Food and Agriculture Organization
of the United Nations

FAO Webinar Series

Earth observation data for agricultural statistics

March-May 2023

Global Network of Data Officers and Statisticians

SESSION 1 : EOSTAT project overall presentation

8 March 2023

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Technical Adviser, Office of the Chief Statistician, FAO

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- Relevance of LCLU maps for official statistics and SDG reporting
- Problem definition
- Challanges
- Solutions:
  - In situ data: enhanced design and field protocol using EO data and GIS
  - Methodological development: crop acreage and dealing with data scarcity
  - Methodological development: crop yield statistics using EO and ysical based modelling
  - Methodological development: reuse of in-situ data
  - Methodological development: convolutional neural network and crop field boundaries
  - SDG 15.4.2

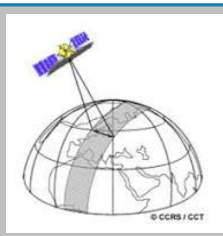
RELEVANCE OF LAND COVER AND CROP MAPS

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 global fundamental geospatial data themes 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.

LAND COVER AND LAND USE SUPPORT MANY SDGS

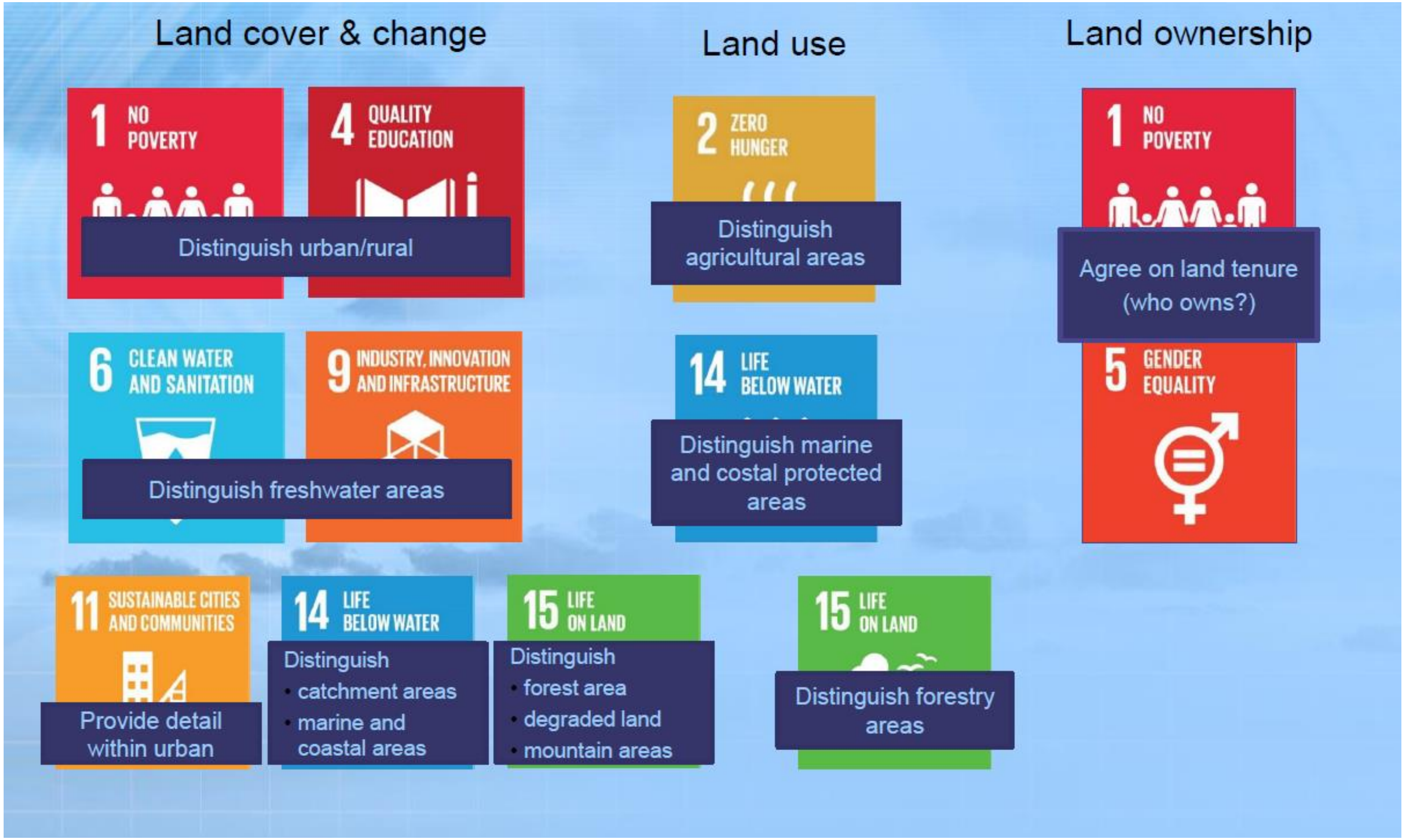
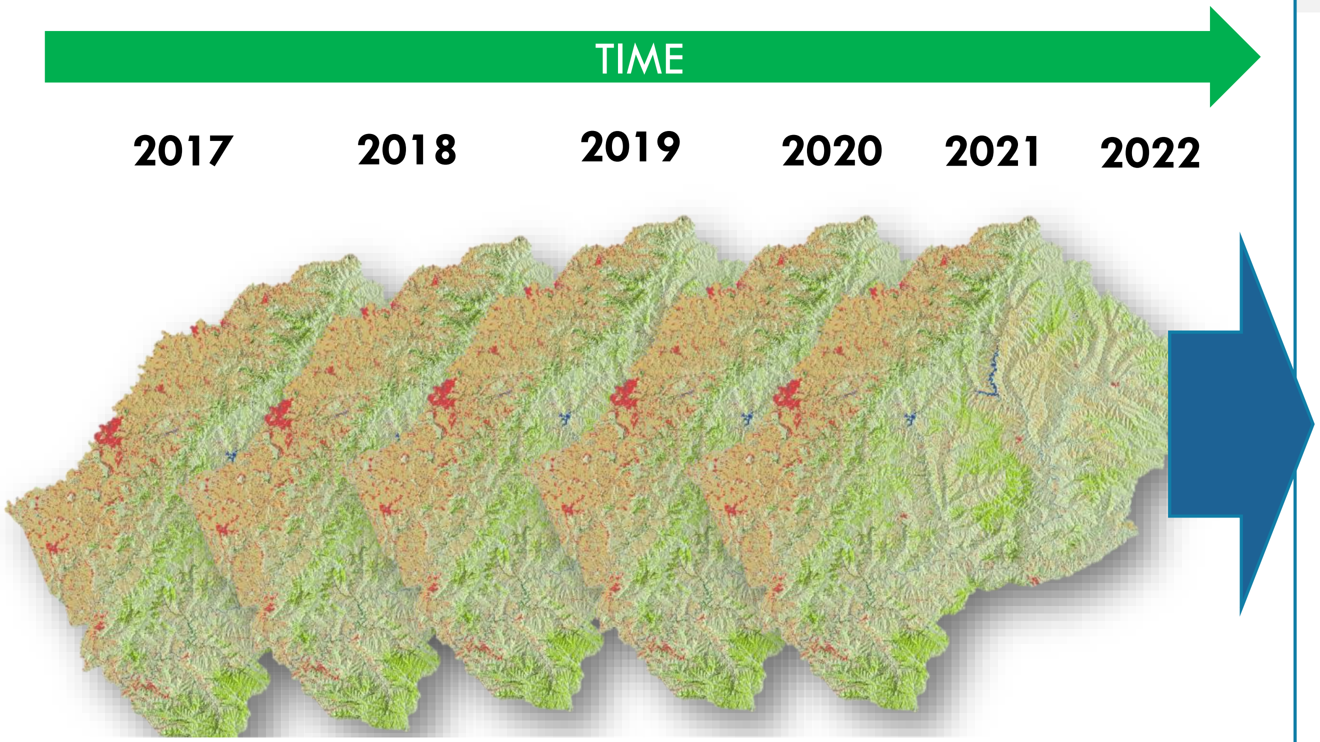


IMAGE CREDITS: Environment Statistics Section, United Nations Statistics Division

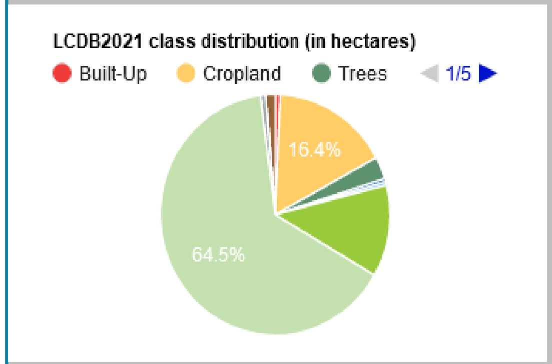
LAND COVER MAPS

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

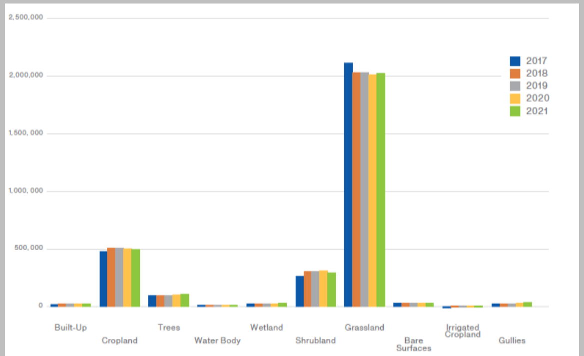


Automatic production of annual national land cover map at 10m resolution. Source: EOSTAT Lesotho 2022.

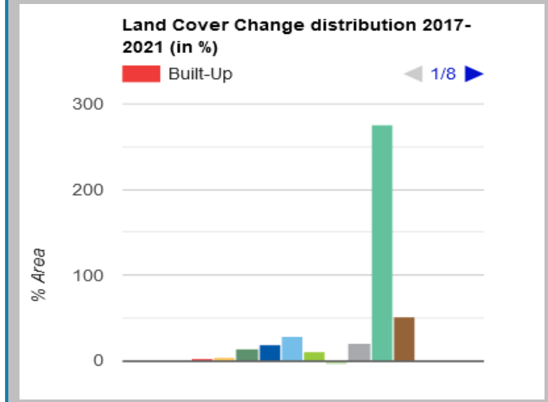
LC statistics



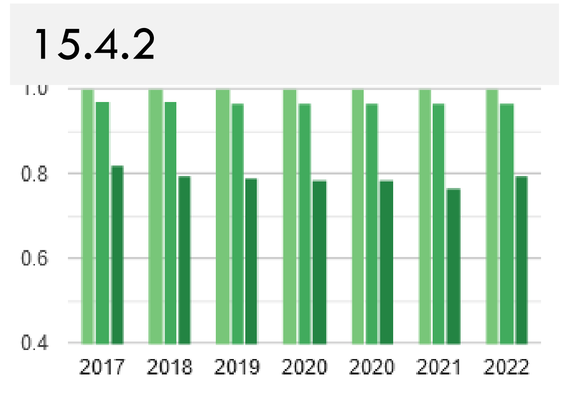
LC trends



LCC statistics



SDG Reporting



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%

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

PROBLEM DEFINITION AND MAIN CHALLENGES IN CROP MAPPING AND YIELD ESTIMATION

EO-STAT

PROBLEM, OBJECTIVE, AND APPROACH

Problem: Collecting and predicating real time crop location and yield is difficult and expensive.

Support countries' capacity to consistently collect agricultural statistics through integrated earth observation data, physical modeling, and ground truth data collection.

Objective

Provide a free tool, publicly hosted for sustainable utility with pilot in-country collaboration and capacity building.

