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Methodology for creating surface water database using GIS tools and remote sensing

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Highlights

- The GIS and remote sensing tools are excellent for processing the hydrographic data.
- Attribute data is essential for the spatial database of the hydrographic network.
- UAV-captured images provide more precise hydrographic data.
- Images can also deliver this information with similar levels of accuracy.

Abstract: Although having a digital surface water database seems obvious in today's digital era, earlier studies show persistent shortcomings, errors, and outdated spatial information on hydrographic networks. A response to this need is the integration of geographical information systems (GIS) and remote sensing tools, using orthophotomosaics from photogrammetric flights in various spectral ranges and converting them into vector data on water extent. Using the example of the Polish administration, this article synthesises the structure of the existing surface water database and proposes a coherent, optimised, and scalable methodology for its development. The workflow covers both attribute design and an automated process for acquiring geometric information with GIS and remote sensing techniques. The methodology includes: (1) analysing attribute requirements through a survey; (2) acquiring and processing photogrammetric imagery from two altitudinal levels (aerial and unmanned aerial vehicle – UAV) and elevation data (digital terrain model/digital elevation model (DTM/DEM) derived from LAS point clouds); (3) automatic water detection using the normalized difference water index (*NDWI*) and elevation model classification; (4) assessing the accuracy of generated stream centrelines by comparing them with global positioning system (GPS) field measurements and performing statistical correlation analysis; and (5) developing a database structure supported by empirical evidence. Such automation enables rapid production of hydrographic information and ensures uniform data acquisition at a supra-regional scale. Consequently, the proposed methodology provides a foundation for a unified, automated, and scalable surface water inventory suitable for national and international applications.

Keywords: aerial imagery, GIS, hydrography, UAV, water database

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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 Taher (2020) studying the degree of irrigation of agricultural areas, or Rahmani (2021) 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 (Absalon *et al*., 2023; Matysik *et al*., 2025).

As repeatedly emphasised 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. As the aforementioned studies have shown, there are discrepancies of over 50% in the use of different names for the same watercourse or in the description of its length in relation to its actual length. In addition, there are significant discrepancies in the course of the riverbed and the mileage in various spatial databases (the discrepancies examined in over 30% of cases exceeded 100 m, and in some cases reached over 2 km). The main reasons for this state of affairs are a separate vectorisation technique, lack of updating and unification on a supra-regional scale (Janczewska, Absalon and Matysik, 2022; Janczewska, Matysik and Absalon, 2023). At this point, it is important to distinguish between the concepts of surface water database and the inventory. An inventory is a register – a catalogue quantifying phenomena (Oleński, 2005; Wojciechowski, 2013). A spatial database, on the other hand, combines information about the location of the objects in question with descriptive attributes (Samson, Lu and Xu, 2017). Search or filtering algorithms allow cataloguing the data collected in the database so that the concept can access the database. Thus, in the hydrographic network, an inventory is a catalogue 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 organises the information collected in the inventory (Mihaylenko *et al*., 2021). 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 (Janczewska *et al*., 2025b).

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) (Messina *et al*., 2020; Alvarez-Vanhard, Corpetti and Houet, 2021; Kubišta and Surový, 2021). 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 levelling (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 (artefacts) (Pervolarakis *et al*., 2023).

Although the most common way of transferring hydrographic data to geoinformation space has been the digitisation of analogue hydrographic maps or manual vectorisation based on orthophotos (Drwal *et al*., 2005; Doskocz, 2015) 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 (DTM) (point cloud classification),
- use of the ArcHydro toolkit to generate a hydrographic network based on the 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 (Rad, Kreitler and Sadegh, 2021). 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*) (McFeeters, 1996; Danaher and Collett, 2006; Feyisa *et al*., 2014).

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 (Sun *et al*., 2024). 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 (Nasir *et al*., 2023).

Taking advantage of the relationship that water always accumulates in depressions, its remote detection is effective using DTM. Due to the overlying land cover, extracting from the point cloud those points that correspond exclusively to the ground is

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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) (Łącka, 2021; ESRI, 2025). 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 (Stateczny *et al.*, 2023).

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 (Baye, 2020).

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.

In addition, the range of remote water detection methods developed is very extensive, and these methods are based on advanced deep learning techniques that generate high-quality (reliable) products. However, as indicated in their review (Janczewska *et al.*, 2025), there is no methodology that combines attribute, geometric and administrative issues. Attempting to develop such a comprehensive methodology is a challenge that the authors of this paper are trying to meet.

