Food and Agriculture Organization of the United Nations

SUSTAINABLE DEVELOPMENT GOALS

# AFRICAN COMMISSION ON AGRICULTURAL STATISTICS

## 28TH SESSION

4–8 December 2023
Johannesburg (South Africa)

AFCAS 28

## LEVERAGING DATA & STATISTICS FOR AGRIFOOD SYSTEMS TRANSFORMATION IN AFRICA

# AGENDA ITEM 10:
# NEW DEVELOPMENTS IN THE USE OF ALTERNATIVE DATA SOURCES FOR AGRICULTURAL STATISTICS

AFRICAN COMMISSION ON **AGRICULTURAL STATISTICS**

# Earth Observations for official Statistics in Africa: experience from pilot projects in countries in Africa.

Presenter: Lorenzo DeSimone, FAO-OCS; Louis Muhigirwa, FAOZW

# EO BIG DATA AND AGRICULTURAL STATISTICS EOSTAT

A) Earth Observations Big Data and Agricultural Statistics
B) Establishment and scope of work of the Task Teak on EO for Agriculture Stats under the joint UN CEAG-CEBD
C) EOSTAT results from projects in countries:

- ❑Zimbabwe
- ❑Senegal and Mali
- ❑Lesotho
- ❑Rwanda

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# Crop acreage, yield and production

- Projected crop production information is critical for a nation's food security (Jayne and Rashid 2010)
- Early and accurate accounting of crop acreage and yield allows for computing production data for rapid response to crises (Savary et al. 2012) as well as monitoring and promoting sound agronomic practices (Singh et al. 2013; Mehrabi and Sepaskhah 2019)
- The perfect knowledge of acreage and yield before harvest plays a critical role in decision making for different stakeholders – from farmers to policy makers to governments for food security to commodities traders (B. Basso, L. Liu, 2019)
- However, difficulties arise in the gathering of statistical information using tradition survey based methods due to the heterogeneity of producer operations, soil condition, and weather events which inhibits the ability of nations to establish explicit yield prediction (Taylor et al. 2007) and timely assessment of crop acreage before the harvest.
- In this context Big data from Earth Observations offer a viable solution as an alternative or an integration to traditional survey based methods

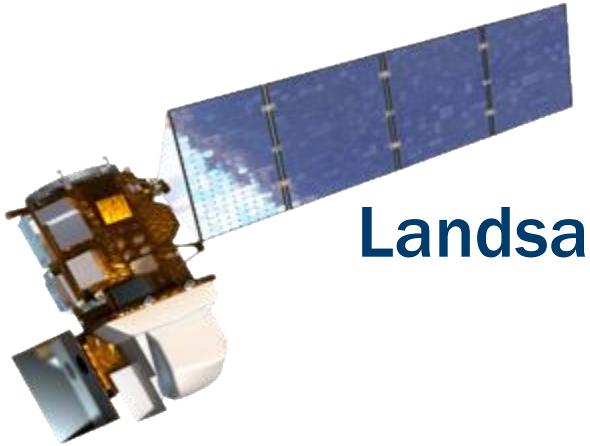
# THE AGE OF BIG EARTH OBSERVATION DATA



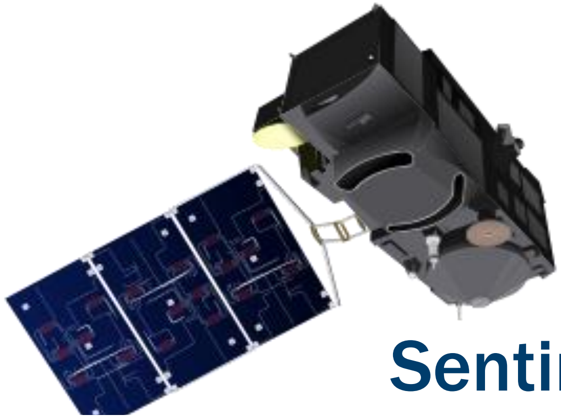
Terra

Sentinel-1/1A

Sentinel-2/2A



Landsat-8



Sentinel-3

CBERS-4/4A

# THE NEW DIGITAL ECONOMY

images: shutterstock

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Low access cost

big data

public APIs

massive use

Google, Weibo, Twitter/X, WeChat, Waze,...

# Silicon Valley comes to Earth observations
# Google Earth Engine:

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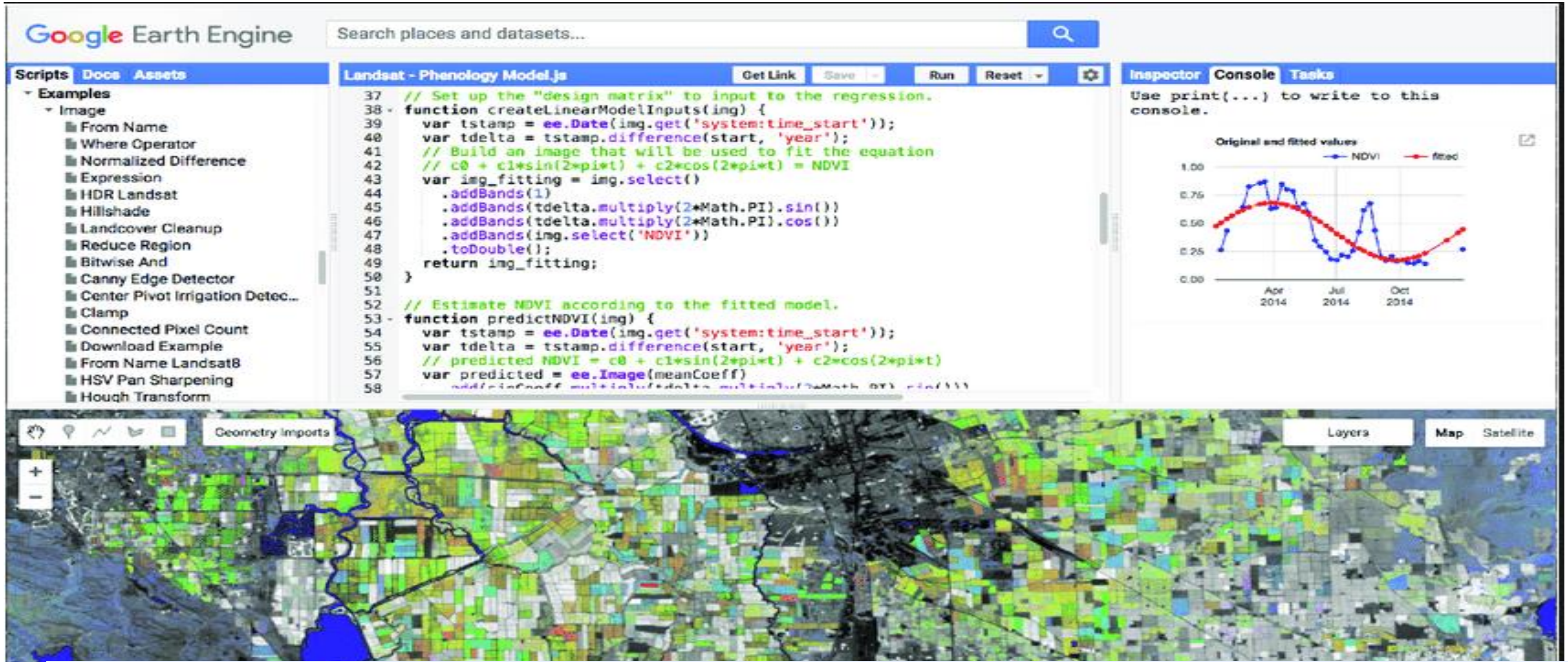
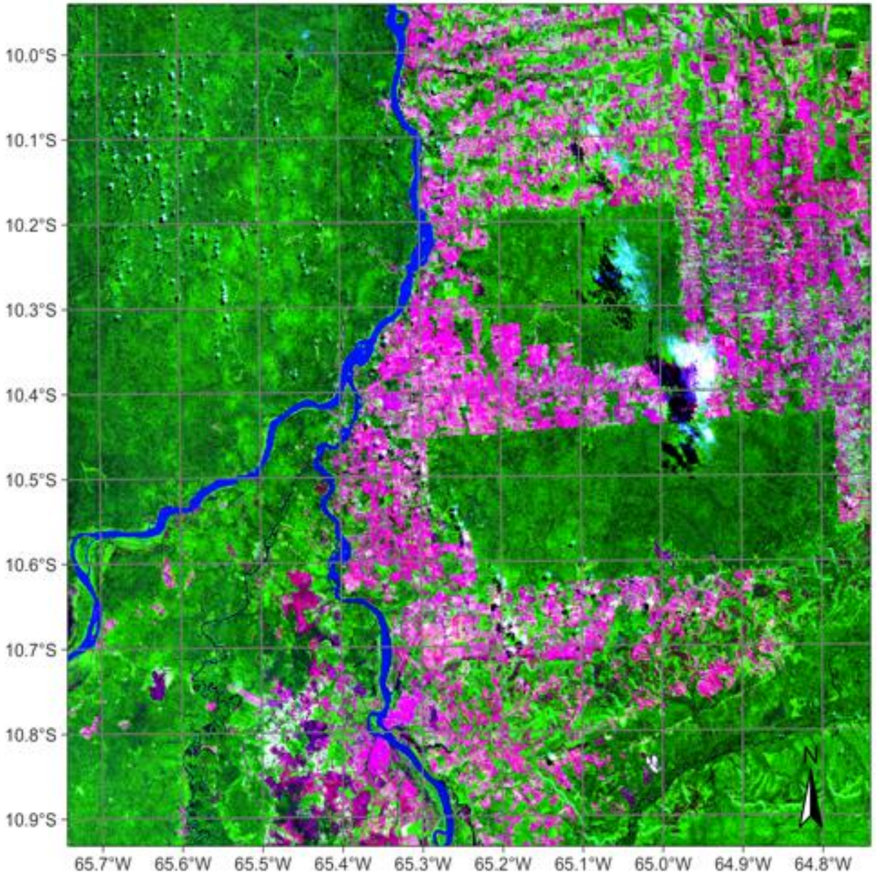



Global enabler (2.000+ papers): low entry cost to big Earth observation data analysis

# Processing data in Microsoft Planetary Computer (MPC)

```
# create a data cube covering an area in the Brazilian Amazon
s2_20LKP_cube_MPC <- sits_cube(
      source = "MPC",
      collection = "SENTINEL-2-L2A",
      tiles = "20LKP",
      bands = c("B02", "B8A", "B11", "CLOUD"),
      start_date = "2019-07-01",
      end_date = "2019-07-28"

)
# plot a color composite of one date of the cube
plot(s2_20LKP_cube_MPC, red = "B11", blue = "B02", green = "B8A",  date = "2019-07-18")
```



# 7 LINES OF CODE TO DEVELOP A NATIONAL LAND COVER MAP

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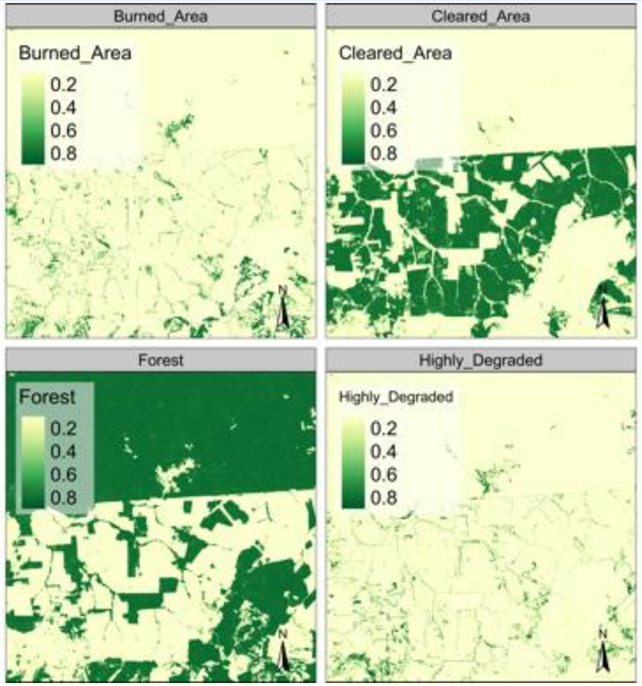
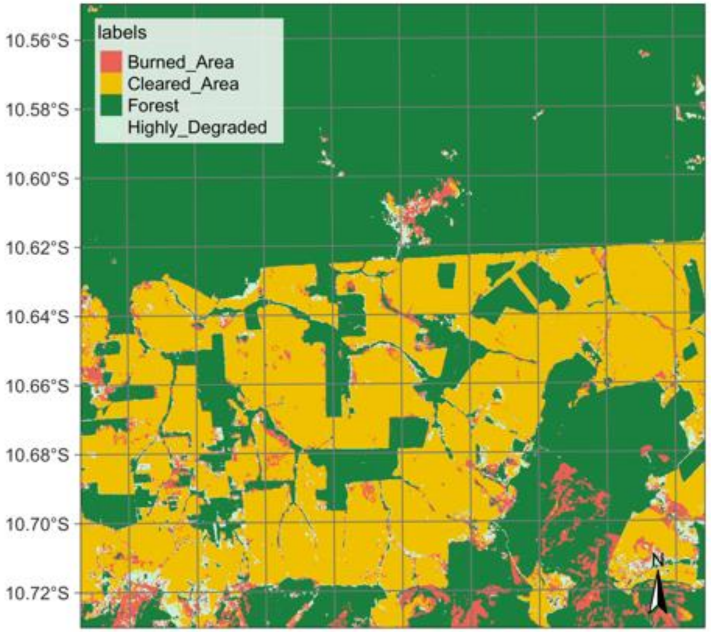
```
# classify data cube
ro_cube_20LKP_probs <- sits_classify
        (data = ro_cube_20LKP,
        ml_model = ltae_model)

plot(ro_cube_20LKP_probs
```



