IMAGIN-e Track: Final submission
DroughtScope

Latitudo 40

September 2023

esa Microsoft ThalesAlenia Space

AI4EO Challenges by ESA Φ-lab

Show us your functional prototype

Please provide a link of your notebook.

https://github.com/latitudo40organization/drought-scope/blob/main/Solution.ipynb

https://github.com/latitudo40organization/drought-scope/blob/main/slides/solution-notebook.pdf

Pitch your solution

Please provide us with the link to your video pitch. For guidance on what you pitch should contain please check this link.

The video can be uploaded to any online platform such as YouTube, Vimeo, etc. The video **does not** have to be public; you can publish it as unlisted or private.

Please do a test before to make sure that the video can be viewed by anyone with the link.

https://youtu.be/2XyiOw1Nu2A

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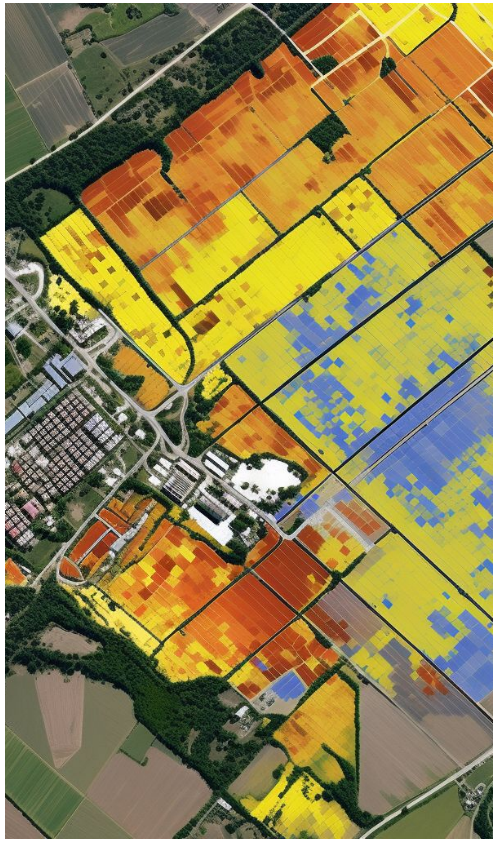
Value proposition



Our solution aims at identifying ***early water stress conditions*** in crops to optimize ***water resource management***.

By exploiting *IMAGIN-e hyperspectral* data, we estimate evapotranspiration (ET) at a plot scale, enabling the derivation of synthetic indicators for early water stress.

A **multi-task deep-learning** network produces a real time crop/no crop classification map together with the Evaporative Stress Index (ESI) product.

Value proposition

Key Benefits

Precision Monitoring
Continuous monitoring with hyperspectral data to raise early warnings, thus enabling timely on-site intervention.

Food Security
Early detection of water stress in crops helps reducing the risk of underproduction, which can lead to food shortages and price spikes.

Cost Savings
Reducing the operational costs for farmers by minimizing water waste.

Sustainable Agriculture
Sustainable farming practices, including efficient water management, are increasingly demanded by consumers and regulators. Our solution helps farmers to meet these requirements, keeping their products marketable and profitable.

Resource Optimization
Our solution optimizes water resource allocation with pinpoint accuracy. Delivering the right amount of water to the right place at the right time reduces wastage and enhances crop health.

Climate Change Adaptation
Efficient water management contributes to climate change mitigation by reducing the carbon footprint associated with excessive irrigation and water pumping. It also aids in adapting to changing climate patterns.

