Food and Agriculture Organization of the United Nations

UN Big Data Regional Hub for Africa

EO BIG DATA AND STATISTICS: RELEVANCE AND KEY ASPECTS

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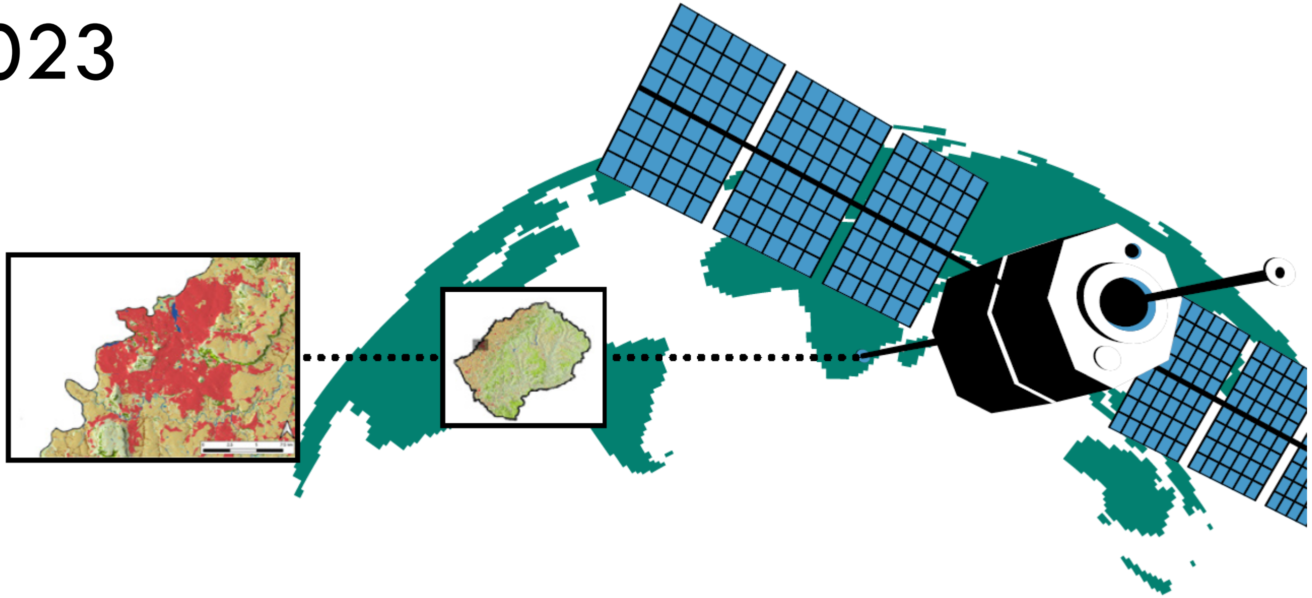
of the United Nations (FAO)

AGENDA

1. Relevance of EO data for land cover and land use statistics
2. UN Task Team on Earth Observations for Agricultural Statistics (Joint CEBD-CEAG)
3. Crop acreage, crop yield and EO data: critical aspects
4. Solutions from EOSTAT 2019-2023
5. UN Task Team WP 2024



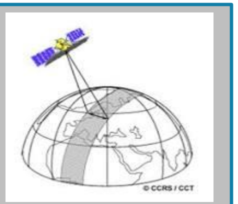
RELEVANCE OF EO DATA FOR LAND COVER AND LAND USE STATISTICS

RELEVANCE OF EARTH OBSERVATIONS DATA, LAND COVER AND LAND USE DATA

Earth Observations (EO) data and geo-spatial information have been early recognized as instrumental to the modernization of National Statistical Offices and in support of operational monitoring of SDGs by the UN (**UN General Assembly resolution, 2015**), and by the main EO coordination bodies such as the Group on Earth Observation (**GEO**) and the United Nations Committee of Experts on Global Geospatial Information Management (**UN-GGIM,** Scott, G., Rajabifard, A., 2017).

EO can be used as complementary and/or alternative data source to produce a variety of official statistics such as **agricultural statistics, environmental statistics** and other **socio-economic statistics.**

- Large geographic scope



- High spatial resolution (disaggregation)

- High temporal resolution (frequent update)

Mission	Number of satellites	Temporal resolution (single satellite)	Temporal resolution (constellation)
SENTINEL-1	2	12 days	6 days
SENTINEL-2	2	10 days	5 days
LANDSAT 7	1	16 days	16 days
WorldView-3	1	1 day	1 day
Terra	1	16 days	16 days

- Free Open Data and Low cost

LAND COVER & LAND USE DATA ARE FUNDAMENTAL

Land cover and **land use** data have been included in the list of the <u>global fundamental geospatial data themes</u> by the Committee of Experts on Global Geospatial Information Management in 2018 (E/C.20/2018/7/Add.1).

Theme title: Land Cover and Land Use
Description Land cover represents the physical and biological cover of the Earth's surface. Land use is the current and future planned management, and modification of the natural environment for different human purposes or economic activities.
Why is this theme fundamental? Land Cover data is required, for example, for developing land management policy, understanding spatial patterns of biodiversity and predicting effects of climate change. It may also help to forecast other phenomena, such as erosion or flooding. It is critical data in national assessments of biodiversity, conservation efforts, and water quality monitoring. The use of the land informs land management impacts, especially on changes in natural resources, agriculture, conservation, and urban developments. Land cover and land use affect the greenhouse gases entering and leaving the atmosphere and provide opportunities to reduce climate change. It is required at a disaggregated level to allow local planning to manage and monitor land use at land parcel level.
Which sustainable development goals (SDGs) will it help to meet? The theme plays a role in SDGs 1, 2, 3, 5, 6, 7, 8, 9, 11, 12, 13, 14 and 15.
Geospatial data features in more detail Land Cover includes artificial surfaces, agricultural areas, forest, semi-natural areas, wetlands and waterbodies etc. Land Use in some ways describes the human activities and the consequences of such activities on the landscape. Both Land Cover and Land Use are separated into different classes based on an agreed classification schema which is usually hierarchical. The data can be represented either as polygons or as a raster. It may also be found as attributes of a land parcel.
Possible sources of geospatial data • Classified Earth observation (EO) data, potentially as a Data Cube; • National datasets relating to environmental information and land parcels; and, • International organisations, Regional United Nations Centre, different levels of public authorities (in particular municipalities) and the private sector.
Existing geospatial data standards Note: This is indicative. Other lists of standards exist and UN-GGIM will seek to work with thematic experts to develop a list of relevant data standards. • ISO 19144-1:2009 – Geographic Information Classification system – Part 1 Classification system structure (last reviewed in and confirmed in 2015); • ISO 19144-2:2012 - Part 2 - Land Cover Meta Language (LCML) (there are limitations on this standard); • ISO 19115:2003 Geographic information – Metadata; and, • INSPIRE data specification on Land Cover and on Land Use.

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

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LAND COVER AND LAND USE SUPPORT MANY SDGS

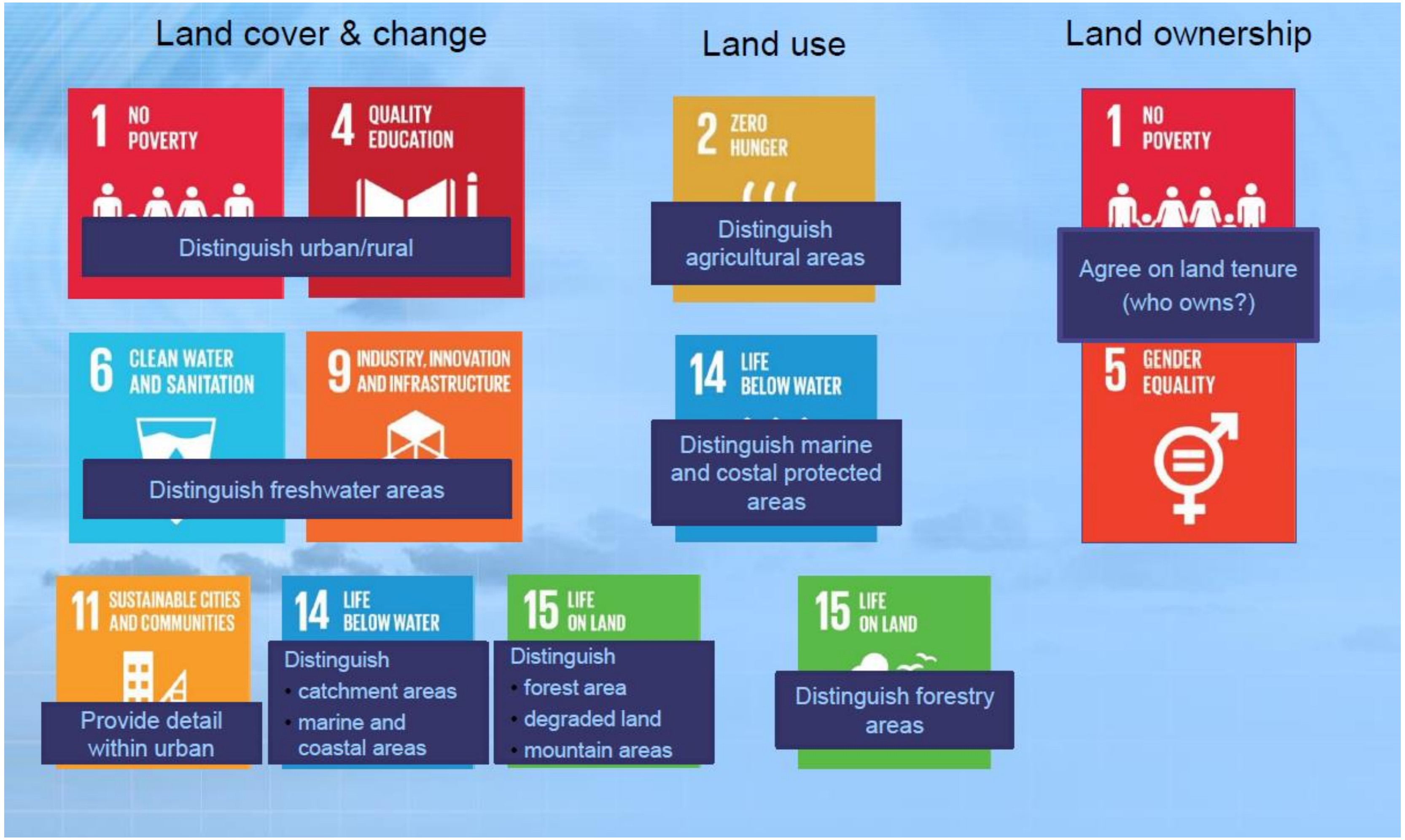
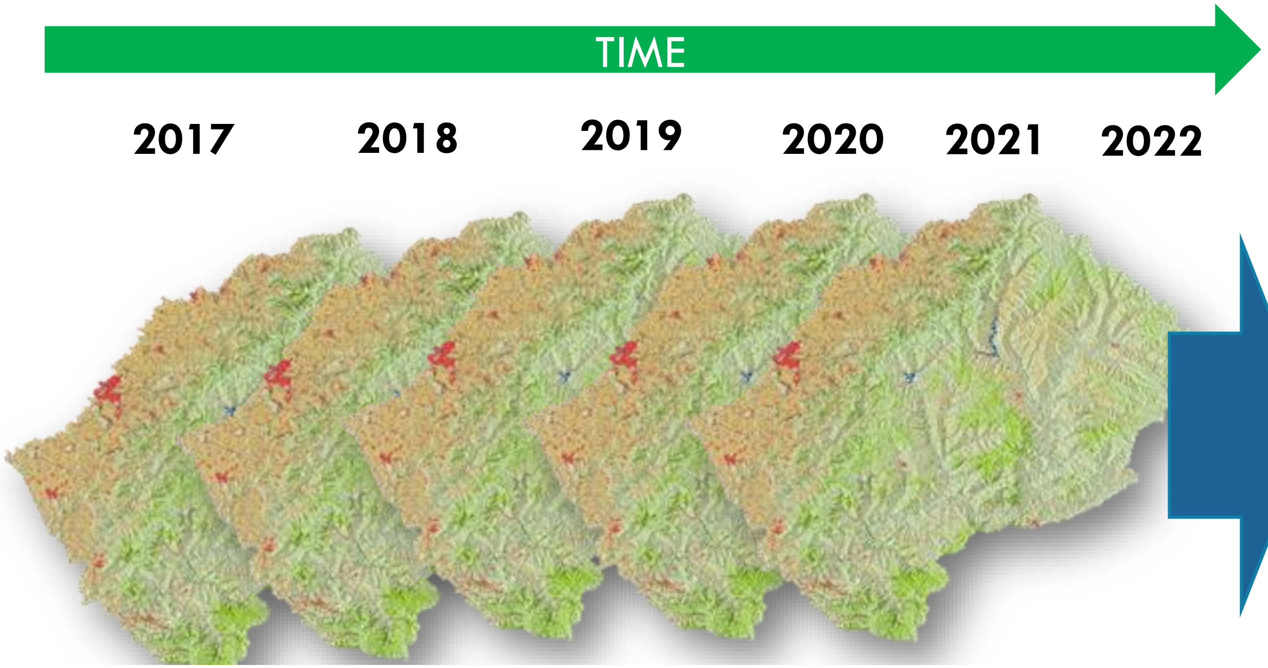


IMAGE CREDITS: Environment Statistics Section, United Nations Statistics Division

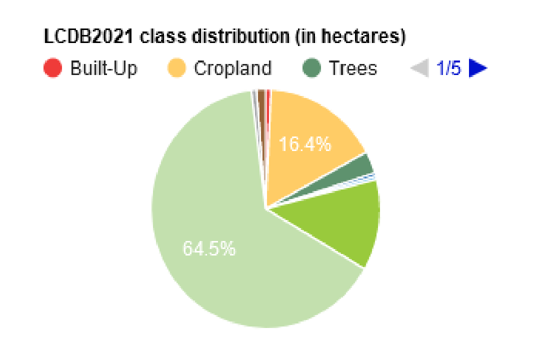
LAND COVER AND LAND USE SUPPORT MANY SDGS

The capacity of a country to produce national land cover maps in a standardized way over time, is essential for the production of a land cover baseline and for systematically updating it, which allows in turn for the production of LC statistics and LCC statistics and for SDG reporting

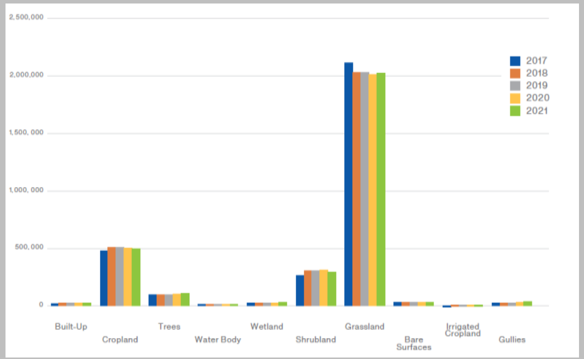


Automatic production of annual national land cover map at 10m resolution. Source: EOSTAT Lesotho 2022.

