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MAPPING OF INLAND EXCESS WATER USING GEOGRAPHICAL INFORMATION SYSTEM AND HIGH-RESOLUTION SATELLITE IMAGES: A CASE STUDY OF SREM, SERBIA

Abstract: Extreme hydrological events, such as floods and droughts, are becoming more frequent as a result of climate change, leading to negative impacts on various economic sectors. The Pannonian-Carpathian Basin is particularly affected by the increasing frequency of hazardous hydrological events. Agricultural production, which is a highly significant economic sector in the region, is particularly vulnerable to these unfavourable climatic conditions. Changes in precipitation patterns and soil moisture levels can lead to reduced crop yields, while floods can pollute water sources and erode fertile soil. Mapping of Inland Excess Water (IEW), also known as ponding water or waterlogged areas, is crucial for informed decision-making, damage compensation, risk management, and future prevention planning. Remote sensing technology and machine learning have been demonstrated to be valuable tools for the mapping of IEW. The 2014 floods in Southeastern and Central Europe serve as a reminder of the importance of effective flood risk management. This study used a Geographical Information System (GIS) and a Semi-automated Classification Processing (SCP) tool to process high-resolution RapidEye satellite images from the 2014 floods in the Srem region of Serbia. The Spectral Angle Mapping (SAM) classification model was used to produce a map of IEW. The SAM model achieved an overall accuracy of 92.68 %. The study found that IEW affected approximately 2.90 % or 99.59 km² of the territory in Srem. The obtained maps can be used by responsible water management agencies to prevent and control excessive inland water.

Keywords: inland excess water, high resolution satellite images, GIS, Semi-automated Classification Processing tool, Spectral Angle Mapping

Introduction

Extreme hydrological events, such as floods and droughts, caused by climate change have become much more prominent in recent years. Over the previous two decades, according to Hirabayashi et al. [1], there is an increase in the frequency of floods by more than 40 %. The Pannonian-Carpathian Basin is also frequently impacted by events such as floods and droughts, which can even occur in the same year. These extreme events have had a negative effect on various economic sectors, particularly agriculture. Changes in precipitation patterns and soil moisture levels can directly affect the quality and quantity of crop yields. Intense rainfall can induce Inland Excess Water (IEW) on farmland, hindering

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cultivation or damaging crop growth. Severe floods can contaminate both surface and groundwater resources, which are crucial for optimal agriculture during droughts. The quality of water used for irrigation is also vital for successful agriculture during dry periods [2, 3]. Surface waters can be contaminated by events like floods, causing waste to be deposited in rivers and requiring regular monitoring and control [4]. Floods can have a direct impact on the erosion and destruction of fertile arable soil, natural ecosystems, and protected nature reserves, as highlighted by Srdevic et al. [5], which are of invaluable importance. Extreme hydrometeorological events can have negative consequences on various sectors of the economy, human health, society and ecosystem as a whole.

IEW, also known as inland water or excess water in some contexts, refers to a flooding phenomenon that occurs when various natural and anthropogenic factors prevent water, often originating from precipitation or snowmelt, from infiltrating the soil or reaching rivers and channels due to limitations in runoff and infiltration [6, 7]. This surplus water accumulates on the surface, temporarily inundating extensive areas, and it can also manifest as the upwelling type, where groundwater emerges on the surface through porous soils, typically observed at the edges of alluvial fans [6]. Different terms, such as waterlogging, ponding water, and others, have been used in scientific literature to describe IEW, reflecting regional and disciplinary preferences [7, 8]. This paper will hereafter employ the term IEW to encompass the aforementioned phenomena.

Mapping areas affected by IEW is a necessary step for obtaining information needed to sustain agriculture, one of the most significant economic sectors in the study area. IEW caused by extreme rainfall can directly impact the volume and quality of crop yields. Mapping these areas helps agricultural producers make informed decisions regarding crop selection and land management, and can also assist in the collection of compensation for damages caused by IEW. Furthermore, it supports the development and implementation of effective protection measures, risk management strategies, and policies for future preparedness for extreme hydrometeorological events. By providing valuable information about the extent of the impact, responsible water management agencies can make well-informed decisions to prevent water damage to agricultural lands.

