Onboard Cloud Detection and Atmospheric Correction with End-to-End Deep Learning Emulators

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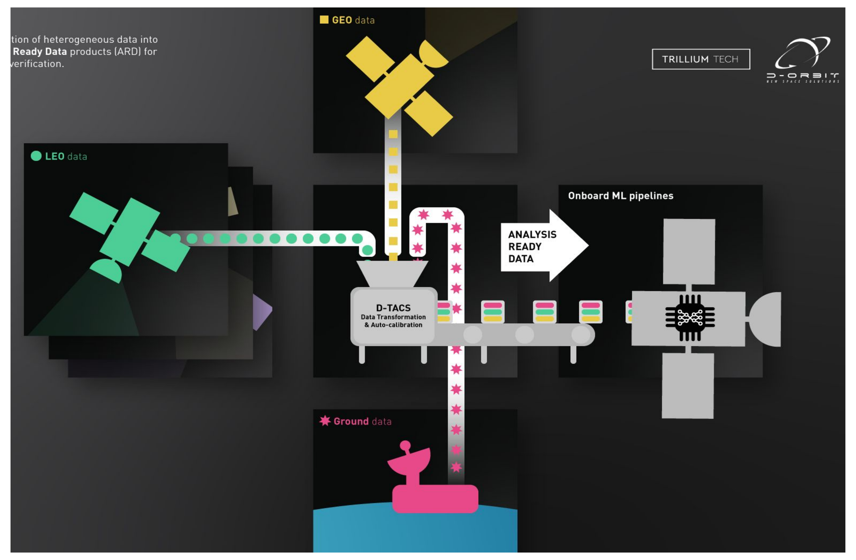
Accurate cloud detection and atmospheric correction ML emulators with very low computational overhead, demonstrated on dedicated onboard hardware

Challenge & Opportunity

Processing data onboard requires the integration and calibration of raw data before it is used by most applications. While this is normal practice on the ground, **creating analysis ready data (ARD) onboard** is challenging due to lower processing capability and memory, and the restricted (if any) access to ancillary data.
For optical sensors, the atmospheric correction process consists of identifying the pixels where the signal from the surface can't be recovered (e.g. clouds) and correcting the perturbations caused by the atmosphere and topography in the rest of the image (caused mainly by thin clouds, aerosols, water vapour, ozone and other atmospheric constituents).

For Sentinel-2, the atmospheric correction process carried out by Sen2Cor is too computationally demanding for onboard hardware.

Deep learning models have been successful emulating many physics based processes. ***Can we emulate the atmospheric correction process at a fraction of the processing cost without sacrificing accuracy?***



