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Discrimination of Tropical Agroforestry Systems in Very High Resolution Satellite Imagery using Object-Based Hierarchical Classification: A Case-Study on Cocoa in Cameroon

Stéphane Dupuy

Camille C. D. Lelong , Cyprien Alexandre

CIRAD, UMR TETIS, Earth Observation for Environment and Land Management, Montpellier, F-34398, France

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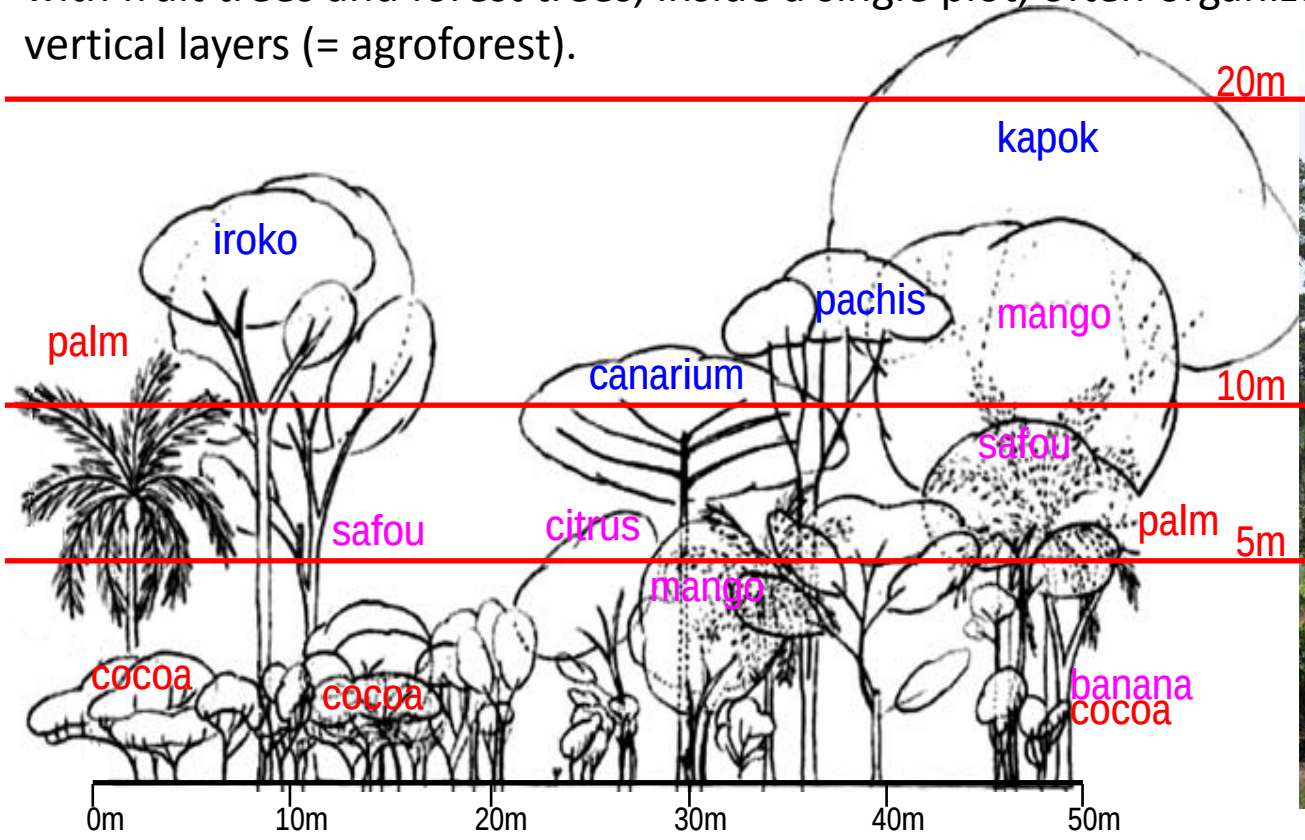
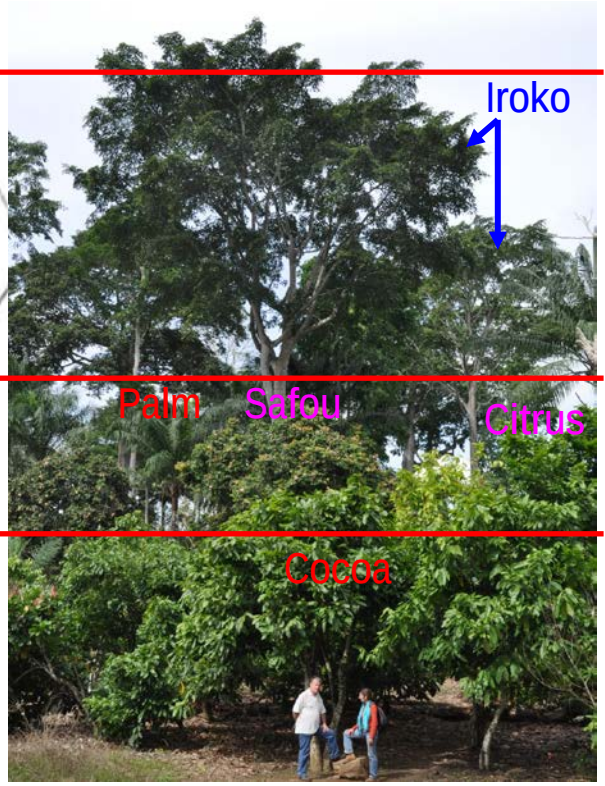
The agroforestry context

Sustainable agriculture = a major issue for the future of mankind, coming in 2 problems:

- **Food security**
- **Environment preservation**

Agroforestry is considered to be a solution / evaluated by agronomists + socio-economists = **Random, complex, and multi-functional association** of cash trees (e.g. cocoa /coffee /palm) with fruit trees and forest trees, inside a single plot, often organized in several superimposed vertical layers (= agroforest).





