Multi-Purpose Land-Cover Change Detection Using Sentinel-1 and Sentinel-2 Data: A Methodological Approach

Marco Corsi[1[x]], Simone Tilia[2[x]], Paolo Macciacchera[3[x]], Quirico D'Amico[4[x]], Flavio Cordari[5[x]], Manuela Caterino[6[x]], Esteban Lombardozzi[7[x]], Paolo Cecamore[8[x]]

[1] e-GEOS, marco.corsi@e-geos.it
[2] e-GEOS, simone.tilia@e-geos.it
[3] e-GEOS, paolo.macciacchera@e-geos.it
[4] e-GEOS, quirico.damico@e-geos.it
[5] e-GEOS, flavio.cordari@e-geos.it
[6] e-GEOS, manuela.caterino@e-geos.it
[7] e-GEOS, esteban.lombardozzi@e-geos.it
[8] e-GEOS, paolo.cecamore@e-geos.it

Abstract. Land cover change (LCC) detection using high-resolution data presents several challenges considering the temporal dynamics and spatial variability. This study introduces a robust methodology that leverages the SIROC (Sibling Regression for Optical Change detection) (Kondmann, L., 2022) algorithm to effectively detect LCC using a pair of satellite acquisitions from the same sensor, covering the same area but acquired at different times.

Our approach utilizes SIROC, an unsupervised model, to identify potential changes between image pairs without the need for manually labeled data. SIROC's capability to generate reliable change detection outputs makes it a suitable choice for many use cases requiring a semi-automatic approach, especially where land feature variability is heterogeneous.

The data are pre-processed by applying coregistration and radiometric correction to ensure spatial and radiometric consistency across all images. Additionally, cloud screening and atmospheric correction are applied to Sentinel-2 data to enhance data quality (Frantz, D., 2019).

This methodology enables the mapping of transitions between land cover classes using diverse inputs from Sentinel-1 and Sentinel-2, offering a scalable and adaptable tool for environmental monitoring and analysis. Future enhancements could integrate additional data sources such as Digital Elevation Models (DEM) to further refine change detection accuracy. The flexibility and reliability of the SIROC-based approach ensure its applicability across various geographical regions and conditions, making it an asset for continuous and accurate land cover change detection.

Introduction

Land cover change (LCC) detection is a fundamental aspect of environmental monitoring, providing critical insights into the dynamic processes that shape terrestrial ecosystems. Accurate detection and analysis of LCC are essential for addressing various environmental and socio-economic challenges, including climate change mitigation, biodiversity conservation, urban planning, and infrastructure development. According to the Intergovernmental Panel on Climate Change (IPCC), land-use and land-cover changes significantly contribute to global greenhouse gas emissions, influencing climate patterns and ecosystem services (IPCC, 2019).

In this context, deforestation and forest degradation are a significant concern due to their implications for biodiversity loss, disruption of water cycles, and carbon emissions (Food and Agriculture Organization [FAO], 2020). Related to forest monitoring, an application of LCC detection is also burned area mapping. The frequency and intensity of wildfires have increased in recent years, exacerbated by climate change and human activities (Bowman et al., 2020). Remote sensing technologies enable the timely and accurate mapping of burned areas at low resolution (Chuvieco et al., 2019) but higher resolution are made possible by modern satellites like Copernicus Sentinels.

As an additional topic, urbanization is a defining trend of the 21st century, with the United Nations projecting that 68% of the global population will reside in urban areas by 2050 (United Nations, 2018). Urban changes, including the expansion of built-up areas and the transformation of land use patterns, are typical use cases of LCC detection methods. In addition, Infrastructure building or damage monitoring relies heavily on LCC detection as the ability to detect changes in infrastructures is important for disaster response, military planning, and compliance assessment with international agreements (Li et al., 2019).

Despite the importance of LCC detection across these applications, several challenges persist, especially when utilizing very high-resolution (VHR) satellite imagery. The limited availability of VHR data, high costs, and the complexity associated with processing and analyzing time-series imagery hinder effective monitoring efforts (Zhu et al., 2017). Traditional change detection methods often require extensive labeled datasets and may not perform effectively in heterogeneous landscapes where land cover types exhibit significant variability.

