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Improving Land Cover Classification with Pixel-level Fusion of SAR and Optical Images Using Hybrid Machine Learning

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Abstract

This study evaluates land cover classification in Sungai Petani using Sentinel-1 SAR, Sentinel-2 optical data, and their fusion. Six classes were mapped: water, vegetation, paddy, oil palm, urban, and roadway. A 1D CNN and a Random Forest were trained on single-sensor and fused feature sets, and a logistic stacking meta-classifier combined CNN and RF probabilities. Single-sensor baselines reached 0.76 accuracy for Sentinel-1 (macro F1 0.75) and 0.85 for Sentinel-2 (macro F1 0.85). Fusion improved performance to 0.91 accuracy for both CNN and RF (macro F1 $\approx$ 0.91), with clear gains in the built classes. The stacked meta-model achieved the best results at 0.93 accuracy and macro F1 0.93, raising urban F1 to 0.83 and roadway F1 to 0.89 while maintaining high scores for water and crops, including oil palm at 0.98 F1. Results show that Sentinel-1 backscatter and Sentinel-2 spectra are complementary, and that fusion with ensemble learning yields more balanced and reliable maps than either sensor alone.

Keywords: Land cover classification, Sentinel-1, Sentinel-2, Data fusion, Convolutional Neural Network, Random Forest, Ensemble learning

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1 Introduction

Land cover maps are fundamental to environmental management and climate analysis, yet single-sensor products often underperform in the humid tropics where clouds and heterogeneous land use are common (Schmitt et al., 2017; Dagne et al., 2023). Optical Sentinel-2 captures spectral patterns tied to vegetation and land use, while radar Sentinel-1 provides structure and moisture cues that penetrate clouds (Solórzano et al., 2021; Altarez et al., 2023). This work investigates their joint use for land cover classification in Sungai Petani, integrating machine learning and deep learning models to fuse complementary information. By combining the two sensors, we aim to produce more balanced and reliable maps across six classes, with particular gains expected in separating urban fabric from roads while retaining strong performance for water and crop types.

2 Method

The study area is Sungai Petani, Kedah. Sentinel-1 Ground Range Detected data with VV and VH polarizations underwent orbit correction, radiometric calibration to sigma-naught in decibels, terrain correction to 10 m, and multi-temporal speckle filtering. Sentinel-2 Level-2A surface reflectance received atmospheric correction, cloud and shadow masking using QA60, and resampling of all bands to a common 10 m grid. Both sensors were co-registered and time-windowed to ensure spatial and temporal consistency (Ahmad et al., 2024).

From these inputs a joint feature set was formed. Sentinel-2 contributed the visible to short-wave infrared bands B2 to B8A, B11, and B12, together with spectral indices NDVI, NDWI, and NDBI. Sentinel-1 contributed VV, VH, the VV to VH ratio, and SAR-oriented indices including RVI and NDVI_SAR (Lei et al., 2022; Kaplan and Avdan 2018). Balanced pixel samples for six classes, namely water, vegetation, paddy, oil palm, urban, and roadway, were labelled in Google Earth Engine and exported. Data were split with stratified sampling into 64 percent training, 16 percent validation, and 20 percent testing. A fixed label encoder and a Min-Max scaler were fitted on the training set only and then applied to the validation and test splits.

Three classifiers were evaluated. A 1D CNN operated on per-pixel feature vectors, using two convolutional blocks with 128 and 256 filters, batch normalization, LeakyReLU activation, max pooling, and dropout, followed by a 512-unit dense layer with L2 regularization and a softmax output (Chabalala et al., 2022). The CNN was trained with Adam at a learning rate of 5×10^{-4} and early stopping, using three input configurations: Sentinel-1 only, Sentinel-2 only, and fused Sentinel-1 plus Sentinel-2 features. A Random Forest with 500 trees and class weighting was trained on the fused features. A logistic regression stacker served as a meta-classifier, learning from the class probability outputs of the CNN and Random Forest using validation predictions to avoid leakage. Evaluation used the held-out test set. Reported metrics included overall accuracy, class precision, recall, F1-score, and confusion matrices (Nijhawan et al., 2019). For qualitative assessment, pixel-level predictions were rendered as Folium overlays to inspect spatial coherence and boundary quality in the heterogeneous landscape of Sungai Petani.

3 Results

Standalone CNNs showed moderate performance, with Sentinel-2 outperforming Sentinel-1 on the balanced test set. The Sentinel-1 model reached 0.76 accuracy (macro F1 0.75), with very high scores for water and oil palm but weak urban and roadway separation. The Sentinel-2 model improved to 0.85 accuracy (macro F1 0.85), lifting vegetation, paddy, and oil palm while still mixing urban and roadway. Fusing Sentinel-1 and Sentinel-2 features raised performance further. Both the fused CNN and the fused RF reached 0.91 accuracy (macro F1 about 0.91). Class balance improved, especially in the built classes: urban F1 rose to about 0.78 and roadway to about 0.83, while vegetation and crop classes remained high (oil palm up to 0.98, paddy around 0.92).

