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Advanced image processing techniques for satellite and airborne data analysis

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Summary. — The burgeoning space economy and the extraction of satellite and airborne data are transforming industries and environmental monitoring. This paper describes activities conducted at the National Research Centre for High Performance Computing, Big Data, and Quantum Computing (ICSC), developed within the framework of Working Group 6 (WP6), "Cross-Domain Initiatives and Space Economy" under Spoke 2, "Fundamental Research and Space Economy". It focuses on three aerial image processing methodologies: spectral index-based image processing, deterministic learning algorithms, and advanced deep learning techniques, highlighting their contributions to environmental monitoring.

1. – Introduction

The ever-increasing availability of satellite and airborne data provides unprecedented opportunities for addressing global challenges in environmental monitoring, agriculture, and renewable energy. In this work, we present three innovative methodologies aimed at leveraging these data sources to solve specific problems:

- The use of spectral indices to detect and monitor vineyard diseases, enabling early intervention and reducing manual labour.
- A deterministic approach for identifying photovoltaic (PV) panels, optimising computational resources while maintaining high accuracy.

- Advanced deep learning models to detect and estimate the damage severity of burnt areas in satellite imagery, offering actionable insights for disaster management.

These methodologies demonstrate the power of combining remote sensing with innovative computational approaches to achieve scalable, accurate, and efficient solutions.

2. – High-resolution image processing for disease detection in vineyards

A pilot study was carried out to use high-resolution airborne imaging to investigate the early detection of grapevine yellows (Flavescence Dorée and Bois Noir) and trunk disease (Esca Complex) in vineyards [1,2]. While traditional ground-based surveys are time consuming and inefficient, airborne surveys using spectral indices have effectively identified early symptoms through leaf colour changes. An acquisition survey was performed in Emilia-Romagna (Italy) using a Radgyro aircraft equipped with environmental sensors, covering 17 hectares of Sangiovese grapevine. The goal was to identify the reddening of vine leaves in the acquired images, one of the main symptoms of Flavescence Dorée, Bois Noir and Esca. The analysis pipeline, depicted in fig. 1, starts with calculating RGB vegetation indices including the Green-Red Vegetation Index (GRVI), Green-Blue Vegetation Index (GBVI), and Blue-Red Vegetation Index (BRVI) in orthomosaic images. These indices were selected to detect leaf colour changes indicative of disease symptoms, such as yellowing or reddening. Threshold filters are applied to isolate specific ranges of each index, resulting in a binary matrix which undergoes a convolution filter to denoise and highlight symptomatic regions. The resolution offered by remote sensing data, as demonstrated in our study, is highly advantageous for generating maps. The output includes a denoised binary matrix overlaid on the original image, an instances map, a density map and an incidence map (fig. 2) in a grid with a cell size of $10\ \text{m} \times 10\ \text{m}$. The results showed a specificity of 0.96 and a sensitivity of 0.56 when comparing the detected areas with ground truth data resulting in an overall classification accuracy of 0.95. This indicated a strong capability to differentiate between healthy and symptomatic plants and a good ability to identify the symptomatic plants. The proposed method forms the foundation for an early warning system that can support on-the-ground monitoring and assist authorities in making strategic decisions, improving the efficiency of interventions and allowing the reduction of the impact of vineyard diseases on crops. The integration of such technology into disease management strategies could significantly reduce the economic impact of these diseases, which are major threats to grapevine health and productivity.