When analysing current achievements in geoinformation and geodesy in the field of remote and automatic object detection, the authors noticed a lack of uniform methodology. For this reason, the aim of this paper is to develop an optimal methodology for water inventory (database), from the acquisition of material to obtaining vector information about the extent of water bodies. Therefore the purpose of this article is to develop a comprehensive, unified, and scalable methodology for creating an up-to-date surface water spatial database by integrating attribute, geometric, and administrative components within one workflow. Firstly, the paper identifies which descriptive attributes are essential for an operational hydrographic database, based on a nationwide survey among water management professionals. Then authors evaluate and optimise the workflow for automatically extracting the geometry of watercourses using GIS tools and remote sensing imagery (aerial and unmanned aerial vehicle (UAV) multispectral data, *NDWI* indices, digital terrain model/ digital elevation model (DTM/DEM) analysis, point clouds). Finally, this article proposes a standardised spatial data structure and an automated processing chain suitable for supra-regional and national water inventories.

STUDY MATERIALS AND METHODS

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 centre of Imielin, and the stream's length is approximately 8.1 km. At its mouth, the riverbed width is about 2.5 m, and the catchment area covers 77.7 km^2. The river bed is largely regulated and equipped with numerous culverts; some sections are conducted in piped segments (Hydroportal, no date).

The Imielinka flows as a right tributary into the Przemsza River near the Dziećkowice 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 (Solon *et al.*, 2018). This area is located in a temperate transitional climate zone, where deciduous and mixed forests prevail. 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 Voivodship (Fig. 1).

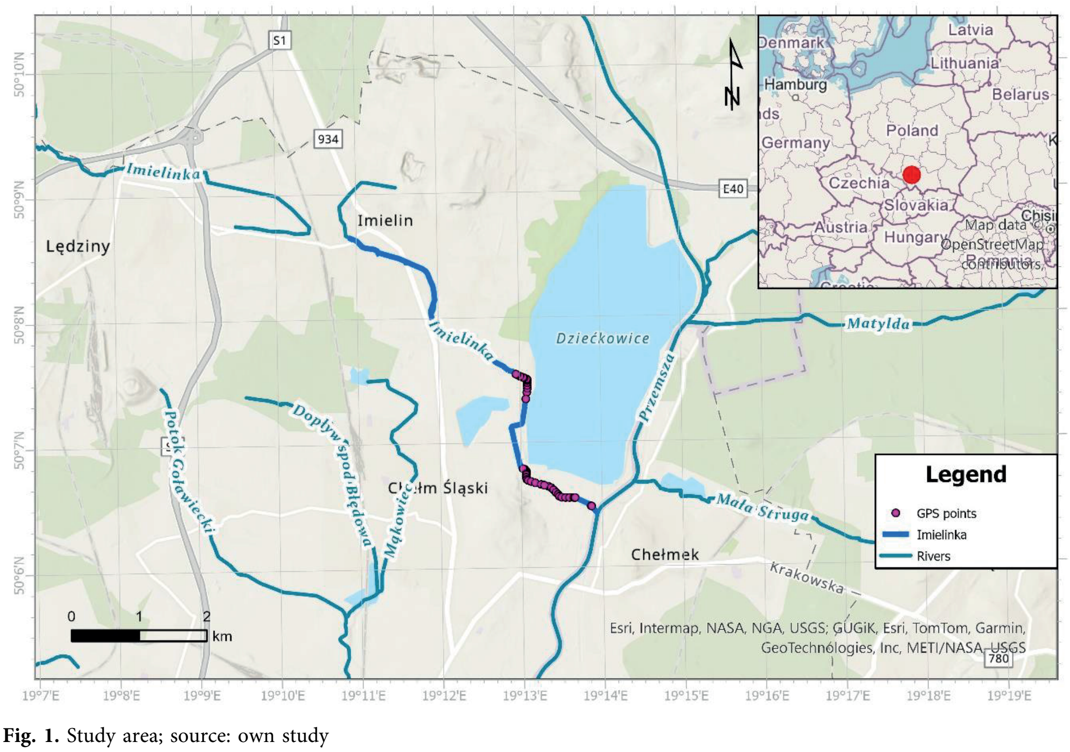

Fig. 1. Study area; source: own study

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The study area was selected due to the knowledge of the actual course of the river in the field, which allowed for the empirical detection of discrepancies with the existing digital Map of the Hydrographic Division of Poland at a scale of 1:10,000.

METHODS

The proposed methodology consists of three interlinked components:
- attribute structure development – identifying essential descriptive fields for the database;
- acquisition and processing of remote sensing material – preparing photogrammetric imagery, spectral indices, and elevation models;
- automated delineation and accuracy assessment – generating watercourse geometry and validating it against GPS field measurements.

Each component builds on the previous one to enable a unified and repeatable workflow.