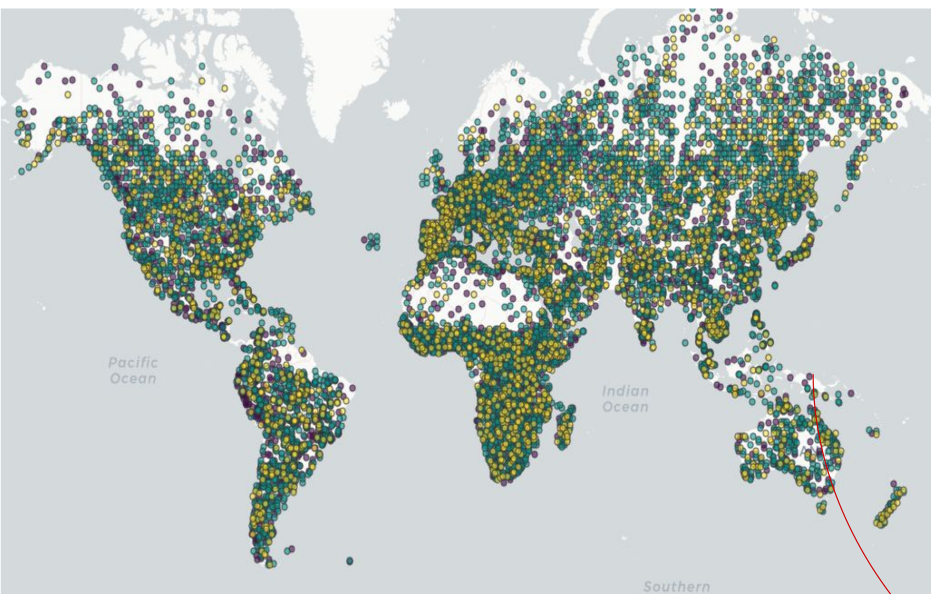
Training Data

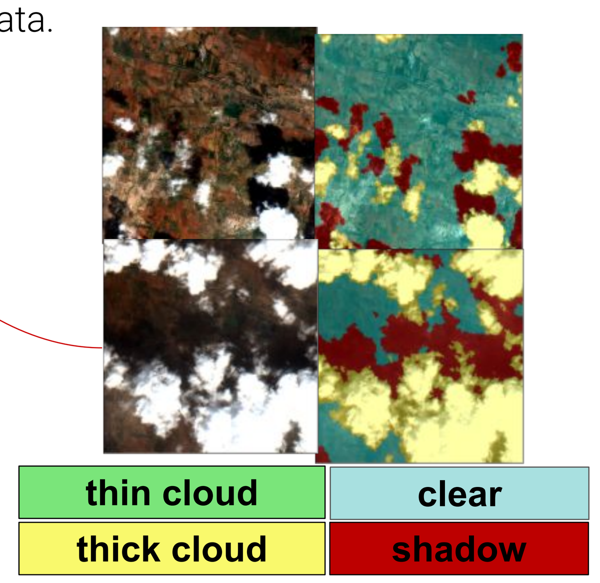
-- *https://cloudsen12.github.io/*

9,,880 different locations and 49,400 image patches (509x509)

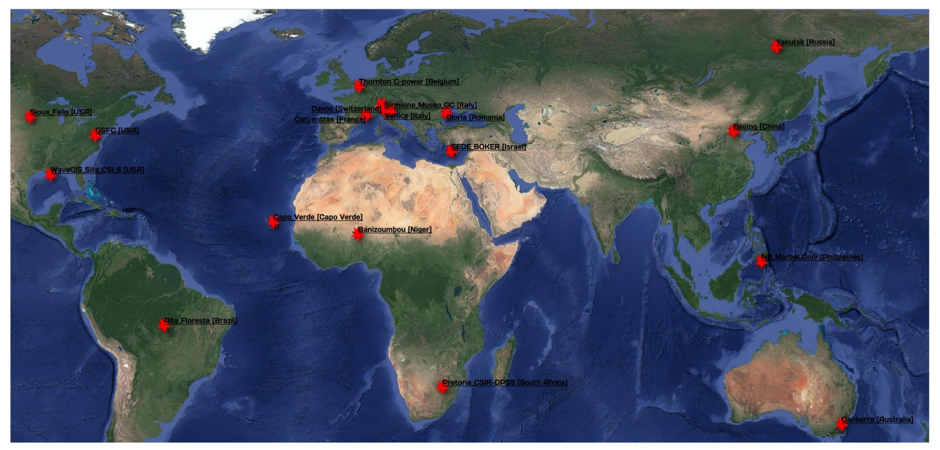
- Manually annotated cloud and cloud shadow labels.

- Sentinel-2 Level 1C and Level 2A data.





