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REMOTE SENSING-BASED CONTOUR MAPPING OF BURGAS LAKE

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ABSTRACT

Effective management of the water resources requires reliable mapping of water bodies, which can be achieved using satellite remote sensing data. Synthetic Aperture Radar (SAR) and multispectral images, especially from satellites such as Sentinel-1, Sentinel-2, and the SWOT mission, provide valuable information for water body mapping and monitoring which can be used for environmental management and disaster response.

SAR sensors offer a major advantage by penetrating clouds and operating independently solar illumination, enabling continuous monitoring regardless of weather conditions. Multispectral imagery, particularly from Sentinel-2, provides valuable spectral information used to identify and map water bodies through spectral indices. The Surface Water and Ocean Topography (SWOT) mission represents a technological breakthrough by combining SAR interferometry with altimetry to measure water surface heights with high spatial resolution. SWOT complements existing satellite constellations by providing detailed water level data critical for hydrological studies.

This research explores various methods for water body mapping, including the use of spectral indices such as the Normalized Difference Water Index (NDWI) and its modified form (MNDWI), SAR, and SWOT data to highlight the differences, advantages and disadvantages of remote sensing-based contour mapping of Burgas lake.

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1. Introduction

The climate changes occurring in recent years have increasingly drawn attention to the protection and monitoring of the Earth's georesources [1]. A key component of the planet's hydrological cycle is water bodies such as reservoirs, lakes, and rivers [2]. They play an important role in maintaining ecological balance. Monitoring water resources is essential for their sustainable management [3]. This includes both analysis of the dynamics of water bodies, such as changes in their contours, and assessing the impact of climate change on them [4]. Water body mapping is crucial not only for georesource management but also for preventing disasters and accidents such as floods [5, 6].

Traditional field studies provide highly accurate data but are labor-intensive, expensive, time-consuming, and limited in the spatial extent that can be effectively monitored. An increasingly popular alternative is remote sensing technology, particularly the use of spaceborne sensors. These methods allow monitoring of large areas in real time, providing a cost-effective solution for mapping water bodies.

Among the most commonly used remote sensing data are optical images. The spectral characteristics of objects are utilized to identify water-covered areas by generating index images. The most widely used index is the normalized difference water index (NDWI) [7, 8] and its enhanced version, the Modified Normalized Difference Water Index (MNDWI) [9]. The use of these indices combined with multispectral images from the European Space Agency (ESA), such as Sentinel-2 satellite, is an effective method for mapping water surfaces. However, satellite imagery also has their limitations, particularly regarding spatial resolution. When using data with different pixel size, resampling is often necessary, and in some cases, pan-sharpening techniques can be applied to enhance data accuracy [10, 11].

Another method that is also used for water surface mapping is Object-Based Image Analysis (OBIA) [12]. This method is often used in addition to classification to improve the ability to distinguish water bodies from areas with similar spectral behavior.

In addition to multispectral images from ESA, SAR products, such as those from Sentinel-1 [13], as well as data from missions like SWOT (Surface Water and Ocean Topography) from NASA and CNES [14], are also increasingly being used. Unlike multispectral images, whose availability is highly dependent on atmospheric conditions, SAR sensors can penetrate clouds and capture images regardless of meteorological factors. Thanks to their longer wavelengths and independence from solar radiation, SAR data are available around the clock and is particularly useful for monitoring water bodies and flood mapping. However, like any method, radar and altimetry data have disadvantages, such as noise and radiometric anomalies. To improve the results, innovative approaches such as combining data from different sensors, use of multitemporal datasets, and noise removal algorithms such as MuLoG can be implemented.

This study aims to apply, compare, and analyze various methods for mapping water bodies. Data from different sensors were used to track changes in the contour of Burgas Lake between April and November 2024. Spectral indices NDWI and MNDWI were applied using multispectral images from Sentinel-2. SAR data were also used, processing all available Sentinel-1 images for the study period, as well as SWOT data for the lake area. The results from the three methods were compared in terms of the area of the water body and the limitations of the applied technological schemes.

2. Study area

The study site for this paper was chosen to be the biggest natural lake in Bulgaria – Burgas Lake. The lake is located near the city of Burgas next to the Black Sea. With a length of 9,6 km, width varying from 2,5 km to 5 km its total area is estimated to be around 27,6 km^2 during its maximum. The lake is relatively shallow with a maximum depth of 1,3 m. The reason for choosing this site is because of the good location in terms of weather conditions and its large size. Weather conditions are very important for optical imagery so choosing a region where clouds are formed less in the summer season, which is the primary period of observation, allows for larger amounts of optical imagery being used. The size is chosen because of SWOT data. As discussed below, SWOT takes only lakes with an area larger than 250 m^2 with a threshold for high precision data of 1 km^2. Choosing a bigger lake leads to having more accurate water masks and making sure one is available for most of the year.

Water in the lake has salinity from around 4 ‰ to 11 ‰, which makes it moderately saline according to [18]. This is mainly due to the connection between the lake and the Black Sea through a 350 m long canal in the east part of the lake. The canal is relatively narrow, making travelling possible with small boats only. This canal can be detected as water when using high resolution satellite imagery which can lead to errors in the calculated area. In the case of using Sentinel-2 and Sentinel-1 imagery the canal was detected several times but it was removed manually, and the area was calculated again. This also happened with one of the SWOT products used in this study where the canal was partially detected just enough to establish the connection between lake and sea which led to the formation of one big polygon feature containing both the lake and part of the Black Sea. In this case the connection was removed and only the lake polygon feature was left (Figure 8).

3. Surface Water and Ocean Topography (SWOT)

SWOT is a joint mission between National Aeronautics and Space Administration (NASA) and Centre National D'Etudes Spatiales (CNES) with additional contributions from the Canadian Space Agency (CSA) and United Kingdom Space Agency. The development of the technology and early design of the mission started in 2015. After the approval of the design, the mission entered its fabrication stage in 2016. The launch of the satellite was on December 16th 2022 and for the first six months after the launch it worked in "fast-sampling" phase with 1-dat repeat orbit at an altitude of 857 km. This mode focuses on collecting data for calibration and validation for which in-situ assets were deployed in different parts of the world covered by the orbit of the mission. After the end of the calibration period, the mission entered its designed 21-day repeat orbit.

The SWOT payload comprises two subassemblies: KaRIn (Ka-band Radar Interferometer) and the nadir payload module, which contains the AMR-S (Advanced Microwave Radiometer), the Poseidon-3C (Positioning Ocean Solid Earth Ice Dynamics Orbiting Navigator) dual-frequency nadir altimeter, the DORIS receiver (Doppler Orbitography and Radio positioning integrated by Satellite) and GPSP (the GPS payload), as well as the LRA (Laser Retroreflector Array). The system also carries X-band communication subsystem for the scientific data downlink.

SWOT provides 2 levels of products – level 1 and level 2. Each instrument provides different products for all 2 levels and some auxiliary data such as precise orbit ephemeris, medium-accuracy orbit ephemeris, satellite center of mass and reconstructed attitude. The most important products for this study are the ones provided by the KaRIn instrument. They are divided into low rate and high rate respectively for oceanography and hydrology and are provided in level 1 and level 2. Level 1 and oceanography centered products and most of the level 2 products are not the focus of this study and will not be discussed further. Level 2 products include a variety of different data:

- L2_HR_RiverSP – provides KaRIn measurements of water surface elevation (WSE), slope and width for predefined river reaches from prior river database (PRD) – [15, 16]. This product is formed from the pixel cloud product using an algorithm that determines which pixels are part of rivers based on data from PRD.
- L2_HR_LakeSP – provides KaRIn measurements of WSE and extent for lakes and lake-like features. Each lake is represented by a polygon with area and WSE attributes. This product is based on the pixel cloud and is formed by an algorithm that determines which pixels are part of a lake. The algorithm uses information from the RiverSP product. This product provides 3 shapefiles – Observation-Oriented Shapefile, PLD-Oriented Shapefile and shapefile containing unassigned features. Each of them has slightly different attribute structures and contain different data.
- The purpose of the product is to provide DEM of floodplain near water features that have been observed during the mission's life.