The use of remote sensing technology for mapping IEW has been effectively employed for an extended period and has proven to be a valuable tool in understanding and managing flood hazards. The research by Sar et al. [9] shows that the integration of remote sensing and GIS-based (Geographical Information System) spatial modelling can be efficiently used for the identification of the risk of waterlogging caused by excessive rainfall and flooding. The results of their study have delimited waterlogged hazard zones and determined the associated risk levels so that this information can be useful for improved planning and management of drainage systems and agricultural activities. Van Leeuwen et al. [7] successfully used passive and active remote sensing data to monitor IEW over large areas in a fully automated way. The author noted that knowledge about the location and duration of inundations aids in taking operational measures against the negative impact of water and also provides information necessary for determining the feasibility of storing water for dry periods. According to Kaushik et al. [10], remote sensing is an efficient and reliable method for evaluating and creating maps of waterlogged areas. In their study, it is recommended that both proactive and reactive measures be taken for the effective management of areas affected by waterlogging. Satellite images obtained from Sentinel and Landsat are most commonly used in scientific research for mapping IEW. High-resolution RapidEye satellite imagery, for water body identification, has been successfully applied by

Namikawa et al. [11] and Nashait et al. [12]. RapidEye satellite imagery is also utilised by authors van Leeuwen and Tobak [13] in their study. According to their research, this form of imagery is suitable for the detection of IEW due to its adequate spectral and spatial resolution, high temporal resolution, and cost-effectiveness. The use of high-resolution images enables the detection of a larger number of water bodies, thus allowing for more precise mapping of IEW areas.

Machine learning has become a popular tool for processing satellite images that are used for the detection of different changes on the earth's surface. It is also a useful tool for mapping rural and urban land cover changes, different natural hazardous events such as landslides, and other issues in water management. Models such as support vector machines, decision trees, and logistic regression can be effectively used for landslide susceptibility assessment as stated by Marjanovic et al. [14]. Oz et al. [15] successfully applied an artificial neural network, decision tree, and logistic regression models for the prediction of water quality classes. Maximum likelihood, minimum distance, and spectral angle mapping have been applied on satellite images to determine land use and cover changes as stated by Revuelta-Acosta et al. [16]. They emphasise the value of using remote sensing to better understand the dynamics of interactions between people and nature. Mirsanjari et al. [17] used satellite images and applied an artificial neural network for determining land cover alterations in urban areas. Decision-makers and planners can benefit from their findings by having additional information about the urban growth pattern.

To accurately determine water surfaces using satellite imagery, machine learning models are also effectively employed. Nashait et al. [12] applied algorithms such as random forest, decision tree, maximum likelihood, and support vector machine for the identification of the water bodies and concluded that random forest achieved the best overall accuracy and kappa accuracy. Demirkesen et al. [18] applied the maximum likelihood method for the determination of the spatial distribution of coastal inundation hazards. In their studies, Kajari et al. [8] successfully used models such as convolution neural network, maximum likelihood, random forest, support vector machine, and artificial neural network, while Szanto et al. [19] used artificial neural network for determining IEW. They highlight that remote sensing technologies are very useful for assessing and monitoring flood damage. Van Leeuwen and Tobak [13] examined several classification methods for identifying IEW, including ISODATA, maximum likelihood, spectral mixture analysis, and feed forward artificial neural network. Among these, the maximum likelihood classification method demonstrated superior performance in terms of accuracy and practicality for operational applications due to its speed and minimal reliance on auxiliary data. Arseni et al. [20] successfully applied spectral angle mapping for flood hazard monitoring. They concluded that semi-automatically spectral angle mapping classification is a useful tool for classifying remote sensing data. Following the example of the aforementioned study, this research employed the Spectral Angle Mapping classification method.