Validation data

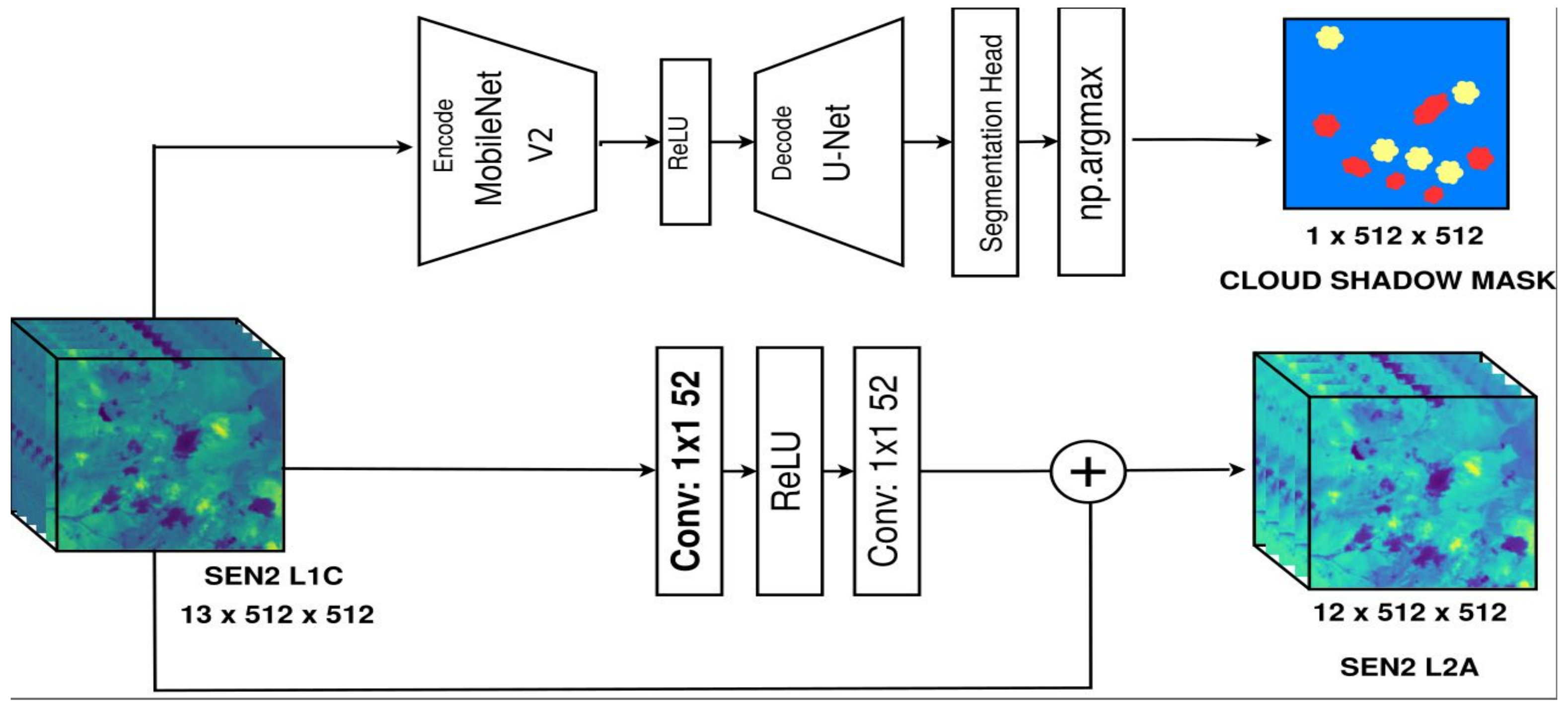


- 19 locations corresponding to aerosol robotic network (AERONET) stations
- Time series of Sentinel-2 images (year 2019)
- Same locations as Doxani et al 2018.

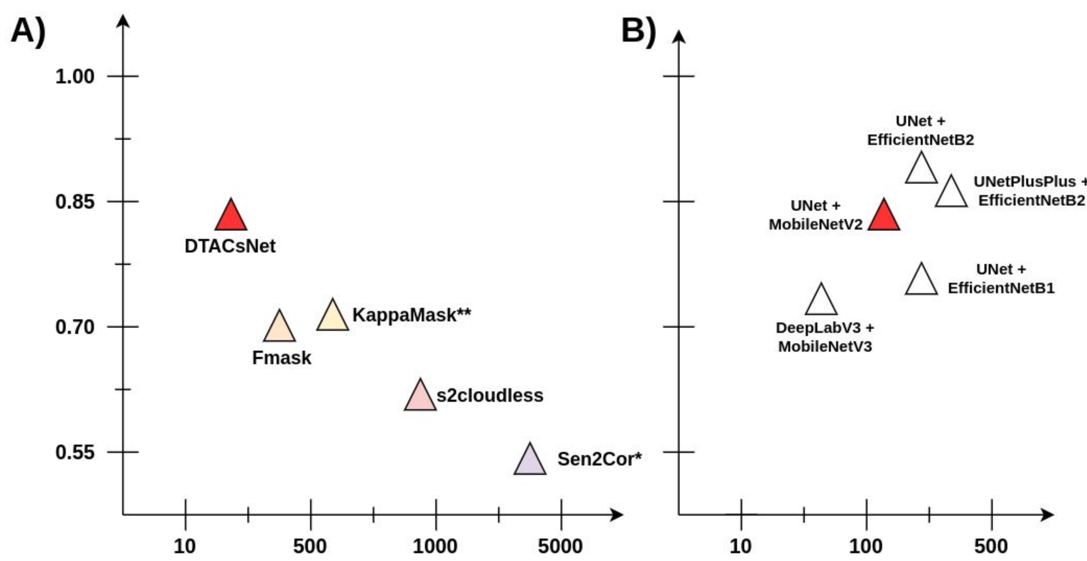
Models

Cloud and cloud shadow detection: trained with the manually annotated cloud and cloud-shadow labels and the level 1C data (non-atmospherically corrected).