The remote-sensing context

Satellite very high spatial resolution images ⇨ spatialized information on:

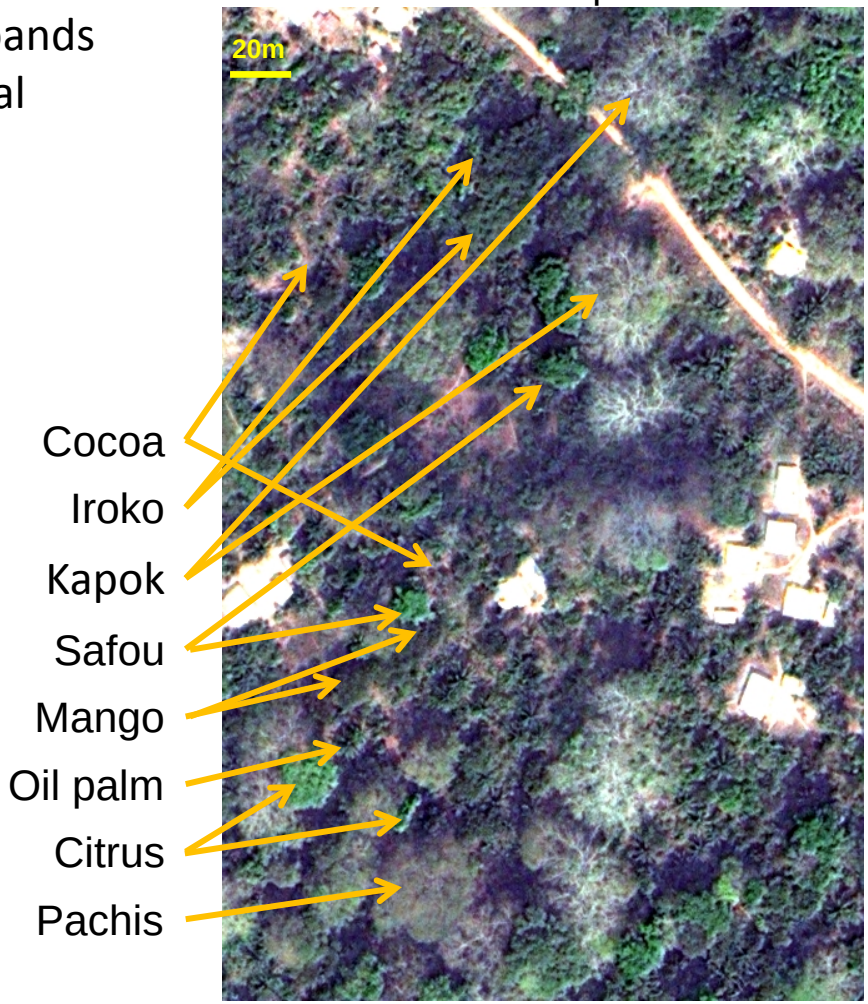
- Landscape structure
- Intraplot structure

Satellite images with a high number of spectral bands ⇨ characterization of the high variability of optical properties of:

- crop systems
- trees

Landscape information

Intraplot information



Cropping systems mapping

1) Delimitation and discrimination of land covers (savannah, crops, tree-covered areas,)

2) Discrimination of specific land-use types among the tree covers:

- traditional cocoa agroforests
- modern agroforestry cocoa plantations
- cocoa monocrops (sunlit)
- other types of groves (citrus, palm…)

⇨ Object-oriented approach combining several steps of segmentation + classification

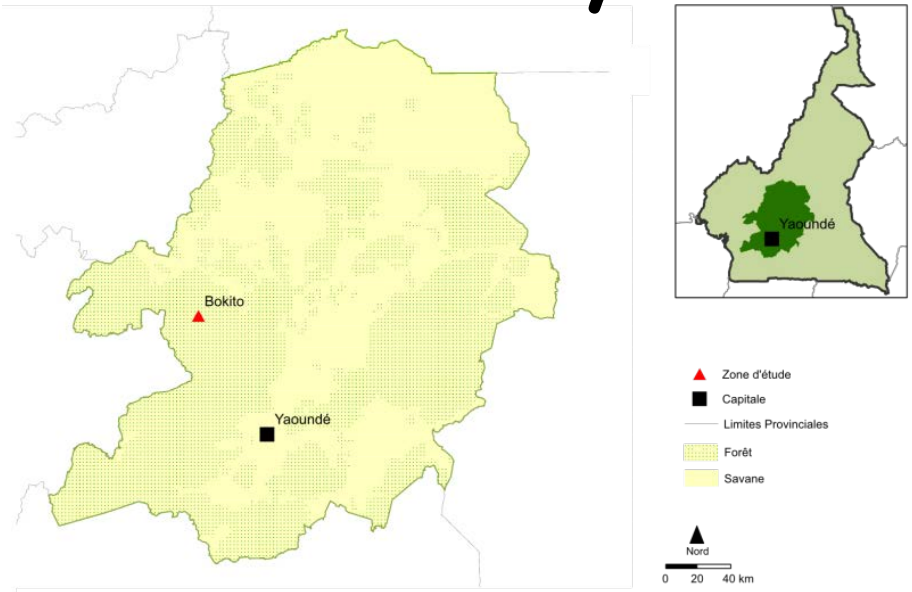
Traditional cocoa agroforest

Modern cocoa + palm grove

Young palm grove

Modern cocoa plantation

Area of study



- Bokito district, Mbam & Inoubou region of Central Cameroon (wet tropical Central Africa)
- Savannah-forest transition zone
- Cocoa planting & food-crops area
- ~ 100km^2

Collected data:

- WORLDVIEW2 acquisition at 0.5/2m in 8 bands (Feb.2011, very cloudy…)
- NASA-SRTM Digital Terrain Model (90m)
- Field survey (>450 geospatialized enquires on land-cover + land-use in tree crops)