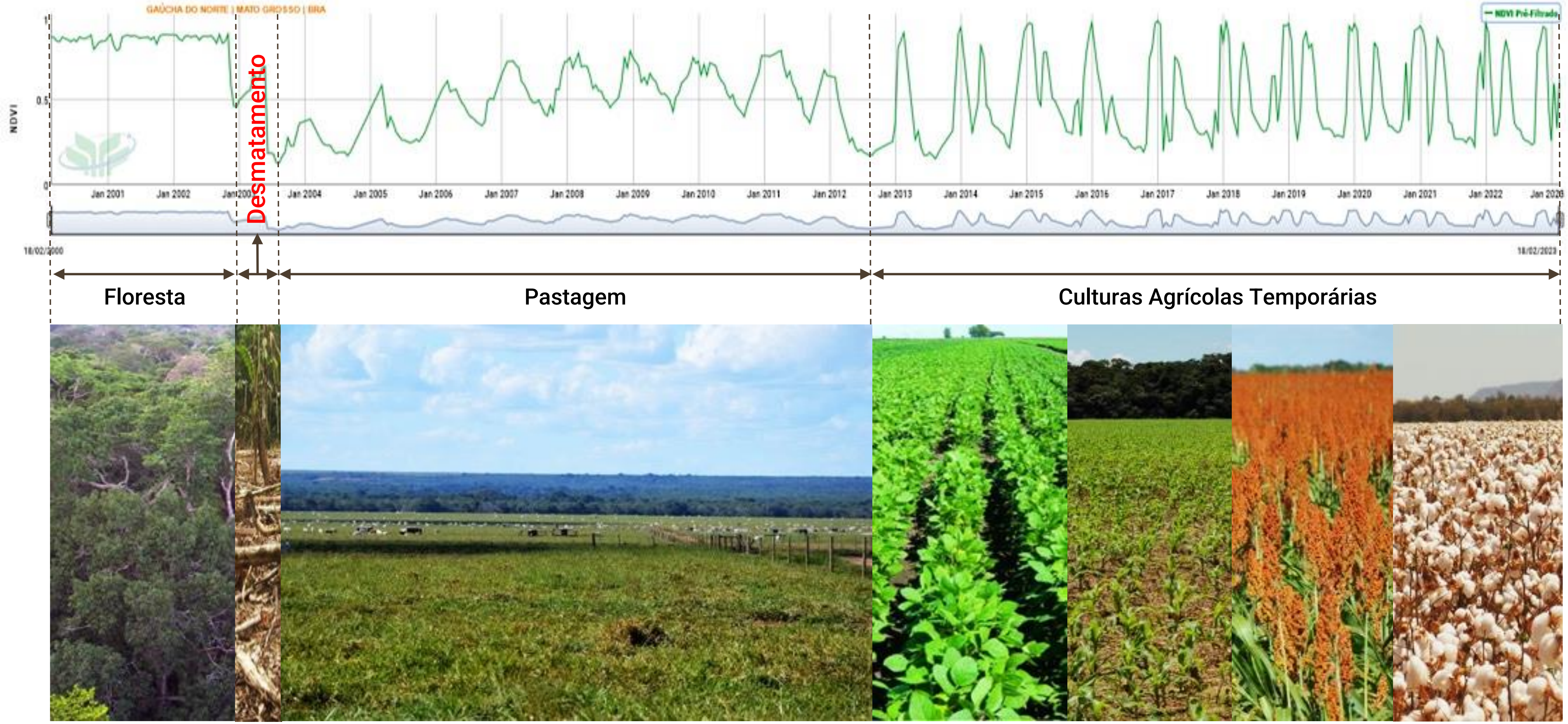

```
# generate thematic map
defor_map <- sits_label_classification
        (cube = ro_cube_20LKP_probs)

plot(defor_map)
```




Source: Gilberto Camara

# WHY EO data time series? Because it shows change!!!




Embrapa Agricultura Digital

Source: EMBRAPA

# 2019 EOSTAT is launched by FAO

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Food and Agriculture Organization of the United Nations
Discover

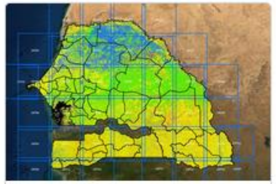
## Use of Earth Observation Data (FAO-EOSTAT)

### FAO-EOSTAT

Launched in 2019, FAO's EOSTAT project uses next generation Earth observation tools to produce land cover and land use statistics. Initially deployed in Senegal and Uganda, then expanded to 21 countries, the innovative approach relies on free of charge Earth observation data, vegetation and climate modelling, as well as field survey data to build countries' capacity to produce seasonal crop type maps, annual land cover maps that are standardized, accurate, granular and validated. FAO and its partners are now seizing the opportunity to expand the project to other countries in Africa, Asia, Latin America and the Caribbean to make agrifood systems more resilient and achieve Zero Hunger.

### Resources

FAO has developed a number of online tools and resources to assist countries in using EOSTAT.


MAP STORY


MAP STORY


ONLINE TOOL

### Related links

FAO Statistics

Hand-in-Hand

United Nations Committee of Experts on food security, agricultural and rural statistics (UN-CEAG)

### Research articles


ONLINE TOOL

**Crop Mapper online tool (Ecuador)**

EOSTAT tool for estimating crop yield for different crops in Ecuador


**FAO-EOSTAT project training**

2023

Launched in 2021 by the Food and Agriculture Organization of the United Nations (FAO), the EOSTAT project uses next generation Earth observation tools...


**Lesotho: Land cover atlas 2017–2023**

2023

The NextGen-Atlas of Lesotho provides information on the land cover distribution at multiple geographical levels and across the time frame 2017-2022:...

Using Standardized Time Series Land Cover Maps to Monitor the SDG Indicator "Mountain Green Cover Index" and Assess Its Sensitivity to Vegetation Dynamics

### External resources

UN Global Working Group on Big Data

United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM)

### Contact

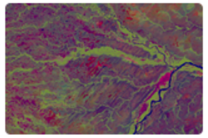
Lorenzo de Simone, Project Lead

### Highlights


**Two awards recognize FAO's innovative use of geospatial technologies**

08/11/2023

The WaPOR water-efficiency portal and a land-cover monitoring project in Lesotho both contribute to SDG monitoring


**FAO, Digital Earth Africa and Frontier SI's collaboration to enhance the use of Earth observations in Africa**

17/06/2022

The Food and Agriculture Organization of the United Nations (FAO), Digital Earth Africa and Frontier SI have initiated a new collaboration to help African countries use Earth observations to produce land cover and crop statistics


**Next generation Earth Observation tools help monitor land cover change in Lesotho**

# Relevance of EO data and the Task Team on EO data for Agricultural Statistics under the joint UNCEAG-UNCEB



A Task Team on Satellite Imagery was first created in 2014 (under the Global Working Group on Big Data for Official Statistics), with a mandate

i)to identify approaches for collecting representative training data;
ii)develop and implement methods using satellite imagery and the training data for producing official statistics, including the statistical application of predictive models for crop production yields.
The task team was later renamed to the **Task Team** on **Earth Observation Data** for **Agriculture Statistics** to not limit the data sources just to satellite imagery.

The main objective of the Task Team is to provide concrete examples of the potential use of EO data for official statistics, to develop and share methods for estimating crop location, crop type and crop yield using optical and SAR data, produce global land cover and land use statistics. In 2017 a "Satellite Imagery and Geospatial Data Task Team report" was published as a handbook providing an introduction to the use of EO data for official statistics, types of sources available anc

# Task Team Composition

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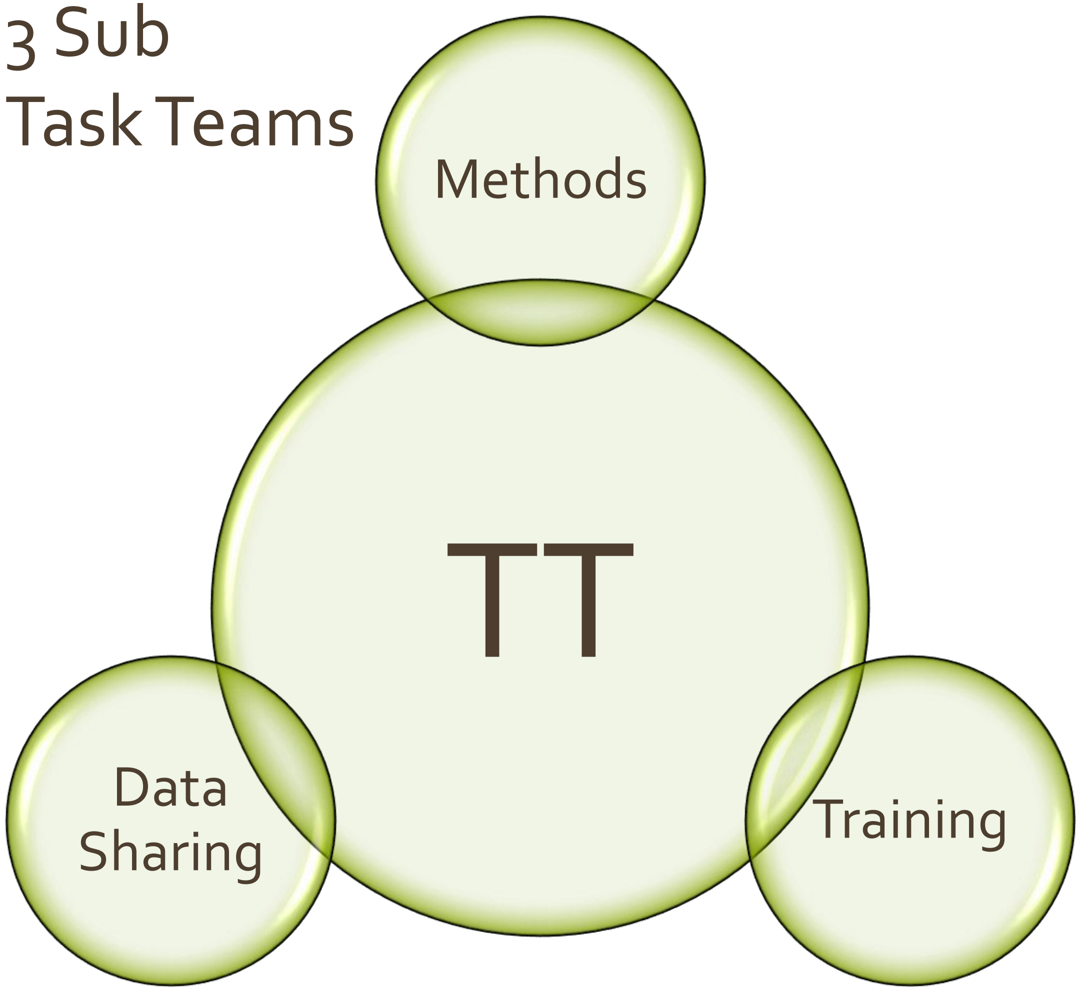
3 Sub
Task Teams




- NSO from countries globally
- UN Agencies (e.g. FAO)
- UN Big Data Regional Hubs
- Development funding bodies (e.g. WB, ADB,
- EO big data providers (Free and Open, e.g. Digital Earth Africa)
- International EO working groups (Data4SDG, GEOGLAM)

The participation to the TT has further expanded as a result of the merge with the Task Team on the Use of Earth Observations fata for Agricultural Statistics established under the **UN-CEAG** (Committee of Experts on food security, AGricolture and rural statistics

# ZIMBABWE

## WINTER WHEAT MAPPING

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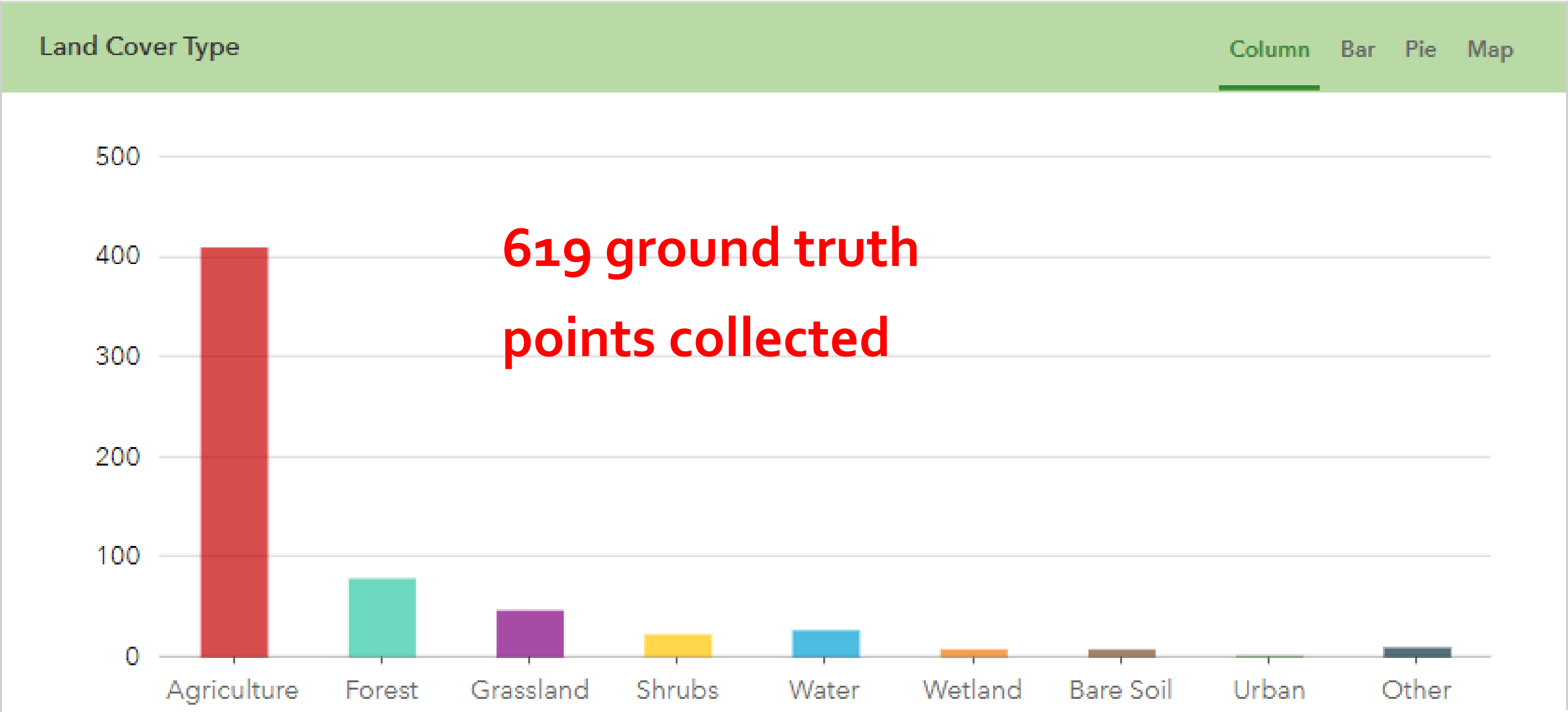
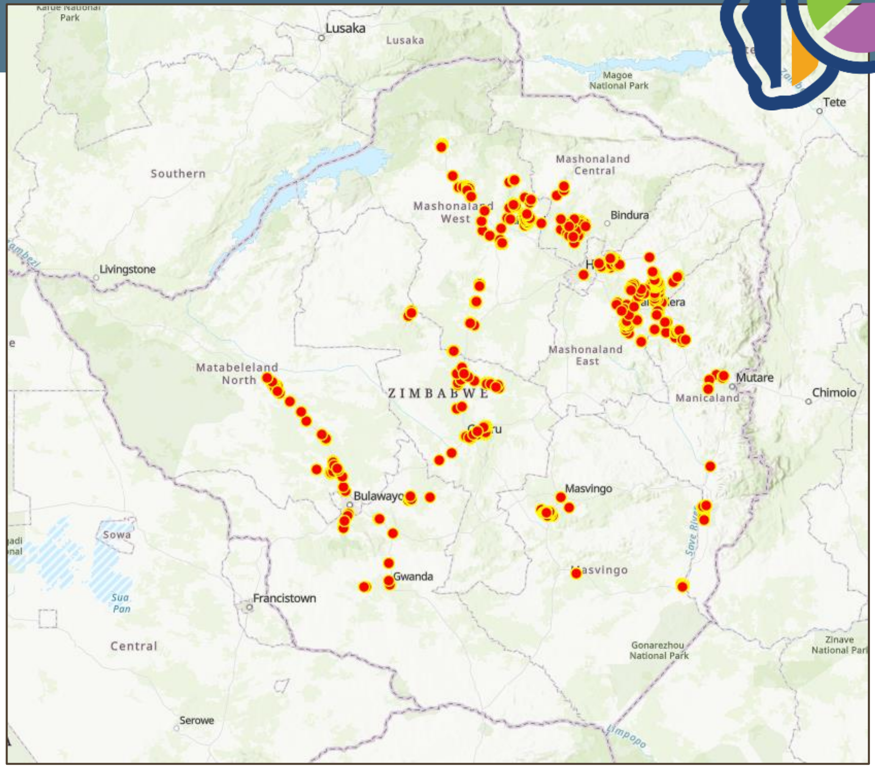
- Survey covered 8 provinces
- 11 enumerators nominated from AGRITEX
- Lenovo android iPad preloaded with Survey123 form (displayed accuracy of ±3.2m



