Multi-Purpose Land-Cover Classification Using Sentinel-2 Data: A Methodological Approach

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Abstract. The extraction of high-resolution land cover data over large areas has many challenges, i.e.: temporal dynamics, spatial variability, noise, and high dimensionality. To address these challenges, we present a comprehensive methodology leveraging Earth Observation satellites data, advanced pre-processing techniques and Artificial Intelligence models. Central to our approach is the use of 4D data cubes, which enable consistent analysis across varying temporal, spatial and spectral dimensions.

Starting from the generation of periodic cloudless composites of Sentinel-2 acquisitions, we employ flexible models derived from Visual Transformers (ViT) (Dosovitskiy, A., 2020), specifically the Time Series Transformer Plus (TSiTPlus) (Oguiza, I.). In this approach, each pixel is represented as a time series, and the model learns to recognize and classify the land cover label based on the spectral signature observed over the period. This allows the model to prioritize significant features, enhancing classification accuracy.

Key components of our methodology are based on a flexible and adaptable process for:
- Data Preparation: Satellite images are pre-processed by applying radiometric correction, cloud screening, and atmospheric correction, enabling the generation of high-quality, analysis-ready data for environmental monitoring applications. (Frantz, D., 2019)
- Model Training: The TSiTPlus model is trained using advanced training frameworks with early stopping and class-balanced sampling, improving generalization and reducing overfitting.
- Model Evaluation and Adaptation: Performance is evaluated using accuracy metrics and confusion matrices, followed by error analysis to refine and retrain the model as needed.

- Deployment: The trained model is deployed in a scalable container service, either on-premises or in the cloud, for efficient land cover classification over large areas.

This methodology has already shown promising results in various use cases, such as land cover mapping, forest health monitoring, and crop monitoring. Future work includes expanding the 4D datacube with additional information, such as integrating data from Sentinel-1 or Landsat satellites, as well as Digital Elevation Models (DEM).

Introduction

Land cover mapping is important for a vast range of environmental sciences, providing data for a multitude of applications including agriculture monitoring, forest management, urban planning, and climate modeling. Accurate and up-to-date land cover information is used for understanding terrestrial ecosystems and their responses to natural and anthropogenic influences (Friedl et al., 2010).

In agriculture, land cover data are utilized to monitor crop conditions, assess agricultural productivity, and support food security initiatives. Satellite-derived land cover maps enable the identification of crop types and the evaluation of phenological stages, which are critical for yield prediction and agricultural modeling (Dorigo et al., 2015). Moreover, generic land cover data support environmental and climate models. Land surface characteristics influence energy balance, hydrological processes, and biogeochemical cycles, which are integral components of climate models (IPCC, 2019). Accurate land cover maps enhance the parameterization of these models, leading to better predictions of climate change impacts and aiding in the development of mitigation and adaptation strategies (Bonan, 2008).

Despite the significance of land cover mapping, extracting high-resolution data over large areas poses several challenges. Temporal dynamics such as seasonal vegetation changes, spatial variability across different ecosystems, noise in satellite data, and the high dimensionality of multispectral imagery complicate the classification process (Zhu et al., 2019). Addressing these challenges requires advanced methodologies that can efficiently process large datasets while maintaining high accuracy.

Advancements in remote sensing technology, such as the European Space Agency's Sentinel-2 satellites, provide high-resolution, multispectral imagery with frequent revisit times, facilitating continuous monitoring of land surfaces (Drusch et al., 2012). The use of four-dimensional (4D) data cubes enables the integration of spatial, temporal, and spectral information, allowing for more comprehensive analysis of land cover changes (Ma et al., 2020).

Furthermore, the application of advanced machine learning models, particularly transformer-based architectures, has shown promise in handling complex classification tasks involving large and high-dimensional datasets (Vaswani et al., 2017). Models like the Time Series Transformer Plus (TSiTPlus) leverage self-attention mechanisms to capture significant temporal and spatial features, improving classification performance in land cover mapping applications (Li et al., 2021). These models can prioritize relevant features and mitigate the effects of noise and class imbalance, addressing key challenges in large-scale land cover classification.

By integrating high-quality satellite data with sophisticated processing techniques and machine learning models, it is possible to overcome existing challenges in land cover mapping. The proposed approach described later has obtained optimal results supporting various applications across environmental monitoring, resource management, and modeling efforts.

Methodology

The proposed methodology integrates pre-processing techniques, deep learning classification models, and post-processing enhancements to improve land cover classification using Sentinel-2 data.

Data Preprocessing

The initial phase involves the preprocessing of Sentinel-2 imagery to produce clean and consistent time series suitable for classification. Satellite observations are often affected by atmospheric conditions, cloud cover, and seasonal variations, which can introduce noise and inconsistencies in the data. To mitigate these issues, the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) processing framework is employed (Frantz, 2019). The FORCE framework facilitates automated radiometric correction, cloud masking, and the generation of Analysis Ready Data (ARD). Specifically, the time series function within FORCE is utilized to generate consistent composites over the study period.