Technical aspects

4

KPIs

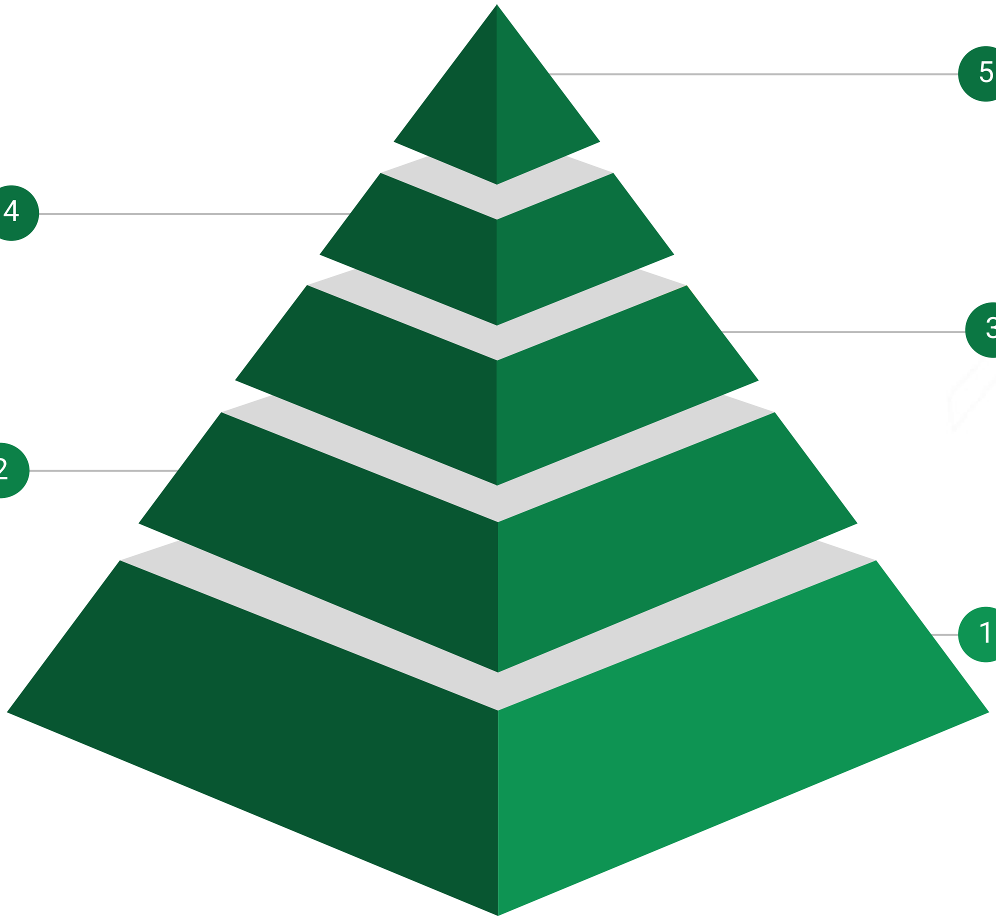
Calculate KPIs on the identified crop-fields to provide specific water stress classes: *very low, low, medium, high, very high*.

2

Crop map

Provisioning of crop **classification maps** together with with **ESI maps** using a **multi-task deep-learning** model trained on WorldCover data. This solution allows for:

- **Contextual understanding:** model captures the interdependencies between land cover and evapotranspiration
- **Resources saving:** using a single network for multiple tasks reduce the computational and memory resources required compared to running separate models



5

Alert

Set Alert thresholds for KPIs based on predefined tables or user-defined values.

3

Filtering by crop map

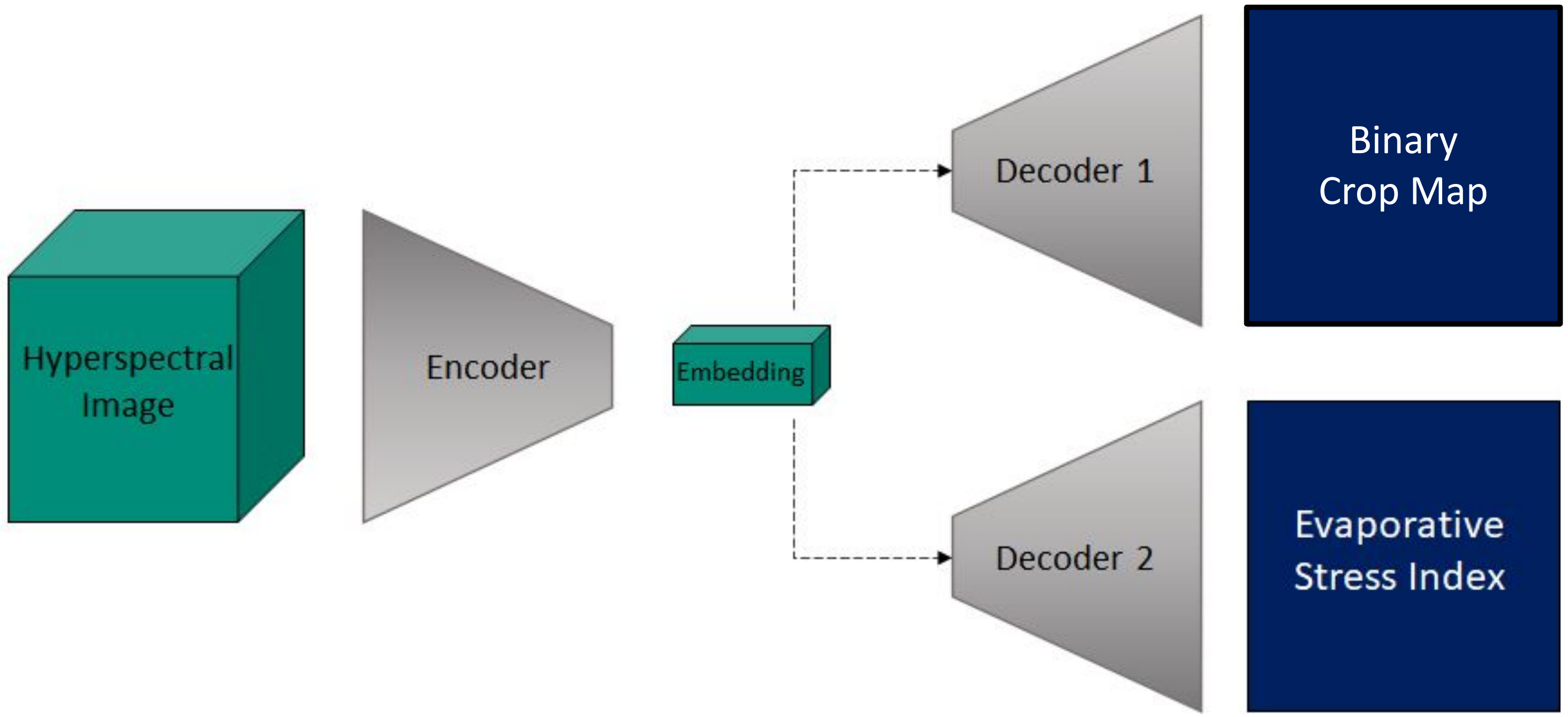
Apply an ESI filter to the fields to identify areas with potential ecological issues.