Preprocessing and new attributes derivation

1. **Orthorectification** on the basis of NASA-SRTM DTM (90m)
2. Radiometric correction to convert digital numbers in top of atmosphere **reflectance** data
3. **Derivation** of the Normalized Difference Vegetation Index **(NDVI),** Soil Adjusted Vegetation Index (**SAVI),** and Brightness Index (**BI)**
4. Cooccurrence texture indices derivation: variance, entropy and correlation at varying kernel sizes (from 3 to 51 pixels) and orientations (0 ; 45 ; 90)
   ⇨**73 texture indices**
5. **Principal component analysis** to select the **more discriminant attributes:**

- **21 texture indices**
- **8 spectral bands**
- **Soil Adjusted Vegetation Index (SAVI)**
- **Brightness Index (BI)**

eCognition segmentation/classification

6 levels of multiresolution **segmentation** + hierarchical **classification**

based on membership functions

Level 1

Scale : 160
Layers : Pan, Y, R, RE, BI

Cloud / shadow

Vegetation

Road / building

Pan= panchromatic
CB= costal
B= blue
Y= yelow
R= red
RE= red edge
NIR = near infra red
BI= Brightness Index
SAVI= Soil Adjusted Veg° Index
Entr19= entropy / 19 pix kernel
Entr23= entropy / 23 pix kernel

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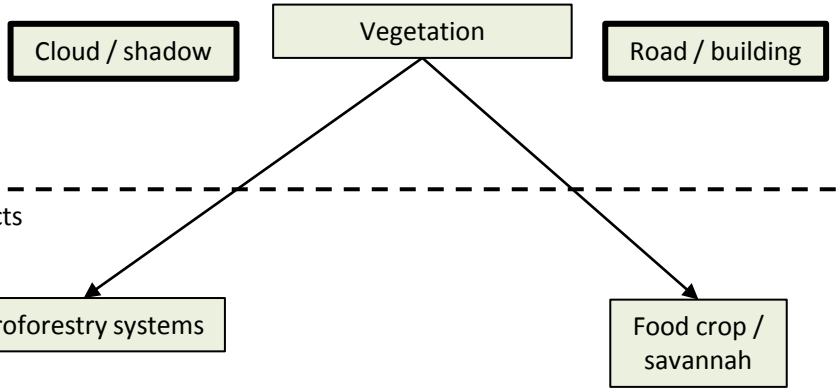

Level 2

Scale : 400
Layers : Pan, R, RE, NIR2, SAVI

Pan= panchromatic
CB= costal
B= blue
Y= yelow
R= red
RE= red edge
NIR = near infra red
BI= Brightness Index
SAVI= Soil Adjusted Veg° Index
Entr19= entropy / 19 pix kernel
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eCognition segmentation/classification

6 levels of multiresolution **segmentation** + hierarchical **classification** based on membership functions

Level 1

Scale : 160
Layers : Pan, Y, R, RE, BI

Cloud / shadow

Vegetation

Road / building

Merging same class adjacent objects

Level 2

Scale : 400
Layers : Pan, R, RE, NIR2, SAVI

Agroforestry systems

Food crop / savannah

Merging same class adjacent objects

Taro

Other low-density vegetation

Burnt area

Level 3

Scale : 400
Layers : Y, R, RE, NIR1, Entr19

Pan= panchromatic
CB= costal
B= blue
Y= yelow
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eCognition segmentation/classification

6 levels of multiresolution **segmentation** + hierarchical **classification** based on membership functions

