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A Machine Learning Algorithm for Urban Vegetation Classification based on Radar and Multispectral imagery from Sentinel Satellites Data

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INTRODUCTION

The presence and health of urban vegetation play a crucial role in the mitigation of environmental and societal challenges by providing ecosystem services.

Machine learning algorithms have revolutionized remote sensing data analysis, offering powerful tools for complex classification tasks.

A comprehensive approach requires a understanding of optical satellite imagery such as that provided by Sentinel-2 and radar satellite imagery provided by Sentinel-1. The limitation of both sensors in vegetation classification depending on weather, time or others factors can lead to lower classification accuracy.

The primary aim of this work is to develop and evaluate a robust machine learning algorithm for accurate urban vegetation classification.

The integrate of radar and multispectral imagery from sentinels satellites leveraged the power of the Random Forest algorithm and the Scikit-learn Python library to generate an high resolution classification.

Illustration of a vegetation studied in Giglio island, Italia

METHOD AND TASK

When we performing our work, the following tasks were set:

- Analysis of Sentinel Satellites Characteristics;
- Analysis and comparison of vegetation indices;
- Development of machine learning algorithm to create a vegetation indices independently based on their accuracy and Kappa Index;
- Development of a proposal fusion approach to create vegetation classification;
- Comparison of density variations among vegetation types

Sentinel satellite images of Giglio island

ANALYSIS OF SENTINEL SATELLITES CHARACTERISTICS

Among the components of ESA's Copernicus program are Sentinel-1 and Sentinel-2. Each part of this platform is designed for a specific remote sensing application. Due to its two-satellite configuration (Sentinel-1A and Sentinel-1B), Sentinel-1 has a revisit time of approximately six days, whereas Sentinel-2 has a revisit time of five days at the equator with its twin satellites (Sentinel-2A and Sentinel-2B). Table I presents the technical specifications of Sentinel-1 and Sentinel-2 images.

SENTINEL-1 AND SENTINEL-2 SATELLITES ILLUSTRATION

Item	Sentinel 1A-1B	Sentinel 2A-2B
Orbit altitude and inclination	693 km, 98.2°	788 km, 98.2°
Sensor	Synthesized aperture radar	Multispectral instrument
Resolution	10 × 10 m	10 m – 20 m – 60 m
Revisit period	12 days (using together A and B, 6 days)	5 days at the equator
Beam mode	Interferometric wide swatch (IW)	–
Bands	C (5.4GHz)	13 spectral bands range from visible and near infrared (NIR) to shortwave infrared (SWIR)
Polarizations	VV-VH	–

TECHNICAL SPECIFICATIONS OF SENTINEL SATELLITE INSTRUMENTS

ANALYSIS OF VEGETATION INDICES

Definition of Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely used metric in remote sensing to quantify vegetation health and density . It operates by measuring the difference between near-infrared (NIR) light, which healthy vegetation strongly reflects, and red light, which vegetation absorbs for photosynthesis. This index is crucial for monitoring plant growth, detecting stress, and informing agricultural and environmental management decisions.

The NDVI is calculated using a specific formula that leverages the distinct reflective properties od vegetation in different light spectrum.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

ANALYSIS OF VEGETATION INDICES

Definition of Radar Vegetation Index (RVI)

The Radar Vegetation Index (RVI) is a crucial metric in remote sensing and agriculture, utilized to assess the health and condition of vegetation using radar data. It is particularly valuable for monitoring crop growth and has been employed in numerous research studies to predict the growth level of crop vegetation over time.

The RVI is derived from Synthetic Aperture Radar (SAR) data, such as that collected by Sentinel-1 satellites. Unlike optical vegetation indices that can be affected by cloud cover, radar signals can penetrate clouds, making RVI a reliable tool for continuous monitoring regardless of atmospheric conditions.

