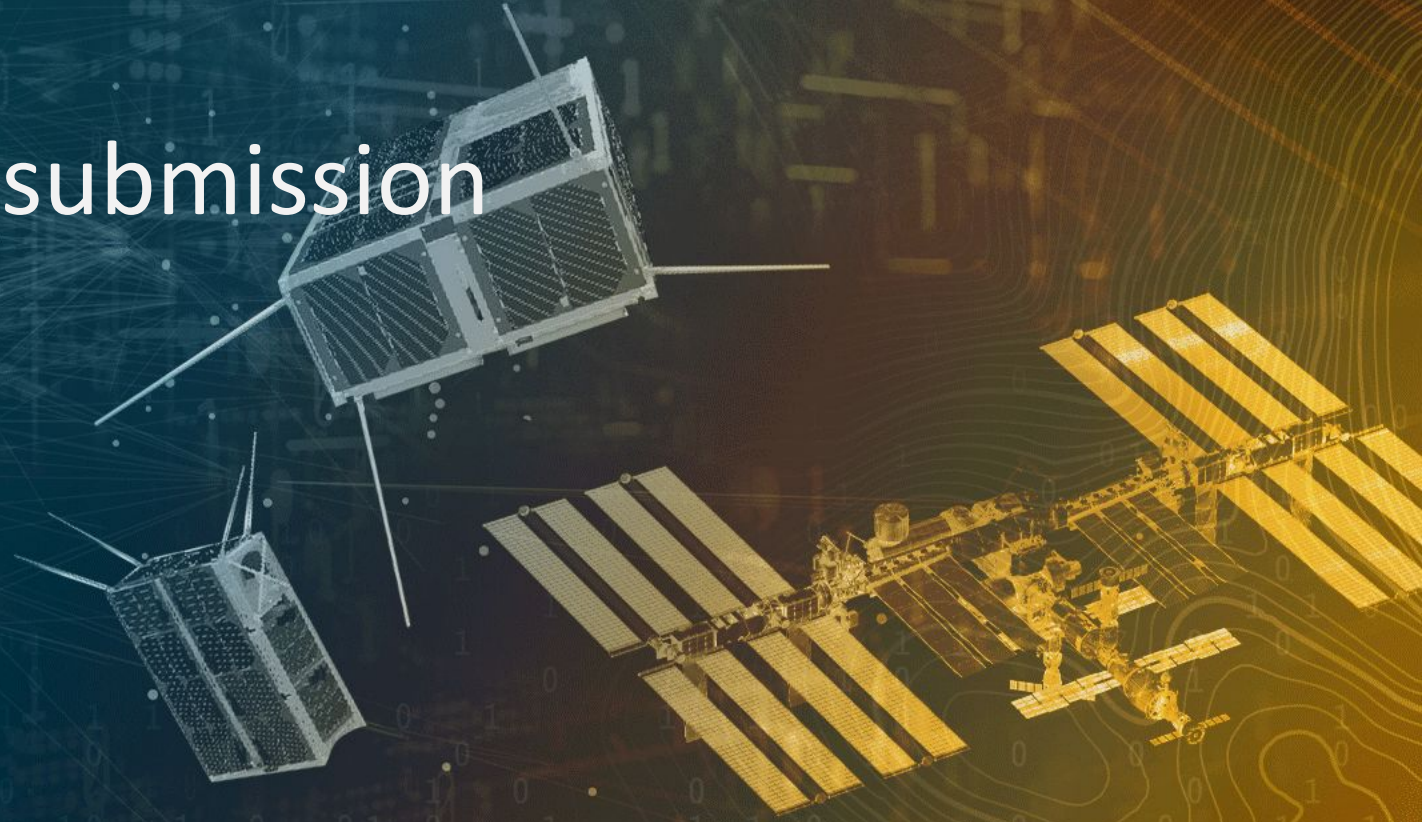


IMAGIN-e Track: Final submission

DroughtScope

Latitudo 40

September 2023



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.