The stacked meta-classifier delivered the best results at 0.93 accuracy with macro F1 0.93. Urban increased to about 0.83 F1 and roadway to about 0.89, while water stayed near perfect and vegetation and crops remained strong. Confusion between urban and roadway dropped noticeably compared with single-sensor runs, consistent with the complementary strengths of SAR structure and optical spectra.

Qualitatively, the meta-classifier on fused Sentinel-1 and Sentinel-2 produced the cleanest, most consistent maps. Roads appeared thin and continuous with fewer urban › roadway swaps, urban blocks were more coherent, and vegetation and crop parcels were filled uniformly. Water boundaries were crisp, and oil palm and paddy fields showed strong internal consistency with fewer edge leaks. By contrast, single-sensor outputs showed familiar artifacts: SAR speckle and urban confusion in the S1 map, and broader urban–roadway mixing in the S2 map. These visual gains align with the metrics, where the fused meta model achieved the highest accuracy (~ 0.93) and macro F1 (~ 0.93).

4 Conclusions

Results show clear complementarity between Sentinel-1 SAR and Sentinel-2 optical data. Single-sensor CNNs reached 0.76 (S1) and 0.85 (S2) accuracy, performing strongly on water and crop classes but struggling to cleanly separate urban and roadway. Fusing sensors raised performance to about 0.91 accuracy for both CNN and RF, and the stacked meta-classifier achieved the best scores at about 0.93 accuracy and macro F1. Qualitative maps matched the metrics: the fused meta model produced the most coherent outputs, with thinner, more continuous roads, cleaner urban blocks, and consistent vegetation parcels.

Remaining errors concentrate at class boundaries and mixed pixels, particularly along urban–road interfaces where 10 m resolution and spectral–structural overlap are limiting. These findings indicate that multi-sensor fusion and ensemble learning provide a practical path to balanced, reliable land-cover maps in heterogeneous tropical settings like Sungai Petani.

Future work should target boundary quality and generalisation. Promising directions include a built-first hierarchical decoder, light morphological thinning for roads, class-aware losses or label smoothing, and models that better exploit spatial context (e.g., U-Net or patch-based CNNs). Broader temporal sampling, refined ground truth for urban subtypes, and evaluation on additional regions such as Kuala Lumpur and Penang would further test robustness and transferability.

References

Ahmad, M. N. et al. (2024). Optical–SAR data fusion based on simple layer stacking and the XGBoost algorithm to extract urban impervious surfaces in global alpha cities. *Remote Sensing*, 16(5).

Altarez, R. D. D., Apan, A., and Maraseni, T. (2023). Deep learning U-Net classification of sentinel-1 and 2 fusions effectively demarcates tropical montane forest's deforestation. *Remote Sensing Applications: Society and Environment*, 29.

Chabalala, Y., Adam, E., and Ali, K. A. (2022). Machine learning classification of fused sentinel-1 and sentinel-2 image data towards mapping fruit plantations in highly heterogeneous landscapes. *Remote Sensing*, 14(11).

Dagne, S. S., Hirpha, H. H., Tekoye, A. T., Dessie, Y. B., and Endeshaw, A. A. (2023). Fusion of sentinel-1 SAR and sentinel-2 MSI data for accurate urban land use-land cover classification in gondar city, ethiopia. *Environmental Systems Research*, 12(1).

Kaplan, G. and Avdan, U. (2018). Sentinel-1 and sentinel-2 data fusion for wetlands mapping: Balikdami, turkey. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives)*, pages 729–734. International Society for Photogrammetry and Remote Sensing.

Lei, T. C., Wan, S., Wu, Y. C., Wang, H. P., and Hsieh, C. W. (2022). Multi-temporal data fusion in MS and SAR images using the dynamic time warping method for paddy rice classification. *Agriculture*, 12(1).

Nijhawan, R., Joshi, D., Narang, N., Mittal, A., and Mittal, A. (2019). A futuristic deep learning framework approach for land use-land cover classification using remote sensing imagery. In *Advances in Intelligent Systems and Computing*, pages 87–96. Springer.

Schmitt, M., Tupin, F., and Zhu, X. X. (2017). Fusion of SAR and optical remote sensing data: Challenges and recent trends. *IEEE*.

Solórzano, J. V., Mas, J. F., Gao, Y., and Gallardo-Cruz, J. A. (2021). Land use land cover classification with U-Net: Advantages of combining sentinel-1 and sentinel-2 imagery. *Remote Sensing*, 13(18).

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