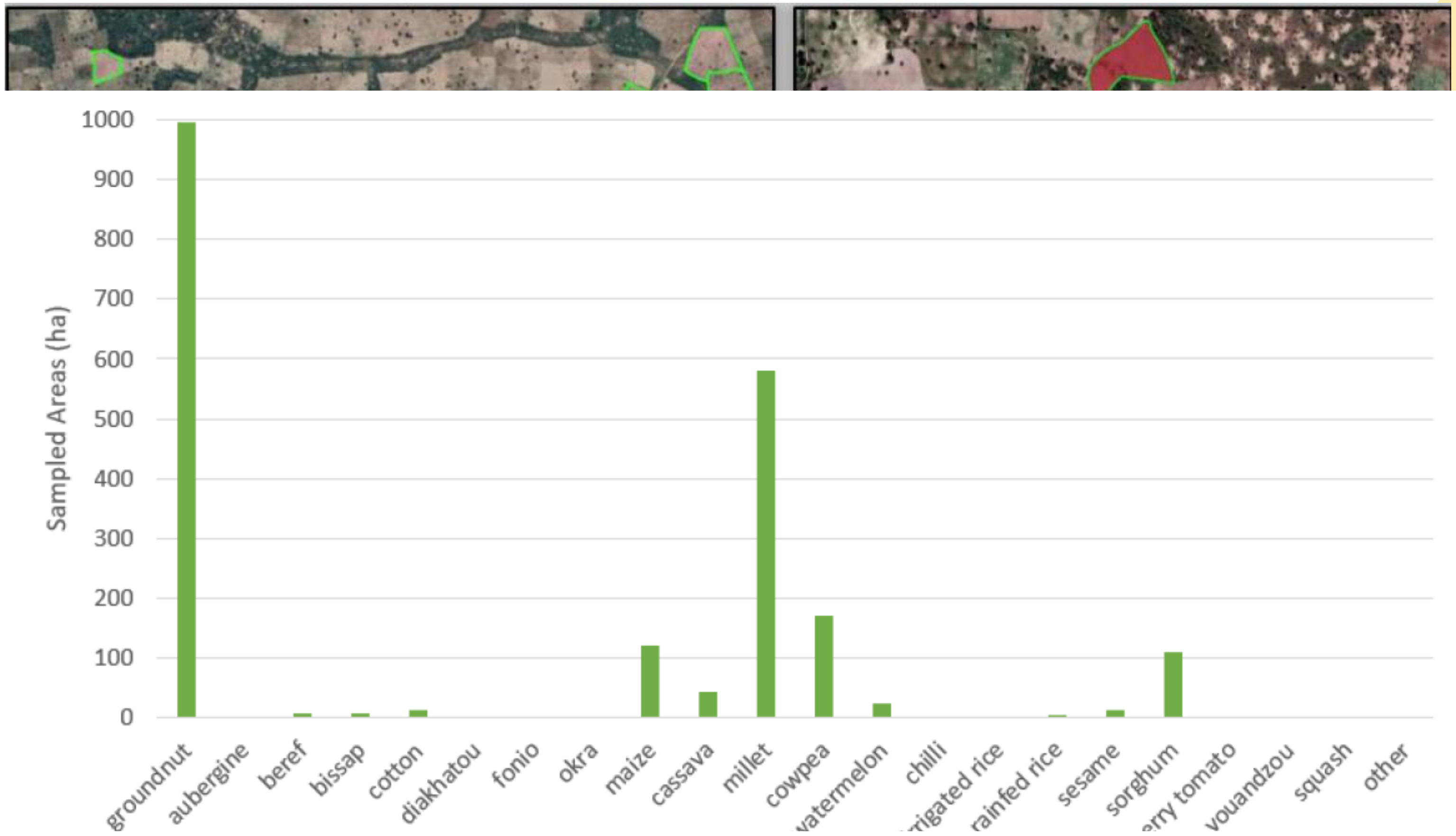
Approach

- **<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

- **Crop type mapping**

  - **Limited availability of in-situ data of adequate quality in countries**
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- **Crop yield forecasting and Mapping**

  - 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**. Crop cuts are often not georeferenced

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

OBJECTIVE OF EOSTAT PROJECT

EOSTAT PROJECT SOLUTIONS:

1. Use of trusted methods (Sen2Agri and Sen4Stat) which rely on Random Forest supervised classifier for crop mapping in countries where in-situ data is available with sufficient quality and quantity.
2. Improved survey design to ensure fitness for EO use, with final goal to increase cost efficiency (less data to collect, but better distributed)
3. Development and testing of data frugal algorithms (e.g. Dynamic Time Warping) and use in countries where in-situ data is a challenge
4. Development of methods for the transferability of in-situ data based on K-means and augmented pheno spectral libraries
5. Integration of physical based crop growth model (SALUS) with Earth Observations data
6. Support the standardization of EO methods in the Agency, across UN agencies and across NSO's
7. On site training, webinars and seminars. Transfer of knowhow and tools.

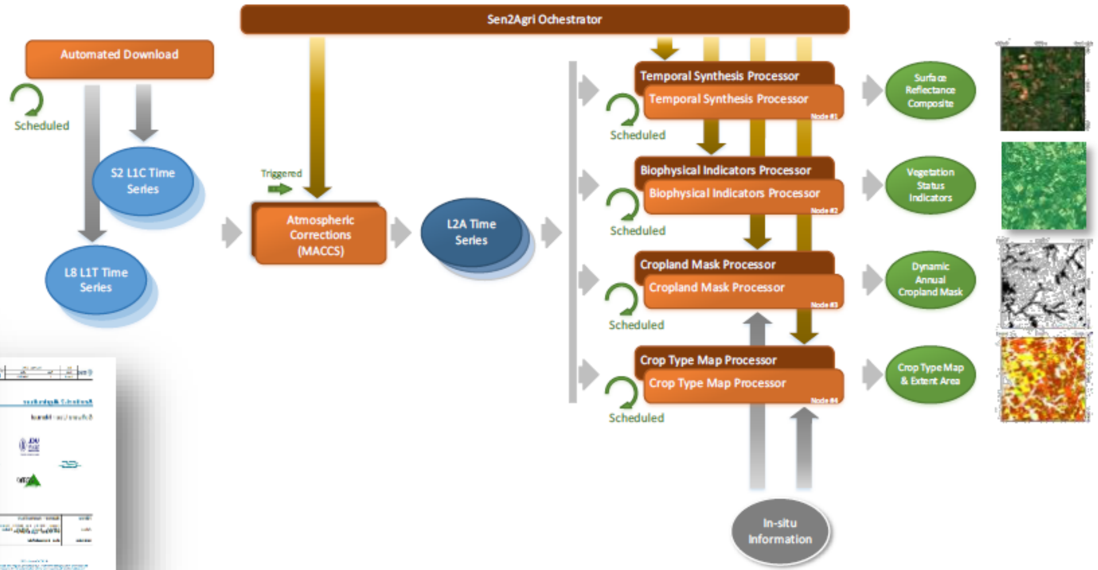
EOSTAT background:

Launched in 2019, its main objective is to support countries' capacity to consistently collect agricultural statistics through integrated earth observation data, physical modeling, and ground truth data collection

USE OF TRUSTED METHODS SENEGAL, UGANDA, EL SALVADOR, MALI

SEN2AGRI

Sen4Stat
Sentinels for Agricultural Statistics



Documenté et accessible sur:
http://www.esa-sen2agri.org/resources/software/

The **Sen2-Agri** system is an operational standalone processing system generating agricultural products from Sentinel-2 (A&B) and Landsat 8 time series along the growing season. These different products consist of:

- Monthly cloud free composites
- Biophysical indicators (NDVI, LAI, fPAR)
- Crop mask, several along the season
- Crop type mask, seasonal

The **Sen4Stat** evolves from the Sen2-Agri system but adds metrics from Sentinel-1 radar images. It includes area estimation and accounts for the crop class accuracy. Finally, it integrates a crop yield module.

SENEGAL 2018 AND 2021

EO-STAT

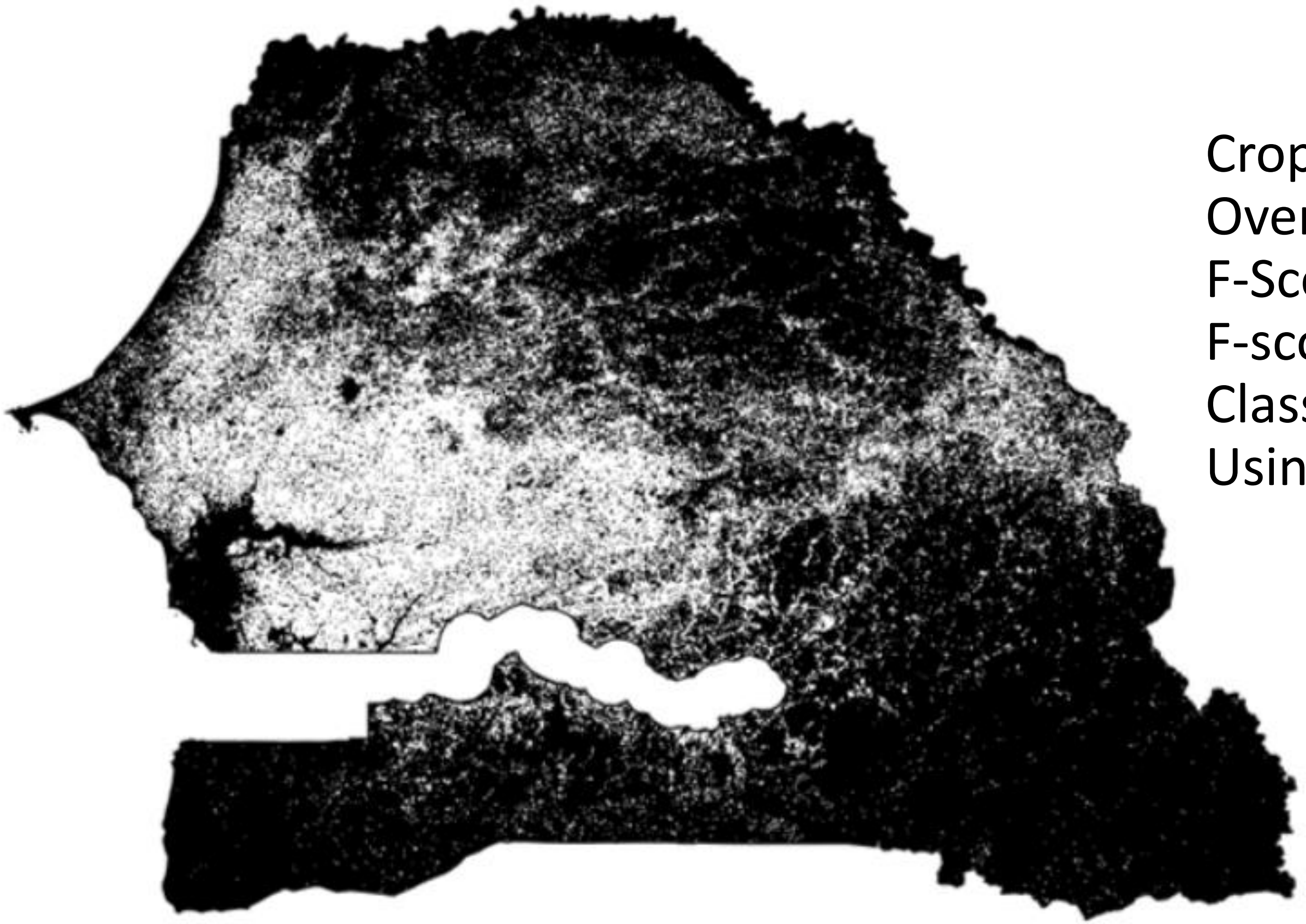
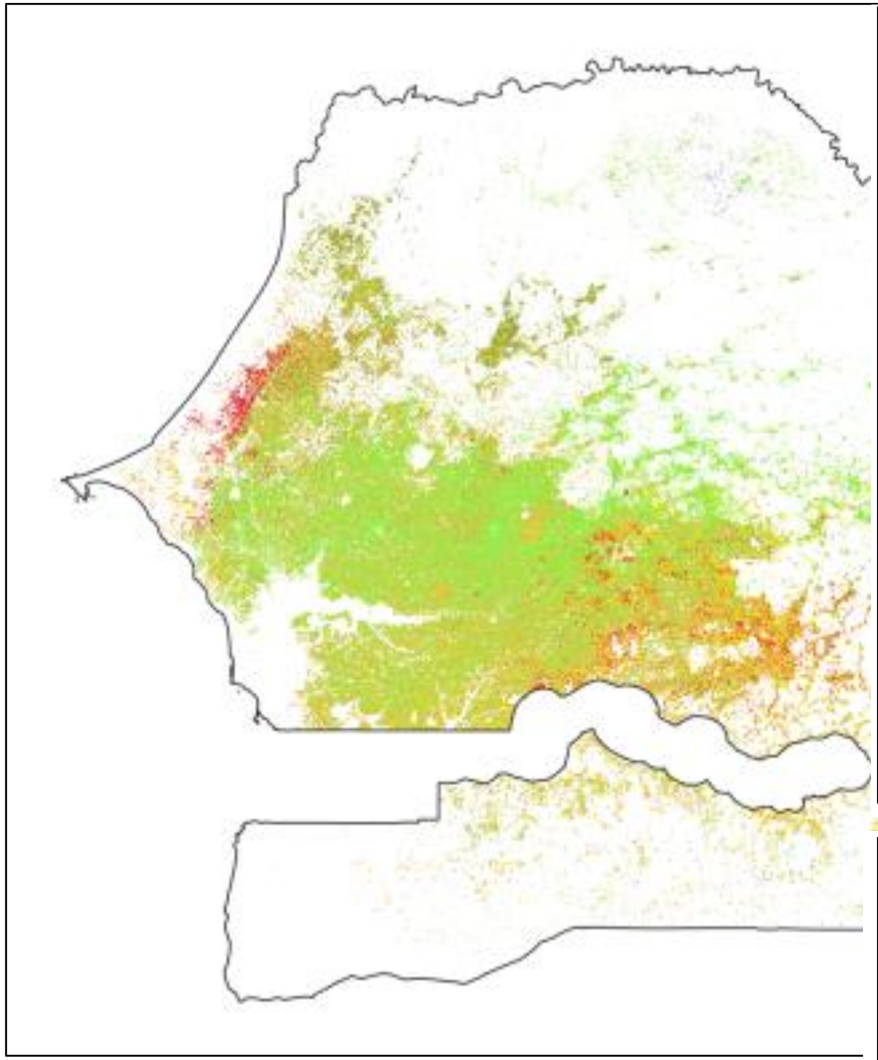


