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BARTOSZ ORZEŁ[1], JAROSŁAW TOKARCZYK[2],
DARIUSZ MICHALAK[3], KAMIL SZEWERDA[4]

# Automated on-demand inventory of coal dumps and heaps using UAV imagery and IoT-driven data processing

## Introduction

Coal has historically played and continues to play a significant role in the energy mix of both Poland and Europe. The coal dependency transformation is based on effective management of coal demand and supply processes through the implementation of information technology. However, the energy landscape is undergoing a profound transformation, with Poland and Europe actively pursuing a transition towards more sustainable and decarbonized energy systems. This shift is driven by growing environmental concerns, international agreements aimed at mitigating climate change, and the imperative to develop secure and resilient energy sources. The Polish project "Dynamic management of

✉ Corresponding Author: Bartosz Orzeł; e-mail: borzel@komag.eu
[1] KOMAG Institute of Mining Technology, Gliwice, Poland; ORCID iD: 0000-0003-1506-4798; e-mail: borzel@komag.eu
[2] KOMAG Institute of Mining Technology, Gliwice, Poland; e-mail: jtokarczyk@komag.eu
[3] KOMAG Institute of Mining Technology, Gliwice, Poland; e-mail: dmichalak@komag.eu
[4] KOMAG Institute of Mining Technology, Gliwice, Poland; e-mail: kszewerda@komag.eu

coal demand, production, resource management, and distribution logistics in an economy implementing a decarbonized energy mix”, known as DynGOSP (GOSPOSTRATEG), represents a strategic national initiative aimed at modernizing the Polish hard coal mining sector in the face of the ongoing energy transition (DynGOSP 2023). Led by a consortium including the Mineral and Energy Economy Research Institute of the Polish Academy of Sciences, with the Ministry of State Assets as a key partner (Mól et al. 2024), the DynGOSP project focuses on developing a comprehensive coal industry management system that spans the entire coal cycle, from the deposit to the end consumer, with a long-term perspective extending to 2050. A central objective of the DynGOSP project is to create a dynamic resource database that accurately determines the quantity of extractable coal reserves in accordance with international standards (Marlęga et al. 2024; Mól et al. 2024). This initiative acknowledges the pressing need for a contemporary approach to managing Poland’s coal resources in a context where the energy mix is gradually decarbonizing. The project also aims to optimize coal demand forecasting, production planning, and distribution logistics to ensure efficiency and sustainability within the sector. The emphasis of the DynGOSP project on establishing a dynamic resource database and optimizing the entire coal cycle strongly underscores the critical need for accurate and real-time inventory data for coal heaps and dumps. The automated on-demand inventory system proposed in this paper, leveraging UAV technology for spatial data acquisition, IoT sensors for continuous monitoring, and QGIS for data processing and volume calculation, directly aligns with and supports the core objectives of the DynGOSP project. By providing precise information on the quantity and potentially the condition of coal heaps and dumps, this type of system can serve as a fundamental technological enabler for achieving the goals of efficient resource balancing, demand forecasting, and supply chain optimization within Poland’s energy sector.

This sector faces a unique set of challenges during this transition, given its historical and ongoing reliance on coal for a substantial portion of its power generation (Clean Air Task Force 2024; Marlęga et al. 2024; Ganti et al. 2025). While the European Union as a whole is committed to phasing out coal to meet ambitious climate targets, Poland’s specific circumstances demand a carefully managed and just transition that considers energy security and socio-economic impacts on coal-dependent regions (European Commission 2018; Bang et al. 2022). This complex scenario underscores the urgent need for innovative solutions to manage existing coal resources during this period of transformation effectively. A fundamental aspect of managing coal resources effectively is the accurate and timely inventory of coal heaps and dumps. Traditional methods for performing these inventories often involve manual surveying techniques. These methods present several limitations, including potential inaccuracies due to the irregular shapes and sizes of heaps and dumps, the challenges of accessing all areas of the stored material, and the inherent risks associated with working on or around large bulk material heaps (Alsayed and Nabawy 2023).

Furthermore, manual surveys are typically labor-intensive and time-consuming, providing only a periodic snapshot of the inventory that may quickly become outdated in dynamic operational environments. The lack of real-time data hinders proactive decision-making and efficient resource allocation (Tamin et al. 2019). To overcome these limitations, there is a growing interest in leveraging modern technologies such as Unmanned Aerial Vehicles (UAVs) and the Internet of Things (IoT) for automated inventory management. UAVs provide a rapid, safe, and cost-effective means of acquiring high-resolution imagery of coal heaps and dumps, enabling the generation of accurate three-dimensional models for volume estimation (Tamin et al. 2019; Surour et al. 2024). Complementing this spatial data, IoT sensors can provide continuous, real-time information on various parameters relevant to the heaps and dumps, such as temperature and moisture content (Madamidola et al. 2024). The DynGOSP project involves IoT technology and informatics tools as central elements of strategic resources management. The algorithm presented in this paper is a part of an informatics tool, the creation of which is a crucial part of DynGOSP (Dyczko et al. 2025).

This integrated approach allows for a more comprehensive and dynamic understanding of the coal inventory. The processing and analysis of the large datasets generated by UAVs and IoT devices demands the use of sophisticated geoinformatics tools (Mesas-Carrascosa 2020). Among these tools, QGIS, an open-source Geographic Information System, stands out as a cost-effective and competent platform for processing UAV imagery and performing accurate volume calculations from the derived Digital Elevation Models (DEMs) (Points North GIS 2024). Its open-source nature makes it particularly suitable for the Polish mining sector as it navigates the economic considerations of the energy transition. The implementation of an automated on-demand inventory system for coal heaps and dumps has significant importance within the context of Poland's energy transition. It aligns directly with the objectives of the Polish project called DynGOSP. This national initiative focuses on the dynamic management of coal demand, production, resource management, and distribution logistics in an economy that is actively implementing a decarbonized energy mix. Accurate and timely inventory data is fundamental to achieving the goals of DynGOSP, enabling efficient resource balancing, demand forecasting, and supply chain optimization in a rapidly changing energy landscape.

The scope of this paper is to present a comprehensive methodology for the automated on-demand inventory of coal dumps and heaps using UAV imagery and IoT-driven data processing. A key focus of this work is to detail the process of volume calculation using QGIS from the UAV-derived data and to highlight the significance of this approach within the context of Poland and Europe's energy transition, particularly in relation to the DynGOSP project.

## 1. UAVS, IoT, and volume calculation as the elements of an automated data processing tool

The use of **Unmanned Aerial Vehicles (UAVs)** for estimating the volume of coal heap materials has gained significant traction across various industries (Alsayed and Nabawy 2023). Studies have explored both **photogrammetry**, particularly Structure from Motion

(SfM) techniques, and **LiDAR** for generating accurate three-dimensional models of heaps and dumps. Comparative analyses consistently demonstrate that **UAV-based methods offer notable advantages in terms of speed, safety, and often, accuracy** when compared to traditional surveying techniques. For instance, Tamin et al. (2019) highlighted the time-consuming nature of Terrestrial Laser Scanning (TLS) compared to UAV-based methods. Similarly, found that UAV photogrammetry is faster and less labor-intensive than GPS-based surveys, while achieving comparable or even better accuracy. Ekpa et al. (2019) also concluded that UAV technology is more time-efficient and provides more detailed surface data than traditional Total Station methods. Several critical factors influence the accuracy of volume estimations derived from UAV data. **Flight altitude and the degree of overlap between captured images** play a crucial role in the quality of the generated 3D model (Ajayi and Ajulo 2021). The strategic placement and accuracy of **Ground Control Points (GCPs)** can also significantly impact georeferencing and overall accuracy. However, some studies suggest that sufficient accuracy can be achieved without GCPs in specific scenarios (Kokamägi and Liba 2020).