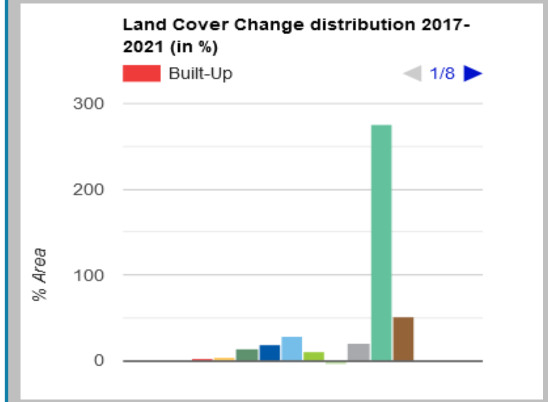
LC statistics



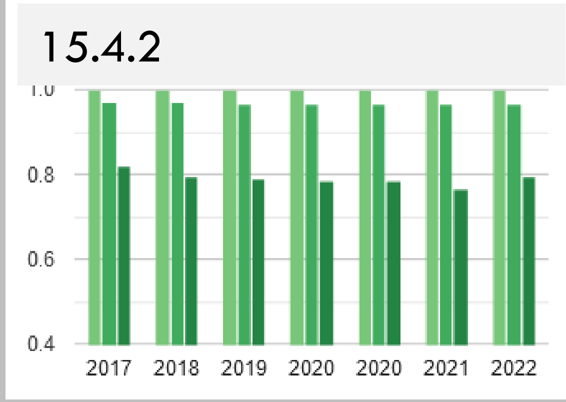
LC trends



LCC statistics



SDG Reporting



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CROP MAPS (LAND USE)

Crop maps inform on the use of the land cover class "agriculture". They are obtained by classifying EO data into crop masks and into crop types maps informing about the crops being cultivated during a given agricultural season.

Applications of crop type maps:

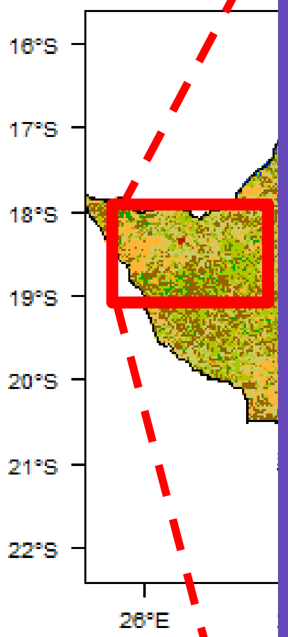
1) Early estimates of crop statistics
2) Crop statistics disaggregation at field level
3) Crop yield forecasting (coupled with modeling)
4) Early Warning
5) Disaster impact assessments
6) Market analysis

Crop type map, EOSTAT Senegal 2018

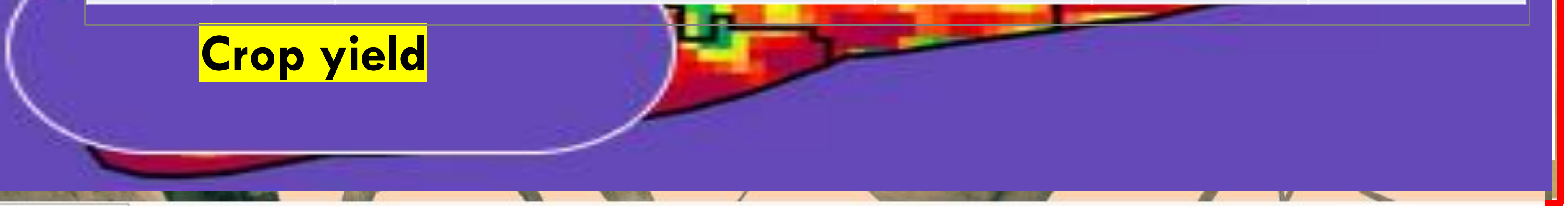
	Cropland		Non cropland	
	hectares	**%**	**hectares**	**%**
Country	4574698	23	15111467	77
Dakar	3140	6%	53488	94%
Diourbel	390382	80%	95664	20%
Fatick	349713	51%	335104	49%
Kédougou	4404	0%	1690633	100%
Kaffrine	1019187	90%	112242	10%
Kaolack	428419	79%	112312	21%
Kolda	157542	11%	1222859	89%
Louga	563763	23%	1902177	77%
Matam	447582	16%	2351109	84%
Sédhiou	50679	7%	684390	93%

	Crop area indicator (ha)
Groundnut	1.510.958
Maize	484.534
Millet	2.077.798
Cowpea	210.070
Sorghum	192.582

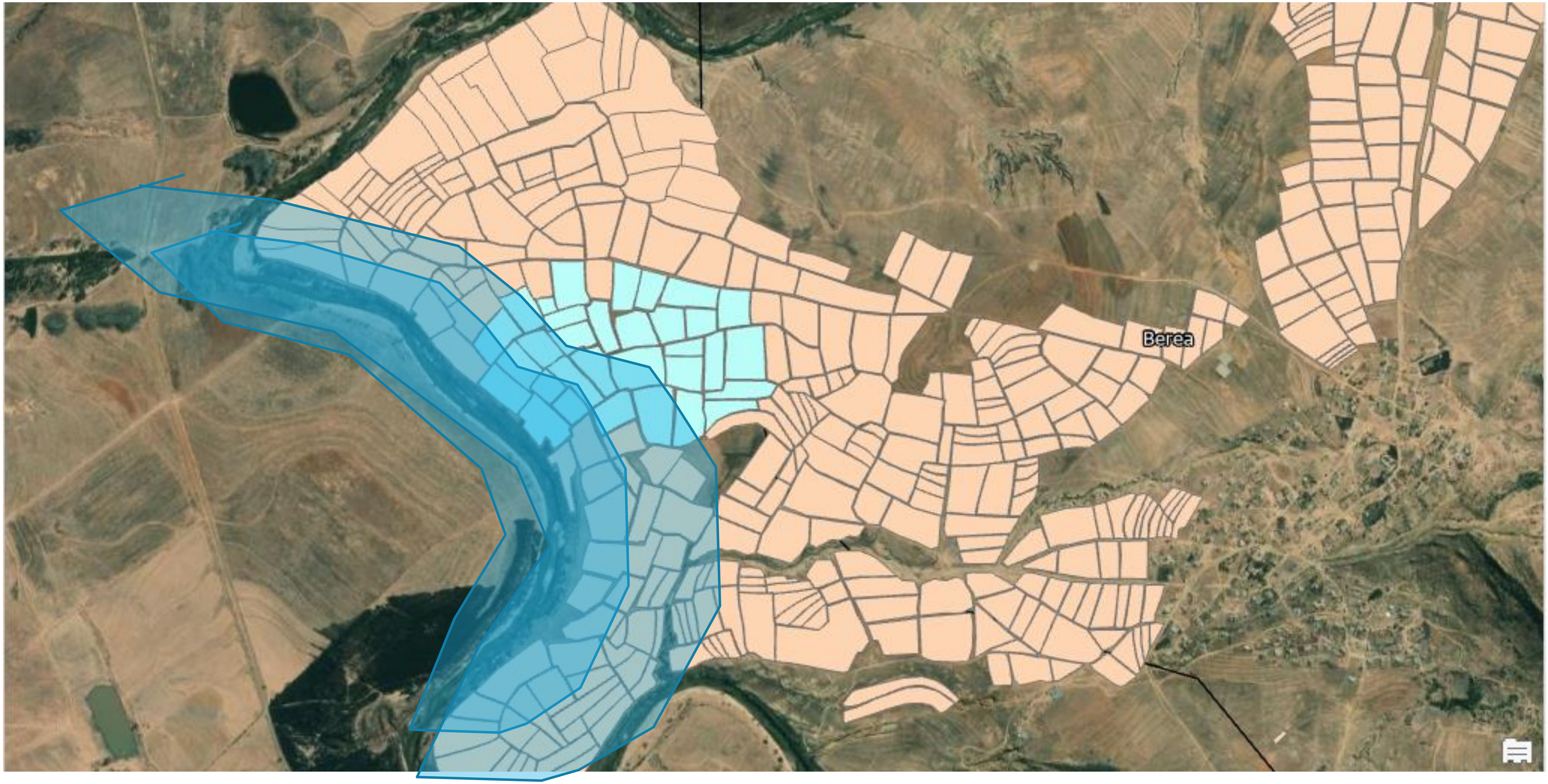
FROM LAND COVER TO LAND USE TO CROP PRODUCTIVITY (YIELD)

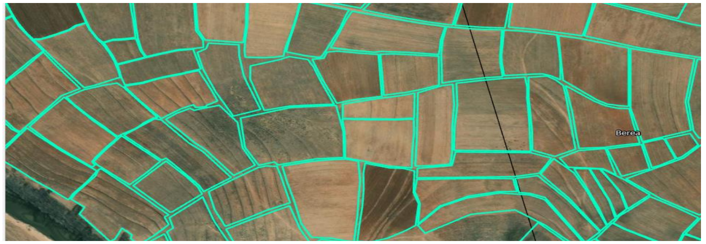


2023	Crop	National	Guayas	Los Rios	Manabi	Loja
1st season	Maize	118127Mt ±0.1%	17464Mt ±1.3%	34944Mt ±0.4%	47602Mt ±2.1%	18117Mt ±6.6%
	Rice	37081Mt ±8.4%	21586Mt ±1.6%	12947Mt ±1.8%		
2nd season	Crop	National	Guayas	Los Rios	Manabi	Loja
	Maize	30296Mt ±0.4%	2522Mt ±0%	25423Mt ±0.7%	1318Mt ±0.2%	1033Mt ±4.9%
	Rice	77884Mt ±9.6%	51486Mt ±0.7%	17248Mt ±0.3%	1972Mt ±0.4%	
3rd season	Crop	National	Guayas	Los Rios	Manabi	Loja
	Maize					
	Rice	27380Mt ±4%	19207Mt ±1.9%	6740Mt ±1.4%	794Mt ±1%	

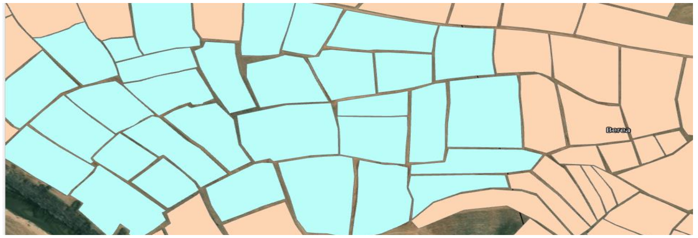


INTEGRATING LAND USE AND FLOOD AND DROUGHT DATA

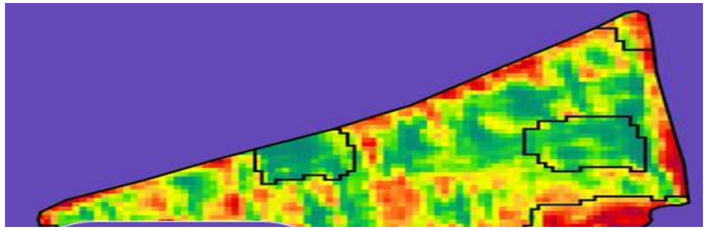




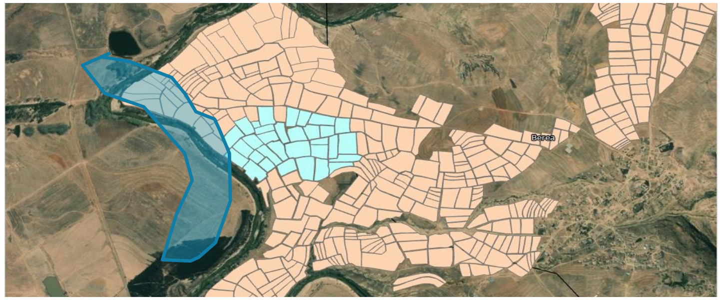
Parcel boundary mapping mapping



Crop type mapping



Crop yield mapping



Integrated forecasting and mapping of droughts and floods

APPLICATIONS

Farmer Registry

- Faciliatates the process of registering farmers and linking Farmer ID to the specific parcels
- Facilitates monitoring the impact of subsidies

Crop statistics

- Early forecast of crop acreage and crop yield

Smart Agriculture

- Real time monitoring of crop conditions
- Precision farming

DRR

- Forecast event
- Assessment of impacts
- Farmer insurance/compensation

UN Big Data Regional Hub for Africa EO-STAT

UN TASK TEAK ON EARTH OBSERVATIONS FOR AGRICULTURE STATISTICS

JOINT EFFORT FROM UNCEAG-UNCEBD

UN TASK TEAM ON EARTH OBSERVATIONS FOR AGRICULTURAL STATISTICS (JOINT CEBD-CEAG)

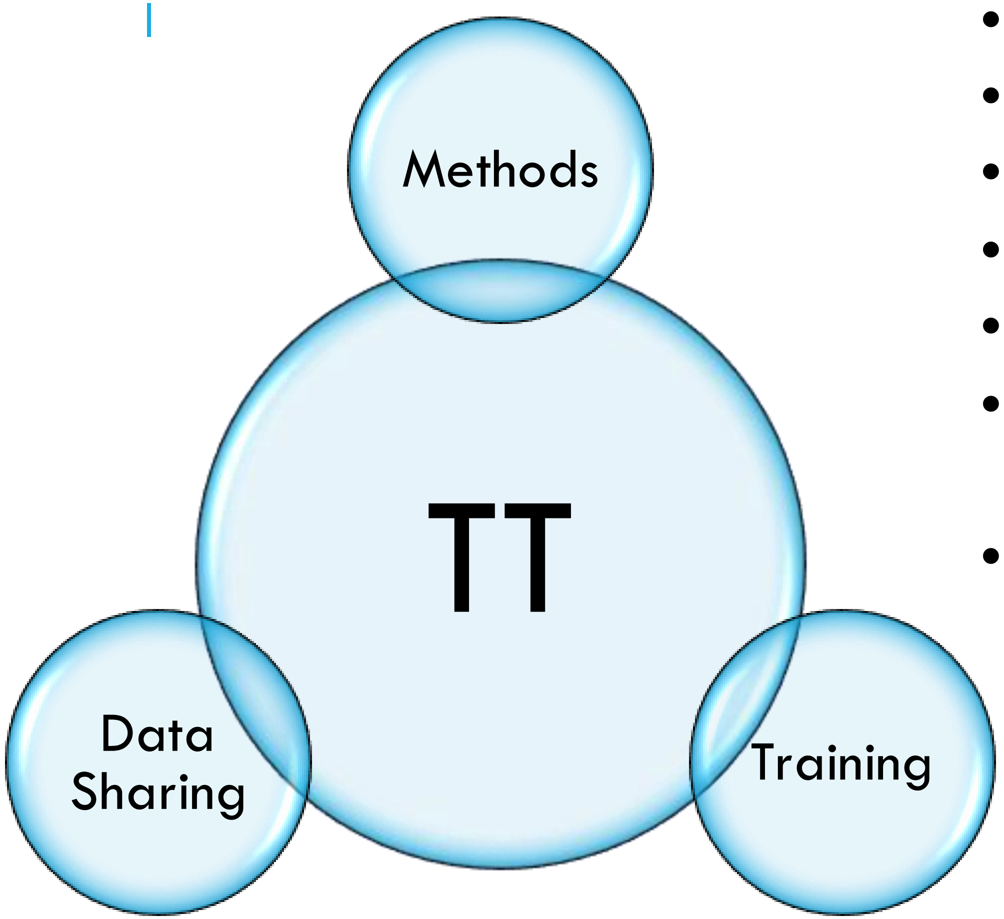
- A Task Team on Earth Observations for Agricultural Statistics was first created in 2014 (under the **Global Working Group on Big Data for Official Statistics established** under the **UN Committee of Experts on Big Data** (UNCEBD). In 2021 the team merged with the TT on EO fro agricultural statistics established by the **Committee of Experts on food security, AGriculture and rural statistics** (UN-CEAG)
- Focus
  - Develop use cases to demonstrate the use of EO data for official statistics
  - Development of Methods for the use of optical and radar data for crop statistics

- Technical reports
- 2017 "Satellite Imagery and Geospatial Data Task Team report"
- 2022 'Trusted Methods: Lessons Learned and Recommendations from Select Earth Observation
- Applications on Agriculture"