In this study LakeSP products were used. Due to its size, the Burgas Lake is part of the observed and prior products. Those products contain both the contour and the area of the lake and are the main products this study aims to compare with the established water detection methods. Because of the additional data presented in the Prior product, it is the product of choice for this study.

The most important data in the product includes "area_total", "area_tot_u", "area_detct" and "area_det_u". These attributes contain the total area of the lake (including both detected water and "dark water"), the uncertainty of that area, the actually detected area by SWOT and its uncertainty [17]. These values are used both as reference for the calculation of standard deviation between optical and SAR images compared to SWOT. It is also used for filtering small pixels detected as water in the bitmap images – explained in more detail in 0.

Another important attribute of SWOT data is the quality flag because it shows how accurate the data for the specific product and features is. This allows for better interpretation of the data and explains big differences in the area between SWOT and the established methods.

4. Spectral water indices

The difference in reflectance characteristics of clear water in different parts of the electromagnetic spectrum has been used for the development of different spectral indices aimed at detecting water while minimizing false detection for different cases. Normally, clear water has high reflectivity in the visible portion of the spectrum, with the highest being in the blue channel, and lower reflectivity in the infrared portion of the spectrum, specifically the NIR and SWIR bands. These characteristics led to the development of a lot of different spectral indices using a variety of bands for specific cases.

In general, the indices can be classified as normalized and non-normalized. Normalized indices use normalized differences between bands in order to achieve image with values varying between -1 and 1. For those types of indices all positive values depict water pixels and all negative – non-water pixel which makes creating bitmap images using threshold of 0 because in theory this should always lead to separating water from non-water features. Some of the earliest developed water indices were based on those principles. The first index was NDWI (Normalized differential water index). It uses the normalized difference between Green and NIR bands to detect water [8]. Some later experiments concluded that using the difference between Green and SWIR1 removes a substantial amount of noise introduced by vegetation and soil when detecting open water bodies [19].

In this study both indices described were used with the appropriate threshold values to calculate the area of Burgas Lake. All images used were processed using SNAP software and a short python script for QGIS in order to ensure that the same parameters are used for the whole dataset.

5. Data processing

This study used data from Sentinel-2 and Sentinel-1 (GRD) to calculate the area of Burgas Lake. All images were collected between April and November 2024. The main goal of the study is to compare the water area calculated from the image data to the results present in SWOT lake dataset.

The data processing was separated between SNAP and QGIS and is different for optical and SAR images.

5.1. Optical image processing in SNAP

The processing chain for Sentinel-2 images in SNAP consists of the following steps (Figure 1):

- Resample – Sentinel-2 images consist of three different band sizes. In order to achieve uniform resolution, resampling was applied to the images. The resample method used a reference band to calculate pixel size and extent. In this case B2 band was used because of its high resolution – 10 m.
- Subset – since the area of interest takes only part of a standard Sentinel-2 image, a subset was created. The boundary of the subset was as close to the lake as possible in order to reduce the amount of water bodies on the scene.

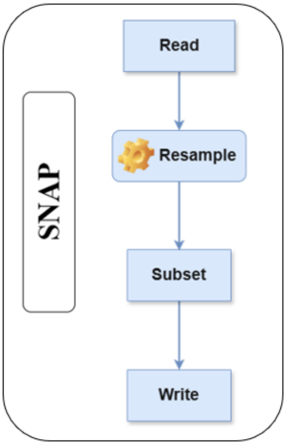

Figure 1. Processing chain for Multispectral images

5.2. SAR images processing in SNAP

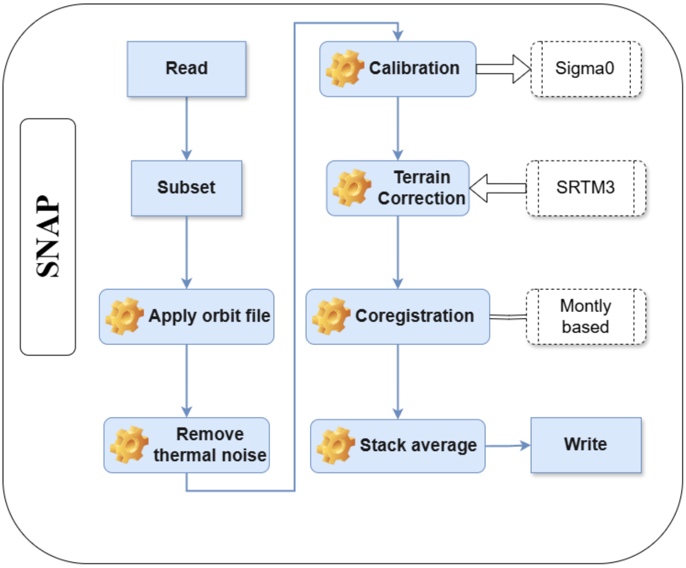

Figure 2. Processing chain for SAR images

The SNAP processing chain for SAR images consists of the following steps (Figure 2):

– Apply orbit file – although the metadata of a SAR product contains information about the orbit state vectors, it is not sufficiently accurate. Thus, using precise orbit files provides more reliable data for the position and velocity of the satellite. This information is then used to update the orbit state vectors. In this paper, Sentinel precise orbit state vectors and a third-degree polynomial have been used.

– Remove thermal noise – thermal noise in SAR products must be removed, as it affects radar reflectivity by artificially increasing it and it also hinders the precision of reflectivity estimates. All Level-1 imagery provides a Look-Up Table (LUT) with information about the noise for each set of measurements. This noise originates from the satellite receiver and represents background energy, provided in linear power and available as discrete points in the LUT. For pixels without corresponding LUT points, bilinear interpolation is used to estimate the thermal noise. In the processing of the data VH polarisation has been selected.

– Calibration – although the raw data has been processed to obtain Level-1 products, this processing usually does not include radiometric corrections. As a result, calibration is required to ensure that the pixel values in the SAR product correspond to the true radar backscatter from the imaged area. For this purpose, the information contained in the product, in the form of four Look-Up Tables (LUTs), is used, for generating the $\sigma^0{}_i$, $\beta^0{}_i$, and γ_i channels respectively, or for converting back to Digital Number (DN). In this process, the intensity values of each pixel are converted to radiometrically calibrated backscatter, in this paper – sigma nought values. To achieve this, the output scaling applied by the processor is reversed, and the desired scaling is applied. The LUTs provide a range-dependent gain, and for the GRD products used in this paper, a constant offset is also applied. This step is especially important when using data from different sensors or, as in the present case, data from the same sensor acquired on different dates.

– Terrain correction – this is the final step in processing each of the images used before coregistration. Terrain correction aims to eliminate geometric distortions in SAR products so that the spatial representation of the data is as close as possible to the real-world surface. It also reprojects the scene into a geographic coordinate system. These distortions result from variations in terrain elevation and the tilt of the satellite sensor. In this article, terrain correction was performed using the SRTM 3Sec digital elevation model and the UTM map projection.

All images used in this paper were pre-processed using the steps described above. To improve the accuracy of the final products used to determine the area and the outline of Burgas Lake, a stack was created from all pre-processed images for the respective month through coregistration. Bilinear interpolation was applied during the coregistration and an optimal master image was selected automatically (Figure 3).

