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Integrating Radar and Multispectral Data from Sentinel Satellites for Accurate Urban Vegetation Classification using Deep Learning Methods

J. B. Ngoua Ndong Avele

Omar Bongo University, Libreville, Gabon

Saint Petersburg Electrotechnical University, St Petersburg, Russia

✉ avelejacques@yahoo.fr

Abstract

Introduction. The Sentinel-1 (equipped with synthetic aperture radar) and Sentinel-2 (equipped with multispectral cameras) satellites are valuable tools for environmental monitoring, particularly for assessing vegetation cover and soil erosion. The data obtained by these systems can be processed using machine learning techniques to generate accurate vegetation classification maps.

Aim. To develop and evaluate machine learning models capable of efficiently fusing Sentinel satellite data to produce more accurate and detailed maps of urban vegetation, essential for urban planning, environmental monitoring, and climate change mitigation. The integration of Sentinel-1 and Sentinel-2 satellite data is intended to overcome the limitations associated with using each data type in isolation, particularly in complex urban environments where spectral signatures can be ambiguous and radar provides only structural information.

Materials and methods. A classification map of urban vegetation on Kotlin Island (St Petersburg) was generated by integrating data from Sentinel-1 (synthetic aperture radar) and Sentinel-2 (multispectral imagery) using the Random Forest algorithm, Tensorflow and Sklearn Python libraries. Conventional urban vegetation mapping often relies on a single data source, leading to limited accuracy and inability to differentiate subtle vegetation types. The vegetation classes considered in this research were coniferous forest, deciduous forest, wetland vegetation, and coastal meadows.

Results. The integrated analysis of radar and multispectral data enabled more accurate identification of erosion-prone zones in non-vegetated areas and more reliable estimation of plant moisture content. Such a fusion approach showed significantly improved classification accuracy and reduced error rate compared to techniques relying on individual indices.

Conclusion. The fusion method demonstrated superior performance in classifying vegetation types, which confirms its potential for applications in remote sensing and environmental monitoring. Future research will focus on integrating radar and multispectral data from Sentinel satellites for urban vegetation classification using the Support Vector Machine algorithm.

Keywords: Sentinel satellites, synthesized aperture radar, multispectral imaging, Random Forest algorithm, machine learning techniques, vegetation classification

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Introduction. Urban vegetation is paramount for maintaining ecological balance in cities, enhancing aesthetic quality, and mitigating such environmental issues as soil erosion and surface water runoff. Densely populated areas, including Kotlin Island in St Petersburg, require robust monitoring of urban green spaces to ensure both plant health and soil stability. The unique geography of the island presents a complex challenge for effective vegetation management. Conventional field surveys are resource-intensive and fail to provide the spatial coverage needed for comprehensive assessment [1].

Accelerating global urbanization is transforming land use patterns and the land cover itself, requiring advanced monitoring and management. This problem requires state-of-the-art technologies for timely and accurate assessment of urban green spaces, which is essential for environmental health and urban planning. The Copernicus program with the Sentinel satellites as its key elements collects comprehensive Earth observation data and, through its user-friendly platform, offers tools for visualization, subsetting, and basic analysis. The Sentinel datasets are useful for applications such as disaster response, precision agriculture, and climate change monitoring, fostering collaborations and knowledge transfer within the scientific community. These satellites provide a substantial amount of information for analysis through combining multispectral imagery from Sentinel-2 with the unique capabilities of synthetic aperture radar (SAR) data from Sentinel-1 [2, 3].

Advanced approaches based on integrating remote sensing techniques are capable of producing comprehensive information on vegetation. Thus, by fusing data from Sentinel-1 (SAR) and Sentinel-2 (multispectral imagery) satellites, a highly detailed and accurate representation of vegetation conditions on Kotlin Island can be achieved [4]. In this study, high-resolution radar images and multispectral data from the Sentinel-1 and Sentinel-2 missions are used. The radar data provides insight into the structural characteristics of vegetation, while the multispectral data capture variations in plant health across different spectral bands. The integration of these data elucidates the understanding of plant moisture levels [3]. Another research aspect involves machine learning methods, such as the Random Forest algorithm, to create an accurate vegetation classification map of Kotlin Island [5].

