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Article

Methodology for Creating Surface Water Database Using GIS Tools and Remote Sensing

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Abstract

Although it seems obvious in today's era of digitization to have an electronic surface water database, as proven in earlier studies, there are still many shortcomings, errors, and a lack of updating spatial information about the hydrographic network despite its dynamic nature. The answer to the need for an up-to-date spatial water database combines GIS and remote sensing tools. Using the example of the Polish administration, this article synthesizes the structure of the surface water database. It develops a scheme for using geoinformation tools to automatically obtain information about the hydrographic network's course. The study also analyzed the optimization of remote sensing input images of medium and low aerial ceiling.

Keywords: hydrography; water database; UAV; aerial imagery

1. Introduction

Geographic Information Systems (GIS) are widely used in water management, and modern hydrological analysis would not be as advanced were it not for the development of GIS. Although analytical algorithms are based mainly on vector data, large-scale data production is possible based on raster photogrammetric materials. Acquisition of data whose reliability and precision allow its final use for analytical purposes is possible thanks to today's developed remote sensing tools. This coupling of GIS and remote sensing tools was used, among others, by S.M. Taher [1] studying the degree of irrigation of agricultural areas, or B. Rahmani [2] designed a catchment management model for flood and drought management. Another widespread application of GIS and remote sensing tools in water management is the remote study of water quality, as demonstrated by the authors in their study on the use of multispectral indicators for remote detection of changes in the amount of chlorophyll or salinity in flowing waters [3,4].

As repeatedly emphasized in previous studies, despite the extensive resources of algorithms enabling precise representation of the hydrographic network in geographic space, existing surface water databases exhibit numerous discrepancies with the actual state. The main reasons for this state of affairs are a separate vectorization technique, lack of updating and unification on a supra-regional scale [5,6]. At this point, it is important to distinguish between the concepts of surface water database and the inventory. An inventory is a register - a catalog quantifying phenomena [7,8]. A spatial database, on the other hand, combines information about the location of the objects in question with descriptive attributes [9]. Search or filtering algorithms allow cataloging the data collected in the database so that the concept can access the database. Thus, in the hydrographic network, an inventory is a catalog of data of hydrographic objects (e.g., natural watercourses, lakes, artificial reservoirs). A water registry assigning the issue of maintenance of water data to a selected entity should therefore

exist legally. A spatial database can be the tool in which such an inventory is created, or it can be a separate entity that spatially or attribute-wise organizes the information collected in the inventory [10]. While the creation of a database is a technical activity, the issue of inventory, especially merged with other regions, remains a substantive difficulty for every administrative level in Poland and around the world [11].

The input material is a key factor in obtaining the final product, such as a database. In the case of remote sensing data acquired within the context of a hydrographic network, the choice of data acquisition altitude is particularly important. Satellite images have low spatial resolution but allow for imaging a large area at a single moment (provided there is no cloud cover). Aerial photos (especially low-altitude ones acquired using an unmanned surface vehicle) allow for the acquisition of high-resolution images, but for large areas, this is a time-consuming process and requires working with BIG DATA. In the case of aerial remote sensing, it is impossible to acquire data for the same hydrological state (images are taken on consecutive days when the water level – the area occupied by water – may change) [12–14]. The issue of terrain relief also remains an important consideration – a photogrammetric raid should be planned for a uniform surface, eliminating the problem of terrain leveling (imaging scale change issues) and exposure (shading). When processing images acquired from a raid crossing different geographic landscapes, there may be disturbances in the measurement and generation of vector information (artifacts) [15].

Although the most common way of transferring hydrographic data to geo-information space has been the digitization of analog hydrographic maps or manual vectorization based on orthophotos [16,17], there are a number of tools that allow automatic generation of information about the course of the hydrographic network.

Among the methods of remote detection of water, the following can be distinguished:

- use of multispectral indicators,
- supervised classification,
- detection of objects based on deep learning algorithms,
- detection of subsidence based on the Digital Terrain Model (point cloud classification),
- use of the ArcHydro toolkit to generate a hydrographic network based on the Digital Terrain Model (DTM),
- contour map generated based on DTM (for water bodies).

The application of a particular method depends, on the one hand, on the availability of data, the technical possibilities in terms of the amount of data processed (hardware performance), as well as the target needs (the precision of processing and the type of output data – for example, linear data or polygons).

With images collected in several spectral ranges, especially in the near infrared, it is possible to perform a pixel algebra that allows for the isolation of pixels whose brightness is characteristic only for water [18]. This relationship forms the basis for indices such as the Near Differenced Water Index (NDWI), the Water Index (WI), and the Automated Water Extraction Index (AWEI) [19–21].