Classification

The classification step involves applying deep learning techniques to perform pixel-based land cover classification. Prior to model training, preparatory steps are undertaken to address challenges such as class imbalance and the acquisition of labeled training data. Class imbalance occurs when certain land cover classes are underrepresented in the dataset, which can bias the classifier towards more prevalent classes. To address this, techniques such as oversampling of minority classes or implementing weighted loss functions during model training are employed. These methods ensure that the classifier maintains sensitivity to all land cover types and does not disproportionately favor dominant classes. Training data are sourced from OpenStreetMap (OSM), an open-source platform providing geospatial data contributed by a global community (Haklay & Weber, 2008).

Training point sampling is conducted to select representative pixels from the Sentinel-2 imagery that correspond to the OSM-derived labels. The sampling strategy ensures adequate spatial distribution and coverage of different land cover types, which is crucial for training a robust classifier. These sampled points form the basis for training the Time Series Transformer Plus (TSiTPlus) model (Dosovitskiy, A. 2020, Oguiza, I.), a deep learning architecture designed for handling sequential data and capturing temporal dependencies (Li et al., 2021). The TSiTPlus model leverages self-attention mechanisms to process the high-dimensional and temporally rich datasets generated from Sentinel-2 imagery. The model's architecture enables it to prioritize significant temporal and spatial features within the time series data, improving classification performance. During training, optimization techniques such as early stopping are applied to prevent overfitting and enhance the model's generalization capabilities.

Post-Processing

Following the classification, post-processing steps are implemented to refine the land cover maps and enhance their applicability for specific use cases. One of the challenges addressed at this stage is the spatial resolution limitation of Sentinel-2 imagery, which, at 10 meters for certain bands, may not adequately capture small or linear features such as narrow roads or streams. To overcome this limitation, land use mapping data are integrated to enrich the classification results. Incorporating land use information allows for the enhancement of attribute details and improves the geometric representation of features that are difficult to classify due to resolution constraints. This integration is achieved through spatial analysis techniques that adjust the classification outputs based on known land use patterns. For example, linear features identified in land use datasets can be overlaid onto the classification results to improve the delineation of roads or waterways. Object-based image analysis methods may also be applied to refine the boundaries and attributes of specific classes, enhancing the overall accuracy of the land cover map. Consistency checks and validation procedures are performed to ensure that the post-processed maps accurately represent real-world land cover. This may involve cross-referencing with higher-resolution imagery or ground truth data where available. The validation process is critical for assessing the reliability of the classification and identifying areas that may require further refinement.

Results

In this section we present some results on generic Land Cover and on Agricultural crop mapping.

The figure displays a comparative analysis between classified land cover data and corresponding Sentinel 2 image. The land cover map, generated using Sentinel-2 imagery, highlights various land use categories shown in the legend.

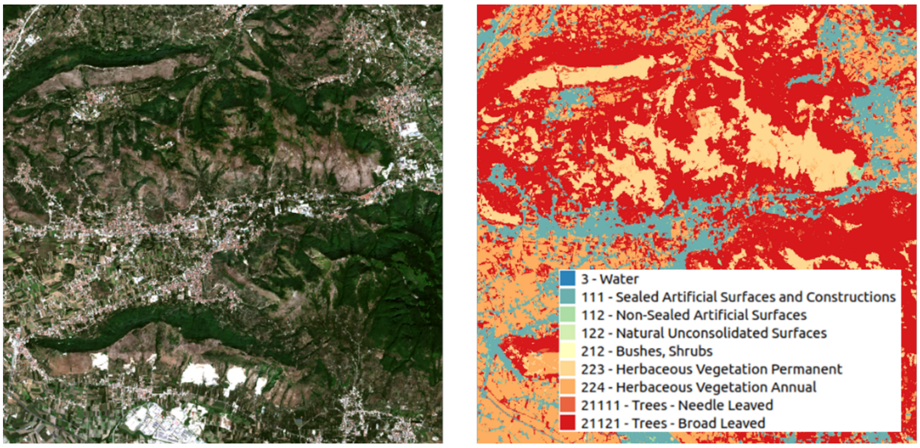

Fig. 1. The figure presents a comparative view of the Salerno area, with the Sentinel-2 satellite imagery displayed on the left and the corresponding land cover classification on the right. The Sentinel-2 image shows the natural and urban features of the region in high-resolution, capturing the heterogeneous landscape, including densely vegetated areas, urban settlements, and agricultural fields. The land cover map on the right, generated through a classification process, categorizes the terrain into distinct classes represented by different colors. For instance, densely vegetated areas such as forests are marked in red, urban areas In cyan, water bodies in blue, grassland areas in light beige, and agricultural lands or open areas in shades of orange or yellow.

