Efficient Sentinel-2 L2A generation with Deep Learning

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DIGITAL TWIN EARTH PROGRAMME



Background

Sentinel-2 satellites provide valuable Earth observation data used worldwide. Currently, the generation of L2A products by the Sen2Cor processor takes around 35 minutes per tile and requires inputs such as L1C data, DEM, and auxiliary data, creating bottlenecks for time-sensitive applications. Our research develops an AI solution that generates L2A products from only L1C data using deep learning, delivering comparable quality to traditional methods but much faster. This technology can be integrated into the Destination Earth ecosystem as a workflow component called Delta Twin.

Dataset

We created a custom dataset (6273 products) for AlSen2Cor covering diverse Central European landscapes (bbox = [3.28, 45.38, 11.2, 50.18]) over 7 years (2018-2025). Our rigorous selection process included only L1C/L2A pairs with processing baseline > N0500, removed unconsolidated products with missing packets, and ensured uniform distribution across cloud cover percentages and seasons. We downloaded Sentinel-2 visible bands [B02, B03, B04] at their native 10m resolution from CDSE and implemented a consistent downscaling workflow using bicubic interpolation to generate 60m resolution data.

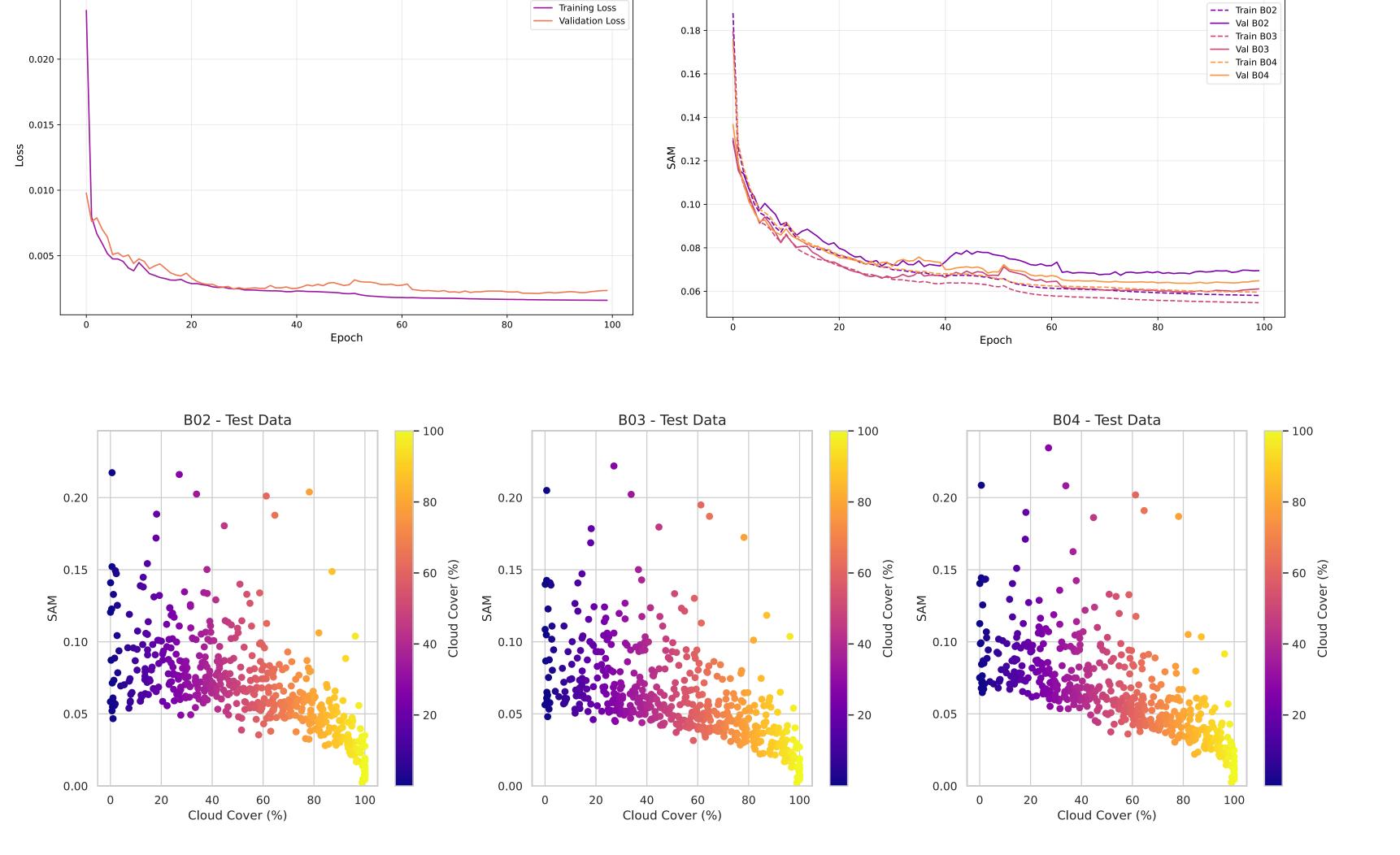
Training Approach & results

- ➤ Model Architecture: Utilized **U-Net with EfficientNet-B2 encoder**
- ➤ L1C products mapped into L2A products without using Aux and DEM data
- Data Preprocessing
 - Normalized all imagery to [0-1] range by dividing reflectance values by 10,000
 - Masked and preserved invalid pixels during processing
- Resized images to 1024×1024
- Metrics:
 - PSNR across spectral bands for valid pixel
 - SAM across spectral bands for valid pixel
 - RMSE across spectral bands for valid pixel
 - SSIM across spectral bands for valid pixel

Training and Validation Loss

> Model saved for the minimum Spectral Angular Mapper define as bellow [radian]

$$\theta(x,y) = cos^{-1} \left(\frac{\sum_{i=1}^{n} x_i y_i}{(\sum_{i=1}^{n} x_i^2)^{\frac{1}{2}} * (\sum_{i=1}^{n} y_i^2)^{\frac{1}{2}}} \right)$$