The calculation of RVI varies depending on the polarization available in the input radar dataset. For dual-polarization (dual-pol) SAR data, such as VH/VV (Vertical-Horizontal and Vertical-Vertical) or HH/HV (Horizontal-Horizontal and Horizontal-Vertical), common formulas are used.

$$RVI = \frac{4 * VH}{VV + VH}$$

ANALYSIS OF VEGETATION INDICES

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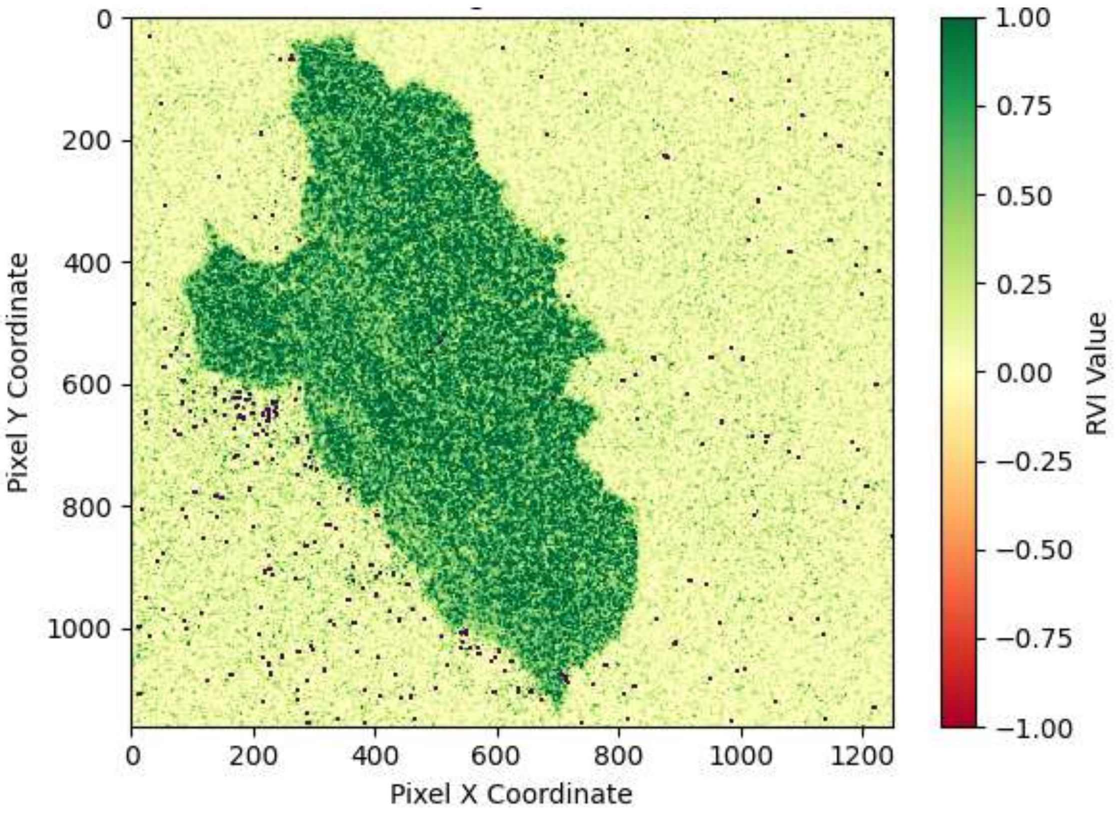
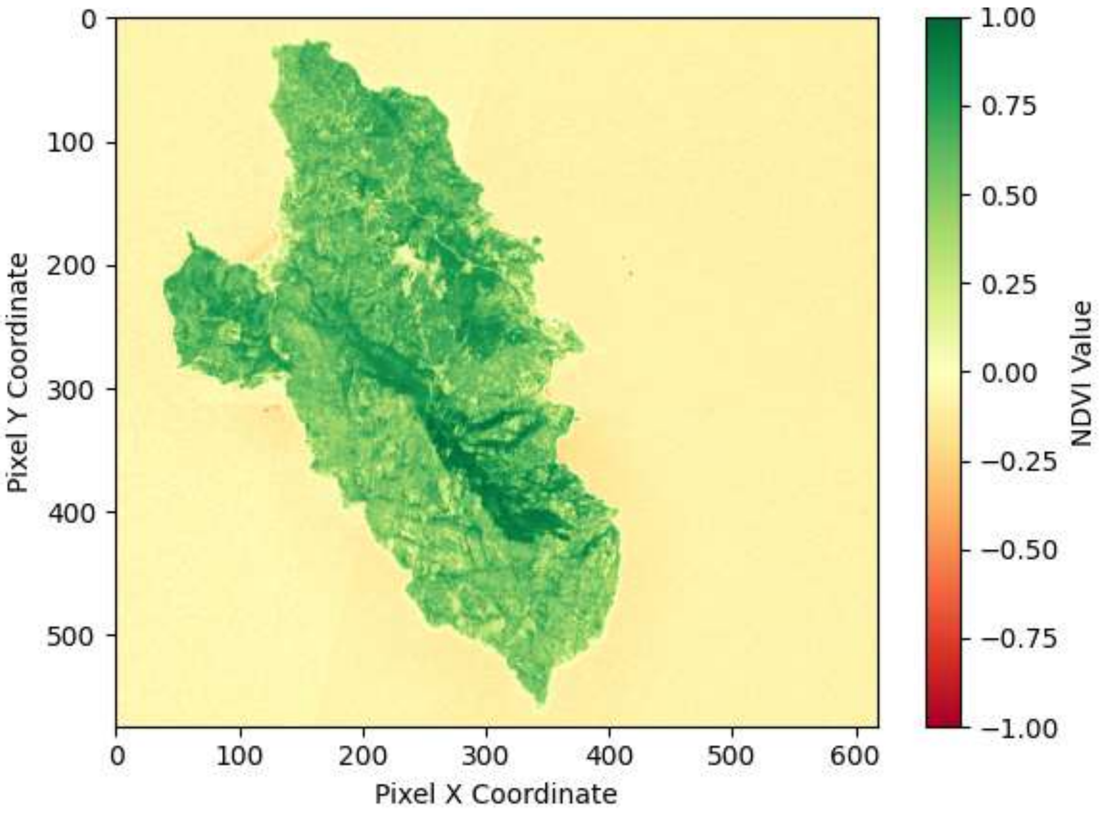
Normalized Difference Vegetation Index and Radar Vegetation Index illustration