Level 1

Scale : 160
Layers : Pan, Y, R, RE, BI

Cloud / shadow

Vegetation

Road / building

Merging same class adjacent objects

Level 2

Scale : 400
Layers : Pan, R, RE, NIR2, SAVI

Agroforestry systems

Food crop / savannah

Merging same class adjacent objects

Taro

Other low-density vegetation

Burnt area

Level 3

Scale : 400
Layers : Y, R, RE, NIR1, Entr19

Merging same class adjacent objects

Other tree grove

Savannah

Annual crop

Level 4

Scale : 200
Layers : Pan, CB, B

Pan= panchromatic
CB= costal
B= blue
Y= yelow
R= red
RE= red edge
NIR = near infra red
BI= Brightness Index
SAVI= Soil Adjusted Veg° Index
Entr19= entropy / 19 pix kernel
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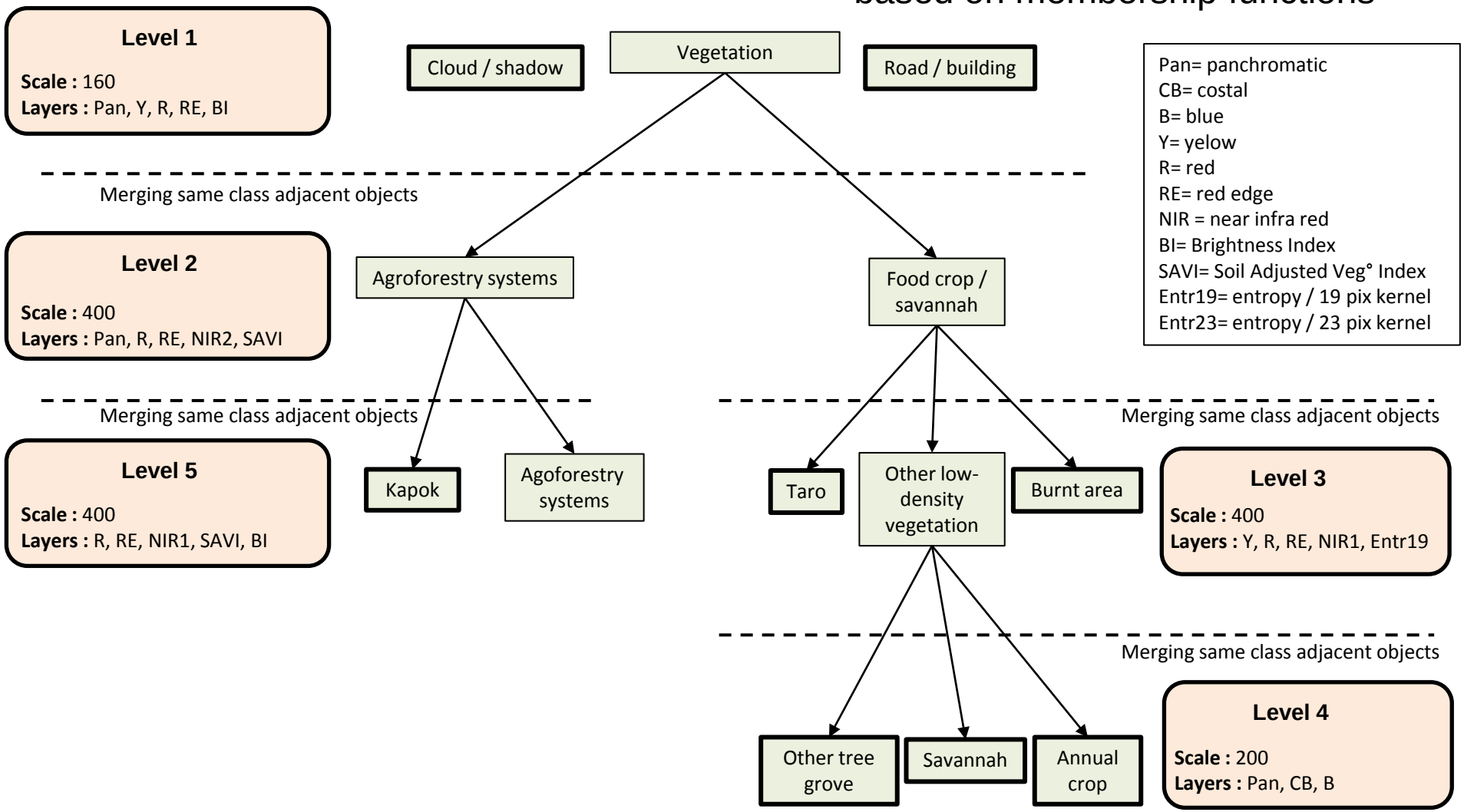
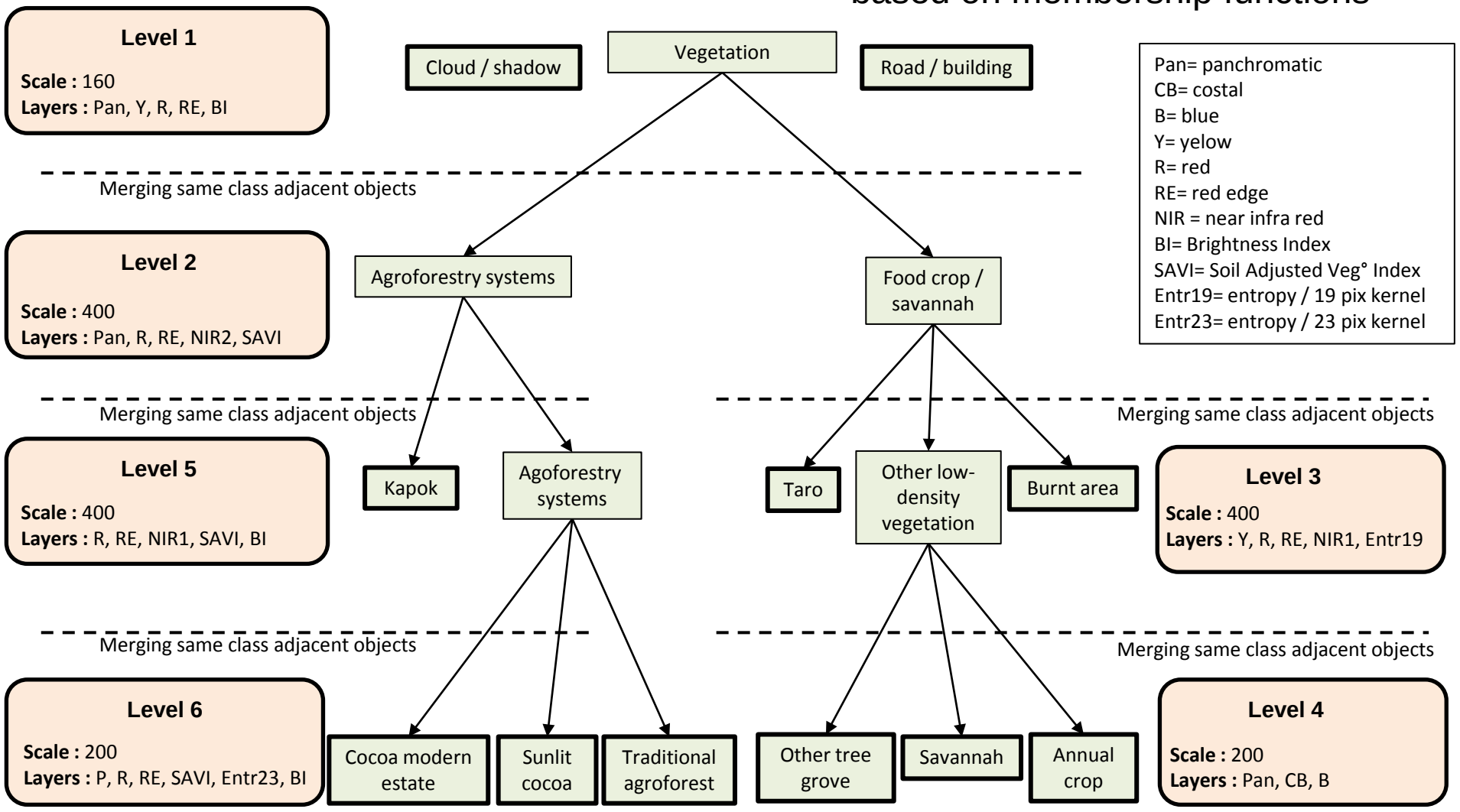
eCognition segmentation/classification

6 levels of multiresolution **segmentation** + hierarchical **classification** based on membership functions



eCognition segmentation/classification

6 levels of multiresolution **segmentation** + hierarchical **classification** based on membership functions