Furthermore, the **quality and resolution of the imagery** captured by the UAV's sensor directly affect the level of detail and precision in the resulting Digital Elevation Model DEM (Alsayed et al. 2025). Alsayed and Nabawy (2023) provide a comprehensive review of these factors and the various techniques employed for coal heap volume estimation in both open and confined environments (Alsayed and Nabawy 2023). While UAV photogrammetry offers a robust and efficient method, its accuracy can be affected by **environmental conditions** such as dust and limited visibility, which are common in mining environments (Alsayed et al. 2025). The geometric complexity and accessibility of the coal heap itself can also pose challenges (Tucci et al. 2019). Research into estimating indoor coal heap volume further highlights the unique difficulties associated with confined spaces and limited GPS availability, factors that may be relevant for covered coal storage facilities (Alsayed and Nabawy 2023). Despite these challenges, the overwhelming evidence suggests that **UAV technology provides a faster, safer, and often more accurate alternative** to traditional coal heap volume estimation methods

The application of the **Internet of Things (IoT)** in inventory management has emerged as a significant area of research, with the potential to revolutionize how materials are monitored (Madamidola et al. 2024). Various types of sensors, including **weight sensors, ultrasonic sensors, and RFID tags**, are being utilized to track inventory levels, location, and condition in real-time. For example, ultrasonic sensors can measure the distance to the top of a coal heap, indicating its level (Salvi et al. 2023). Weight sensors can directly measure the mass of stored materials, while RFID tags can track individual items within a warehouse or storage facility. Weight sensors can directly measure the mass of stored materials, while RFID tags can track individual items within a warehouse or storage facility (Madamidola et al. 2024). The integration of IoT technologies offers numerous benefits for inventory management. It can lead to significant improvements in **accuracy by automating data collection** and reducing the reliance on manual input. **Real-time**

**monitoring capabilities** enabled by IoT can help businesses minimize both stockouts and overstocking, thereby optimizing supply chain operations and improving overall efficiency (Ugbebor et al. 2024).

Furthermore, the data generated by IoT sensors can provide valuable insights for **enhanced decision-making**, allowing for more proactive and responsive inventory management strategies. However, a review of the current literature indicates that the primary focus of IoT applications in inventory management has been primarily directed towards warehousing and retail environments (Ugbebor et al. 2024; Surour et al. 2024; Madamidola et al. 2024). Research specifically addressing the application of IoT technologies for the continuous monitoring of large-scale outdoor coal heaps and dumps, particularly in conjunction with UAV-based volume estimation, appears to be less prevalent. This suggests a potential gap in the current scope.

**Geoinformatics**, an interdisciplinary field that encompasses Geographic Information Systems (GIS), remote sensing, and related technologies, provides powerful tools for managing and analyzing spatial data. **QGIS**, a free and open-source GIS software, has emerged as a versatile and cost-effective platform for processing spatial data, particularly that derived from UAVs (Points North GIS 2024). Its capabilities include the generation of high-resolution **Digital Elevation Models (DEMs)** from aerial imagery obtained by UAVs, a crucial step in accurately estimating the volume of coal heap materials.

QGIS offers various built-in functionalities and plugins specifically designed for volume calculation. For instance, the **Raster Volume Comparison plugin** allows for the calculation of volume differences between two raster layers, which can be used to determine the volume of a coal heap by comparing a DEM of the coal heap with a baseline DEM of the ground beneath it. Other methods involve defining a base elevation or using triangulation techniques to estimate volume (Points North GIS 2024). Numerous studies have validated the accuracy of volume calculations performed in QGIS using UAV-derived DEMs (Points North GIS 2024). These studies often report comparable results to those obtained using traditional surveying methods and proprietary commercial software packages. For example, QGIS, as a geoinformatics tool, can be utilized to estimate earthwork volumes in a road construction project using UAV-derived DEMs, with results found to be within an acceptable range compared to traditional methods. This growing body of evidence underscores the suitability and reliability of QGIS as a key processing tool for accurately estimating coal heap volumes within proposed automated inventory methodologies (Marlęga et al. 2024; Brits and Bekker 2016).

Traditional methods for coal heap inventory often rely on **manual surveying techniques**, which are inherently **labor-intensive**, requiring significant personnel and time to measure large and irregularly shaped heaps and dumps (Dou et al. 2023). The **safety of surveyors** working on steep or unstable coal heaps is also a considerable concern (Alsayed and Nabawy 2023). Furthermore, manual measurements are **prone to human error**, and the resulting data provides only a snapshot in time, failing to capture the dynamic nature of coal heap levels in active mining or power plant operations. Traditional costing approaches in the coal mining industry may also contribute to overlooking the long-term benefits of investing in more accurate inventory management technologies (Lind 2001). Additionally, the properties of coal itself, such as its susceptibility to weathering and atmospheric oxidation during storage, can affect its quality and volume over time (Carpenter 1999). Traditional inventory methods, with their infrequent data collection, may not adequately capture these changes, leading to inaccuracies in long-term resource planning. Overall, traditional coal inventory methods are plagued by several limitations that can lead to inaccurate data, inefficiencies, and safety risks (Stanton 2013).

**Accurate and up-to-date inventory information regarding coal heaps and dumps is of paramount importance** for a multitude of reasons within the coal industry (Dou et al. 2023). Precise inventory data is essential for **efficient operational planning**, enabling mine operators and power plant managers to make informed decisions about coal extraction rates, delivery schedules, and utilization strategies (Dou et al. 2023; Hasan et al. 2024). It also plays a crucial role in **robust financial forecasting**, enabling accurate budgeting and cost control related to coal procurement, storage, and processing (Hasan et al. 2024). Effective **risk management**, particularly concerning the potential for spontaneous combustion in coal heaps, relies heavily on accurate inventory data. Monitoring the size, shape, and internal temperature of heaps, facilitated by precise inventory information, can help identify and mitigate this significant safety and environmental hazard.

Furthermore, accurate inventory data is vital for responsible **environmental stewardship**, enabling the tracking of coal quantities and the management of potential environmental impacts associated with coal storage (Woo et al. 2023). It also allows for the optimization of coal blending operations in power plants to meet specific energy output and emissions targets (Dou et al. 2023). The increasing volatility of global coal prices further underscores the need for accurate and timely inventory data to optimize stock levels, minimize financial risks associated with price fluctuations, and ensure a consistent supply of coal to meet demand (Surour et al. 2024). Ultimately, accurate coal heap data is fundamental for operational efficiency, financial stability, and environmental responsibility within the coal industry.

## 2. Volume calculation algorithm – from aerial images stitching to QGIS software

The automated on-demand inventory of coal dumps and heaps utilizing Unmanned Aerial Vehicle (UAV) imagery demands a robust data processing workflow within a Geographic Information System (GIS) environment. QGIS, an open-source GIS platform, provides a suite of algorithms essential for this methodology, facilitating the transformation of raw UAV imagery into accurate volumetric estimations. The initial and critical step involves generating a Digital Elevation Model (DEM) from the acquired overlapping UAV images. This process, frequently employing Structure from Motion (SfM) photogrammetric