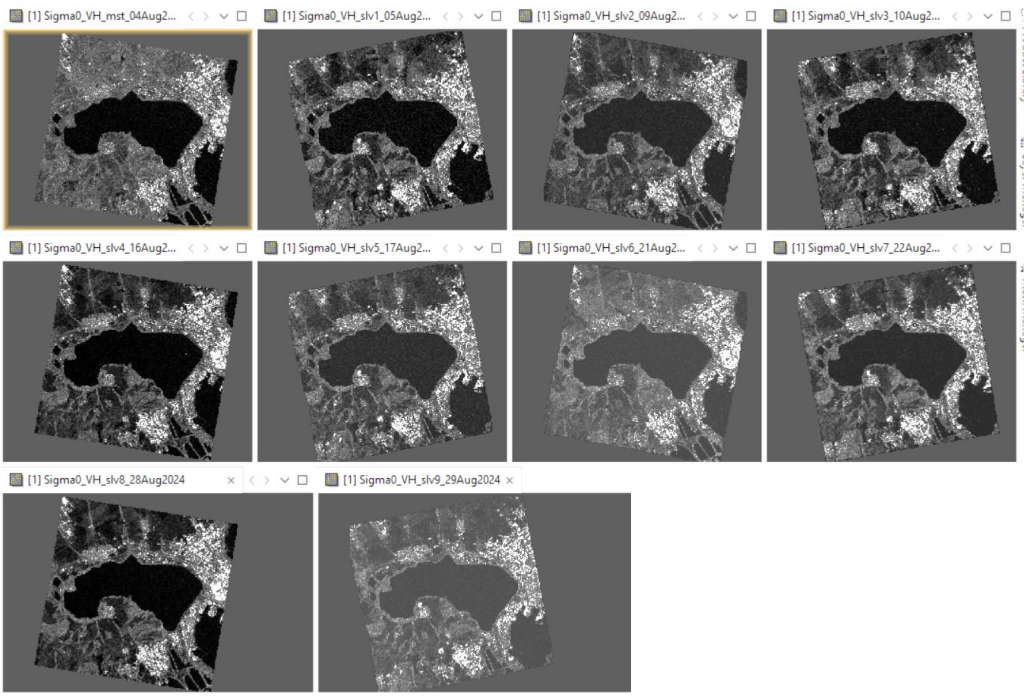

Figure 3. Pre-processed and stacked SAR images for August 2024

Each stack was then mean averaged, which significantly reduces speckle noise and enhances the precision of water body delineation. The subsequent step involved binarization to increase the separability between water and non-water pixels in the images. This enhances the ability to distinguish water surfaces from other land cover types. For this purpose, first the "Linear from/to dB" operation was applied to transform the histogram into a logarithmic scale (Figure 4).

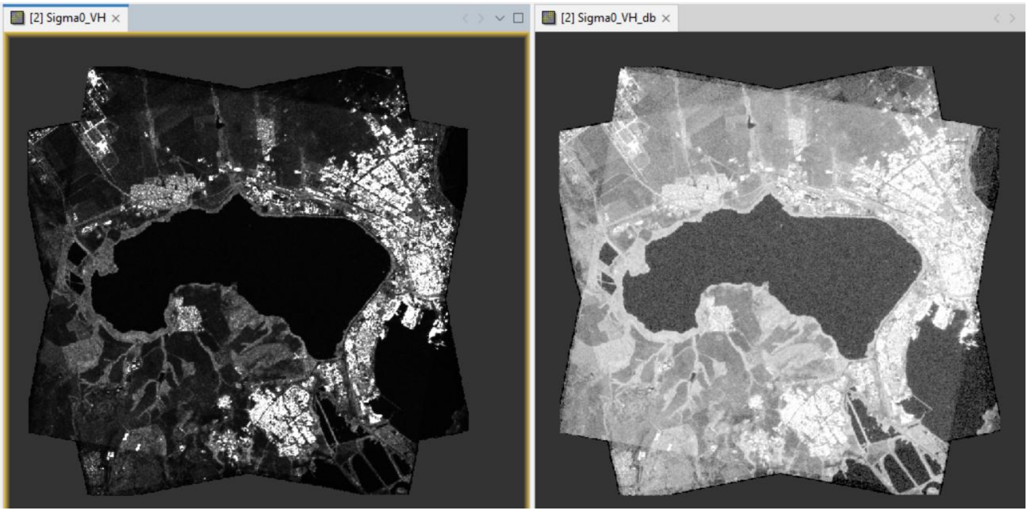

Figure 4. Mean averaged stack before (left) and after (right) histogram transformation

To determine a suitable threshold value for binarization, polygons were drawn over known water surfaces, and statistics were then extracted and analyzed (Figure 5).

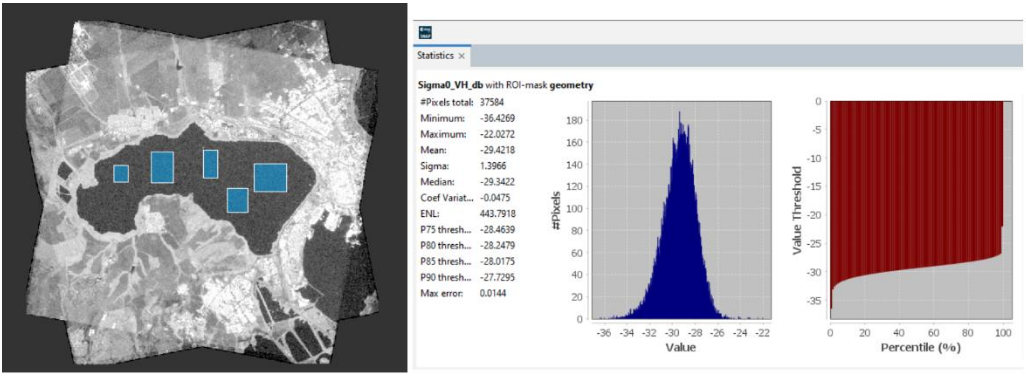

Figure 5. Statistics for August 2024

Based on this analysis, a threshold value of −26 dB was selected for most months, except for the October dataset, where a threshold of −25 dB was applied (Figure 6).

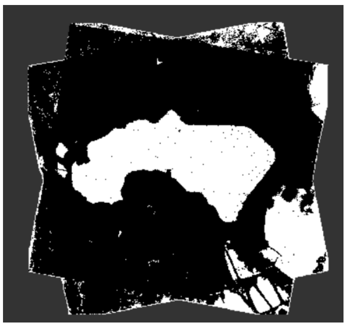

Figure 6. Binarization using a threshold value of −26 dB for August 2024

5.3. Processing in QGIS

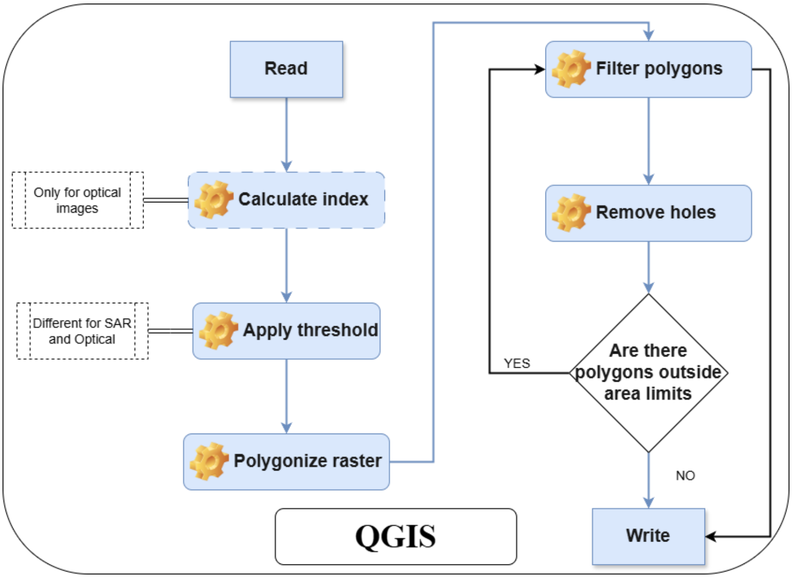

Figure 7. QGIS processing chain

After the pre-processing in SNAP had been completed, all images were exported in GeoTIFF format for further processing in QGIS. Because of the big number of images – 43 optical and 8 SAR stacks, a python script was developed. The script uses some of the built-in functions in QGIS and consists of the following steps (Figure 7):

– Calculating spectral indices – the formulas of both indices were coded into the script together with the required bands for them. For each index the raster calculator algorithm built into QGIS was used to create the bitmap raster image. Because both indices are based on normalized differences, a threshold of 0 was used.

