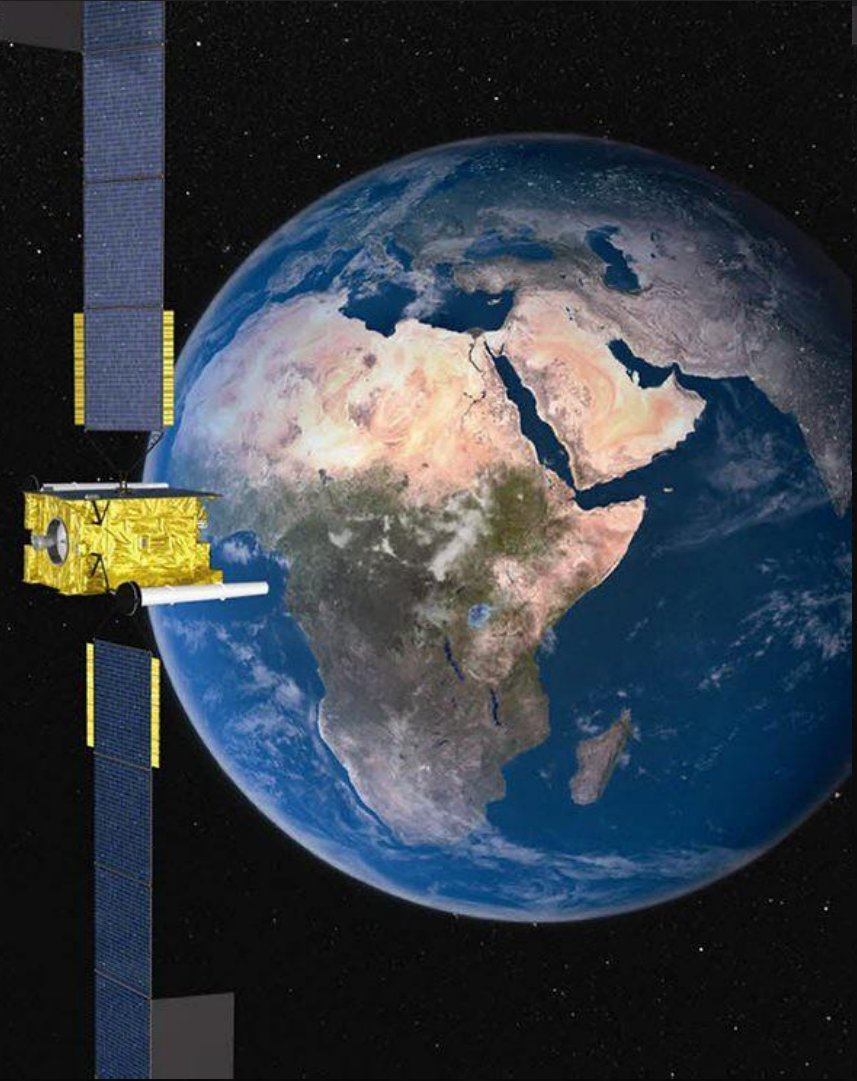




USE of Alternative data sources for the monitoring of SDG environmental indicators:

Satellite Data and Geospatial datasets





CONTENTS

- 1) FAO's role as custodian
- 2) Key advantages of EO data for SDG Monitoring
- 3) Relevance of EO data to indicators under FAO's custodianship
- 4) Examples from SDGs 15, 6 and 2
- 5) EO-STAT



FAO' custodianship of SDGs

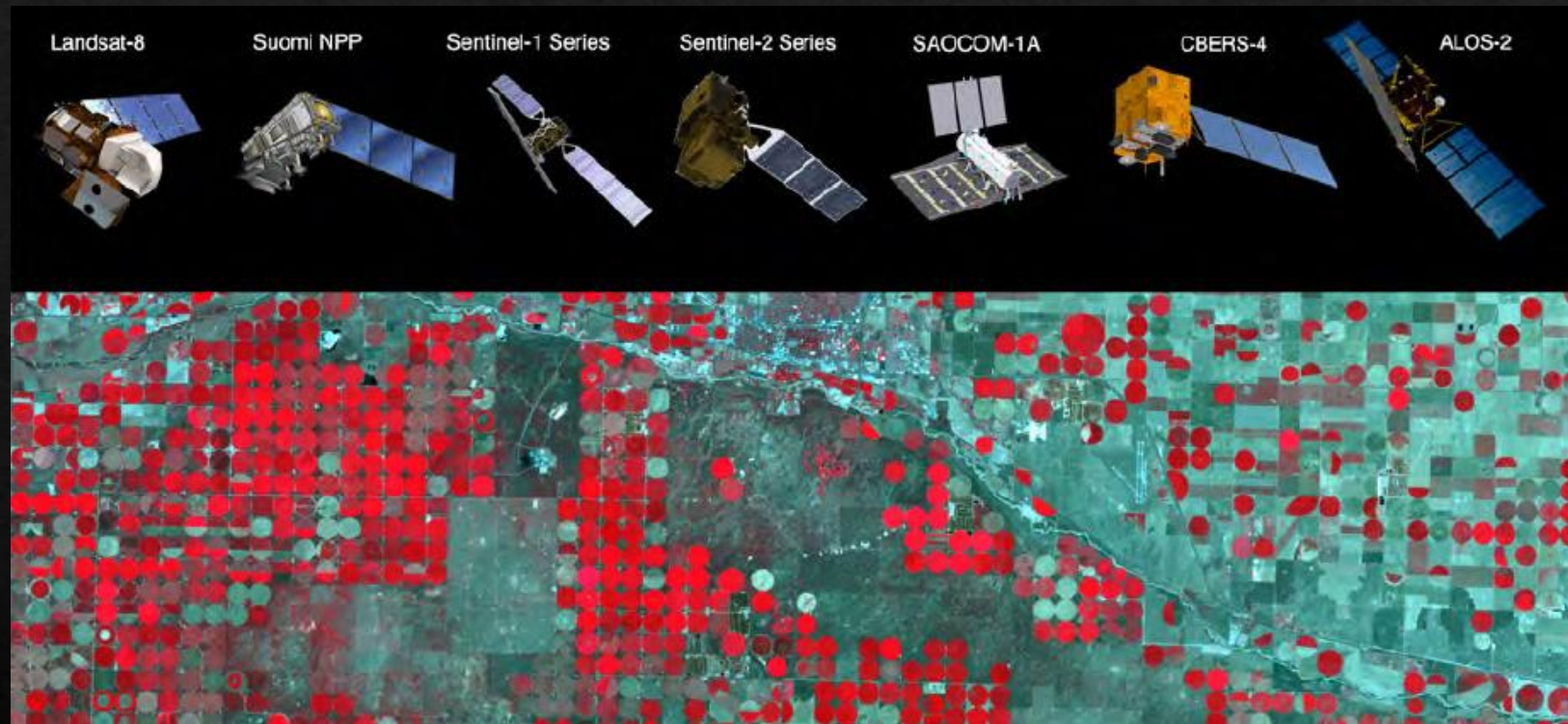
- 1) FAO is custodian agency of 21 SDG indicators. Under this mandate, FAO:
- 2) FAO supports countries to develop the statistical capacity to generate, disseminate and use national data, as well as realign their national monitoring frameworks to SDG indicators.
- 3) Leads the methodological development of indicators, collecting data from national sources, ensuring their comparability and consistency, and disseminating them at global level.
- 4) Contributes to monitoring progress at the global, regional and national levels, providing inputs to the global and regional SDG progress reports, providing analytical reports, and, more recently, developing its own digital SDG progress report