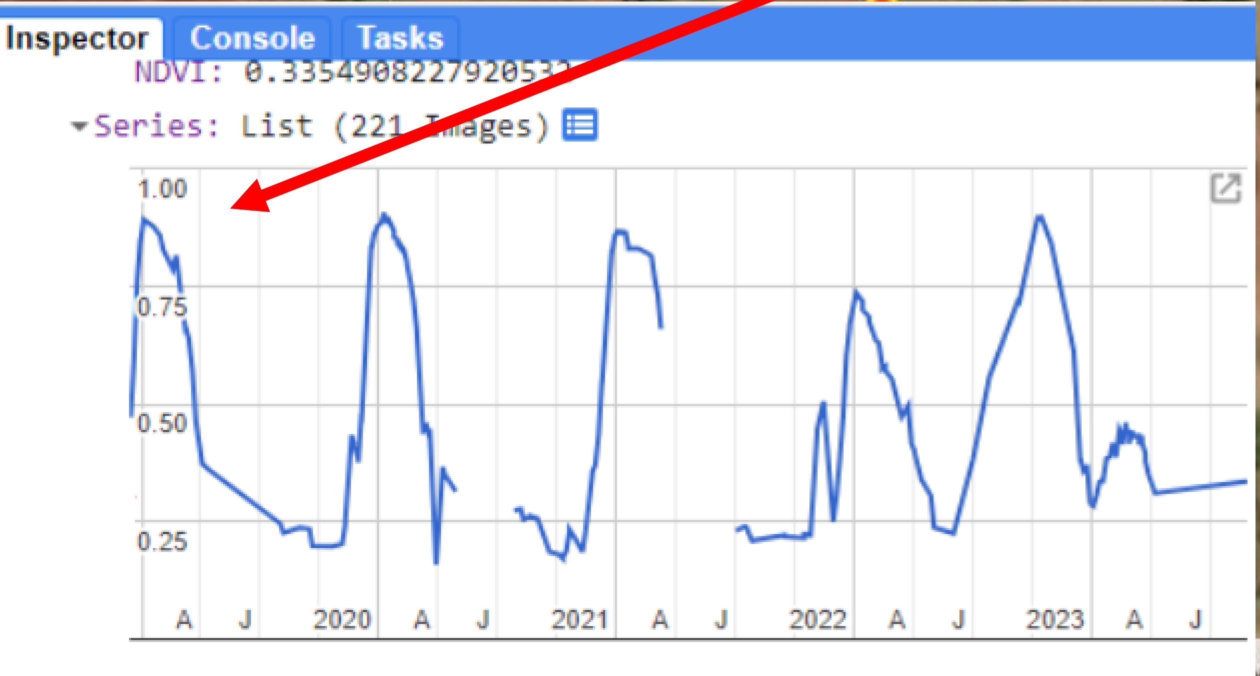

**619 ground truth points collected**

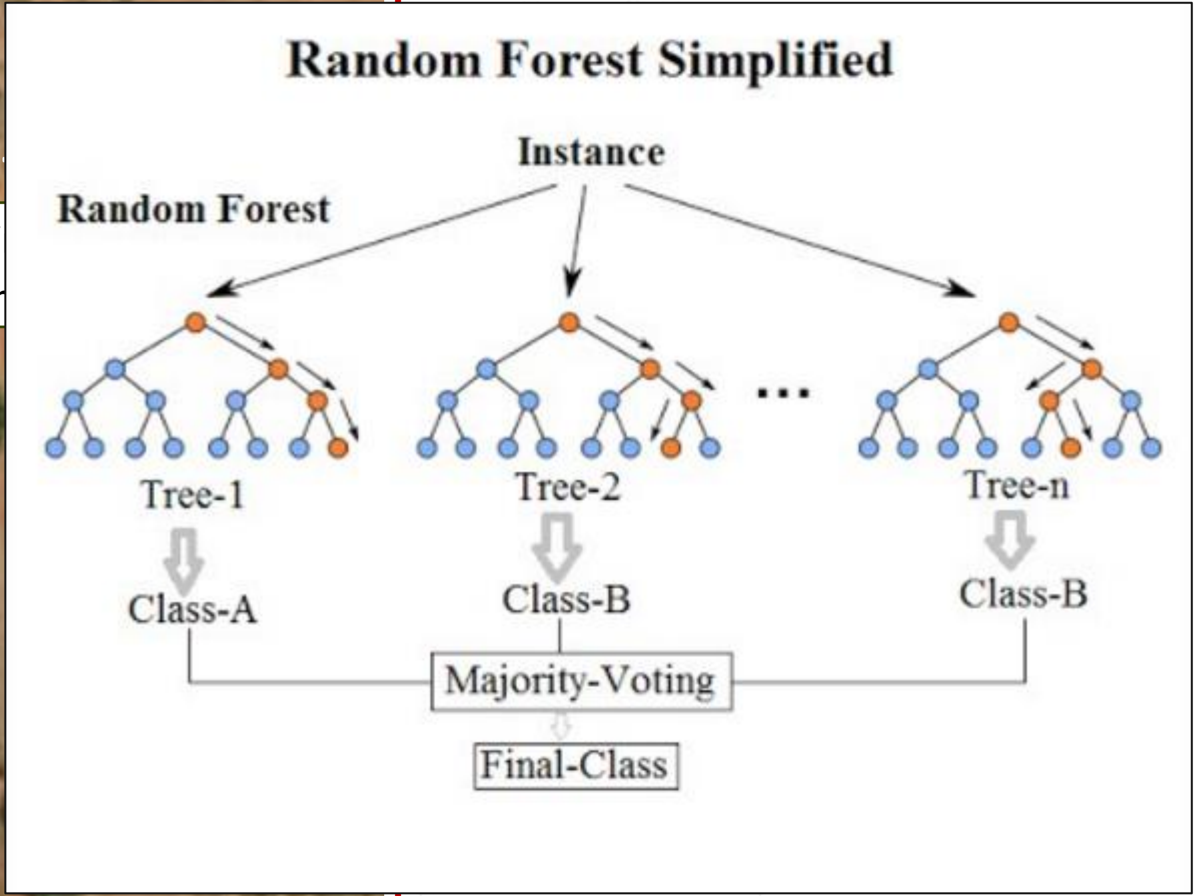


- Observations in the field include:
  - Crop type, yield and management information is recorded
  - Picture is taken

- EO data was used to verify the consistency of the vegeta[…] in time

Wi
Wh




Is this a Crop or Fallow

Crop

Maps Contributors,

# Give users all the data!

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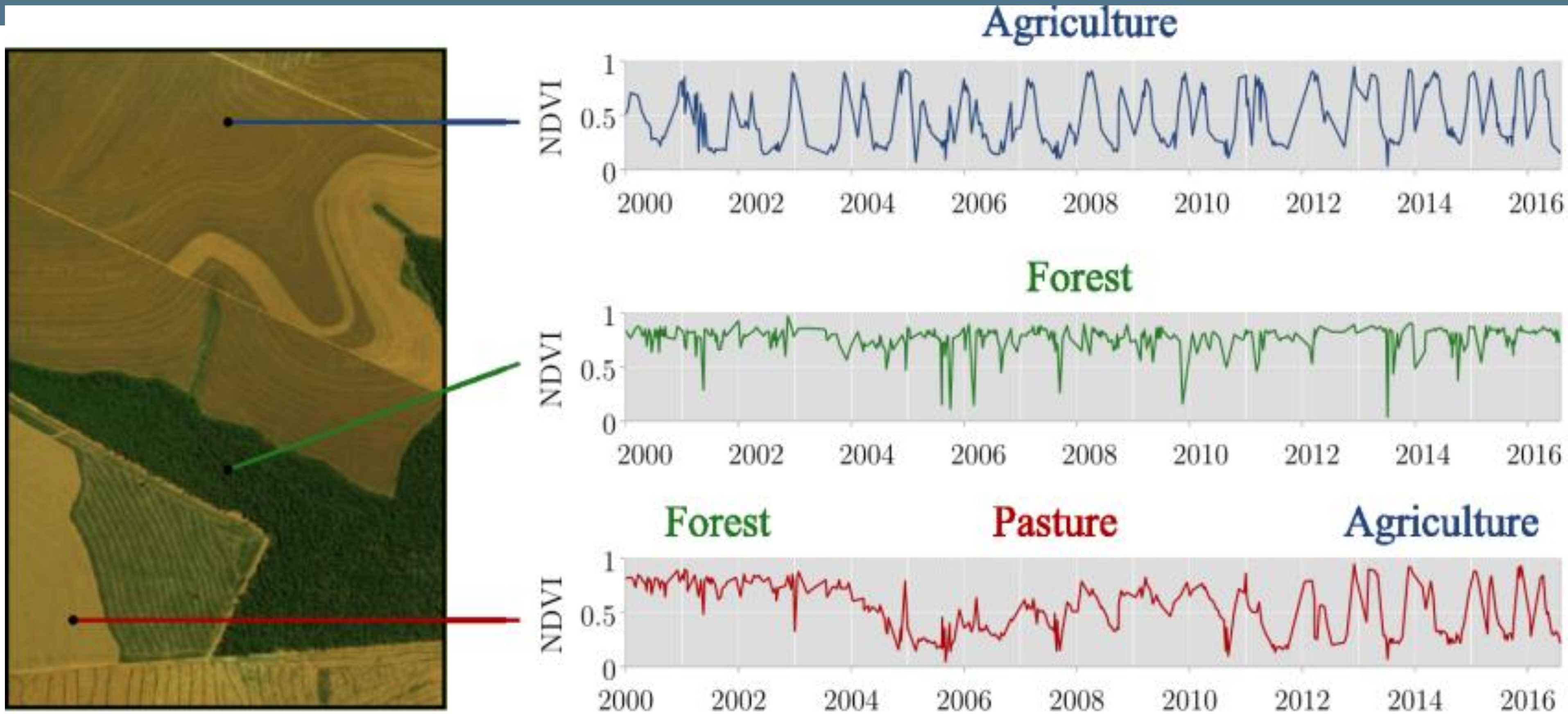


Using time series – significant increase in LUCC accuracy



Source: Gilberto Camara

# Land classification with image time series

BRAZIL DATA CUBE

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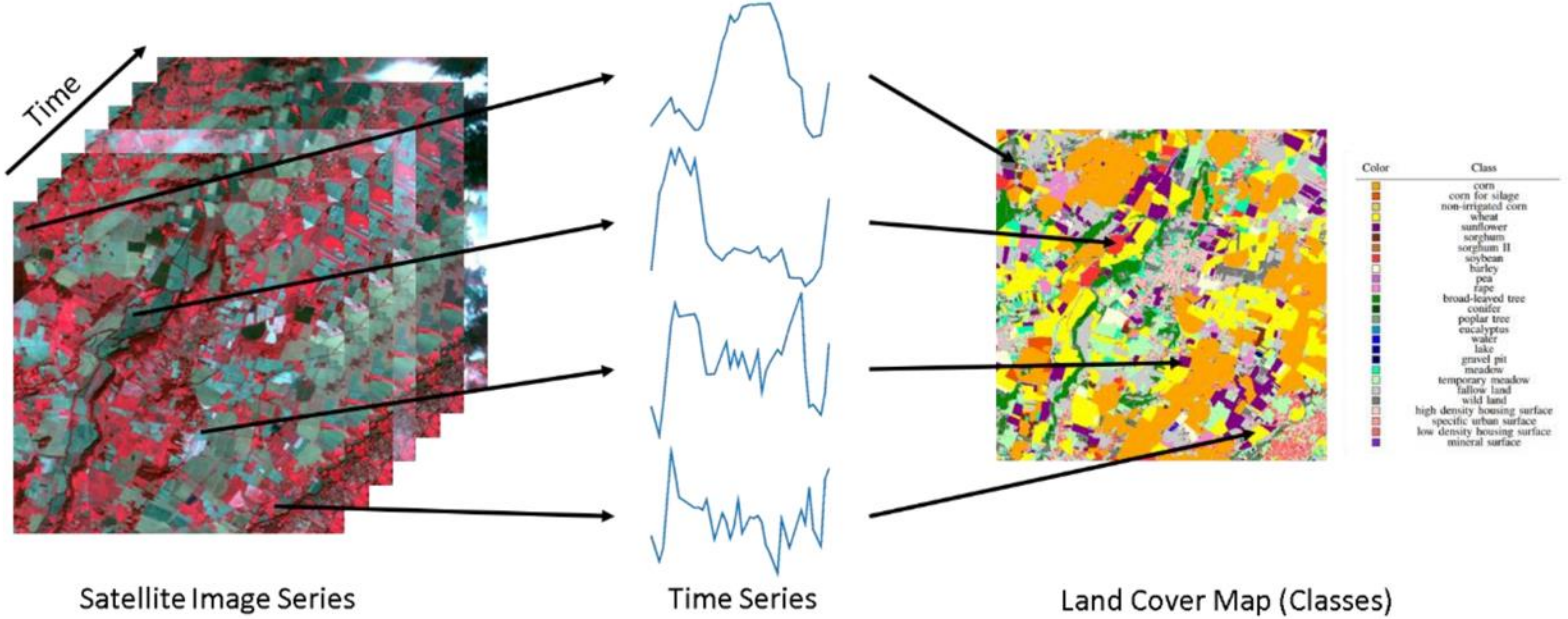
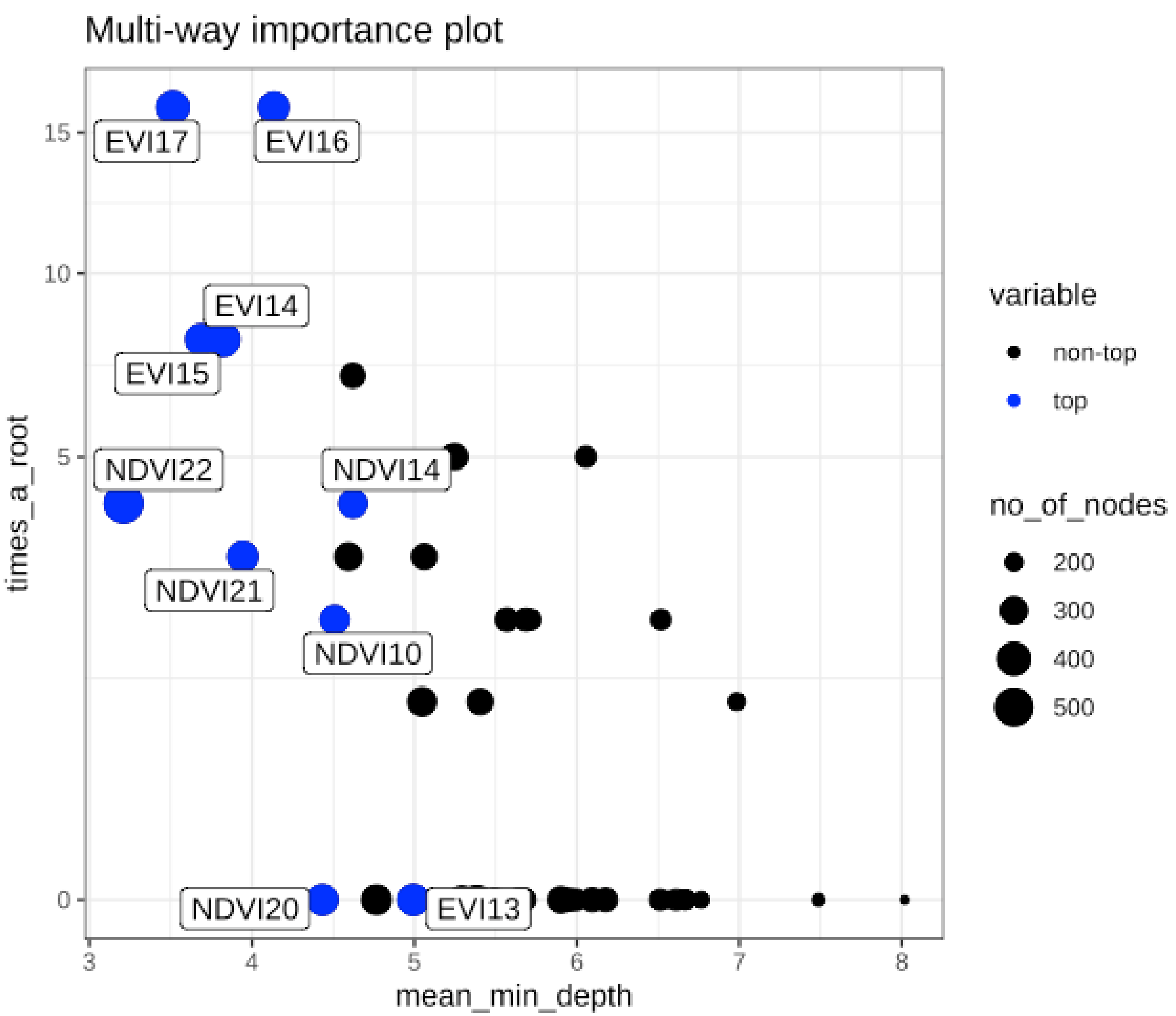