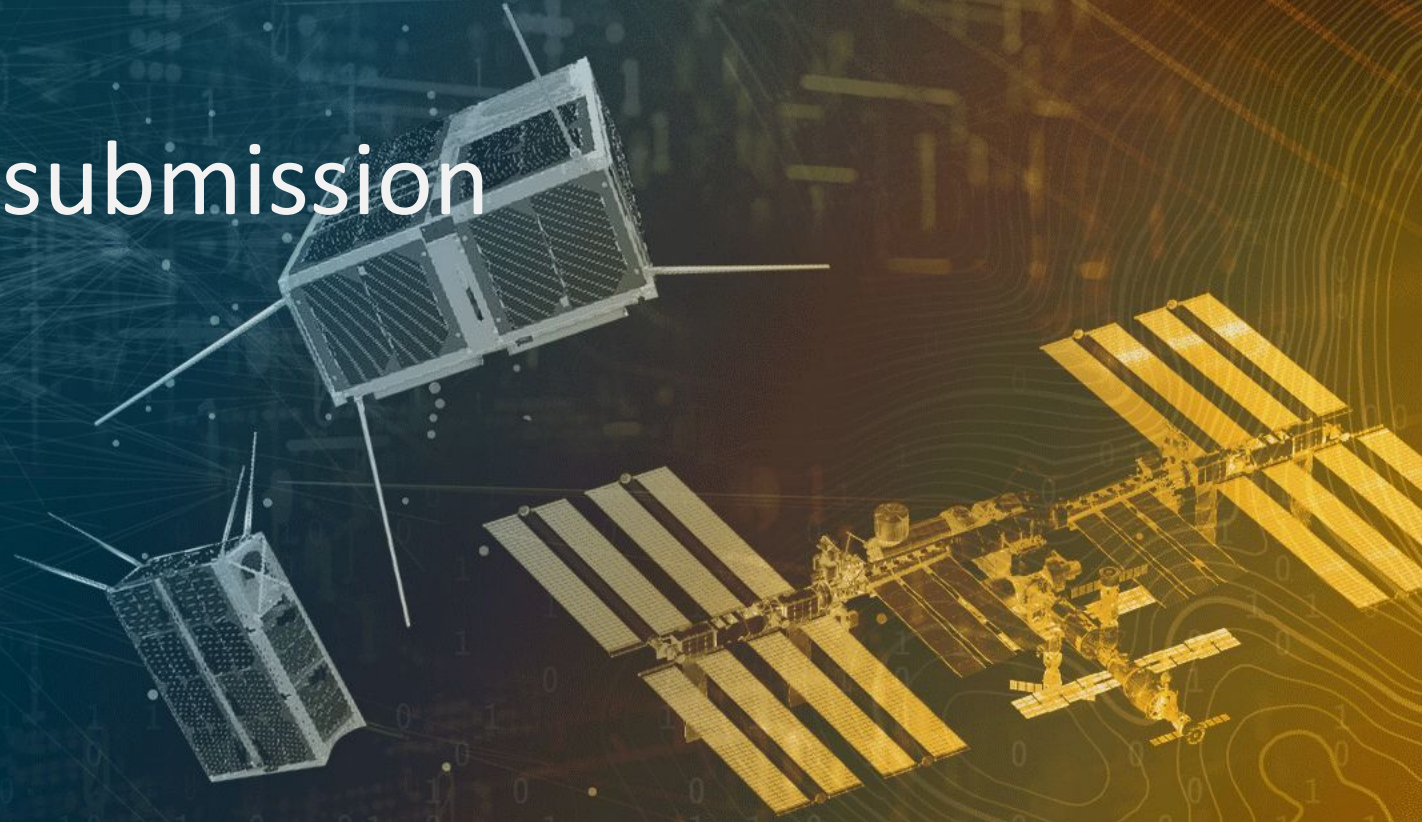
<https://youtu.be/2XyiOw1Nu2A>

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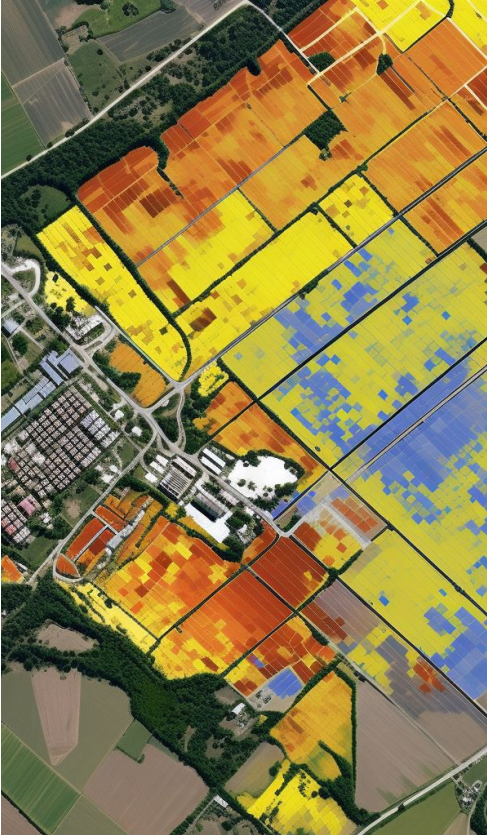
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Value proposition



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.