SDG Indicators under FAO custodianship		Reporting Rate 2020 [reference period 2015–2019]*	% Change (absolute)
2.1.1	Prevalence of Undernourishment	82.1%	-2.0%
2.1.2	Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale	45.9%	16.8%
2.3.1	Volume of production per labour unit by classes of farming / pastoral / forestry enterprise size	1.5%	1.5%
2.3.2	Average income of small-scale food producers, by sex and indigenous status	2.6%	2.6%
2.4.1*	Proportion of agricultural area under productive and sustainable agriculture	0.0%	0.0%
2.5.1.a	Number of plant genetic resources for food and agriculture secured in medium or long term conservation facilities	50.5%* (with reference period 2010–2019)	9.2%
2.5.1.b	Number of animal genetic resources for food and agriculture secured in medium or long term conservation facilities	8.7%	-16.8%
2.5.2	Proportion of local breeds classified as being at risk of extinction	39.3%	5.6%
2.a.1	The agriculture orientation index for government expenditures	58.2%* (53% with reference year to 2017)	2.0%
2.c.1	Indicator of (food) price anomalies	78.1%	67.3%
5.a.1	(a) Percentage of people with ownership or secure rights over agricultural land (out of total agricultural population), by sex; and (b) share of women among owners or rights-bearers of agricultural land, by type of tenure	3.0%	3.0%
5.a.2	Proportion of countries where the legal framework (including customary law) guarantees women's equal rights to land ownership and/or control	8.0%	8.0%
6.4.1	Change in water use efficiency over time	26.0%* (with reference period 2008–2017)	26.0%
6.4.2	Level of water stress: freshwater withdrawal as a proportion of available freshwater resources	64.3%	34.7%
12.3.1	Food Loss Index	0.0%	0.0%
14.4.1	Proportion of fish stocks within biologically sustainable levels	Not applicable	Not applicable
14.6.1	Progress by countries in the degree of implementation of international instruments aiming to combat illegal, unreported and unregulated fishing	56.0%	56.0%
14.7.1	Sustainable fisheries as a percentage of GDP in Small Island Developing States, Least Developed Countries and all countries	54.1%* (with reference period 2011–2019)	54.1%
14.b.1	Progress by countries in the degree of application of a legal / regulatory / policy / institutional framework which recognizes and protects access rights for small-scale fisheries	61.1%	61.1%
15.1.1	Forest area as a percentage of total land area	100.0%	0.0%
15.2.1*	Progress towards sustainable forest management	69.2%	-2.0%
15.4.2	Mountain Green Cover Index	100.0%	6.9%

How satellite data can help SDG monitoring

Geospatial information and satellite earth observations offer unprecedented opportunities to support national and global statistical systems. Key benefits:

- More timely statistical outputs, reduced frequency of surveys
- Spatially-explicit information (disaggregation)
- Improvement of survey design through stratification



Relevance of EO data to the monitoring and reporting of SDG's under FAO custodianship