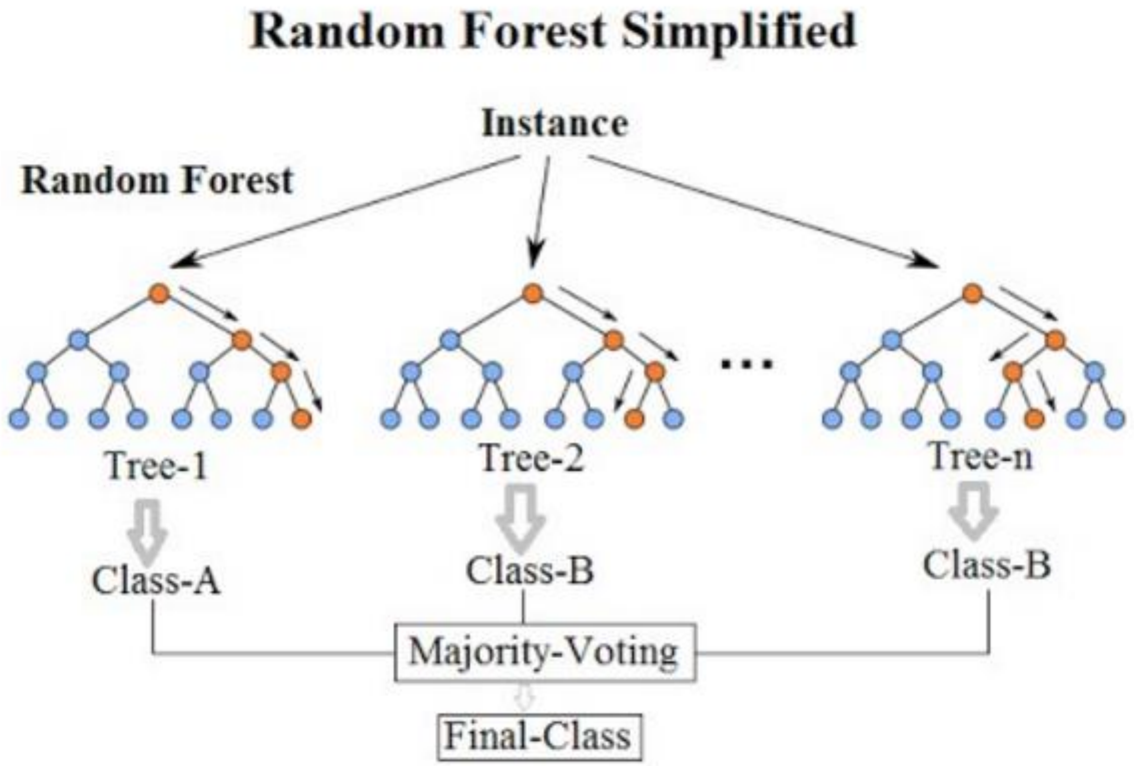



Source: F Petitjean, Monash Univ

# Random forest as one method for time series analysis





# WINTER WHEAT NATIONAL MAP 2023

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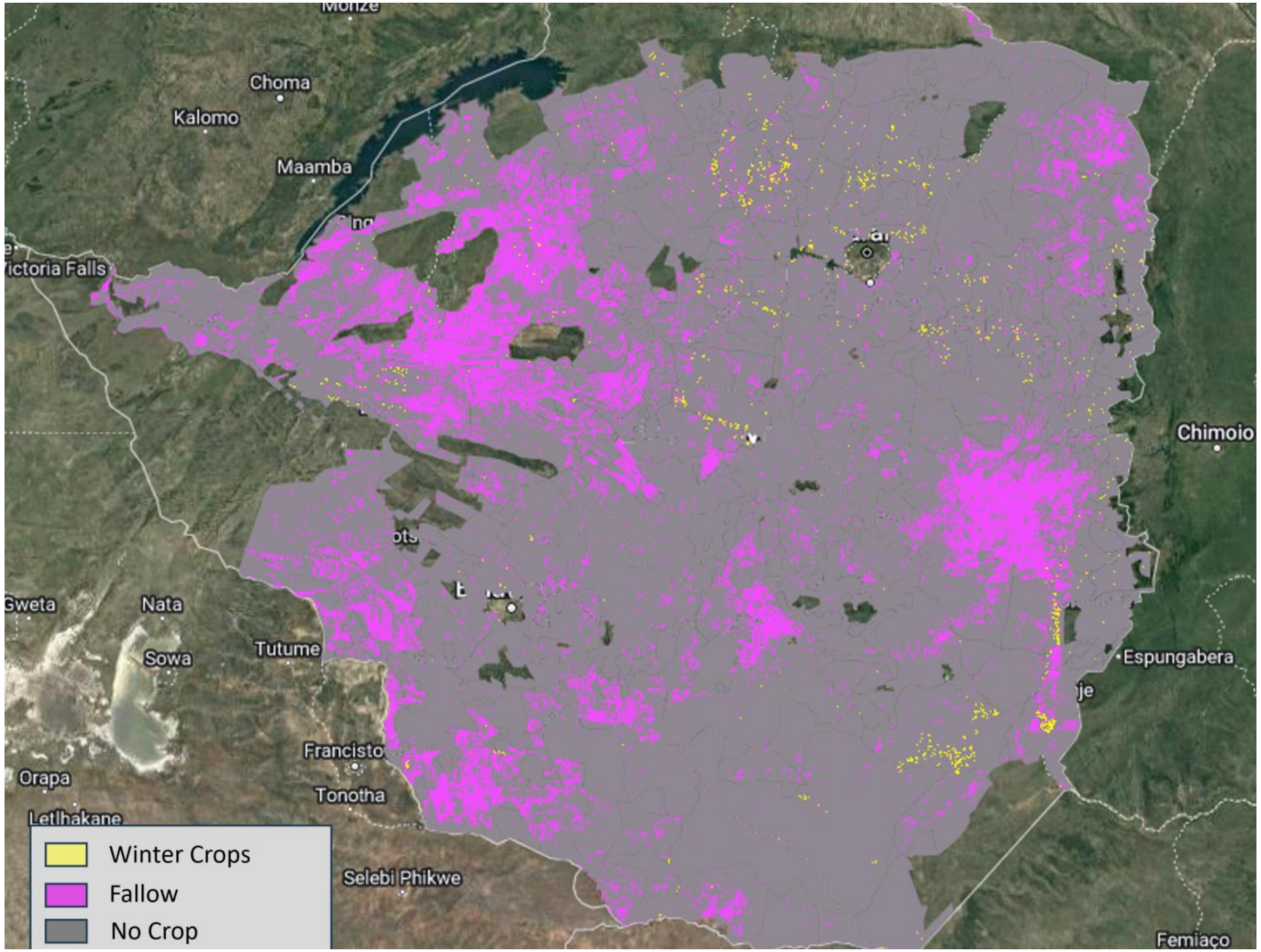