On the other hand, supervised classification is one of the pioneering machine learning methods of classifying pixels based on distance and brightness similarity. Thus, with the help of supervised classification, it is easy to automatically distinguish pixels representative of waters from pixels corresponding to the riverbank's zones [22]. Advanced and contemporary machine learning algorithms have made it possible to detect objects based on models generated from training fields indicating the brightness of pixels corresponding to a given land cover type. However, the use of deep learning for water detection is not limited to vast areas due to, among other things, the large size of the data required to generate and apply the model [23].

Taking advantage of the relationship that water always accumulates in depressions, its remote detection is effective using Digital Terrain Models. Due to the overlying land cover, extracting from the point cloud those points that correspond exclusively to the ground is necessary. If such classification is not already done at the raid stage, it can also be done using algorithms available in GIS software (e.g., Ground classification tool) [24,25]. For remote detection of water extent in a GIS

environment, it may be helpful to create a contour drawing in which a given level delineates the extent of damming of a given reservoir [26].

Another useful tool for generating comprehensive hydrographic network information based on DEMs is ESRI's ArcHydro Tools. Using the toolkit, hydrographic information is generated in vector format based on analysis of runoff direction, flow accumulation, and catchment area [27].

Although the range of methods for remote sensing of waters is wide, each has limitations, while the key element of any hydrographic inventory is a reliable attribute description. For this reason, the final result of this work will be a proposal for a unified spatial structure of the hydrographic database, together with an optimized method of its acquisition (based on remote sensing and GIS) in order to create a consistent water inventory at the supra-regional level.

2. Materials and Methods

2.1. Study Area

The research was carried out on the example of Poland, with particular attention paid to the Imielinka River basin. The Imielinka River is a third-order stream within the Vistula River basin. The Imielinka River's sources are in a forested area in the center of Imielin, and the stream's length is approximately 8.1 km. At its mouth, the riverbed width is about 2.5 meters, and the catchment area covers 77.7 km². The river channel is largely regulated and equipped with numerous culverts; some sections are conducted in piped segments [28].

Imielinka flows as a right tributary into the Przemsza River near the Dzieńkówice reservoir, in the Chełm Śląski area. This region is situated on a highland, within the Chełm mezoregion (341.11), which is part of the Silesian Upland macroregion, in the subprovince of the Silesian-Kraków Upland, and within the Polish Uplands [30]. The area lies within a transitional temperate climate zone, characterized by mixed forests. Administratively, the Imielinka River catchment is located within the municipalities of Lędziny and Chełm Śląski, in southern Poland, in the eastern part of the Silesian Voivodeship (Figure 1).



Figure 1. Study area.

2.2. Attribute Structure

To identify key attribute data for the hydrographic network database, a nationwide survey was conducted among water management specialists – employees of the entity responsible for water management in Poland, the State Water Management Authority (PWD) Polish Waters. Responses were collected in 2024 from 93 participants residing throughout Poland, primarily in the Silesian Voivodeship. Therefore, opinions regarding the structure of the surface water database are not significantly influenced by local hydrographic or historical conditions.

In response to the question "Which information is most important for describing a specific watercourse and should be mandatory in the developing database?" (Scale: 0 – unnecessary; 6 – very necessary), the following options were presented:

- Official name of the watercourse (accurate and recognized),
- Alternative names (used colloquially or in other registers),
- Stream order,
- River basin (name of the receiving waterbody),
- Nature/characteristics (surface water + type and number of relevant documents, uncertain, river or other),
- Responsible entity for maintenance,
- Date of the last update,
- Comments (current issues or problems related to the waterbody).

2.3. Materials

A key aspect of the research involved generating information about the hydrographic network based on imagery processed from photogrammetric flights.

Aerial imagery and the elevation point cloud data were collected during a photogrammetric flight conducted on June 15, 2024, between 4:35 and 7:45 AM by the SP-OPK Diamond DA62 aircraft. Weather conditions on the flight day included an air temperature of +2°C and a pressure of 101.4 hPa. The ground sampling distance (GSD) was less than 0.1 meters, with a cross-track coverage of $q=30\%$ and an along-track coverage of $p=80\%$. The flight direction was east-west. Photogrammetric images were captured in four spectral bands: red, green, blue, and near-infrared (NIR). A CityMapper-2 camera equipped with a D69.146/4.8 146 mm lens and a LiDAR (Light Detection and Ranging) scanner was used. The point cloud density was 7 points per square meter. The pixel size (GSD) was 1.5 meters.