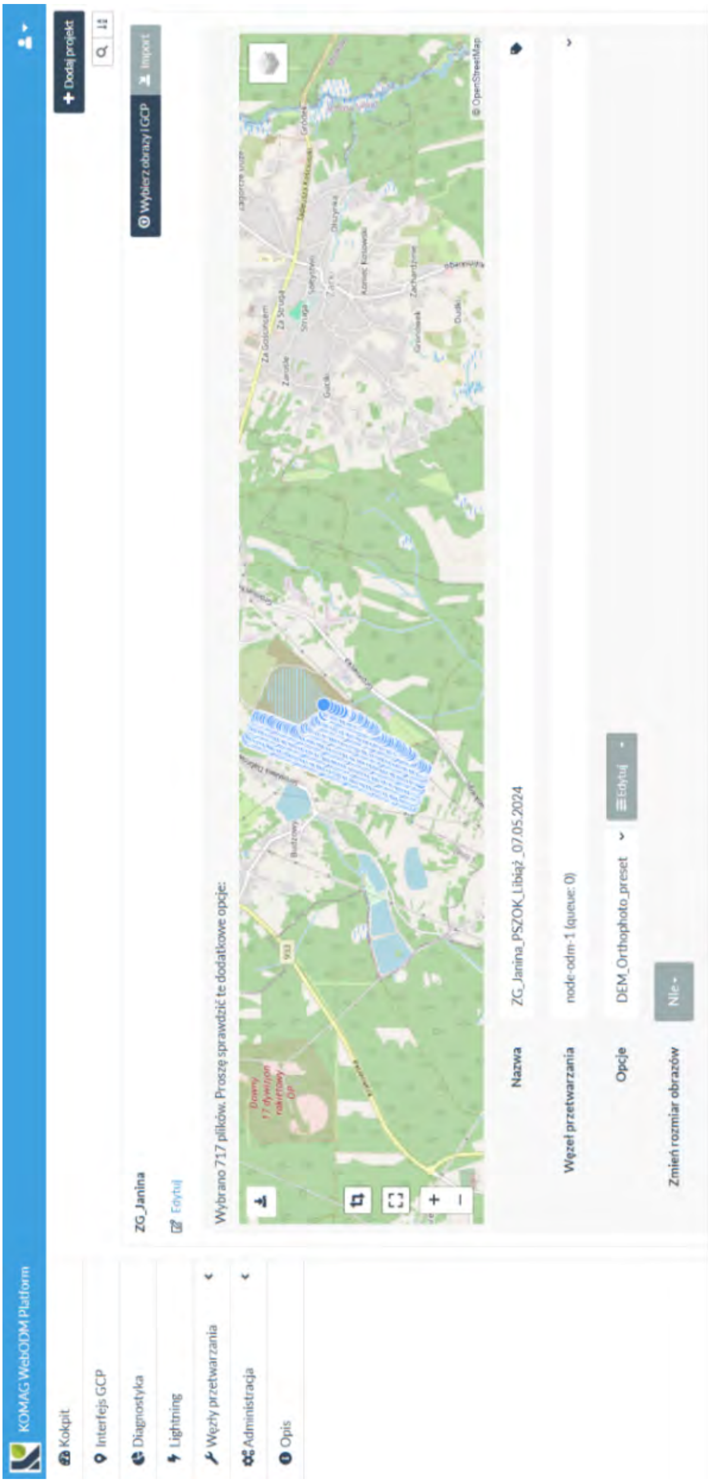


Fig. 1. OpenDroneMap software interface
Source: authors own work based on OpenDroneMap software

Rys. 1. Interfejs oprogramowania OpenDroneMap techniques, yields a raster dataset where each pixel represents the elevation of the terrain surface. The precision of the resultant DEM is important for subsequent volume calculations. It is influenced by factors such as image resolution, the degree of image overlap, and the Real Time Kinematic (RTK) system. The DEM is stitched from aerial images captured by a UAV using OpenDroneMap Software (WebODM). In Figure 1, the OpenDroneMap software interface was presented.

Following DEM generation, QGIS offers several algorithmic approaches for volumetric analysis. Provides a direct method for calculating the volume difference between two raster layers. The Volume Calculation Tool algorithm in QGIS enables volume estimation based on a user-defined polygonal boundary encompassing the coal heap and a selected DEM. This tool typically allows for the specification of a base elevation, crucial for accurately determining the coal heap's volume. An example DEM was presented in Figure 2.

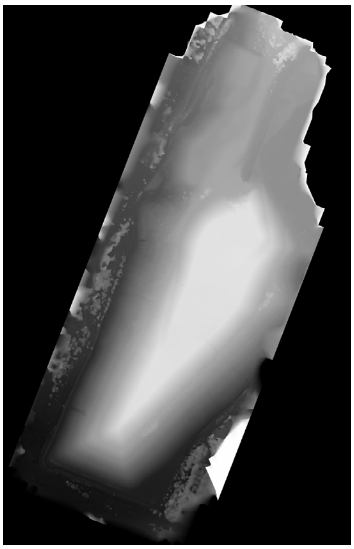

Fig. 2. Digital Elevation Model
Source: authors own work based on OpenDroneMap software

Rys. 2. Numeryczny model nachylenia terenu

A Digital Elevation Model (DEM) is a fundamental raster dataset in geospatial analysis, representing the Earth's topographic surface through a grid of elevation values. These models can be derived from various sources, including satellite imagery, aerial surveys, and LiDAR data, and are essential for analyzing terrain characteristics and changes (Lakshmi and Yarrakula 2019). It is essential to recognize the distinction between various types of elevation models. A Digital Terrain Model (DTM) explicitly represents the bare ground surface, excluding vegetation and man-made structures, whereas a Digital Surface Model

(DSM) includes these features. The choice between a DTM and a DSM depends on the specific application and the nature of the volume change being investigated. For instance, analyzing the volume of a coal heap typically requires a DSM that captures the surface of the material, whereas studying changes in the underlying ground level would demand a DTM. The initial step in the automated workflow involves loading two distinct DEM raster layers into the QGIS Model Designer canvas. These DEMs are intended to represent the surface of the study area at different times or under different conditions. A critical prerequisite for accurate spatial analysis is ensuring that both DEMs are referenced to the exact Coordinate Reference System (CRS). Differences in the CRS can lead to significant misalignments between the datasets, rendering any subsequent calculations unreliable. Therefore, it is often necessary to perform a preliminary step of reprojecting one or both DEMs to a common CRS to ensure spatial compatibility and the validity of the analysis. The selection of an appropriate CRS should be based on the geographic location of the study area and the units of measurement required for the analysis (Points North GIS 2024).

After stitching images in the OpenDroneMap software, the DEM orthophotos are automatically uploaded to the QGIS Server software. To ensure that actions are performed automatically, an algorithm with a sequence of tasks was developed in the QGIS Model Designer. In Figure 3, the first part of the algorithm was presented.

The subsequent processing step in the workflow utilizes the *Clip raster by mask layer* algorithm available in QGIS. This algorithm defines the spatial extent of a raster dataset by using a vector polygon layer as a mask. The input raster is effectively cropped to the boundaries of this mask layer, resulting in an output raster that covers only the area defined

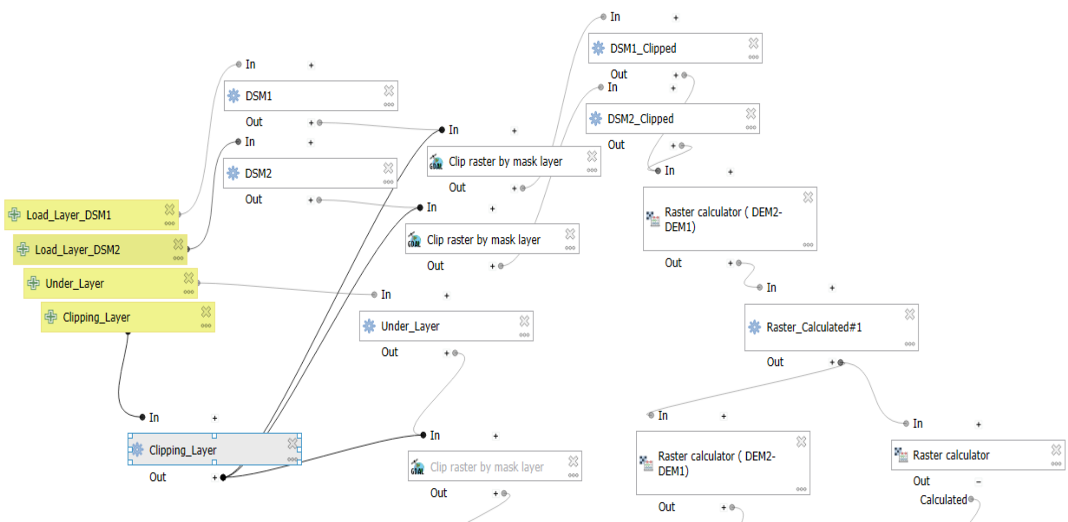


Fig. 3. The first part of algorithm created in QGIS Model Designer
Source: authors own work based on QGIS Model Designer