Sentinel-1 radar signals penetrate cloud cover and provide valuable information on soil moisture content, even under adverse weather conditions. This capability is crucial for identifying areas prone to waterlogging, which poses a significant threat to plant health and is a primary driver of soil erosion. Sentinel-2 multispectral imagery provides detailed information on vegetation indices such as the normalized difference vegetation index (NDVI) and chlorophyll content, allowing the overall health and vigor of urban vegetation to be assessed [6]. In other words, Sentinel-2 multispectral imagery captures information across a wide range of wavelengths, enabling a comprehensive analysis of vegetation characteristics. However, cloud cover and atmospheric conditions often impede optical satellite observations. This is where SAR data becomes particularly valuable [7].

Machine learning algorithms have emerged as a leading approach for remote sensing-based classification tasks. In this context, the Random Forest algorithm appears promising due to its ability to handle high-dimensional data, robustness to noise, and capacity to model complex relationships between spectral and radar features. The use of Random Forest supports effective urban planning strategies, thereby promoting the development of more sustainable and eco-friendly urban environments [8].

Materials and methods. Deep learning methods, the Random Forest algorithm, Tensorflow and Sklearn Python libraries were used to generate an urban vegetation classification map. The following vegetation classes were considered: coniferous forest, deciduous forest, wetland vegetation, and coastal meadows. First, independent vegetation classifications using both the NDVI and the radar vegetation index (RVI) were drawn. To enhance classification accuracy, a combination of NDVI, RVI, the modified normalized difference water index (MNDWI), and the soil adjusted vegetation index (SAVI) was applied. Second, the vegetation classes exhibiting the highest temporal prevalence were identified. Finally, density variations among vegetation types were established using the proposed fusion method.

Ecological analysis of Kotlin Island (St Petersburg). Kotlin Island, located in St Petersburg, is characterized by a unique ecosystem and diverse vegetation. NDVI and RVI indices provide a robust framework for assessing the ecological condition of

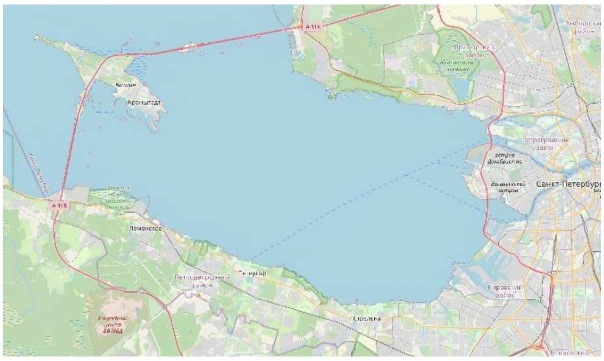

Fig. 1. Location of Kotlin Island (St Petersburg)

the area. These indices derived from remote sensing datasets enable the identification of zones requiring conservation efforts, contribute to erosion prevention, and facilitate monitoring of vegetation health in relation to water availability. The remote sensing datasets integrate Sentinel-1 SAR imagery with Sentinel-2 multispectral data, offering a powerful resource for Earth observation research. These datasets are accessed via the Sentinel Hub platform, developed by the European Space Agency (ESA).

The coastal ecosystem of Kotlin Island is formed by a combination of urban and natural landscapes with extensive green spaces such as parks and gardens that support a wide variety of fauna and flora [9]. Fig. 1 demonstrates the geographical position of Kotlin Island based on the data from OpenStreetMap. For dataset preprocessing, the key vegetation indices of Kotlin Island (St Petersburg), such as NDVI and RVI, should be calculated based on the Sentinel-2 and Sentinel-1 data. NDVI is calculated using near-infrared (NIR) and red spectral bands, representing vegetation reflectance. Conversely, RVI calculation utilizes the ratio of vertical–vertical (VV) and vertical–horizontal (VH) polarizations. The island' soil and vegetation are well adapted to saline conditions typical of coastal environments. Overall, Kotlin Island represents an important ecological zone where urban growth is balanced with environmental preservation.

Indices commonly used for vegetation classification. Sentinel satellite datasets provide a wealth of information for precise mapping or classification of vegetation. In this research, four different indices – NDVI, RVI, MNDWI, and SAVI – were used. The NDVI measures the difference between NIR and red reflectance. The RVI, derived from radar backscatter data, is less sensitive to atmospheric conditions and cloud cover. It provides valuable data even in challenging weather conditions. The MNDWI distinguishes water bodies from vegetation, which is essential for accurate vegetation boundary determination. Finally, the SAVI takes into account the influence of soil background on NDVI readings, which is particularly useful in areas with sparse vegetation or bare soil. The formulas used to calculate these indices are given in Tab. 1 [10].

