AI-Driven Mapping of Buildings, Roads, and Hydrography for Rural Electrification in Togo

5th ECMWF-ESA Machine Learning Workshop

Franco FERNANDEZ LOPEZ, Hugo POUPARD, Fabien CASTEL

13–17 April 2026 | Bologna, Italy

MURMURATION

esa

GDA

This project is funded by the European Space Agency (ESA) under the Global Development Assistance (GDA) Fast EO Co-Financing Facility (FFF). The work was requested by the French Development Agency (AFD) and implemented by Murmuration (FR) in cooperation with Whole from Space (CZ), under a frame contract led by GeoVille (AT).

Research Gap and Aim

Introduction:

Access to reliable electricity remains a major development challenge in rural West Africa. In Togo, national electrification programs aim to expand grid and decentralized coverage, but effective planning is heavily hindered by the lack of accurate, up-to-date spatial data on rural settlements and infrastructure.

Main Goal:

To strengthen rural electrification planning in Togo by integrating satellite-derived intelligence into decision-making tools. We deploy AI techniques to automatically detect buildings, roads, and hydrographic features.

Approach:

We utilize 2023 Sentinel-2 imagery, super-resolved to 5m[3] and 2.5m[1], alongside 0.5m Pléiades data for high-precision assessment. A customized U-Net with a ResNet-34 encoder and Dropout regularization leverages this spectral richness to accurately extract infrastructure footprints.

Methodology & data

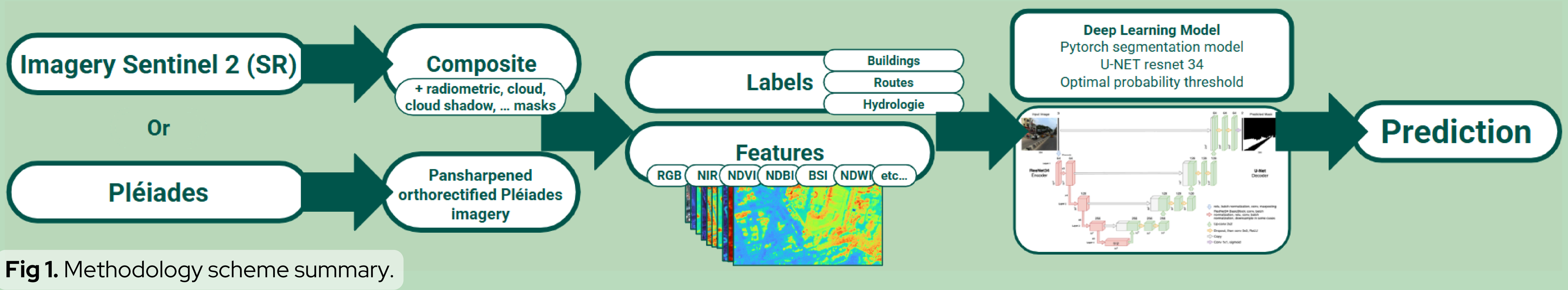

Fig 1. Methodology scheme summary.