Low-altitude images (flight altitude of 108 meters) were obtained using an Unmanned Aerial Vehicle (UAV) DJI Mavic 3 Multispectral, equipped with an RTK module. The flight took place on June 28, 2025. Images were captured in the following spectral ranges: visible (Red, Green, Blue), Red Edge, and Near Infrared (NIR). The pixel size was 5 centimeters.

The acquired images were aligned and processed into orthophotomaps using Agisoft Metashape software in both cases. The point clouds in LAS format were grouped into datasets and processed into a digital elevation model (DEM) and a digital terrain model (DTM) using ArcGIS Pro 3.2.

2.4. GIS Analysis

The process initially involved using orthophotomaps derived from images captured in the Green and NIR bands to generate information about the extent of the hydrographic network automatically. The Near Difference Water Index (NDWI) was calculated using a raster calculator. The NDWI is used to identify the presence of flowing water by analyzing the specific reflectance of the water surface relative to its surroundings. The index was computed through pixel algebra by dividing the green (GREEN) and near-infrared (NIR) bands according to the formula:

$$(GREEN - NIR) / (GREEN + NIR) \text{ [19]}$$

NDWI values range from -1 to 1, with values greater than 0 indicating water-covered areas [31]. The resulting NDWI raster was reclassified in the next step using the equal interval method and then converted into a vector layer.

Point clouds were converted into LAS datasets for further analysis and subsequently transformed into a Digital Elevation Model (DEM). By adjusting the symbology, the lowest points representing the riverbed were identified.

All the abovementioned analyses were performed using ArcGIS Pro 3.2 software.

2.5. Field and Statistical Research

To verify the accuracy of remote detection of the river's course relative to its actual path in the field, measurements were conducted on August 29, 2024, using a GPS receiver Carlson BRx7. A total of 53 points were measured in the PUWG 1992 coordinate system at accessible locations within different parts of the riverbed (see Figure 1).

Subsequently, the distance between the automatically generated line representing the river's course and each measured point within the riverbed was measured using Near Distance. Then, the Pearson correlation coefficient was used to assess the correlation between the distances obtained for the line generated based on aerial images taken at medium and low altitudes.

The Pearson correlation coefficient is defined as the ratio of the covariance between two variables to the product of their standard deviations, and it is calculated using the following formula:

$$\rho = \text{cov}(X, Y) / (\sigma_x * \sigma_y) \text{ [32]}$$

In this context, *cov* represents the covariance, while σ_x and σ_y denote the standard deviations of variables X and Y, respectively. The coefficient's values are confined within the closed interval [-1, 1]. A higher coefficient value indicates a stronger correlation.

3. Results

3.1. Database Structure

Firstly, survey research was conducted among water management specialists in Poland (employees of Polish Waters), in which respondents rated the most important attributes that should be recorded in the water register on a scale from 0 to 6. All respondents (i.e., 93 individuals) indicated the necessity of specifying the official name of the watercourse. Additionally, attributes such as the name of the water body's unit, information about the owner, and the character of the water were considered important. Conversely, the flow direction of the watercourse and the comments field were regarded as less significant. The greatest discrepancies in responses concerned the need to include alternative (other existing) names of the watercourse and the date of data updates (Figure 2). In response to the question about additional necessary attributes, there were frequent suggestions emphasizing the need to determine the mileage of the watercourse, which is only possible once the vector layer depicting the course of the river is accurately defined.