Tab. 1. Indices used for vegetation classification

Index abbreviation	Formulas
NDVI	(NIR – Red)/(NIR + Red)
RVI	4VH/(VV + VH)
MNDWI	(Green – SWIR)/(Green + SWIR)
SAVI	((NIR – Red)/(NIR + Red + L))(1 + L)
NDMI	(NIR – SWIR)/(NIR + SWIR)
761	13

Detailed technical specifications of Sentinel-1 and Sentinel-2 instruments. Sentinel-1 and Sentinel-2 are key components of the Copernicus program developed by ESA. Each mission is designed for specific remote sensing applications. Due to its two-satellite configuration (Sentinel-1A and Sentinel-1B), Sentinel-1 provides a revisit time of approximately six days. Sentinel-2, consisting of two twin satellites (Sentinel-2A and Sentinel-2B), offers a revisit time of five days at the equator. Tab. 2 shows technical specifications of Sentinel-1 and Sentinel-2 imagery. Sentinel-2 uses a push-broom concept combined with a three-mirror anastigmat design with a focal length of approximately 600 mm. The mirrors are made of silicon carbide for optimum thermal stability. The instrument is also equipped with a shutter mechanism for calibration and protection from direct solar illumination. The two satellites are highly complementary. The integration of these datasets significantly improves the accuracy of vegetation mapping and supports environmental monitoring efforts [10].

Training datasets for vegetation classification when using NDVI and RVI in separation. A supervised classification was performed using the Random Forest algorithm. The analysis covered the summer 2024 period, from June to August. Sentinel satellite datasets were accessed through the Sentinel EO Browser online platform that provides access to

Tab. 2. Technical specifications of Sentinel satellites

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 (5.4 GHz)	13 spectral bands range from visible and near infrared (NIR) to shortwave infrared (SWIR)
Polarizations	VV-VH	–

Tab. 3. Sentinel-1 and Sentinel-2 images available

Date of acquisition	Sentinel 1A-1B	Sentinel 2A-2B
06.06.2024–04.06.2024	Radiometric terrain corrected	1C
12.06.2024–11.06.2024	Radiometric terrain corrected	2A
24.06.2024–21.06.2024	Radiometric terrain corrected	1C
12.07.2024–09.07.2024	Radiometric terrain corrected	1C
24.07.2024–24.07.2024	Radiometric terrain corrected	1C
30.07.2024–26.07.2024	Radiometric terrain corrected	1C
11.08.2024–08.08.2024	Radiometric terrain corrected	2A

Copernicus Sentinel data [11]. Sentinel-2 products are available in two processing levels: Level-1C (L1C) and Level-2A (L2A). L1C data provide Top-of-Atmosphere (TOA) reflectance values in cartographic geometry, while L2A data provides Bottom-of-Atmosphere (BOA) reflectance after atmospheric correction. Tab. 3 shows the acquisition date and correction level of the selected images.

The first stage of the study involved training the dataset using the NDVI alone. This approach allows assessment of the efficiency of NDVI in classifying vegetation, when used separately from other methods. Overall accuracy (OA) and the Kappa index are essential metrics for a Random Forest classifier. Overall accuracy shows how well the model performs across all data points, without accounting for deeper nuances such as randomness and imbalance. Conversely, the Kappa Index ensures that performance evaluation is fairer or more reliable in complex scenario such as imbalanced datasets or multi-class classification problems. The results of this training process and the key performance metrics are presented in Tab. 4. The confusion matrix obtained by Random Forest classification is shown in Fig. 2. Values 0, 1, 2, and 3 on the *X*- and *Y*-axes correspond to the following vegetation types: 0 for coniferous forest; 1 for deciduous forest; 2 for wetland vegetation and 3 for coastal meadows. In this case, OA is equal to 80 %. It indicates that every instance was classified correctly, i. e., flawless performance in distinguishing different types of vegetation.