Figure 3-11. Overview of the cropland mask (V1.0) at national scale (black = non cropland, white = cropland)

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

Crop Acreage Statistics

2018, National Crop Type map 10m



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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
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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%

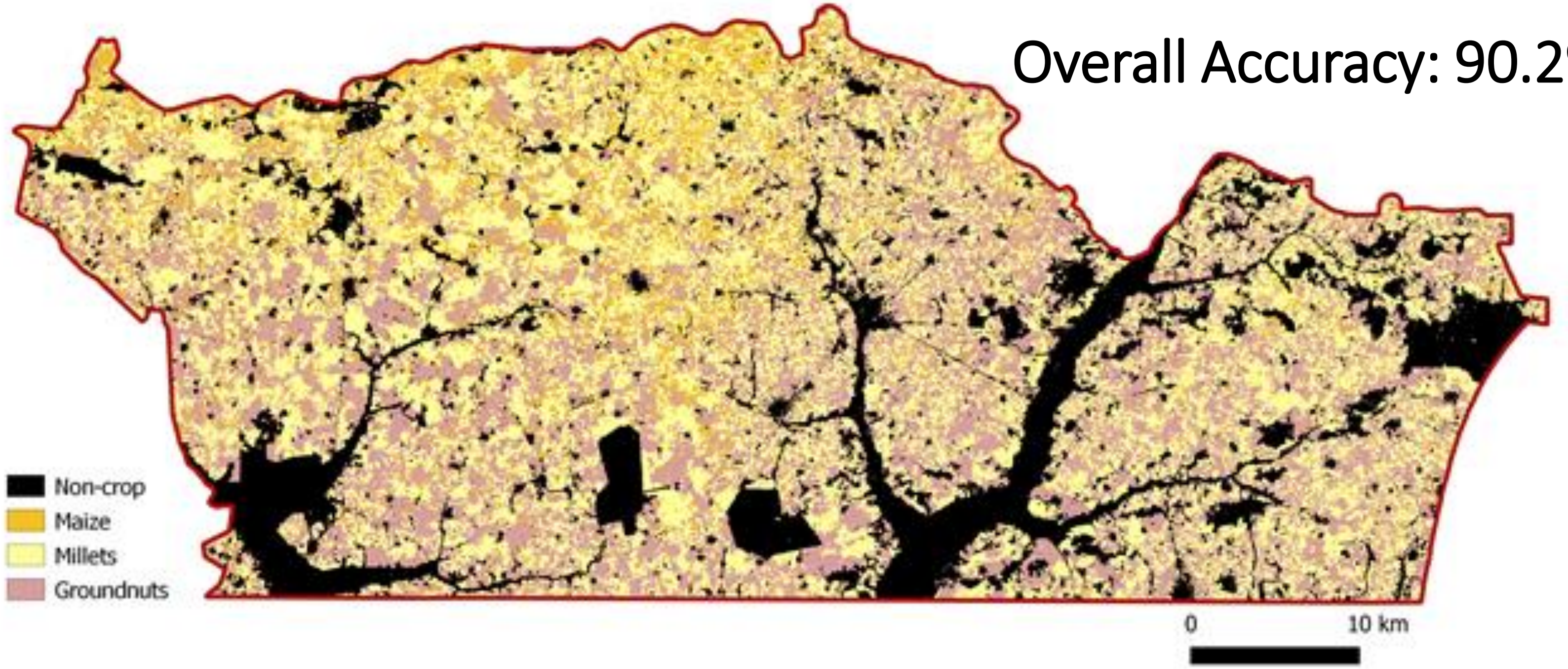
PILOT IN NIORO DISTICT 2021

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

Expressed in number of pixels

		Field survey: Non crop	Field survey: Maize	Field survey: Millet	Field survey: 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%



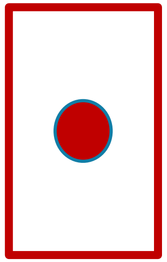
OPTIMIZING SURVEY DESIGN AND FIELD PROTOCOL

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

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



MALI – AREA FRAME

Recommendations based on a design independent

- Stratification based on cropping intensity (0% - 3
  ESA WorldCover land cover map
- Random selection of 300 segments (500m X 600n
- Manual digitizing (on-screen) of homogenous (
  imagery for each segment
- MapMe, used for the teams navigation (driving tc
- - ODK Collect, used to collect field data (answerin
- - Qfield, used to assess the crop block/parcel bou

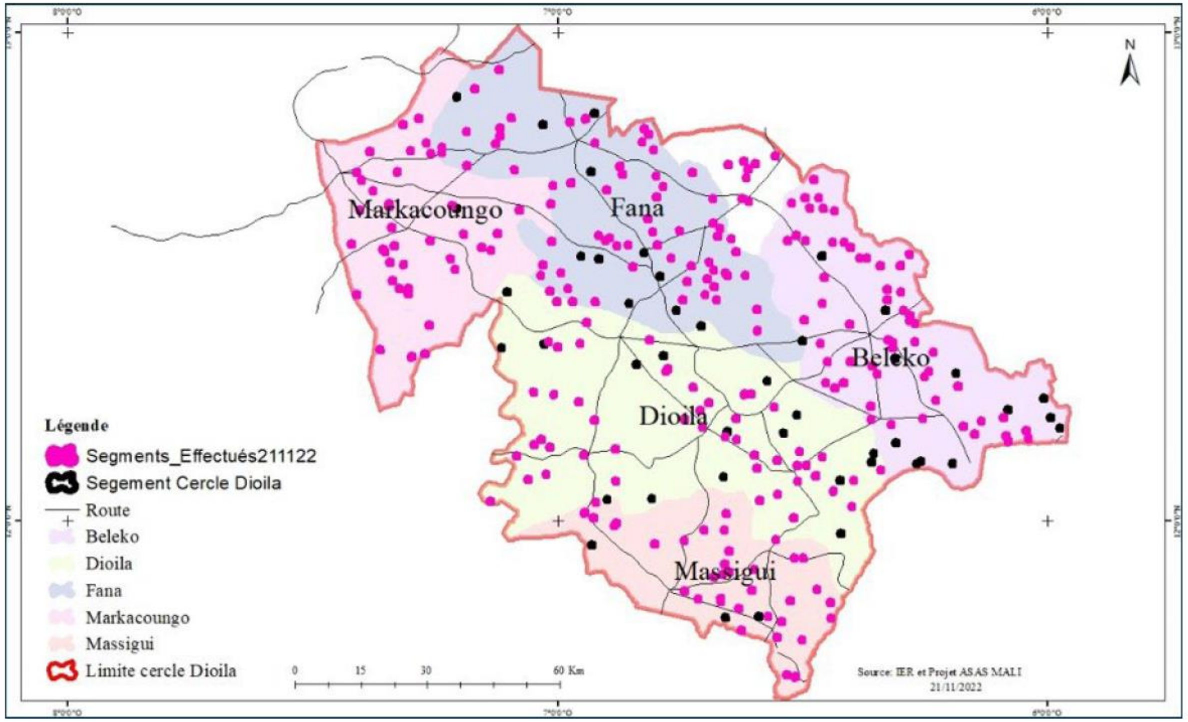


Figure 21. Localization of the segments visited by the end of November 2022

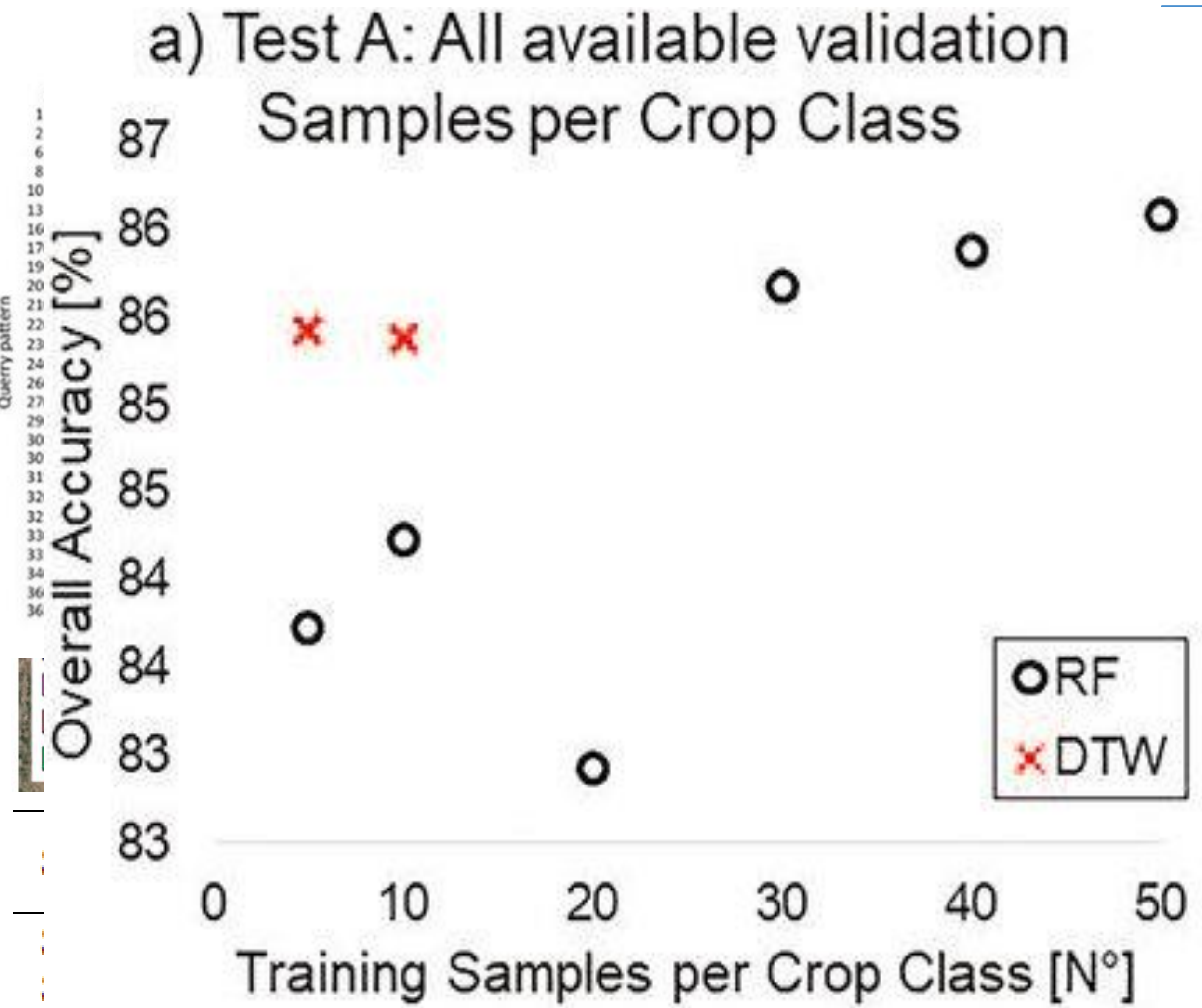
METHODOLOGICAL DEVELOPMENT

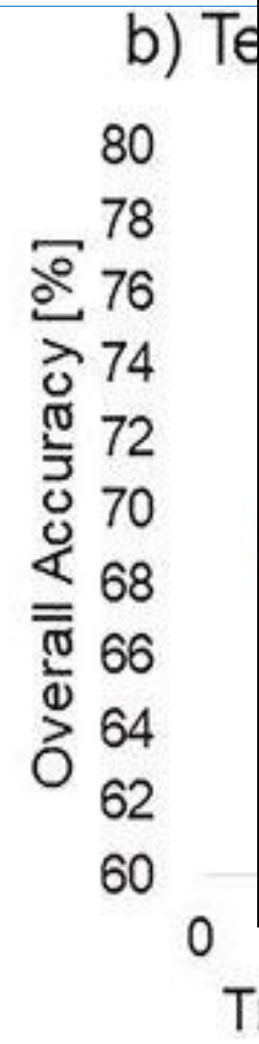
DATA FRUGAL CLASSIFICATION ALGORITHMS - DTW