ATTRIBUTE STRUCTURE

To identify key attribute data for the hydrographic network database, a nation-wide survey was conducted online in 2024 among water management specialists – employees of the entity responsible for water management in Poland, the State Water Holding Polish Waters (Pol.: Państwowe Gospodarstwo Wodne Wody Polskie), of whom 93 responded. Work experience of most of them was less than 5 years. Since the research was conducted among employees throughout Poland (not only in the southern region), opinions regarding the structure of the surface water database are not significantly influenced by local hydrographic or historical conditions. The structure of the respondents is presented in Figure 2.

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:
A) official name of the watercourse (accurate and recognised);
B) alternative names (used colloquially or in other registers);
C) stream order;
D) river basin (name of the receiving waterbody);
E) nature/characteristics (surface water + type and number of relevant documents, uncertain, river or other);
F) responsible entity for maintenance;
G) date of the last update;
H) comments (current issues or problems related to the waterbody).

MATERIALS

A key aspect of the research involved generating information about the hydrographic network based on imagery processed from photogrammetric flights. In order to optimise the methodology, two data acquisition levels (low and medium) were compared.

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 a.m. 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

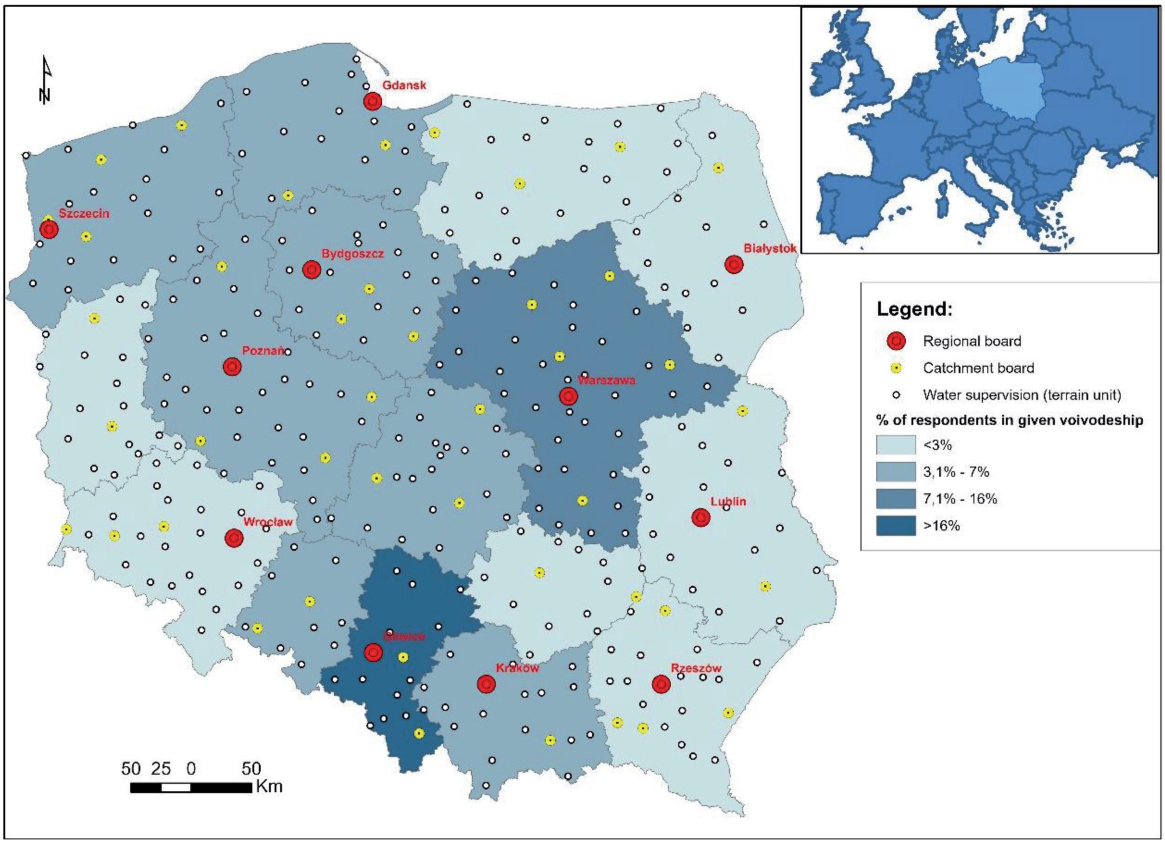

Fig. 2. Structure of respondents; source: own study

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sampling distance (GSD) was less than 0.1 m, 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 CityMap-per-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 m.

Low-altitude images (flight altitude of 108 m) 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 cm.

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.