Food and Agriculture Organization of the United Nations

UNBigData

# WINTER WHEAT NATIONAL MAP 2023

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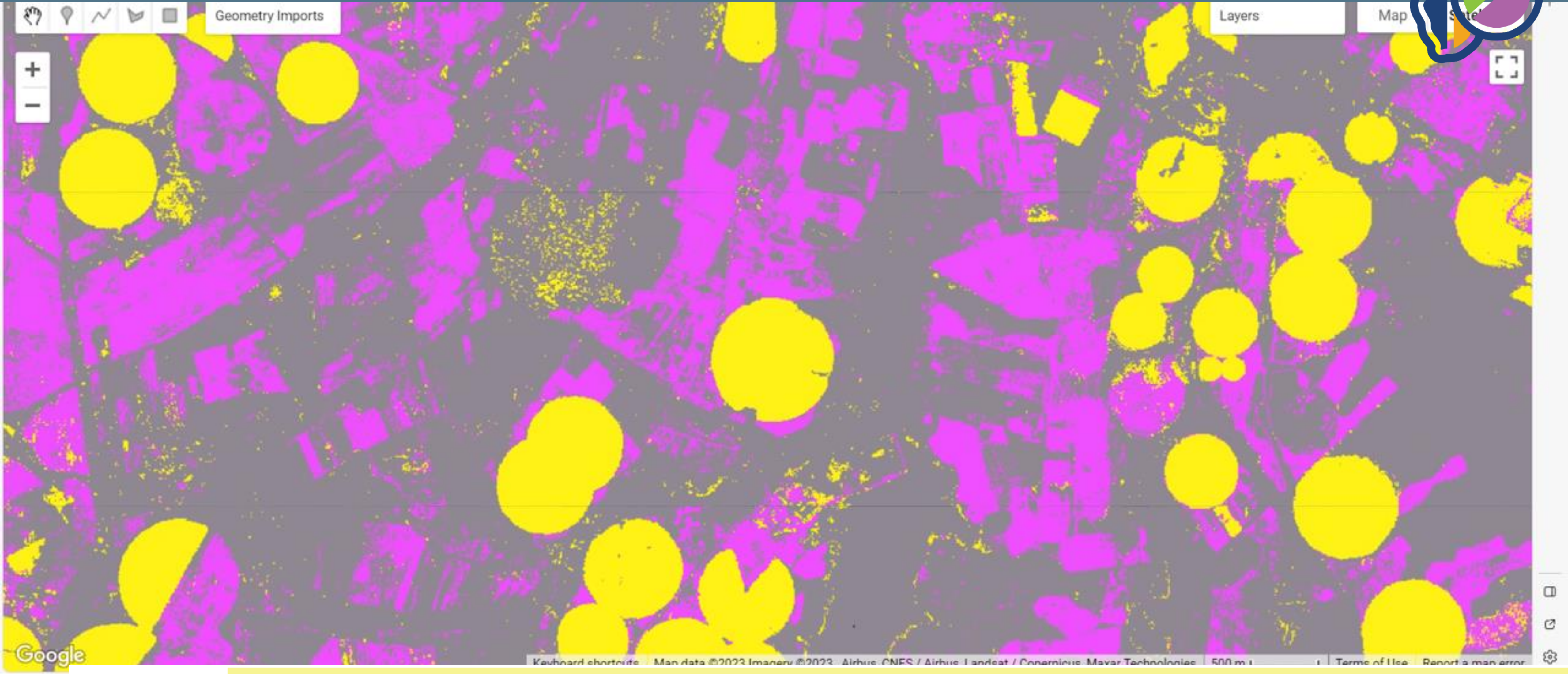
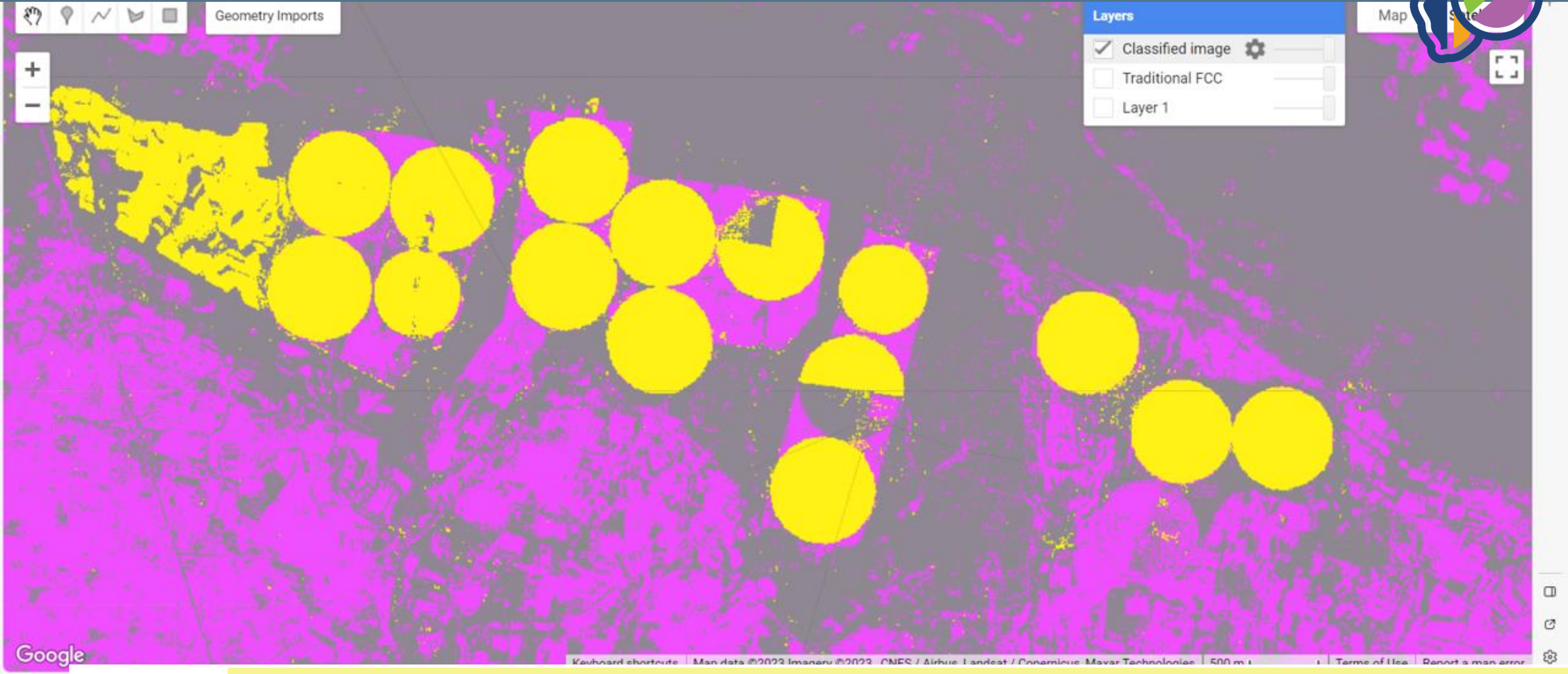
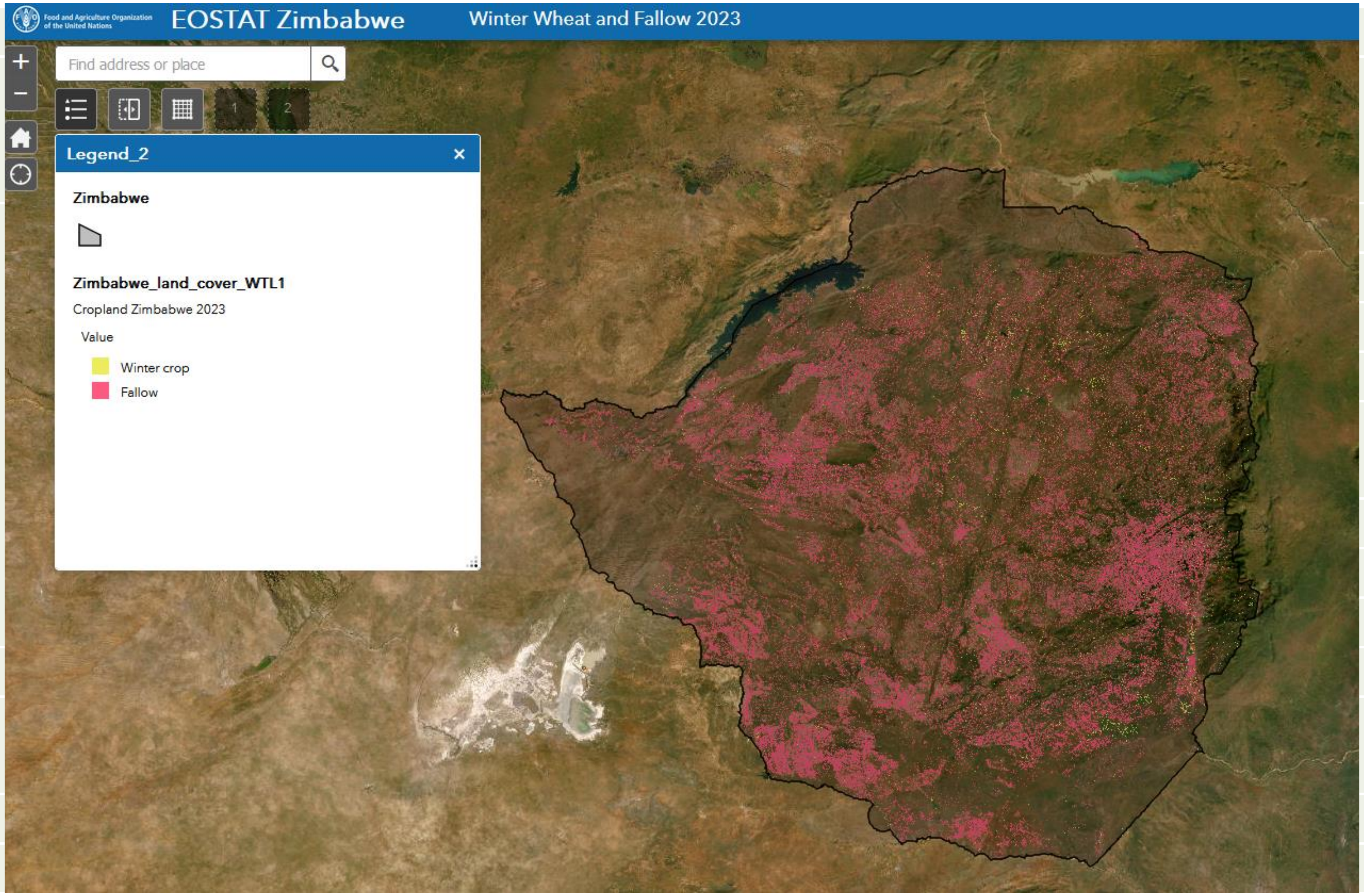


# WINTER WHEAT NATIONAL MAP 2023

AFCAS 28



# ACCURACY




| User Acc |
|---|
| 0.98 |
| 0.93 |
| 0.94 |
| 0.96 |
| |
| 0.53 |
| 1.00 |
| 0.82 |
| 0.92 |

- 202 ground truth data used for accuracy assessment
- Overall Accuracy = **86%**
- Kappa statistic = **0.9**
- WorldCover local accuracy – OA = 78%

# SENEGAL

## CROP MAPPING AND YIELD

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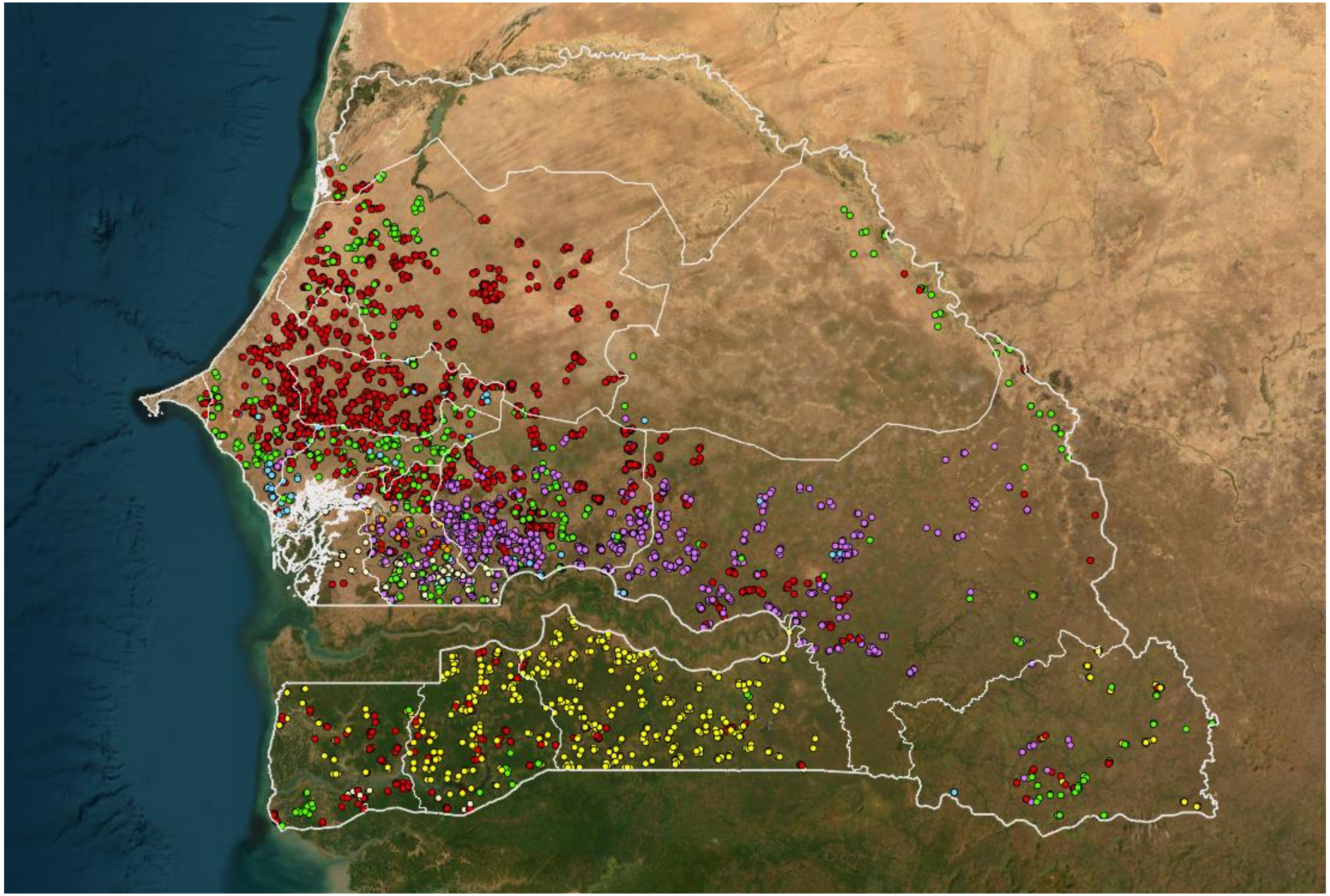

Earth engine app, 2021. [online]. [Cited December 2023]. https://www.earthengine.app/

# PILOT SURVEY IN NIORO DISTICT 2021

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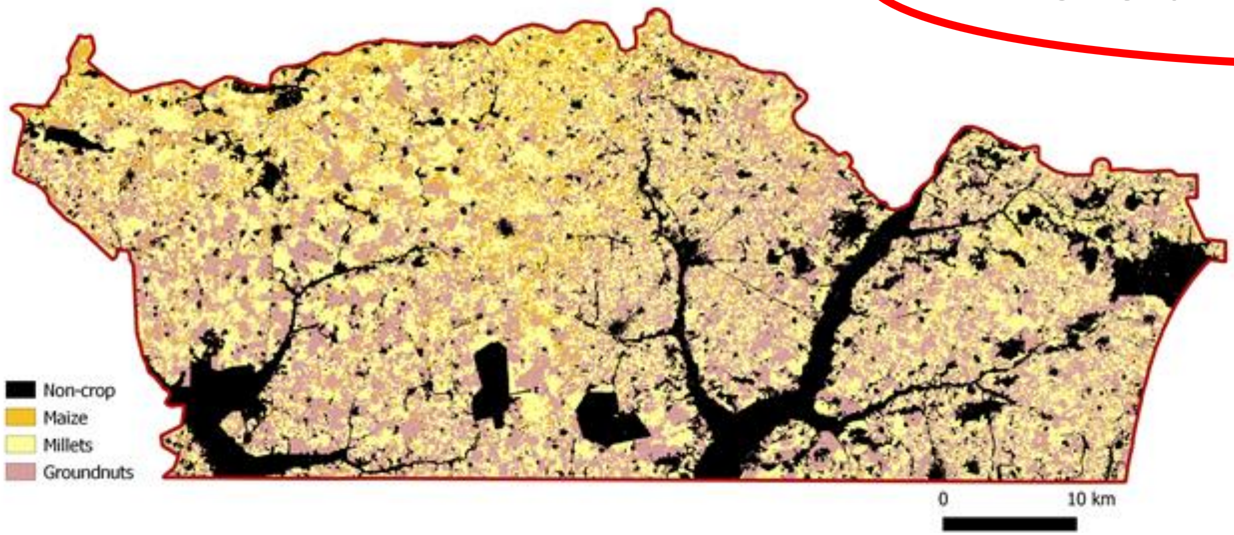
Sen4Stat
Sentinels for Agricultural Statistics

- An optimized field survey protocol was implemented during the AAS 2021 in one district (NIORO) leading to higher quaility in-situ data, leading to high accuracy in crop type map

Expressed in number of pixels

| | | Field survey | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Non crop | Maize | Millet | Groundnut | UA | Contaminations (%) | Omissions (%) |
| Crop type map | Non crop | 2169 | 84 | 95 | 58 | 90.15 | 20.49 | 9.85 |
| | Maize | 0 | 596 | 17 | 11 | 95.51 | 17.34 | 4.49 |
| | Millet | 378 | 19 | 2742 | 14 | 86.96 | 6.10 | 13.04 |
| | Groundnut | 181 | 22 | 66 | 3210 | 92.27 | 2.52 | 7.73 |
| | PA | 79.5 | 82.7 | 93.9 | 97.5 | | | |

Overall Accuracy: 90.2%



# EFFICIENCY FROM THE USE OF EO DATA

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| Crop type | Standard error of estimators of proportions | | **Efficiency of satellite data** |
|---|---|---|---|
| | Field data only | Field & satellite data | |
| Maize | 1,37 | 1,62 | **0,72** |
| Millet | 3,37 | 1,73 | **3,79** |
| Groundnut | 3,34 | 1,78 | **3,52** |

The table shows preliminary results in terms of cost-effectiveness for the area estimation from the integration of EO data with survey data. The table shows contrasting results on the basis of the analysis of the sampling variance of the estimators. The results are based on a preliminary work that needs to be reviewed, corrected and deepened.

# CROP YIELD ESTIMATION

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- FAO and the Ministry of Agriculture and the Bureau of Statistics collaborated on the use of EO data to predict crop yield
- A regression model was used to regress crop yield Leaf Area Index (LAI) derived from Sentinel 2 data
- In-situ data:
  - Yield measurements were collected from hundreds of crop plots in the Nioro district.
  - Depending on the crop, the size of the measurement square varies between 5 and 25 m². In the first investigation, the yield squares were considered georeferenced with the field ID and measurement square in the ODK application.