Rys. 3. Pierwsza część algorytmu stworzonego w QGIS Model Designer by the mask. This process is crucial for ensuring spatial alignment between the two loaded DEMs. For accurate cell-by-cell calculations in the later stages of the workflow, it is essential that the rasters being compared have identical spatial extents and that their corresponding pixels represent the exact locations on the ground. This is achieved by applying the same mask layer to both initially loaded DEMs. Selecting an appropriate mask layer is a key consideration in this step. The mask should define the specific area of interest for the volumetric analysis, such as the boundary of the industrial site, the perimeter of the dump or heap, or any other relevant spatial extent. The accuracy and precision of this mask layer directly influence the accuracy of the clipped DEMs and, consequently, the final volume calculation. A well-defined mask ensures that the analysis is focused on the relevant area, excluding any extraneous data that could introduce noise or inaccuracies into the results. For instance, if the goal is to calculate the volume of a specific coal heap, the mask layer should precisely delineate the base of that coal heap. The workflow incorporates a third raster layer, often referred to as the *Under Layer* or *Bottom Layer*, which plays a vital role in establishing a reference surface for volume calculation. This layer represents an estimation of the base level of the dump or heap, providing a crucial benchmark against which the height and volume of the deposited material can be measured. The *Bottom Layer* is typically derived from survey points collected by a surveyor at the industrial site. These points represent discrete measurements of the elevation of the ground surface or the base upon which the dump has been formed. To create a continuous raster surface from these scattered point measurements, a process known as spatial interpolation is employed.

Spatial interpolation techniques in GIS aim to estimate values at unsampled locations based on the values of known neighboring points. QGIS software offers a range of interpolation methods, each with its underlying assumptions and suitability for various types of data and terrain. Standard techniques include Inverse Distance Weighting (IDW), which assumes that the influence of a known point decreases with distance, Kriging, a geostatistical method that considers both distance and spatial autocorrelation in the data, Triangulated Irregular Network (TIN), which creates a surface from triangles formed by connecting the nearest neighbor points, Natural Neighbor, which uses Voronoi tessellation to determine weights based on the area of influence, and Spline, which fits a smooth surface through the data points by minimizing curvature (Points North GIS 2024; QGIS Documentation 2025). The selection of the most appropriate interpolation method is critical for generating a reliable *Bottom Layer*. Factors, such as the spatial distribution of the survey points, the density of the measurements, and the expected characteristics of the underlying surface, should be carefully considered. For instance, if the base of the dump is expected to be relatively smooth, a method like Spline might be suitable. Conversely, if there is significant local variation, Kriging or IDW with optimized parameters might provide a better representation. Furthermore, the interpolation process involves defining various parameters specific to the chosen method, such as the search radius or the number of neighboring points to consider, which can significantly influence the resulting interpolated surface. The effect of the *TIN interpolation* algorithm usage was presented in Figure 4.

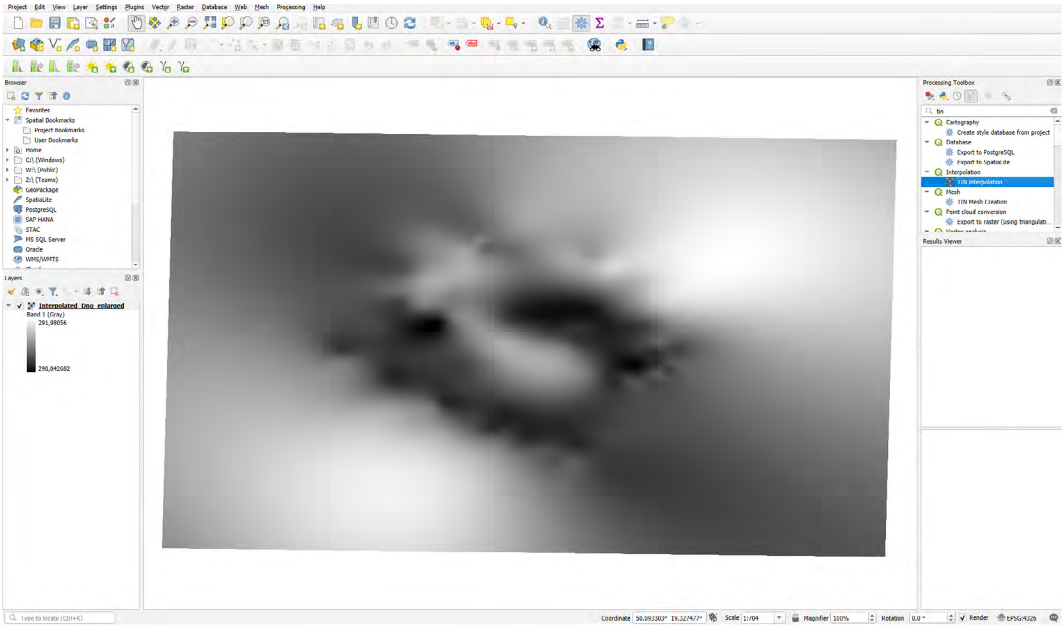

Fig. 4. Bottom of the heap interpolated from points in QGIS software
Source: authors own work based on QGIS software

Rys. 4. Dno sterty interpolowane z punktów w oprogramowaniu QGIS

Having prepared the necessary raster layers, the subsequent step in the QGIS Model Designer workflow involves loading the two previously clipped DEM layers and the interpolated *Bottom Layer* into the Model Designer environment. It is important to ensure that these layers are correctly referenced within the model, as their order and identification will be crucial for the subsequent volume calculation using the *Raster calculator* algorithm. The Model Designer interface allows users to visually connect the outputs of previous steps (the clipped DEMs and the interpolated layer) as inputs to the following processing stage. The core processing step for calculating the volumetric difference is performed using the *Raster calculator* algorithm in QGIS. This powerful tool enables users to perform cell-wise mathematical operations on raster layers by defining custom expressions. In this specific workflow, the expression used is *B@1-A@1*. This expression instructs the *Raster calculator* to subtract the value of the first band (1) of raster layer *A* from the value of the first band (1) of the raster layer *B* for each corresponding cell in the two rasters. The *Raster calculator* input fields were presented in Figure 5.