As of 2021, FAO is cochair of the TT, jointly with INEGI and WB

TASK TEAM COMPOSITION

3 Sub Task Teams



Participation:

- UN Big Data Regional Hubs
- 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 data for Agricultural Statistics established under the **UN-CEAG** (Committee of Experts on food security, AGriculture and rural statistics

UN Global Big Data Hub established in China

UN Big Data Regional Hub for Africa

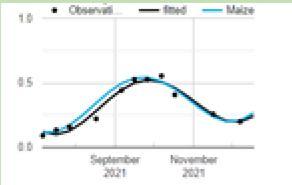
CROP ACREAGE, CROP YIELD AND EO DATA: KEY CHALLANGES

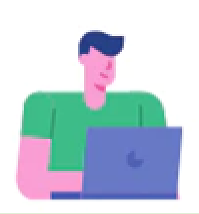
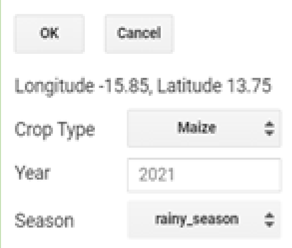
TYPICAL CROP MAPPING WORKFLOW

1 Load region/samples

- Load crop library
- Load AEZ
- Load districts


3 In Situ data collection/QaQc

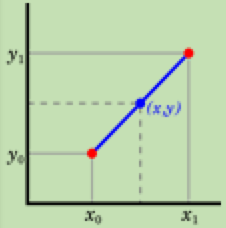



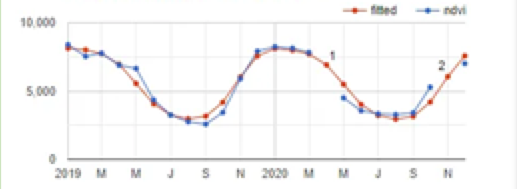
2 Preprocessing

Cloud masking – S2 cloudless


Interpolation



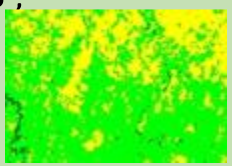
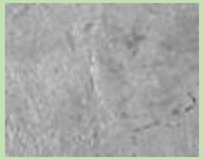
Linear interpolation



Harmonic model

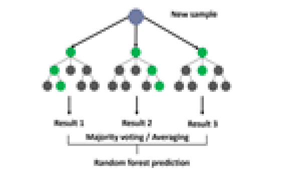
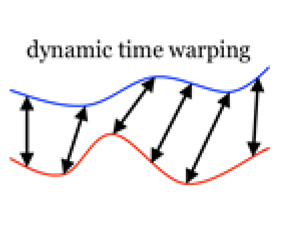
Feature selection

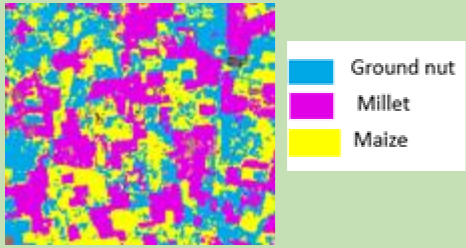
S2 BANDS - 'B2', 'B3', 'B11', 'B12', 'ndvi'
S1 – VV, VH

4 Image classification

- Select number of samples for classification
- Agricultural season
- Sensors
- Algorithm



Validation, Visualize & Download map 5

High demand for in-situ data and data scarcity

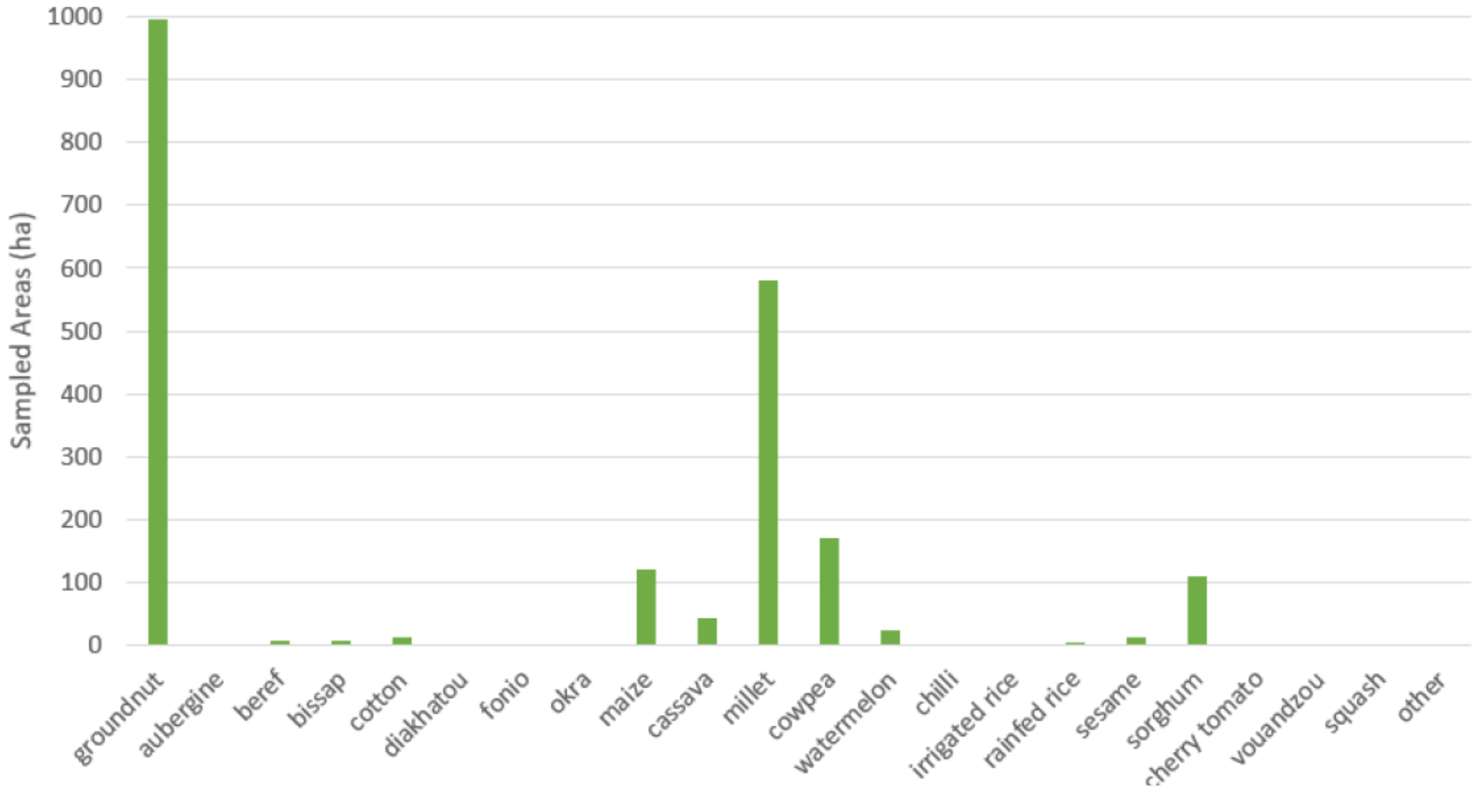
- **<u>Crop type mapping</u>**

  - Limited availability of in-situ data of adequate quality in countries
  - High dependency of supervised classification methods on large amounts of in-situ data of adequate quality, while this resource is rare to find in countries
  - Low transferability of training data and models to different agricultural epochs and to different countries
  - High cloud coverage in specific climatic zones which impairs the use of optical satellite data

- **<u>Crop yield forecasting and Mapping</u>**

  - Traditional methods of yield estimation depend on crop cutting but they lack rigorous and standardized protocols for harmonized data collection. Yield forecasts based on limited number of crop cutting remains **highly uncertain due to the large spatial variability of samples**.

  - EO models based on regressions of crop yields on vegetation indexes derived from Satellite images have low accuracy



Unbalanced sampling: oversampling of dominant crops and under sampling of minor crops, resulting in low accuracy of maps

High demand for in-situ data and data scarcity

JECAM
Joint Experiment for Crop Assessment and Monitoring

GROUP ON EARTH OBSERVATIONS

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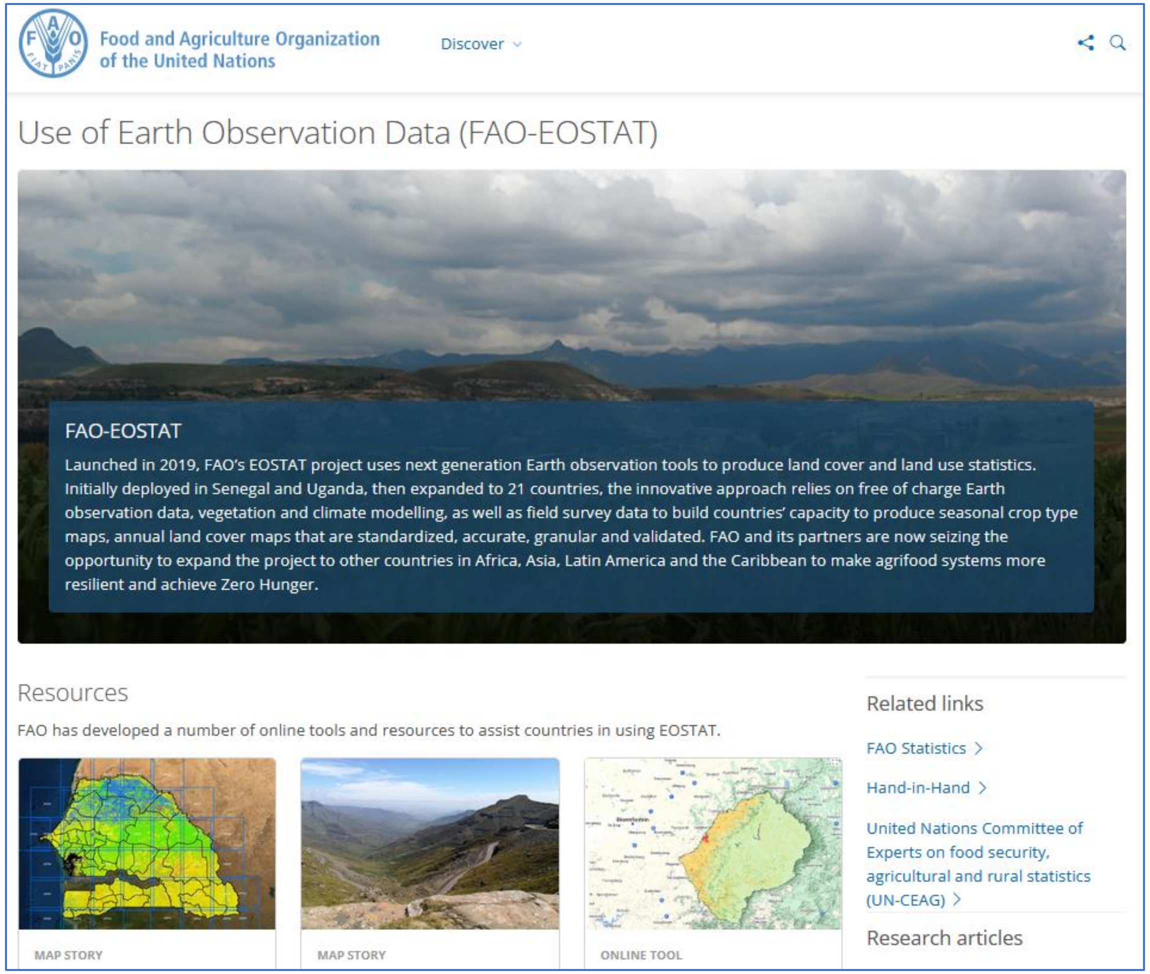
EOSTAT PROJECT: FAO’S RESPONSES TO CHALLENGES

EOSTAT was launched by FAO in 2019 as the geospatial branch of the Data Lab



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

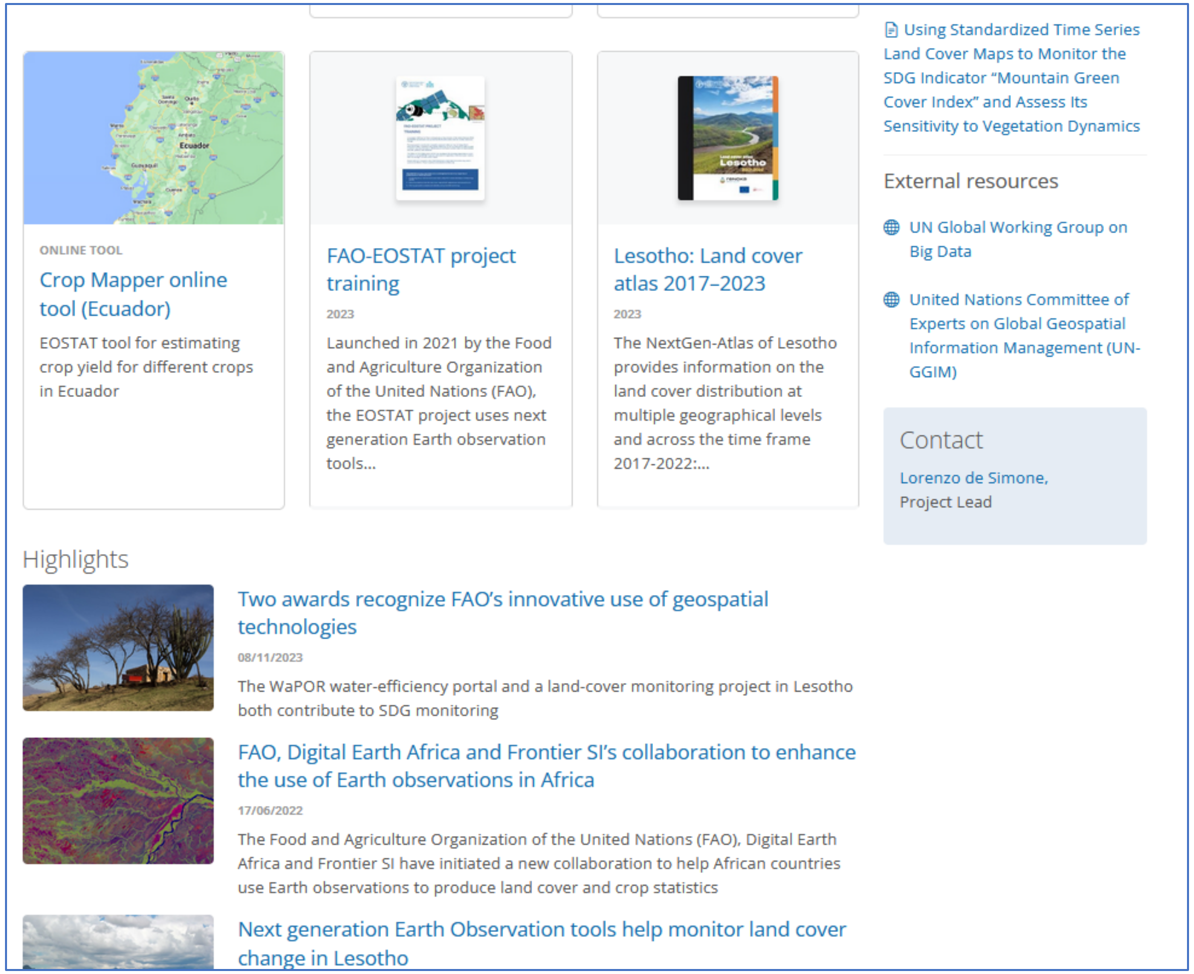
Related links

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

How does EOSTAT support countries in practical terms?