Definition of Radar Vegetation Index (RVI)



Definition of Normalized Difference Vegetation Index (NDVI)

ANALYSIS OF VEGETATION INDICES

The Modified Normalized Difference Water Index (MNDWI) is designed to improve the detection and delineation of open water surface, it uses the green and shortwave infrared (SWIR) bands of the electromagnetic. The Soil Adjusted Vegetation Index is modification of NDVI that is designed to minimize the influence of soil brightness on vegetation index values, it introduces a soil brightness correction factor denoted as L into NDVI equation accounting the differential reflectance of the soil in red and near-infrared bands.

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

$$SAVI = \frac{NIR - Red}{NIR + Red + L} * (1 + L)$$

DEVELOPMENT OF A FUSION APPROACH TO CREATE A PRECISE FIRE SEVEITY MAP

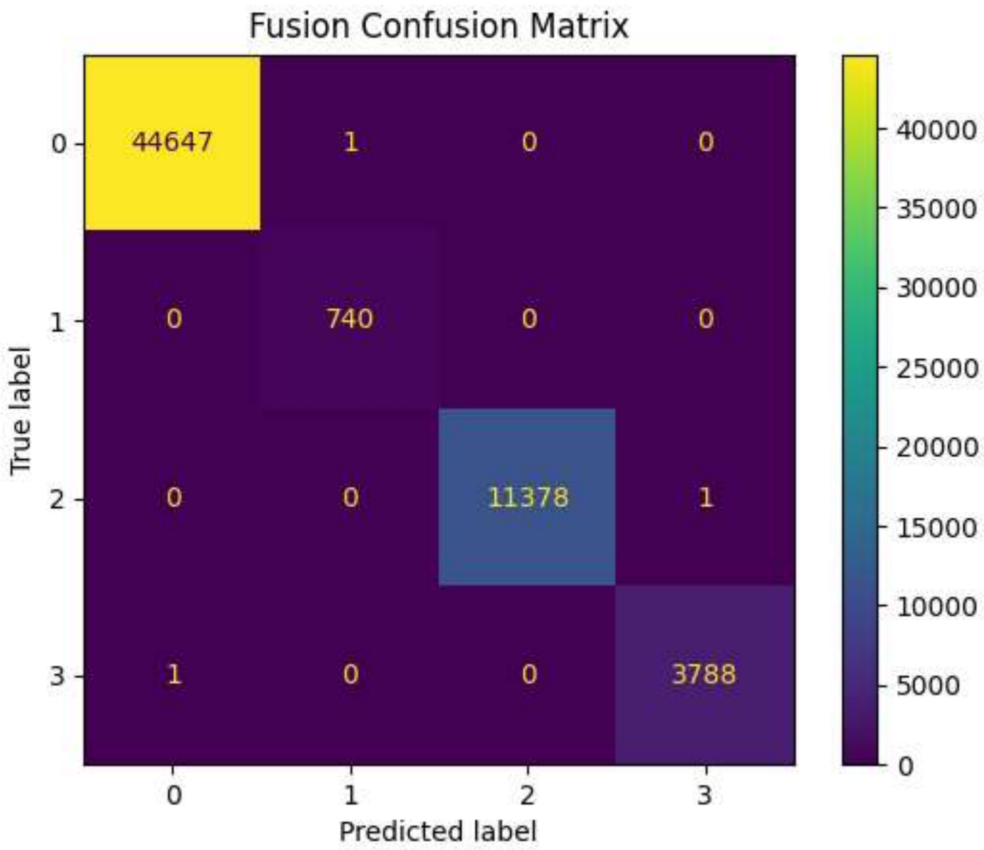
The analysis leverages the power of the Random Forest Algorithm. We used vegetation classes, including: . To create a fusion approach, we combined Normalized Difference Vegetation Index, Radar Difference Vegetation Index, Modified Normalized Difference Water Index and Soil Adjusted Vegetation Index. The process begins with data acquisition and pre-processing. This typically involves obtaining satellite imagery such as Sentinel-1 and Sentinel-2, due to their suitable spatial and spectral resolutions.

Merging these indices (NDVI, RVI, MNDWI, SAVI) within a random forest offers several advantages. The NDVI and SAVI provide robust spectral measures of vegetation amount and vigor while SAVI corrects the soil effects, RVI supplies structural/woody-biomass contrast, MNDWI removes the water or wet soil confusers. The radar-derived RVI provides additional structural information in terms of woody biomass and vertical volume scattering. By combining them, the Random Forest Algorithm can exploit the unique information content of each index, allowing for a more comprehensive and accurate assessment of vegetation classification than with a single index.