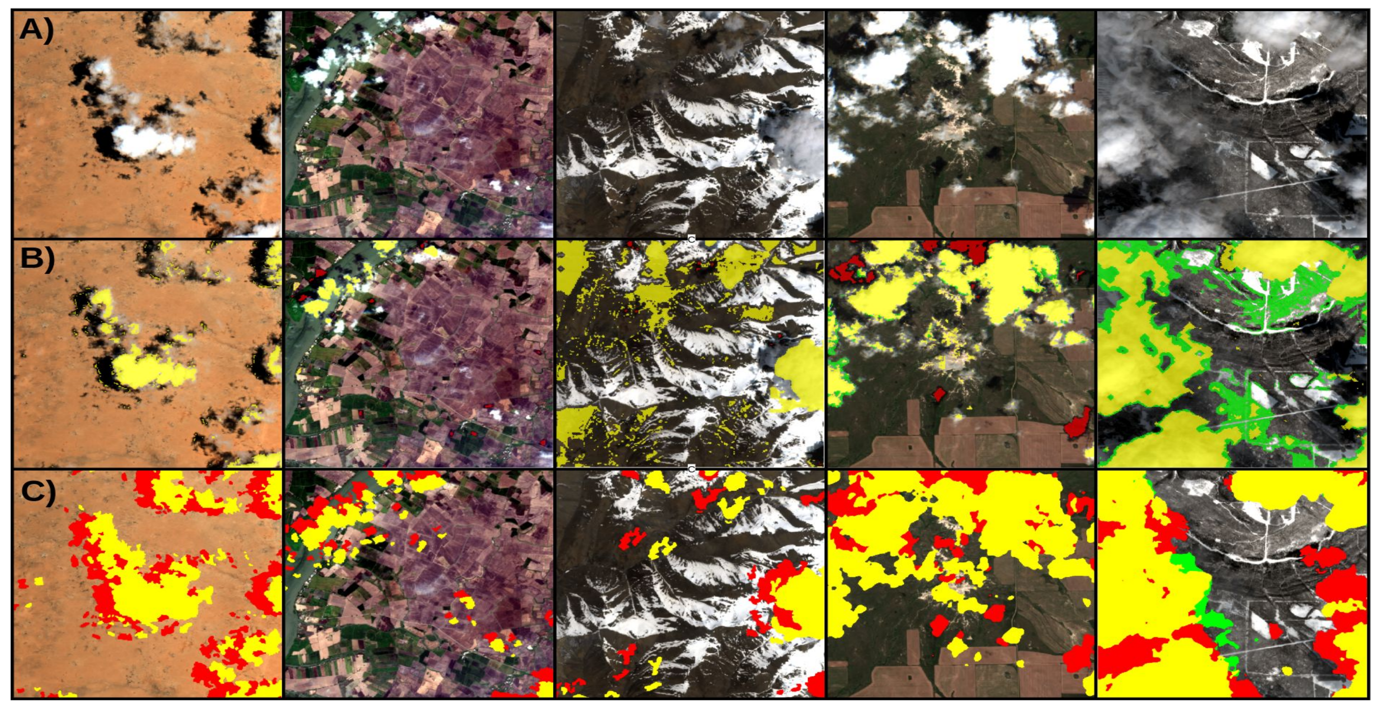
Atmospheric correction: trained with atmospherically corrected images from Sen2Cor (Level 1C input, Level 2A output). Model trained to minimise mean squared error. We mask the clouds in the output when computing the loss.