In the context of this workflow, *A@1* likely refers to the interpolated *Bottom Layer*, representing the base level of the dump or heap. *B@1*, on the other hand, typically refers to one of the clipped DEMs, which represents the upper surface of the terrain, potentially including the dumped material. Therefore, the result of this subtraction is a new raster layer

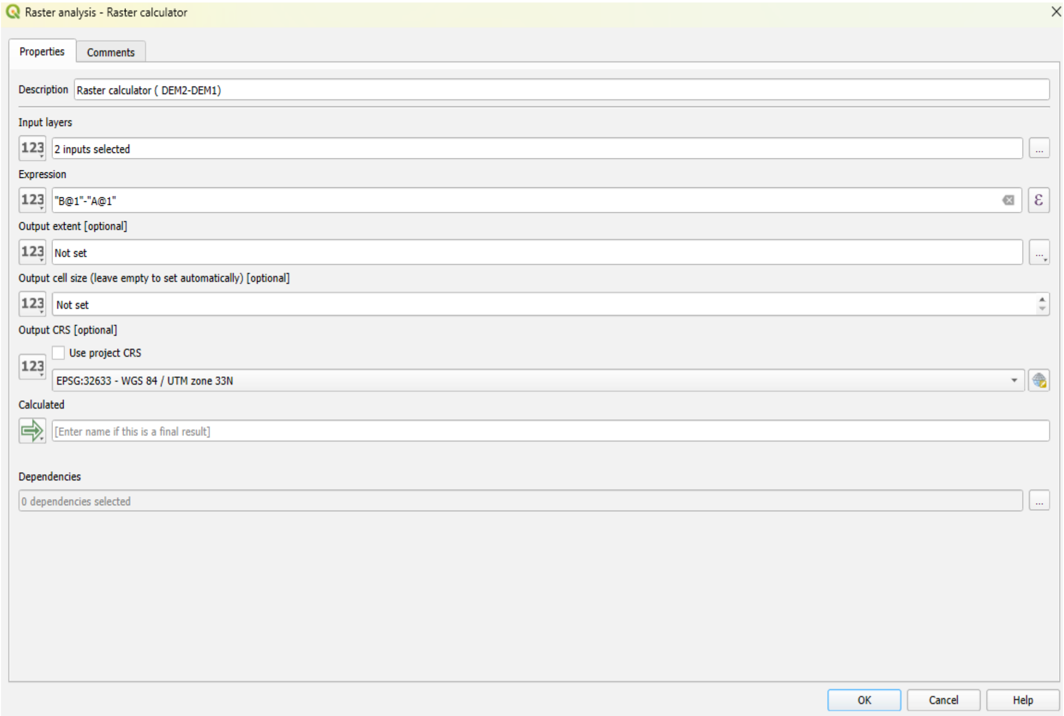


Fig. 5. Input fields in the *Raster calculator* algorithm
Source: authors own work based on QGIS software

Rys. 5. Pola wejściowe w algorytmie kalkulatora rastrowego

where each cell's value represents the vertical difference in elevation between the upper surface and the base level at that specific location. This difference effectively indicates the height of the material above the estimated bottom surface. Alternatively, if the goal is to measure the change in volume over time, *A@1* could represent the earlier clipped DEM, and B@1 the later one, with the resulting raster showing the elevation gain or loss between the two time periods. To ultimately determine the volume, these height differences need to be considered in conjunction with the area represented by each pixel in the raster dataset. While the *Raster calculator* directly computes the height difference, the total volume is derived by implicitly summing these height values across the entire raster and multiplying by the area of a single pixel.

The final step in the automated workflow involves loading the resulting raster layer, generated by the *Raster calculator*, into the QGIS Layers panel. This output raster is a direct representation of the calculated volume difference between the two input surfaces. Suppose the interpolated *Bottom Layer* was used as the reference (*A@1*). In that case, positive values in the output raster indicate areas where the upper surface (*B@1*) is above the base level, signifying the presence of the dump or heap. Conversely, negative values (if any) would suggest areas where the current surface is below the estimated base level. Suppose the calculation was performed between two DEMs from different time points. In that case, positive values indicate an increase in elevation (material accumulation), while negative values indicate a decrease (material removal or erosion). The effect of algorithm execution to this point was presented in Figure 6.

To obtain a quantitative measure of the total volume of material added or removed, further analysis of this output raster is typically required. QGIS offers several tools for this purpose, including the *Raster layer statistics* function, which calculates the sum of all cell values in the raster. Multiplying this sum by the area of a single pixel yields the total volume. Additionally, the *Raster surface volume* tool in QGIS provides more advanced options for calculating volume based on a defined base level. The units of the input DEMs determine the

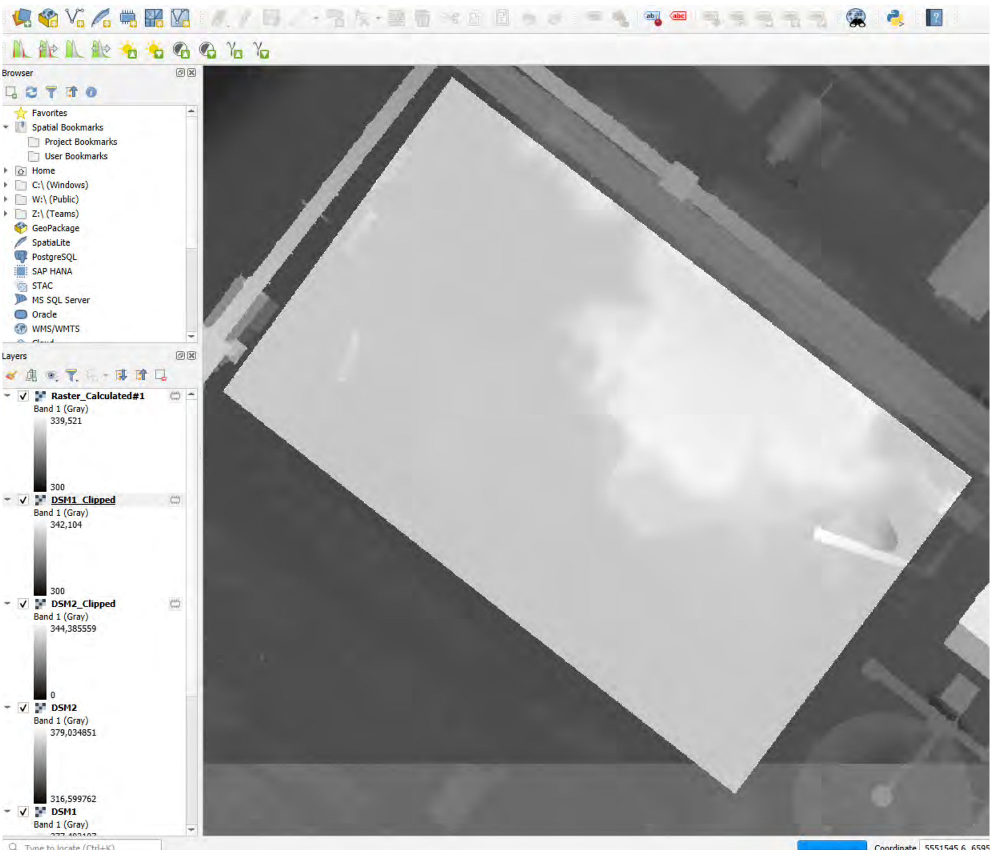


Fig. 6. Algorithm executed to the described point
Source: authors own work based on QGIS software

Rys. 6. Algorytm wykonany do opisanego punktu units of the calculated volume. If the horizontal and vertical units of the DEMs are in meters, the resulting volume will be in cubic meters. This unit consistency across all input layers is essential for obtaining meaningful volume estimations.

Although the algorithm can calculate the difference between the two levels above the ground, there is a problem with "bad pixels" around the layers, which should be treated as the mean of the pixels around them. Such "bad pixels" were shown in Figure 7.

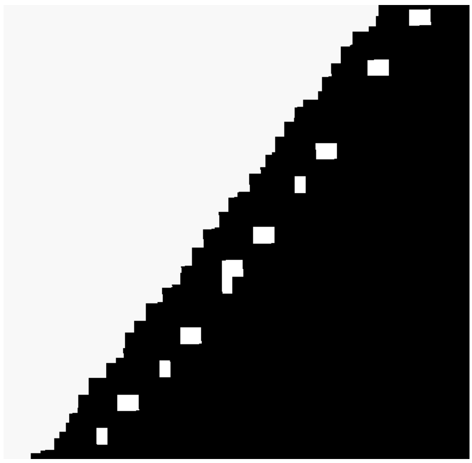

Fig. 7. "Bad pixels" in magnification
Source: authors own work based on QGIS software

Rys. 7. Złe piksele w powiększeniu

The value of these pixels should be the mean of the neighboring ones. To ensure that the value of pixels like that will be neutral, the second part of the algorithm was developed. Its parts were presented in Figure 8.