Classification validation

- Random extraction of 660 validation points, characterized out of field enquiry or photointerpretation
- Confusion matrix derivation

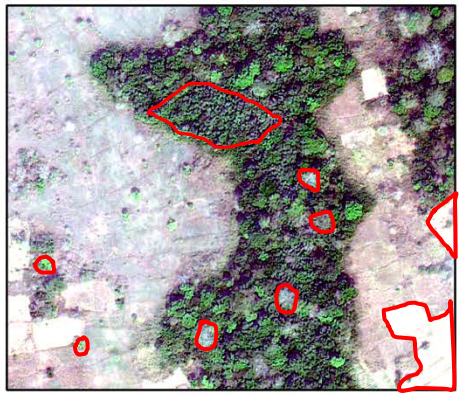
↳ **Global accuracy = 85% - Kappa = 0.84**

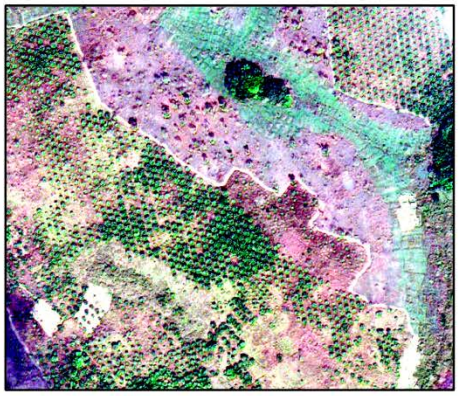
↳ Very high accuracy for most of the classes:

- roads and buildings: 95%, burnt areas: 86%
- food crops: 96%, annual crops: 90%
- **Agroforests: 92%,** modern cacao agroforestry plantation: 92%
- Other tree groves (palm): 98%

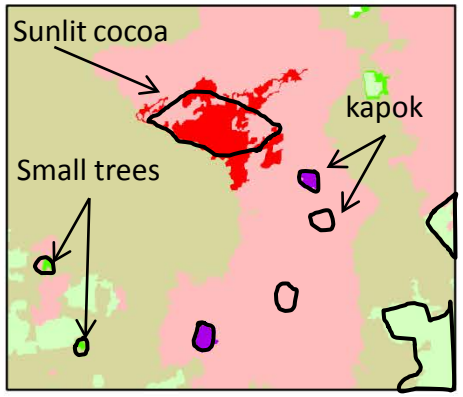
↳ Lower accuracy for savannah: 79**%,** kapok: 74%, sunlit cocoa: 73%, taro: 71%

