and perspectives
  - integration of **other sensors' imagery** (***Venμs, Sentinel-1***)
  - improvement of the classification strategy (**hierarchical classifiers**)
  - $\rightarrow$ enabling the use of **prior knowledge** on *crop surfaces* (crop models) and *landscapes* (spatial modelling)
  - $\rightarrow$ integrating novel **Deep Learning approaches** for pre-processing (*e.g. gapfilling*) and classification

Acknowledgements and References

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