Near difference water index (*NDWI*) values were reclassified into 0.1-wide bins using equal-interval classification. Pixels with *NDWI* > 0 were retained as potential water areas. A minimum mapping unit of 1 m^2 was applied to remove isolated artefacts. For geometric simplification, tolerance values of 0.05–0.10 m (UAV) and 0.2–0.3 m (aerial) were used to avoid excessive generalisation. The scope of analysis included a full comparison of both acquisition altitudes, cross-validation with DTM minima, and evaluation of geometric alignment with field-measured points.

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 *NDWI* was calculated using a raster calculator (the tool in ArcGIS Pro 3.2.0). The *NDWI* is used to identify the presence of flowing water by analysing the specific reflectance of the water surface relative to its surroundings. The index was computed through pixel algebra by dividing the green and near-infrared (NIR) bands according to the Equation (1) (McFeeters, 1996):

$$(\mathrm{green} - \mathrm{NIR})/(\mathrm{green} + \mathrm{NIR}) \tag{1}$$

Near difference water index (*NDWI*) values range from −1 to 1, with values greater than 0 indicating water-covered areas (McFeeters, 2013). Before further processing, the radiometric and geometric quality of all input imagery was assessed. Image quality control included inspection of shadow artefacts, saturation levels, local overexposure, and spectral noise. Radiometric normalisation was applied to reduce brightness heterogeneity. 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.

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 Fig. 1).

To validate the remotely derived centrelines, each GPS measurement was treated as an independent reference point representing the riverbed centre. Distances between these points and the automatically generated polylines were calculated using the Near Distance tool. Validation accounted for spatial constraints such as steep banks and canopy obstruction, which limited access to certain segments. Accuracy was measured using basic statistics (mean, median, minimum, maximum) and by assessing the proportion of points located more than 1 m and 2 m from the generated line. Statistical reliability was further confirmed using Pearson correlation and the non-parametric Sign test to determine whether both acquisition methods produce distributions consistent with field data.

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 Equation (2) (Cohen, 1988):

$$\rho = \mathrm{cov}(X, Y)/(\sigma x \cdot \sigma y) \tag{2}$$

where: cov = covariance, σx and σy = 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.

RESULTS AND DISCUSSION

DATABASE STRUCTURE

Firstly, survey research was conducted. 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 (Fig. 3). In response to the question about additional necessary attributes, there were frequent suggestions emphasising 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.

Based on the survey results, the authors in Figure 4 propose a scheme for a surface water database that can act as an inventory.

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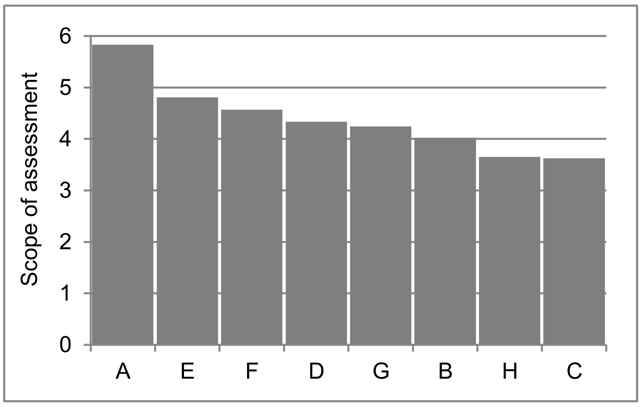

Fig. 3. Results of the survey regarding important attributes of the surface water database; A = official name of the watercourse (accurate and recognised), B = alternative names (used colloquially or in other registers), C = stream order, D = river basin (name of the receiving waterbody), E = nature/characteristics (surface water + type and number of relevant documents, uncertain, river or other), F = responsible entity for maintenance, G = date of the last update, H = comments (current issues or problems related to the waterbody); source: own study

It should be noted that the length field should include the length according to the field information in kilometres (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).

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 (Fig. 5):

1. Creation of an orthophotomosaic from images acquired in the green spectrum and the NIR spectrum.

   Processing details:
   - images were aligned using a structure-from-motion algorithm in Agisoft Metashape, including interior orientation parameters and camera calibration;
   - dense point clouds were generated using multi-view stereo reconstruction, followed by mesh creation and orthorectification;
   - orthophotomosaics were exported at the native pixel size of the input imagery (0.1 m for aerial photographs; 0.05 m for UAV photographs);
   - radiometric normalisation was applied to reduce inter-image brightness fluctuations caused by varying illumination conditions;
   - the resulting green and NIR mosaics became the basis for spectral water detection.
2. Processing of orthophotomosaics based on the *NDWI*.