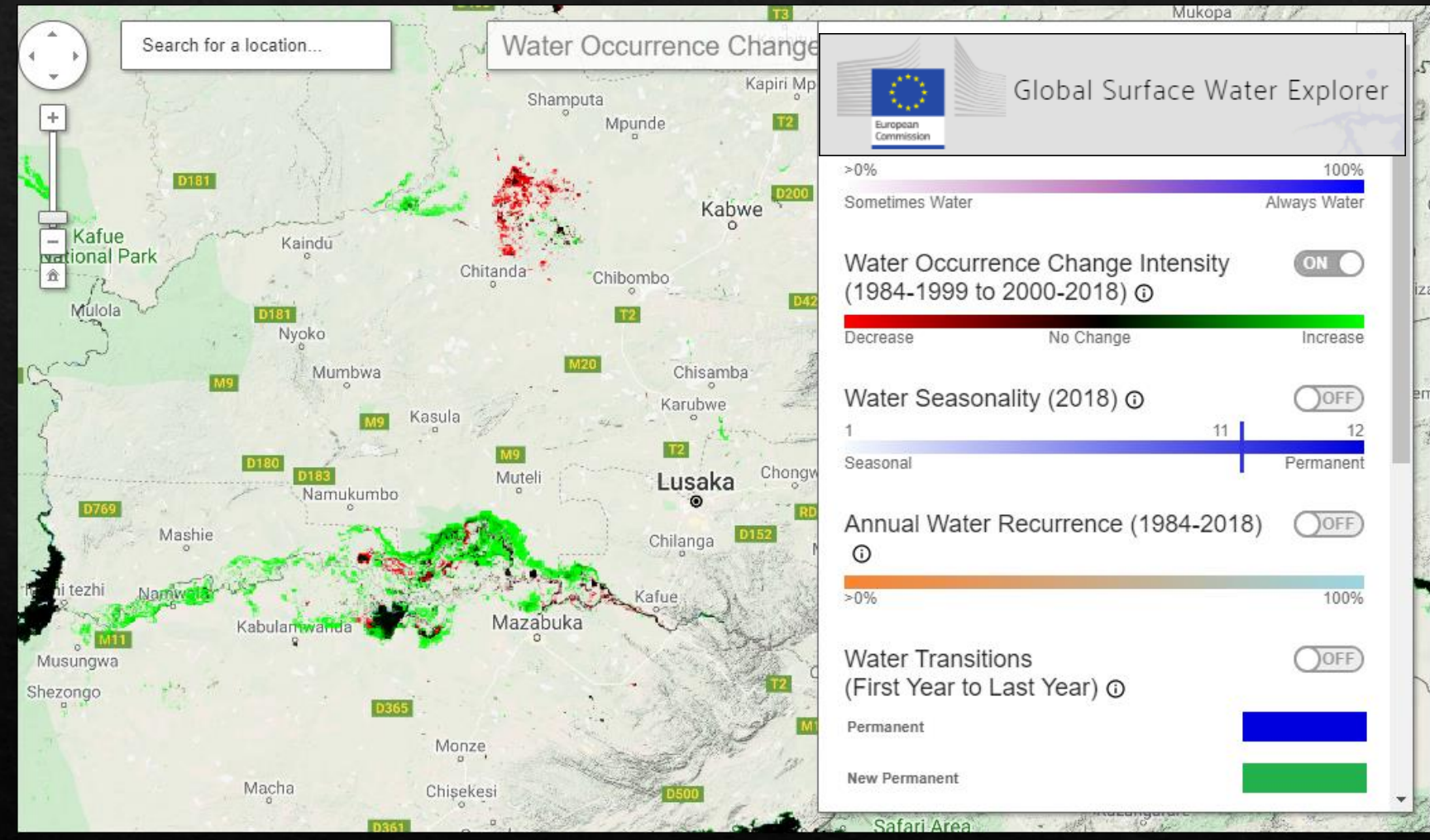
SDG Indicator		Role or Earth Observations			
		Primary source	Secondary source or proxy	Disaggregation	Survey design
2.1.1	Hunger		✓		✓
2.1.2	Severity of food insecurity		✓		✓
2.3.1	Productivity of small-scale food producers		✓	✓	
2.3.2	Income of small-scale food producers		✓	✓	
2.4.1	Agricultural sustainability	✓	✓	✓	
5.a.1	Women's ownership of agricultural land				✓
5.a.2	Women's equal right to land ownership				✓
6.4.1	Water use efficiency	✓	✓	✓	✓
6.4.2	Water stress	✓	✓	✓	✓
12.3.1	Global food losses		✓	✓	
14.4.1	Fish stock sustainability		✓		
14.6.1	Illegal, unreported underregulated fishery		✓		
15.1.1	Forest area	✓		✓	✓
15.2.1	Sustainable forest management	✓		✓	✓
15.4.2	Mountain Green Cover Index	✓		✓	✓



Earth observation for water related SDG

Satellite observations of the water cycle cover a broad range of parameters and at present hydro-meteorological and space agencies around the world are operating instruments to monitor all phases of the cycle.

SDG example: 6.6.1: change in extent of water-related ecosystems



Geospatial data for **SDG 6.4.1** (Change in water use efficiency over time)

Satellite observation, alone or in combination with model-based data, can inform on WUE in agricultural sector.

Observable variables for agriculture: biomass (and yield, if crop is known); water consumption (actual evapotranspiration).