The first step in this QGIS *Modeler part 2* algorithm is to automatically detect and flag raster cells within the DEM input that exhibit unusually low elevation values, which are hypothesized to represent data errors. This initial filtering process serves to isolate potential problematic areas within the dataset for further scrutiny and correction. In this specific step, the conditional expression if (*A@1* < –300, 1, 0) is used. Here, *A@1* is a convention within the QGIS *Raster calculator* to refer to the first band (and typically the only band containing elevation data in a standard DEM) of the input raster layer, where *A* acts as a placeholder name for the original DEM loaded into the QGIS Modeler. The condition < –300 tests whether the elevation value of a given cell in the input DEM is less than –300. The selection of –300 as the threshold for identifying these anomalously low values is a critical parameter that should ideally be informed by a thorough understanding of the expected elevation range within the study area and the potential characteristics of errors that might be present.

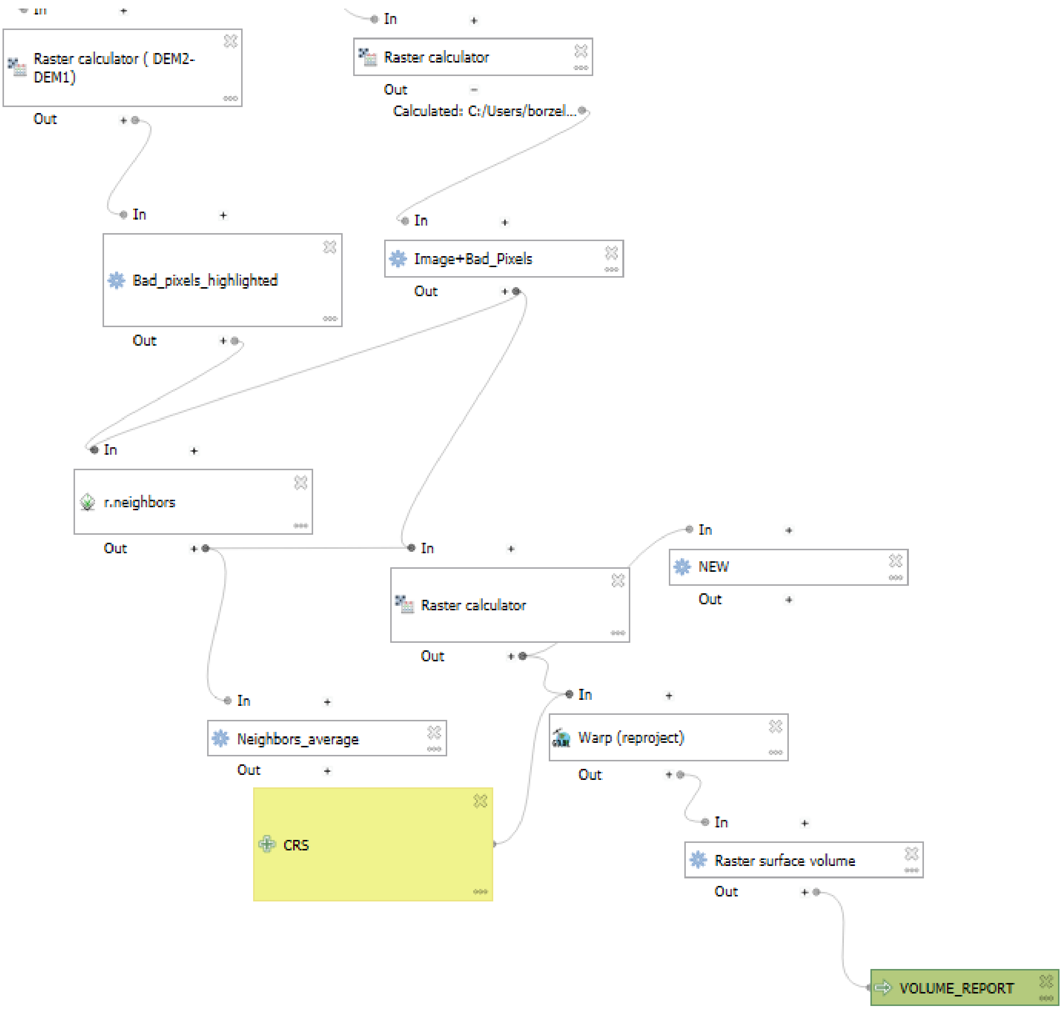


Fig. 8. Second part of the algorithm
Source: authors own work based on QGIS software

Rys. 8. Druga część algorytmu

Value 1 is assigned to the corresponding cell in the output raster if the condition is evaluated as true, effectively classifying these cells as "bad pixels" that exhibit unusually low elevation. Conversely, the value zero is assigned to the cell in the output raster if the condition is false, indicating that the elevation value is greater than or equal to –300, and thus the pixel is considered valid. The *if function* in the *Raster calculator* provides a direct mechanism for implementing this conditional classification, returning one specified value if a condition is met and another value if it is not. The result of this *Raster calculator* operation is a new binary raster layer. In this layer, each cell will contain either value 1 (denoting an identified "bad pixel" with an anomalously low elevation) or value 0 (representing a valid pixel). This binary raster mask will serve as a selection layer in the subsequent steps of the workflow, allowing for targeted processing of the identified potential errors.

Following the automated identification of potential "bad pixels" based on the elevation threshold, the next crucial step in the workflow is to inspect the spatial distribution of these flagged cells visually. This visual quality control measure is essential for gaining a deeper understanding of nature and spatial patterns of potential data errors, which might not be readily apparent from a simple examination of numerical values alone. Visualization plays a fundamental role in Geographic Information Systems, enabling analysts to explore spatial data, identify trends, and assess data quality. In QGIS, the binary raster layer generated in Step 1 can be easily styled to visually distinguish the "bad pixels" (where the cell value is 1) from the valid pixels (where the cell value is 0). This styling can be achieved through the Layer Styling panel accessible from the QGIS Layers panel. One practical approach is to utilize either the *Singleband pseudocolor* or the *Paletted/Unique values renderer*. The *Paletted/Unique values renderer* is particularly well-suited for visualizing binary rasters, as it allows the user to assign a specific color to each unique pixel value present in the layer (in this case, 0 and 1). Furthermore, clusters of "bad pixels" concentrated in a particular geographic area might point towards localized data corruption or terrain-specific challenges encountered during data collection. This visual feedback provides crucial context that informs the subsequent steps in the workflow, particularly in deciding whether the chosen correction method (neighborhood averaging) is appropriate or if alternative error mitigation strategies might be required.

The next stage in the workflow involves applying the *r.neighbors* algorithm, a powerful tool provided by the GRASS GIS software and seamlessly integrated into QGIS through the Processing Toolbox. This algorithm is designed to analyze raster data by examining the values of cells within a user-defined neighborhood around each cell in the input raster layer and then calculating a new value for the central cell based on a specified function applied to these neighboring values. In this workflow, the *r.neighbors* algorithm is applied to the *original* elevation raster (the DEM before any corrections were made). The primary goal of this step is to compute a replacement elevation value for each of the "bad pixels" that were identified in Step 1, utilizing the elevation information from their surrounding valid neighboring pixels. A key aspect of this process is the use of the "bad pixel" mask, which was generated in Step 1, as a selection layer. By specifying this binary mask as a selection layer, the *r.neighbors* algorithm is instructed to perform its neighborhood analysis and calculation *only* for those cells in the original DEM that correspond to the "bad pixels" (i.e., where the mask has a value of 1). For all other cells in the original DEM (where the mask has a value of 0, indicating valid pixels), the algorithm effectively bypasses the calculation, and their original elevation values are retained in the output of this step. The *r.neighbors* algorithm is configured to calculate the *average* elevation value of the valid neighboring pixels for each of the highlighted "bad pixels". The *average* method calculates the arithmetic mean of the elevation values of all non-NULL cells within the defined neighborhood.