   To delineate water surfaces, the normalized difference water index (*NDWI*) was computed in ArcGIS Pro using the raster calculator:

$$NDWI = (\text{green} - \text{NIR})/(\text{green} + \text{NIR})$$

The calculation was performed at native raster resolution to avoid losing detail in narrow watercourses.

NDWI values typically fall between −1 and +1; the positive portion of this range represents pixels more reflective in the green band than in NIR – characteristic of water.

Output rasters were inspected for noise caused by shadows, asphalt surfaces, and vegetation occlusion.

This product served as the primary spectral indicator for distinguishing open water from the surrounding environment.

3. Reclassification of *NDWI* orthophotomosaics (equal intervals at 0.1 intervals).

   The *NDWI* raster was reclassified using equal-interval classification with bins of 0.1 width (e.g. from −1.0 to −0.9, from −0.9 to −0.8, …, from 0.9 to 1.0).
4. *NDWI* values greater than 0 – representing potential water – were isolated as a separate class. Raster to polygon transformation (classes representing *NDWI* values > 0).

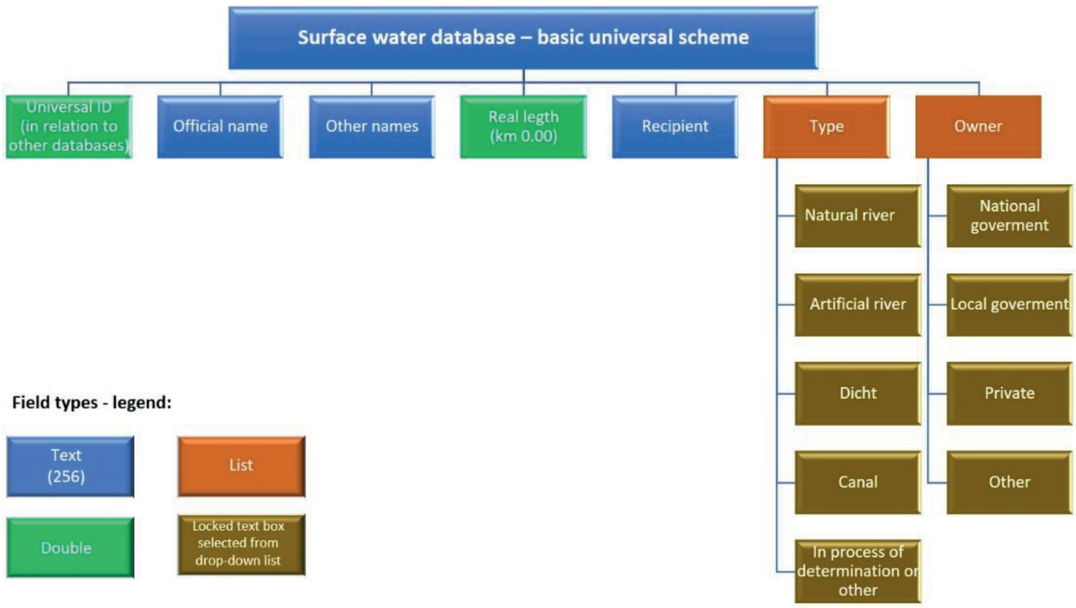

Fig. 4. Proposed attribute scheme of the watercourse layer; source: own study

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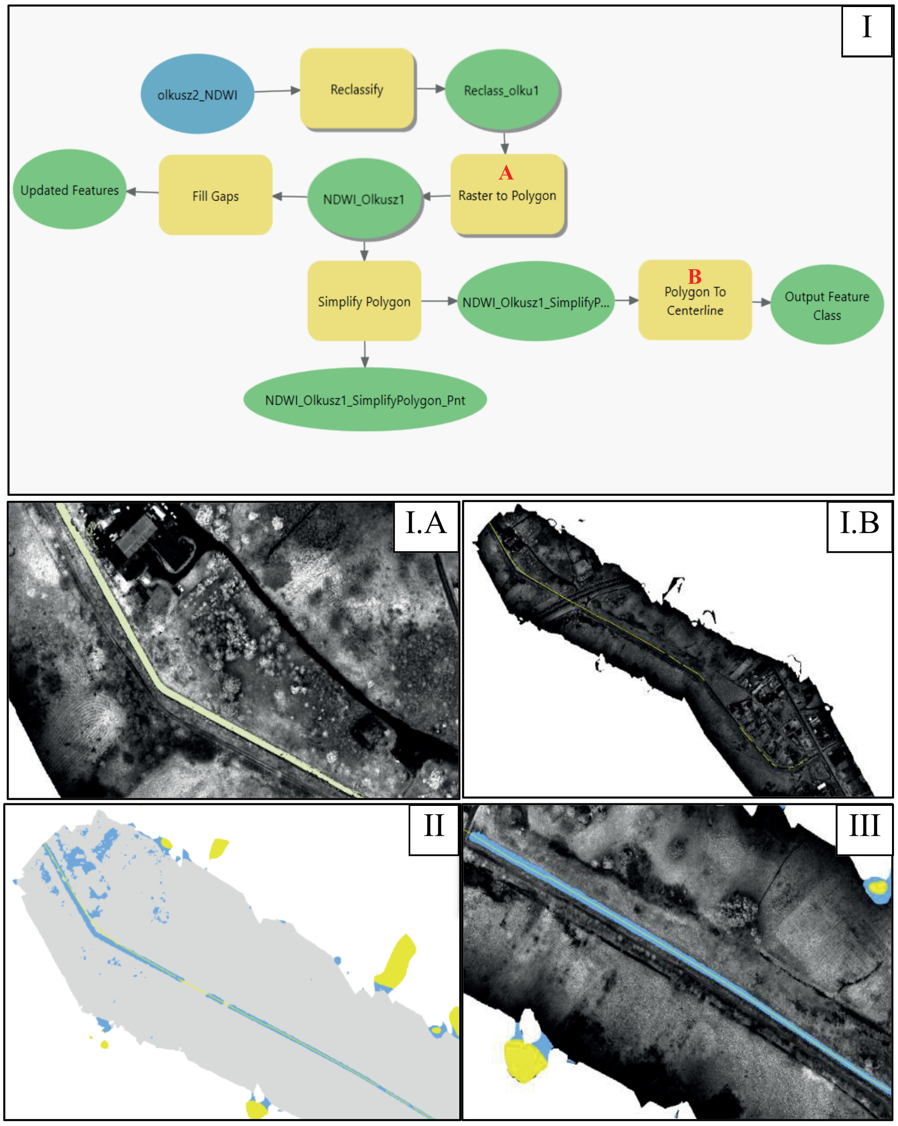

Fig. 5. Representation of the method of converting a photogrammetric imagery into vector layer: I = workflow of processing *NDWI* imagery to produce hydrographic network information automatically; I.A = the effect of using the raster to polygon tool – the extent of the river in the form of a vector polygon; I.B = the effect of using the Polygon to centreline tool – producing a line depicting the course of a watercourse based on the generated polygon representing the river reach; II = changing the symbolisation of the DEM so that only areas representing the elevation of 348 m a.s.l. are visible; III = symbolisation of the DEM so that only areas representing the elevation of 348.5 m a.s.l. are visible; source: own study

The following steps were done:
- using Raster to Polygon tool in ArcGIS Pro with the "simplify polygons = NO" parameter to preserve detail;