To address these challenges, this study has selected a robust methodology that leverages the SIROC (Spatial Context Awareness for Unsupervised Change Detection in Optical Satellite Images) algorithm for effective LCC detection using minimal bi-temporal images. The SIROC algorithm was introduced by Kondmann et al. (2022) as an unsupervised change detection method that incorporates spatial context awareness to enhance detection accuracy in optical satellite imagery. SIROC leverages the spatial relationships between pixels to effectively distinguish between true land cover changes and noise or transient phenomena. By modeling the local neighborhoods of pixels, the algorithm captures structural and contextual information that is critical for accurate change detection in heterogeneous landscapes. The proposed methodology offers a scalable and adaptable tool for environmental monitoring and analysis. Sentinel-1's synthetic aperture radar (SAR) capabilities provide all-weather, day-and-night imaging, while Sentinel-2's multispectral optical data contribute detailed spectral information (European Space Agency [ESA], 2020). The combination of these data sources enhances the robustness of change detection outcomes, ensuring applicability across different geographical regions and environmental conditions.

This study aims to demonstrate the effectiveness of a methodology based on the SIROC combined with operational tools for the generation of change detection maps in an flexible and adaptable way.

Methodology

The implementation of the our methodology is based on the following steps:

1. Data Acquisition and Preprocessing: Bi-temporal images from Sentinel-1 and Sentinel-2 are obtained for the study area. Preprocessing includes radiometric calibration, atmospheric correction for optical data using FORCE library (Frantz, D, 2019), speckle filtering for SAR data, and precise geometric co-registration to ensure accurate pixel alignment (ESA, 2020).
2. Feature Extraction and Index Calculation: Appropriate spectral bands and indices are selected based on the specific use case:
   a. Urban Areas: RGB bands and SAR backscatter coefficients (Kondmann et al.)
   b. Forests: SWIR bands and vegetation indices sensitive to biomass (Tucker, C. J., Kondmann et al.)
   c. Burned Areas: NBR and dNBR indices.
   d. Agriculture: MSAVI, NDVI, and other crop-specific indices (Tucker, C. J., Kondmann et al.)
3. Application of SIROC Algorithm: The SIROC algorithm processes the extracted features, modeling the local spectral-spatial distributions and computing change probabilities. Algorithm parameters are tuned according to the characteristics of the input data and the land cover types under investigation.
4. Change Map Generation and Refinement: Change probability maps are generated and thresholded to produce binary change maps. Post-processing techniques, such as morphological filtering, are applied to refine the results and eliminate noise.
5. Validation and Accuracy Assessment: The detected changes are validated using ground truth data, high-resolution imagery, or existing land cover maps. Performance metrics, including overall accuracy and the kappa coefficient, are calculated to assess the effectiveness of the methodology (Congalton & Green, 2019).

Results

In this section we present some results on Urban and Forest monitoring domain.

Urban environments are characterized by diverse materials and complex structures, making change detection challenging. The LCC tool addresses this by combining the red, green, and blue (RGB) bands from Sentinel-2 with synthetic aperture radar (SAR) data from Sentinel-1. Optical RGB bands provide detailed spectral information about surface materials, while SAR data offer insights into surface roughness and structural features regardless of weather conditions or illumination (Gong et al., 2017). Here are some examples derived from SAR and Optical data.

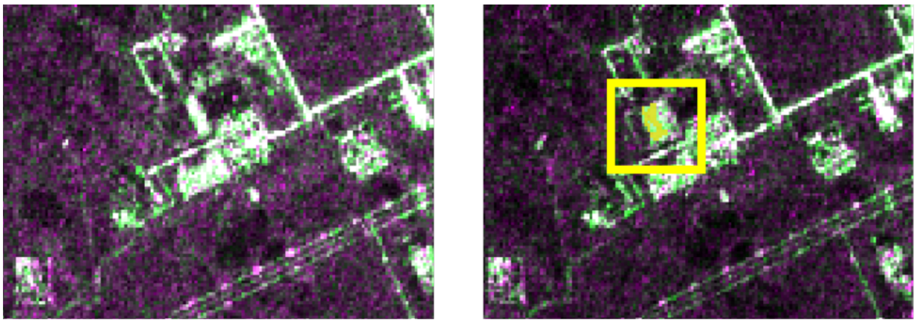

Fig. 1. Comparison of Sentinel-1 SAR imagery from two different dates highlighting infrastructure changes. The image on the left, taken on November 10, 2021, shows the pre-change condition, while the image on the right, captured on November 22, 2021, illustrates the post-change scenario, with the detected change highlighted in the yellow box.