Examples from FAO WaPOR database

$$WUE = A_{we} \times P_A + I_{we} \times P_I + S_{we} \times P_S$$

Where:

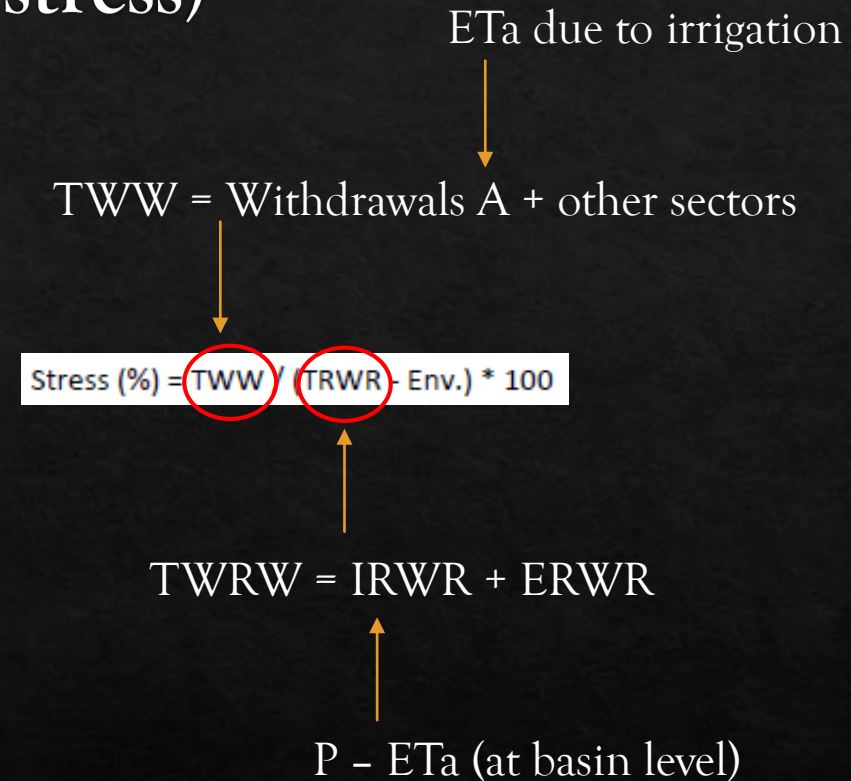
- WUE = Water use efficiency (USD/m³, or EUR/m³);
- A_{we} = Irrigated agriculture water use efficiency (USD/m³ or EUR/m³);
- I_{we} = Industrial water use efficiency (USD/m³ or EUR/m³);
- S_{we} = Services water use efficiency (USD/m³ or EUR/m³);
- P_A = Proportion of water withdrawn by the agricultural sector over the total withdrawals;
- P_I = Proportion of water withdrawn by the industry sector over the total withdrawals;
- and
- P_S = Proportion of water withdrawn by the service sector over the total withdrawals.

Geospatial data for **SDG 6.4.2** (Water stress)

Satellite observation, in combination with model-based data, can partially inform on TWW (for agriculture) and TRWR.

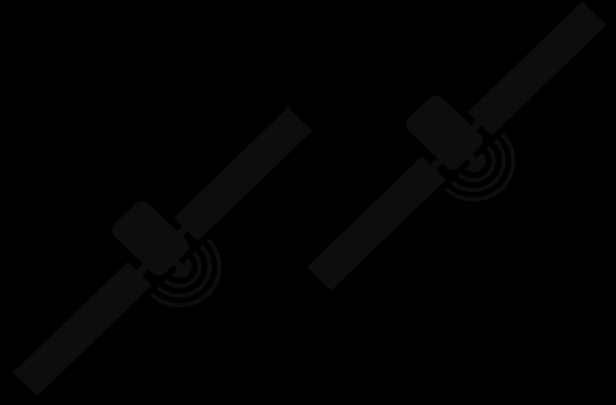
Observable variables: precipitation (P), water consumption (actual evapotranspiration, ETa).

Examples from FAO Water Accounting





How WaPOR works

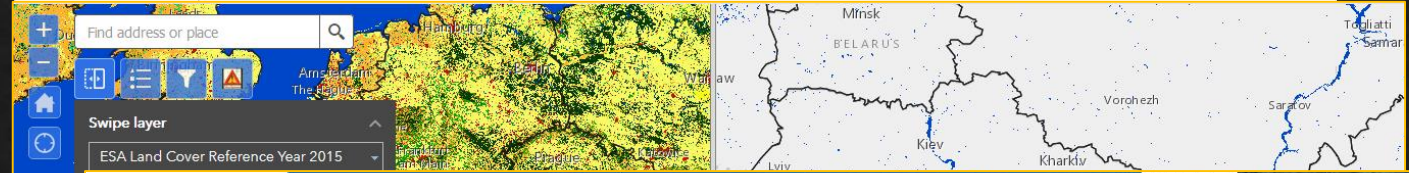


Consortium:





Geospatial data for SDG 15.4.2 (Mountain Green Cover Index)



- In 2020 FAO:
- 1) Produced a global MGCI time series 2000-2018 with national estimates disaggregated by mountain range. Land cover statistics were also calculated
 - 2) Results were shared with countries to support SDG reporting
 - 3) Developed an EO tool to facilitate validation
 - 4) Developed an MCGI StoryMap app to raise awareness and describe methodology
 - 5) Submitted paper to peer review journal (in process)

Office of the Chief Statistician (...)

Mountain Green Cover Index: revised metadata

15.4.2: M

remote sensing

Article

Using standardized time series land cover maps to monitor the SDG indicator "Mountain Green Cover Index" and assess its sensitivity to vegetation dynamics.