3. – Deterministic learning algorithms for object identification

Remote sensing is valuable for estimating the potential green energy production in a community by detecting and calculating the number of PV panels. A deterministic algorithm is proposed for identifying PV panels in aerial images without using machine learning [3]. By analysing colour distributions, the method quickly detects panels based on characteristic colours, even when these overlap with other elements, without needing large annotated datasets. It automatically selects the significant PV colours, ensuring efficiency across varied environments. The pipeline involves:

- *Colour extraction*: PV images from [4] are classified to extract characteristic RGB values from labelled regions (LR). Only colours more prevalent in LR than in the background (BR) are kept, and extreme pixels (very dark or highly saturated) are

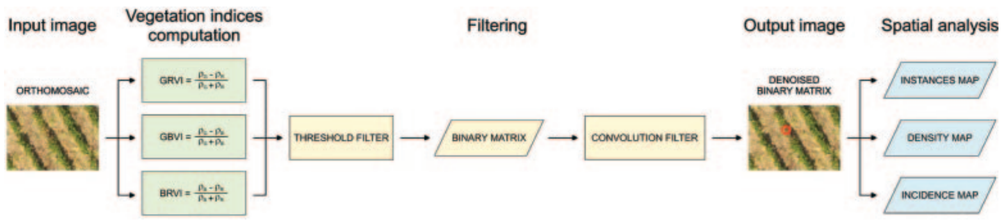


Fig. 1. – Software pipeline elaborated for automating the process analysis. The input is the georeferenced orthomosaic from which the red (R), green (G) and blue (B) reflectance values are extracted and used to compute the vegetation indices. After the application of the threshold and convolution filters, the matrices are classified to obtain a denoised matrix employed to produce the thematic maps in a GIS environment.

excluded. The outcome is a collection of RGB colour values characteristic of PV panels, which are subsequently searched for in an unknown image, as seen in the green-highlighted pixels in fig. 3.

- *Background removal*: Colours common to both LR and BR are discarded, focusing on unique panel features.

- *Tile-based refinement*: A sliding 5×5 px tile turns blue if over 75% of its pixels are green, and an 11×11 px tile further refines the detection to confirm consistently identified regions.

The results, reported in fig. 4, show that the deterministic algorithm outperforms several machine learning models in both evaluation metrics and speed, achieving high recall and interpretability without extensive annotations. This approach is especially suited for areas with limited computational resources or where transparency is crucial.

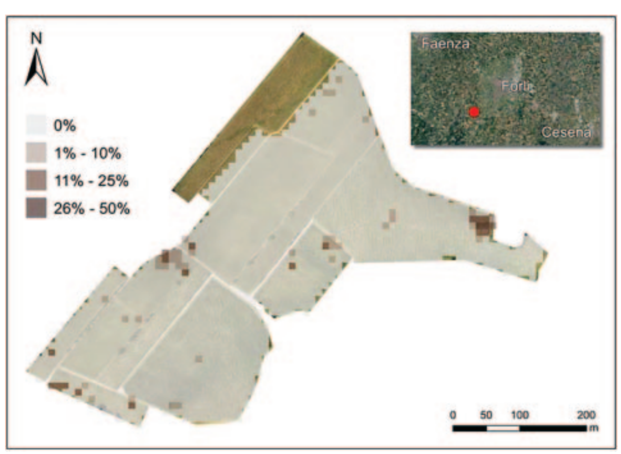


Fig. 2. – Incidence map of the experimental site. Each grid cell of 10 m $\times$ 10 m is classified on the basis of the number of potential symptomatic plants detected.

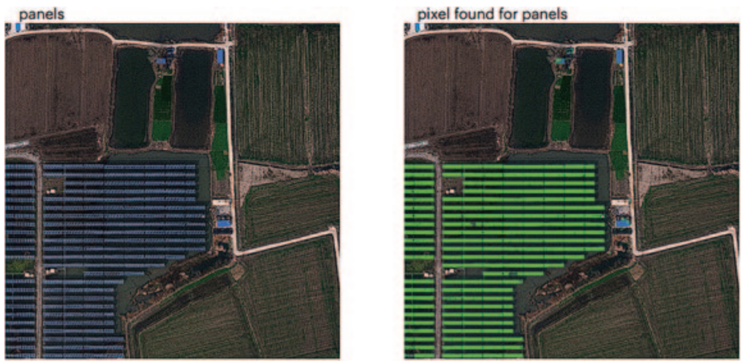


Fig. 3. – Detection of photovoltaic (PV) panels using a deterministic algorithm based on pixel-level analysis. The left image shows the original aerial image of a photovoltaic installation, highlighting the physical layout of the panels within the surrounding landscape. The right image presents the output of the deterministic algorithm, where green overlays indicate pixels successfully identified as part of the photovoltaic panels. Figure from [3].