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.

Food Security

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

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.

Cost Savings

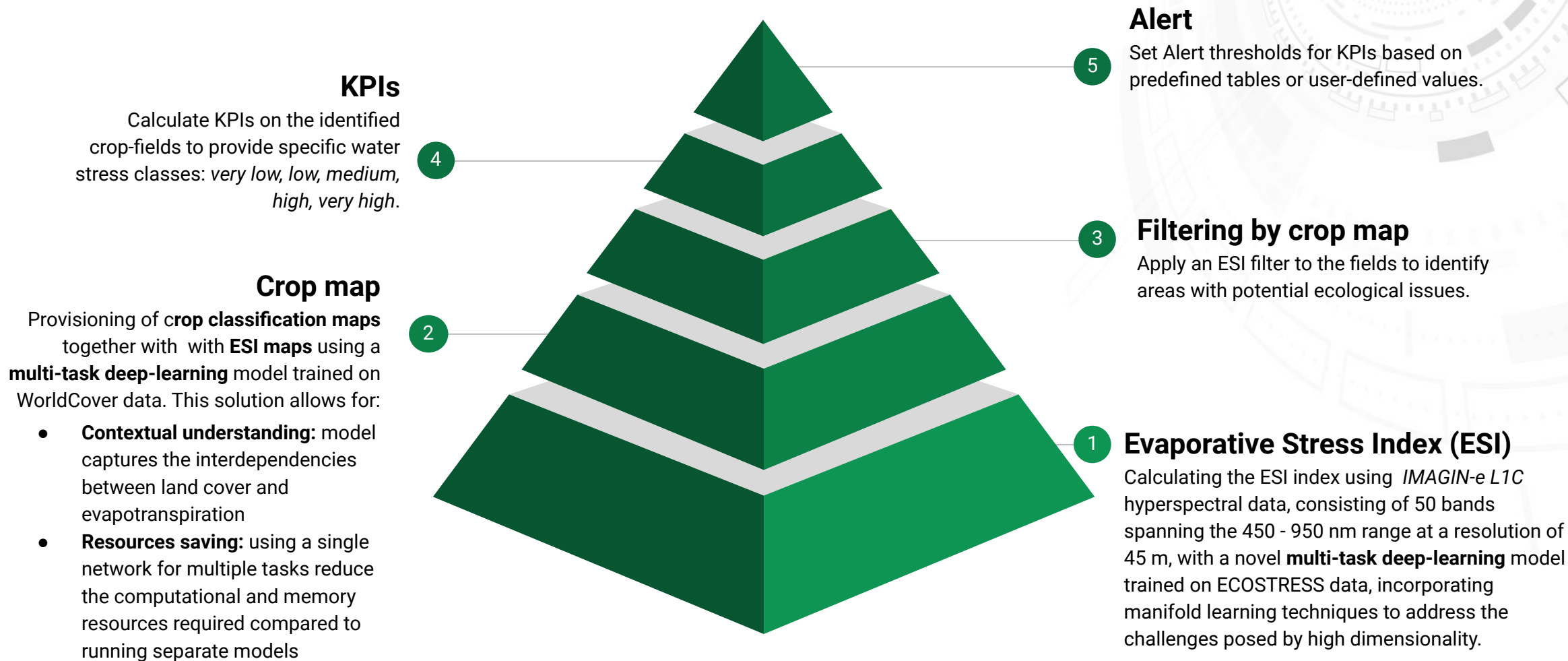
Reducing the operational costs for farmers by minimizing water waste.