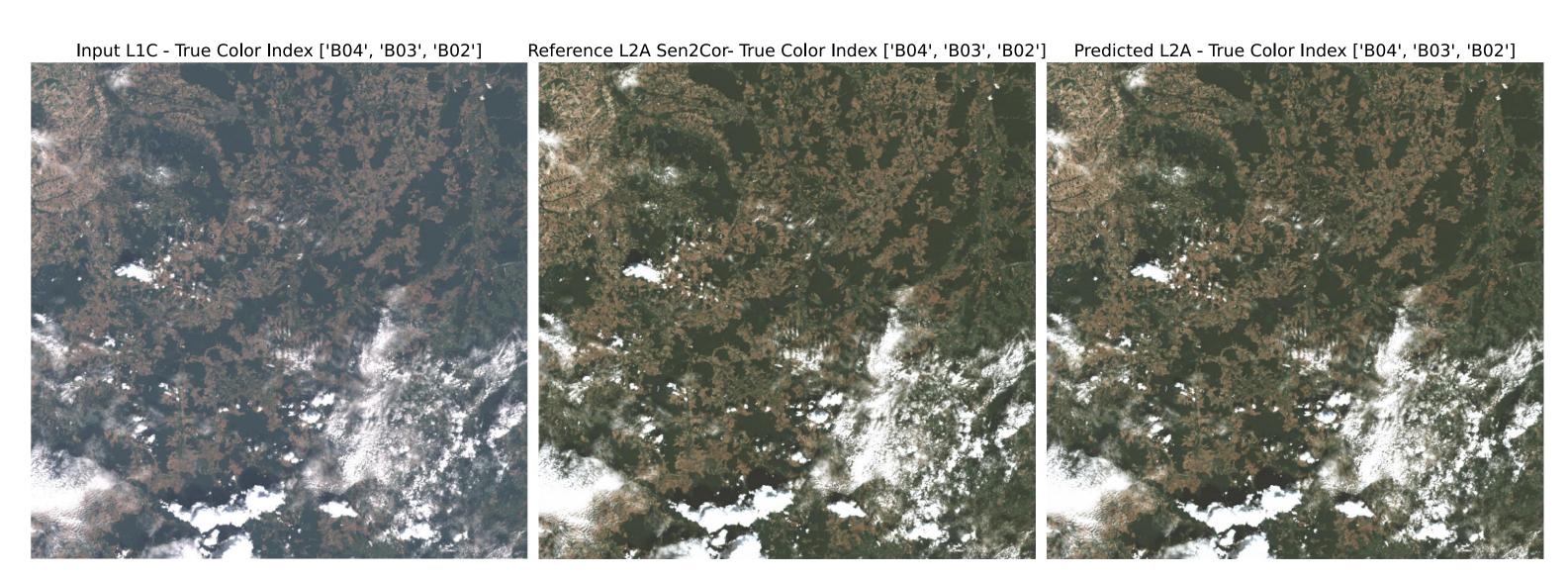


SAM Evolution During Training - Dataset V3

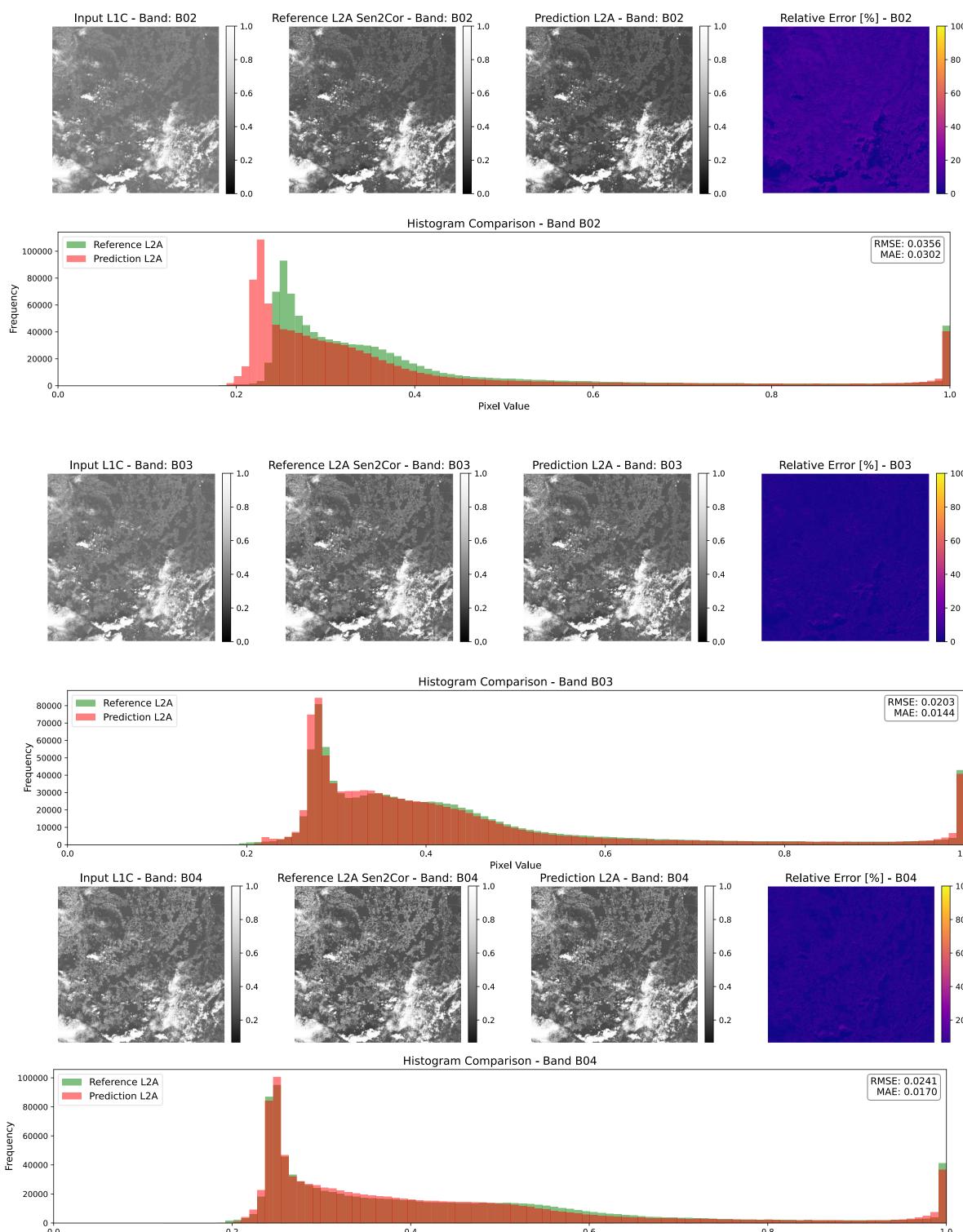
The model achieved excellent performance across all visible bands, with RMSE values below 0.04, PSNR values exceeding **25**, and SSIM scores above 0.93, indicating **high-quality atmospheric correction**. Spectral Angle Mapper (SAM) measurements remained consistently low (0.06-0.069), demonstrating the model's ability to **preserve spectral characteristics while correcting atmospheric effects in Sentinel-2 imagery.**