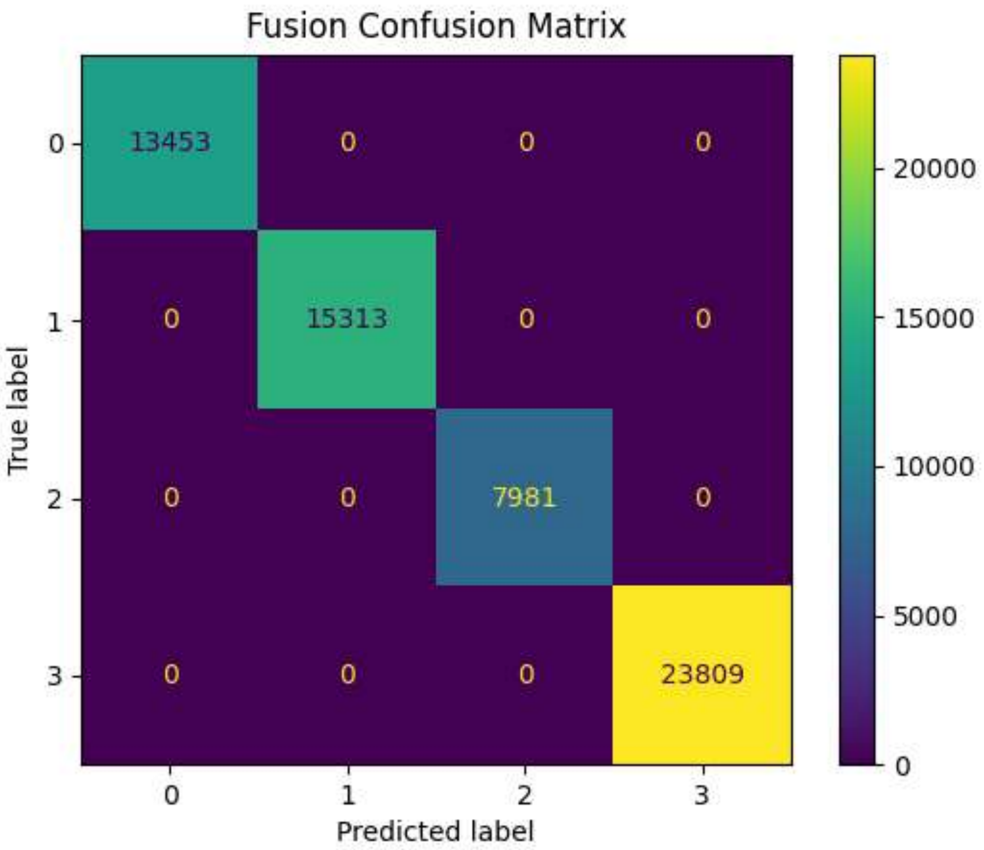
The ensemble nature of Random Forest also contributes to higher accuracy and robustness compared to single-tree methods or simpler classification algorithms.

DEVELOPMENT OF A FUSION APPROACH TO CREATE A PRECISE FIRE SEVEITY MAP

Confusion matrix of forest fire indices independently and in combination illustrations