To perform this neighborhood averaging, it is necessary to specify both the size and the shape of the neighborhood. The neighborhood size is typically defined by an odd integer representing the dimensions of a square moving window (e.g., a size of 3 results in a 3 × 3 window, a size of 5 in a 5 × 5 window, and so on). The shape of the neighborhood can also be specified, for instance, as a square or a circle. The chosen size and shape of the neighborhood directly determine which surrounding cells are considered when calculating the average for the central "bad pixel". For example, a 3 × 3 square neighborhood will consider the eight cells immediately adjacent to the central "bad pixel". In contrast, a larger or differently shaped neighborhood would include a different set of neighboring cells in the calculation. The output of the *r.neighbors* algorithm, when configured in this manner, is a new raster layer. In this layer, at the precise spatial location of each "bad pixel" identified in Step 1, the cell value represents the calculated average elevation of its valid neighboring pixels, derived from the original DEM.

For all other locations in the raster (corresponding to the pixels that were initially deemed valid based on the threshold), the cell value in this output layer will be the same as the original elevation value from the input DEM (due to the application of the selection mask). A potential conditional expression that can be use within the *Raster calculator* to accomplish this imputation is: *if (bad_pixels@1\ == 1, averaged_values@1\, \"original_dem@1*. In this expression, *bad_pixels@1* refers to the binary mask layer produced in Step 1, where cells identified as "bad pixels" have a value of 1, and valid pixels have a value of 0. The term *averaged_values@1* refers to the output raster layer from Step 3, which contains the calculated average elevation values for the spatial locations that corresponded to the "bad pixels" in the mask. It's important to note that for the locations of pixels that were initially considered valid, this *averaged_values@1* layer will likely retain the original DEM values due to the selection mask applied in Step 3. Finally, *original_dem@1* refers to the original, uncorrected Digital Elevation Model layer. The final output resulting from this *Raster calculator* operation is a new, corrected DEM. In this corrected DEM, the original anomalously low elevation values at the spatial locations identified as "bad pixels" in Step 1 have been effectively replaced with the locally averaged elevation values calculated in Step 3. Crucially, the elevation values at all other spatial locations within the DEM, which were initially considered valid based on the elevation threshold, remain unchanged from the original DEM. This step completes the process of correcting the identified potential errors in the DEM using a local neighborhood averaging technique.

The final step in this QGIS Modeler-based workflow involves performing a geometric correction on the entire corrected raster layer that resulted from Step 4. This correction is achieved through the *Warp (reproject)* operation, a standard tool available within QGIS. Raster reprojection is a fundamental geospatial process that transforms a raster dataset from its original Coordinate Reference System (CRS) into a specified target CRS. The *Warp (reproject)* tool in QGIS, which often leverages the functionality of utilities from the Geospatial Data Abstraction Library (GDAL), provides a user interface for performing this raster reprojection. When using this tool, the user needs to specify several key parameters to define the reprojection process. These parameters include: the Input layer, which in this case is the corrected DEM resulting from the imputation in Step 4; the Target CRS, which is the desired coordinate system for the reprojected raster (this selection should be based on the specific requirements of the study area and the intended spatial analyses, with a projected CRS in meters being generally preferred for volume calculation if the elevation values are also in meters); and the Resampling method, which determines how the pixel values from the original raster are transferred to the new pixel grid of the target CRS (standard methods include Nearest Neighbor, Bilinear Interpolation, and Cubic Convolution). The *Warp (reproject)* operation results in a new raster layer that represents the geometrically corrected DEM, now transformed into the specified target CRS, which is *EPSG:2177 – ETRF2000-PL*.

The last part is to calculate the volume of the terrain represented by the reprojected and corrected DEM layer. This is accomplished using the *Raster surface volume* algorithm, a built-in QGIS tool accessible through the Processing Toolbox. The final output of the *Raster surface volume* algorithm provides a quantitative measurement of the volume. The units of this volume will be in cubic units, consistent with the linear units of the Coordinate Reference System of the input raster. This final step provides the desired quantitative result, representing the volume of the terrain after the initial correction for anomalously low elevation values and the geometric correction through reprojection. The result of the performed algorithm was presented in Figure 9.

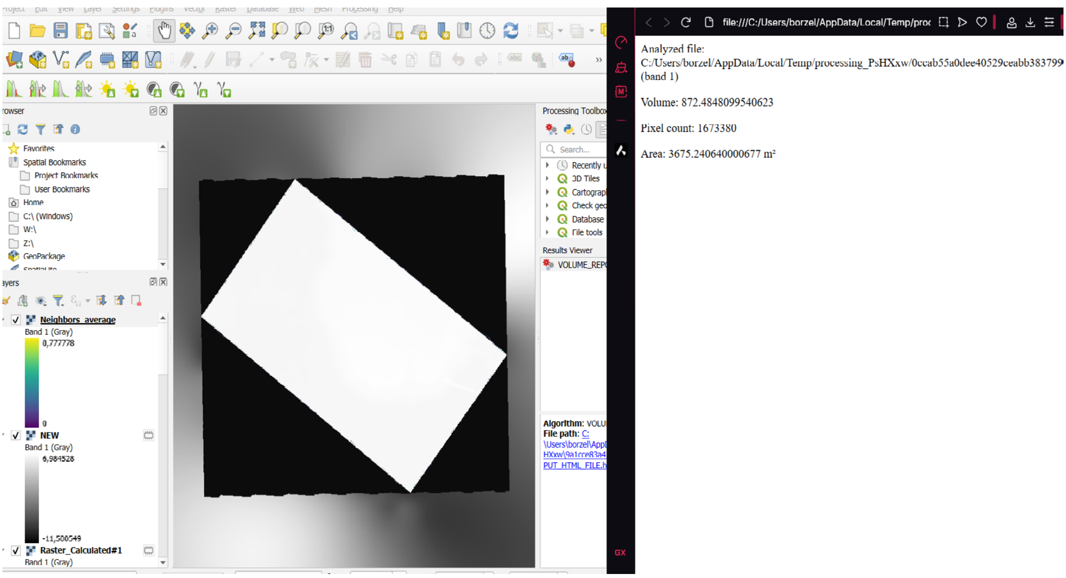


Fig. 9. Result of the performed algorithm with report
Source: authors own work based on QGIS software

Rys. 9. Wynik wykonanego algorytmu wraz z raportem

The performed algorithm's main result is the report, which contains information about Volume in cubic meters ($m^3$), Pixel count and calculated area in square meters ($m^2$). However, this solution needs improvements before exporting in the form of Python code and running within QGIS Server software. The first step is to simplify the algorithm logic by eliminating intermediate steps, such as loading layers, etc. Also editing and simplification of the Python code automatically generated in the QGIS application is necessary. Development of a solution based on the operation of the QGIS Server application and the logic of application design, used to automate the process of calculating the difference in the volume changes of spoil tips, referring to the QGIS Server application.

