**EO MAJI**

**EO Africa explorers**

**State of The Art Review**

V1

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**Document Release Sheet**

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# Introduction

## Project objective

This project aims to implement a prototype for irrigation mapping and crop yield estimation using inputs from the scientific ECOSTRESS and PRISMA missions. The final aim is to develop workflows, in collaboration with the African Early Adopters and EO partner(s), that support African irrigation and food security management, as well as transfering these R&D learnings and results to African end-users and stakeholders. More specifically the project objectives in this project can overall be listed as:

* Exploration of the capabilities for future operational Copernicus missions (LSTM+CHIME) to estimate ET and crop water stress.
* Investigate the potential of PRISMA hyperspectral observations and thermal-based crop stress metrics to improve crop yield/biomass estimations to support agricultural monitoring
* Complement the ET retrievals with crop yield, in order to acquire a better understanding of water use efficiency (WUE) of cultivated landscapes.
* Direct involvement of Africal Early Adopters, in order to secure the usefulness and applicability of the prototype.
* Publish the findings in a freely available code repository and as scientifically peer-reviewed papers, as well as to promote the codes through other outreach activities such as development of digital notebooks.

All activities are to be carried out within the duration of the project lifetime from 1 December 2022 to 30 November 2024.

## Scope of Document

This document presents the Agile Development Plan (PMP) which will be the formal, approved document used to guide agile prototype and toolbox development in the project “EO MAJI – EO Africa Explorers” (ESA AO/1-11038/21/I-DT).

## Reference documents

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| REF-1 | Statement of Work: ESA-EOP-SD-SOW-0250 – EO AFRICA EXPLORERS |
| REF-2 | EO MAJI proposal dated 18/02/2022 |
| REF-3 | Clarification request from ESA dated 06/06/2022 |
| REF-4 | Response to clarification dated 22/06/2022 |
| REF-5 | Contract No. 4000139395/22/I-DT |

# Methods

## Starting point

### Sharpening and sensor fusion

For land surface temperature (LST) data sharpening and sensor fusion a new physics-based approach to downscaling has been developed which combines high resolution optical data with coarser resolution thermal data. The approach utilises the information from the high resolution optical data to provide a sub-pixel variability in emissivity while crucially weighting the information from the coarser resolution thermal data based on the respective uncertainties in a covariance matrix.

A downscaled LST product is derived by taking LST from the Sea and Land Surface Temperature (SLSTR) product at 1 km resolution and using Sentinel-2 derived Land Surface Emissivity (LSE) data to iteratively update the LST in an Optimal Estimation (OE) scheme. In this methodology the OE scheme will assimilate the medium resolution SLSTR LST and the Sentinel-2 LSE and attempt to minimise the difference between the SLSTR calculated Bottom-Of-Atmosphere (BOA) brightness temperatures (BTs) and simulated BOA BTs generated from the SLSTR LST and the Sentinel-2 LSE. This would be an operation performed at the resolution of the Sentinel-2 data.

The processing first obtains the normalised difference vegetation index (NDVI) from the Sentinel-2 data and maps the SLSTR LST data onto the Sentinel-2 NDVI pixel grid. The NDVI data is used with the NDVI threshold method[[1]](#footnote-1) to estimate the LSE.

The re-gridded SLSTR LST combined with the original coarse resolution LSE associated with the pixel in the Split-Window processing (whether this be explicit or through biome estimation) is used with Planck’s Law to estimate the BOA BT values. In order to transfer the traceable uncertainties from the Split-Window algorithm, the random component of the total uncertainty from the SLSTR LST algorithm is applied as a noise on these BOA BT values using a Gaussian random distribution.

The SLSTR LST is then used with the Planck function again, but this time with the LSE derived from the Sentinel-2 NDVI threshold method. Two sets of BOA BTs are evaluated and the differences used to iteratively update the estimate for LSE used in the retrieval until an empirically determined threshold is reached from where there is no longer any significant improvement to be made by further iteration.

This methodology produces a full uncertainty breakdown including both the input total uncertainty of the SLSTR LST retrieval as well as the uncertainties due to the downscaling. The use of the SLSTR LST means that any additional uncertainties are a result of the retrieval process and the surface parameters, as the atmospheric uncertainty should have been fully captured in the SLSTR LST retrieval.

## Irrigation delimitation

Irrigated agricultural areas can be distinguished from adjacent agricultural parcels or natural areas either through:

1. Excess ET or crop vigour
2. Sudden increase in soil moisture and actual evapotranspiration which cannot be explained by other factors (e.g. change in weather or vegetation cover).