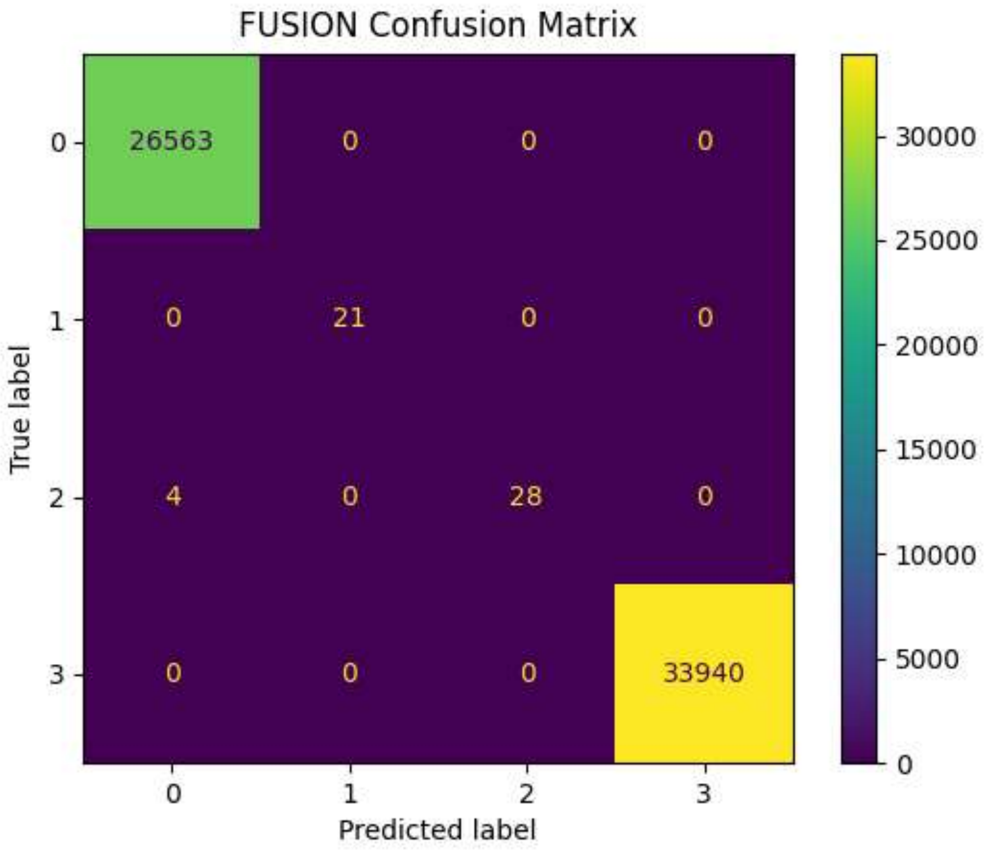
NDVI Confusion Matrix



RVI Confusion Matrix

DEVELOPMENT OF A FUSION APPROACH TO CREATE A PRECISE FIRE SEVEITY MAP

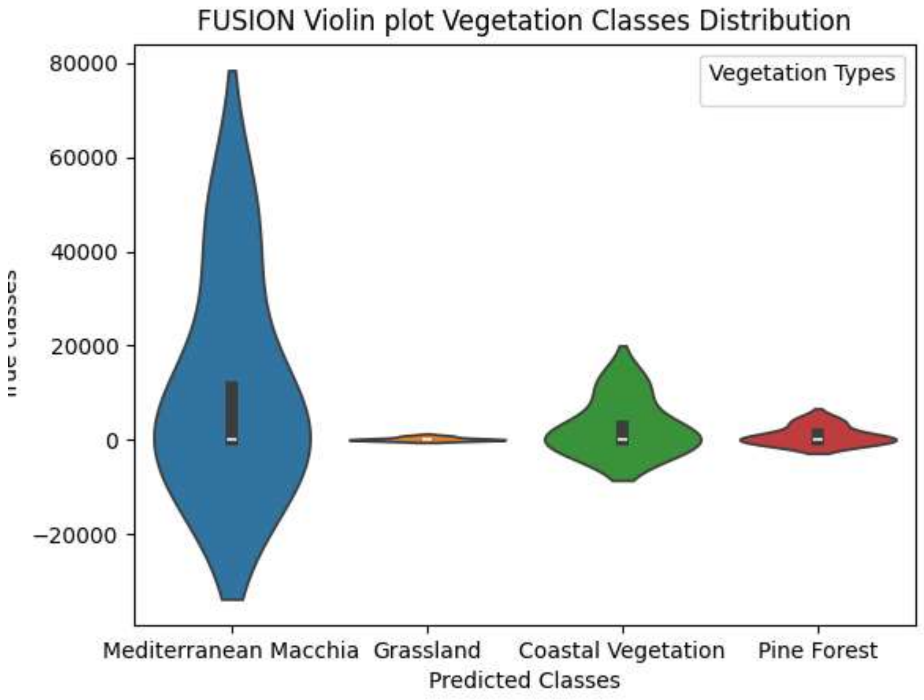
Confusion matrix of forest fire indices independently and in combination illustrations