In May 2014, Southeast and Central Europe were hit by devastating floods caused by a low-pressure cyclone. Serbia and Bosnia and Herzegovina were heavily impacted by the heavy rainfall, with agriculture being devastated hardest [21]. The month prior, the region experienced unstable weather conditions, with increased cyclonic activity. The floods resulted in significant damage to necessary infrastructure and crops, leading to a significant loss of income for farmers and other agricultural stakeholders. Adverse hydrometeorological events that caused floods in 2014 showed us the importance of effective flood risk management and the need for continued research to better understand

and mitigate the impacts of such events. It is crucial to analyse the causes of floods, evaluate the effectiveness of measures taken to mitigate damage, and plan for future prevention and risk management.

The aim of this study is to improve the mapping of IEW, which is caused by heavy rainfall, by using high-resolution satellite images within a GIS environment and employing the classification model Spectral Angle Mapping (SAM).

Material and methods

Study area

The Srem region is located in the north of Serbia, in the southern part of the Pannonian Plain between $44^{\circ}38' - 45^{\circ}15'N$ and $19^{\circ}00' - 20^{\circ}22'E$ (Fig. 1). The northern and southern borders of the Srem are clearly defined by the Danube, to the north, and the Sava River to the south. The western border of the Srem is determined by the administrative border with Croatia, while the eastern border is determined by the Danube River. The Srem region covers an area of 3478.06 km^2 . The Northern region of the Srem, excluding the Danube floodplain, spans a total area of 1468 km^2 , representing approximately one-third of the entire region. This area is distinguished by its elevated terrain, with the highest point of the Fruska Gora mountain standing at an elevation of 538 meters above sea level, the highest point in the region. Despite this, the majority of the region has elevations lower than 100 meters above sea level, with the lowest area being the Sava floodplain near Belgrade, which is situated at an elevation of just 71 meters above sea level.

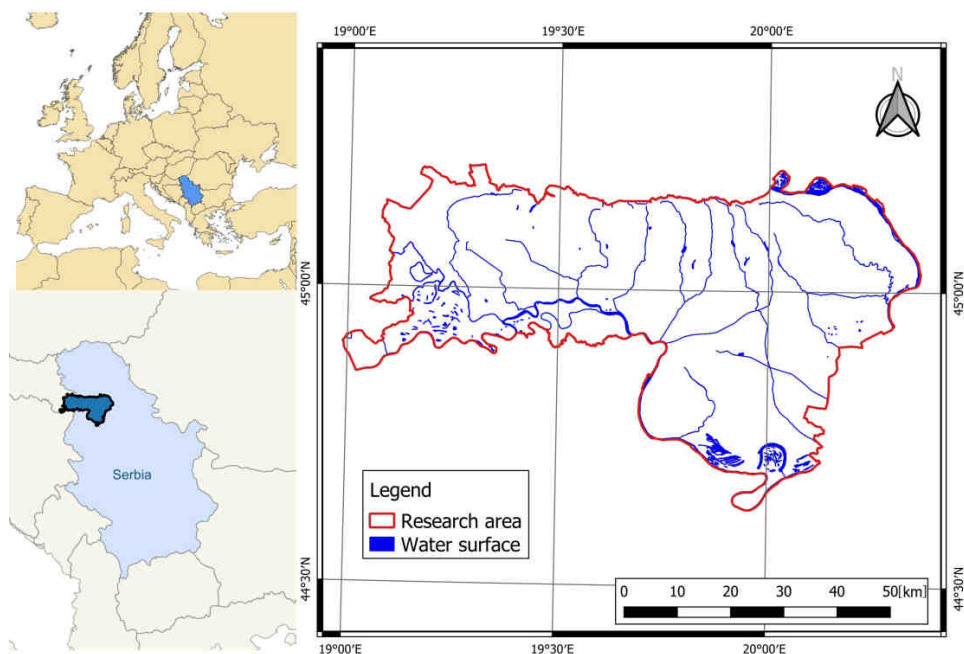


Fig. 1. Investigated area of the Srem (Serbia)