1

Evaporative Stress Index (ESI)

Calculating the ESI index using *IMAGIN-e L1C* hyperspectral data, consisting of 50 bands spanning the 450 - 950 nm range at a resolution of 45 m, with a novel **multi-task deep-learning** model trained on ECOSTRESS data, incorporating manifold learning techniques to address the challenges posed by high dimensionality.

What is the architecture of your AI model?



*As a novelty, we introduced a **multi-task neural architecture**, proposed ad hoc for this task, that processes a hyperspectral tensor: **an encoder** network creates a high-level embedding used by **two decoders**. The first, trained with a cross-entropy loss function, generates a **crop map**. The second, employing a Mean Absolute Error function, predicts the **ESI map**. The total loss is calculated from both tasks, optimizing them simultaneously. The shared representation learning used enhances efficiency.*

Technical feasibility and scientifically correctness

- **Scientific consistency**: Our solution exploits the correlation between evapotranspiration and spectral range of IMAGIN-e data (VNIR 450 - 950 nm). This evidence is provided by the scientific literature[1] and confirmed by by by the results of our experiments.

- **Data Quality and Representativeness**: The first version of the dataset includes areas accounting for *diversity of crops*, *soil types*, *climate conditions*, and *water stress scenarios* (see red dots in the Figure).

[1] M. Marshall, P. Thenkabail, T. Biggs, K. Post, "Hyperspectral narrowband and multispectral broadband indices for remote sensing of crop evapotranspiration and its components (transpiration and soil evaporation)", Agricultural and Forest Meteorology, vol. 218-219, pp. 122-134, 2016.

Technical feasibility and scientifically correctness

Our solution involves a **165 MB** model, which becomes **50MB** with Quantization Aware Training, **compliant** with the onboard **computational** resources of 32 GB, as outlined in the specifications.

Moreover, our solution is meaningful for the IMAGIN-e mission because it needs to provide **real-time responses**, which aligns with the core purpose of the mission itself.

Inference times was approximately *5 seconds* using an Intel(R) Core(TM) i7-10750H CPU and 16GB of RAM (*without GPU*) for an area of about 700 km^2.

Validation of the model

Crop Detection Classification metrics	Evaporative Stress Index (ESI) Regression metrics	Model Size
Accuracy: 0.8	**RMSE**: 0.1	**Model Size**: 165 MB
Recall: 0.8		**Parameters**: 40 M
Precision: 0.6		
F1-Score: 0.7		