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Abstract: Earth Observation (EO) data have been recognized as an important tool to support countries in monitoring their progress toward implementing the Sustainable Development Goal (SDG) targets, thanks to their wide availability, spatial coverage, frequent updates, and low end-user cost. The Food and Agriculture Organization of the United Nations (FAO) is the custodian agency for 21 out of the 231 SDG indicators. To fulfil this responsibility, it has invested in EO data from the outset, among others by developing a new SDG indicator directly monitored with EO data: SDG indicator 15.4.2, the Mountain Green Cover Index (MGCI), for which FAO produced initial baseline estimates in 2017. The initial methodology foresees visual interpretation of land cover types at sample locations defined by a global regular grid that was superimposed on satellite images using. While this solution allowed FAO to establish a first global MGCI baseline and produce MGCI estimates for the large majority of countries, several reporting countries raised concerns regarding: i) the objectivity of the method; ii) the difficulty in validating FAO estimates; iii) the limited involvement of countries in estimating the MGCI; and iv) the indicator's limited capacity to account for forest encroachment due to agricultural expansion as well as the understated expansion of green vegetation in mountain areas, resulting from the effect of global warming.

To address such concerns, in 2020 FAO introduced a new data collection approach that directly measures the indicator through a quantitative analysis of standardized land cover maps (European Space Agency Climate Change Initiative Land Cover maps - ESA CCI-LC). In so doing, this new approach addresses the first three of the four issues, while it also provides stronger grounds to develop a solution for the fourth issue - a solution that FAO plans to present to the Interagency and Expert Group on SDG indicators (IAEG-SDG) at its autumn 2021 session.

This paper i) describes the new approach to estimate the MGCI indicator using ESA's CCI-LC and ii) assesses the accuracy of the new approach; iii) reviews the limitations of the current SDG indicator definition to monitor progress towards SDG target 15.4 and iv) reflects on possible further adjustments to the indicator methodology in order to address these.

Keywords: SDG 15.4.1, MGCI, Land Cover, ESA-CCI, GLC-LC100

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remote sensing

MDPI

Input Data

- Land cover time series
- Mountain elevation layer

Software

- QGIS + plugin for GEE
- Google Earth Engine
- ArcGIS
- Python (GDAL, Numpy libraries)

MGCI model

- Reclassify land cover map into binary green and non green cover map
- Calculate zonal statistics within Mountain elevation range
- Calculate the ratio of the area of green cover over the total mountain area

1. Introduction

In September 2015, the United Nations General Assembly adopted the 17 Sustainable Development Goals (SDGs) for Sustainable Development, comprising 17 Sustainable Development Goals (SDGs) and 169 targets aiming to cover the three dimensions of growth, social inclusion, and environmental sustainability. To monitor countries' progress, the UN Statistical Commission (UN-SC) established the Intergovernmental Group of Experts (IGES) on SDG indicators. In addition, the UN-SC established the 169 SDG targets in an internationally comparable evidence-base with which to catalyze the achievement of sustainable development while "leaving no one behind".

The Food and Agriculture Organization of the United Nations (FAO) is one of the 15 agencies and, as such, is responsible for providing data and, as such, is supporting countries' efforts in computing and reporting. FAO has consistently supported the adoption of geospatial information as an important instrument to monitor progress towards SDG targets. Through not a panacea for solving all the SDG data needs, as often heralded, EO data can significantly improve the availability, quality, and cost of data. EO data have been clearly recognized by the UN General Assembly as an important instrument to monitor progress towards SDG targets (GEO), the United Nations Committee of Experts on the Integration of Statistical Information (UN-CEIS), the IAEG-SDG Working Group on the Integration of Statistical Information (IAEG-SDG-Working Group on the Integration of Statistical Information), and the IAEG-SDG Working Group on the Integration of Statistical Information.

Among the list of SDG indicators for which geospatial information is an important instrument to monitor progress towards SDG targets, SDG indicator 15.4.2, the Mountain Green Cover Index (MGCI), the MGCI monitors land cover (green and non-green) in mountain areas (based on the notion that mountains are the state of health of mountains, and, therefore,



Geospatial data for 2.4.1

(Proportion of agricultural area under productive and sustainable agriculture is based on farm surveys as the primary data source)

2.4.1 is a complex land-based indicator defined as:

$$SDG2.4.1 = \frac{\text{Area under productive and sustainable agriculture}}{\text{Agricultural land area} *}$$

The nominator includes 11 sub-indicators, among which the prevalence of soil degradation which embeds further 4 sub-sub indicators.