– Polygonising the image – the bitmap raster image is polygonised using the QGIS algorithm.

– Area filtering – since SWOT data is used for reference, filtering based on the detected areas by SWOT prior products is applied to the data from the bitmap image. The script takes the area detected by SWOT and deletes all polygon objects whose area is smaller or bigger than $\pm$ 10 % of the detected area. This ensures the removal of very small and very big features. This can cause images from dates with small amounts of cloud or fog to be removed due to low accuracy. It is important to note that for the SAR images the threshold was extended to $\pm$ 20 % because of the specifics in processing explained in 0. Because of the lower temporal resolution of SWOT compared to Sentinel-1 and Sentinel-2, significantly less data per month is available. The SWOT product with the smallest temporal offset was selected in this case. Calculations are based on the difference between month and day for each image and the SWOT product. The minimal difference is then recorded and the product with the closest date is chosen as reference.

– Hole removal – the resulting polygon has some small holes due to spectral values. If those holes are within the polygon feature, they are removed. The “Delete holes” algorithm is used for this purpose.

– Secondary area filtering. Sometimes clouds near the AOI are also classified as water in bitmap images. They contain large amounts of holes with different sizes but because they are within a single polygon feature formed from the cloud, they are removed in the “Hole removal” step. In some cases, the resulting polygon feature can be filtered using the same filtering technique applied during the polygonising process.

This script assures consistent parameters use for all images and the results are comparable. The result of the script is a vector layer with polygon geometry that consists of polygon features for all indices that passed the area filtering criteria.

5.4. SWOT processing

Products of level 2 are generally fully processed and ready to be used by the user with no additional processing. However, after reviewing all data for the mentioned time period it was discovered that some data products had Burgas Lake and part of the Black Sea within the same polygon feature (Figure 8). This causes the attributes in the table to be wrongfully assigned to the lake when they are for the whole detected area. In order to solve this problem, the feature was split into several parts using Google satellite imagery as reference.

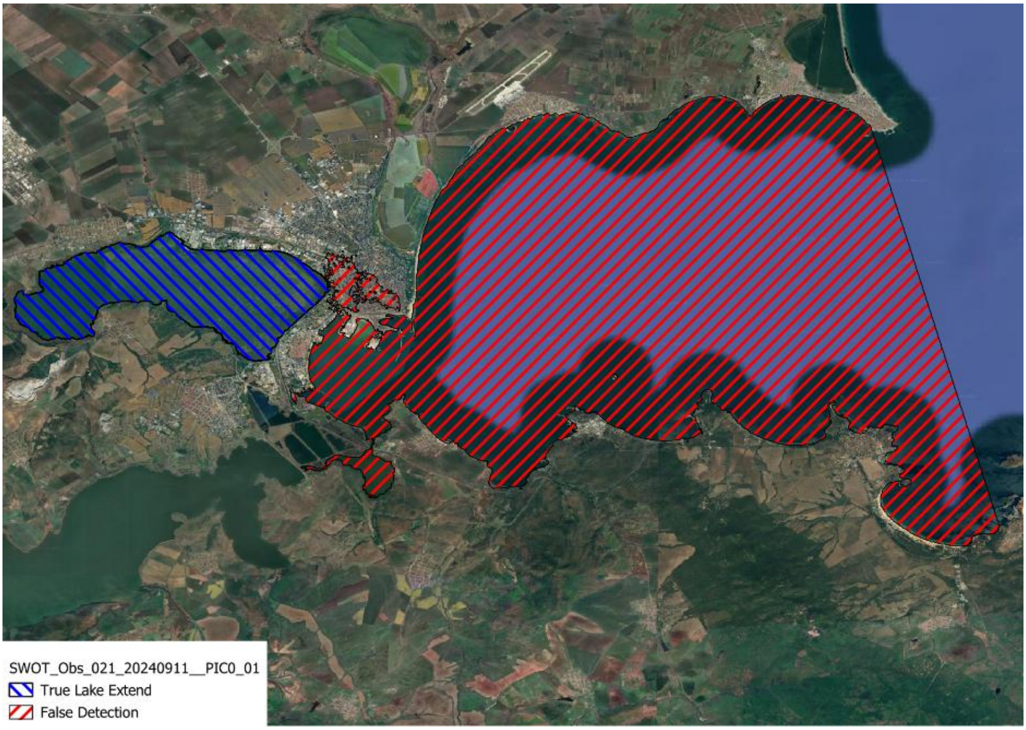

Figure 8. Example of SWOT data where the lake and the sea are part of the same polygon feature

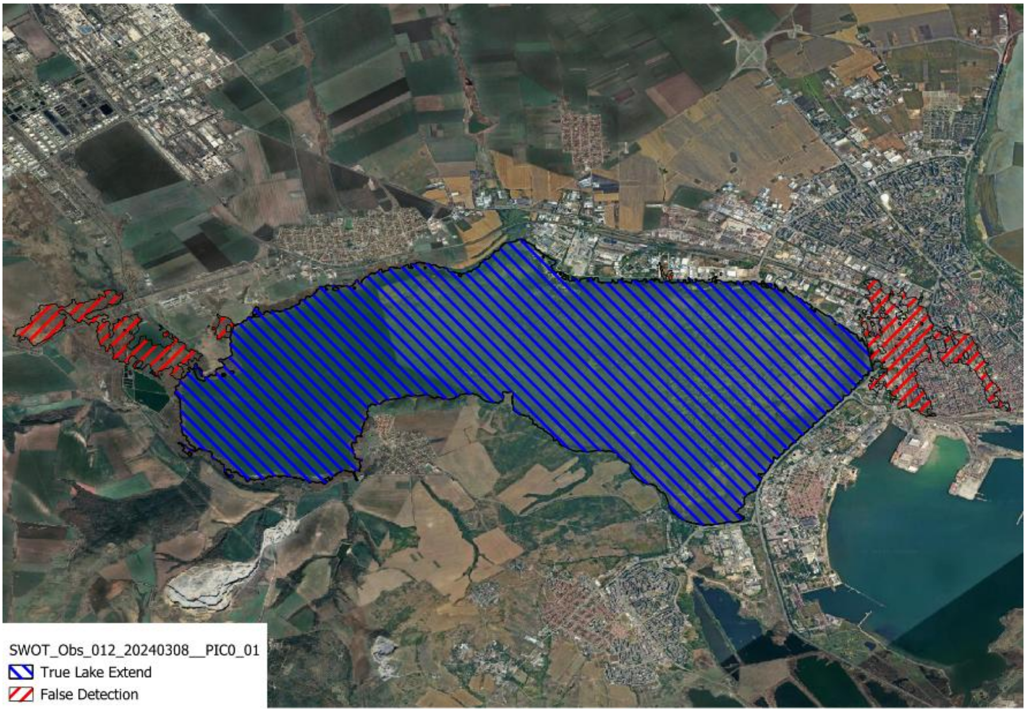

Figure 9. Example of wrong detection of water features in SWOT data

Another issue with the polygons was false detections (Figure 9). Those include parts of the city or areas outside the lake contour. In this case, again, the feature was split into several parts aiming to remove the falsely detected parts. The contour was kept as close as possible to the original.

After removing the wrong detected features, the area was calculated again using the built in functions in Qgis. It is important to note that the built-in functions calculate area in a different way compared to SWOT so even on an original feature the area will always be different. This difference (< 1 %) was considered negligible.

6. Results

The results of this study can be grouped into two main comparisons: (1) between the established water detection methods, namely the two spectral indices NDWI and MNDWI and SAR imagery, and (2) between the SWOT-derived lake extent and the results from these established methods. Both comparisons are presented in tabular and graphical form for clarity, and monthly cartographic schemes are included to illustrate contour differences.