- extracting only those polygon classes representing *NDWI* > 0;
- removing isolated artefacts smaller than a predefined minimum mapping unit (e.g., <1 m^2), which typically result from shadows or reflective surfaces.

5. Simplifying the polygon representing the river reach and converting it into a line.
   Polygons representing the water surface were simplified and converted into a single linear representation of the channel.
   Procedure:
   - polygon boundaries were smoothed using the Simplify Polygon tool (tolerance: ca. 0.05–0.10 m for UAV data; 0.2–0.3 m for aerial imagery);
   - the simplified polygons were passed into the Polygon to Centerline tool to generate a skeletonised representation approximating the channel's midline;
   - manual inspection removed erroneous branches caused by backwater zones, flooded vegetation, or small side pools.
6. Verification with DEM at 0.5 m interval of the lowest points of the terrain (riverbed) – from the mouth downstream.
   Spectral detection alone can be affected by vegetation, shadows, or built infrastructure. Therefore, the automatically generated centreline was validated using elevation data.
   Verification workflow:
   - DEM/DTM rasters derived from LAS point clouds were symbolised in ArcGIS Pro at 0.5 m elevation intervals;
   - areas representing local minima – corresponding to the riverbed – were visually and analytically compared with the *NDWI*-derived centreline;

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– the verification proceeded from the mouth upstream, ensuring logical hydrological direction and continuous flow path;
– misalignments were corrected by snapping the line to DEM-derived low points or by adjusting manually where both datasets showed limitations.

Why this matters:

– in vegetated river corridors, *NDWI* may detect water beneath tree canopy with low accuracy, while DEM/DTM can reveal subtle terrain depressions;
– conversely, DEM/DTM may contain noise in steep or forested areas, where *NDWI* provides better spectral discrimination;
– the combined use of both data sources increases reliability and reduces geometric uncertainty.