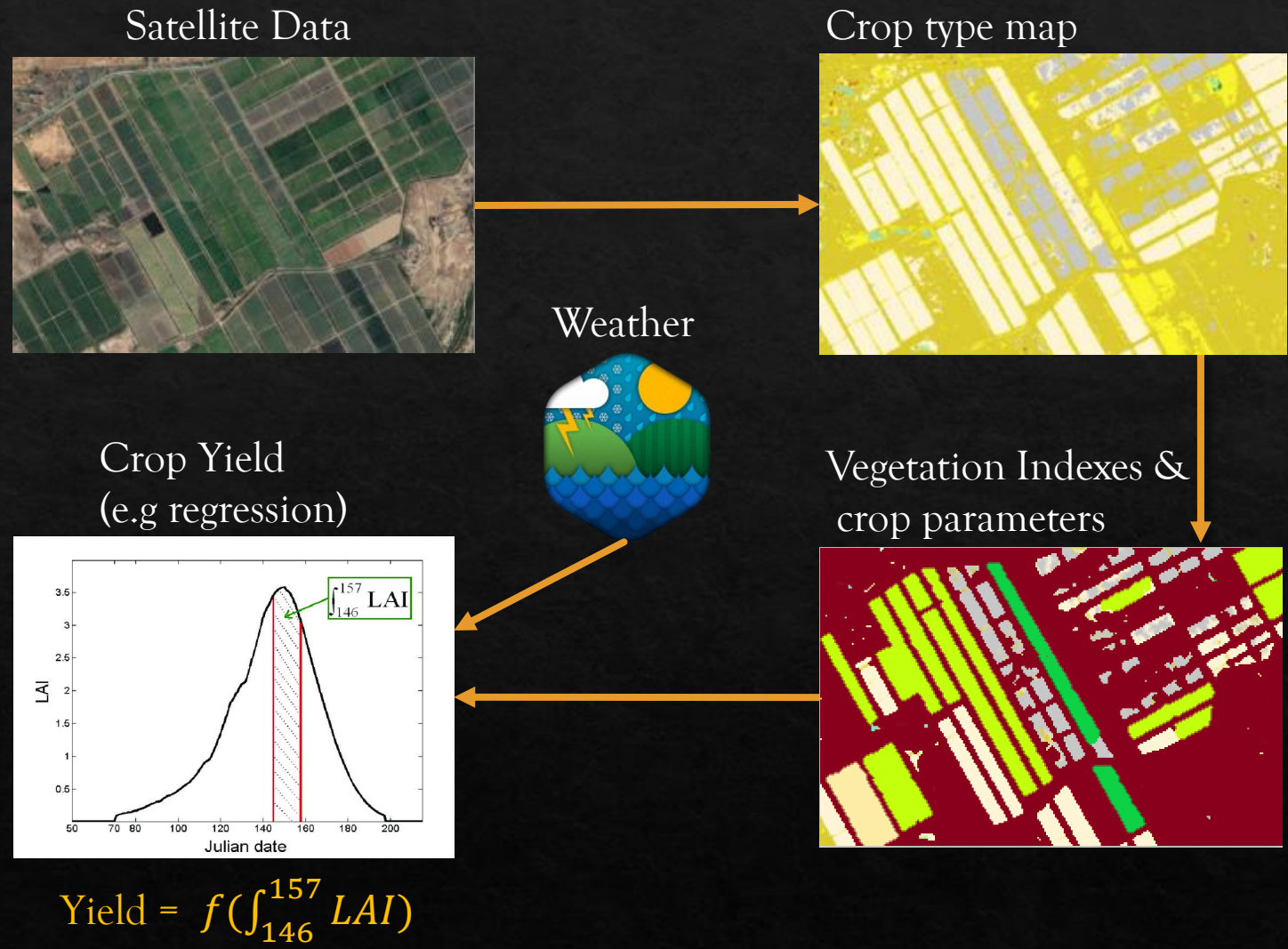
EO data can be used as key data source, or as complementary. It can be used to improve survey design.

Subindicator	Theme	Sub-indicator	Relevance of EO Data		
			Key data source	Complementary data source	Improve survey design
1	Land productivity	Farm output value per hectare		Crop productivity	✓
2	Profitability	Net farm income			✓
3	Resilience	Risk mitigation mechanisms		Farm diversification	✓
4	Soil health	Prevalence of soil degradation	Soil erosion, Reduction in soil fertility, Salinization of irrigated land, and Waterlogging		✓
5	Water use	Variation in water availability	Actual Evapotranspiration and Interception		✓
6	Fertilizer pollution risk	Management of fertilizers		Use of cover crops and buffer strips along waterways	✓
7	Pesticide risk	Management of pesticides		Crop rotation and the planting time	✓
8	Biodiversity	Use of agro-biodiversity-supportive practices		Natural or diverse vegetation on a farm, diverse farm production, and crop or crop/pasture rotation.	✓
9	Decent employment	Wage rate in agriculture			✓
10	Food security	Food insecurity Experience Scale (FIES)			✓
11	Land tenure	Secure tenure rights to land			✓

Land Productivity

Crop type maps can be used to estimate yield and productivity.

- Different approaches can be used depending on availability of in situ data (Regression, Inversion, AI)
- Based on relationship between yield observed in the field and vegetation index time series derived from satellite data
- Estimation through Harvest Index



Soil health

1. Soil erosion
2. Reduction in soil fertility
3. Salinization of irrigated land
4. Waterlogging

$$\text{RUSLE } A=R*K*LS*C*P$$

A is the average annual soil loss (t ha⁻¹ y⁻¹)

R is the rainfall-runoff erosivity factor

K is a soil erodibility factor

LS is a slope length-steepness factor (dimensionless)

C is a cover management factor (dimensionless)

P is a support practice factor (dimensionless)



EO DATA
Precipitation
Digital Elevation Model
NDVI
Land Cover



Soil health

1. Soil erosion
2. Reduction in soil fertility
3. Salinization of irrigated land
4. Waterlogging

EO data be used to make an approximation of soil fertility based on crop growth.

This can be done with the Normalized Difference Vegetation Index (NDVI) based on satellite data

Another proxy for soil fertility could be **SOC**. When available, national SOC maps can be used, however, there are also several global datasets available

EO DATA
NDVI
Crop Type Map
Precipitation
SOC map



Soil health

1. Soil erosion
2. Reduction in soil fertility
3. Salinization of irrigated land
4. Waterlogging

Multispectral and hyperspectral data can be used to detect, monitor, and map the salinity in the soil.

The spectral reflection of salt features at the soil surface has been used as a direct indicator.

There is also an indirect approach to detect areas affected by soil salinity, namely by using the performance level of vegetation

EO based Vegetation Indexed and Salinity Indexes

NDVI	$\frac{Red - NIR}{Red + NIR}$
Soil adjusted vegetation index (SAVI)	$\frac{(NIR - R)}{(NIR + R + L)} (1 + L)$
Salinity index (SI-T)	$(R / NIR) * 100$
Brightness Index (BI)	$\sqrt{R^2 + NIR^2}$
Normalized difference salinity index (NDSI)	$(R - NIR) / (R + NIR)$
Salinity Index (SI)	$\sqrt{B * R}$
Etc.	