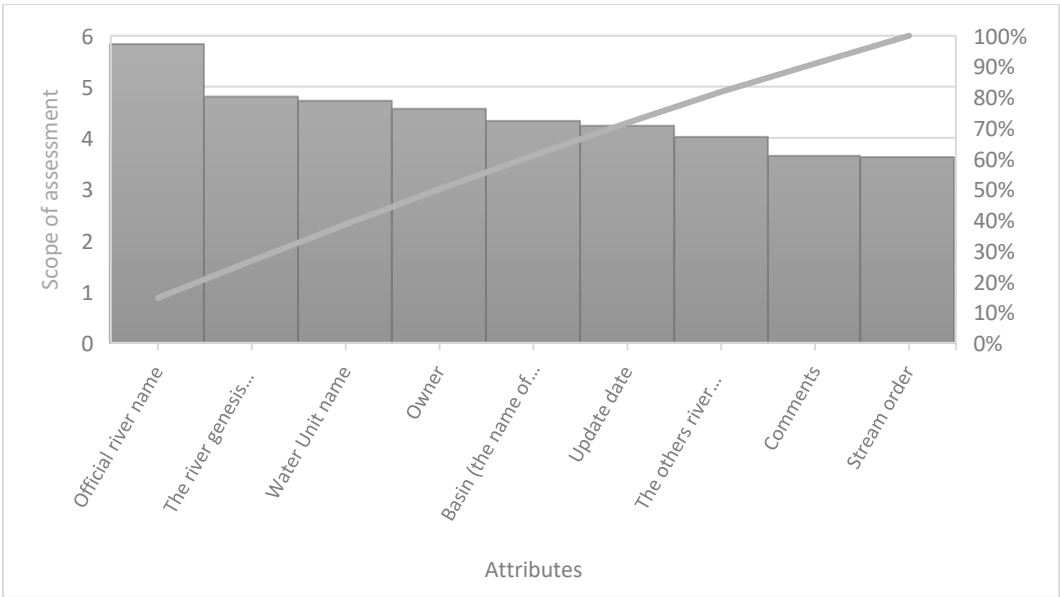


Figure 2. Results of the survey regarding important attributes of the surface water database. Own study.

Based on the survey results, the authors in Figure 3 propose a scheme for a surface water database that can act as an inventory. It should be noted that the length field should include the length according to the field information in kilometers (in the format of 0.00), as it will be different from the length of the polyline representing the watercourse (due to the transformations associated with the relief when converting the length using the algorithm).

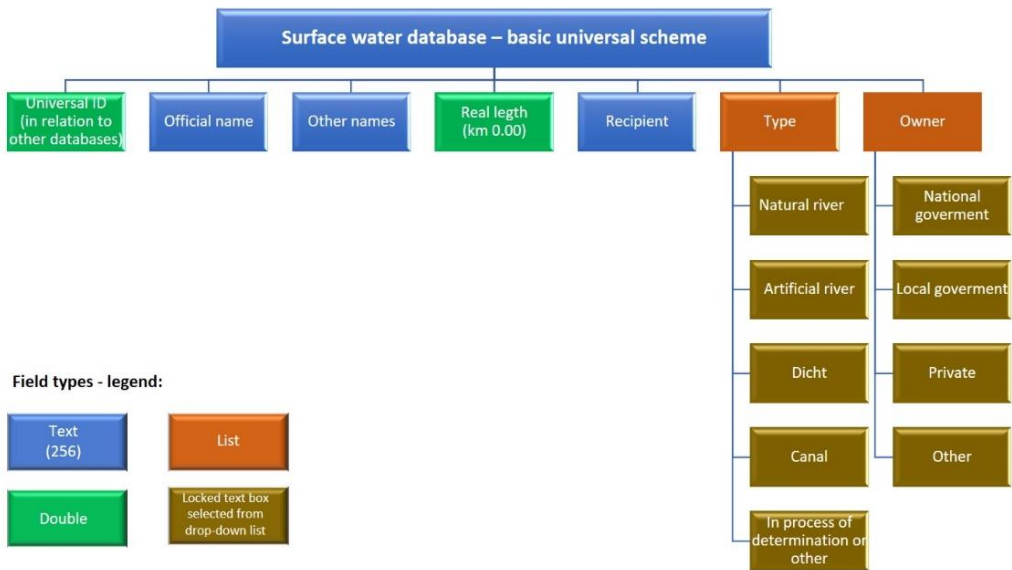


Figure 3. Proposed attribute scheme of the watercourse layer.

3.2. The Current Course of the Hydrographic Network – Workflow

Once the attribute structure has been created, the next step is to properly drawing in the objects. Based on previous research (under publication), the following scheme for processing photogrammetric images into vector data about the hydrographic network was adopted (Figure 4):

1. Creation of an orthophotomosaic from images acquired in the Green spectrum and the NIR spectrum.
2. Processing of orthophotomosaics based on the NDWI index.

- 3. Reclassification of NDWI orthophotomosaics (equal intervals at 0.1 intervals).
- 4. Raster to polygon transformation (classes representing NDWI values > 0).
- 5. Simplifying the polygon representing the river reach and converting it into a line.
- 6. Verification with DEM at 0.5 m interval of the lowest points of the terrain (riverbed) - from the mouth downstream.