- Establish a project team with nominated experts from NSOs and line Ministries concerned with agricultural statistics
- Discuss and understand their expectations from Earth Observations
- Review current methods for the collection of field data and production of official crop statistics. Adjustment of field survey protocols (**AAS** and **Census**)
- Identify requirements
- Co-design of solutions and co-creation of tools, automation of routines
- Training
  - Workshops
  - On-the-job training
  - Webinars

ZIMBABWE

ZIMBABWE

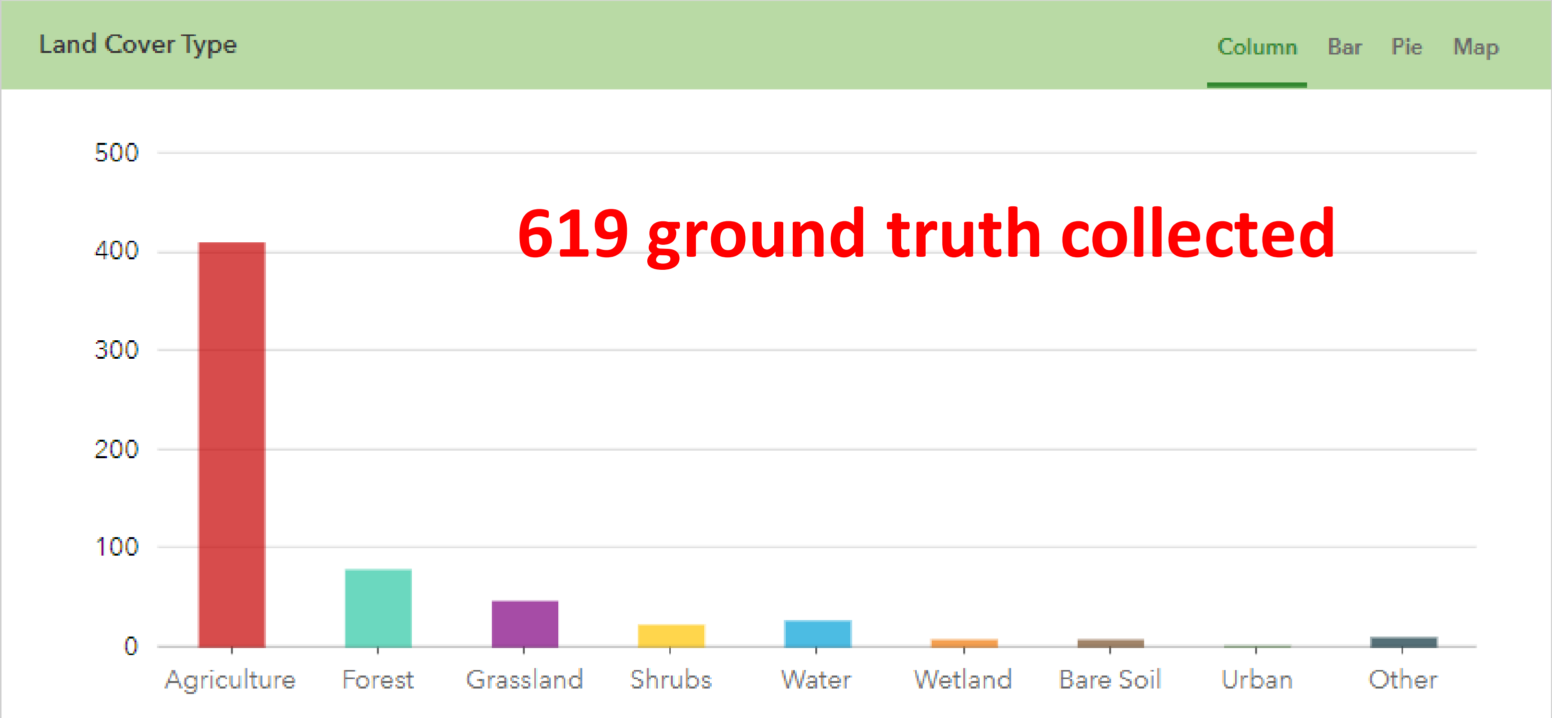
WINTER WHEAT MAPPING

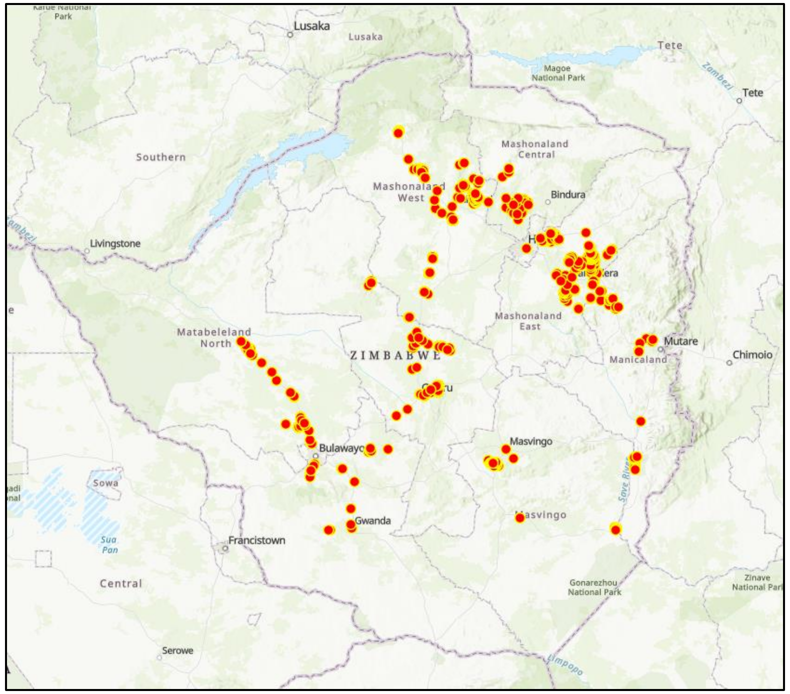
Zimbabwe Emergency Food Production Project (ZEFPP) project funded by the African Development Bank

National partners

- Ministry of Agriculture
- ZIMSTAT
- ZINGZA

- Survey implemented 8 provinces
- 11 enumerators nominated from AGRITEX
- Lenovo android iPad preloaded with ESRI Survey123





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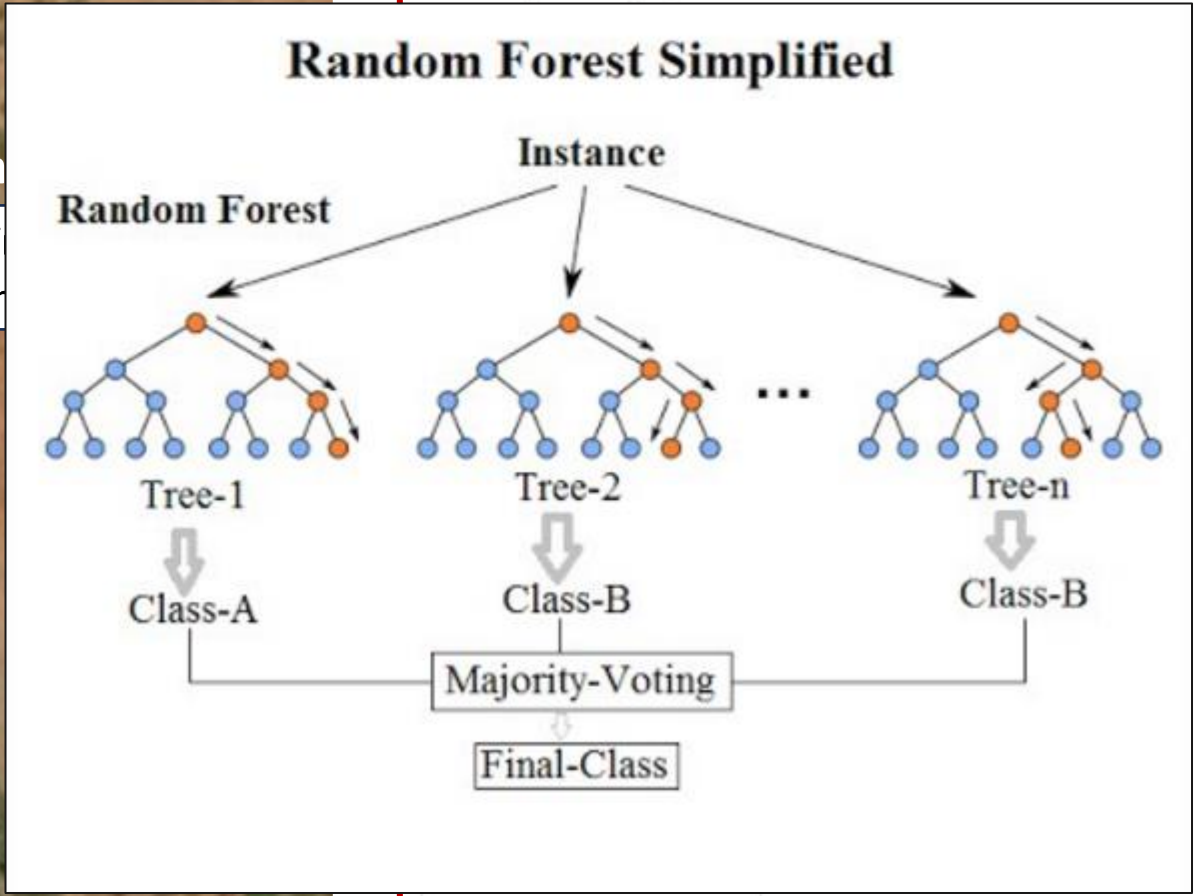
- Observations in the field include:
  - Crop type, yield and management information is recorded
  - Picture is taken
- EO data was used to verify the consistency of the vegeta
in time

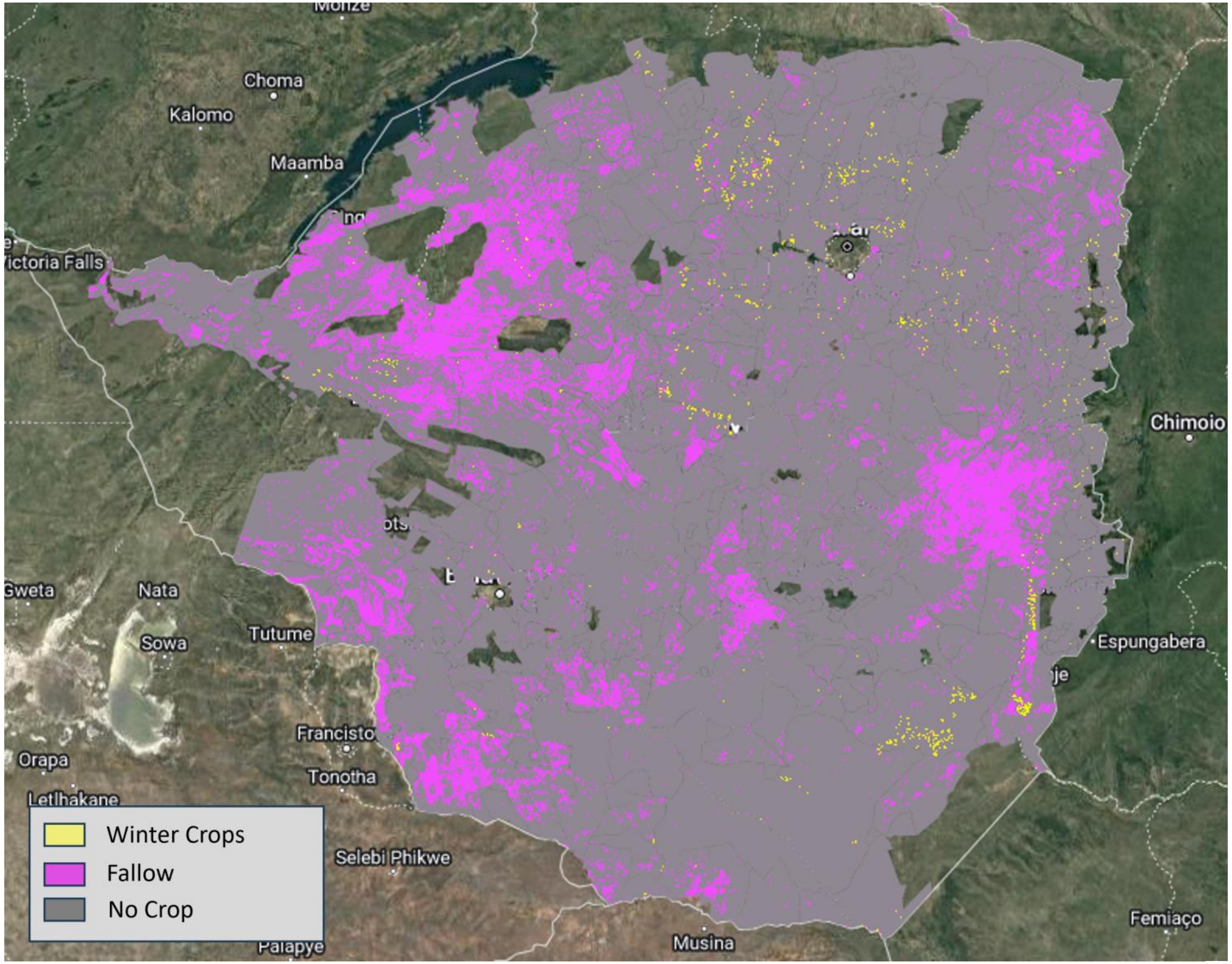


Is this a Crop or Fallow

Crop

Maps Contributors,

WINTER WHEAT NATIONAL MAP 2023

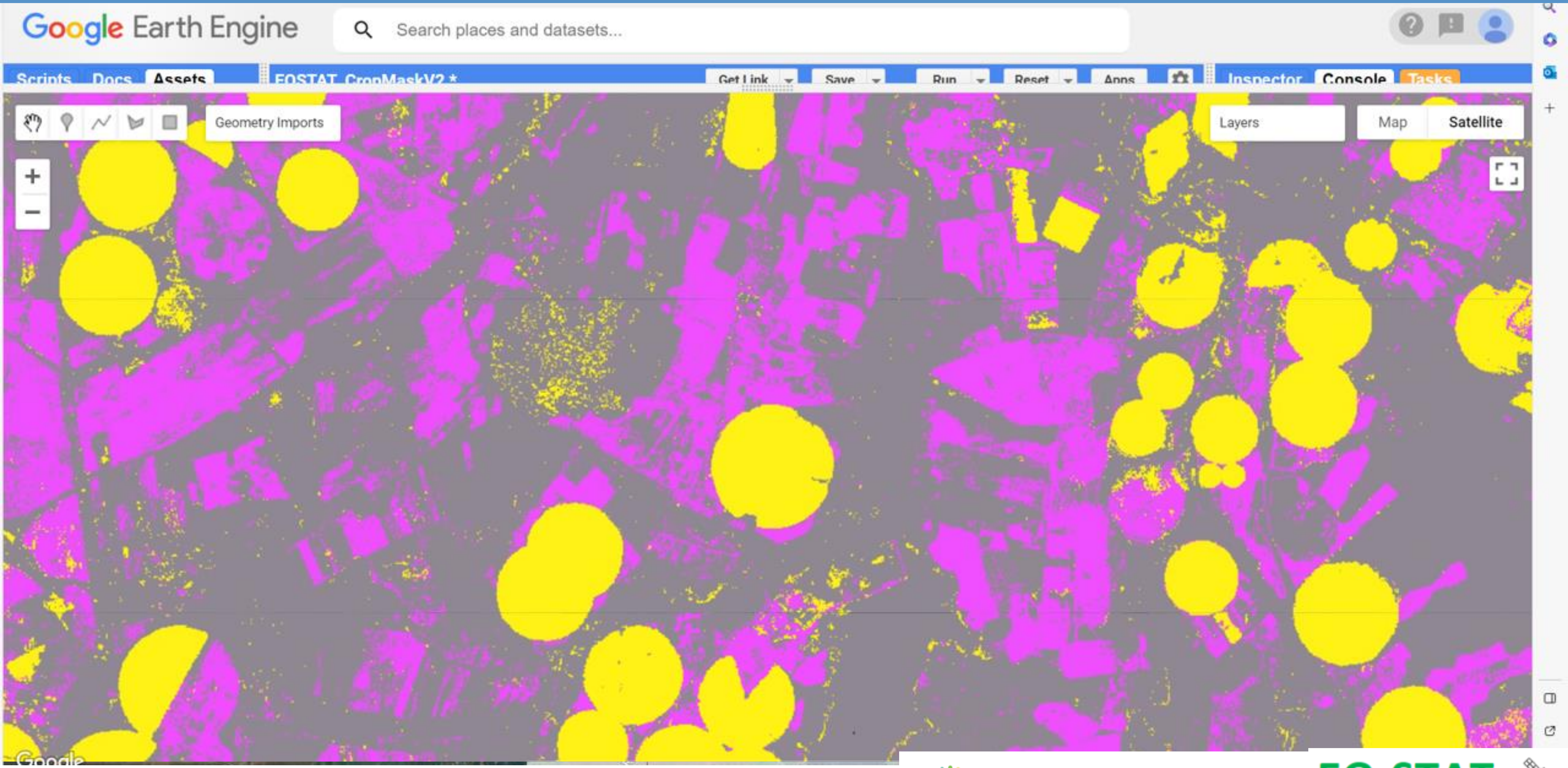


- 202 ground truth data used for accuracy assessment
- Overall Accuracy = **86%**
- Kappa statistic = **0.9**
- WorldCereal local accuracy – OA = 78%