Tab.4. Performance metrics table of Random Forest Classification with NDVI

Vegetation classes	Precision value	Recall value	f1–Score value	Support value
Coniferous forest	0.92	0.88	0.90	515 253
Deciduous forest	0.78	0.82	0.80	26 187
Wetland vegetation	0.75	0.70	0.72	57 311
Coastal meadows	0.70	0.80	0.75	106 425

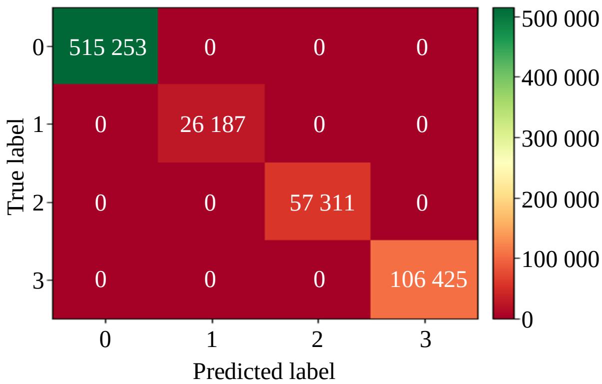

Fig. 2. NDVI confusion matrix evaluation

The second stage of the study involved training the dataset using the RVI alone, with the purpose of assessing its efficacy in classifying vege-

Tab.5. Performance metrics of Random Forest classification with RVI

Vegetation classes	Precision value	Recall value	f1–Score value	Support value
Coniferous forest	0.70	0.75	0.72	33 203
Deciduous forest	0.75	0.68	0.71	1247
Wetland vegetation	0.80	0.70	0.75	3697
Coastal meadows	0.90	0.95	0.92	70 5353

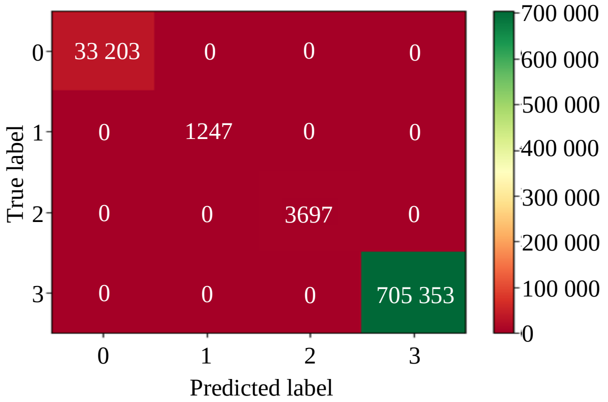

Fig. 3. RVI Confusion matrix evaluation

tation. The outcomes of this procedure are illustrated in Tab. 5 and Fig. 3, where the confusion matrix obtained by Random Forest is presented. In this case, OA is equal to 76 %. The model also correctly predicts the outcome of all the instances. This level of performance is sufficient, considering challenges related to radar sensor limitations and vegetation complexity. The confusion matrices presented in Figs. 2 and 3 and the performance metrics in Tab. 4 and 5 show that coniferous forest is best identified by NDVI. In contrast, radar-based indices are more suited for predicting independently coastal meadows.

Fusion approach using deep learning techniques. The first step of the proposed fusion approach involves the efficiency analysis of the NDVI, MNDWI and SAVI used in combination for classifying different types of vegetation [12, 13]. Tab. 6 and Fig. 4, *a* show the confusion matrix obtained by the Random Forest classifier and the respective performance metrics. The combined use of NDVI, MNDWI and SAVI achieved an overall accuracy of 90 %.

The second step of the proposed fusion method involves the assessment of the combined efficiency of RVI, MNDWI and SAVI in distinguishing vegetation types [14, 15]. The results of this procedure are displayed in Tab. 7 and Fig. 4, *b*, showcasing the confusion matrix and metrics parameters generated by Random Forest. The achieved overall accuracy was 87 %.

Tab. 6. Performance metrics table of Random Forest Classification with NDVI_MNDWI_SAVI

Vegetation classes	Precision value	Recall value	f1–Score value	Support value
Coniferous forest	0.85	0.88	0.86	496 664
Deciduous forest	0.75	0.72	0.73	64 830
Wetland vegetation	0.70	0.68	0.69	139 772
Coastal meadows	0.65	0.60	0.62	2835

Tab. 7. Performance metrics obtained by Random Forest classification with RVI, MNDWI, and SAVI

Vegetation classes	Precision value	Recall value	f1–Score value	Support value
Coniferous forest	0.95	0.93	0.94	13 564
Deciduous forest	0.92	0.90	0.91	534 779
Wetland vegetation	0.88	0.87	0.87	142 610
Coastal meadows	0.85	0.80	0.82	14 223