Soil health

1. Soil erosion
2. Reduction in soil fertility
3. Salinization of irrigated land
4. Waterlogging

The Modified Normalized Difference Water Index (MNDWI) is a time and cost-effective tool to identify waterlogged areas.

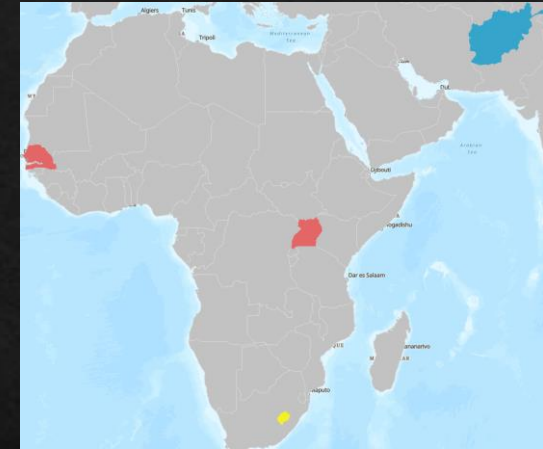
The index ranges from -1 to +1, where positive values indicate water and negative values vegetation.

The MNDWI is based on the Normalized Difference Water Index (NDWI) of McFeeters (1996). The MNDWI is a better index than NDWI for extracting water features mixed with vegetation from the satellite image.

EO DATA	
MNDWI	$\frac{G - SWIR}{G + SWIR}$



What is EO-STAT ?



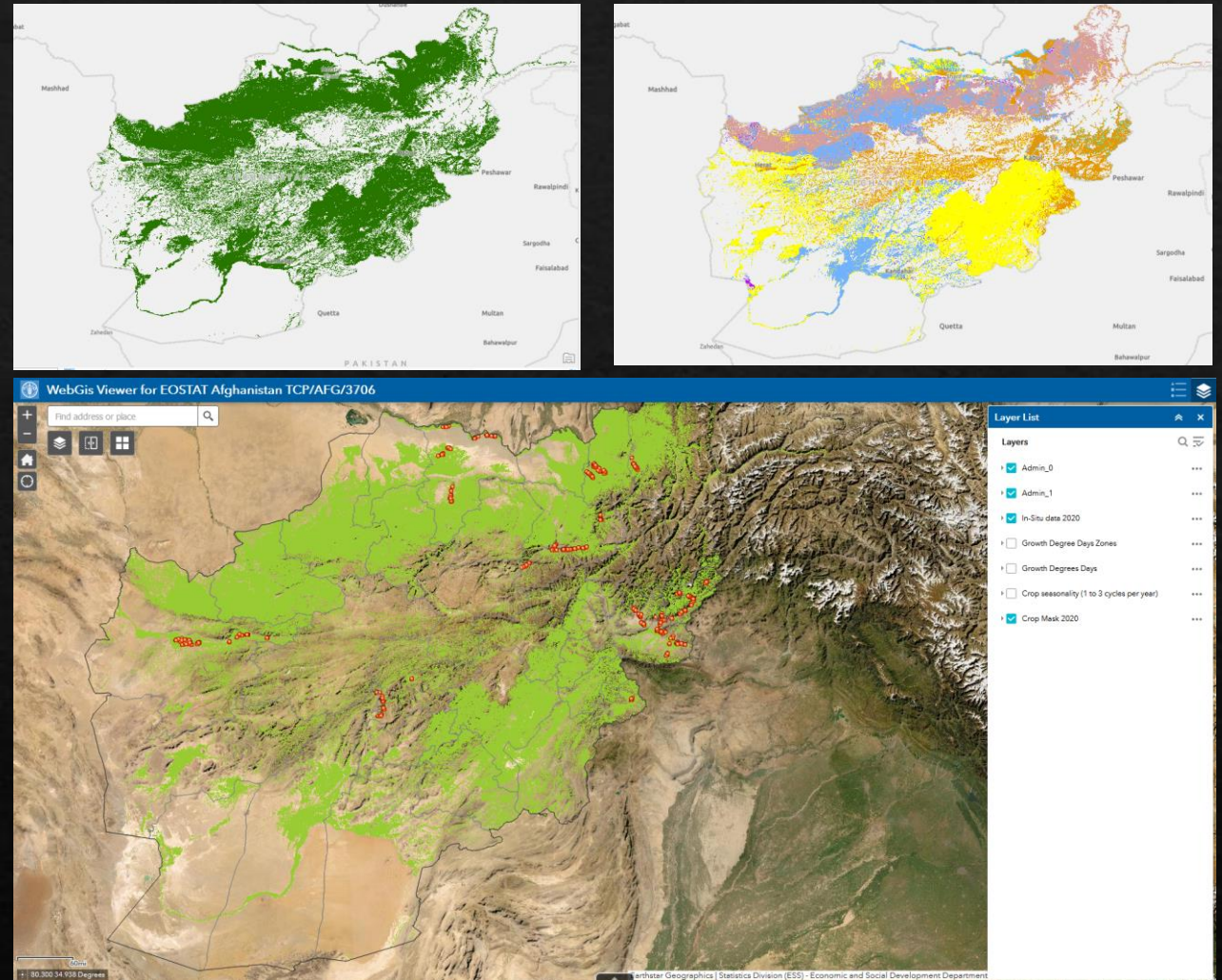
- ◆ EO-STAT is an FAO initiative led by the Office of the Chief Statistician, aiming at building capacity in countries in the use of EO to produce national agricultural statistics and support the process of modernization of agricultural statistical systems.
- ◆ 4 pilots are implemented: **Senegal**, **Uganda**, **Afghanistan** and **Lesotho**.
- ◆ Principal national counterparts: DAPSA, UBOS, NSIA, MAFS
- ◆ Data pipeline and analysis using Sen2Agri deployed on the UN Global Platform, and Google Earth Engine