Verification of the course of a watercourse based on DTM/DEM is ineffective in an area densely covered with vegetation (numerous artefacts – elevations or inability to extract points representing the ground). In general, however, using the appropriate symbolisation, it is easy to extract the lowest points in relation to the environment, i.e. those representing the course of the riverbed. Normalized difference water index, 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.

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 centre 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 unfavourable terrain. Table S1 presents the distances from the measured points, obtained using the GPS receiver, to the line determined from aerial imagery and UAV images.

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 (Tab. 1).

The line drawn from the aerial photo is located more than 2 m from the point measured in the field in the centre 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 centre 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 1. 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

Statistical quantity	Distance of the GPS point from the line determined from	
	aerial imagery	UAV imagery
Maximum	6.36562417398	4.84815567378
Minimum	0.07921604258	0.04516403421
Average	1.40603674223	1.27317336645
Median	1.08062597602	0.78263403733

Source: own study.

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 (Fig. 6). To confirm the high agreement, a non-parametric Sign test was also performed, yielding a p-value of 0.892. Since p-value > 0.05, the null hypothesis H0: 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.

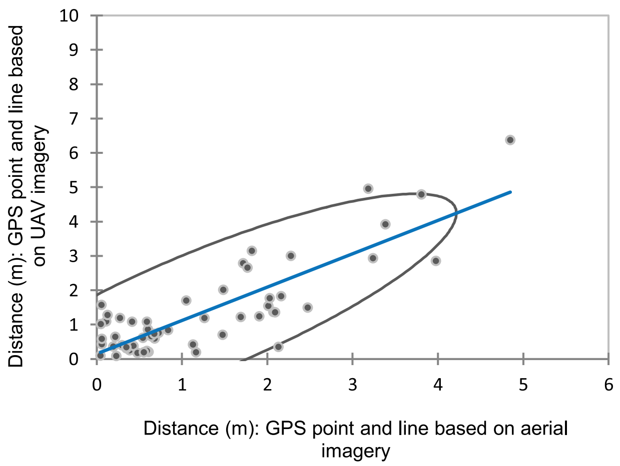

Fig. 6. The result of Pearson's correlation between the distances of the lines drawn based on medium- and low-altitude aerial photos from points in the Imielinka watercourse bed; source: own study

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 (Bernardo *et al.*, 2024). The desired scope of such data often results from the empirical experience of operators who input and process the data (Żywiołek and Nedeliaková, 2019). Therefore, the universal range of attribute data for water records

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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 (Dritsas and Trigka, 2025). 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 kilometre 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) (Janczewska, Matysik and Absalon, 2023). 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.) (Cadieux *et al*., 2020; Xiangyong and Yindi, 2021; Janczewska *et al*., 2025a).

It should be noted here that data consistency (including hydrographic data) is desirable and enshrined in international documentation. Examples include the INSPIRE Directive (Directive, 2007) and the USGS National Hydrography Dataset, as the authors emphasise in their earlier research (Janczewska *et al*., 2025b). The INSPIRE Directive (Directive, 2007) highlights the importance of harmonised spatial data infrastructures among member countries, promoting the use of standardised data frameworks and quality requirements to ensure data reliability and interoperability. Taking a step further, the USGS National Hydrography Dataset in the United States provides a comprehensive and geometrically consistent hydrographic database, which is updated and validated regularly due to quality control procedures (USGS, 2025).

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°) 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 (Zhou *et al*., 2021; Mehmood *et al*., 2022). Other noise sources include variability in lighting conditions during data acquisition (e.g., local cloud cover) and incorrect interpretation of the reflected wave spectrum (Gawlikowski *et al*., 2022). Consequently, there are issues with pixel classification based on similarity in radiometric resolution (Dai *et al*., 2025). The information obtained about the course of the Imielinka River based on the normalized difference water index (*NDWI*) 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 statistical comparison demonstrated that despite differences in acquisition altitude, both methods yielded highly consistent geometric results, as confirmed by a strong and statistically significant correlation ($r = 0.836$). The relatively small difference between median and mean values indicates that errors were not dominated by extreme outliers but were evenly distributed along the river course. The analysis shows that UAV imagery slightly improves local accuracy, whereas aerial imagery provides stable performance over longer sections. These results confirm that the workflow remains robust under varying acquisition conditions and can be adapted to different environments.

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, Łącka (2021), based on the DEM created from photos acquired with the UAV, analysed 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 (Jussila, Koski and Kettunen, 2024). 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 symbolisation 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 (Stateczny *et al*., 2023).

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 both lines ran correctly within the riverbed, because the width of the riverbed at the mouth was 2 m (which is wider than the magnitude). 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 (Cha *et al*., 2024). Statistical studies, however, have shown a high convergence between lines drawn based on aerial photographs of both medium and low ceilings.