Cloud Detection Results

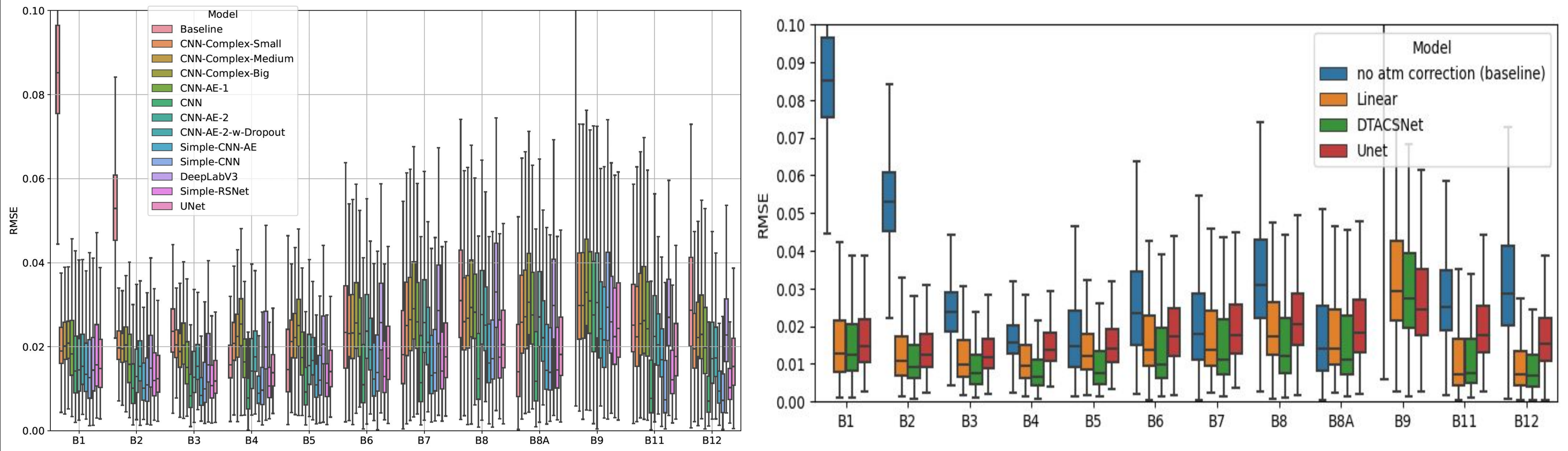


Inference time vs F2-score of A) different state-of-the-art cloud detection models B) different architectures tested. F2-score computed in the CloudSEN12 test set. Latency measured in GPU in a full S2 scene. In red the selected architecture



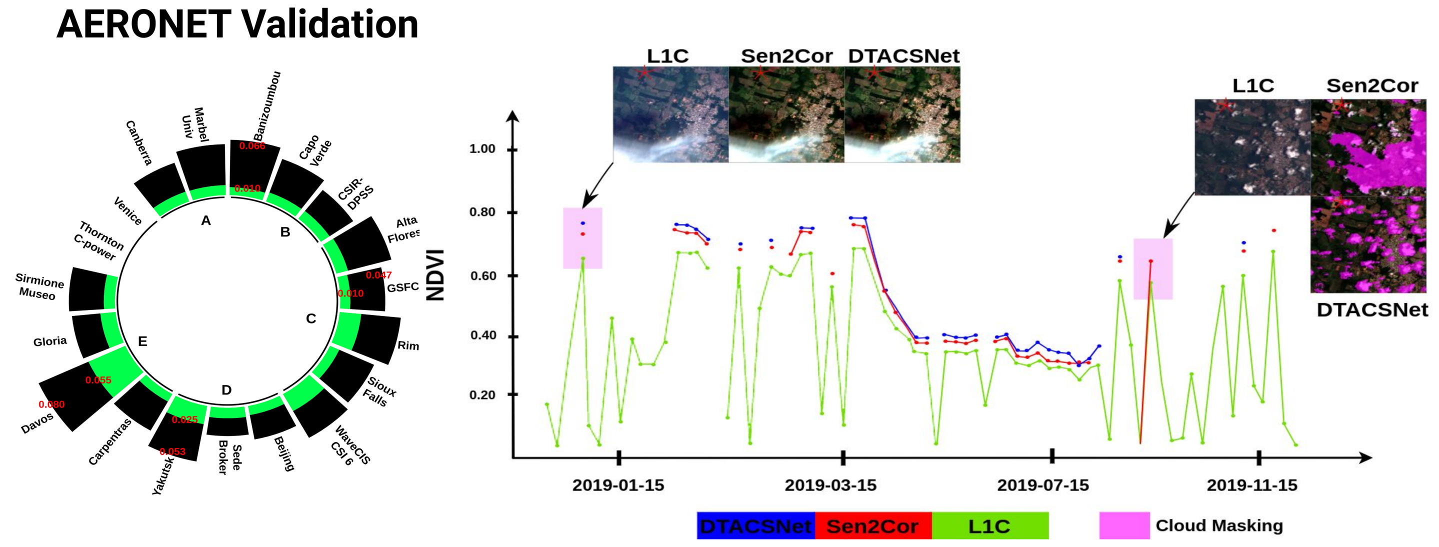
■ Thick cloud ■ Thin cloud ■ Cloud shadow