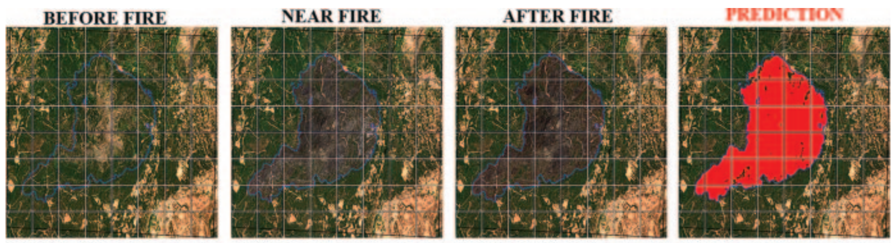
4. – Deep learning for satellite imagery

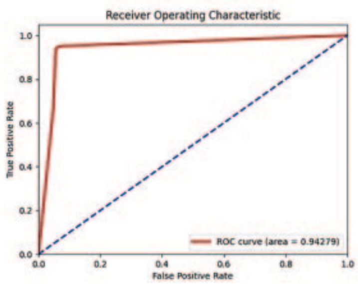
Deep learning models have shown great promise in large-scale environmental monitoring, particularly in detecting and mapping burnt areas using satellite imagery. The combination of multispectral images and advanced deep learning architectures provides powerful tools for disaster management and recovery planning. The focus of this study is on the detection and mapping of burnt areas from Sentinel-2 images, provided under the Copernicus Programme [5] and accessible via the Sentinel Hub API [6]. The dataset comprises 114 multispectral images (all 12 Sentinel-2 spectral bands) of size 2048×2048 pixels with a spatial resolution of 10 meters, sourced from the Copernicus Emergency Management Service (EMS [7]). These images cover various fire events across Europe, primarily in the Mediterranean region. For each fire event, a temporal series of three

Dataset	Size	Accuracy	Precision	Recall	F1 Score	IoU
Ground	458	0.963	0.918	0.901	0.897	0.833
Cropland	146	0.971	0.931	0.938	0.931	0.877
Grassland	42	0.952	**0.953**	0.881	0.912	0.844
SalineAlkali	53	**0.982**	0.913	**0.958**	0.934	0.878
Shrubwood	77	0.975	0.934	0.956	**0.944**	**0.897**
WaterSurface	140	0.974	0.915	0.928	0.917	0.852
max in	ESSD 2021, 13, 5389–5401	0.981	0.960	0.903	0.931	0.877

Phase	Average Execution Time per Image
Image Classification	2.42 s
cPV Colours Extraction	1.63 s
PVs Detection (3 passes)	9.25 s
Image Denoising	3.16 s

Fig. 4. – Performance metrics and execution times for PV panel detection across different datasets. The upper table summarizes detection performance across six land-cover types. The highest values for each metric are highlighted, with a comparison with a benchmark study [4]. The lower table details the average execution time per image for each processing phase in the detection pipeline. Figure from [3].