Tab. 8. Performance metrics obtained by Random Forest classification with NDVI, RVI, MNDWI, and SAVI

Vegetation classes	Precision value	Recall value	f1–Score value	Support value
Coniferous forest	0.98	0.97	0.97	268 757
Deciduous forest	0.97	0.95	0.95	67 910
Wetland vegetation	0.94	0.93	0.93	142 218
Coastal meadows	0.92	0.90	0.91	225 216

The final step of the fusion method involves analyzing the efficiency of NDVI, RVI, MNDWI and SAVI when used in combination in differentiating vegetation types. The outcomes of this analysis are presented in Tab. 8 and Fig. 4, *c*, which illustrate the confusion matrix and performance metrics obtained by Random Forest. The achieved overall accuracy was 95 %.

Comparison of density variations among vegetation types using the proposed fusion method. This section of the study focuses on the analysis of density variations across different vegetation types, using the developed fusion method.

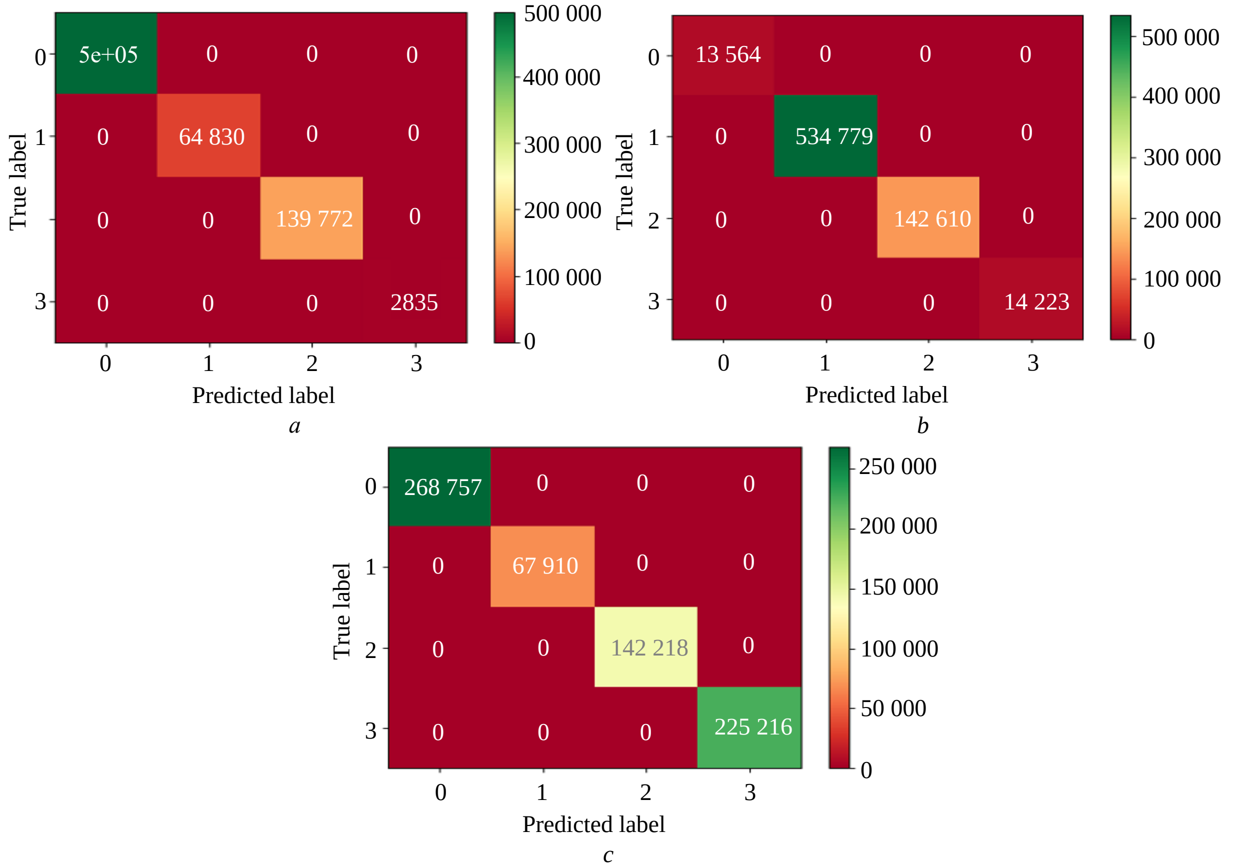

Fig. 4. Fusion confusion matrix evaluation: *a* – NDVI, MNDWI and SAVI; *b* – RVI, MNDWI and SAVI; *c* – NDVI_RVI, MNDWI and SAVI