The first comparison assesses the consistency between optical and SAR-derived lake extents. Due to the lower temporal resolution of SAR data (monthly composites), fewer data points were available relative to optical imagery. Consequently, monthly averages were also computed for the spectral indices to ensure comparability. These averages were calculated separately for NDWI and MNDWI and the resulting values were then used to determine differences in surface water area relative to SAR observations. The results are reported in both square kilometers and as relative percentages (Tab. 1), with percentages calculated using the respective spectral index as the reference.

Table 1. Comparison between spectral indices and SAR for area of detected water

Difference between NDWI index and SAR area			
Date	**Area [km²]**	**Diff_SAR [km²]**	**Diff_SAR [%]**
April	23,919	0,460	1,92 %
May	23,754	0,289	1,22 %
June	23,592	0,103	0,44 %
July	23,560	0,100	0,42 %
August	23,670	0,247	1,04 %
September	23,806	0,336	1,41 %
October	23,808	0,236	0,99 %
November	23,781	0,313	1,32 %
Difference between MNDWI index and SAR area			
Date	**Area [km²]**	**Diff_SAR [km²]**	**Diff_SAR [%]**
April	24,083	0,624	2,59 %
May	23,937	0,471	1,97 %
June	23,871	0,382	1,60 %
July	23,816	0,355	1,49 %
August	23,814	0,391	1,64 %
September	23,851	0,381	1,60 %
October	23,864	0,292	1,22 %
November	23,828	0,360	1,51 %

Analysis shows that SAR consistently estimates a smaller water extent compared to both NDWI and MNDWI across all months. The largest discrepancies occur in April, with the smallest in the summer for NDWI and in late autumn to early winter for MNDWI. The maximum observed difference is 0,46 km² (1,92 %) for NDWI and 0,62 km² (2,59 %) for MNDWI. These discrepancies, while modest, may be attributed to local geographic conditions. Burgas Lake is surrounded by low vegetation, which can influence radar backscatter due to SAR's oblique look angle. In contrast, optical sensors acquire data near the nadir, resulting in different shoreline responses.

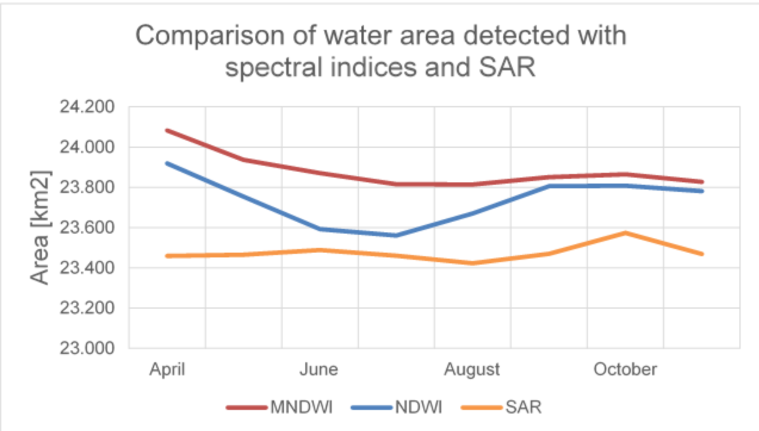

Figure 10. Differences between NDWI, MNDIW and SAR imagery expressed as water area

The variation between NDWI and MNDWI is likely due to differences in spectral band selection. MNDWI uses the SWIR1 band, which provides stronger contrast against land and vegetation, enabling improved detection of narrow inlets and small water bodies connected to the lake. SAR, however, may miss these features due to spatial resolution and incidence angle limitations. Additionally, steep banks around small water bodies can result in double-bounce reflections, increasing SAR signal intensity in non-water areas.

These trends are illustrated in Figure 10, which visualizes the consistent differences between SAR and optically derived surface water estimates throughout the observation period.

The second stage of the analysis compares water extent estimates derived from NDWI, MNDWI, and SAR imagery to those obtained from SWOT data. As SWOT acquisitions occur approximately every 21 days, more temporal data points were available than for SAR, which is available on a monthly basis. To enable consistent monthly comparisons, temporal averaging was applied to the SWOT data.

As previously noted, (Section 0), SWOT Level 2 products include a quality flag for each feature. This flag ranges from 0 to 3, with 0 indicating high-quality data, and 3 signifying data that are generally unreliable. Specifically, flag 0 denotes no known errors; flag 1 indicates potential large errors that warrant verification; flag 2 corresponds to high likelihood of significant errors; and flag 3 indicates unusable data. In this study, the majority of SWOT observations were of good quality, with only two products flagged as level 1 and one product in October flagged as level 2 (degraded).

To incorporate these quality indicators into the monthly averaging process, a weighted average was calculated using the following equation:

$$Wi = 3 - quality_{flag}, \tag{1}$$

where Wi is the assigned weight for each observation based on its quality level.

$quality_{flag}$ is the assigned quality value in the product attributes.

After computing the weighted monthly averages for both the total and corrected SWOT-derived areas, the absolute differences with respect to the established methods (NDWI, MNDWI, SAR) were calculated. These results are summarized in Table 2. In this case, only absolute differences are reported, without normalization to percentages.

Analysis of the results yields several key observations:

– **Uncorrected SWOT data** can exhibit substantial deviations, with errors ranging from 0,54 km² to over 2 km². Notably, the September result is excluded from this comparison, as it required correction due to the lake and sea being merged into a single feature (see Figure 8).

– **SWOT-derived areas** tend to be more consistent with the spectral index estimates than with SAR results; however, prior to contour correction, discrepancies remain significant across all methods.

– **Applying contour corrections** markedly improves agreement between SWOT and the other datasets. Post-correction differences range from 0,1 km² to 1,1 km² (1,5 km² for SAR comparisons). Specifically, 75 % of corrected SWOT estimates differ from NDWI and MNDWI by less than 0,75 km² and from SAR by less than 1 km².

– As illustrated in Figure 11, the largest discrepancy occurs in April for the uncorrected “Total” area, which is substantially reduced after correction. In contrast, the smallest differences in the “Corrected” area appear in August and July – months where the uncorrected data had large deviations. These findings underscore the importance of contour correction in improving SWOT data reliability.

Table 2. Differences between SWOT and the established methods

Month	AREA [km^2]					SWOT quality
	NDWI	MNDWI	SAR – VH	$SWOT_{tot}$	$SWOT_{corr}$	
Apr	23,919	24,083	23,459	26,250	23,973	1
May	23,754	23,937	23,465	25,592	25,025	0
Jun	23,592	23,871	23,489	24,480	24,546	0
Jul	23,560	23,816	23,460	25,554	24,479	0
Aug	23,670	23,814	23,423	24,376	23,682	0
Sep	23,806	23,851	23,470	24,029	24,029	0
Oct	23,808	23,864	23,573	24,408	24,312	0, 2
Nov	23,781	23,828	23,468	24,965	24,787	1
Month	AREA DIFFERENCES [km^2]					
	$SWOT_{tot}$			$SWOT_{corr}$		
	NDWI	MNDWI	SAR – VH	NDWI	MNDWI	SAR – VH
Apr	2,331	2,167	2,791	0,054	-0,110	0,514
May	1,838	1,655	2,126	1,271	1,089	1,560
Jun	0,888	0,609	0,991	0,954	0,675	1,057
Jul	1,993	1,738	2,094	0,919	0,664	1,019
Aug	0,706	0,562	0,953	0,012	-0,132	0,259
Sep	0,223	0,179	0,559	0,223	0,179	0,559
Oct	0,599	0,543	0,835	0,503	0,447	0,739
Nov	1,184	1,137	1,497	1,006	0,960	1,319

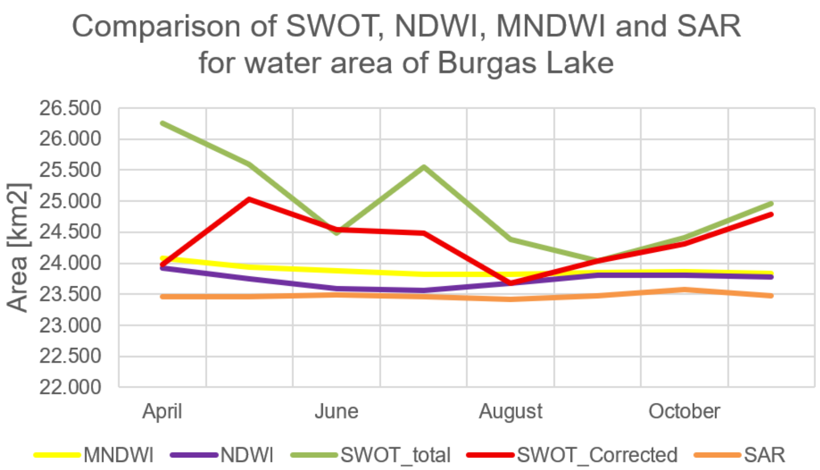

Figure 11. Comparison between SWOT and the established methods for water area

Monthly results are also presented in the cartographic schemes. Each scheme contains the whole lake and also some specific area where the biggest differences are present. The cartographic schemes can be seen in Figure 12 – Figure 19.