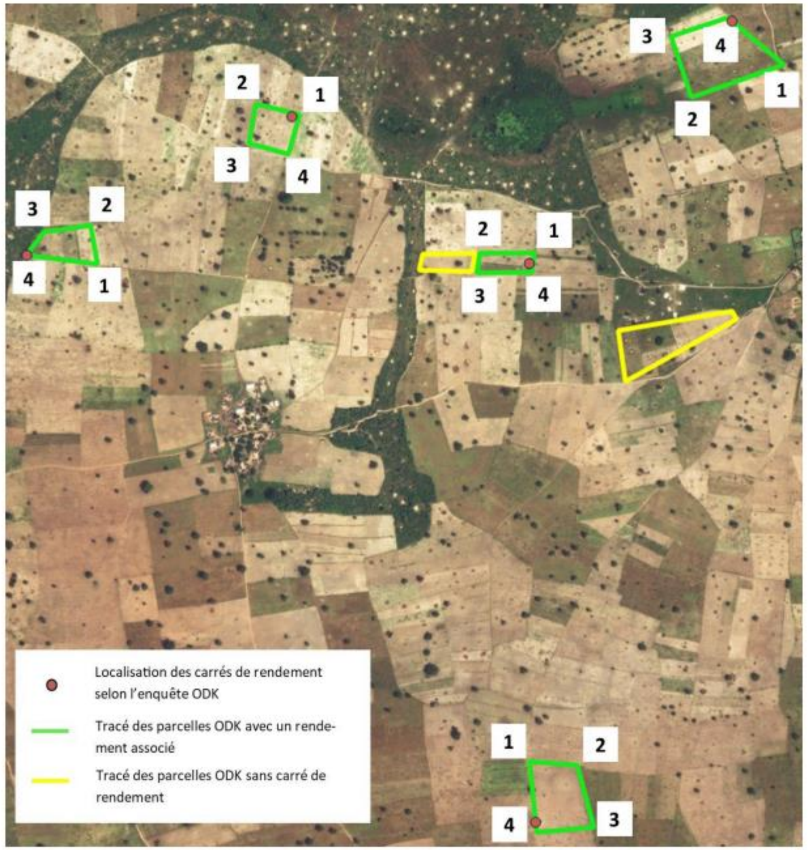


Figure 2: Location of crop cutting squares

# RESULTS

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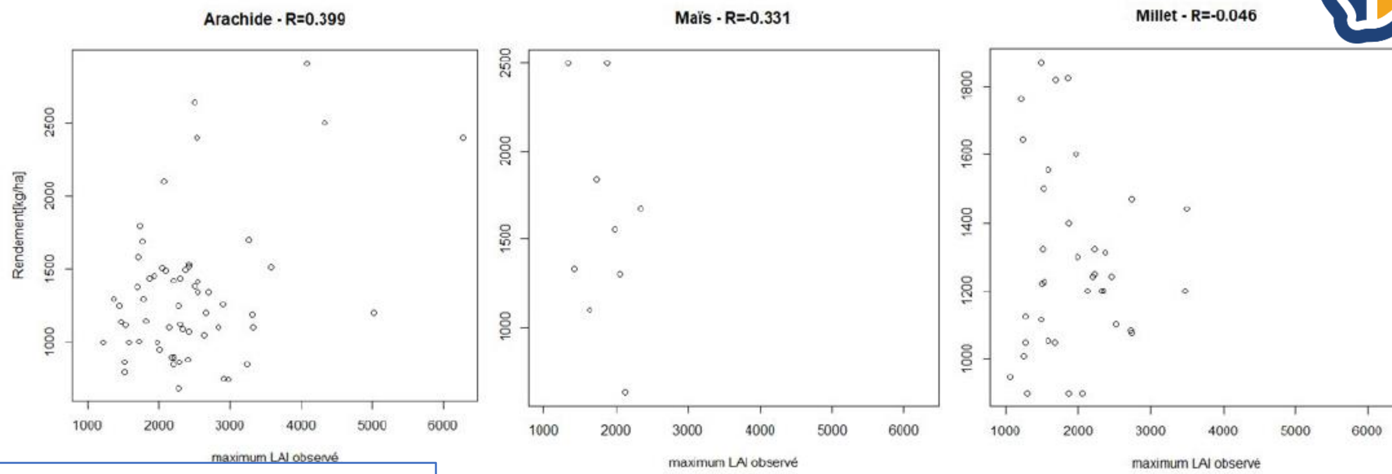
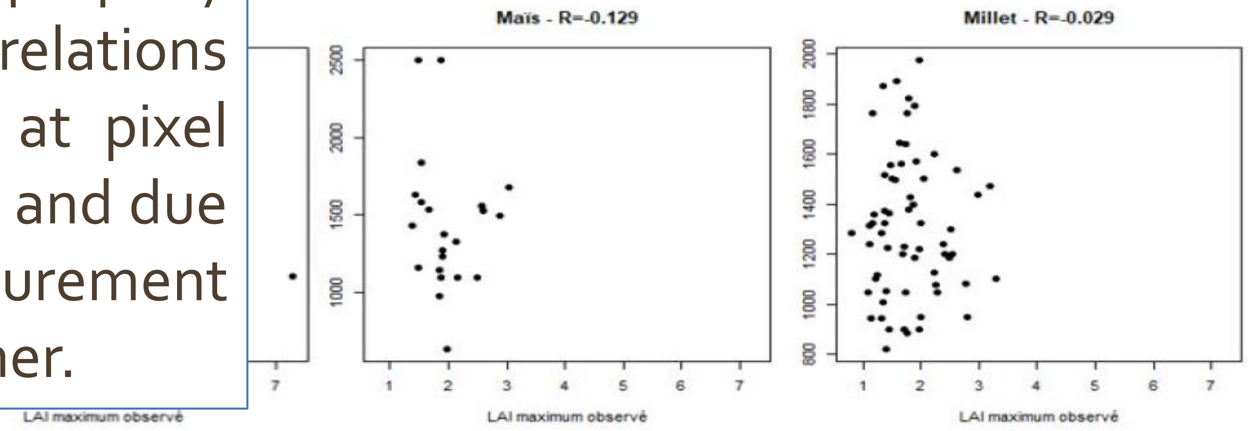
- Poor correlations were found between LAI and observed yield These relations, neither at pixel nor field level, did not allow training a yield model providing satisfactory performance



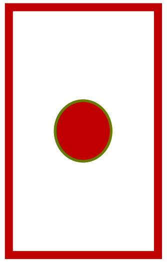

e pixel associated to the measurement square, compared to measured yield for the three main crops of Nioro

- During technical discussion with experts, it emerged that measurement squares were not properly georeferenced, explaining the weak correlations between features and the measured yields at pixel level. As only one measure was taken by fields and due to the field heterogeneity, 16 squares of measurement were not representative of the entire fields either.



# ADJUSTMENT OF SURVEY DESIGN

**RECOMMENDATIONS ENDORSED BY DAPSA AND IMPLEMENTED IN THE AAS 2022/2023**



**SENEGAL** – LIST FRAME

- **Recommendations** derived from pilot survey implemented in Nioro district during the AAS 2021:
- Geo-reference parcel boundary with GPS
- Add additional GPS point in the middle of the parcel with the tablet and the Survey Solutions software
- GPS point in the crop-cutting plot

**MALI – AREA FRAME**

- **Recommendations** based on a design independent from an of
- Stratification based on cropping intensity (0% - 30% ; 30% - 6 map
- Random selection of 300 segments (500m X 600m) within the c
- Manual digitizing (on-screen) of homogenous crop block/parce
- MapMe, used for the teams navigation (driving to the place of
- - ODK Collect, used to collect field data (answering a form abou

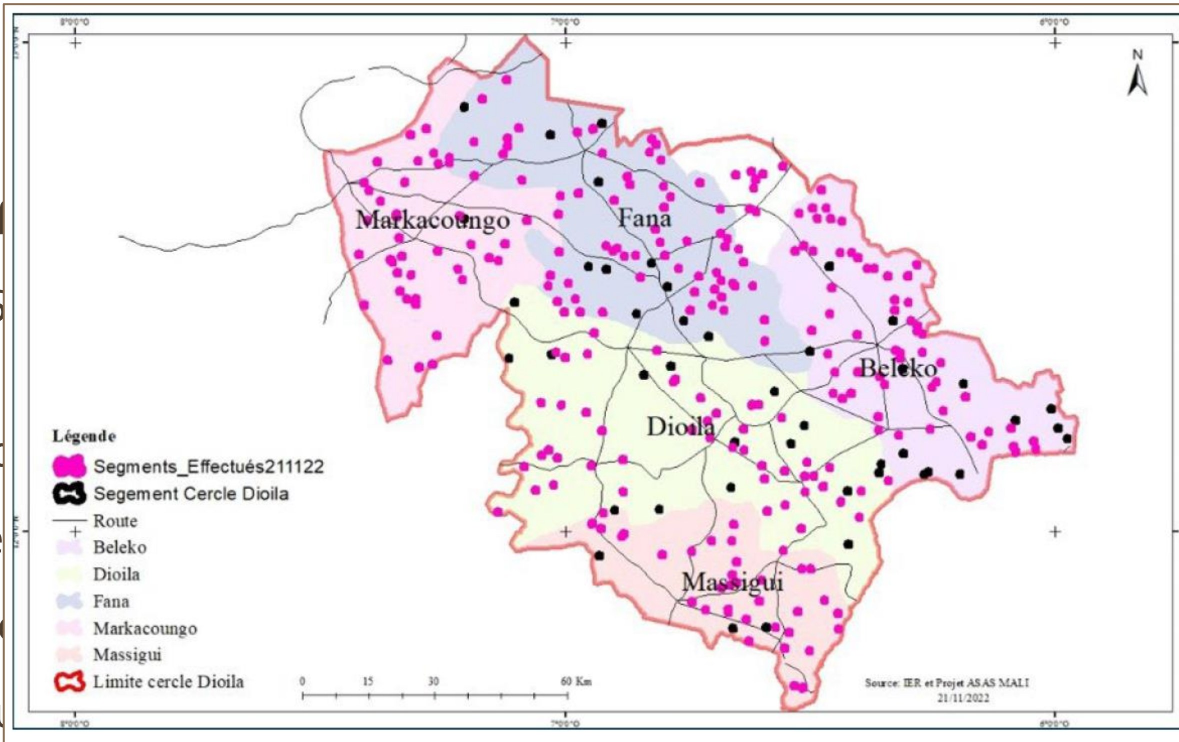



Figure 21. Localization of the segments visited by the end of November 2022

# LESOTHO

## Land Cover Statistics and SDG monitoring and reporting

## 15.4.2 MGCI

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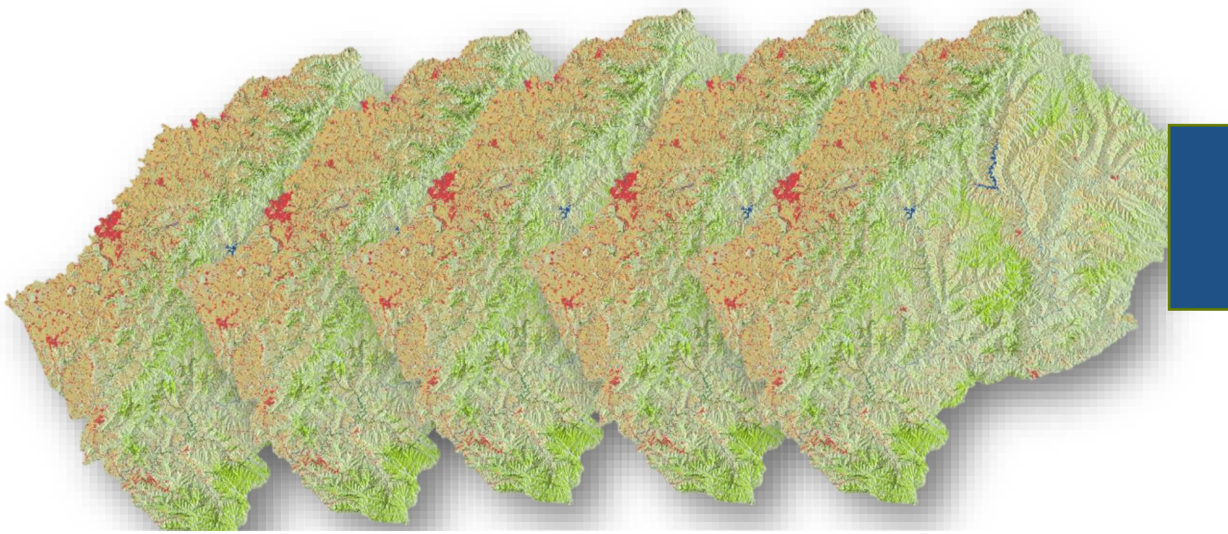
The capacity of a country to produce national land cover maps in a standar[...] production of a land cover baseline and for systematically updating it, whic[...] statistics and LCC statistics and for SDG reporting

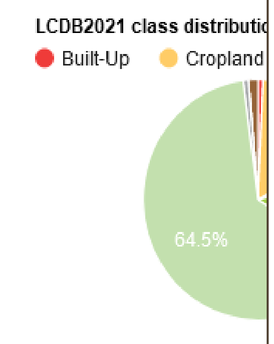
TIME

2017 2018 2019 2020 2021 2022

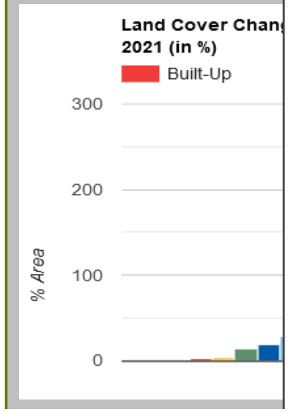


Automatic production of annual national land cover map at 10m resolution. Source: EOSTAT Lesotho 2022.

## LC statistics




## LCC statistics




*remote sensing*

*Article*

**Operational Use of EO Data for National Land Cover Official Statistics in Lesotho**

Lorenzo De Simone [1,*], William Ouellette [2] and Pietro Gennari [1]

1 Office of the Chief Statistician, Food and Agriculture Organization of United Nations, 00153 Rome, Italy; pietro.gennari@fao.org
2 FAOLS, Maseru 7588, Lesotho; william.ouellette@fao.org
* Correspondence: lorenzo.desimone@fao.org

**Abstract:** The Food and Agriculture Organization of the United Nations (FAO) is building a land cover monitoring system in Lesotho in support of ReNOKA ('we are a river'), the national program for integrated catchment management led by the Government of Lesotho. The aim of the system is to deliver land cover products at a national level on an annual basis that can be used for global reporting of official land cover statistics and to inform appropriate land restoration policies. This paper presents an innovative methodology that has allowed the production of five standardized annual land cover maps (2017–2021) using only a single in situ dataset gathered in the field for the reference year, 2021. A total of 10 land cover classes are represented in the maps, including specific features, such as gullies, which are under close monitoring. The mapping approach developed includes the following: (i) the automatic generation of training and validation datasets for each reporting year from a single in situ dataset; (ii) the use of a Random Forest Classifier combined with postprocessing and harmonization steps to produce the five standardized annual land cover maps; (iii) the construction of confusion matrices to assess the classification accuracy of the estimates and their stability over time to ensure estimates' consistency. Results show that the error-adjusted overall accuracy of the five maps ranges from 87% (2021) to 83% (2017). The aim of this work is to demonstrate a suitable solution for operational land cover mapping that can cope with the scarcity of in situ data, which is a common challenge in almost every developing country.

