Assessment of Surface Water Detection Using Sentinel-1 SAR Data: Case Study Vojvodina Province

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This study assesses the utility of Sentinel-1 Synthetic Aperture Radar (SAR) data for surface water detection in Vojvodina province. Using multi-temporal SAR imagery from January 2022 to April 2024, machine learning classifiers including Random Forest, KDTree KNN, and Maximum Likelihood were employed to classify water bodies and non-water areas. Polarized indices derived from Sentinel-1 data, such as the Polarized Ratio, Normalized Difference Polarized Index, and Dual-Polarized Water Index, were utilized to enhance water body detection. Despite challenges in accurately identifying narrow canals, the study achieves a notable overall accuracy of 92.68% with Random Forest, 92.08% with KDTree KNN, and 91.58% with Maximum Likelihood for water classification. Producer accuracy for the water class ranges from 87.75% to 89.65%, while User's accuracy exceeds 96.50% across all classifiers. The calculated Cohen's Kappa coefficients of 0.83 to 0.85 indicate substantial agreement between predicted and reference data, underscoring the effectiveness of Sentinel-1 SAR data in surface water detection. However, spatial resolution limitations present ongoing challenges, particularly in accurately delineating narrow water features like canals. Future research directions include refining algorithms to enhance classification accuracy and addressing these challenges in diverse environmental contexts.

Key Words: *Synthetic Aperture Radar, Sentinel-1, Random Forest, KDTree, Maximum Likelihood*

1. INTRODUCTION

Water and rivers are extremely important for humanity, as they are essential for our survival and play crucial roles in different aspects of our lives and the surroundings. Primarily, they serve as vital sources of fresh water, necessary for drinking, hygiene, farming, and industrial operations. Lack of clean water from rivers would greatly impact human health, agriculture, and economic undertakings.

Rivers are essential for transportation, business, and industry. Throughout history, they have been important trade routes, having aided in the transportation of goods and people throughout history, they remain key players in worldwide trade connections. Moreover, industries like hydroelectric power generation, fishing, and tourism depend on river assets for financial success.

From an environmental standpoint, rivers play a role in climate control and conservation. They impact local and regional weather patterns by methods such as evaporation and transpiration, along with managing water cycles and helping to prevent floods and droughts. Maintaining the health of river ecosystems is crucial for lessening the effects of climate change and protecting our natural resources [1].

Detecting surface water is crucial for several reasons, including environmental management, disaster response, water resource planning, and scientific research. Mainly, accurate surface water detection provides insights into the distribution, extent,

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and dynamics of water bodies, enabling effective management of water resources and ecosystems.

Environmental management relies on surface water detection to monitor changes in aquatic habitats, wetlands, and riparian zones. Understanding the spatial and temporal distribution of surface water helps in assessing the health of ecosystems, identifying areas of conservation importance, and implementing measures for habitat restoration and protection of biodiversity [2].

In disaster response and risk mitigation, early detection of surface water is critical for assessing and monitoring flood occurrences, which can have severe consequences for populations, infrastructure, and agriculture. Surface water detection-based early warning systems make it easier to organize evacuations, coordinate emergency responses, and conduct flood control measures in order to reduce human casualties and property damage.

Surface water detection is also an important part of water resource planning and management. By precisely mapping water bodies, authorities may estimate water availability, monitor changes in water levels and quality, and make educated decisions about water distribution, irrigation management, and drought response tactics. This knowledge is critical for guaranteeing the long-term use of water resources and maintaining water security for both human consumption and environmental demands [3].

In addressing the challenge of surface water detection, researchers have two primary options: optical or radar remote sensing methods. Each approach offers distinct advantages and considerations, shaping their suitability for different applications and environmental conditions.