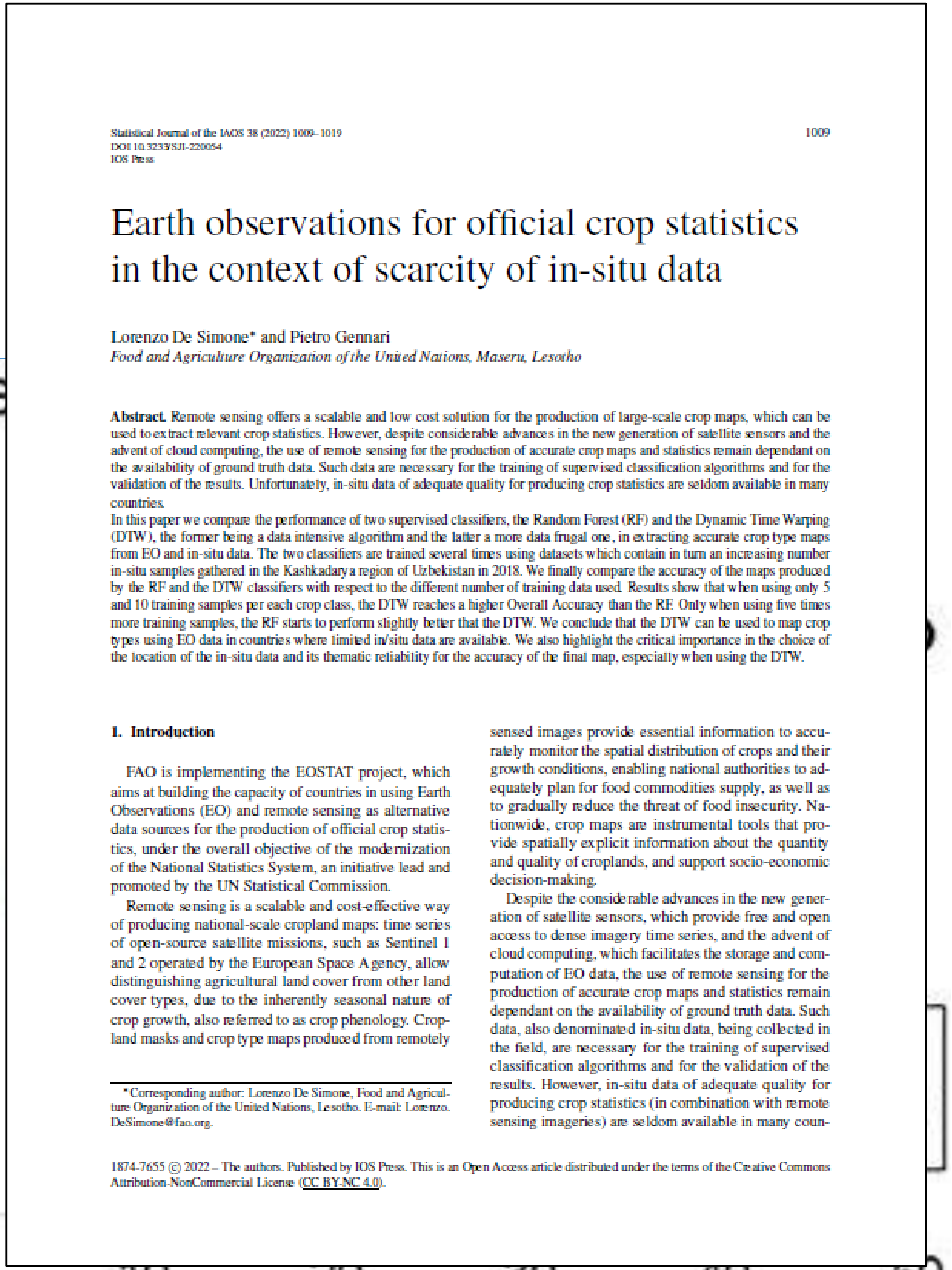
AFGHANISTAN, ECUADOR, CAMEROON

METHODOLOGICAL DEVELOPMENT

Comparative analysis of performance of Random Forest vs Dynamic Time Warping in the context of scarcity of in-situ data







Statistical Journal of the IAOS 38 (2022) 1009–1019
DOI 10.3233/SJI-220054
IOS Press

Earth observations for official crop statistics in the context of scarcity of in-situ data

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Abstract. Remote sensing offers a scalable and low cost solution for the production of large-scale crop maps, which can be used to extract relevant crop statistics. However, despite considerable advances in the new generation of satellite sensors and the advent of cloud computing, the use of remote sensing for the production of accurate crop maps and statistics remain dependant on the availability of ground truth data. Such data are necessary for the training of supervised classification algorithms and for the validation of the results. Unfortunately, in-situ data of adequate quality for producing crop statistics are seldom available in many countries.
In this paper we compare the performance of two supervised classifiers, the Random Forest (RF) and the Dynamic Time Warping (DTW), the former being a data intensive algorithm and the latter a more data frugal one, in extracting accurate crop type maps from EO and in-situ data. The two classifiers are trained several times using datasets which contain in turn an increasing number in-situ samples gathered in the Kashkadarya region of Uzbekistan in 2018. We finally compare the accuracy of the maps produced by the RF and the DTW classifiers with respect to the different number of training data used. Results show that when using only 5 and 10 training samples per each crop class, the DTW reaches a higher Overall Accuracy than the RF. Only when using five times more training samples, the RF starts to perform slightly better that the DTW. We conclude that the DTW can be used to map crop types using EO data in countries where limited in/situ data are available. We also highlight the critical importance in the choice of the location of the in-situ data and its thematic reliability for the accuracy of the final map, especially when using the DTW.

1. Introduction

FAO is implementing the EOSTAT project, which aims at building the capacity of countries in using Earth Observations (EO) and remote sensing as alternative data sources for the production of official crop statistics, under the overall objective of the modernization of the National Statistics System, an initiative lead and promoted by the UN Statistical Commission.

Remote sensing is a scalable and cost-effective way of producing national-scale cropland maps: time series of open-source satellite missions, such as Sentinel 1 and 2 operated by the European Space Agency, allow distinguishing agricultural land cover from other land cover types, due to the inherently seasonal nature of crop growth, also referred to as crop phenology. Cropland masks and crop type maps produced from remotely sensed images provide essential information to accurately monitor the spatial distribution of crops and their growth conditions, enabling national authorities to adequately plan for food commodities supply, as well as to gradually reduce the threat of food insecurity. Nationwide, crop maps are instrumental tools that provide spatially explicit information about the quantity and quality of croplands, and support socio-economic decision-making.

Despite the considerable advances in the new generation of satellite sensors, which provide free and open access to dense imagery time series, and the advent of cloud computing, which facilitates the storage and computation of EO data, the use of remote sensing for the production of accurate crop maps and statistics remain dependant on the availability of ground truth data. Such data, also denominated in-situ data, being collected in the field, are necessary for the training of supervised classification algorithms and for the validation of the results. However, in-situ data of adequate quality for producing crop statistics (in combination with remote sensing imageries) are seldom available in many coun-

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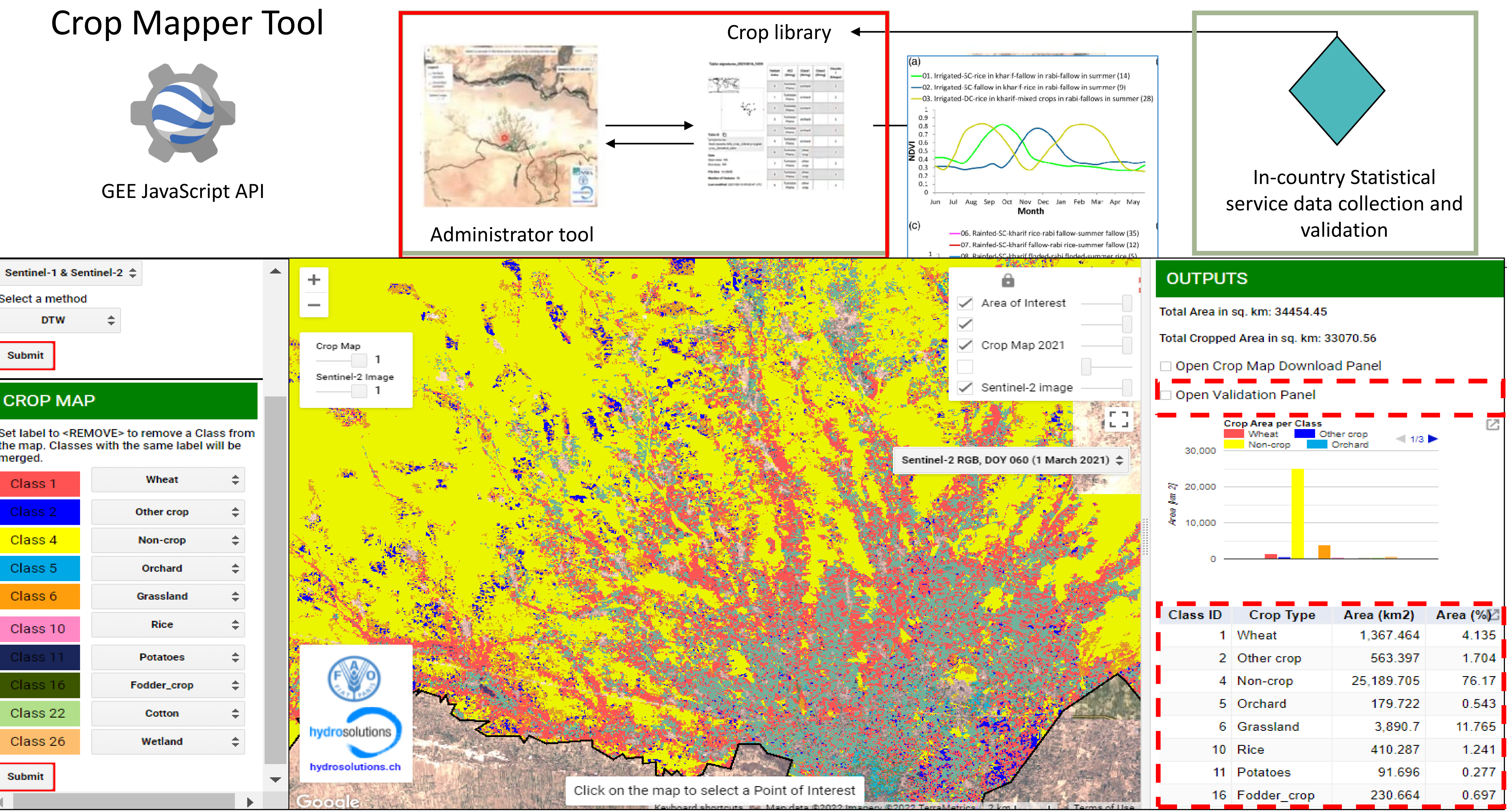


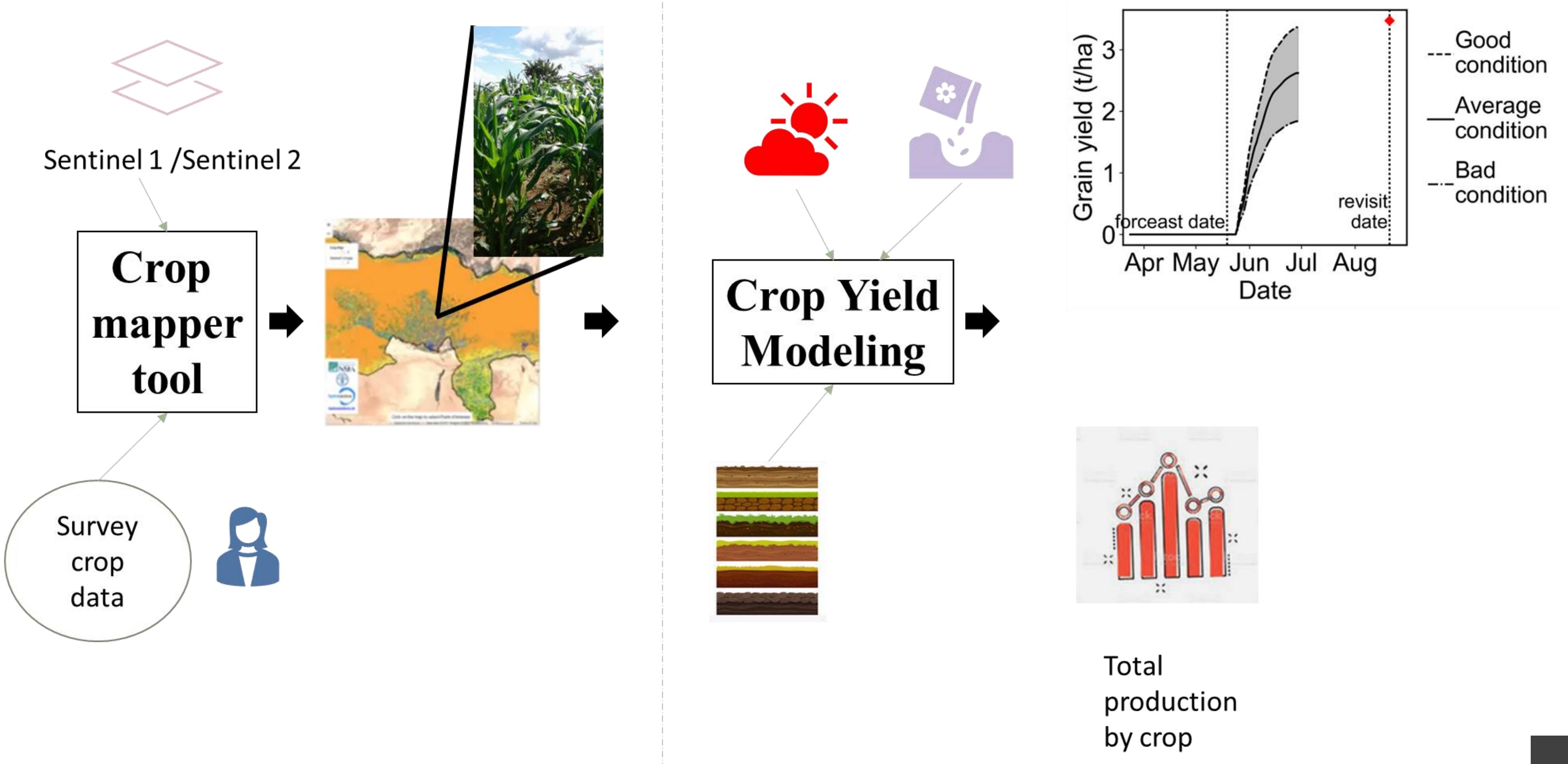
Crop Mapper Tool
GEE JavaScript API
Crop library
Administrator tool
(a)
01. Irrigated-SC-rice in kharif-fallow in rabi-fallow in summer (14)
02. Irrigated-SC-fallow in kharif-rice in rabi-fallow in summer (9)
03. Irrigated-DC-rice in kharif-mixed crops in rabi-fallows in summer (28)
NDVI
Jun Jul Aug Sep Oct Nov Dec Jan Feb Mar Apr May
Month
(c)
06. Rainfed-SC-kharif rice-rabi fallow-summer fallow (35)
07. Rainfed-SC-kharif fallow-rabi rice-summer fallow (12)
In-country Statistical service data collection and validation
Sentinel-1 & Sentinel-2
Select a method
DTW
Submit
CROP MAP
Set label to <REMOVE> to remove a Class from the map. Classes with the same label will be merged.
Class 1 Wheat
Class 2 Other crop
Class 4 Non-crop
Class 5 Orchard
Class 6 Grassland
Class 10 Rice
Class 11 Potatoes
Class 16 Fodder_crop
Class 22 Cotton
Class 26 Wetland
Submit
Crop Map
Sentinel-2 Image
Area of Interest
Crop Map 2021
Sentinel-2 image
Sentinel-2 RGB, DOY 060 (1 March 2021)
hydrosolutions
hydrosolutions.ch
Click on the map to select a Point of Interest
Google
OUTPUTS
Total Area in sq. km: 34454.45
Total Cropped Area in sq. km: 33070.56
Open Crop Map Download Panel
Open Validation Panel
Crop Area per Class
Wheat
Other crop
Non-crop
Orchard
1/3
30,000
20,000
10,000
0
Area (km 2)
Class ID | Crop Type | Area (km2) | Area (%)
1 | Wheat | 1,367.464 | 4.135
2 | Other crop | 563.397 | 1.704
4 | Non-crop | 25,189.705 | 76.17
5 | Orchard | 179.722 | 0.543
6 | Grassland | 3,890.7 | 11.765
10 | Rice | 410.287 | 1.241
11 | Potatoes | 91.696 | 0.277
16 | Fodder_crop | 230.664 | 0.697