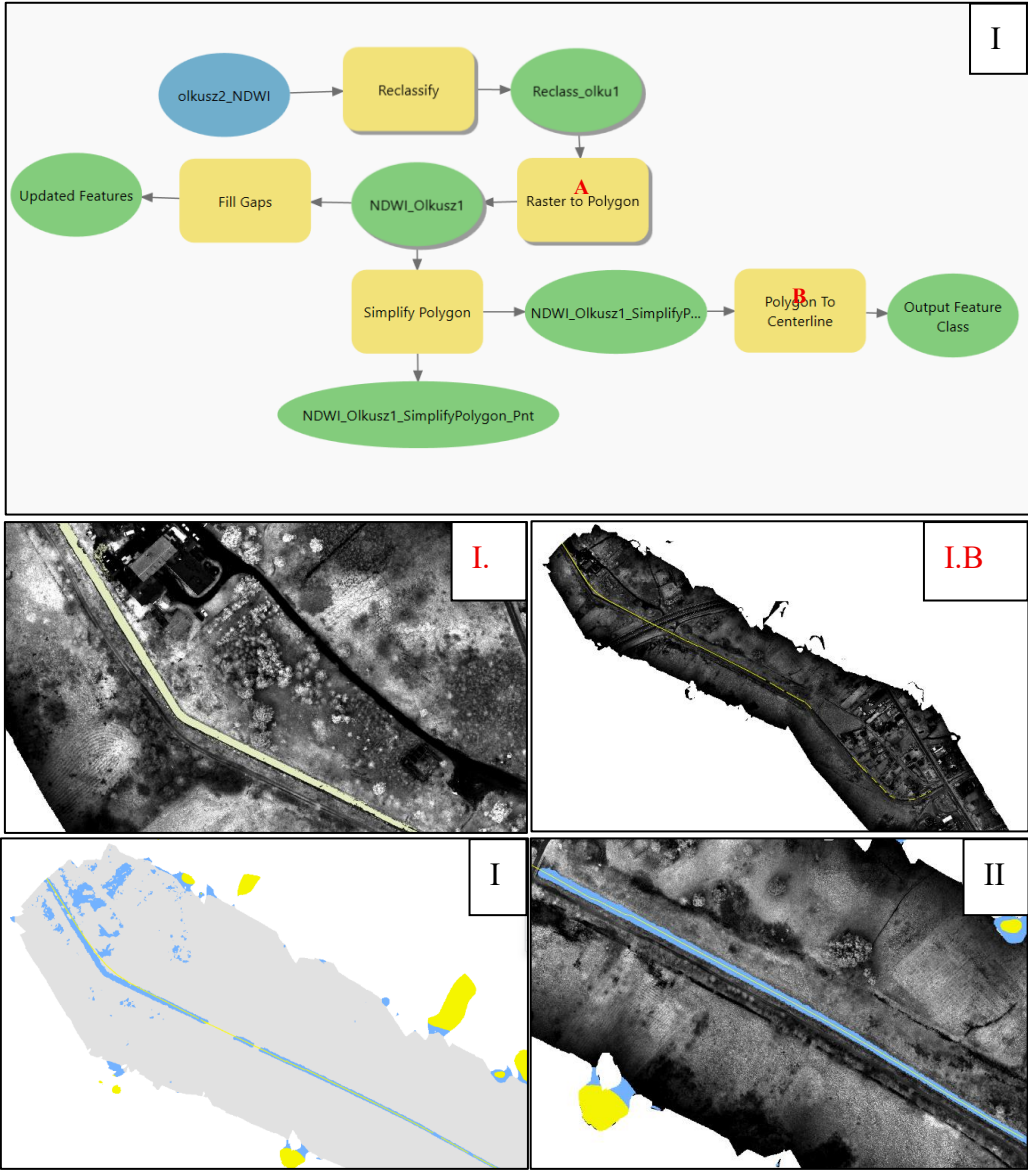


Figure 4. I - workflow of processing NDWI imagery to produce hydrographic network information automatically. I.A - the effect of using the raster to polygon tool - the extent of the river in the form of a vector polygon. I.B - the effect of using the Polygon to centerline tool - producing a line depicting the course of a watercourse based on the generated polygon representing the river reach. II - changing the symbolization of the DEM so that only areas representing the elevation of 348 m above sea level are visible. III - symbolization of the DEM so that only areas representing the elevation of 348.5 m above sea level are visible.

Verification of the course of a watercourse based on DTM/DEM is ineffective in an area densely covered with vegetation (numerous artifacts - elevations or inability to extract points representing the ground). In general, however, using the appropriate symbolization, it is easy to extract the lowest points in relation to the environment, i.e. those representing the course of the riverbed. NDWI, on the other hand, does an excellent job of penetrating through vegetation and detecting water between plants.