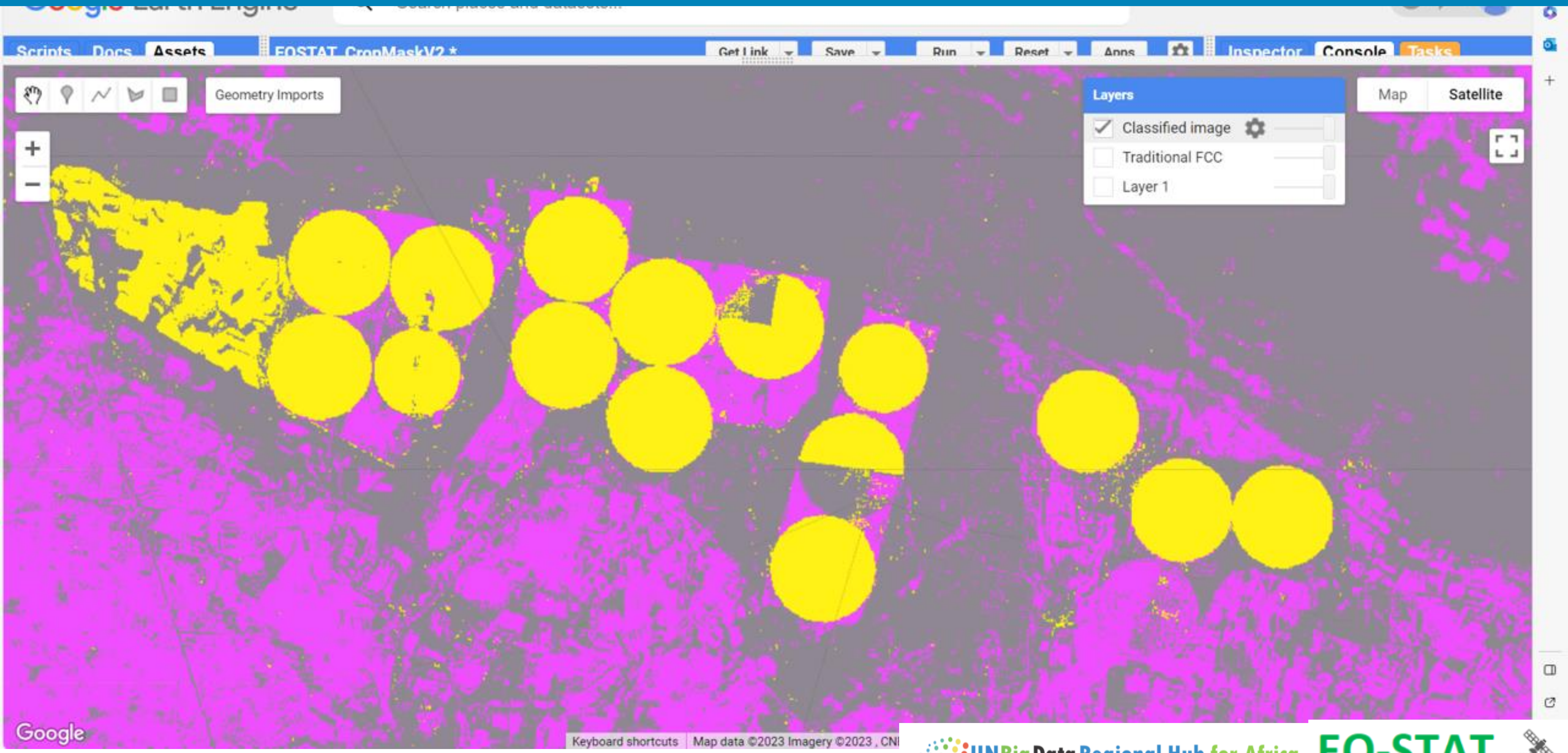
		Reference Data									
		Wheat	Water	Built-up	Forest	Grassland	Bare	Fallow	Shrubs	Row Sum	User Acc
Classification Data	Wheat	58	0	0	1	0	0	0	0	59	0.98
	Water	1	13	0	0	0	0	0		14	0.93
	Built-up	0	0	33	0	0	2	0	0	35	0.94
	Forest	1	0	0	47	1	0	0	0	49	0.96
	Grassland	0	0	2	1	8	0	0	4	15	0.53
	Bare	0	0	0	0	0	6	0	0	6	1.00
	Fallow	0	0	0	0	2	0	9	0	11	0.82
	Shrubs	0	0	0	0	0	0	1	12	13	0.92
	Col Sum	60	13	35	49	11	8	10	16	202	
	Prod Acc	0.97	1.00	0.94	0.96	0.73	0.75	0.90	0.75		
	OA	0.86									
	Kappa	0.90									