The largest part of the region, which covers 1634 km² or 47 % of the total area, is composed of black soil. This type of soil is rich in organic matter and minerals, providing ideal conditions for growing crops. The second largest area, 452 km² or 13 % of the total, is the meadow soil. These specific pedological characteristics render the territory of Srem a highly suitable for agriculture. Agriculture is a major sector in the region, with cereals constituting 70 % of the crops grown [22]. The combination of black soil and meadow creates a diverse and productive landscape that supports a wide range of crops, from wheat and corn to vegetables and fruit. In addition to agriculture, Srem is also home to a variety of natural habitats, including wetlands, forests, and grasslands, which support a diverse array of plant and animal species.

The climate in the Srem area is moderate continental type, characterised by warm summers and cold winters. The average annual temperature stands at 10.3 °C, while the average annual precipitation amount to 579 mm [23]. The distribution of precipitation is uneven; the highest volume occurs in June, measuring 82.3 mm, and the lowest in February, at 26.3 mm [23]. December is the month with the most days of precipitation. The predominant winds are dry and come from the east and northeast, while winds that bring precipitation are from the west.

Satellite image source, processing procedure, and tools

RapidEye were a constellation of five satellites that operated between 2009 and 2020. The satellites had a swath width of 77 km, a ground sampling distance (nadir) of 6.5 m at a reference altitude of 630 km, and a pixel size (orthorectified) is 5 m and can be used for mapping and monitoring floods. RapidEye's instrument produced multispectral imagery that captured data in five different wavelength bands listed in Table 1.

RapidEye's multi-spectral bands

Table 1

Band number	Band 1	Band 2	Band 3	Band 4	Band 5
Band name	Blue	Green	Red	Red Edge	Near-Infrared
Wavelength [nm]	440-510	520-590	630-685	690-730	760-850

The remote sensing data processed in this study were obtained from the RapidEye satellite constellation and accessed on January 18th, 2023 through the Planet Labs PBC Earth imaging company [24]. The study area experienced significant precipitation from May 13 to May 17, 2014, with 187 mm of rain falling in total during that time. The most significant amount of rain fell on May 15, reaching 69.1 mm [23]. Satellite imagery for May 19th and 21st, 2014, which were captured immediately after heavy rainfall, were used to classify water areas. The first image covers the western and central part of the Srem region and was obtained on May 19, 2014, and identified as 20140519 in the RapidEye reference frame. The second image, obtained on May 21, 2014, and identified as 20140521, covers the eastern part of the Srem region. Both images are in the GeoTIFF format and have been geometrically rectified and mosaicked together into one image. They are located in the UTM projection 34N zone using the WGS-84 reference ellipsoid.

To determine the pixels that characterise water, it is necessary to analyse the spectral reflectance properties. The remote sensing method is based on the measurement of reflected or emitted radiation from various objects [18]. The objects in the field differently reflect or absorb solar radiation depending on their characteristics. The reflection properties of

an object depend on the material and its physical and chemical state, surface roughness, and geometrical features. By analysing differences in spectral reflectance, different objects and surfaces on the earth can be identified [25]. The characteristic of water surfaces is that they have high absorption within the spectral range corresponding to the Near-Infrared band of the RapidEye satellite (Band 5 with a spectral wavelength range of $0.76 \mu\text{m}$ - $0.85 \mu\text{m}$). This property enables very easy detection of water surfaces and water bodies using remote sensing. To facilitate the differentiation of water surfaces in the creation of the training dataset, a colour composition of RGB = 532 (where RGB represents NIR-RED-GREEN) was utilised [11, 18, 20]. To ensure a satisfactory outcome for the training dataset, points and polygon samples were employed for bright and dark water bodies, rivers, lakes, channels, and IEW. The method of simple random sampling was utilised. The training dataset was uniformly distributed from the entire research area, and consisted of 200 polygons and points. Only areas with retained water bodies were included for training; saturated soil without visible surface water was excluded from consideration. Additionally, high-resolution satellite images available on Google Earth Pro from May 21, 22, and 23, 2014 were used to further determine the existence of water bodies for the selected training dataset.