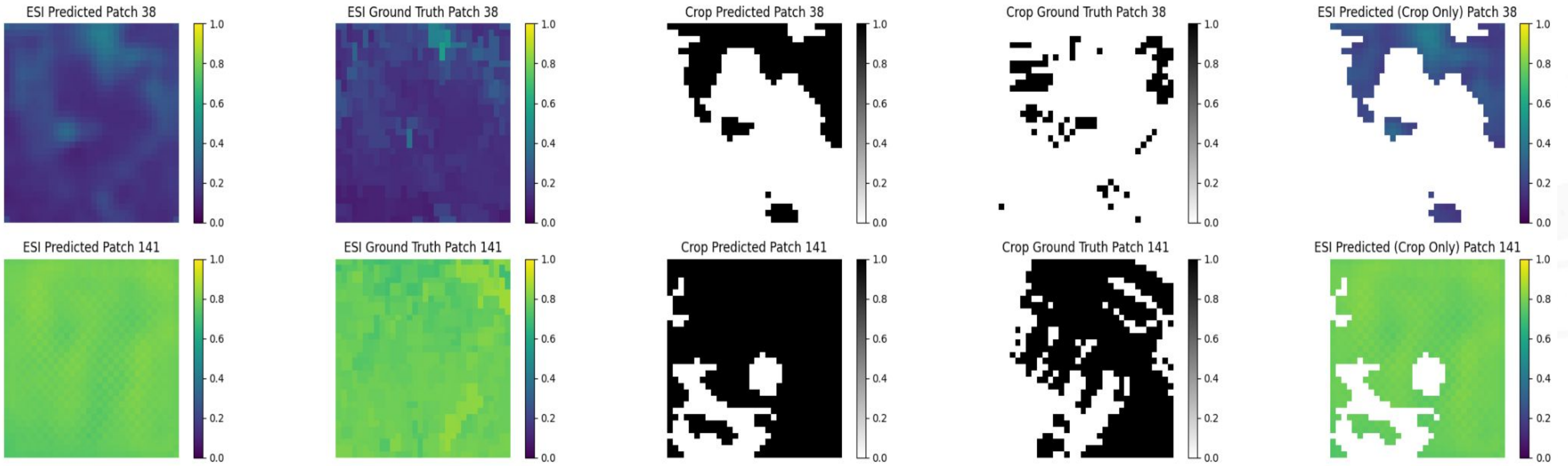
We used a 70-15-15 holdout split; the division was made after performing a shuffle over random and representative areas in **Europe**

Validation of the model

ESI predicted | **ESI Ground Truth** | **Crop map predicted** | **Crop Ground Truth** | **ESI predicted filtered on crop maps**

Clip 1

Clip 2



Examples of produced maps and corresponding ground truth on the **test set**

Contribution to open science

We use only **open-data** from the **ESA WorldCover** dataset as ground truth for crop maps. **ECOSTRESS** data will serve as a reference for ESI during model training, with a spatial resolution of approximately 70 metres. They will be **rescaled** to 45 metres to ensure consistency with the input HS data.

Our architecture is designed specifically to **save weights** by sharing one encoder for multiple tasks

A **new dataset** for ESI and Crop Classification

The literature has already highlighted the correlation between narrowband indices and Evapotranspiration. With this prototype solution, we have demonstrated promising results at a **European** scale. It would be even more intriguing to study its scalability on a **global** level and *share* the findings with the scientific community

Share results with scientific community

The team

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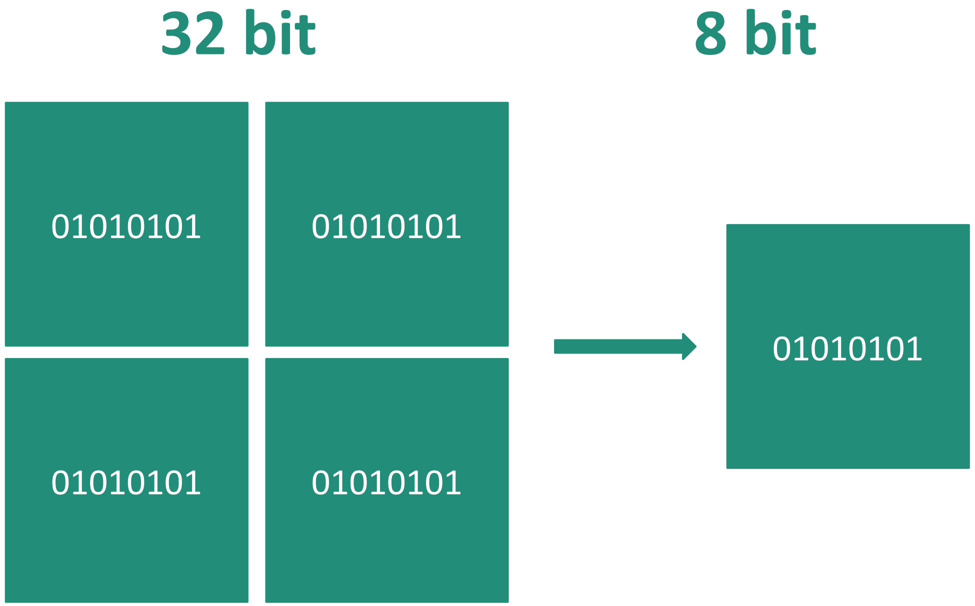
PhD in Remote Sensing & Senior Researcher

Quantization experiments: first results



By implementing Quantization Aware Training (QAT), we managed to significantly shrink our model down to a mere 50MB. Nonetheless, it's worth noting that this reduction in model size has had some impact on our test set metrics. Specifically, for the ESI task, we observe an increase in the Root Mean Square Error (RMSE), which now stands at 0.5.

In addition to the ESI metrics, let's also delve into the performance metrics for our crop detection task, which are as follows:

- Accuracy: 0.8
- Precision: 0.7
- Recall: 0.3
- F1-Score: 0.4