1. Imagery retrieval, masking and applying model enhancing

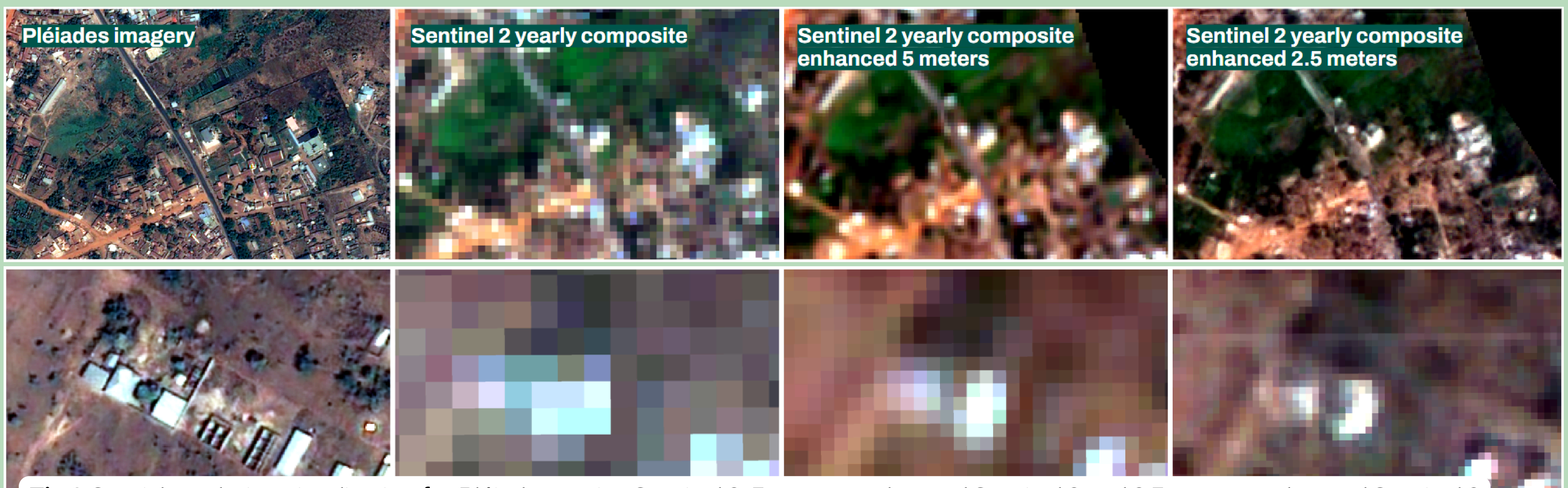

Fig 1. Spatial resolution visualization for Pléiades, native Sentinel 2, 5-meters enhanced Sentinel 2 and 2.5-meters enhanced Sentinel 2

2. Labeling and features production

Fig 2. Model labeling, red for buildings, green for paved roads and orange for unpaved roads

Table 1. Models features.

Model	Features
Sentinel-2 Super Resolution (5m)	B2, B3, B4, B8, B11, B12, NDVI, NDWI, NDTI, GNDVI, SAVI, MNDWI, NSI, NDBI, BSI
Sentinel-2 Super Resolution (2.5m)	B2, B3, B4, B8, NDVI, NDVI, NDWI, GNDVI, SAVI, NSI, BSI
Pléiades (0.5m)	Red, Green, Blue, NIR, NDVI, SAVI, NIR_std_7x7, NIR_std_11x11, Green_entropy_small, Green_entropy_large, NDVI_mean_7x7, NDVI_std_7x7, NDVI_homogeneity_7x7

3. Model Architecture (ResNet 34[2, 4, 5])

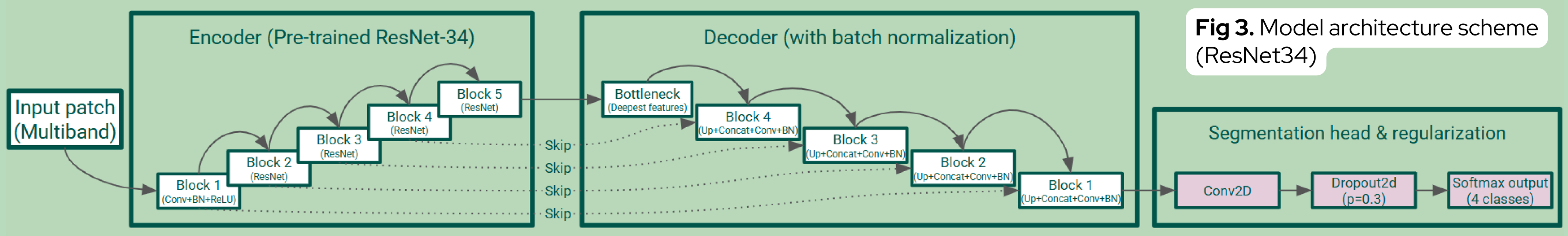

Fig 3. Model architecture scheme (ResNet34)