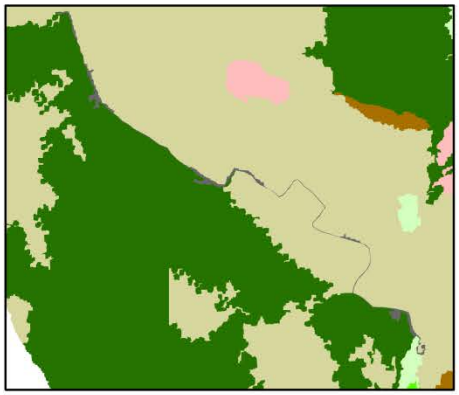
Tree cover mapping





0 125 250 m

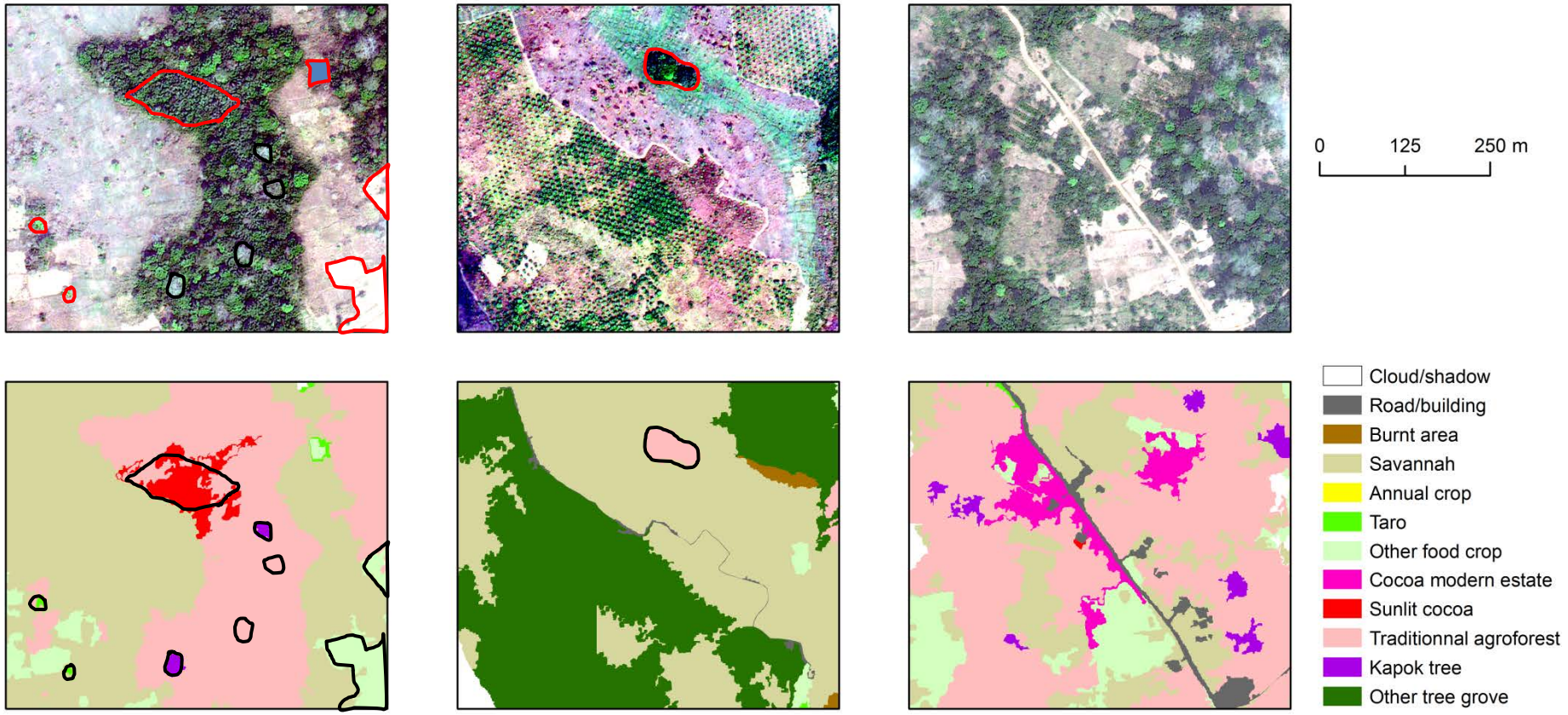




- Cloud/shadow
- Road/building
- Burnt area
- Savannah
- Annual crop
- Taro
- Other food crop
- Cocoa modern estate
- Sunlit cocoa
- Traditionnal agroforest
- Kapok tree
- Other tree grove

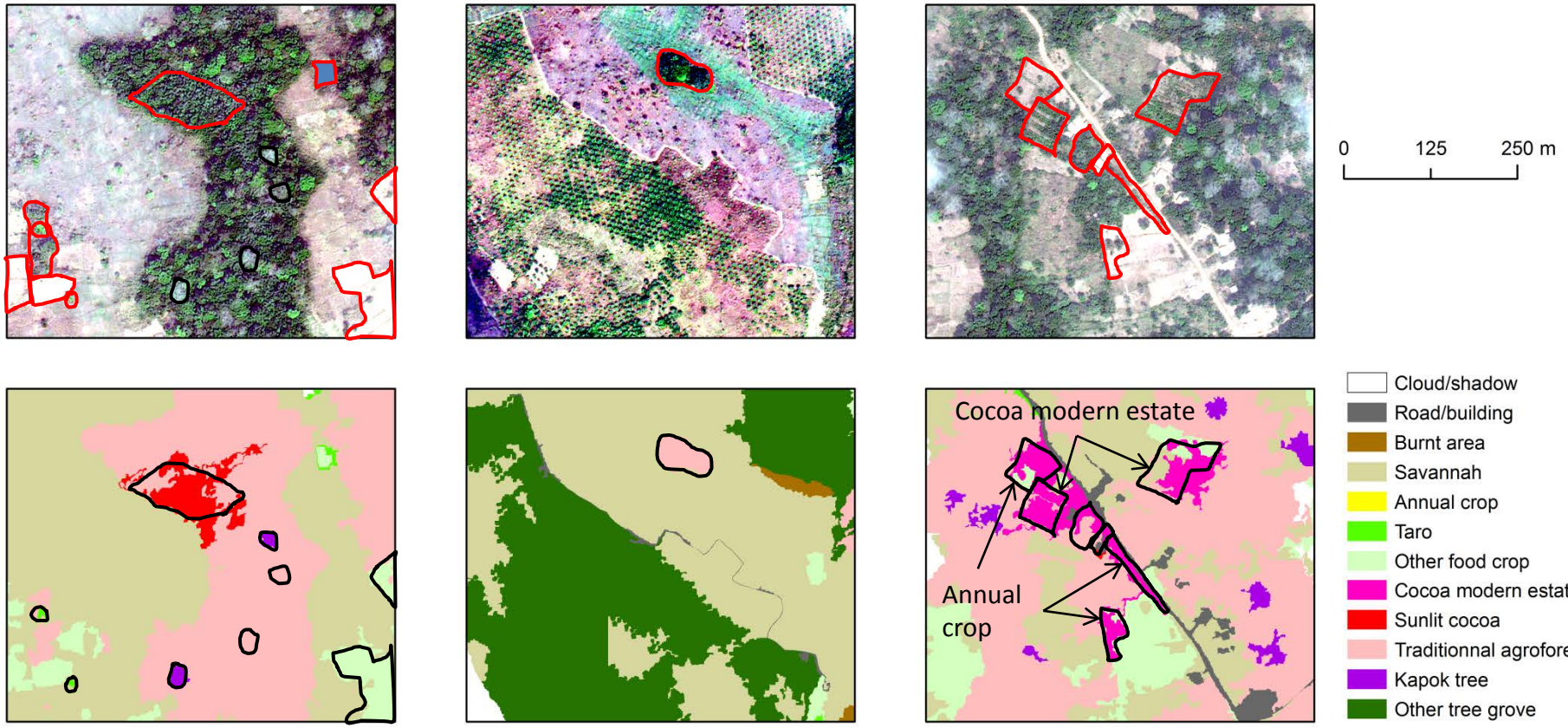
- Good mapping of the cropland with good discrimination of agroforests and savannahs,
- Good mapping of the small patches inside the savannah like small agroforests or food crops.
- Nice detection of sunlit cocoa patch inside the agroforest.
- Many kapok trees are missing
- Some small trees are misclassified as taro