Agricultural Crop monitoring

The image illustrates a result derived from the proposed methodology, showcasing a crop classification map generated by the Land Cover processor for monitoring soybean and coffee plantations in a remote Brazilian region. The methodology integrates Sentinel-2 satellite data with advanced time series analysis, leveraging NDVI cycles to differentiate between crops and monitor their growth phases. This result exemplifies how the processing framework accurately captures spatial and temporal crop patterns, supporting precision agriculture and resource management in geographically isolated areas (Drusch et al., 2012; Dorigo et al., 2015).

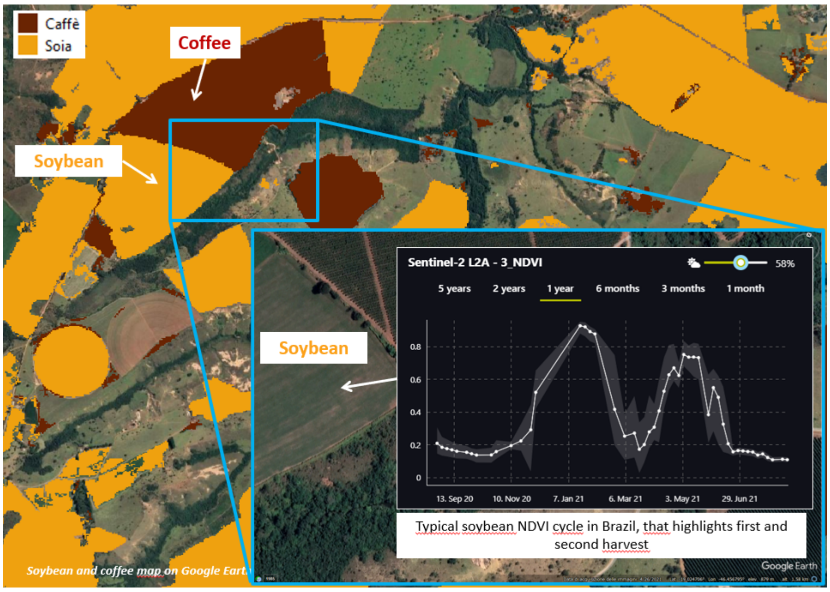

Fig. 2. The image illustrates a map of soybean and coffee crops generated using the Land Cover processor, specifically designed for remote monitoring of agricultural regions. The map, produced from Sentinel-2 data, highlights distinct crop areas: orange polygons represent soybean fields, while brown polygons indicate coffee plantations. An inset displays a typical Normalized Difference Vegetation Index (NDVI) cycle for soybean in Brazil, which is used to track crop growth phases, showing both the first and second harvest periods. This kind of remote sensing facilitates precision agriculture and crop management in geographically isolated areas.

Conclusions

This study presents a comprehensive methodology for land cover classification using Sentinel-2 data, advanced time series analysis, and machine learning techniques. The methodology addresses key challenges such as cloud cover, temporal variability, and class imbalance through a careful preprocessing workflow using the FORCE framework and the Time Series Transformer Plus (TSiTPlus) model for classification. By integrating satellite data with crowdsourced information from OpenStreetMap, the process enhances both the accuracy and detail of land cover maps, especially in remote or data-scarce regions. The results, including the accurate monitoring of agricultural crops like soybean and coffee and generic land cover generation, demonstrate the potential of this approach to support precision agriculture, sustainable resource management, and environmental monitoring.

Bibliografic References

1. Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., Houlsby, N.: An Image

is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv preprint arXiv:2010.11929 (2020)

2. Oguiza, I.: TSiT: PyTorch implementation based on ViT (Vision Transformer). Available at: https://timeseriesai.github.io/tsai/models.tsitplus.html
3. Frantz, D. (2019). FORCE—Landsat + Sentinel-2 analysis ready data and beyond. Remote Sensing, 11(9), 1124.
4. Bonan, G. B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science*, 320(5882), 1444-1449.
5. Drusch, M., et al. (2012). Sentinel-2: ESA's Optical High-Resolution Mission for GMES Operational Services. *Remote Sensing of Environment*, 120, 25-36.
6. Dorigo, W., et al. (2015). Reflective Remote Sensing and Data Assimilation Techniques for Agroecosystem Modeling. *International Journal of Applied Earth Observation and Geoinformation*, 9(2), 165-193.
7. FAO. (2017). *The future of food and agriculture – Trends and challenges*. Food and Agriculture Organization of the United Nations.
8. Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., & Huang, X. (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114(1), 168-182.
9. IPCC. (2019). *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*. Intergovernmental Panel on Climate Change.
10. Li, X., Liu, Y., Wu, J., & Tseng, V. S. (2021). A Time Series Transformer Based Method for Land Cover Classification Using Sentinel-2 Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 8975-8986.
11. Ma, X., He, Y., & Li, X. (2020). Spatiotemporal analysis of remote sensing data using 4D data cubes. *International Journal of Applied Earth Observation and Geoinformation*, 87, 102023.
12. Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, 109(40), 16083-16088.
13. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems* (pp. 5998-6008).
14. Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2019). Deep learning in remote sensing: A comprehensive review and list of resources. *IEEE Geoscience and Remote Sensing Magazine*, 5(4), 8-36.