METHODOLOGICAL DEVELOPMENT

INTEGRATION OF EO DATA WITH PHYSICAL BASED CROP GROWTH MODEL

ECUADOR, CAMEROON

INTEGRATION OF EO DATA AND PROCESS-BASED CROP GROWTH MODELLING

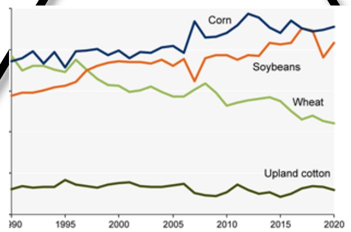


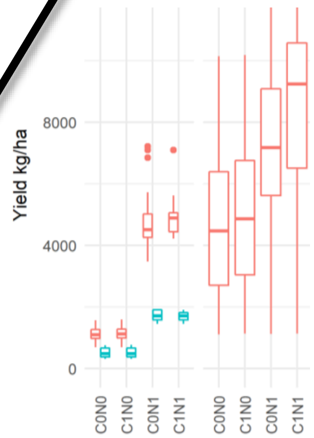
Innovation

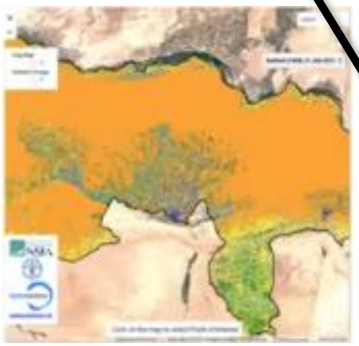
INTEGRATION OF EO DATA WITH PROCESS-BASED CROP GROWTH MODELL SALUS (SYSTEM APPROACH TO LAND USE SUSTAINABILITY)

Yield History

Accurate Yield Information Cycle





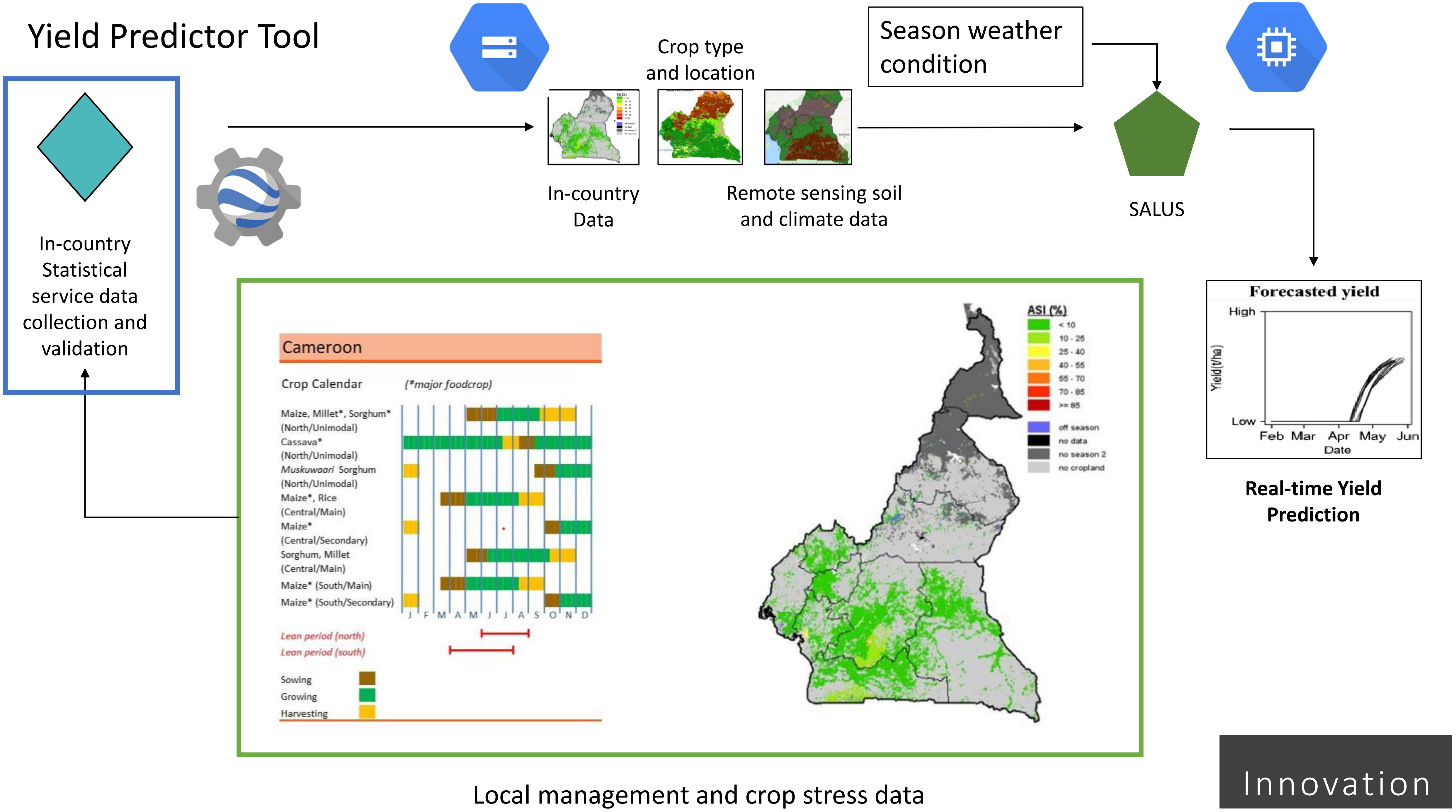


MICHIGAN STATE UNIVERSITY

SALUS Crop Modeling

Real time Crop mapper

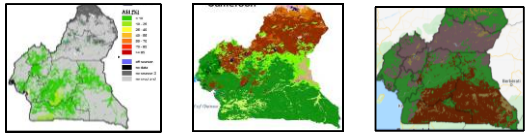
Yield Predictor Tool



Yield Predictor Tool

Real-time weather conditions during the season can be evaluated

Crop type and location

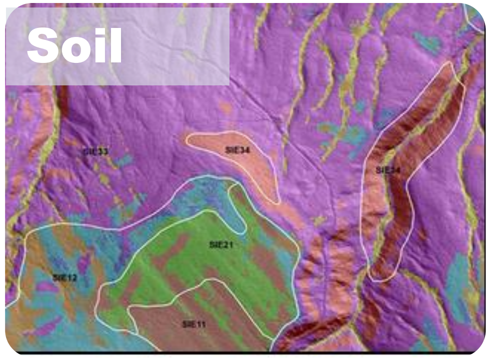


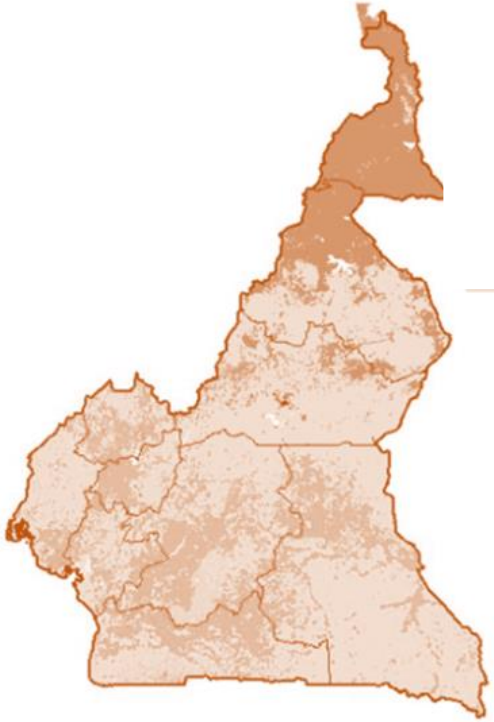
In-country Data

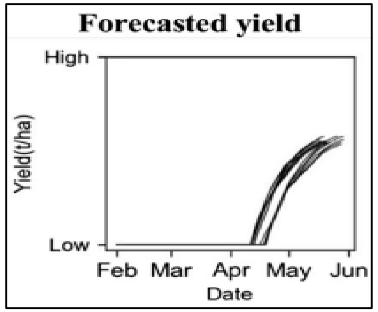
Remote sensing soil and climate data

Season weather condition

SALUS





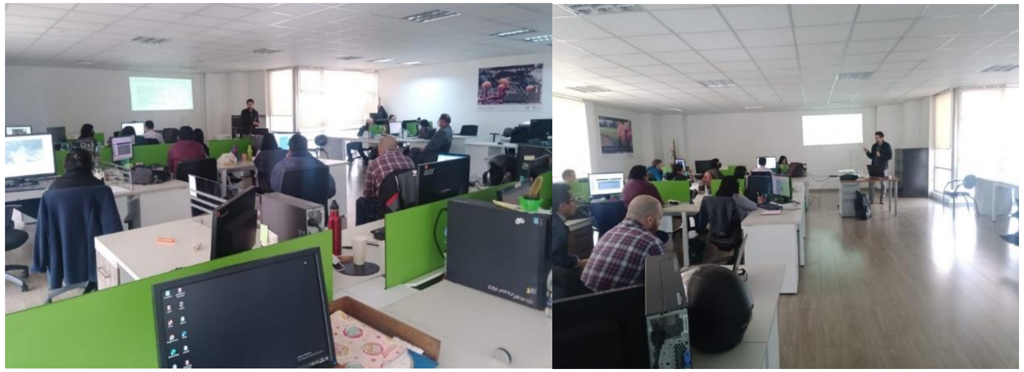


Real-time Yield Prediction

Simulation of all plausible yield outcome for major crops for each agroecological zone.