A spatial inventory of waters is crucial for proper water management. On the one hand, it indicates the nature and course of the hydrographic network, which is essential for all design work (when watercourses or water facilities are crossed). This inventory also serves broadly understood administration, for example in determining land-use categories. In cases of incorrect classification, land that is not flowing water may be excluded from civil-law transactions (Ustawa, 2017). However, the most important issue for which having an accurate water inventory is essential remains flood protection. These data serve as inputs, among others, for flood hazard and flood risk maps, and form the basis for strategic decisions during high-water events and for preventing them.

It should also be emphasised that the research was motivated by discrepancies in domestic databases. These discrepancies, as well as differences in the timeliness and quality

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of data (or simply the lack thereof), are even more pronounced at the international level. The proposed methodology is universally applicable (applicable at the international level) and complies with current standards, as well as meeting the requirements of strategic documents calling for data interoperability.

Importantly, it is essential to include relevant attribute data on data acquisition parameters, which is a requirement of the ISO 19115 standard (International Organization for Standardization, 2014). This international standard for geographic information metadata advocates for detailed documentation of data quality, positional accuracy, and lineage, facilitating data sharing and integration across different systems (ISO 19115-1, 2014). Also another ISO 19157 (International Organization for Standardization, 2023) should be considered – the norm for data quality assessment, which is particularly important when using neural networks for terrain classification. What is more, there are international best practices, such as the USGS LIDAR Base Specification, which emphasise the importance of point density for accurate terrain modelling and feature extraction (USGS, 2025). There are therefore many guidelines and standards whose application will also ensure the interoperability of hydrographic data on both a national and international scale. The proposed methodology is designed to be applicable internationally, as it aligns with major global standards for hydrographic data management, including INSPIRE guidelines in the European Union, the USGS National Hydrography Dataset framework in the United States, and ISO 19115 and ISO 19157 requirements for metadata and data quality. By documenting acquisition parameters, processing lineage, and accuracy metrics, the workflow supports interoperability between national water databases. This makes it suitable for transboundary river management, international reporting obligations, and harmonised hydrological modelling across administrative borders.

CONCLUSIONS

The presented research identified a comprehensive and optimal methodology for creating water inventory, from the acquisition of hydrographic data, through its processing, to the creation of vector information on the extent of watercourses. By combining stakeholder-driven attribute requirements with empirically tested geoprocessing procedures, the article provides a complete methodological framework that bridges the current gap between administrative, geospatial, and remote sensing practices in water database creation. 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. The survey indicated unanimous agreement on the necessity of the official watercourse name, high relevance of ownership, basin, and water character, and lower priority for flow direction and comment fields, with a notable demand for including mileage, resulting in a robust and broadly applicable attribute scheme. Normalized difference water index (*NDWI*) analysis proved most effective when applied to UAV imagery, while DEM/DTM verification benefited from aerial LiDAR due to superior ground-point penetration. Accuracy evaluation showed UAV-derived centrelines to be marginally closer to GPS measurements (1.27 m vs. 1.40 m), though both methods exhibited strong concordance (r = 0.836; p = 0.892), confirming the scalability and reliability of aerial photogrammetry for large-area mapping. In addition, in order to achieve the optimisation objective, we investigated which remote water detection threshold is more effective. 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.

This study introduces a unified and scalable methodology that integrates practitioner-defined attributes, advanced GIS and remote sensing workflows, and standardised procedures aligned with INSPIRE, ISO, and USGS guidelines, enabling automated and rapid generation of consistent hydrographic data. The approach demonstrates high geometric reliability from both aerial and UAV sources and delivers practical value for water management applications, including spill detection, flood modelling, emergency response, legal boundary delineation, and pollution impact assessment.

The application of the proposed methodology may primarily have administrative significance in terms of optimal water management. By using a uniform method of data collection, processing and updating, it is possible to immediately determine the location of events on surface waters (e.g. oil spills, fish kills), model flood risk or respond to emergency situations (forecasting and decision-making regarding the current extent of water). In addition, it enables the regulation of legal status (extent and ownership of registered plots) and verification of the cumulative impact of pollution.

The best input materials to accurately map the hydrographic network in space are a DTM (generated from a dense LAS point cloud with a symbolisation interval of approximately 0.5 m) and multispectral images processed using the *NDWI*. 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 optimise this process and explore the use of machine learning tools or neural networks (like a U-Net or CNN) to reduce the memory needed for processing.

SUPPLEMENTARY MATERIALS

Supplementary material to this article can be found online at: https://www.jwld.pl/files/Supplementary_material_69_Janczewska.pdf.

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CONFLICT OF INTERESTS

The authors declare that they have no conflict of interest.

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