UN Big Data Regional Hub for Africa EO-STAT

WINTER WHEAT NATIONAL MAP 2023

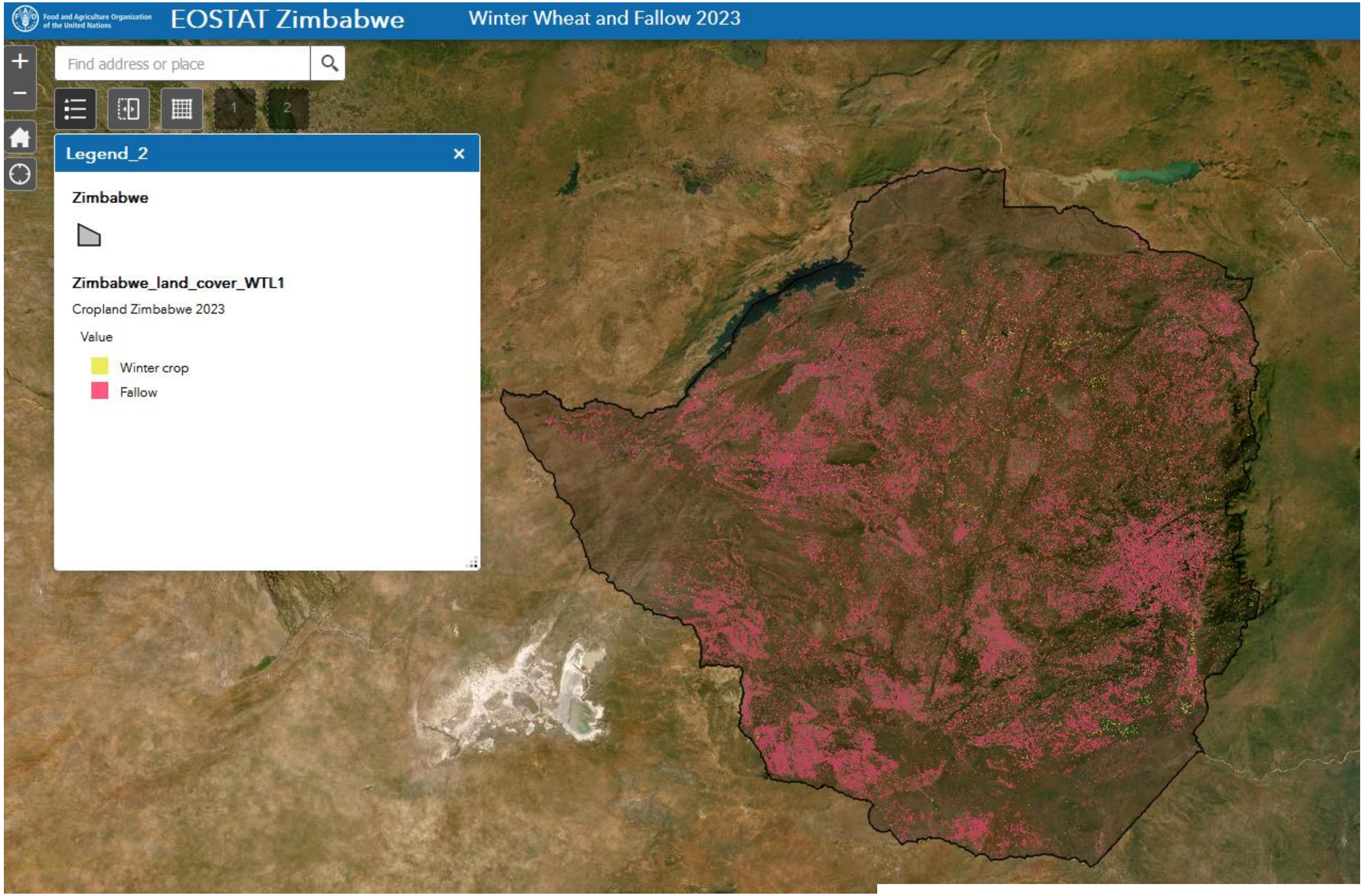


WINTER WHEAT NATIONAL MAP 2023

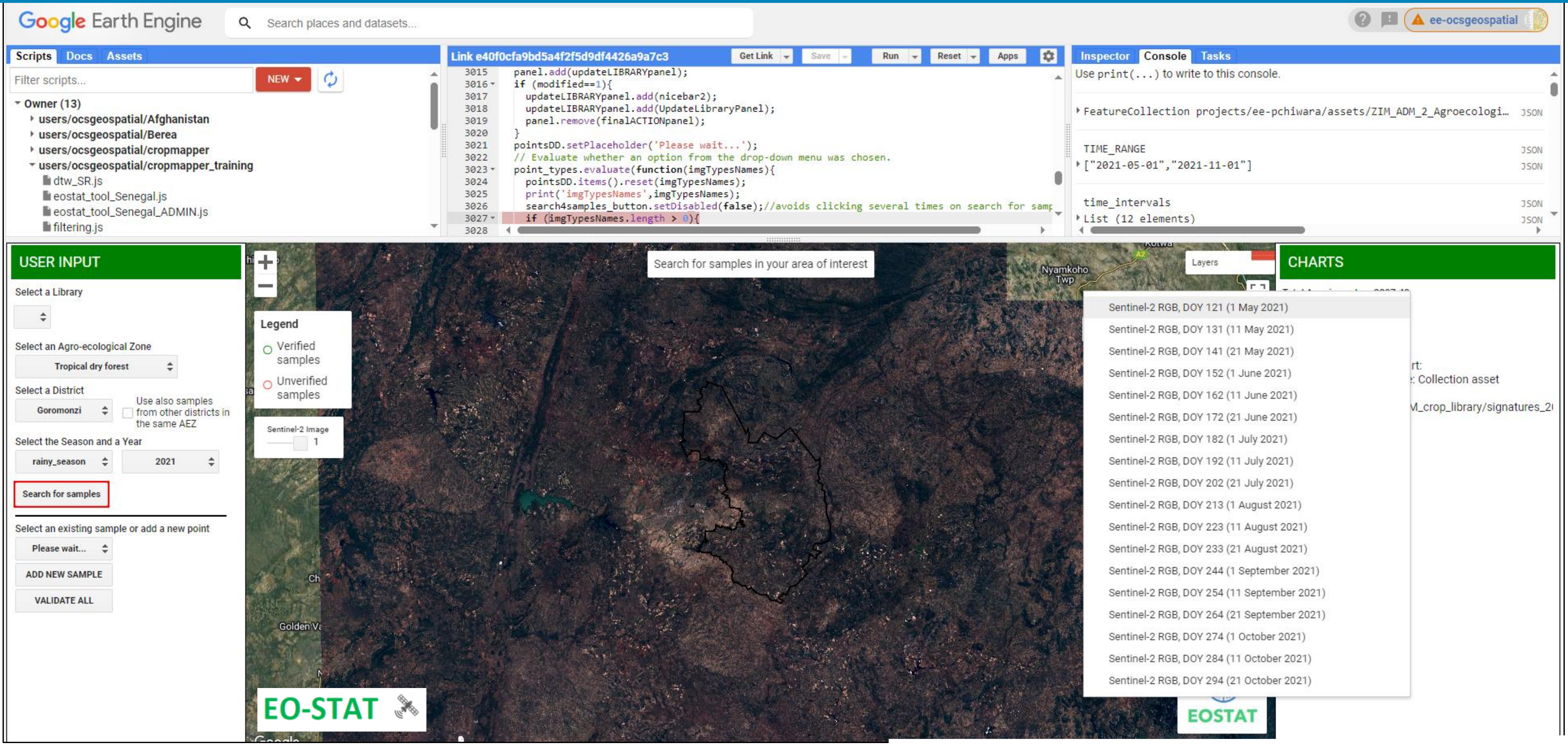


UN Big Data Regional Hub for Africa EO-STAT

WINTER WHEAT WEB-GIS

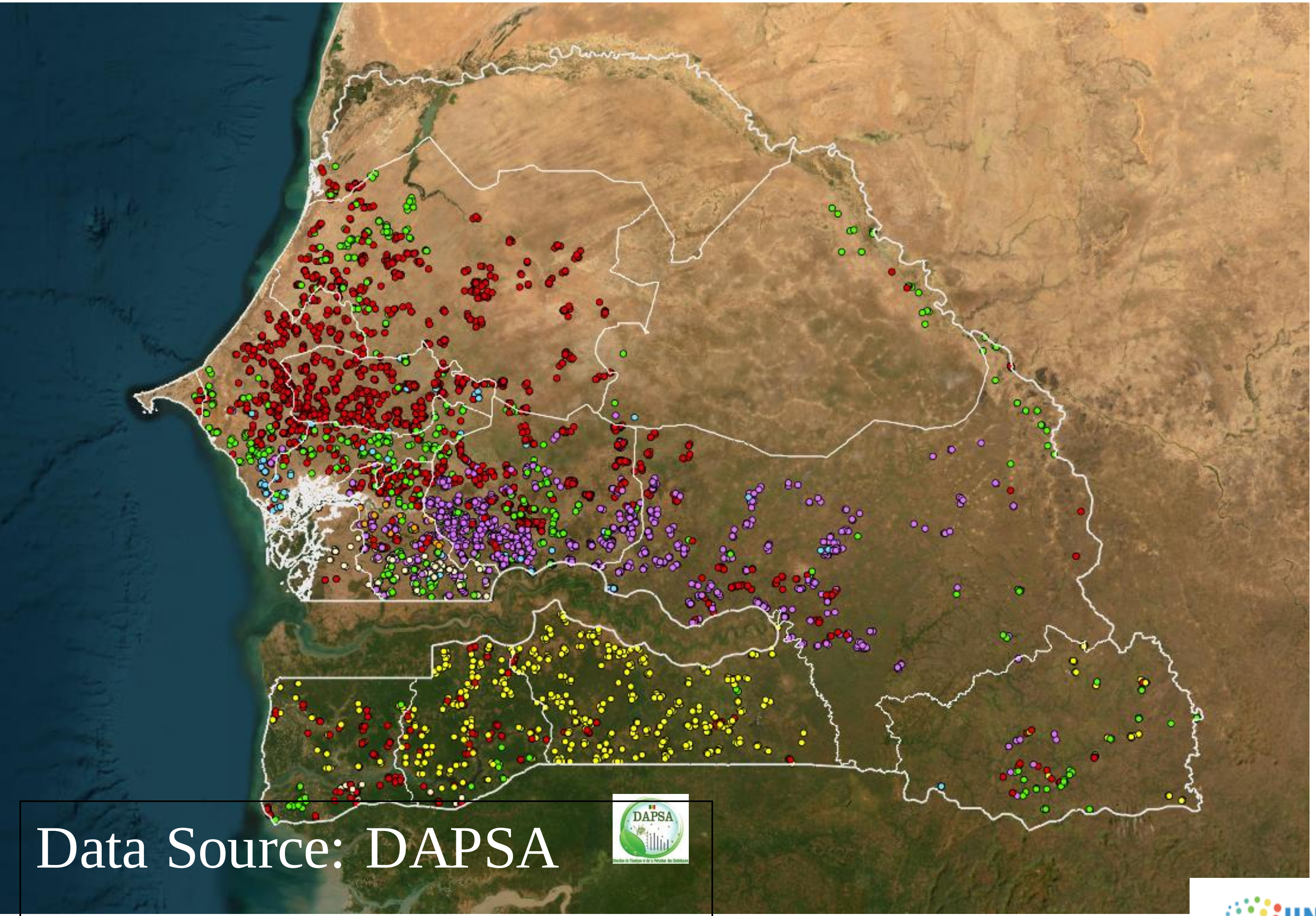


FROM SCRIPTS TO A GRAPHIC USER INTERFACE AND AUTOMATED ROUTINES



SENEGAL

SENEGAL



Data Source: DAPSA

The project started in 2019, currently supported

<u>National partners</u>

- DAPSA
- ANSD

CROP MASK

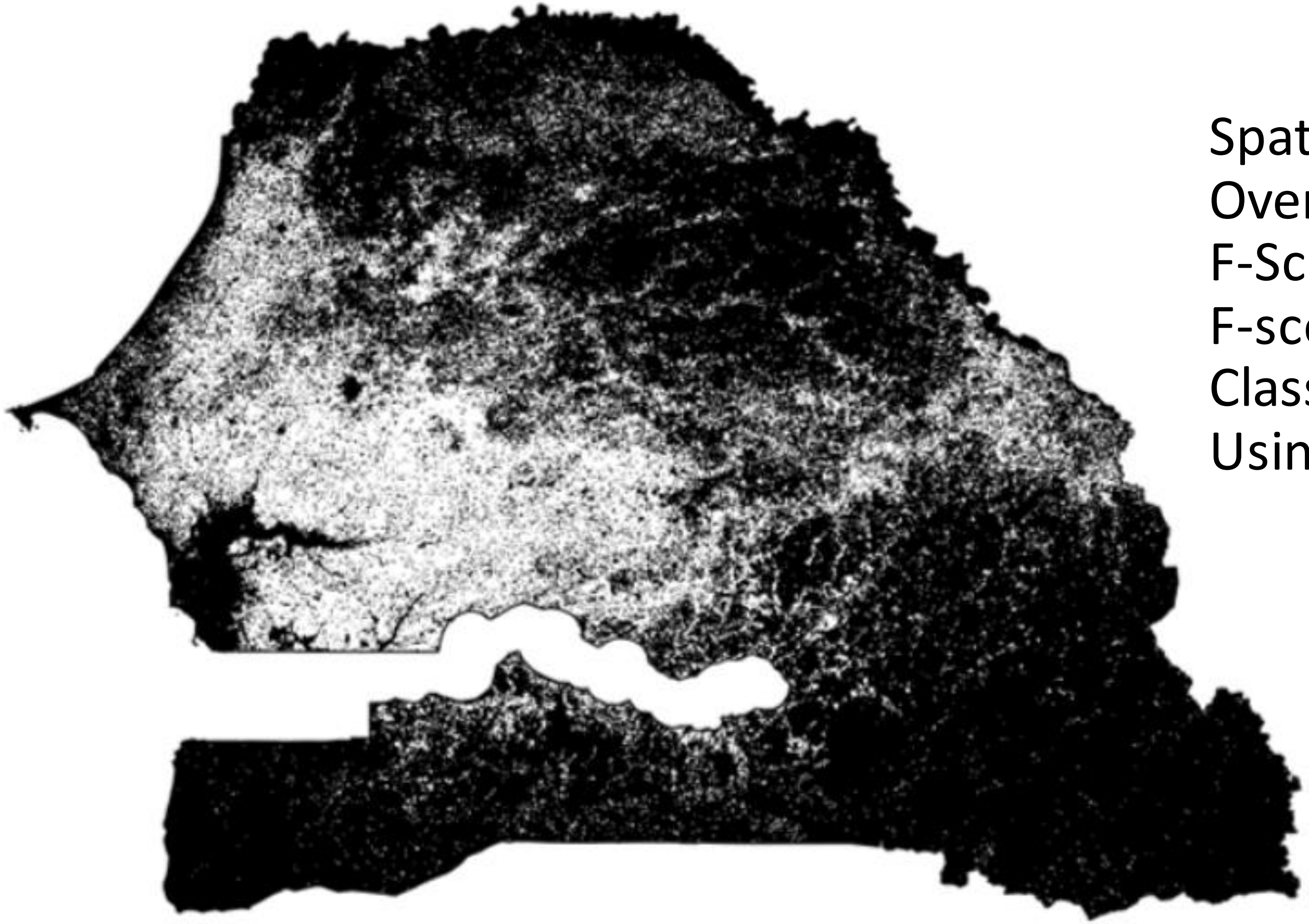


Figure 3-11. Overview of the cropland mask (V1.0) at national scale (black = non cropland, white = cropland)

Spatial resolution: 10m
Overall Accuracy: 96%
F-Score for crops: 97%
F-score for non-crops: 98%
Classification using Random Forest
Using Sentinel2 time series

EO-STAT

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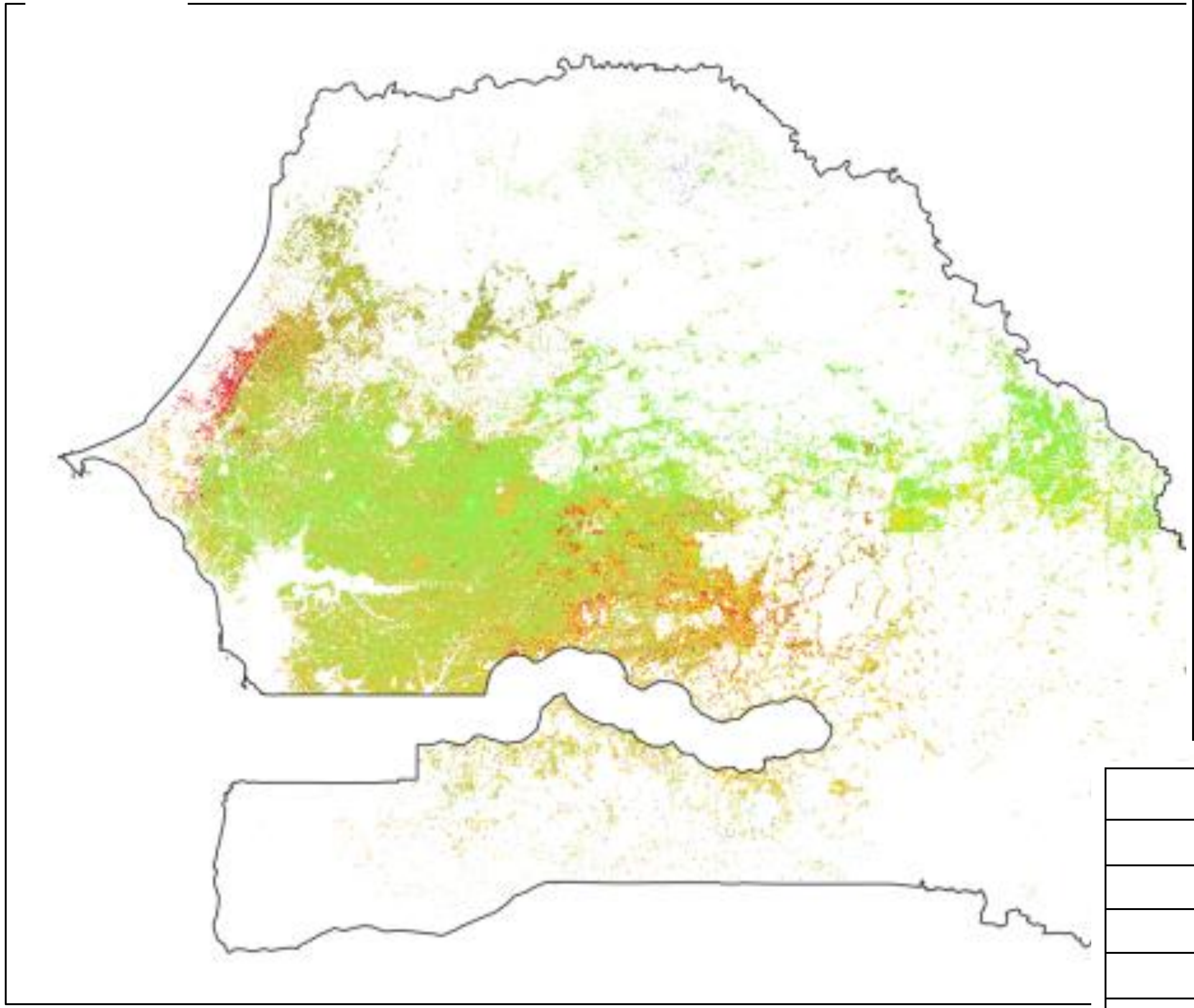
CROP TYPE MAP



	Cropland		Non cropland	
	hectares	%	hectares	%
Country	4574698	23	15111467	77
Dakar	3140	6%	53488	94%
Diourbel	390382	80%	95664	20%
Fatick	349713	51%	335104	49%
Kédougou	4404	0%	1690633	100%
Kaffrine	1019187	90%	112242	10%
Kaolack	428419	79%	112312	21%
Kolda	157542	11%	1222859	89%
Louga	563763	23%	1902177	77%
Matam	447582	16%	2351109	84%
Sédhiou	50679	7%	684390	93%
Saint-Louis	65970	3%	1959737	97%
Tambacounda	760424	18%	3525889	82%
Thiès	330131	50%	333853	50%
Ziguinchor	3360	0%	732009	100%

	Crop area indicator (ha)
Groundnut	1.510.958
Maize	484.534
Millet	2.077.798
Cowpea	210.070
Sorghum	192.582

VALIDATION OF RESULTS

	Groundnut	Maize	Millet	Cowpea	Sorghum	Other crops	
Groundnut	13172	289	233	178	79	184	93%
Maize	578	1110	284	0	136	162	49%
Millet	631	600	6282	87	193	88	80%
Cowpea	329	19	81	1203	1	20	73%
Sorghum	106	651	162	0	590	42	38%
Other crops	959	46	239	257	104	2076	56%
	83%	41%	86%	70%	53%	81%	78%

PILOT SURVEY IN NIORO DISTICT 2021

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

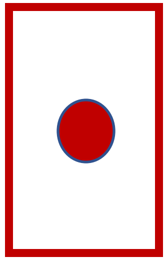
Expressed in number of pixels

		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%

ADJUSTMENT OF SURVEY DESIGN

RECOMMENDATIONS ENDORSED BY DAPSA AND IMPLEMENTED IN THE AAS PROTOCOL



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

EFFICIENCY FROM THE USE OF EO DATA

Crop type	Standard error of estimators of proportions		**Efficiency of satellite data**
	Field data only	Field & satellite data	
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 encouraging results based on the analysis of the sampling variance of the estimators.

CROP YIELD ESTIMATION

- 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 data collected in the field with Leaf Area Index (LAI) derived from Sentinel 2 data
- <u>In-situ data</u>:
  - ❑ 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.

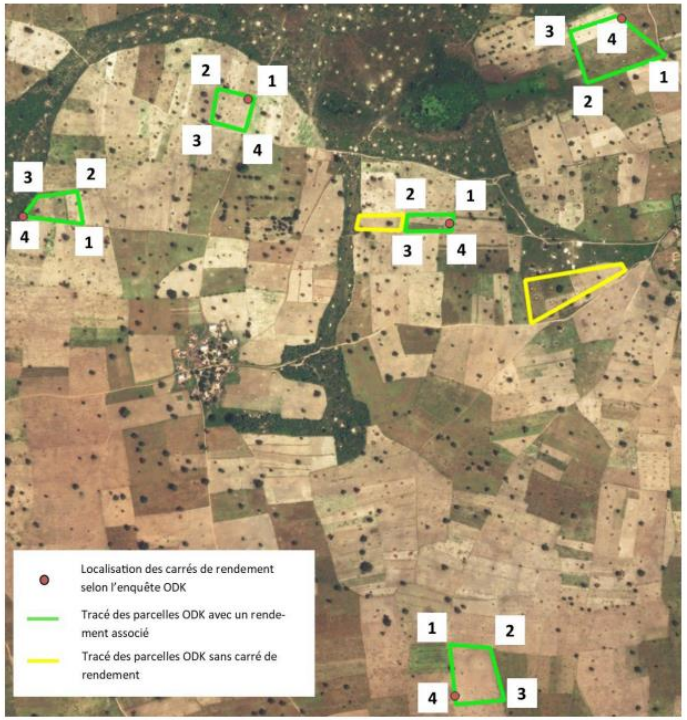
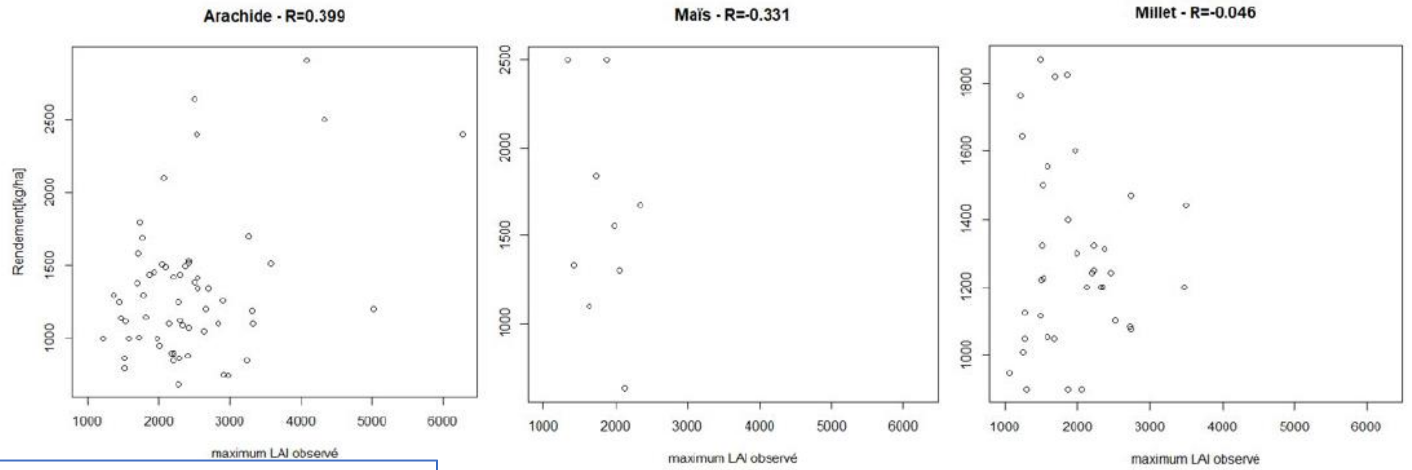


Figure 2: Location of crop cutting squares

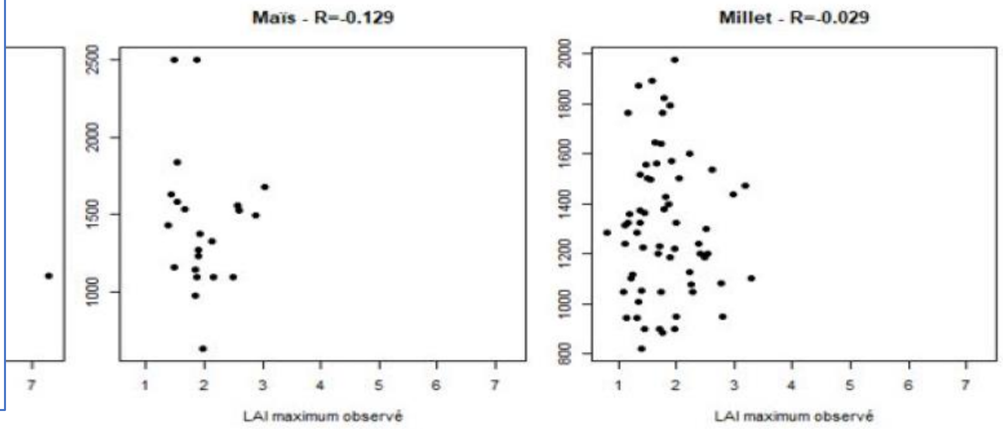
RESULTS

- 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



- 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.