**Keywords:** supervised classification; automatic generation of training and validation data; Sentinel-2 temporal composites; Random Forest Classifier; land cover class accuracy stability

check for updates

**Citation:** De Simone, L.; Ouellette, W.; Gennari, P. Operational Use of EO Data for National Land Cover Official Statistics in Lesotho. *Remote Sens.* 2022, 14, 3294. https://doi.org/10.3390/rs14143294

Academic Editors: Conghe Song and Dino Ienco

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Published: 8 July 2022

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**1. Introduction**

Land Cover (LC) maps can be used to extract key information for a series of national applications, such as environmental monitoring, identification of land degradation trends, spatial planning, and for a wide range of scientific research fields. However, continuous monitoring and reporting of land cover maps requires regular updating, the use of standardized methods, and the adoption of a robust validation framework ensuring that every estimate is accurate and consistent over time. Such land cover mapping solutions are very rare to find in countries due to the inherent technical and financial challenges found in both traditional and modern LC mapping methods.

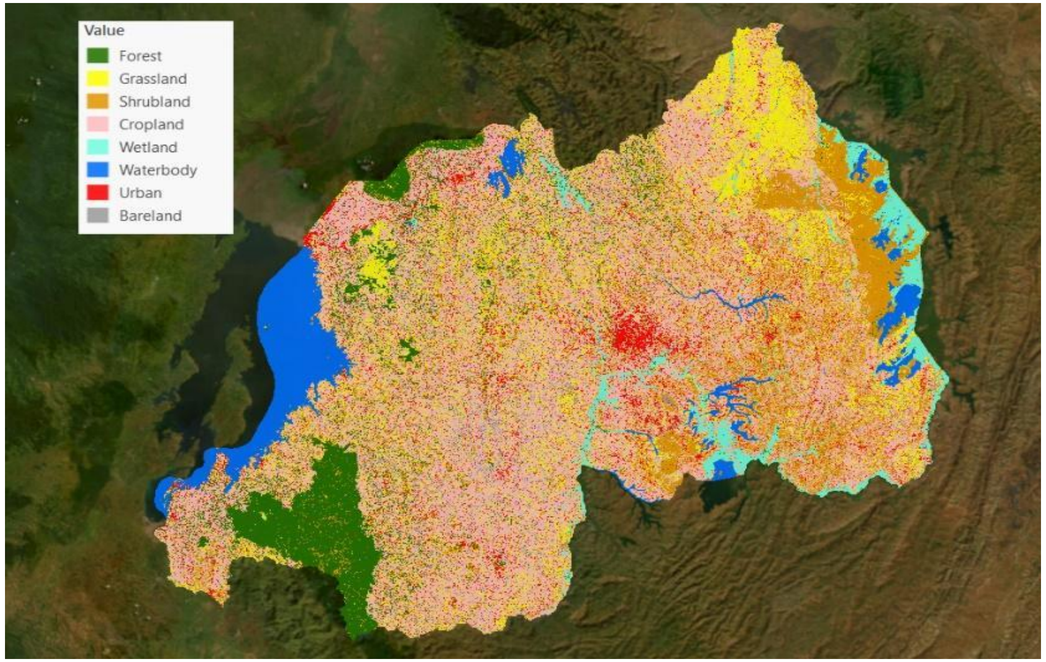
The most traditional methods that have been typically used in the last two decades have been based, initially, on visual image interpretation and pixel (or object) classification, relying on the use of very high-resolution images (commercial satellite images and orthophotos), and subsequently, on the combination of Earth Observations and in situ data for calibration and validation of automatic classification models. Such solutions have been extensively used in the research community [1–4].

FAO adopted a visual interpretation approach in 2015 to deliver the first edition of the Lesotho Land Cover Atlas [5]. The methodology relied on a manual labeling of segmented

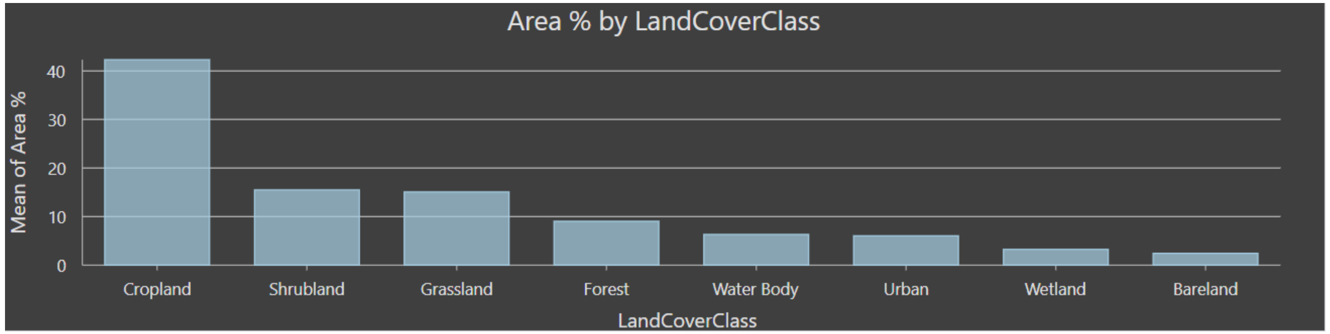
Remote Sens. 2022, 14, 3294. https://doi.org/10.3390/rs14143294 https://www.mdpi.com/journal/remotesensing

# RWANDA

## modernization of national land cover mapping methodology

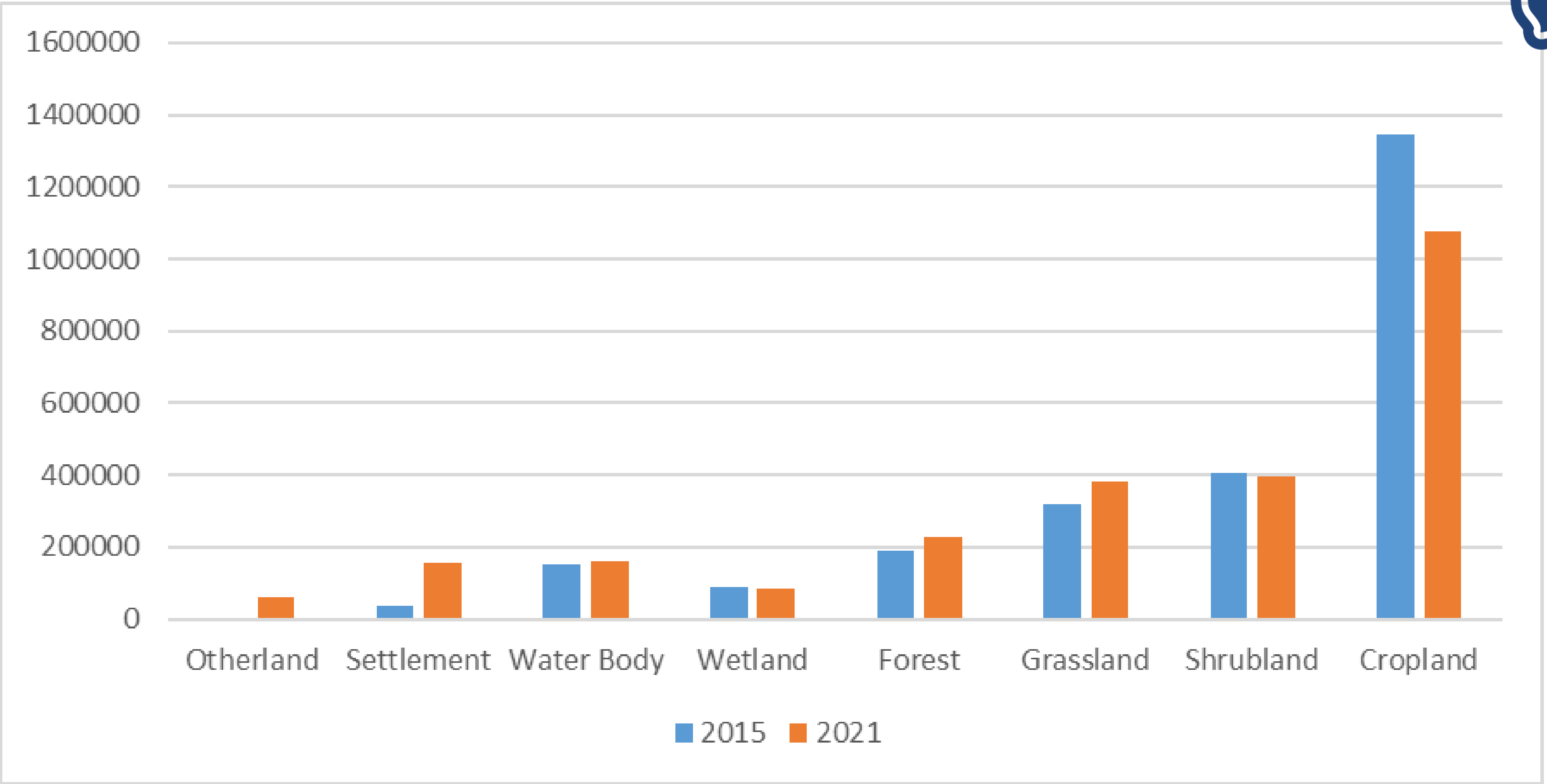



| | | Predicted class | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Forest | Grassland | Shrubland | Cropland | Wetland | Water Body | Urban Settlement | Bare Land | User accuracy |
| True class | Forest | **937** | 4 | 12 | 41 | 0 | 2 | 1 | 3 | **0.94** |
| | Grassland | 28 | **887** | 26 | 30 | 1 | 0 | 19 | 9 | **0.89** |
| | Shrubland | 4 | 35 | **522** | 408 | 5 | 1 | 18 | 7 | **0.52** |
| | Cropland | 26 | 269 | 336 | **1257** | 1 | 5 | 94 | 12 | **0.63** |
| | Wetland | 5 | 5 | 51 | 80 | **845** | 13 | 1 | 0 | **0.85** |
| | Water Body | 1 | 0 | 0 | 0 | 0 | **962** | 1 | 0 | **0.99** |
| | Urban Settlement | 2 | 12 | 11 | 205 | 0 | 1 | **754** | 15 | **0.75** |
| | Bare Land | 6 | 9 | 13 | 347 | 2 | 0 | 204 | **419** | **0.42** |
| | Producer accuracy | **0.93** | **0.73** | **0.54** | **0.53** | **0.99** | **0.98** | **0.69** | **0.90** | |




- First prototype produced without any in-situ data for baseline 2021
- Overall Accuracy 76%

# Comparison of Land Cover area 2015 -2021



# Less deatail 2015

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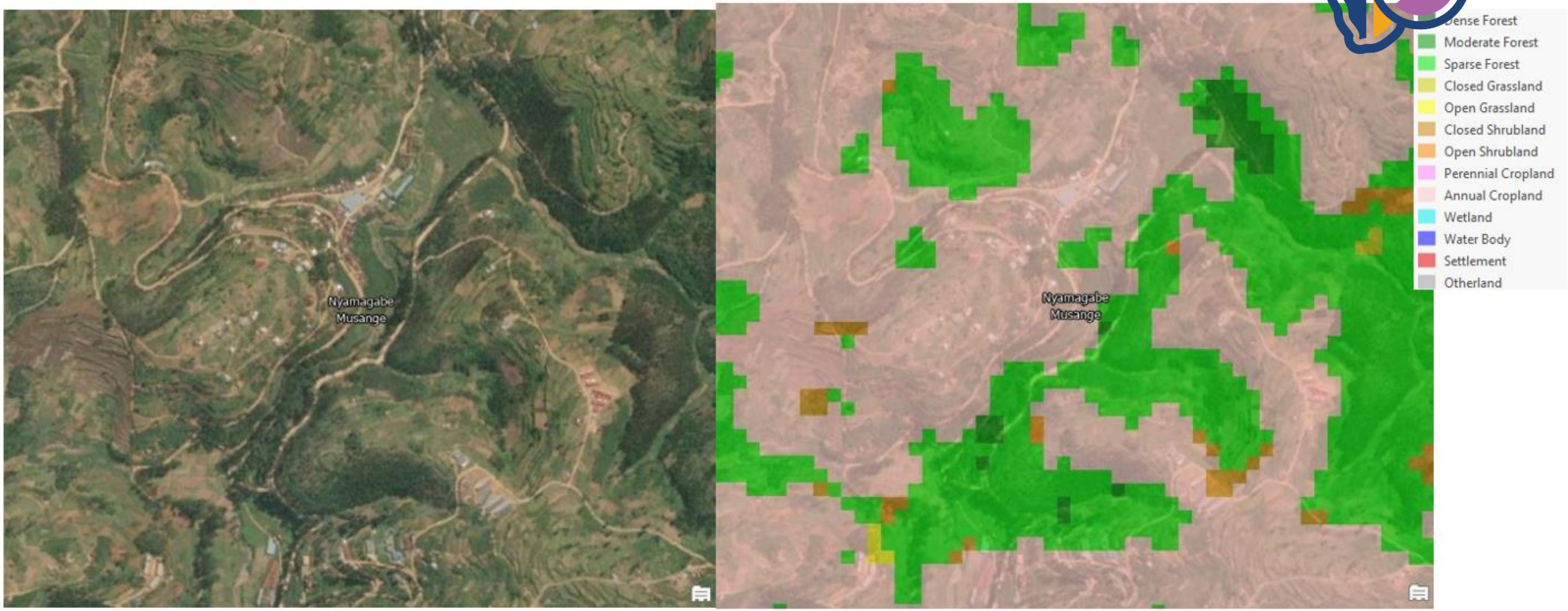


Very high-resolution image of the landscape within Nyamagabe-Musanoe Sector (29.5730° E, 2.2809° S); b) LC map 2015, depicting mainly cropland and sparse forest and very limited minor patches of Moderate forest and closed Shrubland.