When comparing radar to optical methods of acquiring data for surface water detection, several key differences and advantages emerge. Radar Remote Sensing, such as that provided by sensors like Sentinel-1, utilizes microwave wavelengths to penetrate cloud cover, vegetation, and even soil, allowing for all-weather, day-and-night imaging capabilities. This means that radar data acquisition is not hindered by atmospheric conditions or sunlight availability, making it particularly useful for monitoring surface water in cloudy or dark environments where optical sensors may struggle to capture clear imagery. Additionally, radar signals are sensitive to surface roughness and moisture content, enabling the detection of subtle variations in water presence and dynamics. On the other hand, optical Remote Sensing, represented by sensors like Sentinel-2, relies on the reflection of sunlight across different wavelengths of the electromagnetic spectrum to capture images. While optical sensors provide higher spatial resolution and detailed spectral information, they are limited by cloud cover and cannot penetrate vegetation or soil, which may obstruct the view of surface water features. Consequently, the choice between radar and optical data depends on factors such as environmental conditions, desired spatial resolution, and specific research objectives, with radar offering unique advantages for surface water detection in challenging or adverse conditions.

2. DATA AND STUDY AREA

Vojvodina, situated in the northern part of Serbia, is a region distinguished by its diverse geography, abundant waterways, and fertile plains. Geo-graphically, it lies within the Pannonian Basin, a vast lowland area characterized by flat terrain and rich alluvial soils. The region is bordered by the Danube River to the north, the Tisa River to the east, and the Sava River to the south, with Hungary to the north and Croatia to the west.

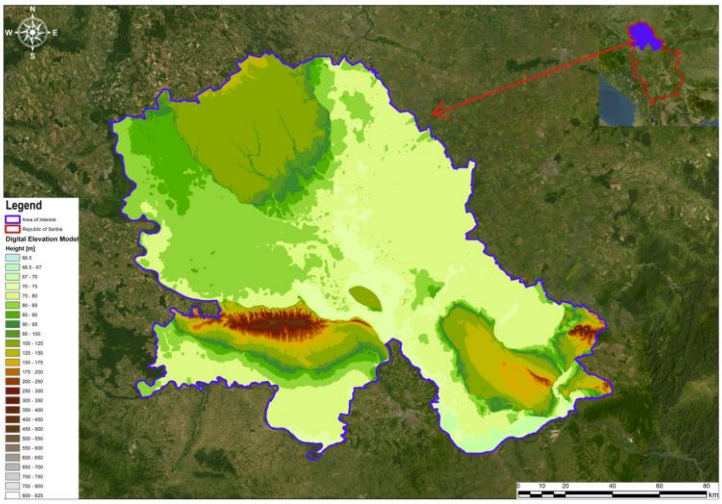

Figure 1 - Study Area

Vojvodina encompasses a total area of 21.500 square kilometers within the specified boundaries. Vojvodina is a rather flat plain with altitudes ranging from 68 to 120 metres above sea level. The Fruška Gora (538 m) and Vršac Mountains (639 m) rise above the broad plain, gently sloping southeastward.The rivers and waterways of Vojvodina are integral to its landscape and economy. The Danube, Europe's second-longest river, flows along Vojvodina's northern border. It serves as a major transportation artery and a vital source of water for irrigation and industry. The Tisa River, originating in the Carpathian Mountains, traverses eastern Vojvodina, while the Sava River forms part of the region's southern boundary, joining the Danube near Belgrade.

In addition to its rivers, Vojvodina is crisscrossed by an extensive network of canals and irrigation channels. These channels were historically constructed to drain marshlands, regulate water levels, and facilitate agriculture. These waterways play a crucial role in managing water resources and mitigating flood risks, particularly during periods of heavy rainfall or snowmelt.In Figure 1, the study area is depicted, showcasing the Vojvodina region in northern Serbia.

The territory of Vojvodina, in accordance with the conditions of its formation, represents a specific pedogeographical region, i.e., a steppe and forest-steppe area of the Pannonian Plain and its peripheral part, which is covered in geomorphological terms by [4]:

- Alluvial deposits on river terraces, where fluvisols, semigley soils, swampy black soils, marshy-gley soils, and halomorphic soils develop.
- Loess plateaus with chernozem and loess terraces where chernozem-gleyed soils and solonetz develop.
- Aeolian sand with types including arenosols, rendzinas, and chernozems.