Afghanistan

- In situ data gathered from NSIA
- Algorithm dev and benchmarking
- Crop mask
- Crop seasonality map
- Crop type map
- Map viewer [Link](#)
- Training

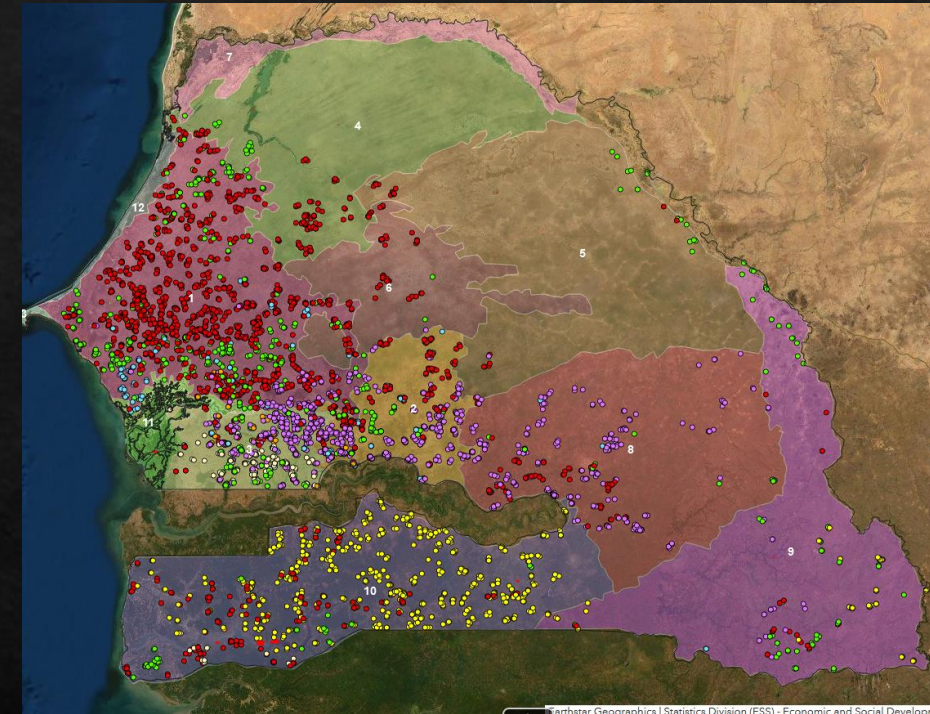
NEXT STEPS Q2-Q4 2021

- Automatisation of crop classification and development of a google app
- Training



Senegal

- Sen2Agri tool box deployed on UNGP
- Historical situ data gathered from DAPSA and QA-QC
- Prototype crop mask produced
- Crop type map produces
- 4 Trainings delivered (field work and Sen2Agri toolbox)

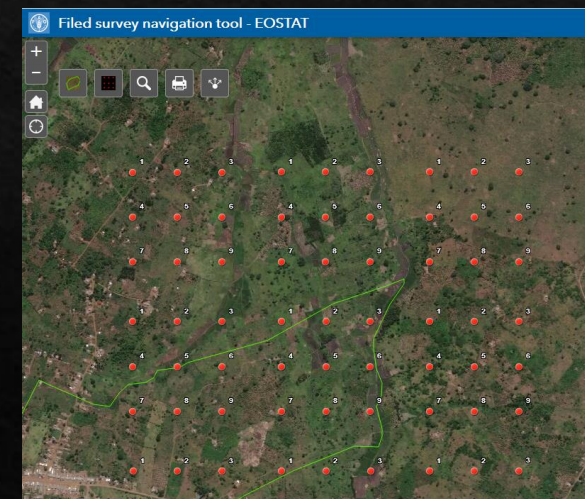
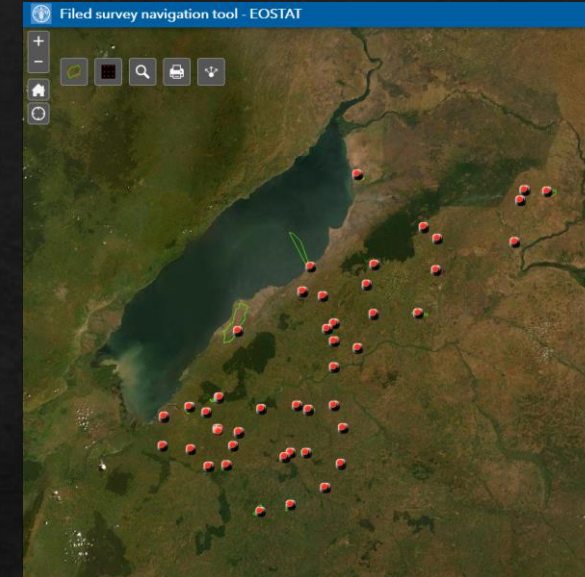


Uganda

- Ad hoc field survey protocol developed and implemented
- 1 training delivered on best practices in field data collection

NEXT STEPS Q1-Q2 2021

- Development of crop mask and crop type map
- Extraction of crop acreage statistics and crop yield
- Hands-on webinar



Thank you