The initial stage of this analysis involved a detailed examination of the violin plot in Fig. 5, *a* generated from the first iteration of the fusion approach by combining the NDVI, MNDWI and SAVI. It can be seen from Fig. 5, *a* that the combination of NDVI, MNDWI and SAVI yields an excellent level of coniferous forest prediction. Such forests are characterized by a high density of evergreen trees, leading to elevated NDVI values. The use of SAVI can minimize soil effects, allowing for a more accurate detection of coniferous forest cover. The prediction accuracy of deciduous forest is lower, due to seasonal leaf loss. While SAVI still aids in detecting deciduous forest trees, the variability in leaf cover throughout seasons may lead to less consistent predictions. The prediction effectiveness of wetland vegetation is moderate due to the presence of water, which is influenced by MNDWI. The poor prediction of coastal meadows is due to low reflectance values across all indices.

The second stage included a detailed analysis of the violin plot in Fig. 5, *b*, obtained from the second iteration of the fusion approach by integrating RVI, MNDWI and SAVI. The combination of RVI, MNDWI and SAVI may yield a marginal level of coniferous forest prediction due to its distinct structural characteristics that may not be as pronounced in radar data as those of deciduous forest. For comparison, deciduous forest is predicted with a high level of accuracy, because a combination of SAVI and RVI captures variations in leaf area throughout seasons. Fair prediction of wetland vegetation is achieved by a combination of RVI and SAVI. The diverse plant species found in wetlands may lead to mixed signals in RVI and SAVI, resulting in fair but not perfect predictions. The marginal level of coastal meadow prediction is related to its spectral signature overlap with other land cover types, leading to ambiguity in predictions.

The final stage of this analysis involved a comprehensive examination of the violin plot in Fig. 5, *c*, derived from the third iteration of the fusion approach by combining NDVI, RVI, MNDWI and SAVI. This fusion resulted in perfect predictions of coniferous forest. This type of vegetation exhibits a strong reflectance in the NIR spectrum due to chlorophyll content, thus producing a perfect prediction model. While the fused indices provide