Innovation

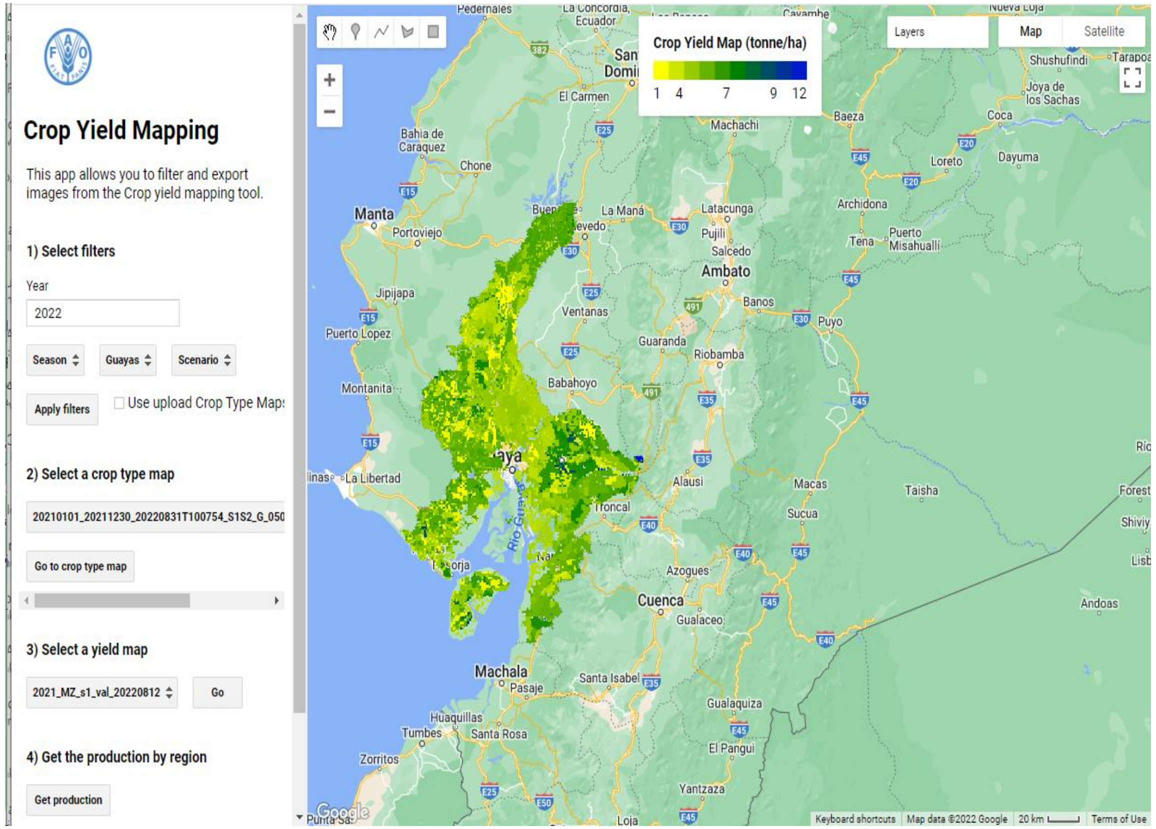
ONLINE AND ON-SITE TRAINING OF EXPERTS FROM MINISTRY OF AGRICULTURE



The Minister of Agriculture of Ecuador, **Bernardo Manzano**, engaged in the discussion on the importance of prediction of Maize and Rice ahead of time to balance export and import amounts.

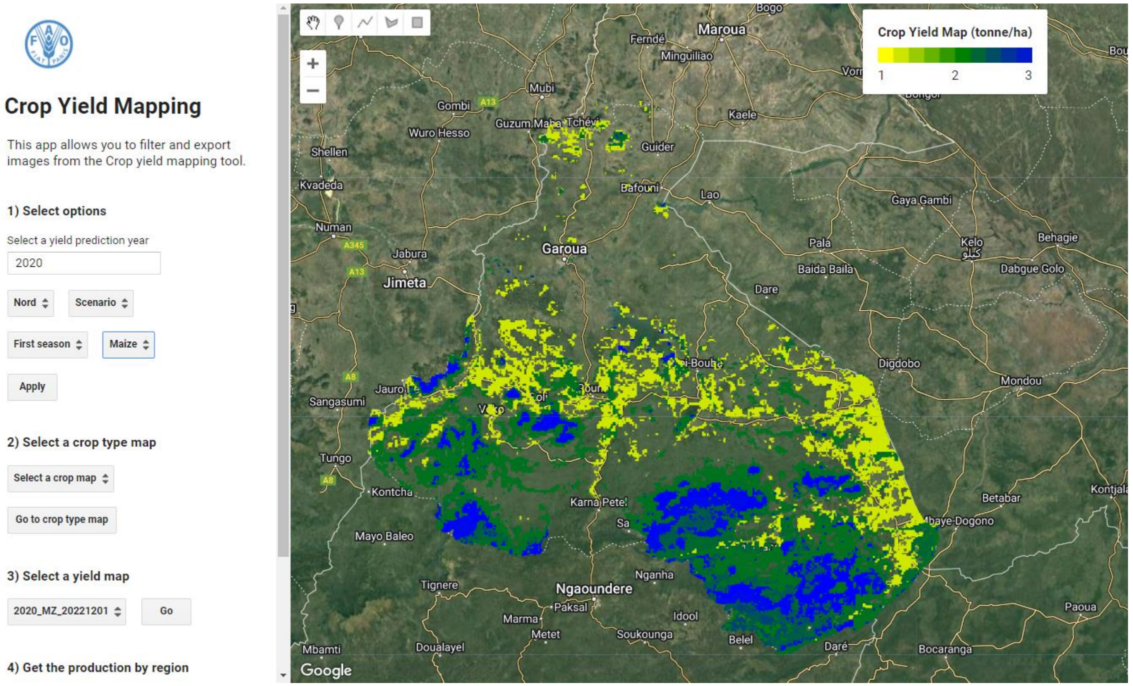
Ecuador End user tool: overview

https://msu-cropmapper.users.earthengine.app/view/ecuador-end-user



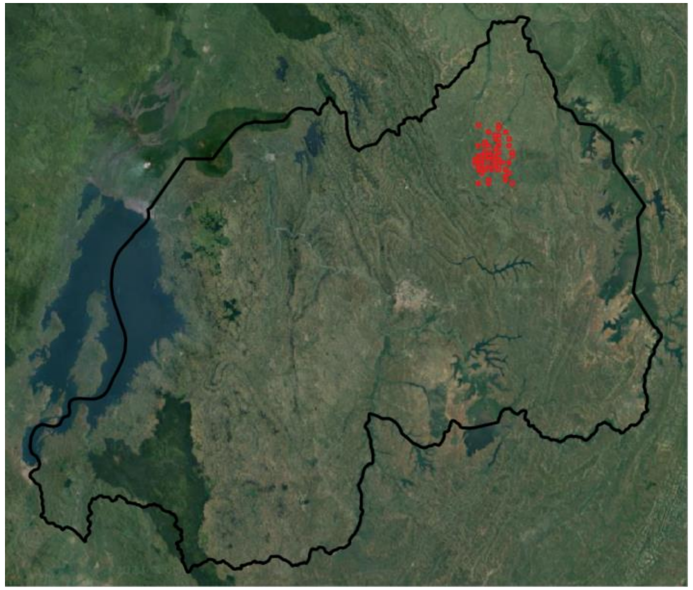
Cameroon End user tool: overview

https://msu-cropmapper.users.earthengine.app/view/cameroon-crop-yield-mapper



FIELD BOUNDARIES MAPPING

CROP BOUNDARY DELINEATION - PROGRESS



CNN and transfer learning Model: credits to Sherrie Wang, UC Berkley

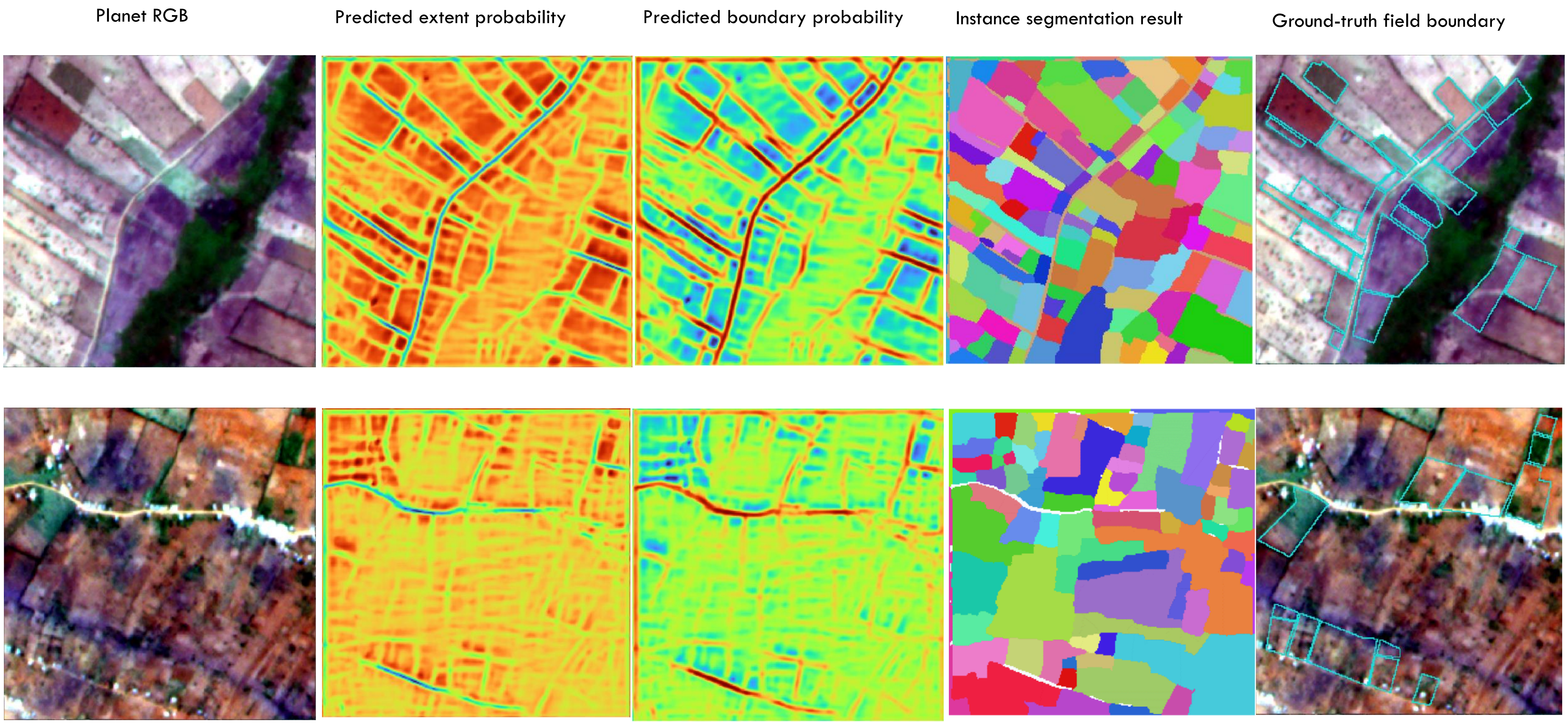
Rwanda:

- Use of NASA Harvest Competition dataset
  - 70 tiles (256*256 pixels) of Planet imagery
  - Validation dataset covering 1532 individual crop fields
- Processings conducted:
  - Batch preparation of imagery and ground-truth data (band stacking, converslon from boundary to extent)
  - Field extent prediction using Sherrie's module/function and pre-trained model
  - Field instance segmentation
  - Prediction and segmentation results assessment, export (with geospatial information added)

Mozambique:

- Selected areas with dense crops from user provided AOIs
- Processing conducted:
  - Script to batch download Planet imagery using API
  - Batch preparation of Planet images (clipping and band extraction)
  - Field extent prediction and instance segmentation, export (with geospatial information added)

Crop boundary delineation – Rwanda Results



Mean F1 score: 0.91
Median IoU: 0.42

METHODOLOGICAL DEVELOPMENT

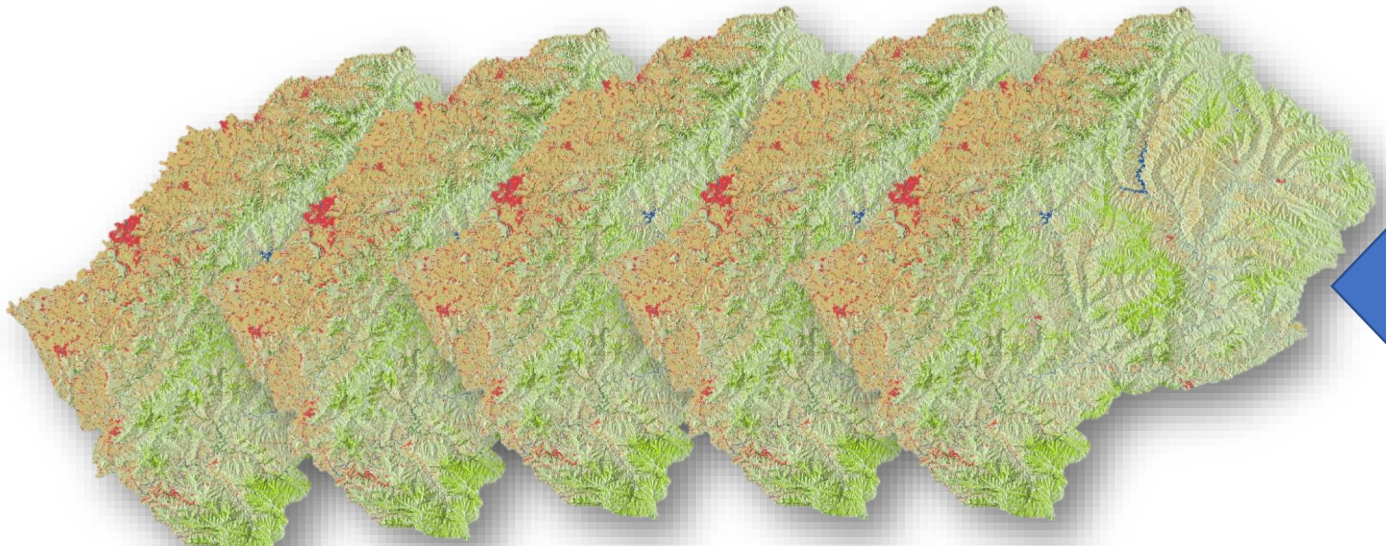
ARTIFICIALLY UPDATING IN-SITU DATA

LESOTHO

METHODOLOGICAL DEVELOPMENT

TIME

2017 2018 2019 2020 2021 2022



Automatic production of annual national land cover map at 10m resolution

Existing Reference Dataset(s)