This area is renowned for its diverse landscape and abundant water resources, making it an ideal focal point for our analysis of surface water detection using Sentinel-1 SAR data. Encompassing the major rivers such as the Danube, Tisa, and Sava, as well as numerous lakes, wetlands, and agricultural fields characteristic of the Vojvodina plains, the study area offers a geographically diverse range of surface water features. The aim of focusing on this region is to assess the effectiveness of Sentinel-1 imagery in detecting surface water dynamics and identifying water bodies of varying sizes and characteristics.

The analysis utilizes time-series Sentinel-1 data spanning from January 1, 2022, to April 2024, comprising a total of 52 scenes. Sentinel-1 data provides valuable information on surface water dynamics due to its frequent revisit times and all-weather imaging capability. This dataset enables the detection of temporal changes in surface water extent over the study period.

Table 1. Sentinel-1 Mission and Data Characteristics

Mission Identifier	Instrument acquisition mode	Product type	Processng level	Resolution Class	Polarizaton
S1A	*Interferometric Wide swath - IW*	*GRD*	*Level-1*	*"H" – High resolution*	*Dual (VV/VH)*

Temporal analysis of the Sentinel-1 data reveals fluctuations in surface water patterns over time. These variations may be influenced by seasonal changes, inter-annual variability in precipitation, land use alterations, and anthropogenic activities.

In this study, Sentinel-1A Synthetic Aperture Radar (SAR) imagery, encompassing both VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive) polarizations, served as the primary data source.

The Level-1 Ground Range Detected (GRD) product, specifically the Interfero-metric Wide (IW) swath data, was acquired through batch downloads via the ESA Copernicus Open Access Hub API. These GRD products were previously processed to account for detection, multi-looking, and ground range projection, utilizing the Earth ellipsoid model WGS84 [5].

The European Space Agency's Copernicus programme includes the Sentinel-1 mission, comprising two satellites launched on April 3, 2014, and April 22, 2016. These satellites operate in opposite polar sun-synchronous orbits at an altitude of 693 km, with a repeat cycle of 12 days and 175 orbits. This setup yields a repeat frequency of 24 hours at high latitudes and 3 days at the equator. The SAR system onboard operates within the C-band (5.407 GHz) frequencies and offers four acquisition modes: Stripmap (SM), Interferometric Wide swath (IW), Extra-Wide swath (EW), and Wave (WV) [6].

3. METHODOLOGY

3.1. Sentinel – 1 Preprocessng

In order to ensure the accuracy, dependability, and interpretability of the final results, preprocessing is an essential stage in the analysis of remote sensing data, including Sentinel-1 imagery.

Preprocessing included the following steps:

- Applying Orbit File;
- Thermal Noise Removal;
- Calibration;
- Speckle Filtering;
- Range Doppler Terrain correction,
- Conversion to dB
- Creating a multi-temporal stack

Typically, orbit state vectors that are included in the metadata of SAR products are not precise. After a few days, the exact orbits of satellites are ascertained and made available days or weeks after the product is generated. Applying a precise orbit from SNAP enables the automatic download and updating of orbit state vectors for every SAR scene in the product metadata, giving precise information about the position and velocity of the satellite [7].

The removal of thermal noise is a critical pre-processing stage in eliminating disturbances from a sensor's thermal properties. This noise can potentially affect the precision of subsequent analyses and degrade the quality of radar imagery. Therefore, it is imperative to address this issue effectively to maintain the integrity of the data [8].

Speckle, caused by the interference of waves reflected from numerous elementary scatterers, appears as granular noise in SAR images. [9].

The process of „speckle filtering“ lowers speckle in order to improve image quality. Speckle is prevented from spreading during ongoing procedures (such as terrain correction or conversion to dB) when such a method is carried out at an early stage of processing SAR data. When trying to identify microscopic spatial features or texture in a picture, speckle filtering should be avoided since it may exclude important information. Because it can retain edges, linear features, point targets, and texture information, the improved Lee filter has been proven to be better for visual interpretation than previous single product speckle filters [10].