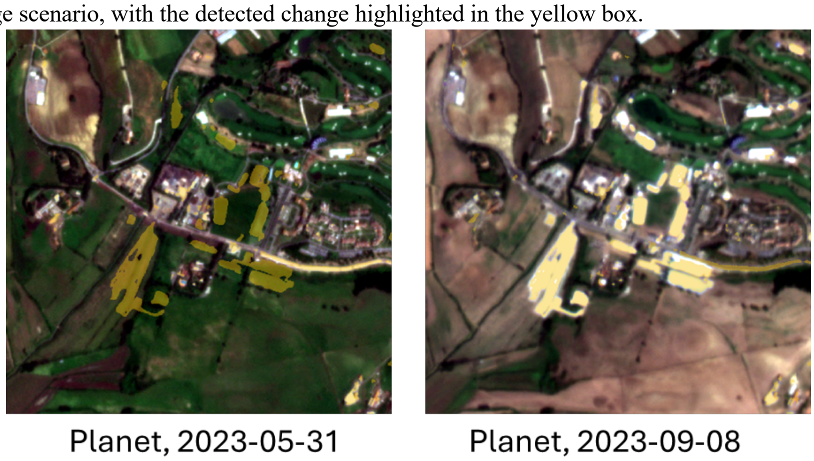

Fig. 2. Comparison of Planet optical imagery from two different dates showing land cover changes. The image on the left, taken on May 31, 2023, depicts the pre-change condition, while the image on the right, captured on September 8, 2023, shows the post-change scenario. The yellow-highlighted areas indicate the detected changes in land cover due to rapid changes due to the construction of a Golf field.

Forest Change Detection and Burned Area mapping with SWIR Bands

Detecting changes in forested areas, including deforestation and degradation, requires sensitivity to vegetation structure and moisture content. The short-wave infrared (SWIR) bands from Sentinel-2 are particularly effective for this purpose due to their responsiveness to water content in vegetation (Skakun et al., 2017). The LCC tool utilizes SWIR bands to improve the SIROC algorithm's ability to identify changes in forest biomass and canopy cover. By focusing on SWIR spectral information, the methodology enhances the detection of subtle changes within forests, such as selective logging or forest thinning. The spatial context modeling in SIROC helps distinguish between natural seasonal variations and anthropogenic alterations. For burned area mapping, spectral indices that highlight fire-induced changes in vegetation are employed. The Normalized Burn Ratio (NBR), which utilizes the near-infrared (NIR) and SWIR bands, is sensitive to the presence of charred vegetation and ash (Key & Benson, 2006). The differenced NBR (dNBR) accentuates the contrast between pre- and post-fire conditions. Here are some results from Multi-spectral data.

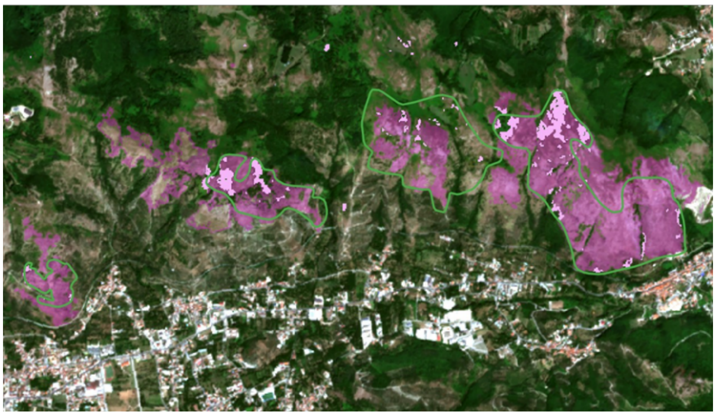

Fig. 3. Comparison of optical imagery showing burned area detection using a land cover change detection methodology. The violet regions indicate the areas detected by the algorithm, representing the initial assessment of burned areas. The green boundaries outline the estimated extent of the burned areas at the end of the fire season.

Conclusions

In this paper we demonstrated that by integrating a robust unsupervised change detection algorithm like SIROC and selecting spectral bands and indices for different use cases, the proposed methodology effectively detects land cover changes across various environments. The spatial context awareness and unsupervised nature of SIROC, combined with the fusion of Sentinel-1 and Sentinel-2 data, provide a robust and adaptable approach for monitoring urban development, forest alterations, burned areas, and agricultural dynamics.

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