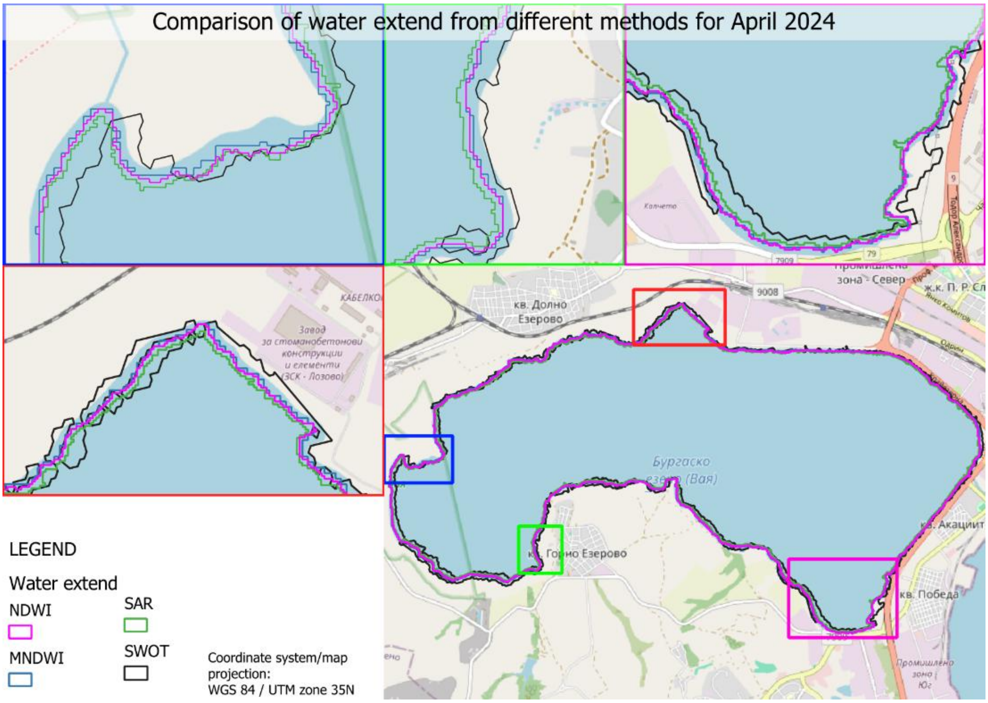

Figure 12. Difference in contours between SWOT, NDWI, MNDWI and SAR for April

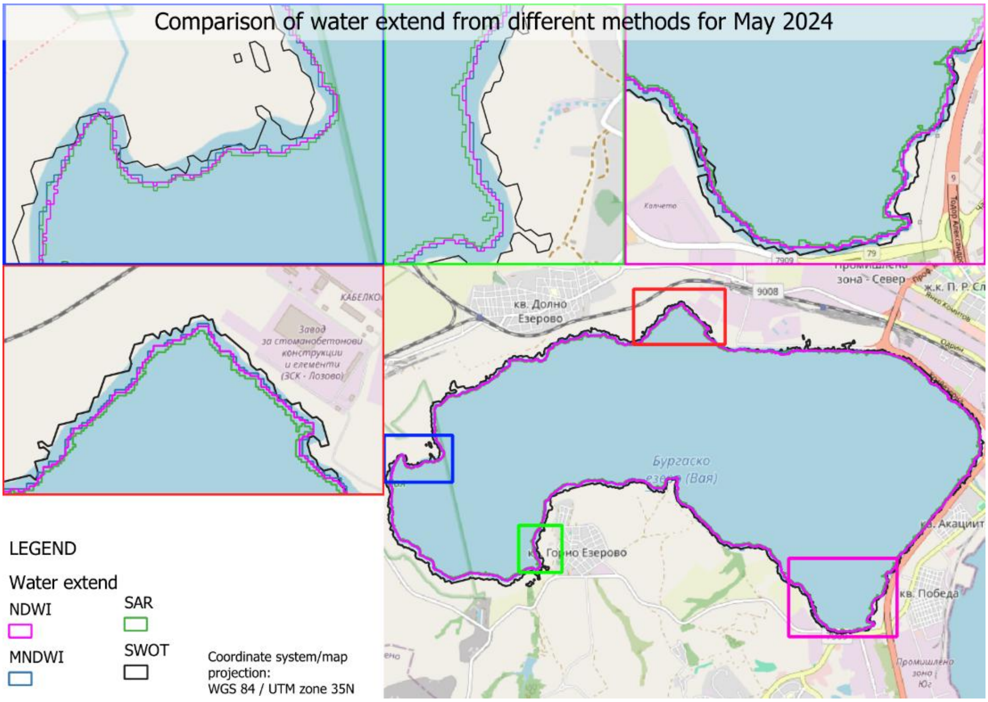

Figure 13. Difference in contours between SWOT, NDWI, MNDWI and SAR for May

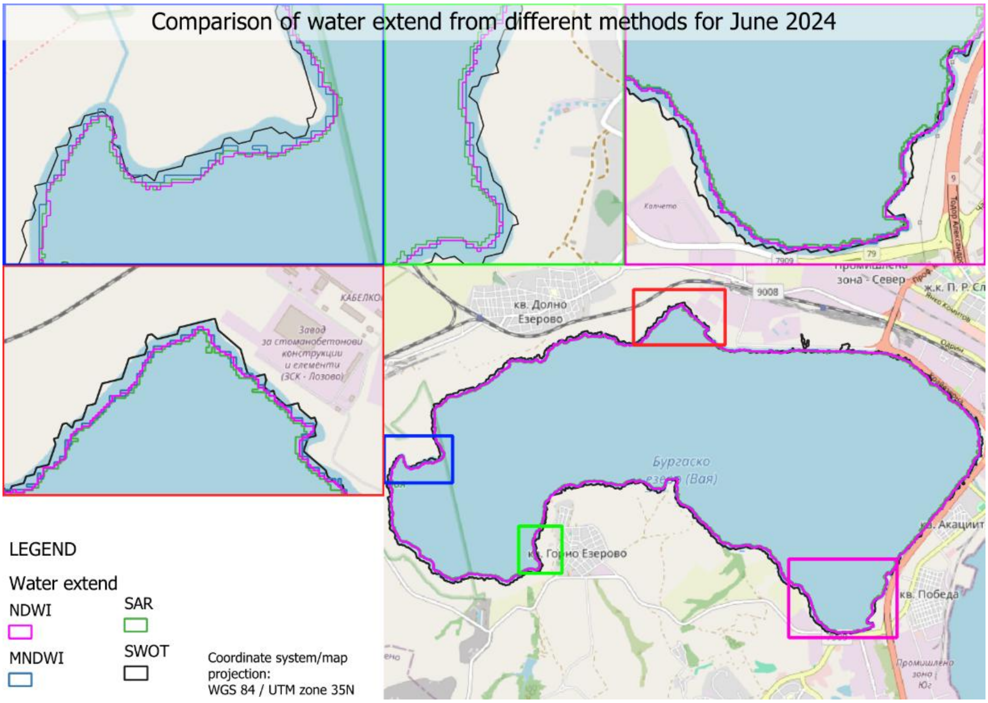

Figure 14. Difference in contours between SWOT, NDWI, MNDWI and SAR for June