For the processing of satellite imagery, the open-source software Quantum GIS (QGIS) version 3.28.2 (released on December 16, 2022) and the Semi-automated Classification Processing (SCP) tool developed by Congedo (released in 2021) [26] were utilised. During the process of classification of pixels, the Spectral Angle Mapping (SAM) algorithm with a zero threshold was used.

Cloud cover and shadows represent a problem in processing multi-spectral satellite images. The mask layer was generated and then used to eliminate cloud coverage and shadows from the satellite images, ensuring a more accurate representation of the study area.

For the purpose of accuracy assessment, a stratified random sampling technique was employed using the QGIS plug-in AtACaMa (Accuracy Assessment of Thematic Maps). Only areas with visible water bodies were used for validation, while areas with wet soil but no visible water were left out. A separate dataset, distinct from the one used for training, was systematically collected across the entire study area for model validation.

The producer's accuracy, user's accuracy, overall accuracy, omission error, commission error, kappa, and F_1 -score were calculated for the Water and No water classes. User's accuracy is used to measure the correctness and reliability of the data, and represents the percentage of correctly allocated pixels out of the total number of pixels of a particular class; it is the complement of the probability of commission error [27, 28]. Producer's accuracy is calculated based on the number of pixels that are not classified into their true class. It represents the degree of correspondence between the information provided by the producer and the actual ground truth data; it is the complement of the probability of omission error [27, 28]. According to Rosenfield and Fitzpatrick-Lins [29] the kappa coefficient is emphasised as a reliable metric for evaluating thematic classification accuracy in remote sensing. This coefficient utilise data from the error matrix, which includes both commission and omission errors. The F-measure, also known as the F_1 -score, serves as the harmonic mean of precision and recall, with its value ranging from 0 to 1; a higher F-measure value suggests better classification performance [30]. Overall accuracy represents the ratio of correctly assigned pixels to the total number of pixels in a sample. A map is defined as accurate if its overall accuracy is greater than 85 %, with each

individual accuracy not being less than 70 %; if this condition is not met, reclassification is obligatory, according to Thomlinson et al. [31].

The final map of IEW was produced by removing permanent water bodies. The data on permanent water bodies was obtained from the responsible institution, the Public Water Management Company (WMC Vode Vojvodine), which has authority over the region Srem.

Spectral angle mapping (SAM)

Spectral angle mapping is an automatically generated supervised machine learning technique with a spectral classifier that serves to determine the spectral similarity between given image spectra and reference spectra in an n (n represents the number of spectral range) dimensional space using the calculation of the angle between spectra [32, 33]. Reference spectra are spectra that can be obtained through fieldwork or directly from satellite photos. Spectral angle mapping calculates the spectral angle between the spectral signatures of the image pixel and the trained spectral signatures. The spectral angle θ is defined as follows by Kruse et al. [34]:

$$\theta(x, y) = \cos^{-1} \left(\frac{\sum_{i=1}^n x_i y_i}{(\sum_{i=1}^n x_i^2)^{\frac{1}{2}} * (\sum_{i=1}^n y_i^2)^{\frac{1}{2}}} \right) \quad (1)$$

where x is the spectral signature vector of the image pixel, y is the spectral signature vector of the training region, and n is the number of bands in the image.

Therefore, the pixel belongs to the class that has the smallest angle, or in other words:

$$x \in C_k \Leftrightarrow \theta(x, y_k) < \theta(x, y_j) \forall k \neq j \quad (2)$$

where C_k is the land cover class k , y_k is the spectral signature of class k , and y_j is the spectral signature of class j .