Using both methods complementarily, it is possible to indicate the actual course of the hydrographic network with high accuracy. A DEM or DTM gives a general terrain picture, while NDWI helps isolate water even among dense vegetation.

3.3. Comparison of Accuracy with Field Measurements

To investigate whether the information obtained from aerial imagery captured at medium altitude (aerial photogrammetric flight) is consistent with the data derived from low-altitude remote sensing (collected using UAV), the polylines generated based on these data were compared against ground survey measurements.

The measurements were performed using a precise GPS receiver at locations where it was possible to mark a point in the center of the watercourse. It should be noted that there was no possibility to delineate the full course of the river in the field for safety reasons, such as steeply terraced banks, dense vegetation, or unfavorable terrain. Table 1 presents the distances from the measured points, obtained using the GPS receiver, to the line determined from aerial imagery and UAV images.

Table 1. The distances from the measured points, obtained using the GPS receiver, to the line determined from aerial imagery and UAV images.

Lp.	X	Y	Distance of the GPS point from the line determined from the aerial imagery	Distance of the GPS point from the line determined from the UAV imagery
1	5553662.3240	6587091.9930	0.20123473581	0.61120941410
2	5553662.3270	6587091.9710	0.22340259726	0.58918978673
3	5553686.1510	6587094.2920	1.35950727815	2.07412499404
4	5553713.1050	6587067.2010	2.92393379020	3.24197553216
5	5553721.9260	6587044.2420	2.84521831154	3.97735801300
6	5553653.0730	6587091.7100	0.24468030310	0.39026633416
7	5554854.3470	6587100.8930	0.35596994974	0.19725880052
8	5554755.5080	6587085.6840	0.37687069952	0.43301925788
9	5554912.2290	6587108.4610	0.08891688128	0.04516403421
10	5554955.8490	6587106.4790	1.48677535474	2.47426261953
11	5555727.5200	6585817.5230	2.77874144754	1.71913735639
12	5555711.9850	6585831.1430	6.36562417398	4.84815567378
13	5555711.2750	6585890.7730	0.69380229373	1.47682472104
14	5555697.5570	6585935.5130	4.94803593652	3.18517533876
15	5555678.6000	6585977.7690	0.39531537535	0.30010402643
16	5555680.9010	6585986.4630	0.18469115902	1.16614456089
17	5555687.3960	6585998.6640	3.91787638830	3.38646075770
18	5555755.0850	6585797.8010	4.77991842586	3.80750225173
19	5553631.0354	6587091.0778	0.16705608049	0.47832405239
20	5553597.6801	6587094.1407	0.82979868294	0.83749625632
21	5553565.6094	6587099.7812	0.84969382634	0.60206937165
22	5553549.1327	6587120.8339	1.08993086869	0.11473010311
23	5553533.5209	6587164.4437	1.21307440569	1.69010130833
24	5553515.0806	6587228.2676	2.00632118934	1.48428215329
25	5553490.7273	6587313.5387	1.69091614127	1.05099721187
26	5553460.9580	6587419.8051	1.18033018455	0.27592336952
27	5553477.3579	6587362.1554	1.08074277965	0.41587973953
28	5553444.4476	6587458.6399	1.08050917238	0.58891686599
29	5553409.7457	6587495.5614	1.27261485667	0.12798261565
30	5553373.3508	6587530.0708	1.01081128972	0.05102895381

31	5553342.2554	6587560.4140	0.41149089872	1.12897692129
32	5553316.0771	6587581.5558	3.14377384887	1.82133974934
33	5553300.4576	6587616.8566	2.65135737292	1.76841489041
34	5553295.8684	6587670.9995	1.53467329132	2.01262285992
35	5553297.0140	6587733.1934	0.64178147057	0.21846785248
36	5553296.2717	6587794.4748	0.75140323050	0.72777181835
37	5553296.8354	6587813.2238	0.30973076970	0.35170007331
38	5553176.3561	6588051.7690	0.18380912995	0.55485449285
39	5553170.9389	6588058.2142	1.22971799893	1.90816198374
40	5554994.3451	6587106.4858	0.61276807592	0.54403990244
41	5555028.7390	6587105.3119	0.58972287695	0.68233765549
42	5555045.3585	6587103.6421	0.65729132994	0.64137737006
43	5555053.2452	6587098.2304	1.56409946928	0.06006766963
44	5555067.4833	6587062.8263	0.42401330593	0.06154681054
45	5555075.8673	6587040.5248	0.58260147118	0.06338715582
46	5555089.5262	6586997.8929	1.35501815801	2.09386247506
47	5555115.4572	6586952.9630	2.99398821416	2.27722926894
48	5555121.9778	6586938.5733	0.72520992772	0.67550889887
49	5555680.6777	6586026.3729	1.76458335455	2.03021234630
50	5555673.2435	6586060.9894	1.82312584075	2.16272172264
51	5555668.7313	6586084.4511	0.34458405986	2.13136738382
52	5555669.6648	6586107.1519	0.07921604258	0.23351891460
53	5555671.3579	6586129.5683	0.33592788335	0.35176127483
54	5555673.0572	6586152.4489	1.18634532812	1.26309929097