Climate Change Adaptation

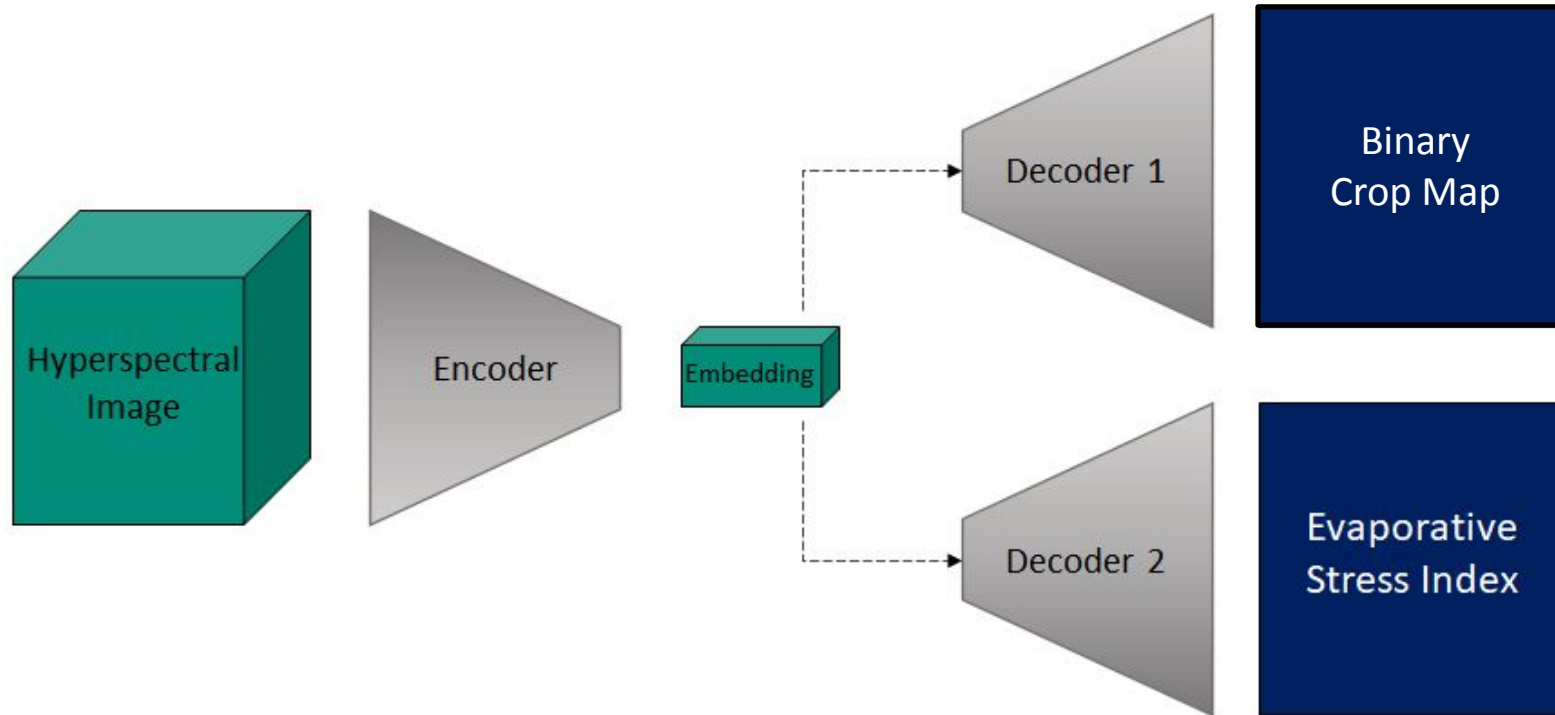
Efficient water management contributes to climate change mitigation by reducing the carbon footprint associated with excessive irrigation and water pumping. It also aids in adapting to changing climate patterns.



Technical aspects



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 scientific 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 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 scientific 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 km².