Evaluation metrics	
Best Threshold	0.4
Accuracy	0.94
Precision	0.95
Recall	0.95
F1 Score	0.95
Dice	0.92
Jaccard	0.86

Fig. 5. – Temporal sequence and prediction results of burnt areas using satellite imagery and ConvLSTM-based deep learning. The top row illustrates the temporal progression of fire impact, from "Before Fire", through "Near Fire", to "After Fire" (post-event burnt area), with the model predictions shown in the final panel. The blue outline indicates the ground truth perimeter of the burnt region provided by the Copernicus EMS [8], while the predicted areas are overlaid in red, demonstrating strong alignment with the ground truth. The bottom left panel presents the Receiver Operating Characteristic (ROC) curve with a highlight on the AUC metric. The bottom right table summarizes evaluation metrics for the model.

images was used: one before the fire, one during or near the fire, and one after the fire. The images were divided into 256×256 pixel patches, and only patches containing at least 1% burnt area were included in training and evaluation. To enhance the robustness of the model, data augmentation techniques, such as random rotations and mirroring, were applied. The proposed architecture is a U-Net-like model with Convolutional Long Short-Term Memory (ConvLSTM) layers. This design is particularly effective for spatiotemporal data, as it combines the strengths of convolutional neural networks (CNNs) for spatial feature extraction and LSTMs for capturing temporal dependencies. A 5-fold cross-validation was performed on the training dataset of 95 images to ensure the model robustness. The remaining 19 images were reserved for final testing to evaluate performance on unseen data. The model demonstrated stable convergence and generalization, with loss and accuracy curves stabilising around 75–100 epochs. The evaluation metrics highlight the model's strong performance, with an overall accuracy of 94%, and precision, recall, and F1 scores at 95%. The Dice coefficient and Jaccard index values are 0.92 and 0.86, confirming the effective segmentation of burnt areas. The ROC curve achieved an AUC score of 0.94, demonstrating strong discriminatory power. The top panel of fig. 5 shows the temporal progression of fire impact, with model predictions closely aligning with ground truth burnt areas, while in the bottom panel, the ROC curve and the evaluation metrics are reported. These findings underscore the potential of deep learning techniques in large-scale environmental monitoring and post-disaster recovery. By leveraging the temporal and spectral richness of Sentinel-2 data, the proposed approach provides accurate and actionable insights for mitigating the impact of wildfires and supporting recovery efforts.

5. – Conclusions and future prospects

The three presented projects underscore the potential of advanced computational methods using satellite and aerial imagery for diverse tasks, ranging from agriculture to renewable energy and environmental monitoring. Future work will focus on integrating the strengths of these projects to explore cross-domain applications and synergies. A key area of research will be utilising multi-satellite data, combining imagery from platforms with varying spectral bands, spatial resolutions, and revisit times. For instance, integrating high-resolution Sentinel-2 data with other satellite platforms offering complementary capabilities, such as Synthetic aperture radar or thermal imaging, could enhance the precision and scope of monitoring tasks. Such an approach could contribute to vineyard disease detection, improve the temporal tracking of burnt areas, and provide even more reliable identification of photovoltaic panels. Collaborative experiments will also investigate joint data processing pipelines that unify methodologies, such as integrating spectral index-based techniques with deterministic learning and deep learning frameworks. This could pave the way for unified systems capable of addressing multiple environmental and industrial challenges within a single platform. By fostering collaboration between these projects and leveraging the full spectrum of satellite data, these efforts will contribute to creating comprehensive and efficient solutions for environmental monitoring and resource management, ultimately supporting sustainable development on a global scale.

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REFERENCES

[1] Strati V. *et al.*, EGU24-10773, presented at the European Geosciences Union General Assembly (2024).
[2] PERBACCO project website at `https://www.fe.infn.it/radioactivity/activities/perbacco/index.html`.
[3] Marletta D. *et al.*, *Technologies*, **11** (2023) 174.
[4] Jiang H. *et al.*, *Earth Syst. Sci. Data*, **13** (2021) 5389.
[5] European Commission, Copernicus Programme, available at `https://www.copernicus.eu/`.
[6] Sentinel Hub API, Copernicus Sentinel-2 Data Access, available at `https://www.sentinel-hub.com/`.
[7] Copernicus Emergency Management Service, Dataset, available at `https://emergency.copernicus.eu/`.
[8] Copernicus Emergency Management Service (©2022 European Union), EMSR617, available at `https://emergency.copernicus.eu/mapping/list-of-components/EMSR617`.