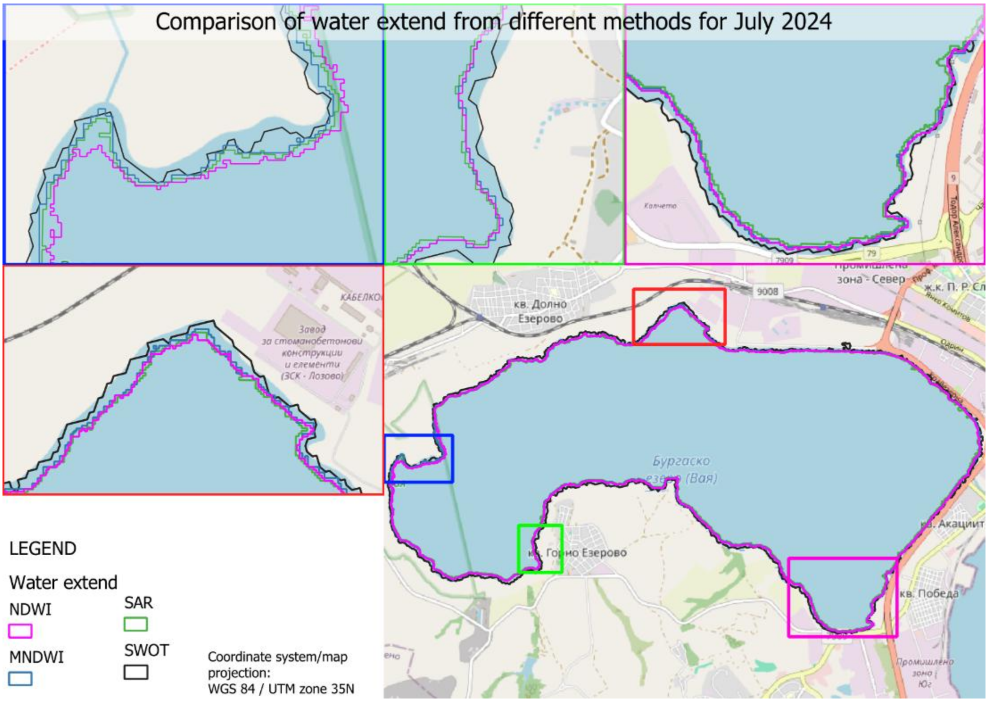

Figure 15. Difference in contours between SWOT, NDWI, MNDWI and SAR for July

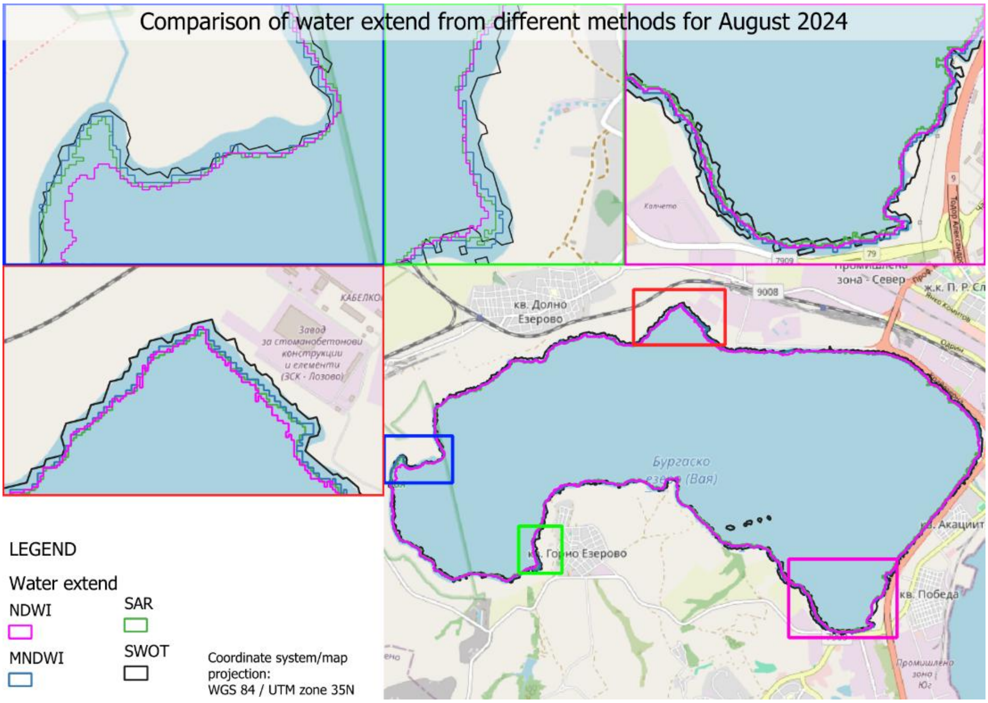

Figure 16. Difference in contours between SWOT, NDWI, MNDWI and SAR for August

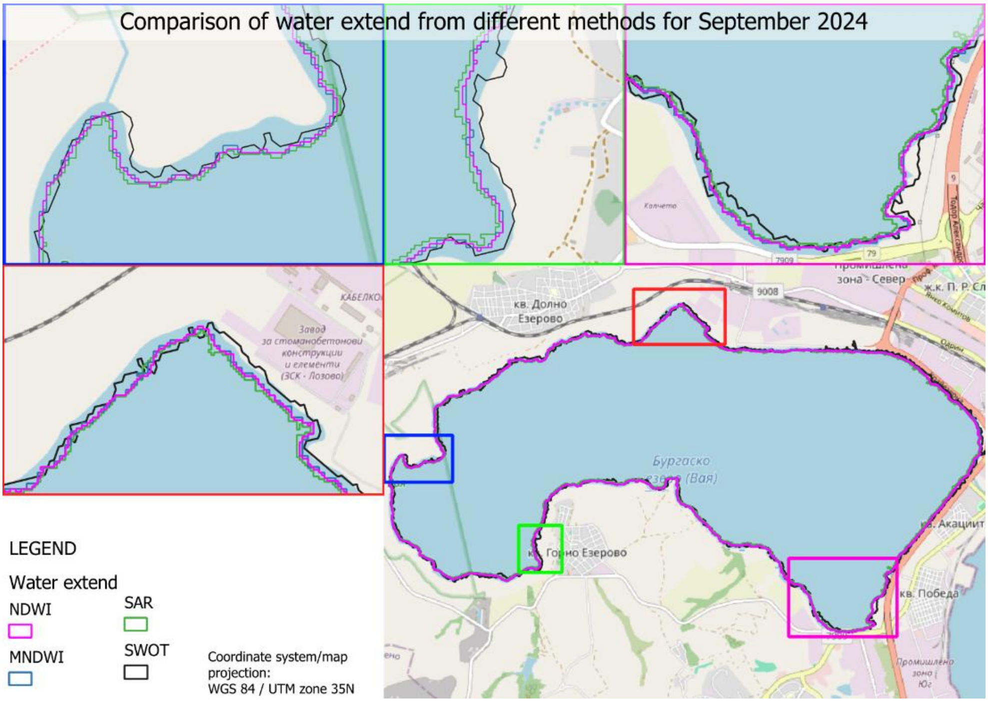

Figure 17. Difference in contours between SWOT, NDWI, MNDWI and SAR for September