Range Doppler terrain correction utilizes a digital elevation model to adjust the location of each pixel, correcting geometric distortions caused by topography, including shadows and foreshortening.

Finally, a logarithmic transformation is used to convert the unitless backscatter coefficient to dB as part of the preprocessing routine.

Prior to the surface water detection analysis, a multi-temporal stack of Sentinel-1 data was generated using the Sentinel Application Platform (SNAP).

The study further involved the creation of a validation dataset using a RGB composite of Sentinel-2 data acquired on April 25, 2024. This dataset comprises 14,164 points distributed across the study area. Each point in the dataset is assigned to one of two classes: Water or Non-water.

Through photo interpretation, each point within the dataset, totaling 14,164 points across the study area, was manually labeled as either Water or Non-water based on the visual characteristics observed in the RGB composite. Water bodies, characterized by distinct spectral signatures and spatial patterns, were identified and classified accordingly, while non-water features such as land cover types were also delineated. By visually inspecting the imagery and assigning class labels to each point, the validation dataset offers a reference for evaluating the performance of the detection algorithm and validating the results.

3.2. Sentinel 1 – indices

To enhance the detection of surface water bodies, several indices were derived from the VV and VH polarization data of Sentinel-1 imagery. These indices included the Polarized Ratio (VV to VH), Normalized Difference Polarized Index (NDPI), Normalized VH Index, Normalized VV Index, and the Dual-Polarized Water Index (SDWI). Each index was computed to exploit the distinctive backscatter characteristics of water bodies compared to other land cover types. The expressions for these indices are presented in Table 2.

Table 2. Polarized indices derived from Sentinel-1 SAR data

Index	Equation	Ref.
Polarized Ratio (VV to VH)	$\frac{\sigma_{VV}}{\sigma_{VH}}$	[11]
Normalized Difference Polarized Index	$\frac{\sigma_{VV} - \sigma_{VH}}{\sigma_{VV} + \sigma_{VH}}$	[12]
Normalized VH index	$\frac{\sigma_{VH}}{\sigma_{VV} + \sigma_{VH}}$	[12]
Normalized VV index	$\frac{\sigma_{VV}}{\sigma_{VV} + \sigma_{VH}}$	[12]
Dual-Polarized water index	$\ln(10 \times \sigma_{VH} \times \sigma_{VV})$	[14]

3.3. Classification Methods

To classify surface water bodies from the derived indices, several machine learning classifiers were employed. These classifiers were chosen for their effectiveness in handling high-dimensional remote sensing data and their ability to provide robust classification results. The classifiers used in this study included the Random Forest Classifier, KD-Tree K-Nearest Neighbors (KNN) Classifier, and Maximum Likelihood Classifier (MLC).

The Random Forest Classifier is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification. It is highly effective in dealing with large datasets and can handle overfitting issues by averaging multiple trees. The KD-Tree K-Nearest Neighbors (KNN) Classifier classifies a data point based on the majority class among its k-nearest neighbors, which are determined by distance metrics. The KD-Tree structure efficiently organizes the data for rapid nearest neighbor searches, making the classification process faster. The Maximum Likelihood Classifier (MLC) is a statistical method that assigns each pixel to the class with the highest probability based on the pixel's spectral signature. It assumes that the data for each class in each band are normally distributed and calculates the probability of a pixel belonging to a specific class.

3.4. Validation and Accuracy Assessment

Quantitative analysis involves assessing the agreement between the flood extent delineated in the generated map and the water features observed in the reference images. This can be achieved through different statistical measures like the Kappa coefficient, Producer and User's Accuracy, and F1 score. These metrics offer quantitative insights into the accuracy, completeness, and correctness of the flood mapping results.

Various metrics utilize the information from the four components of a binary confusion matrix: true positives (TPs), true negatives (TNs), false positives (FPs), and false negatives (FNs). In this context, the emphasis is on four commonly employed metrics in geomatics. Specifically, for per-class accuracy, the metrics encompass the producer's and user's accuracy for the positive class, commonly known as recall and precision, respectively.