The first approach is more classical often and takes form of supervised or unsupervised land-cover classification[[2]](#footnote-2). It is particularly suited to regions with distinctive dry season during which there is sharp contrast between irrigated agriculture and rainfed agricultural or natural areas. The contrast can take form of increased vigour or greenness, often captured using NDVI, or increased ET in the irrigated parcels compared to other areas. It can also be observed in the structure of vegetation and detected with SAR data, such as the one acquired by Sentinel-1 satellites[[3]](#footnote-3). Regardless of the parameter used, or the combination of them, the first step of classification consists of creating temporal composites and indices, e.g. 25th percentile, median and 75th percentile of a parameter over the temporal compositing period. That period is usually monthly or seasonal. This data is then used in a classification model, such as random forest, to separate irrigated and non-irrigated agriculture. Depending on the regional conditions (e.g. temperate versus semi-arid climate) the classification can obtain an overall accuracy of between 50%-90%.

The second approach is based on identifying irrigation events through monitoring of changes in top-soil soil moisture[[4]](#footnote-4) . This method can also be employed with evapotranspiration instead of soil moisture. The ratio of actual to potential ET ((ETa/p) should be used in order to avoid changes in ET due to changes in weather (e.g. increased wind speed) or crop cover (e.g. quick development of leaves) being attributed to irrigation. This ratio is closely related to root-zone water availability and therefore is mainly influenced by irrigation or rainfall events.

The method separates changes in the ratio of actual to potential ET due to either rain or irrigation. At the same time, it attempts to capture even small irrigation events (e.g. drip irrigation) while remaining robust to uncertainty in the estimation of ET. This is achieved by first calculating the change in ETa/p between the time on which we irrigation is to be detect and most recent previous time on which ET estimates are available. This change is calculated both locally (i.e. at individual pixel level) and regionally (i.e. as an average change in all agricultural pixels within 10 km window). The local and regional changes are then compared to a number of thresholds to try to detect if:

(a) There is no input of water into the soil (e.g. local ETa/p does not increase above a threshold)

(b) There is input of water into the soil but due to rainfall (e.g. increase in regional ETa/p is over a threshold and larger or similar to increase in local ETa/p)

(c) There is input of water to the soil due to irrigation (e.g. increase in local ETa/p is over a threshold and significantly larger than increase in regional ETa/p)

Detected irrigation events are further split into low, medium and high probability based on another set of thresholds. Since irrigation is normally applied on a larger area, the raster map with per-pixel irrigation events is cleaned up by removing isolated pixels in which irrigation was detected.

The second approach is reported to achieve overall accuracy of 80%-90%. Compared to the classification method, it has the benefit of being able to detect individual irrigation events. It is also able to perform even in periods and regions in which rainfall events are recorded at the same time as irrigation events. In addition, the second method can be considered a hybrid physical-empirical approach and while it might benefit from localised fine-tuning it does not require extensive local calibration or training. Finally, as its main inputs it uses data which is expected to be further improved in this project (actual and potential ET) and those improvements can then hopefully lead to improved delineation of irrigated areas.

1. Sobrino, J. A., Jimenez-Munoz, J. C., Soria, G., Romaguera, M., Guanter, L., Moreno, J., Martinez, P. (2008). Land surface emissivity retrieval from different VNIR and TIR sensors. IEEE Transactions on Geoscience and Remote Sensing, 46(2), 316-327. doi:10.1109/TGRS.2007.904834 [↑](#footnote-ref-1)
2. Magidi, J.; Nhamo, L.; Mpandeli, S.; Mabhaudhi, T. Application of the Random Forest Classifier to Map Irrigated Areas Using Google Earth Engine. Remote Sens. **2021**, 13, 876. https://doi.org/10.3390/rs13050876 [↑](#footnote-ref-2)
3. Pageot, Y.; Baup, F.; Inglada, J.; Baghdadi, N.; Demarez, V. Detection of Irrigated and Rainfed Crops in Temperate Areas Using Sentinel-1 and Sentinel-2 Time Series. Remote Sens. **2020**, 12, 3044. https://doi.org/10.3390/rs12183044 [↑](#footnote-ref-3)
4. Bazzi, H.; Baghdadi, N.; Fayad, I.; Zribi, M.; Belhouchette, H.; Demarez, V. Near Real-Time Irrigation Detection at Plot Scale Using Sentinel-1 Data. Remote Sens. **2020**, 12, 1456. https://doi.org/10.3390/rs12091456 [↑](#footnote-ref-4)