Tree cover mapping



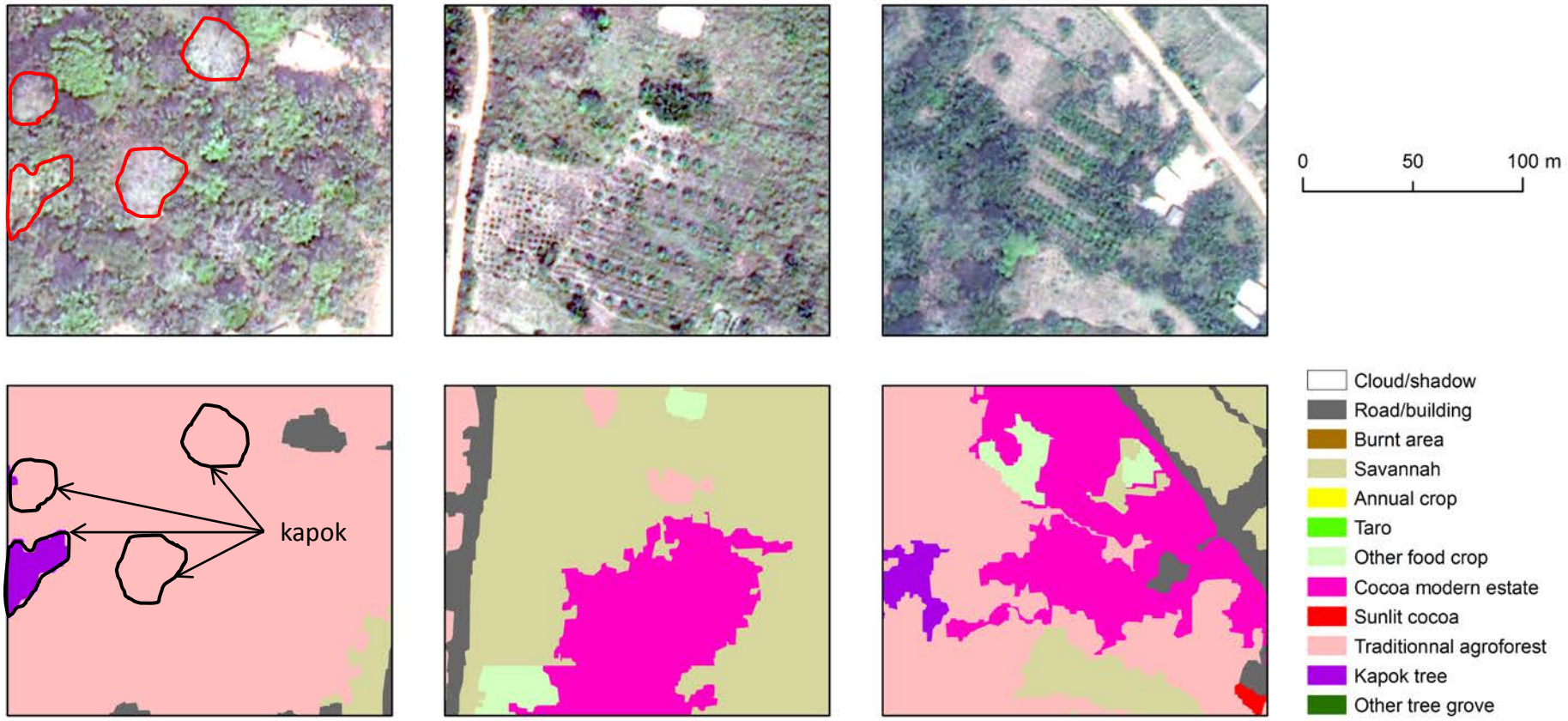
- Good recognition and mapping of an oil palm grove
- Good mapping of agroforest patches inside the savannah

Tree cover mapping



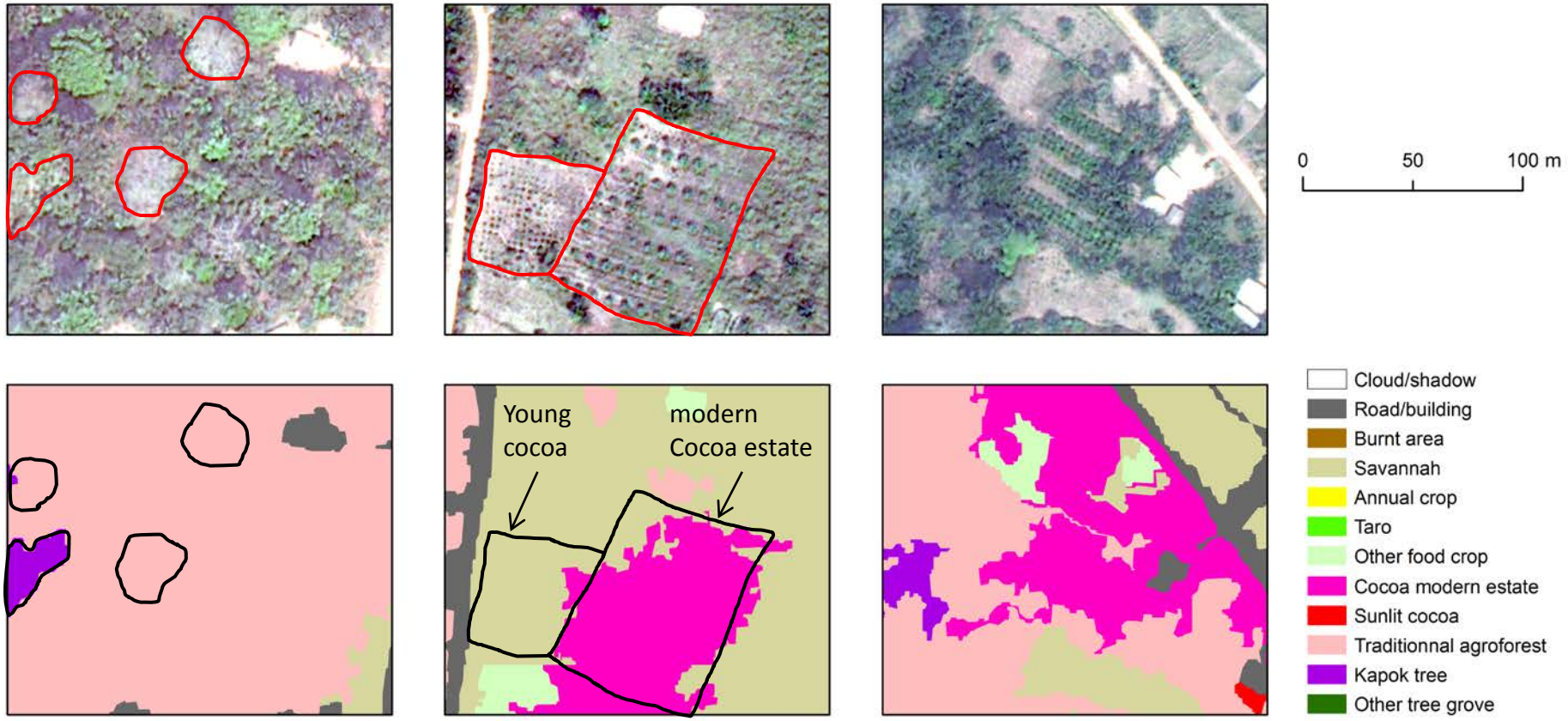
- Interesting recognition of the cocoa modern estates but sometimes with very bad delimitation (segmentation error)
- Misclassification of an annual crop including some isolated trees as sunlit cocoa