Cluster 1 (e.g Bare Surface) Cluster 2 (e.g. Trees) Cluster n (e.g. Water)

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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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

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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

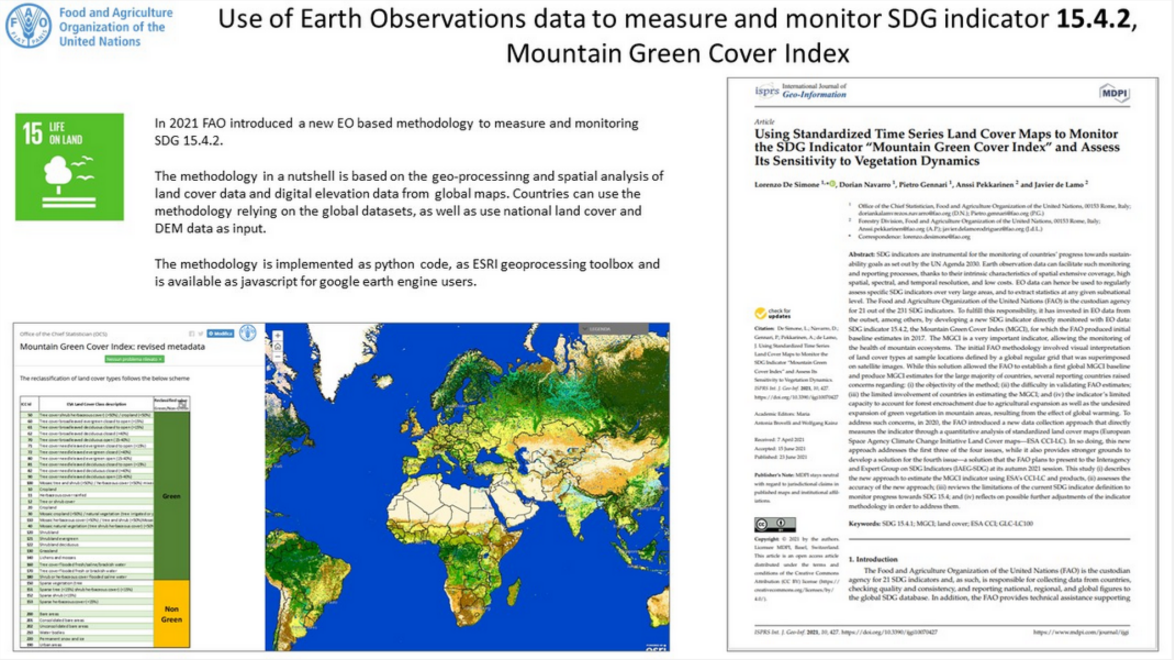
STANDARDIZATION THE CASE OF SDG 15.4.2

SDG 15.4.2: EXAMPLE OF METHODOLOGICAL DEVELOPMENT AND STANDARDIZATION

Safeguarding mountain vegetation: FAO receives 2021 GEO Sustainable Development Goals Award

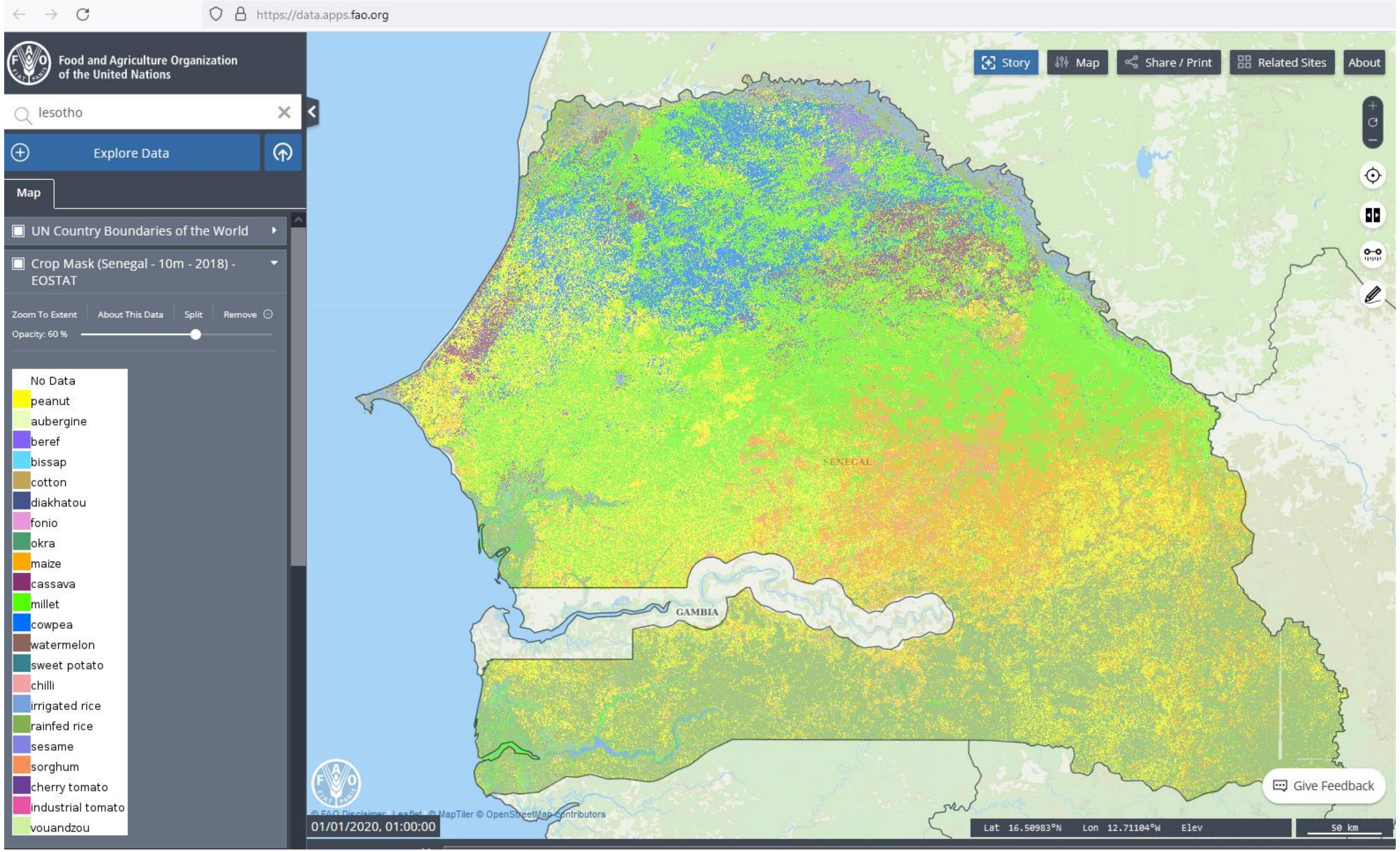
SDG Custodian Agency: Food and Agriculture Organization of the United Nations

The Food and Agriculture Organization of the United Nations (FAO) developed a new method to measure and monitor SDG indicator 15.4.2 (Mountain Green Cover Index, MGCI) leveraging free and open Earth observation data sets from land cover time series, ground truth land cover, and mountain elevation range. By integrating Earth observation data into the official methodology, the FAO achieved a series of important results including the standardization of input and methodology that has allowed for internationally comparable results. The use of validated input layers, in turn, has allowed for accuracy measures associated with the MGCI estimates, leading to increased transparency. The MGCI computation is based on a quantitative model of spectral and textural characteristics of satellite time series data. This ensures objectivity of the MGCI estimation, as opposed to the subjectivity of visual interpretation that was used for the previous reporting cycle. Countries that have national land cover maps and digital elevation models with higher accuracy compared to global products can use this as inputs into the new FAO methodology. The FAO has supported countries in the validation of the MGCI estimates for 2021 by sharing their estimates with countries and asking to validate them using a WebGIS App, which facilitates the assessment of green vegetation cover in mountain areas.



EOSTAT MAPS

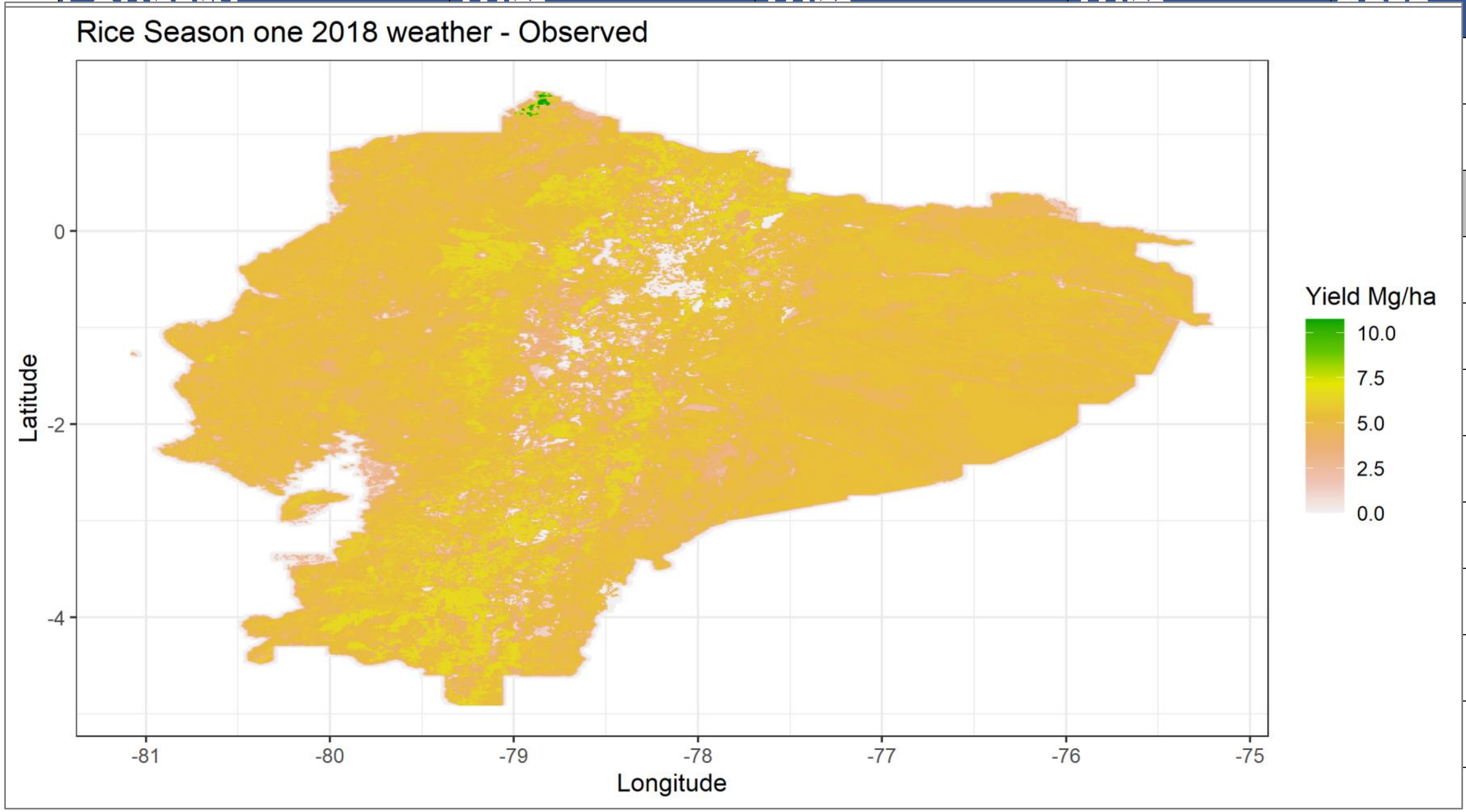
HIGH-RES GEOSPATIAL DATA PUBLISHED TO THE FAO HIH GEOSPATIAL PLATFORM



- 64 national maps developed since 2020
- Accessible through the Hand in Hand Geospatial Platform of FAO