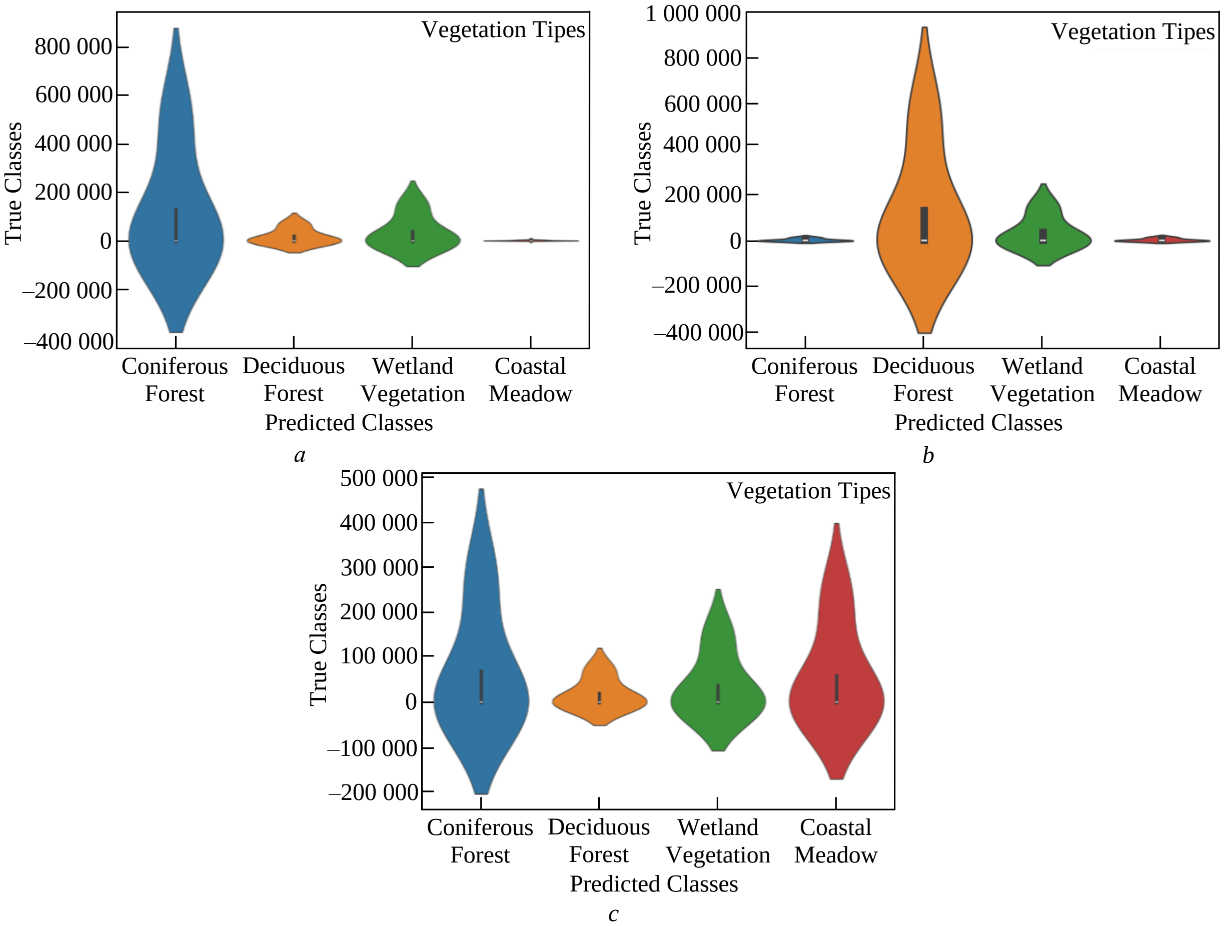

Fig. 5. Vegetation classes distribution: *a* – Vegetation classes distribution (NDVI, MNDWI and SAVI); *b* – Vegetation classes distribution (RVI, MNDWI and SAVI); *c* – Vegetation classes distribution (NDVI, RVI, MNDWI and SAVI)

moderate predictions of deciduous forest due to seasonal variations in the leaf area index, they still capture essential characteristics that allow for reasonable classification accuracy. The integration of MNDWI enhances the capacity of the model to identify wetland area by highlighting water presence alongside vegetation cover. In addition, the model is capable of producing perfect predictions by leveraging the distinct spectral signatures associated with coastal flora and proximity to water bodies.

Results. In this study, the Random Forest algorithm was implemented using two different independent training sets: one for the NDVI and another for the RVI. Additionally, three iterations of the proposed fusion approach were employed, integrating NDVI, RVI, MNDWI and SAVI. The results and comparison of all proposed training models are presented in Tab. 9, 10 and 11. The classification results can be seen in Fig. 6.

Discussion. The conducted research demonstrates the advantages of the proposed fusion method for generating accurate vegetation classification maps using the Random Forest algorithm. Vegetation classification is an essential task in ecological research, land cover

Tab. 9. Performance metrics obtained by Random Forest classification with RVI, MNDWI, and SAVI

Model	Overall Accuracy, %	Kappa Index, %
NDVI	76	70
RVI	80	73
NDVI, MNDWI, SAVI	87	80
RVI, MNDWI, SAVI	90	87
NDVI_RVI, MNDWI, SAVI	95	90

Tab. 10. Classification result by class for the Random Forest algorithm

Vegetation types	NDVI	RVI	NDVI MNDWI SAVI	RVI MNDWI SAVI	NDVI_RVI MNDWI SAVI
Coniferous forest	Present	Present	Present	Present	Present
Deciduous forest	Present	Present	Present	Present	Present
Wetland vegetation	Present	Present	Present	Present	Present
Coastal meadows	Present	Present	Present	Present	Present

Tab. 11. Class-wise agreement level for the Random Forest classification

Vegetation types	NDVI	RVI	NDVI MNDWI SAVI	RVI MNDWI SAVI	NDVI_RVI MNDWI SAVI
Coniferous forest	Perfect	Very slight	Perfect	Slight	Perfect
Deciduous forest	Very slight	Poor	Fair	Perfect	Moderate
Wetland vegetation	Slight	Poor	Moderate	Fair	Almost perfect
Coastal meadows	Fair	Perfect	Poor	Slight	Perfect

mapping, and agricultural management. Individual spectral indices, such as NDVI, RVI, MNDWI and SAVI, are widely used. However, these indices have limitations in distinguishing spectrally similar vegetation types or in areas with a complex canopy structure. The fusion approach that integrates multiple indices or different types of remote sensing data provides a richer feature space for training the Random Forest algorithm.