# More deatail 2021

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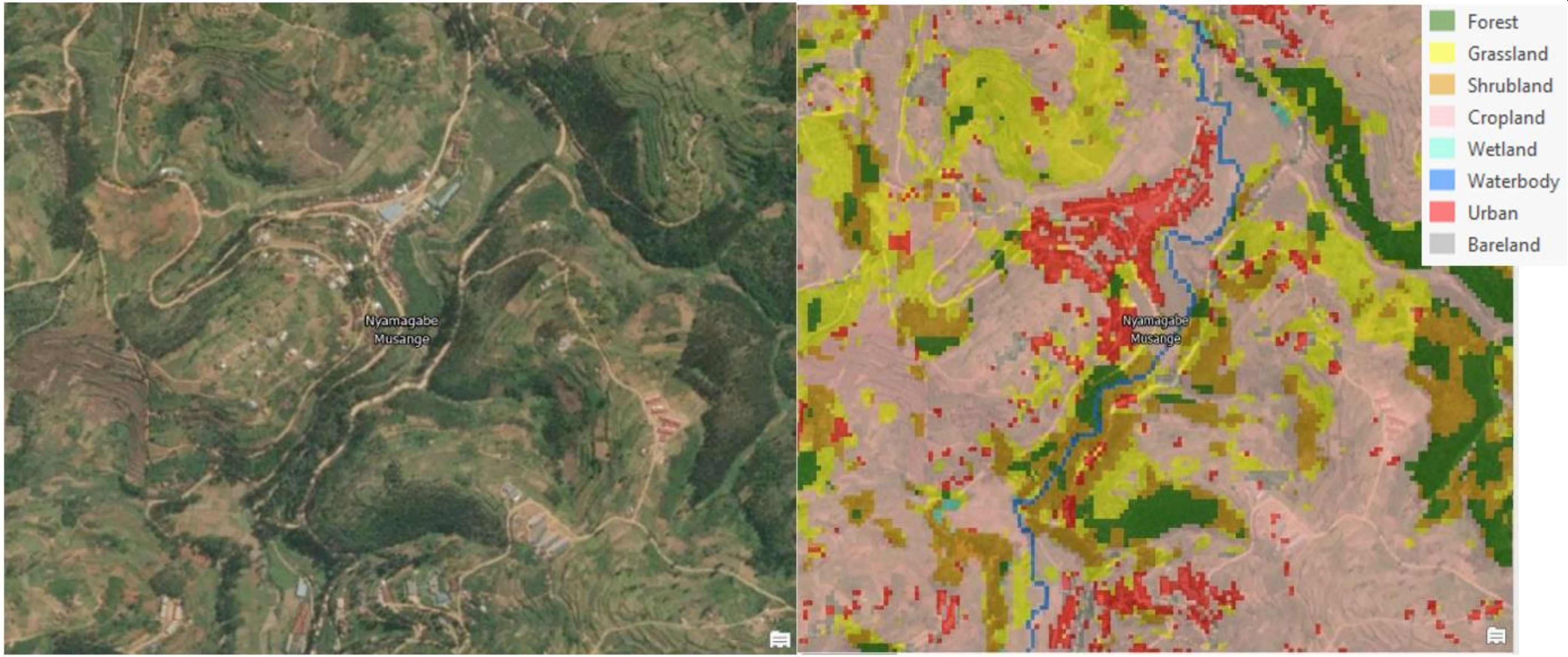



LC map 2021 depicting settlement features, waterbodies, forest, shrubland, grassland and cropland for the same area.

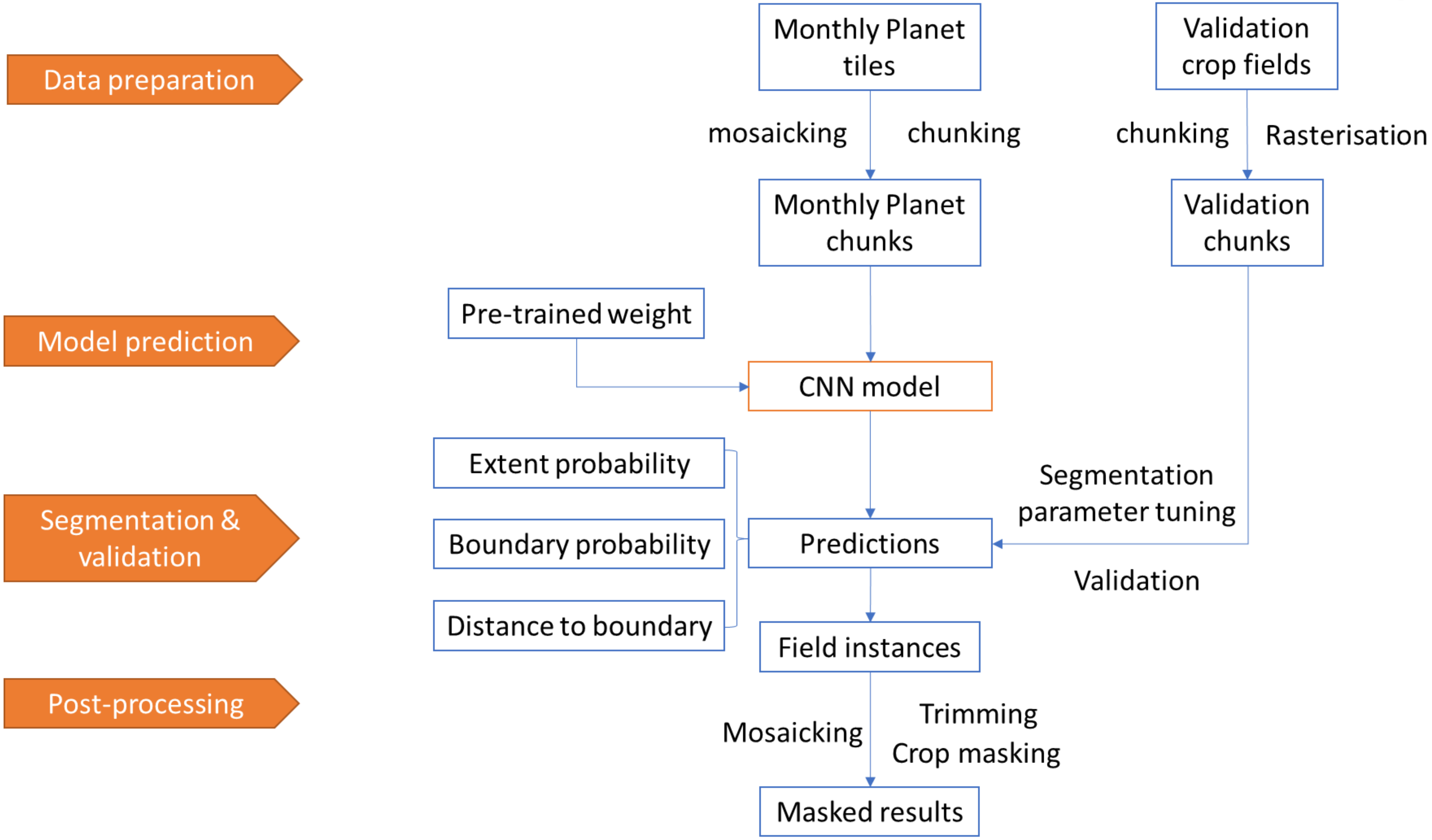
# Field Boundary mapping

- The method developed by Wang et al. (2022) was tested by FAO's using Digital Earth Africa to delineate field boundaries, with pre-trained model weights provided by Dr Sherrie Wang.
- Principal aspects of the model:
- It a method for accurate, scalable field delineation in smallholder systems.
- Fields are delineated with state-of-the-art deep learning and watershed segmentation.
- Transfer learning and weak supervision reduce training labels needed by 5× to 10×
- 10,000 new crop field boundaries were generated in India and publicly released.

The method employes a **DECODE** (DEtect, COnsolidate, and DElinetate) method, where a deep Convolutional Neural Network (CNN) called **FracTAL ResUnet** was introduced for multi-task semantic segmentation (Waldner et al., 2021).

The **FracTAL ResUNet** is a multitasking encoder–decoder network largely based on ResUnet-a (Diakogiannis et al. 2020) and was first introduced by Waldner et al. (2021) to create production-grade field boundaries in Australia.

# Field Boundary mapping



# Field Boundary mapping

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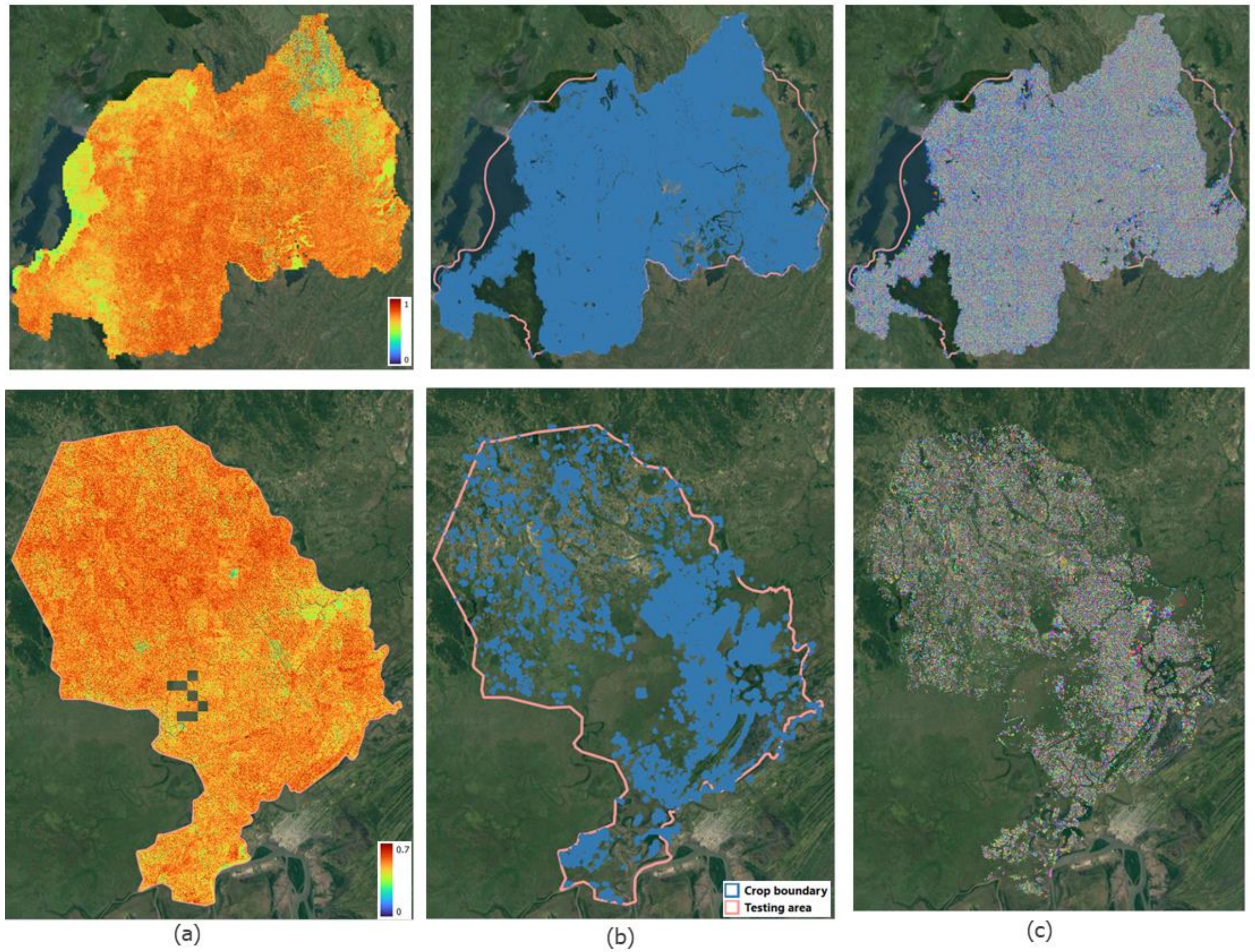


Crop boundaries delivered for Rwanda (top row) and Mozambique (bottom row). (a) Crop boundary probability raster.

# Validation

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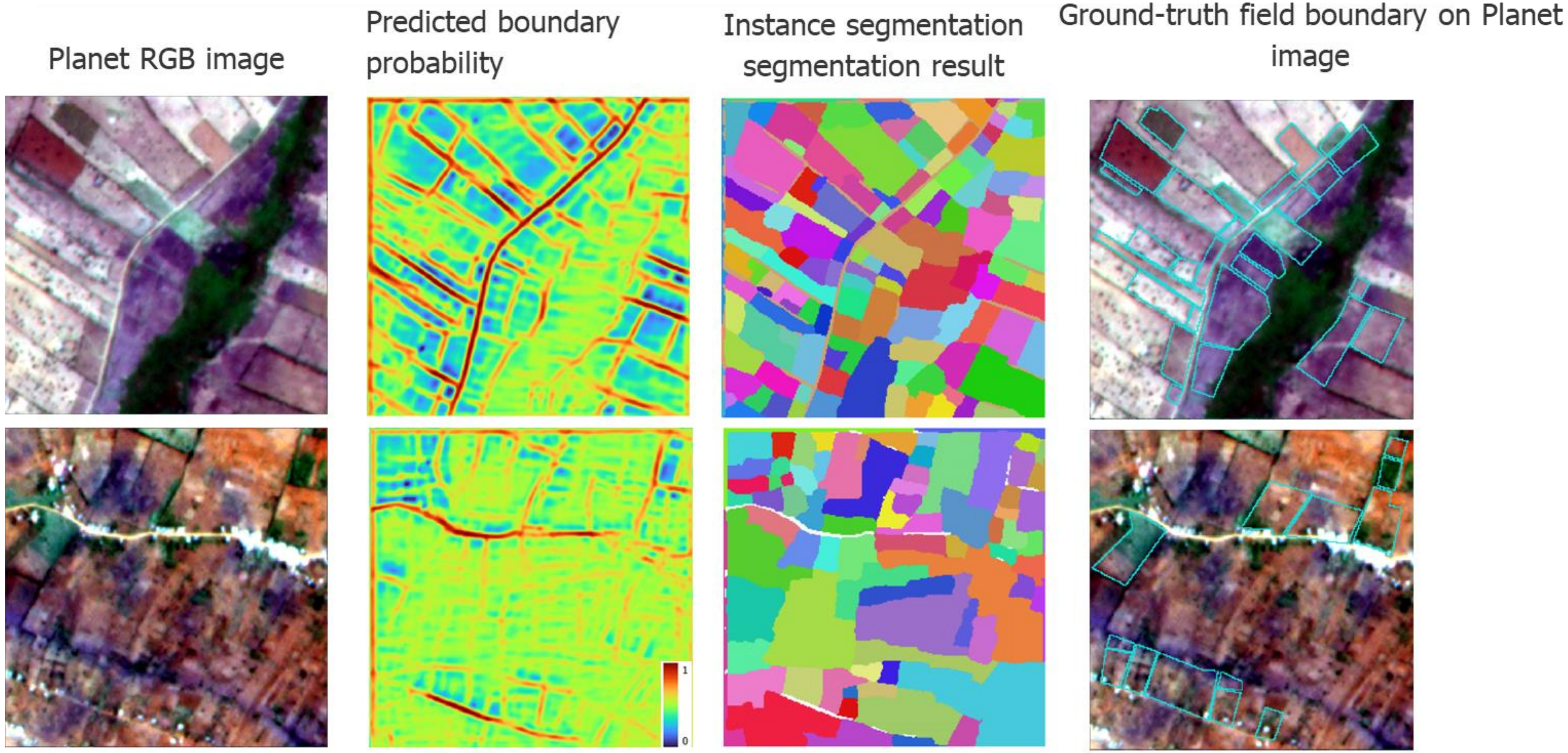


The boundaries are well delineated with high probabilities, especially considering that the model was trained on a different region. Nevertheless, some over-segmentation and under-segmentation can be observed. A mean **F1 score** of **0.91** and a median **IoU** of **0.42** were derived through validation against the validation dataset.

# Reflection points for feedback from Members of AFCAS

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1) relevance of the EOSTAT programme for the production of statistics in their respective countries with a focus on:

    1) Crop acreage
    2) Crop yield
    3) Crop plot boundaries mapping

2) challenges found in the use of EO data for land cover mapping, SDG indicator monitoring and reporting, including the Mountain Green Cover Index (MGCI), crop type mapping, crop acreage and yield estimates, and express their most pressing methodological and/or capacity development needs;

3) Take note of the UN-CEAG/CEBD proposed areas of work for 2024-27, share recommendations and suggestions for the finalization of this programme of work and expression of interest in becoming members of the task force

# Thank you for your attention!

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