Results and discussion

In this study, the region of Srem, Serbia, was analysed using available satellite imagery from May 19th and 21st, 2014. Available satellite imagery encompasses 3442.72 km² of the region of Srem. However, no satellite images were available for the western part of the region, measuring 35.34 km², during the studied period, so this portion was excluded from the analysis. These missing areas in the study region are depicted in Figures 2 and 4.

The amount of cloud coverage present on the obtained satellite images was minimal, accounting for less than 0.05 %. A mask layer was generated and applied to remove this small cloud coverage and shadows.

The training dataset, polygons, and points were created using colour composite RGB = 532, which representative example is shown in Figure 3a. Using the training dataset, the SAM classification model was applied and a thematic map was produced, consisting of two categories: Water (including permanent water bodies) and No water (which includes all other surfaces: forests, agricultural land, roads, railways, urban areas, etc.), presented in Figure 2. A representative example of the results is shown in Figure 3b.

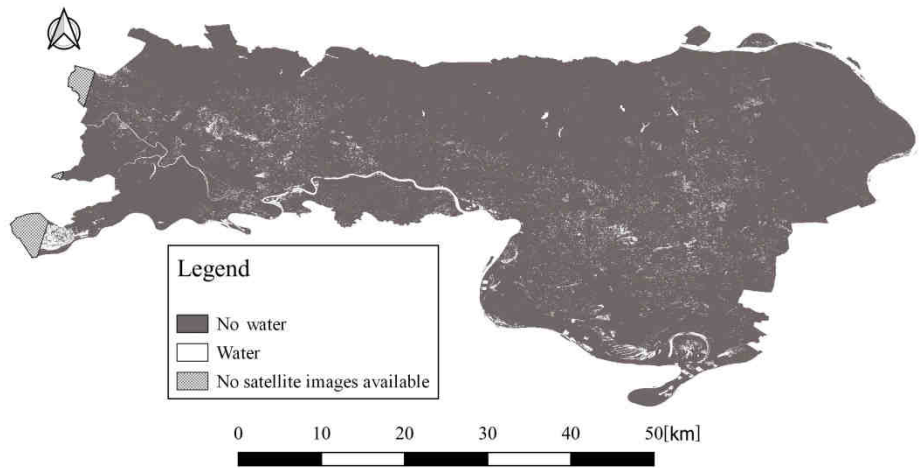


Fig. 2. Coverage of Inland Excess Water areas and permanent water bodies obtained by SAM method

To verify the accuracy of the applied method, the QGIS plugin AcATaMa was used, employing a stratified random sampling method with an overall expected standard error of 0.5 %. Accuracies for Water and No water classes were calculated and are displayed in Table 2. The overall accuracy achieved an exceptionally high level of 92.68 %, potentially suggesting robust performance. Based on the obtained accuracy results, it can be found that the produced map is considered accurate according to [31]. However, this figure, while noteworthy, does not capture the nuances associated with class-specific performance. The producer’s accuracy was high for both Water and No water classes, 93.83 % and 92.38 % respectively, signifying reliable classification from a ground truth perspective. More detailed inspection of the user’s accuracy reveals a distinct disparity: 76.00 % for Water and 98.31 % for No water. This discrepancy illustrates that, while the model is highly efficient at correctly classifying No water regions, it tends to misclassify other surfaces as Water more frequently, thereby raising the false positive rate for this particular class. To offer further insight, omission and commission error rates were analysed. Omission error rates of 6.17 % and 7.62 % for Water and No water, respectively, indicate a relatively low incidence of false negatives. The commission error rate for the Water class stood at 24.00 %, accentuating its susceptibility to false positives. The F_1 scores, which serve as harmonic means of precision and recall, are 0.83 for Water and 0.95 for No water. Although these scores are high, the lower F_1 score for Water indicates room for improvement in minimising both false positives and false negatives for this class. The kappa statistic further confirms these findings, with a value of 0.79 indicating substantial agreement yet indicating room for further improvement.