This study employed the Random Forest algorithm, a powerful ensemble learning method well suited for handling high-dimensional data and less prone to overfitting than other classification algorithms. Class-wise agreement for the Random Forest classification is given in Tab. 11. By using the diverse feature set obtained through data fusion, subtle differences between vegetation classes can be captured more effectively. Increased classification accuracy and reduced error rates are direct benefits of the proposed fusion approach. The improved accuracy of the resulting vegetation map (Fig. 6) has significant implications for biodiversity conservation, agricultural yield prediction, deforestation monitoring, etc.

Conclusion. The present study has achieved improved classification of urban vegetation on Kotlin Island (St Petersburg), thus demonstrating the substantial benefits of integrating multiple data sources for environmental analysis. The findings underscore two principal outcomes.

First, the data fusion approach enables a more precise identification of erosion-prone zones in non-vegetated areas and facilitates estimation of plant moisture content. This result is consistent with basic principles in landscape ecology and remote sensing, where multispectral and multi-source data fusion is essential for capturing complex ecological patterns and processes.

Second, the results clearly demonstrate the superiority of the fusion approach over individual index-based methods. The fusion methodology yields a significantly higher classification accuracy and reduced error rates across all studied vegetation types. This finding is consistent with established research in environmental monitoring and geospatial sciences, which highlights that data integration techniques enhance both the thematic resolution and reliability of land cover classification.

Moreover, these advancements have practical implications for ecosystem management. Accurate mapping of erosion-prone areas supports targeted conservation efforts and sustainable land use planning, which are critical priorities emphasized in contemporary forest ecology literature.

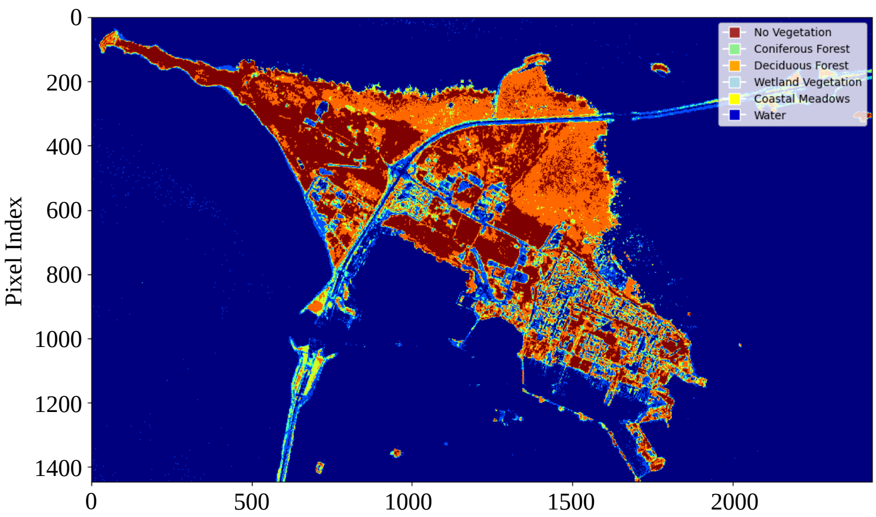

Fig. 6. Resulting vegetation classification map

In summary, this study confirms that integrated data analysis not only refines our understanding of diverse plant environments but also provides actionable information for ecological management. The proven effectiveness of this fusion approach supports its wider adoption in future environmental assessments.

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Information about the authors

Jacques B. Ngoua Ndong Avele, Bachelor in Omar Bongo University, Libreville, Gabon, Master's degree in Quantum and Optical Electronics (2024, Saint Petersburg Electrotechnical University). Postgraduate student of the Department of Radio Engineering Systems in Radio Navigation and Radar of Saint Petersburg Electrotechnical University. The author of 6 scientific publications. Area of expertise: Earth remote sensing; lidars; radars; unmanned aerial vehicles; spacecraft; machine learning.

Address: Saint Petersburg Electrotechnical University, 5 F, Professor Popov St., St Petersburg 197022, Russia
E-mail: avelejacques@yahoo.fr
https://orcid.org/0009-0004-6564-0743