These metrics are derivable from [15]:

$$Producer's\ accuracy\ (PA) = \frac{TP}{TP+FN} \quad (1)$$

$$User's\ accuracy\ (OA) = \frac{TP}{TP+FP} \quad (2)$$

The F1 score is a widely utilized metric in binary classification tasks, and it can also be applied to multi-class classification by calculating it separately for each class and then averaging the results. The F1 score is a metric that combines the Producer's and User's Accuracy, giving a well-rounded evaluation of a model's performance in classification tasks. It is determined by taking the harmonic mean of Producer's and User's Accuracy), resulting in a consolidated value that reflects both aspects effectively.

The formula for calculating the F1 score is:

$$F_1 = \frac{2 \times TP}{2 \times TP+FP+FN} \quad (3)$$

The F1 score reaches its optimal value at 1 when both Producer's and User's Accuracy are maximized, indicating that the model achieves high precision and recall simultaneously. The Cohen's Kappa coefficient, commonly known as Kappa, is a statistical measure that assesses the level of agreement between observed and expected classifications, taking into consideration the potential for agreement to happen randomly. This metric is valuable for assessing the effectiveness of classification models, particularly in the context of imbalanced datasets.

The formula for calculating Cohen's Kappa coefficient is [16]:

$$k = \frac{p_o - p_e}{1-p_e} \quad (4)$$

where p_o and p_e:

$$p_o = \frac{TP+FN}{TP+TN+FP+FN} \quad (5)$$

4. DISCUSION AND RESULTS

In Table 3, the Producer and User's Accuracy metrics for water and non-water classes are presented across three classifiers: Random Forest, KDTree KNN, and Maximum Likelihood. These metrics offer insights into the reliability and effectiveness of the surface water detection process, showcasing the accuracy of classifying areas as surface water bodies and non-water areas.

Table 3 provides additional metrics, such as Overall Accuracy, F1-score, and Cohen's Kappa statistics for the classifiers mentioned above.

Table 3. User's and Producer's Accuracy

Classifier	Class	Producer Accuracy [%]	User Accuracy [%]
Random Forest	Water	89.65	97.11
	Non - water	96.58	87.89
KDTree KNN	Water	88.63	97.02
	Non - water	96.50	86.86
Maximum Likelihood	Water	87.75	96.99
	Non - water	96.50	85.97

Table 4. Provides additional metrics, such as Overall Accuracy, F_1 – score and Cohen's Kappa statistics.

Classifier	Overall Accuracy [%]	F_1 - score	Cohen's Kappa
Random Forest	92.68	0.92	0.85
KDTree KNN	92.08	0.91	0.84
Maximum Likelihood	91.58	0.90	0.83

The analysis of water body detection using Sentinel-1 data yielded promising results, as depicted in Table 3 and Table 4. Table 3 presents the User's and Producer's Accuracy specifically for the water class across different classifiers. The Producer's Accuracy for the water class stood at 89.65% with Random Forest, 88.63% with KDTree KNN, and 87.75% with Maximum Likelihood, demonstrating a strong capability in identifying water areas.

Furthermore, the high User's Accuracy of 97.11% for the water class with Random Forest, 97.02% with KDTree KNN, and 96.99% with Maximum Likelihood signifies a reliable classification of water pixels among all pixels classified as water by the used classifiers.

Table 4. provides additional accuracy metrics, revealing an Overall Accuracy of 92.68% with Random Forest, 92.08% with KDTree KNN, and 91.58% with Maximum Likelihood specifically for water classification.

The F1-score, measuring the balance between precision and recall for water surface classification, was calculated at 0.92 with Random Forest, 0.91 with KDTree KNN, and 0.90 with Maximum Likelihood, indicating a robust performance of the model in accurately delineating water surfaces. Moreover, Cohen's Kappa coefficient of 0.85 with Random Forest, 0.84 with KDTree KNN, and 0.83 with Max-imum Likelihood underscores a substantial agreement between the extracted and the reference data for water surface detection.