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



MALI

EXPERIMENTAL SURVEY DESIGN

MALI – AREA FRAME

- based on a design independent from an official agricultural survey.
- Stratification based on cropping intensity (0% - 30% ; 30% - 60% ; 60% - 100%) based on the ESA WorldCover land cover map
- Random selection of 300 segments (500m X 600m) within the different zones.
- Manual digitizing (on-screen) of homogenous crop block/parcel using Google Earth /Bing imagery for each segment
- MapMe, used for the teams navigation (driving to the place of each segment);
- - ODK Collect, used to collect field data (answering a form about crop type and crop aera);
- - Qfield, used to assess the crop block/parcel boundaries and to modify them when needed.

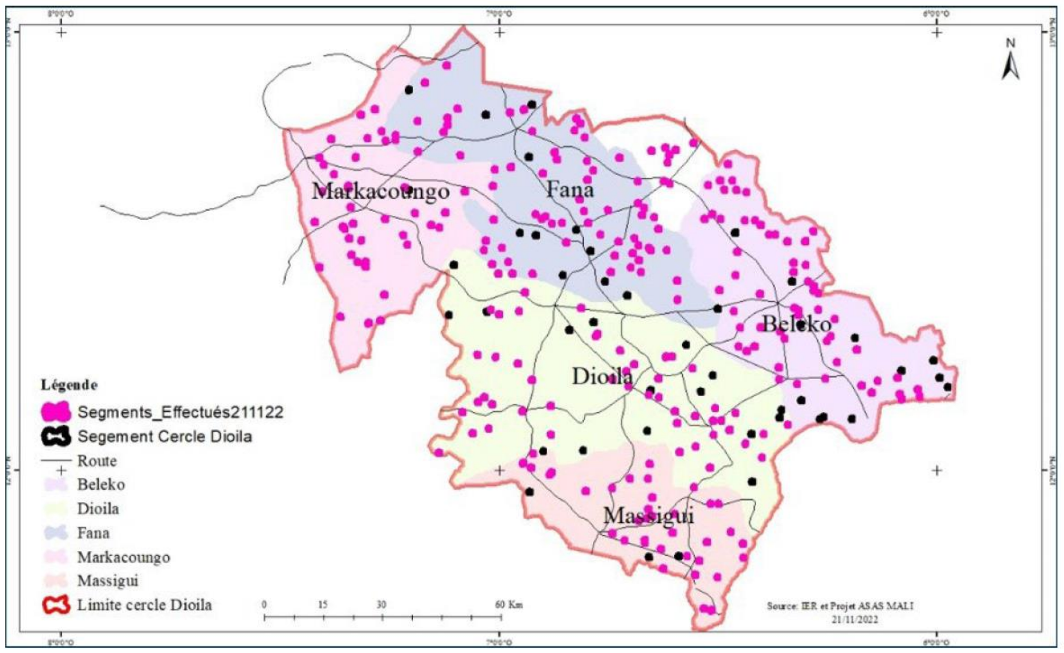


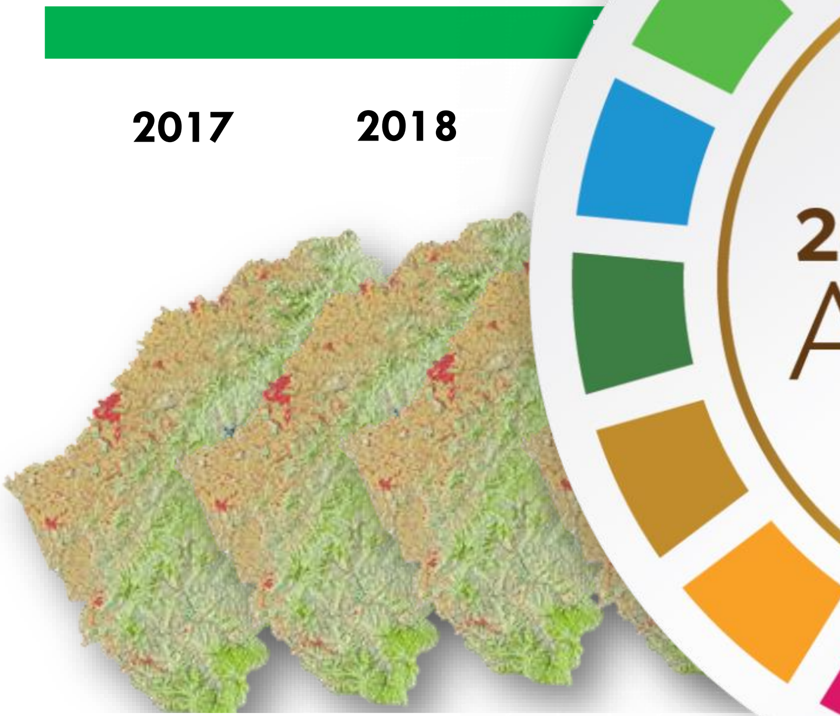
Figure 21. Localization of the segments visited by the end of November 2022

Study partners: Université des Sciences Sociales et de Gestion de Bamako), nominated experts by the national institutions (Institut d'Economie Rurale" (IER) from the "Ministère du Développement Rural" and the "Cellule de Planification et de Statistique" (CPS)

LESOTHO

LAND COVER & LAND COVER CHANGE STATISTICS &SDG

In collaboration with the Bureau of Statistics an operational system has … of standardized annual national land co… …matic extracti… …nd SDG 15.4.2 reporting



Automatic production of annual national … 10m resolution.

remote sensing
MDPI

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]

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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

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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

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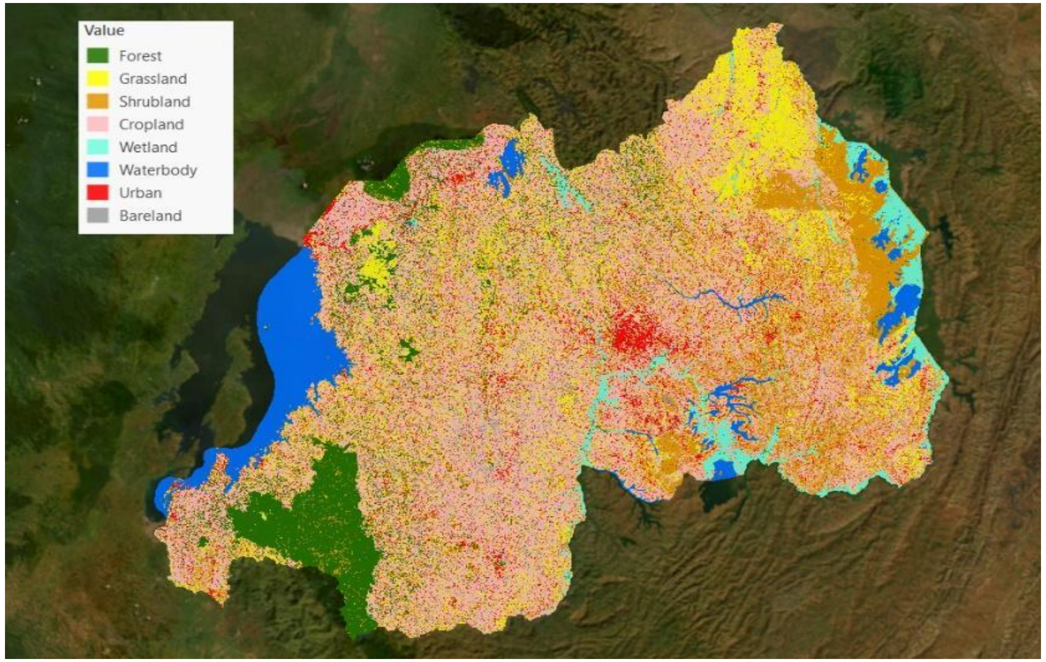
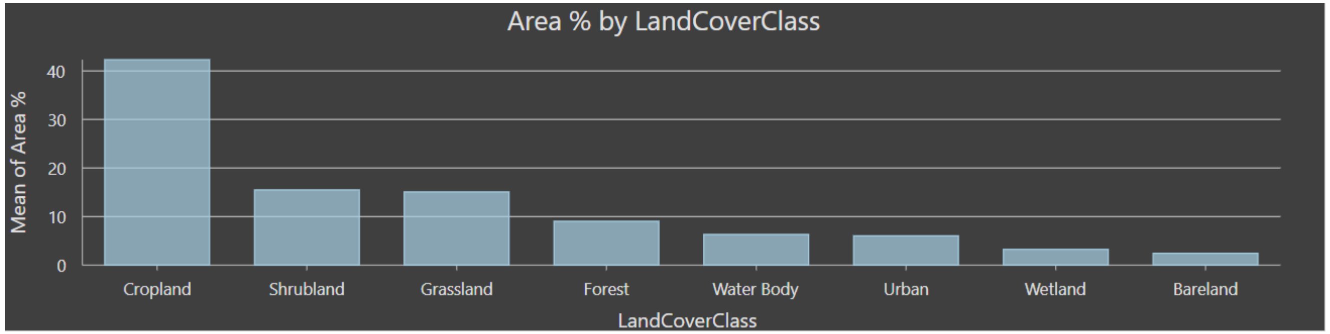
RWANDA

MODERNIZATION OF THE NATIONAL LAND COVER MAPPING METHODOLOGY

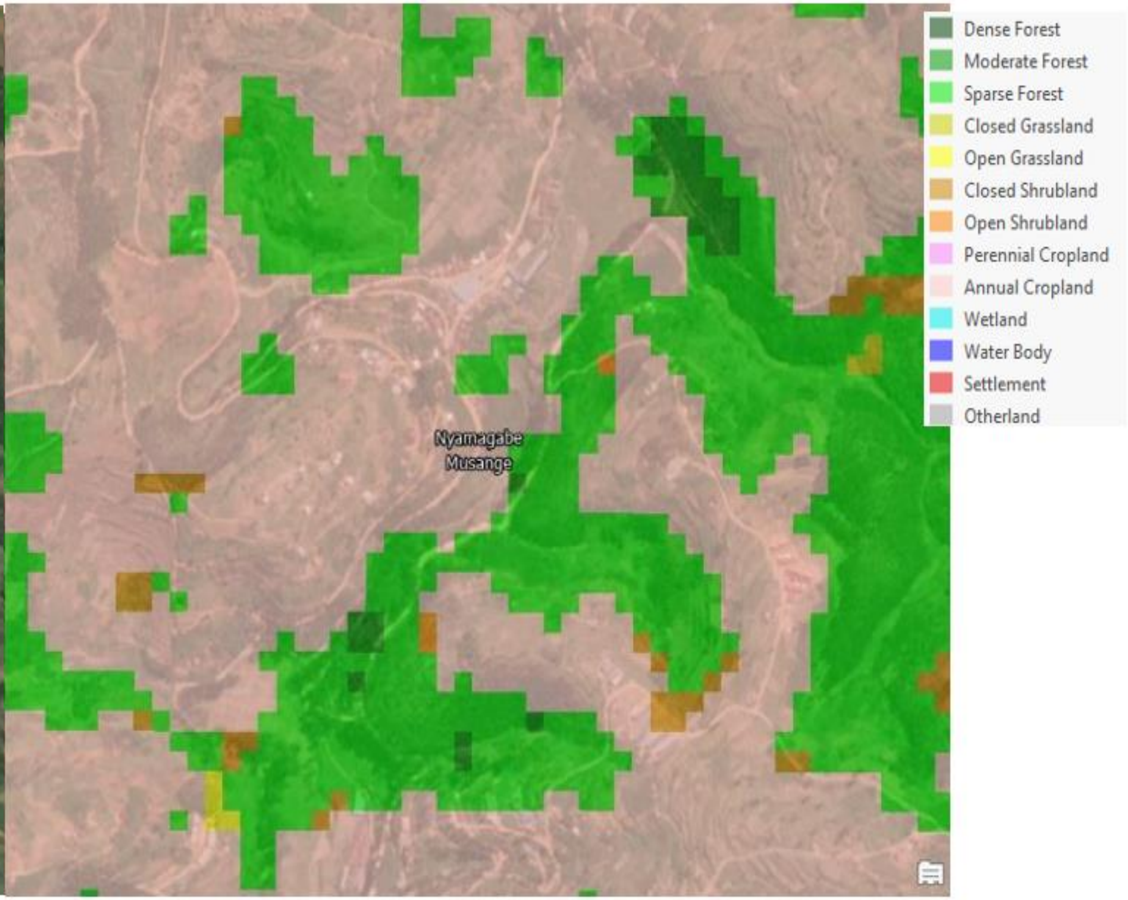


		Predicted class								
		Forest	Grassland	Shrubland	Cropland	Wetland	Water Body	Urban Settlement	Bare Land	User Accuracy
True class	Forest	**937**	4	12	41	0	2	1	3	**0.94**
	Grassland	28	**887**	26	30	1	0	19	9	**0.89**
	Shrubland	4	35	**522**	408	5	1	18	7	**0.52**
	Cropland	26	269	336	**1257**	1	5	94	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**	