Table 2

Accuracy assessment

Class	Producer’s accuracy [%]	Omission error [%]	User’s accuracy [%]	Commission error [%]	F_1 -score
Water	93.83	6.17	76.00	24.00	0.83
No water	92.38	7.62	98.31	1.69	0.95
Overall accuracy [%]		92.68	Kappa		0.79

To further validate the information obtained regarding the location and extent of IEW, high-resolution satellite imagery from Google Earth Pro captured during the period of May 21st to 23rd, 2014 was utilised. Polygons of flood areas were created on the Google Earth Pro images and compared with the obtained maps. A high degree of agreement was established between the resulting map and the satellite images from Google Earth Pro. The image of a representative example of IEW from Google Earth Pro (dated May 21st, 2014) is depicted in Figure 3c.

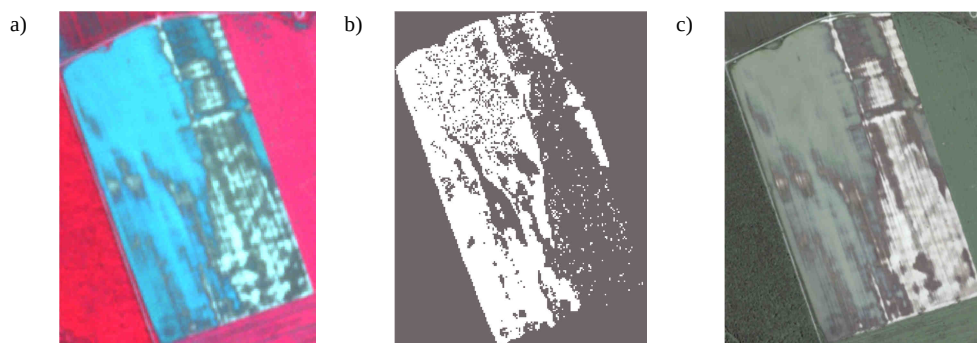


Fig. 3. Representative example of Inland Excess Water on study area: a) colour composite RGB = 532 of RapidEye's satellite images (May 19, 2014), b) results after SAM classification, c) image from Google Earth Pro

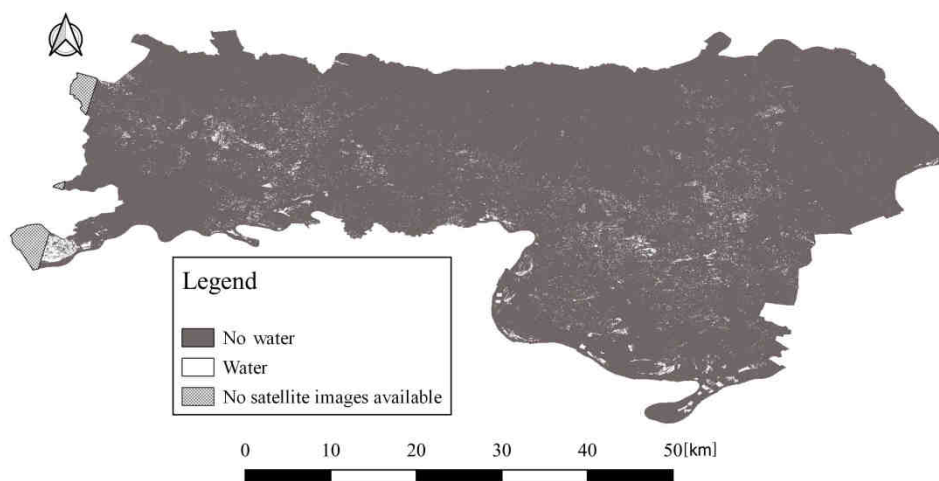


Fig. 4. Coverage of Inland Excess Water areas obtained by SAM method without permanent water bodies

Following the application of classification techniques and determining the areas containing water, surfaces permanently covered by water (such as rivers, canals, and lakes) were eliminated using a generated mask layer. Figure 4 shows the research area without any permanent water bodies and with IEW. Table 3 shows the results of the calculations made for the locations with IEW.