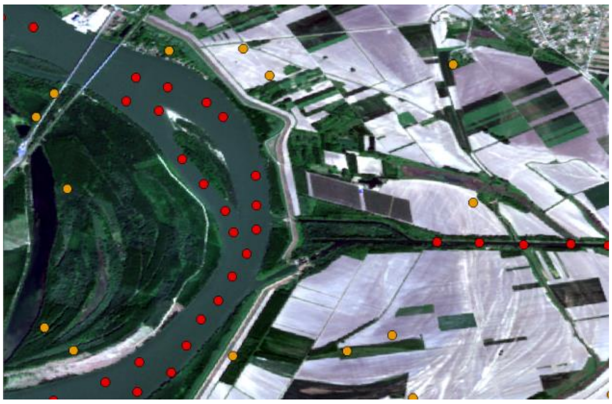

Figure 2 - Sentinel-2 RGB composite with validation points (red – water; orange – non water)

Figure 3 - Random Forest Classification Map of Surface Water Bodies

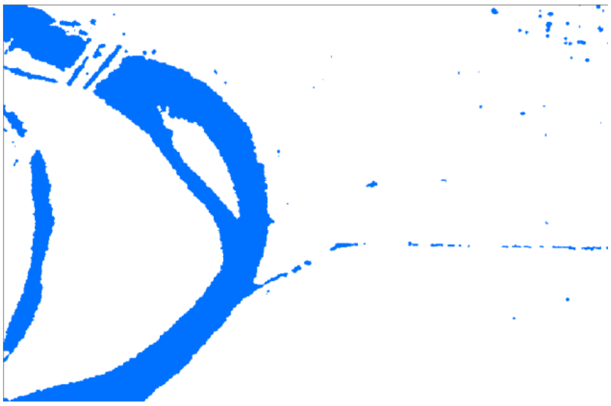

Figure 4 - KDTree Classification Map of Surface Water Bodies

Figure 5 - Maximum Likelihood Classification Map of Surface Water Bodies

Figure 3 shows the classification of surface water bodies using the Random Forest classifier. The high User's Accuracy of 97.11% and Producer's Accuracy of 89.65% for the Water class underscore its effectiveness in identifying water areas despite challenges posed by narrow features.

Figure 4 illustrates the classification results achieved with the KDTree KNN classifier. With a User's Accuracy of 97.02% and Producer's Accuracy of 88.63% for the Water class, this classifier also demonstrates robust performance in delineating water surfaces.

Figure 5 displays the classification outcomes obtained from the Maximum Likelihood classifier. It achieved a User's Accuracy of 96.99% and Producer's Accuracy of 87.75% for the Water class, reaffirming its capability in accurately detecting water bodies despite the inherent challenges. These classification maps provide visual representations of how each classifier performs in identifying surface water bodies, reflecting their respective strengths and areas for potential improvement in handling narrow water features and maintaining accuracy in water body detection algorithms.

The lower Producer's accuracy for Water class may be attributed to the presence of numerous narrow canals within the study area. These narrow water features may pose challenges for the classification algorithm, resulting in misclassification of pixels as non-water. The limited spatial resolution of the Sentinel-1 data may contribute to this misclassification, as narrow water bodies may not be adequately captured or distinguished from surrounding land cover types.

The spatial resolution of the imagery may contribute to the difficulty in detecting narrow features, as the limited pixel size may not adequately represent the width of the canals. Furthermore, variations in canal filling levels over time could lead to fluctuations in backscatter intensity, further complicating the detection process. Thus, while lowering the threshold may enhance the detection of narrow canals, it necessitates careful consideration of the tradeoffs between false positives and false negatives, ultimately highlighting the importance of balancing accuracy and comprehensiveness in water body detection algorithms.

5. CONCLUSION

Based on the comprehensive analysis and results presented, the application of Sentinel-1 data coupled with machine learning classifiers has proven effective in detecting surface water bodies. The study utilized a robust preprocessing pipeline, including orbit correction, thermal noise removal, calibration, speckle filtering, terrain correction, and conversion to dB, ensuring the reliability and accuracy of the derived data.