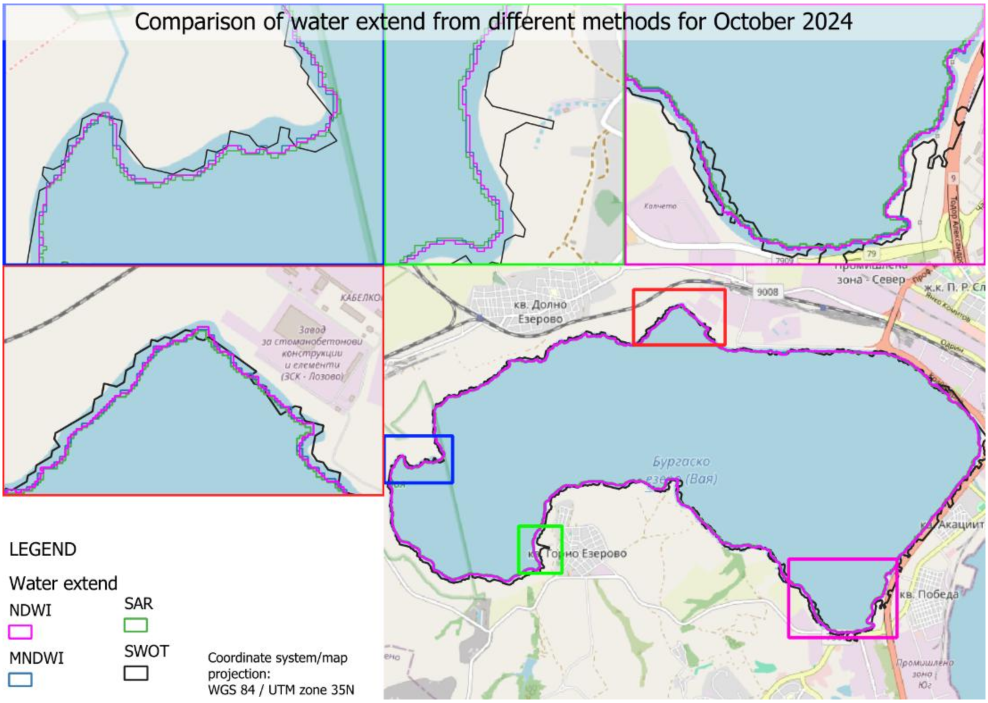

Figure 18. Difference in contours between SWOT, NDWI, MNDWI and SAR for October

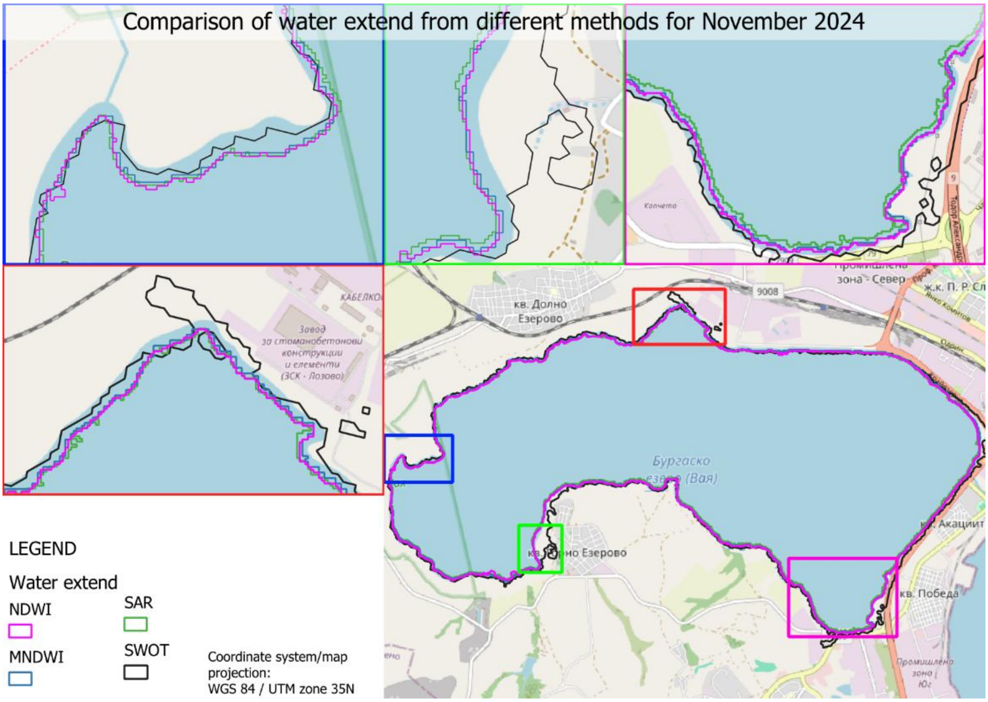

Figure 19. Difference in contours between SWOT, NDWI, MNDWI and SAR for November

7. Conclusion

SWOT is a recently launched mission designed to measure water surface elevation and extent, providing hydrologically relevant data at a 21-day temporal resolution. In this study, a comparison was performed between SWOT-derived lake products – specifically for the water extent of Burgas Lake, and established remote sensing methods based on spectral indices and SAR imagery.

Preliminary analysis of the SWOT data revealed several cases of false detection, including merging of the lake outline with adjacent parts of the Black Sea, as well as misclassification of urban areas and land features as water. While some of these errors are flagged by SWOT quality indicators, the quality flag attribute is not consistently reliable. Manual correction of such errors substantially improves the delineation of water extent; however, significant discrepancies may still remain.

The established methods used in this study – spectral indices (NDWI and MNDWI) and SAR data – offer more precise delineation of water extent but lack the ability to estimate water surface elevation. Moreover, spectral indices are affected by weather conditions and environmental factors such as vegetation, built-up areas, and wet soils. SAR, while not weather-dependent, is affected by the sensor's viewing geometry, which can reduce accuracy in areas with steep terrain or narrow channels.

Both traditional methods also require additional pre- and post-processing, which is largely automated in the SWOT Level 2 products. Despite the need for occasional manual correction, SWOT proves to be a reliable and promising source of simultaneous water extent and elevation data at regional scales.

In summary, this study demonstrates that SWOT data, when validated and corrected using classical methods, can provide comprehensive lake monitoring capabilities. The integration of SWOT with traditional remote sensing approaches offers a robust framework for the unsupervised monitoring of lake dynamics, particularly in data-sparse or inaccessible regions.

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КАРТОГРАФИРАНЕ НА ОЧЕРТАНИЕТО НА БУРГАСКОТО ЕЗЕРО ПО ДАННИ ОТ ДИСТАНЦИОННИ ИЗСЛЕДВАНИЯ

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Ключови думи: *PCA, SWOT, NDWI, MNDWI, дистанционни изследвания, картографиране на водни обекти*

РЕЗЮМЕ

Ефективното управление на водните ресурси изисква надеждно картографиране на водните обекти, което може да бъде постигнато чрез използване на сателитни данни от дистанционни изследвания. Радари със синтетична апертура (SAR) и мултиспектрални изображения, особено от сателити като Sentinel-1, Sentinel-2 и мисията SWOT, предоставят ценна информация за картографиране и мониторинг на водни обекти, която може да бъде използвана за опазване на околната среда и реагиране при бедствия.

SAR сензорите имат съществено предимство, че могат да проникват през облаци и да функционират независимо от слънчевата енергия, което позволява непрекъснат мониторинг независимо от метеорологичните условия. Мултиспектралните изображения, особено от Sentinel-2, предоставят спектрална информация, полезна за разпознаването и картографирането на водни тела чрез спектрални индекси. Мисията SWOT представлява технологичен пробив, като съчетава SAR интерферометрия с алтиметрия за измерване на височината на водната повърхност с висока пространствена разделителна способност. SWOT допълва съществуващите сателитни системи, предоставяйки детайлни данни за водните нива, които са от съществено значение за хидроложките изследвания.

Настоящата статия разглежда различни методи за картографиране на водни тела, включително използване на спектрални индекси като нормализирания разликов воден индекс (NDWI) и неговата модифицирана форма (MNDWI), SAR и SWOT данни, с цел да се изтъкнат различията, предимствата и недостатъците на картографиране на контурите на Бургаското езеро чрез дистанционни методи.

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