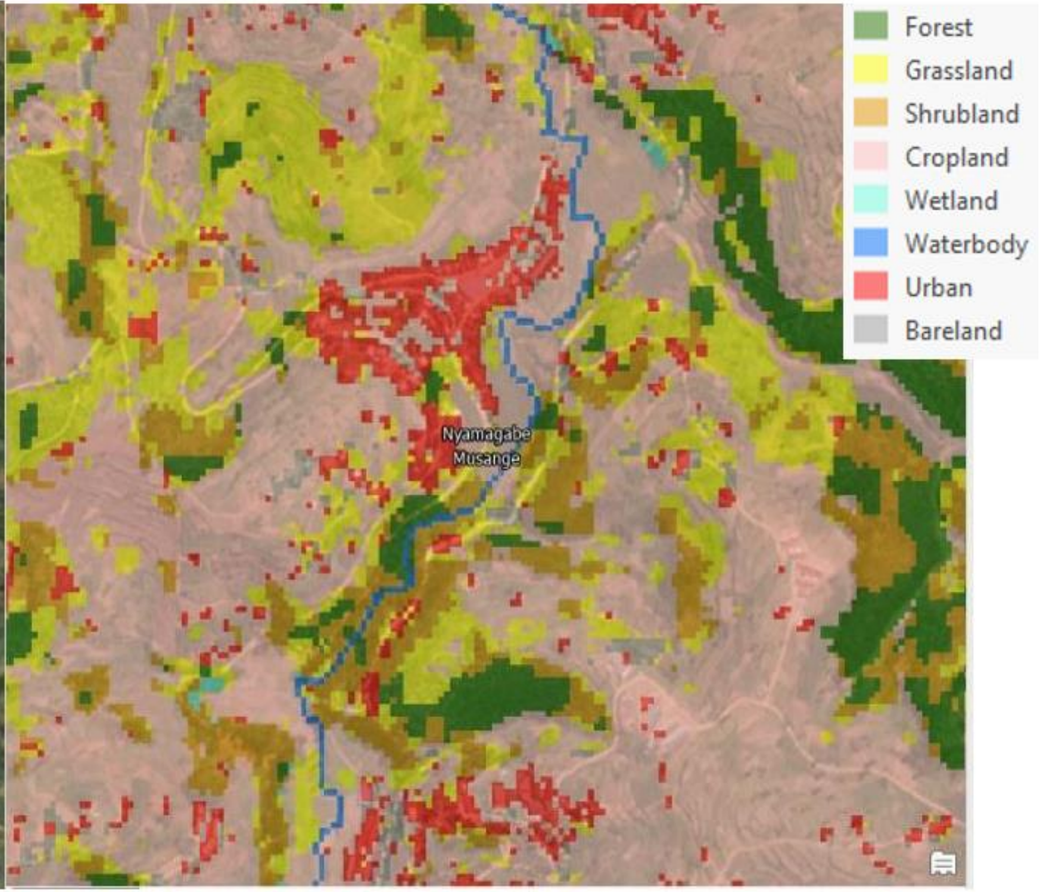


- First prototype produced without any in-situ data for baseline 2021
- Overall Accuracy 76%

HIGH GENERALIZATION OF MODEL AND LACK OF DETAIL IN THE LC MAP 2015



HIGH MODEL SPECIFICITY AND SENSITIVITY
HIGHER DETAIL IN LC MAP 2021



Digital Earth AFRICA

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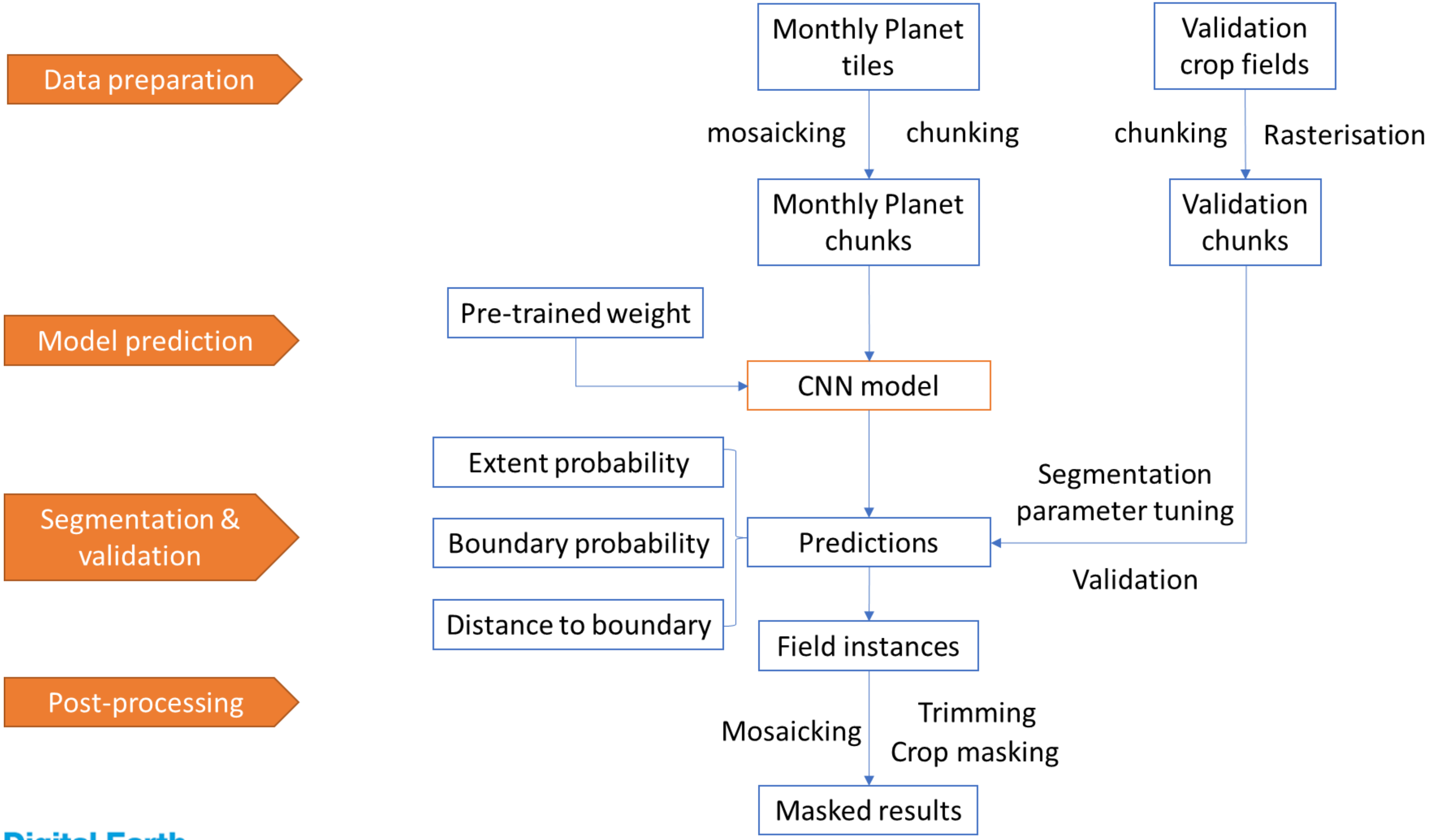
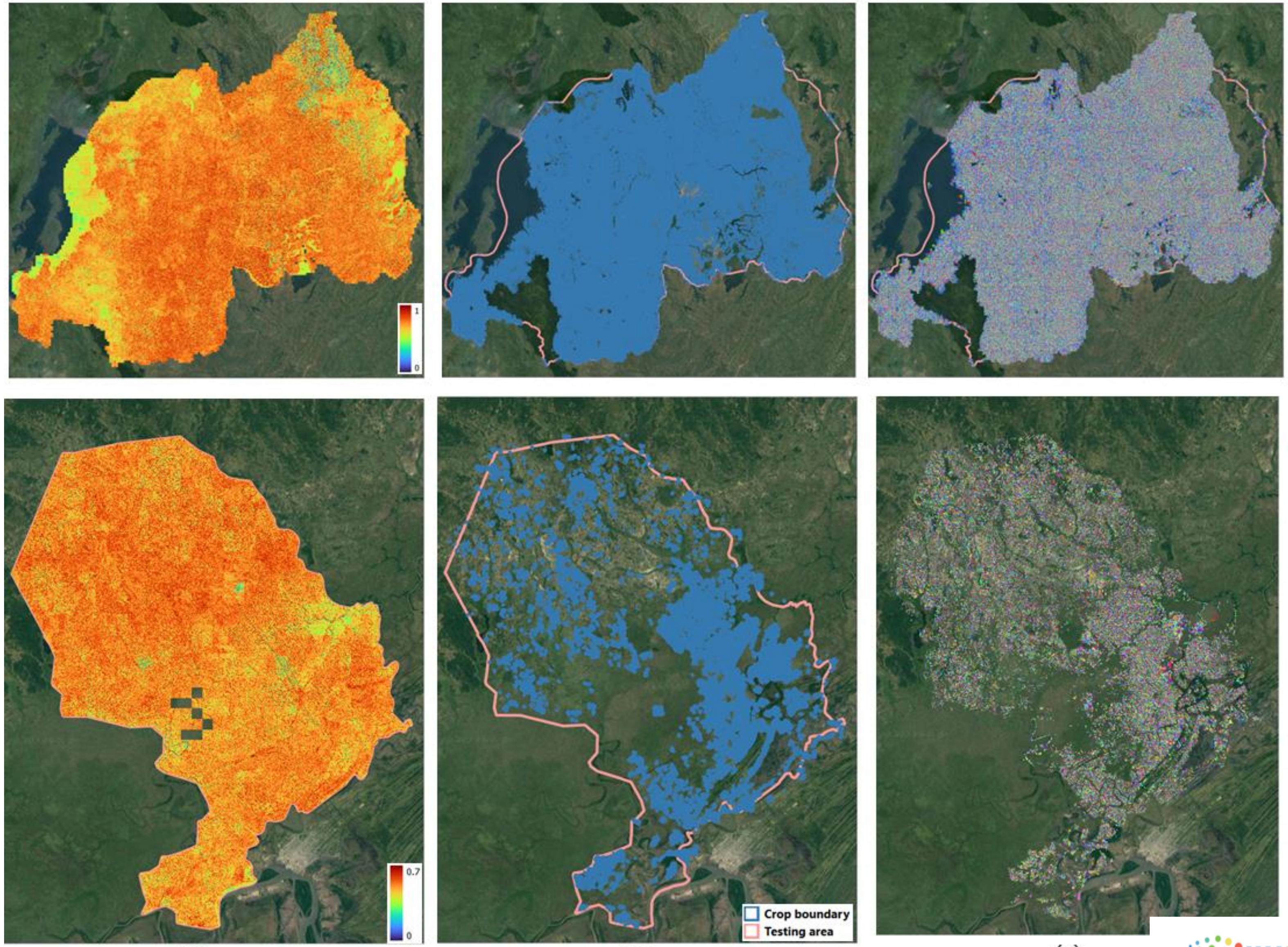
FIELD BOUNDARY MAPPING



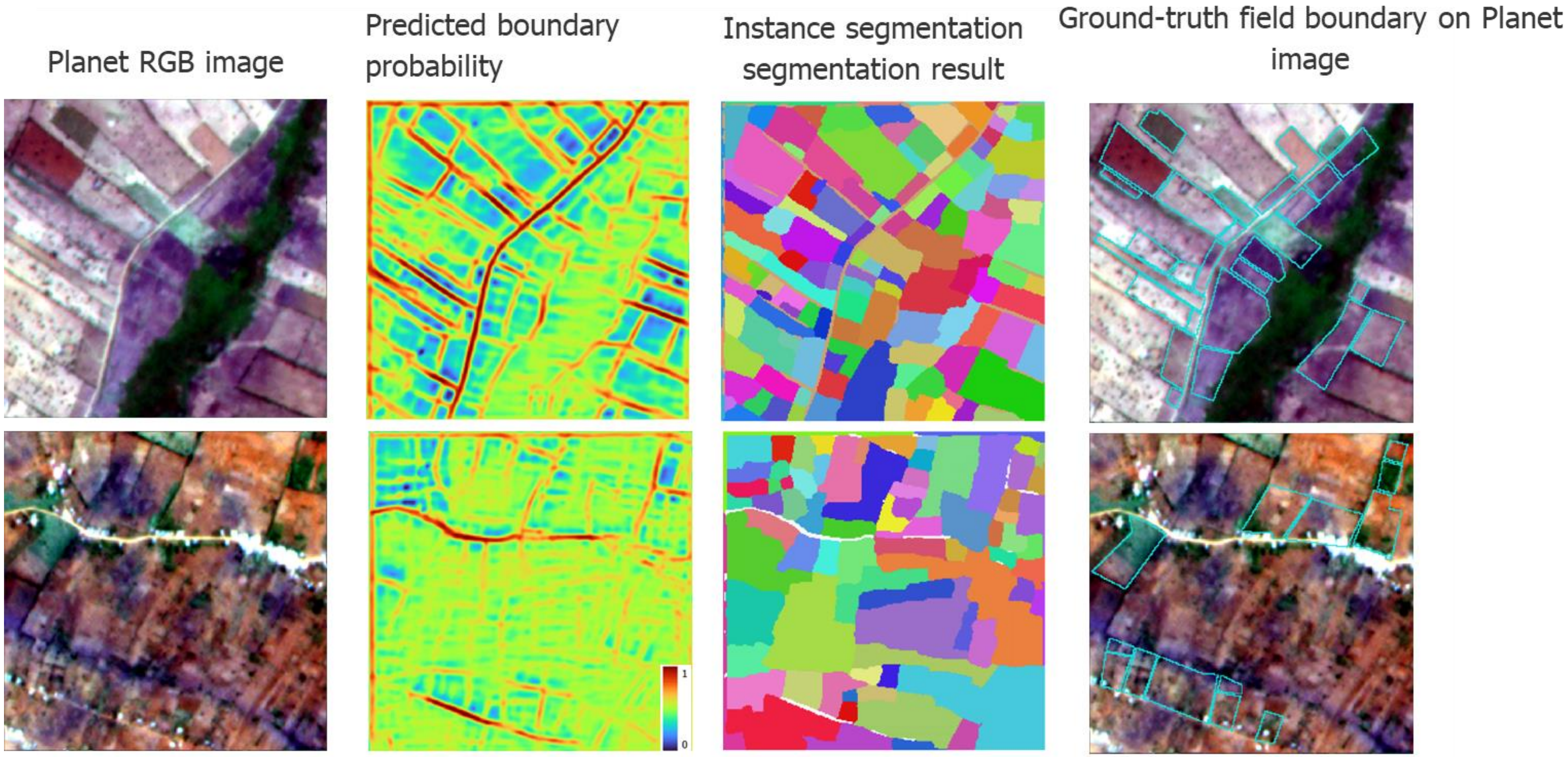
FIELD BOUNDARY MAPPING



(a) (b) (c)

Crop boundaries delivered for **Rwanda** (top row) and **Mozambique** (bottom row).

FIELD BOUNDARY VALIDATION



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.

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MICHIGAN STATE UNIVERSITY

BigData UN Global Working Group

GEO GROUP ON EARTH OBSERVATIONS

Digital Earth AFRICA

REFLECTION POINTS

Reflection points for feedback from Members of AFCAS

1) To All: what is the relevance of the EOSTAT activities to your work and mission.
Example of EOSTAT activities
   1) Adjusting and optimization of field survey design (e.g. AAS)
   2) Crop type mapping and crop statistics (acreage and yield)
   3) Land cover mapping and LC statistics
   4) Crop plot boundaries mapping

2) To NSOs and concerned institutions: which challenges do you find in the use of EO data for land cover mapping, SDG indicator monitoring and reporting, crop type mapping, crop acreage, and yield estimates? Can you share your most pressing methodological and/or capacity development needs;

3) To Regional Organizations: how can we mobilize resources to support NSOs work in geospatial, how can we collaborate more to ensure and strengthen harmonization and standardization of methods and EO based results.

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

THANK YOU

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