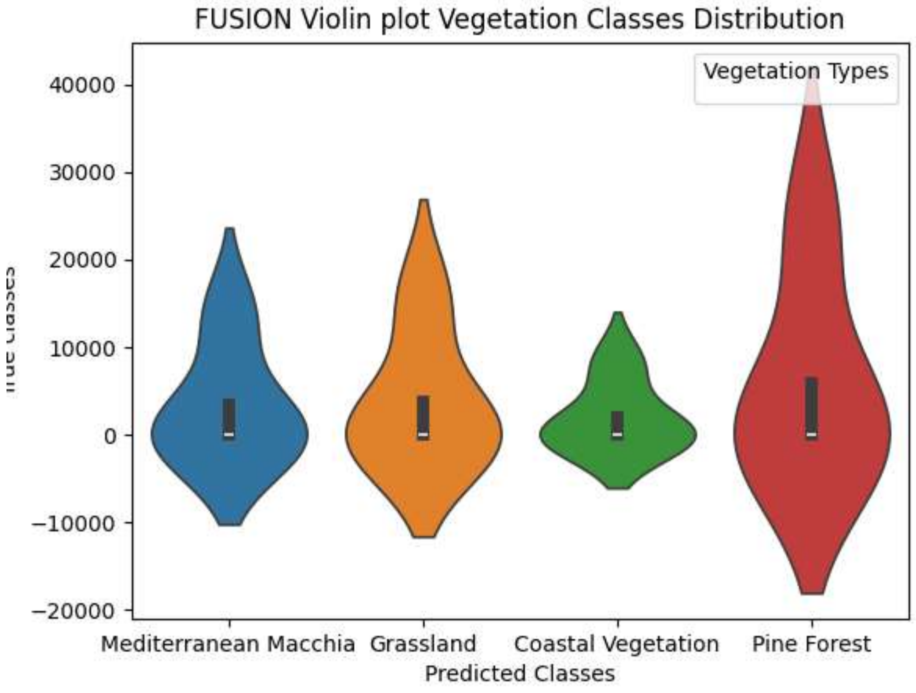
Ndvi_RVI,MNDWI,SAVI Confusion Matrix

COMPARISON OF DENSITY VARIATIONS AMONG VEGETATION TYPES USING

This part of the study concentrates on the analysis of the variations of density among different vegetation types, using the fusion approach proposed

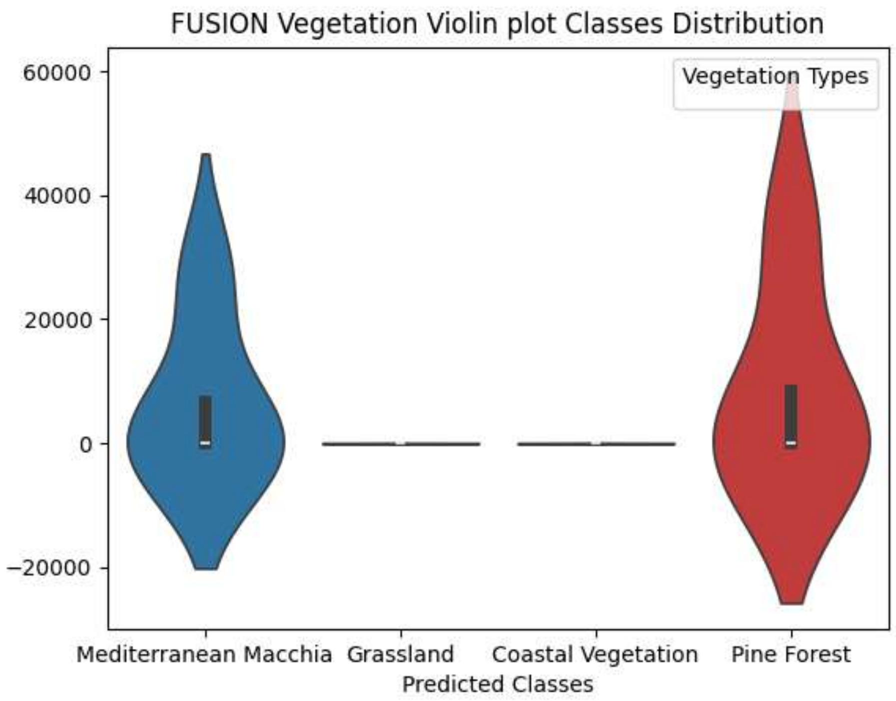


Vegetation Classes Distribution (NDVI, MNDWI, SAVI)