BAND	SAM ↓	RMSE ↓	PSNR ↑	SSIM ↑
B02	0.069	0.05	25.9	0.938
B03	0.060	0.04	27.2	0.938
B04	0.064	0.04	26.9	0.940

Table.1: Model evaluation on test data (530 samples)

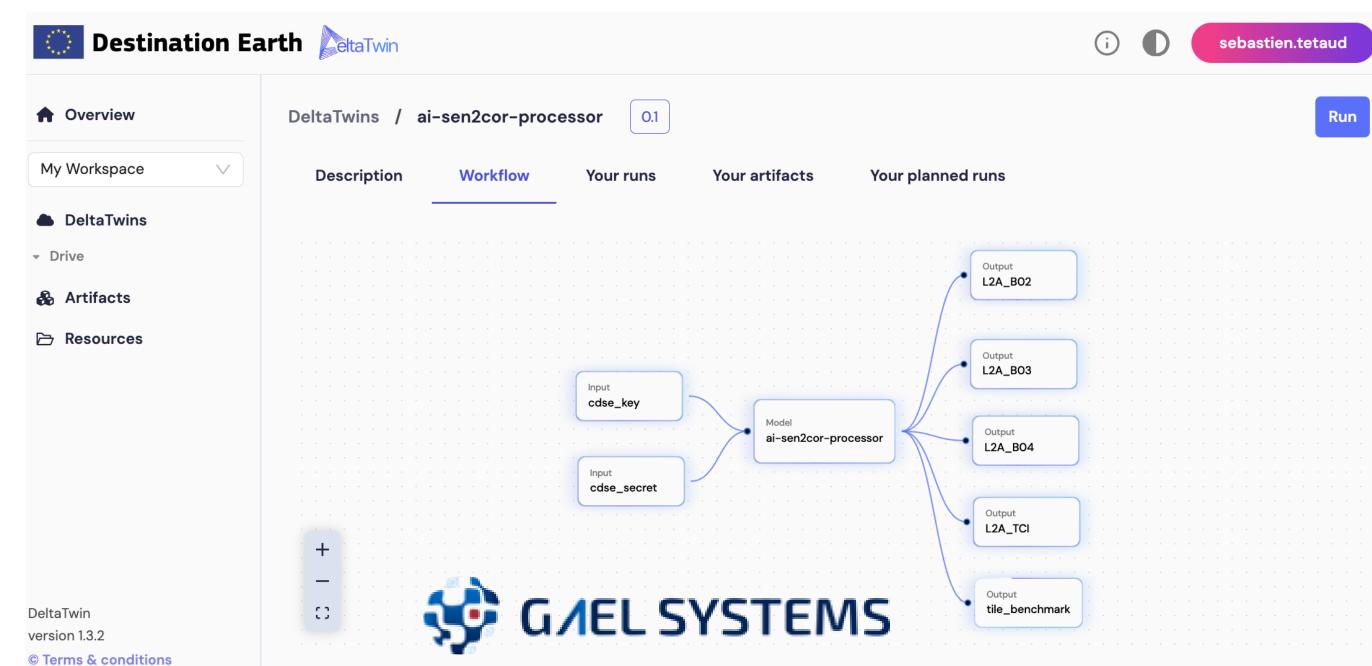


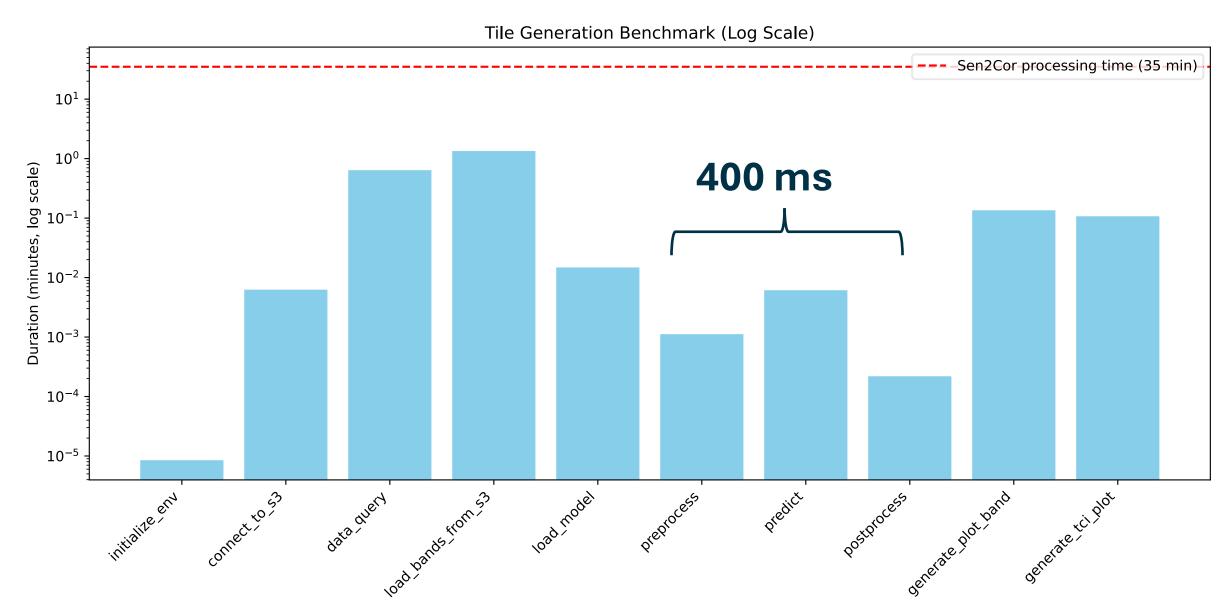
Random Tile generation from test data: PSNR: B02: 28.5, B03: 31.67, B04: 29.6 SSIM: B02: 0.94, B03: 0.94, B04: 0.94, SAM: B02: 0.06, B03: 0.05, B04: 0.06



Production phase with DestinE Delta Twin:

DeltaTwin® service provides a web application to graphically view workflows, schedule and execute workflow at production level with the possibility to be reusable by everyone. The inference pipeline has been implemented and put in production within a Delta Twin component and successfully demonstrated its capability to ship fast a research project to a production services.





Conclusion and Future Work

We demonstrated the capability for Sentinel-2 L2A generation using DL, maintaining high spectral fidelity (SAM \leq 0.07) and visual quality (SSIM >0.93) across all visible bands while processing tiles in just 400 ms and deployed the inference pipeline in a Delta Twin. Building on these promising results, our future work will focus on:

- Enhanced dataset development with all spectral bands
- Adoption of more advanced architectures like Stable Diffusion/Vision Transformers
- Develop data driven workflow for NRT production.