Validation of the model

Crop Detection Classification metrics

Accuracy: 0.8

Recall: 0.8

Precision: 0.6

F1-Score: 0.7

Evaporative Stress Index (ESI) Regression metrics

RMSE: 0.1

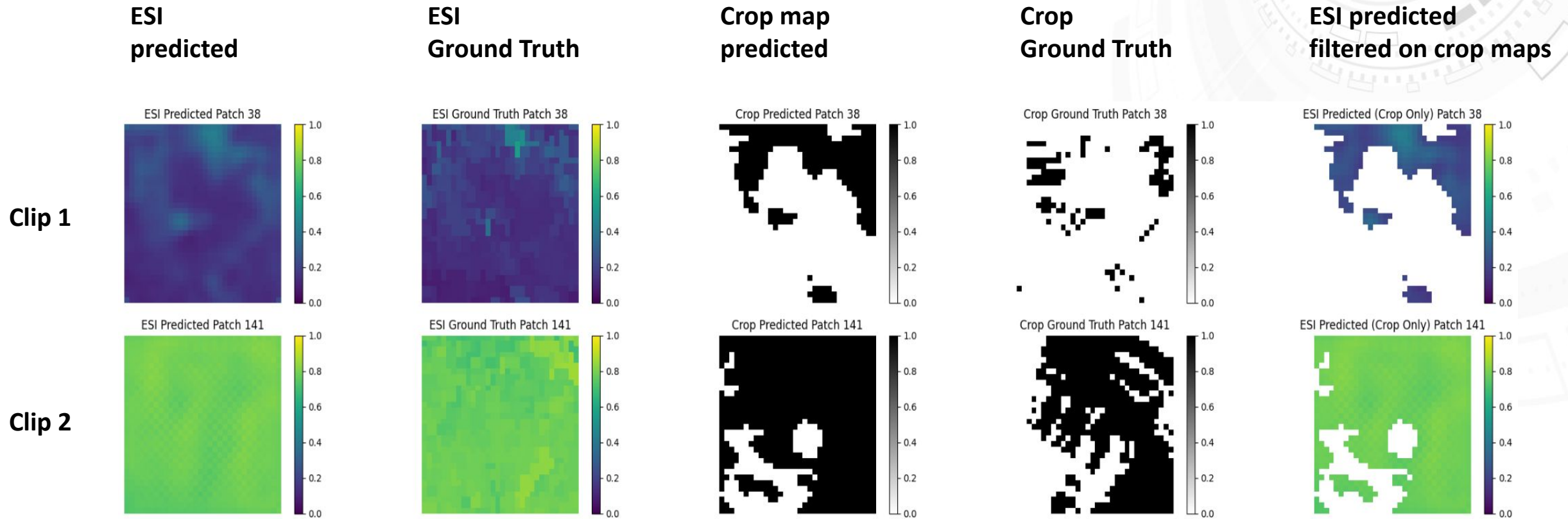
Model Size

Model Size: 165 MB

Parameters: 40 M

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



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.

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

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

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

Share results with scientific community

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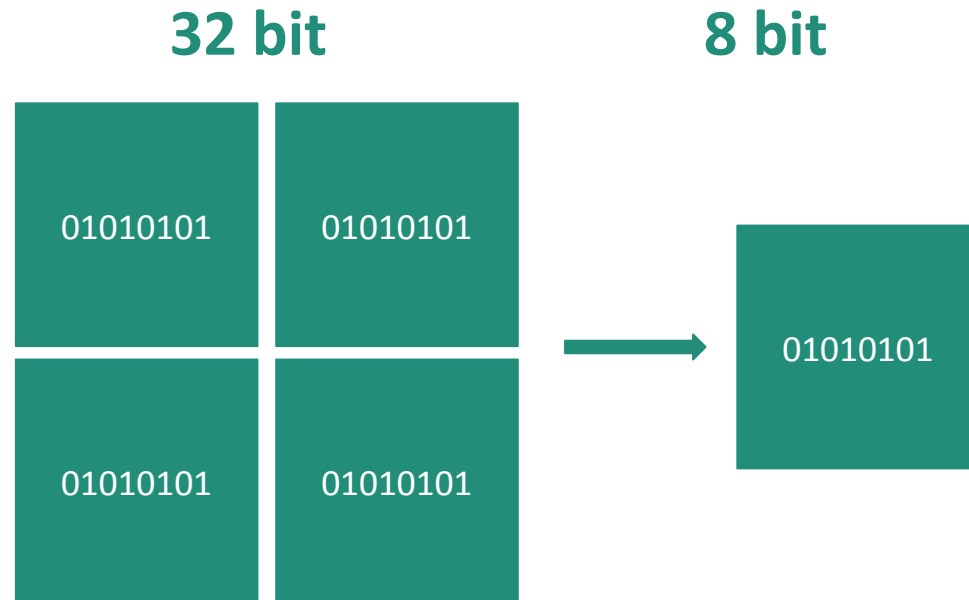


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Quantization experiments: first results



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