ECUADOR
MAIZE & RICE, AREAGE AND YIELD, FROM 2018 THROUGH 2023

Country	Crop Type 10m	Crop yield 10m	Land Cover 10m	In Situ data



ECUADOR

MAIZE & RICE, AREAGE AND YIELD, FROM 2018 THROUGH 2023

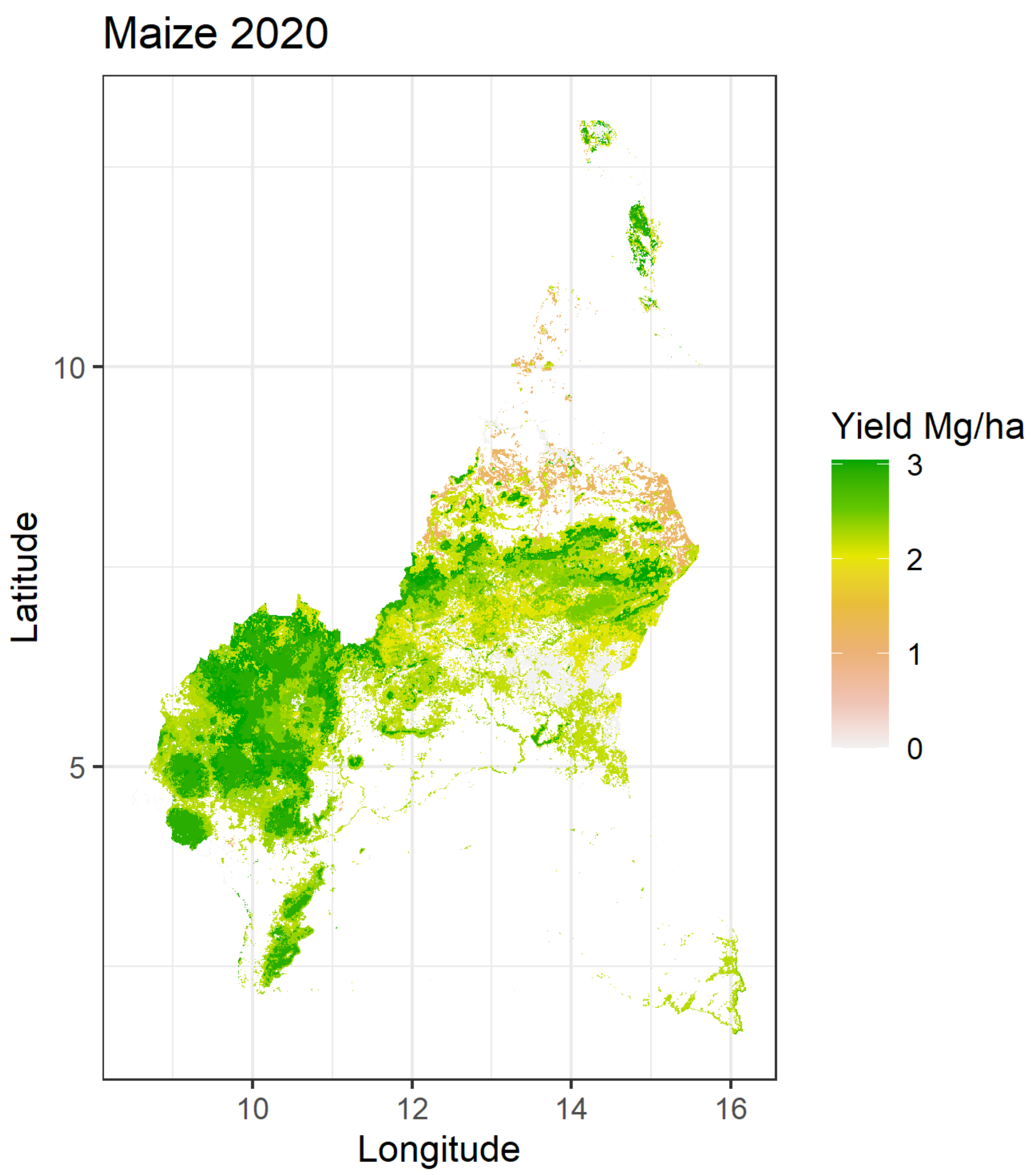
2023	Crop	National	Guayas	Los Rios	Manabi	Loja
1st season	Maize	118127Mt ±0.1%	17464Mt ±1.3%	34944Mt ±0.4%	47602Mt ±2.1%	18117Mt ±6.6%
	Rice	37081Mt ±8.4%	21586Mt ±1.6%	12947Mt ±1.8%		
2nd season	Crop	National	Guayas	Los Rios	Manabi	Loja
	Maize	30296Mt ±0.4%	2522Mt ±0%	25423Mt ±0.7%	1318Mt ±0.2%	1033Mt ±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%	

Longitude

Crop production statistics at national and subnational level (Mega Tons)

CAMEROON

RICE, CASSAVA, MAIZE, SORGHUM, FROM 2012 THROUGH 2020



RWANDA AND MOZAMBIQUE, LC 2021

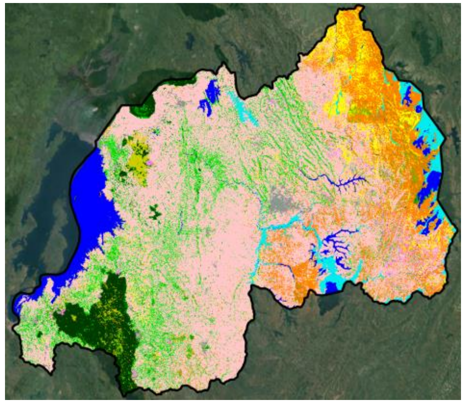
Updated land cover maps for Rwanda and Mozambique 2021

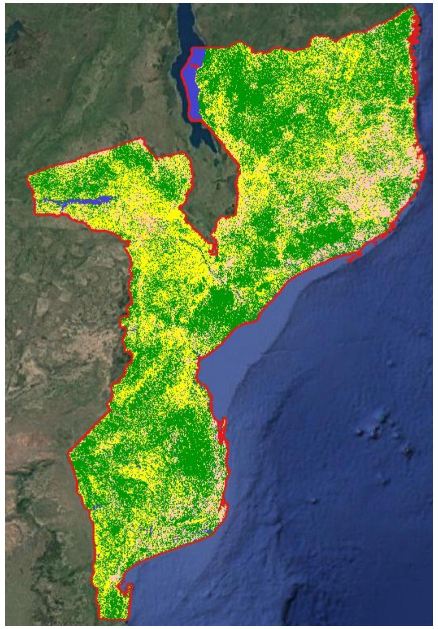
Land cover mapping workflow prototype – open source, user friendly

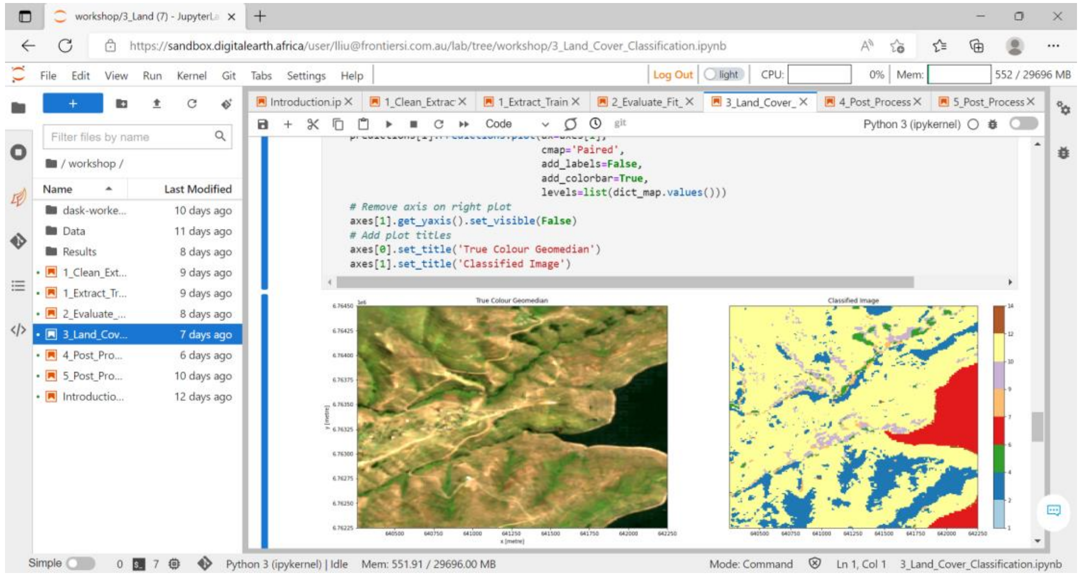
Upcoming online workshop training:

Introduction webinar

Two online training sessions through DE Africa Sandbox

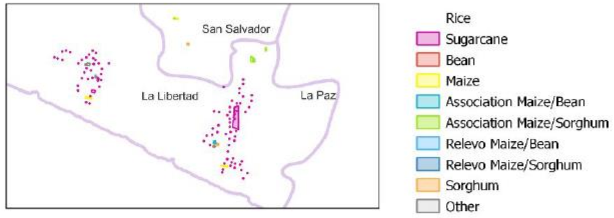


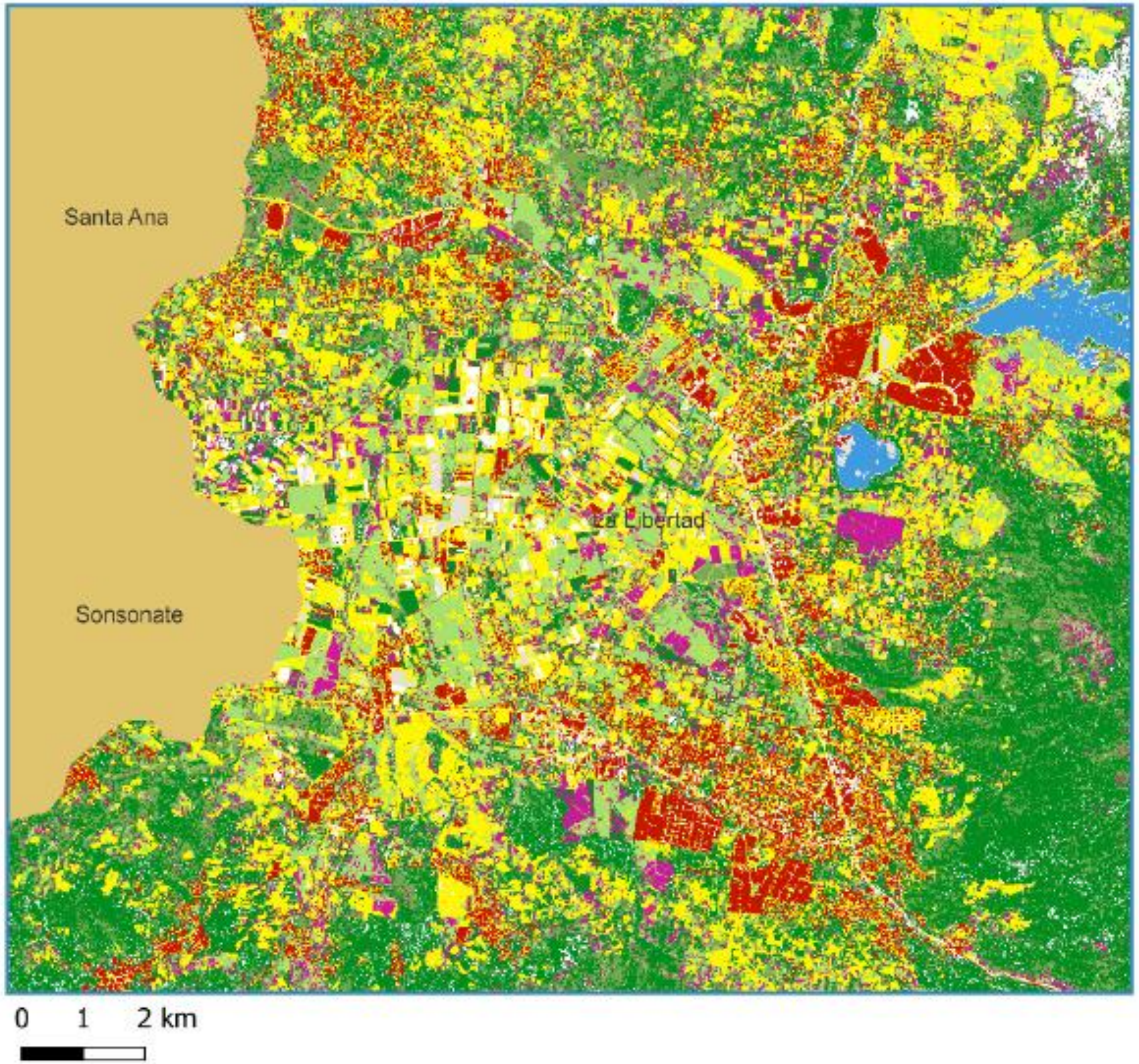


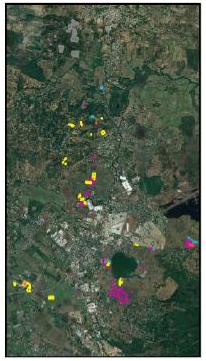


EL SALVADOR, 2022

Ad hoc survey implemented in the departments of La Libertad and Cuscatlán until the end of December 2022.







ADVANTAGES OF EOSTAT APPROACH

Advantages of EOSTAT approach to crop mapping

- Earth Observation (EO) have shown to be capable of quantifying areas and type of crops under cultivation at the district, region and country level.
- The novel method is independent of self-reporting data coming from local authorities and scalable.
- Can cope with in situ data scarcity
- Increase cost efficiency of field survey
- The application of the FAO EO-Stat Crop Mapper has shown to be able to reproduce measured yield observation. The systems can scale up results to larger areas beyond the small sample of costly data collection.
- EO-model based results are science-based and demonstrated to capture the complex feedbacks between soil, climate, management and genetics.
- The FAO-STAT Crop Mapper based on EO linked with process-based crop simulation models can revolutionize how crop yield and areas are estimated.

THANK YOU

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