Table 3

Inland Excess Water and non-Inland Excess Water areas

Class	Pixel count	Area [km ²]	Percentage [%]
Water	3983488	99.59	2.90
No water	133725094	3343.13	97.10
Sum	137708582	3442.72	100.00

Following significant rainfall in May 2014, it was discovered that roughly 99.59 km² was covered by IEW. As would be predicted, the majority of IEW areas were found close to the Sava River, in former riverbeds and meanders, and areas of flat and low-lying topography. In addition to the IEW that accumulated on the surface due to the topographical characteristics of the terrain and poor soil permeability, a portion of the floods also resulted from the overflowing of the Sava River in areas in close proximity.

Conclusion

The application of remote sensing technologies in this study has proven to be very useful in the process of mapping areas affected by Inland Excess Water (IEW). Utilising high-resolution RapidEye satellite images, and image processing tools such as QGIS and SPC, the SAM model achieved an overall accuracy of 92.68 % and a Kappa coefficient of 0.79. These results are indicative of a strong agreement between observed and predicted classifications. The robustness of the producer's accuracy for both Water and No water classes underscores the model's reliability in identifying these categories. Although the study acknowledges a somewhat lower user's accuracy for identifying water areas, these limitations are not critical. They provide directions for further research and potential improvements to the model.

Remote sensing, in combination with GIS and machine learning models, constitutes a powerful tool for the identification of the IEW caused by heavy rainfall. Satellite images can be utilised for the rapid mapping of large areas, and the detection and quantification of water bodies, mapping of which would otherwise require extensive fieldwork. Given that the distribution and extent of IEW are highly dynamic, they depend on weather conditions and the soil permeability.

Approximately 2.90 % or 99.59 km² of the territory in Srem was found to be under IEW after heavy rainfall caused by a low-pressure cyclone in May 2014. To mitigate the negative impact of heavy rainfall and IEW, several measures can be taken. One such measure is the construction of additional drainage systems and the maintenance of existing ones to prevent the accumulation of water. In specific cases, horizontal pipe drainage or biodrainage can be implemented for the drainage of excess water and for preventing retention of IEW [35]. It is also possible to consider the construction of additional reservoirs in higher altitude areas to retain a certain amount of water, which can then be utilised for irrigation during dry periods. For future research, updated high-resolution images from other satellites on platforms such as Planet, Landsat, or Sentinel could be utilised. Specifically, Sentinel-1 SAR imagery offers weather-independent capabilities that are advantageous for flood detection. In addition to the aforementioned method, it is possible to combine satellite images after different rain events of varying intensities to obtain more accurate data on areas susceptible to IEW.

It is essential to note that although the SAM model exhibited high accuracy, additional research is essential to identify the most suitable classification methods for this study area. Alternative methods for classification, as discussed in other research papers concerning IEW [8, 13, 19], should be considered in future studies to potentially enhance mapping accuracy. Moreover, it is recommended to explore the utilisation of other machine learning models that have proven effective in the detection of other forms of excess water, including floods, as well as to employ cutting-edge techniques in the field of machine learning.

To manage water resources effectively, IEW must be continuously monitored. This study contributes to the development of a methodology for the fast and precise detection of floods through automation. The fast and precise detection of areas affected by extreme climate conditions is essential for mitigating their adverse impact on the environment, economy, infrastructure, and human life. Precisely mapping the regions vulnerable to IEW is possible thanks to the use of remote sensing, GIS, and machine learning models. The utilisation of these data can promote research into hydrology, meteorology, and climate change as well as aid in disaster preparedness, regional planning, and agricultural decisions. Through the provision of early warnings for potential flood threats and the facilitation of informed decision-making, our approach can support sustainable water management.

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