The width of the riverbed at the mouth is 2 m, while the maximum distance of automatically drawn polylines (based on NDWI and DTM/DEM) is more than 6 m for aerial photos, and more than 4 m for drone photos. For the distance of GPS points from the polylines drawn automatically from low-altitude photos, the other basic statistics (mean or median) are also lower (Table 2).

The line drawn from the aerial photo is located more than 2 m from the point measured in the field in the center of the trough in 18.5% (10 points out of 54). In the case of the line drawn from photos taken with a UAV, 14 points out of 54, i.e. 26%, are located more than 2 m from the point measured in the field.

The line drawn from aerial photography is located more than 1 m from the point measured in the field in the center of the trough in 52% (28 points out of 54). As for the line drawn from photos taken with a UAV, 25 points out of 54 i.e. 46% are located more than 1 m from the point measured in the field.

Table 2. Basic statistical quantities about the distances from the measured points, obtained using the GPS receiver, to the line determined from aerial imagery and UAV images.

	Distance of the GPS point from the line determined from the aerial imagery	Distance of the GPS point from the line determined from the UAV imagery
MAX	6.36562417398	4.84815567378
MIN	0.07921604258	0.04516403421
AVERAGE	1.40603674223	1.27317336645
MEDIAN	1.08062597602	0.78263403733

Therefore, a general trend indicates that the river's course was delineated with greater accuracy based on photogrammetric data collected through low-altitude remote sensing.

Additionally, a Pearson correlation test was conducted to examine whether there is a correlation between the distances of the lines drawn from aerial images and low-altitude images relative to

points marked with GPS in the Imielinka watercourse. The correlation coefficient was 0.836, which is statistically significant (Figure 5). To confirm the high agreement, a non-parametric Sign test was also performed, yielding a p-value of 0.892. Since $p\text{-value} > 0.05$, the null hypothesis H_0 : The two samples follow the same distribution can be accepted. Statistical analyses thus demonstrated a high similarity between the course of the watercourse delineated based on aerial imagery at medium and low altitudes.

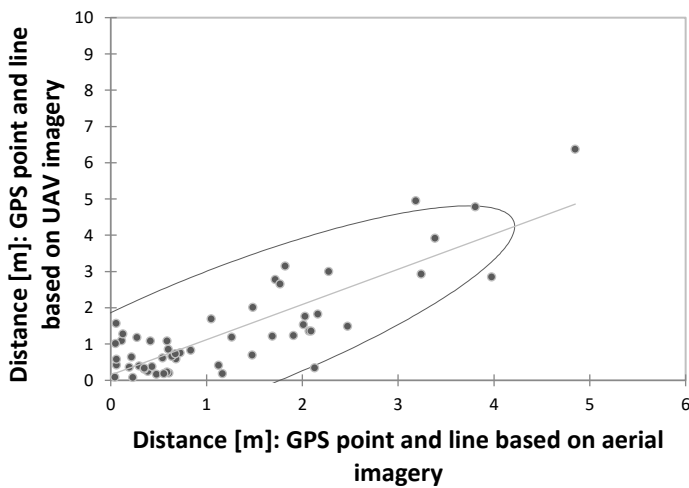


Figure 5. The result of Pearson's correlation between the distances of the lines drawn based on medium- and low-altitude aerial photos from points in the Imielinka watercourse bed.

4. Discussion

The foundation of any spatial database is attribute data. These data determine the ability to generate queries for definition or selection and produce a spatial image according to specified criteria [29]. The desired scope of such data often results from the empirical experience of operators who input and process the data [33]. Therefore, the universal range of attribute data for water records presented in this work is based on survey data among water management employees. However, it should be noted that the survey was conducted exclusively in Poland, and the level of technological advancement and needs, including geographic information systems and remote sensing systems, vary across different regions of Europe and the world [34]. For this reason, survey results, although conducted in various geographic regions, may exhibit subjectivity, undermining the universality of the proposed database.