Atmospheric Correction Results



RMSE distribution in reflectance units across the different patches in the CloudSEN12 test set for each of the bands in the level 2A output. **Left** results of architecture search. **Right** results of selected models vs baselines.

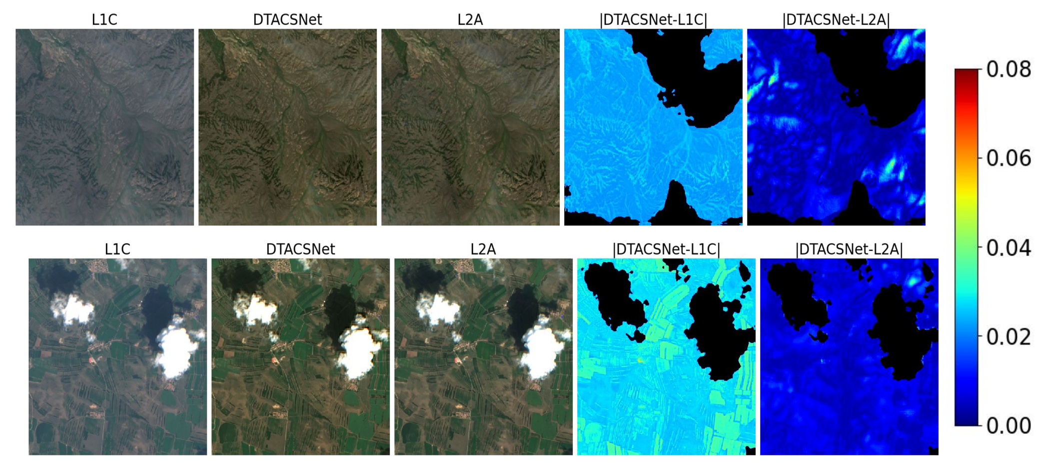
AERONET Validation



Left: RMSE results for each location in the AERONET validation dataset. In green DTACSNet in black the baseline.
Right: time series of NDVI over Alta Foresta station.

DTACSNet end-to-end emulator

First column, top of atmosphere Sentinel-2 level 1C image, second column, output of our atmospheric correction emulator (DTACSNet), third column Sentinel-2 level 2A operational model (Sen2Cor, column L2A), fourth column difference between model output and top of atmosphere image, fifth column difference between operational atmospheric correction model and DTACSNet.



	Cloud Masking	Surface Reflectance	DTACSNet	Total (I/O)
GPU	21.21 seconds	18.50 seconds	39.71 seconds	73.00s
CPU	127.75 seconds	33.89 seconds	161.64 seconds	195.03s
RAM	1342 MB (1024x1024)	331.1 MB (1024x1024)	1342 MB (1024x1024)	
Sen2Cor v2.10.0	1347.22s			

Table. Inference time and memory footprint of the model processing a full Sentinel-2 scene (10,980x10,980)

Conclusions

- DTACSNet is 7 times faster than Sen2Cor in CPU,
- DTACSNet has an average error of 1.4% which is on the same magnitude as Sen2Cor validation (1.8% Doxani et al 2018)
- DTACSNet doesn't require ancillary data

G. Doxani et al., "Atmospheric Correction Inter-Comparison Exercise," Remote Sensing, vol. 10, no. 2, Art. no. 2, Feb. 2018, doi: 10.3390/rs10020352.