Indices derived from Sentinel-1 imagery, such as the Polarized Ratio, Normalized Difference Polarized Index, and Dual-Polarized Water Index, were instrumental in enhancing the identification of water bodies amidst various land cover types. These indices leverage the distinctive backscatter characteristics of water, highlighting their utility in remote sensing applications.

The evaluation of classification performance across Random Forest, KDTree KNN, and Maximum Likelihood classifiers demonstrated high accuracy metrics for detecting water surfaces. Specifically, the Random Forest classifier exhibited notable Producer's and User's Accuracy, achieving 89.65% and 97.11% respectively for the Water class. Similarly, KDTree KNN and Maximum Likelihood classifiers also performed well, emphasizing their robustness in classifying water bodies despite challenges posed by narrow water features.

Overall, the study achieved an impressive Overall Accuracy of 92.68% with Random Forest, 92.08% with KDTree KNN, and 91.58% with Maximum Likelihood for water classification. The F1-score and Cohen’s Kappa coefficients further underscored the models' efficacy in balancing precision and recall, affirming their reliability in water surface detection.

However, challenges such as the spatial resolution limitations of Sentinel-1 data, particularly in detecting narrow water features like canals, were identified. These limitations may lead to occasional misclassifications, highlighting the need for careful consideration of threshold adjustments to optimize detection accuracy while managing trade-offs between false positives and false negatives.

In conclusion, the integration of Sentinel-1 data with advanced preprocessing techniques and machine learning classifiers presents a robust approach for monitoring and mapping surface water dynamics. Future research could focus on refining algorithms to better handle spatial resolution challenges and further improving classification accuracy in diverse environmental contexts. This study contributes valuable insights and methodologies applicable to broader applications in hydrology, environmental monitoring, and disaster management using remote sensing technologies.

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REZIME

PROCENA DETEKCIJE POVRŠINSKIH VODA KORIŠĆENJEM SENTINEL-1 SAR PODATAKA: STUDIJA SLUČAJA REGIJA VOJVODINA

Ova studija procenjuje korisnost podataka sintetičkog radara sa aperturom (SAR) Sentinel-1 za detekciju površinskih voda u pokrajini Vojvodini. Korišćenjem ševremenskih SAR snimaka od januara 2022. do aprila 2024. godine, primenjeni su mašinsko učenje klasifikatori uključujući Random Forest, KDTree KNN i Maximum Likelihood kako bi se klasifikovale vodene površine i oblasti koje nisu vode. Polarizovani indeksi izvedeni iz Sentinel-1 podataka, kao što su Polarizovani odnos, Normalizovani diferencijalni polarizovani indeks i Dualno-polarizovani indeks za vodu, korišćeni su kako bi se poboljšala detekcija vodenih površinskih tela. Uprkos izazovima u preciznom identifikovanju uskih kanala, rezultati dostižu značajnu ukupnu tačnost od 92,68% sa Random Forest, 92,08% sa KDTree KNN i 91,58% sa Maximum Likelihood klasifikatorom za klasifikaciju vodenih površina. Proizvođačeva tačnost za klasu vode kreće se od 87,75% do 89,65%, dok korisnička tačnost prelazi 96,50% kod svih korišćenih klasifikatora. Kappa koeficijenti od 0,83 do 0,85 ukazuju na značajan stepen saglasnosti između predviđenih i referentnih podataka, ističući efikasnost Sentinel-1 SAR podataka u detekciji površinskih voda. Međutim, ograničenja prostorne rezolucije predstavljaju stalni izazov, posebno u preciznom razgraničavanju uskih vodnih karakteristika poput kanala. Budući istraživački pravci uključuju usavršavanje algoritama radi poboljšanja tačnosti klasifikacije i rešavanje ovih izazova u različitim ekološkim slučajevima.

Ključne reči: *radar sa sintetičkom blendom, Sentinel-1, slučajna šuma, KD stablo, maksimalna verodostojnost*