The surveys often indicated that there was a lack of information on the length of the watercourse. Creating a layer with the kilometer markers requires a few simple steps (dividing the line representing the watercourse into equal segments and determining points at the beginning and end of each segment) [6]. However, determining the river's length properly depends on accurate spatial databases, publicly available as official, unified, and geometrically correct data sources (which helps avoid discrepancies in data sets, etc.) [35–37].

Every method of verifying or delineating a linear object's course has limitations. Although it might seem that marking the watercourse in the field would allow for the most precise indication of its course, it should be noted that it was impossible to obtain the coordinates of a point located within the watercourse in many cases. The reasons included a lack of access to the watercourse (e.g., steep banks with an inclination $>80^\circ$) or obstructions such as trees overhanging the watercourse that disturb positioning.

Dense vegetation both within the watercourse and along the banks is the most common cause of noise in remote sensing imagery [38,39]. Other noise sources include variability in lighting

conditions during data acquisition (e.g., local cloud cover) and incorrect interpretation of the reflected wave spectrum [40]. Consequently, there are issues with pixel classification based on similarity in radiometric resolution [41]. The information obtained about the course of the Imielinka River based on the NDWI index calculated from aerial images was significantly less precise (in many places, the watercourse was not visible or asphalt/concrete surfaces had similar values to water) compared to the results obtained using this index on drone-acquired images.

The inverse relationship, on the other hand, was noted in the case of digital models. In the case of aerial imagery, it was a DTM based on a point cloud, from which it was possible to select only those points that represent the ground (tool: generate ground). In the case of imaging obtained from a drone, only a DEM with a lower spatial resolution was created. In areas where the riverbed was covered, the DEM was completely unhelpful in determining the course of the watercourse. Despite this, M. Łacka [24], based on the DEM created from photos acquired with the UAV, analyzed the shoreline zone.

Nevertheless, high-density point elevation data from airborne laser scanning is commonly used to detect aquatic objects. This is due to the high sampling density, including between vegetation and other objects covering the watercourse. Increasingly, models based on neural networks are being used to classify a given terrain layer automatically [42]. Thus, in the case of laser scanning, it is not the data acquisition ceiling that matters, but the density of points per square meter. For this reason, in the presented research, the manual symbolization of a DEM produced based on a point cloud made it possible to indicate the river's course in its entirety. Another way is to generate contour drawings or modified terrain profiles [26].

Considering the basic statistical quantities, the line based on low-altitude imageries was closer to the points measured in the field than the line determined based on aerial imageries. On average, however, this magnitude did not exceed 1.4 m (so it should be assumed that both lines ran correctly within the riverbed, the width of which at the mouth was 2 m). However, the selection of the data acquisition ceiling is an individual parameter depending on the purpose of the study. The higher the ceiling, the lower the accuracy, but the greater the range of imaging done under uniform atmospheric conditions [43]. Statistical studies, however, have shown a high convergence between lines drawn based on aerial photographs of both medium and low ceilings.

5. Conclusions

Previous studies by the authors revealed significant discrepancies and issues (such as time consumption and lack of automation) in achieving a comprehensive inventory of surface waters. A key element is a reliable database of surface waters that accurately depicts the hydrographic network in space and describes its attribute-wise.

Based on existing knowledge and conducted analyses, the presented research proposed an optimal attribute structure and workflow for the automated acquisition and processing of photogrammetric imagery into vector information of the hydrographic network. It was found that although images acquired using UAVs offer higher precision (compared to points measured within the watercourse using a precise GPS receiver), aerial images can also provide this information with comparable accuracy.

The best input materials to accurately map the hydrographic network in space are a DTM (generated from a dense LAS point cloud with a symbolization interval of approximately 0.5 meters) and multispectral images processed using the NDWI index. In this way, the automatically delineated line representing the watercourse falls within the riverbed boundaries. Even field measurements of the watercourse course using a GPS receiver are not feasible for capturing the entire course. Therefore, it is impossible to find a perfect and universal method; the key lies in optimally selecting input materials and methods, considering cost and time efficiency.

The choice of data acquisition altitude depends on the scope of the project and the desired accuracy. A significant ongoing challenge is the raster or scanning data size and the required storage

capacity. Further research is necessary to optimize this process and explore the use of machine learning tools or neural networks to reduce the memory needed for processing.

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