Results

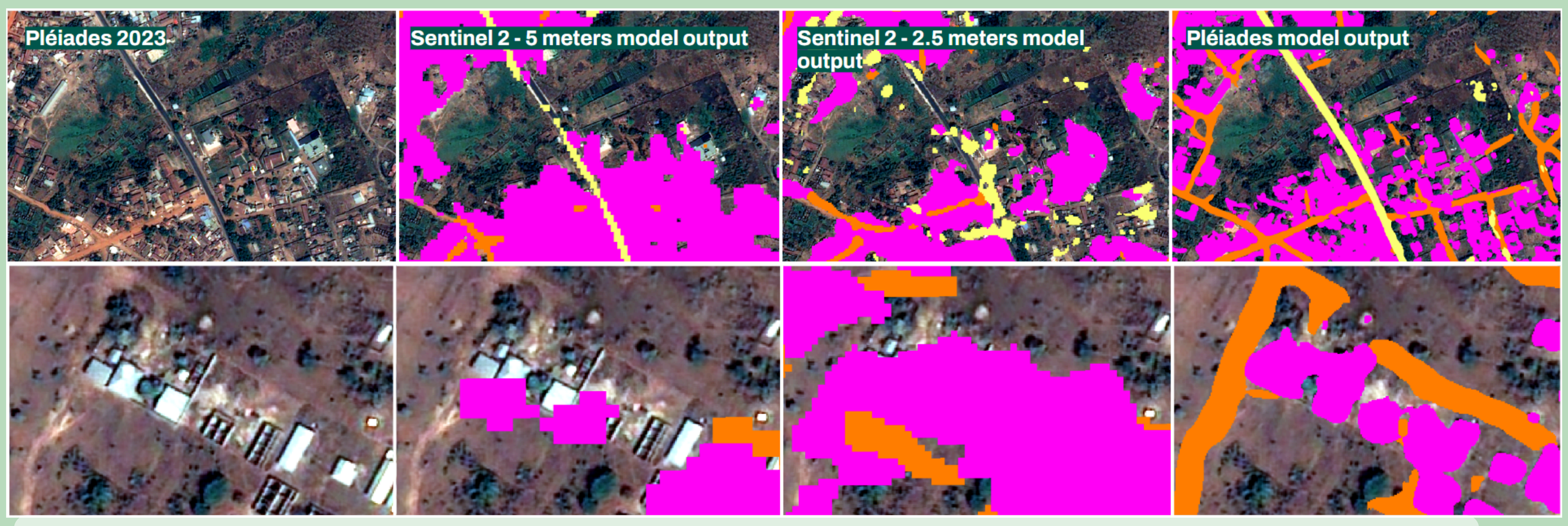

Fig 4. Models results inference. January 7th 2022 for Pléiades and 2024 mosaic composite for Sentinel 2 models. Violet for buildings, yellow for paved roads and orange for unpaved roads.

Model & Resolution	Overall Accuracy	F1-Score Macro	F1 - score Background	F1 - score Buildings	F1 - score Paved roads	F1 - score Unpaved roads
Sentinel 2 (5m)	0.662	0.627	0.751	0.483	0.782	0.491
Sentinel 2 (2.5m)	0.657	0.587	0.752	0.445	0.639	0.512
Pleiades (0.5m)	0.835	0.748	0.893	0.584	0.723	0.790

Table 2. Models results. Overall Accuracy: The percentage of total pixels correctly classified across all categories. F1-Score: The harmonic mean of Precision (exactness) and Recall (completeness).

Conclusions & Limitations

This study demonstrates that satellite-derived intelligence, particularly through high-resolution imagery, provides a robust foundation for rural electrification planning in Togo. While the Pléiades-based model offers the highest reliability for infrastructure footprinting, several technical trade-offs influence its practical deployment:

Resolution vs. Accuracy: The Granularity Gap

- Pléiades (0.5m) is the only model achieving the precision required for individual Building and Road identification, reaching an overall accuracy of 83.5%.
- Sentinel-2 (5m & 2.5m), despite super-resolution techniques, struggles with small-scale rural features, leading to significant over-prediction (low precision) in built-up areas.

Class-Specific Performance & Infrastructure Logic

- Paved Roads show high recall across all models, indicating that the spectral signature of paved surfaces is distinct even at lower resolutions.
- Unpaved Roads and Buildings are frequently confused with the Background in Sentinel-2 data due to their similar spectral profiles to bare soil and dense vegetation, respectively.

Validation & Scaling Limitations

- Ground Truth Scarcity: Validation is limited by the lack of exhaustive national vector data in rural Togo, making it difficult to assess the "true" omission rate in remote regions.
- Economic Scalability: While Pléiades provides superior results, its cost may limit nationwide updates. The 2.5m super-resolved Sentinel-2 remains a more scalable, albeit less precise, alternative for preliminary regional screening.

Comparison: Sentinel-2 (5m) vs. Sentinel-2 (2.5m)

While both models utilize super-resolution, their performance and spectral inputs offer a distinct trade-off for rural infrastructure detection:

- Spectral Depth vs. Spatial Detail: The 5m model benefits from a richer feature set, including Short-Wave Infrared (SWIR) bands (B11, B12) and indices like NDTI and MNDWI. This likely explains its slightly higher Overall Accuracy (0.662) and superior Paved Roads F1-score, as SWIR is highly effective at differentiating specialized land covers.
- The 2.5m "Noise" Trade-off: Increasing resolution to 2.5m using only visible/NIR bands improved the F1-score for Unpaved Roads, suggesting that spatial sharpness helps define narrow linear features. However, the loss of SWIR bands resulted in a lower Macro F1-score (0.587 vs. 0.627), indicating that for general rural classification, spectral variety can be more impactful than a 2x increase in spatial resolution.

Hydrography

- Due to high spectral confusion between water bodies, shadows, and moist soils in the U-Net predictions, the hydrography class was removed from the machine learning pipeline.
- A more reliable hybrid approach is suggested, for instance, utilizing the OSMnx Python module to retrieve validated waterways and lakes from OpenStreetMap (OSM) data, ensuring higher topological consistency for electrification constraints.

References

1. European Space Agency (ESA). (2024). OpenSR-Test: Benchmarking dataset for Sentinel-2 super-resolution algorithms [Computer software]. GitHub. https://github.com/ESAOpenSR/opensr-test
2. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition [ResNet]. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
3. Michel, J., Viñasco-Salinas, J., Inglada, J., & Hagolle, O. (2025). sentinel2_superresolution: Super-resolution of 10 Sentinel-2 bands to 5-meter resolution [Computer software]. Evoland Land Monitoring Evolution / GitHub. https://github.com/Evoland-Land-Monitoring-Evolution/sentinel2_superresolution
4. Ronneberger, O., Fischer, P., Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28
5. Ulmas, P., & Liiv, I. (2020). Segmentation of Satellite Imagery using U-Net Models for Land Cover Classification. 10.48550/arXiv.2003.02899.

Contact : support@murmuration-sas.com
Site : https://murmuration-sas.com