Tree land-use recognition



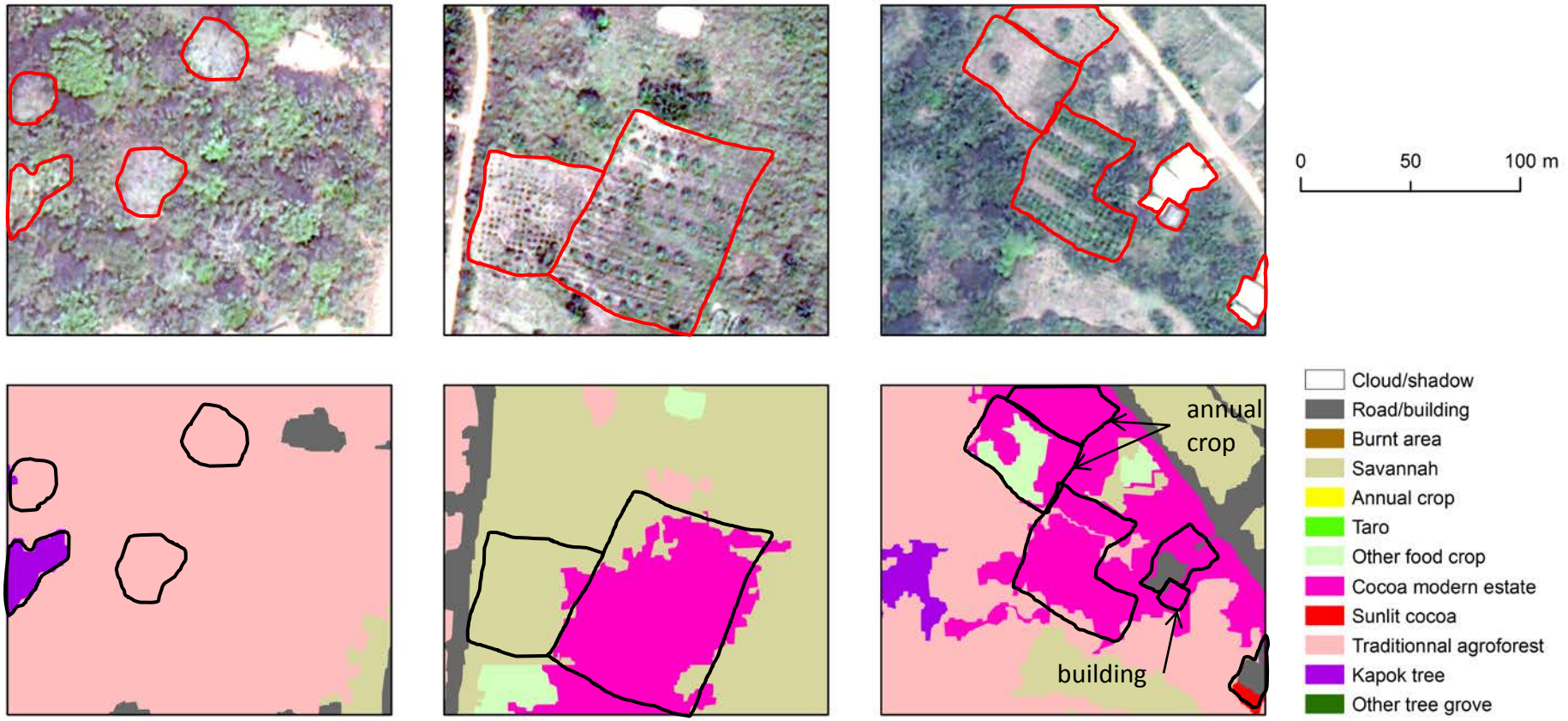
- Good discrimination between the different cocoa agroforestry systems
- Agroforests are very well delimitated ⇨ potential to map different tree species?
- Still some kapok missing… maybe not the easiest type of tree to discriminate?

Tree land-use recognition



- Misclassification of young a cocoa grove as savannah, due to small size of trees ⇨need of a complementary level of segmentation or smaller kernel texture indices

Tree land-use recognition



- Zoom on the modern cocoa plantation with the strong defficiency of the segmentation leading to very bad classification of the area

Conclusion and perspectives

Thematic classification is well reached but suffers from **local errors in segmentation**.

Classification nomenclature should be improved, increasing also its reliability.
Eg. additional classes should be integrated:

- Natural forest vs. agroforest discrimination (in an enlarged image frame).
- Big trees (other than kapok) delimitation and various species recognition
- Distinction of various types of traditionnal agroforests (composition, density, mean and maximum tree size…)

⇨ Application on a new WV2 mono-acquisition (dec. 2013, no cloud)

Some solutions should arise from the use of stereo imagery (height info)!

Encouraging results, providing with **a map of high global accuracy and value:**

- spatialized information about the cropland structure & the implantation and distribution of the various agroforestry systems.
  - ↳ GIS to analyze the relationships between agroforestry settings and altitude (needs for precise DTM), hydrography, road infrastructure…
- intraplot structure and complexity, through the localization and density of entities like sunlit cocoa patches, kapok trees, and eventually at some future: other tree species (to be further analyzed), and the estimation of tree crown.
  - ↳ dispositive of production and/or environmental services evaluation of the cropping systems.

Thank you for your attention !

Contacts:
camille.lelong@cirad.fr
stephane.dupuy@cirad.fr

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