Vegetation Classes Distribution (RVI, MNDWI, SAVI)

COMPARISON OF DENSITY VARIATIONS AMONG VEGETATION TYPES USING



Vegetation Classes Distribution (NDVI_RVI, MNDWI, SAVI)

RESULTS AND DISCUSSION

The results showed a perfect 100% accuracy and Kappa Index in all the predictions. In this work, the Random Forest Algorithm was implemented based on two different independent training sets, one for the Normalized Difference Vegetation Index (NDVI) and another one for the Radar Vegetation Index (RVI). In addition, three different proposed fusion methods were applied to combine Normalized Difference Vegetation Index (NDVI), Radar Vegetation Index (RVI), Modified Normalized Difference Water Index (MNDWI), and Soil-Adjusted Vegetation Index (SAVI). The results and comparison of all proposed training models are presented in Tables II, III and IV.

RESULTS AND DISCUSSION

Model	Overall Accuracy (%)	Kappa Index (%)
NDVI	100	100
RVI	100	100
NDVI, MNDWI, SAVI	100	100
RVI, MNDWI, SAVI	100	100
NDVI_RVI, MNDWI, SAVI	100	100

OVERALL ACCURACY AND KAPPA INDEX OF RANDOM FOREST CLASSIFICATION

Vegetation types	NDVI	RVI	NDVI MNDWI SAVI	RVI MNDWI SAVI	**NDVI_RVI MNDWI SAVI**
Mediterranean Macchia	Present	Present	Present	Present	**Present**
Grassland	Present	Present	Present	Present	**Present**
Coastal vegetation	Present	Present	Present	Present	**Present**
Pine forest	Present	Present	Present	Present	**Present**

CLASSIFICATION RESULT BY CLASS FOR THE RANDOM FOREST ALGORITHM

RESULTS AND DISCUSSION

Vegetation types	NDVI	RVI	NDVI, MNDWI, SAVI	RVI MNDWI SAVI	NDVI_RVI, MNDWI, SAVI
Mediterranean Macchia	Perfect	Poor	Perfect	Moderate	Perfect
Grassland	Fair	Poor	Very Slight	Moderate	Poor
Coastal vegetation	Slight	Poor	Moderate	Fair	Poor
Pine forest	Slight	Perfect	Fair	Perfect	Perfect

Agreement level by class for the Random Forest Classification

CONCLUSION

In this paper, vegetation classification was comprehensively analyzed using both the Normalized Difference Vegetation Index (NDVI) and the Radar Vegetation Index (RVI), separately. However, to enhance the accuracy of our classification, we integrated additional indices, mainly the Modified Normalized Difference Water Index (MNDWI) and the Soil Adjusted Vegetation Index (SAVI), to develop a robust fusion approach.

Our finding showed that the fusion approach increased not only the classification accuracy but reduced errors considerably as compared to using individual indices alone. It allowed us to give an insight into the dynamics of vegetation density variations across different types of classes by identifying vegetation classes with the highest temporal prevalence. The results highlight how the combination of multiple spectral indices leads to more accurate vegetation analysis.

Overall, this fusion method performed better in vegetation-type classification, hence promising a great future for its use in remote sensing and environmental studies.

Our future work focuses on integrating Radar and Multispectral Data from Sentinel satellites for Urban Water Classification using machine learning

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