## 3. Discussion and conclusions

The use of UAVs for data acquisition in conjunction with IoT for real-time monitoring and advanced volume calculation techniques represents a significant innovation within the DynGOSP Project. This integrated approach is a solution for automated data processing in coal management, overcoming many of the limitations associated with conventional methods. Traditional methods for assessing coal heap volumes, for instance, often involve manual surveying techniques that are not only time-consuming and labor-intensive but also expose personnel to potential hazards within the mining environment (Kuinkel MS 2023; GAO RFID Inc. 2025). UAVs equipped with high-resolution cameras and advanced sensors can rapidly capture detailed imagery of heaps and dumps from multiple perspectives and on demand. This data can then be processed using dedicated or open-source software to generate accurate three-dimensional models, enabling precise volume calculations, even for large heaps and dumps located in areas with limited accessibility (TerraDrone Arabia 2023). Using spatial data, IoT devices deployed across mining sites can provide continuous streams of information on various environmental parameters and the operational status of equipment. This real-time monitoring capability enables proactive responses to changing conditions and potential issues, thereby enhancing both safety and efficiency. The combination of these technologies within DynGOSP creates a novel automated system that provides comprehensive, timely, and accurate data, thereby significantly improving the capabilities for coal management (Dyczko et al. 2025; DynGOSP 2023). The innovative nature of this integrated solution is particularly evident when considered within the specific context of coal management and the unique objectives of the DynGOSP Project (Dyczko et al. 2025; Mól et al. 2024). DynGOSP is designed to facilitate the dynamic management of the entire coal lifecycle, encompassing demand forecasting, production optimization, and logistical efficiency. The automated data processing tool, featuring UAVs for inventory assessment and potential monitoring of extraction activities, as well as IoT for real-time tracking of production parameters and precise volume calculation, directly supports this objective by providing the necessary data for informed decision-making (Kurniawan and Cahyadi 2023; Dyczko et al. 2025).

Furthermore, a key aim of DynGOSP is the development of a dynamic resource database (Mantey and Aduah 2021; DynGOSP 2023; Dyczko 2024; Marlęga et al. 2024; Mól et al. 2024; Dyczko et al. 2025). UAVs can provide up-to-date information on coal heaps and dumps, as well as potentially extraction sites, aligning perfectly with this goal and ensuring that the resource database remains current and accurate. Polish researchers are increasingly exploring the potential of UAVs in various mining applications, including surveying mine sites, monitoring heaps and dumps, and even quantifying methane emissions (Dyczko et al. 2025). This UAV technology and approach to data management provide a strong foundation upon which the DynGOSP project can build and innovate. The true innovation of the DynGOSP approach lies in the synergistic integration of these technologies specifically to address the dynamic and complex requirements of coal management within the Polish context, representing a significant advancement beyond the individual applications of UAVs and IoT in isolation.

Presented in this paper is an automated approach to calculating the volume of heaps and dumps, which integrates UAVs, IoT, and geoinformatics tools, offering substantial advantages. Conventional coal heap measurement using techniques like Global Navigation Satellite System (GNSS) surveying can be physically demanding, time-consuming, and may expose surveyors to hazardous conditions (Equinox's Drones 2024). UAV-based volume calculation, on the other hand, is faster, safer, and capable of delivering higher accuracy and a richer dataset (Mantey and Aduah 2021). IoT-enabled monitoring provides a continuous stream of data, unlike the periodic snapshots obtained through manual inspections, allowing for proactive intervention in response to evolving conditions. The integrated nature of the DynGOSP solution provides a more comprehensive and real-time understanding of coal resources and operational parameters compared to the isolated data points collected through traditional methods. This holistic view presents opportunities to develop the Digital Coal-Platform solution, one of the main objectives of the DynGOSP project.

The integrated solution described within the context of the DynGOSP project is about to apply advanced technologies to coal management in Poland. While Polish researchers have explored the individual applications of UAVs for surveying and environmental monitoring, and the use of IoT within the DynGOSP information system, the specific combination of these technologies with advanced volume calculation for the dynamic management of the entire coal lifecycle, as envisioned by DynGOSP, likely represents a unique value to practical coal heaps and dumps logistics and management. This approach is part of a broader national trend to modernize the coal industry and enhance operational efficiency through the adoption of new solutions (Marszowski and Iwaszenko 2021). The DynGOSP project, therefore, not only addresses immediate challenges in the Polish coal sector but also contributes to the advancement of knowledge and the development of innovative tools for sustainable coal resource management in the long term.

While offering numerous advantages, the presented approach also presents several inherent limitations. These limitations are connected to technological, environmental, regulatory, and organizational domains, and addressing them is important for the successful deployment and long-term effectiveness of such a system within the DynGOSP Project. UAV technology faces constraints related to battery life, which can limit flight duration and the extent of coverage in a single mission. The performance of UAVs is susceptible to adverse weather conditions, such as strong winds, heavy rain, or fog, which can lead to flight cancellations or lower data quality. From a data perspective, the accuracy of volume calculations derived from UAV imagery can be influenced by factors such as vegetation growth obscuring the heaps and dumps, as well as the precise distribution of ground control points used for georeferencing. However, this was improved by using an RTK system. Data security and privacy are also significant concerns associated with both UAV and IoT systems, necessitating robust cybersecurity measures to prevent unauthorized access and data leaks.

Additionally, the potential limitation lies in over-reliance on automation, which could lead to a reduction in human oversight and a risk of misinterpreting data if contextual understanding is lost (Multimodal 2023). Within the specific context of coal mines in Poland, the broader level of automation and informatization remains relatively low compared to other industries, suggesting potential infrastructural and technological gaps that could hinder the seamless integration of advanced UAV and IoT systems. Additionally, when dealing with large datasets generated by automated systems in coal mines, issues such as data heterogeneity, privacy concerns related to sensitive safety information, and the inherent difficulty in establishing causal relationships from correlational big data can present significant limitations (Sun 2024). Therefore, careful consideration of these multifaceted limitations is essential for the effective design and implementation of the proposed automated data processing tool within the DynGOSP project.

In its current state, the algorithm successfully generates reports detailing coal volume in cubic meters, pixel count, and calculated area in square meters from detailed orthophotomaps derived from UAV imagery. The precision of these Digital Elevation Models (DEMs), which is fundamental for accurate volume calculations, is directly influenced by factors such as image resolution, the degree of image overlap, and the application of a Real-Time Kinematic (RTK) system. The DEMs are processed using the OpenDroneMap software for stitching. A significant challenge encountered during this phase involved the presence of "bad pixels" around the layers, which necessitated a specialized correction mechanism. The authors addressed this by developing a second part of the algorithm to automatically detect and flag unusually low elevation values (e.g., less than –300) and replace them with the average elevation of valid neighboring pixels using the *r.neighbors* algorithm. This approach ensures data quality and significantly contributes to the reliability of subsequent volume calculations.

Ensuring the algorithm's repetitiveness and reliability across various geospatial data types is paramount. While the manuscript does not explicitly detail "most of the file types", the workflow demonstrates consistent processing of raster data (DEMs). It implies compatibility with vector mask layers derived from geospatial formats. A critical finding is the absolute necessity of referencing all DEMs to the exact Coordinate Reference System (CRS) for accurate spatial analysis. Discrepancies in CRS can lead to significant misalignments and unreliable calculations. The authors determined that for their specific application in central Poland, EPSG:2177 (ETRF2000-PL) is the most appropriate projected CRS, as it is consistent with volume calculations where elevation values are in meters. The consistency of units across input layers is crucial for meaningful volume estimations. The document does not indicate the use or appropriateness of the EPSG 3857 projection in this context.

GPS accuracy, particularly RTK positioning for UAVs, has proven crucial for the effective operation and reliability of the algorithm. The authors' experience confirms that RTK systems significantly improve the precision of the resultant DEMs. This heightened precision is crucial for the accuracy of volume estimations, particularly considering factors such as vegetation growth and ground control point distribution, which can otherwise impact data quality. The integration of RTK technology directly addresses a key limitation in UAV-derived data quality, ensuring that the foundational spatial information for volume calculation is as accurate as possible.

For the algorithm to be seamlessly integrated and utilized as a QGIS Server Python input, optimization for reliability is a necessary next step in its development. The current solution, while functional, requires simplification of its logic by eliminating intermediate steps, such as explicit loading of layers, which can introduce inefficiencies in an automated server environment. Furthermore, editing and refining the Python code automatically generated by the QGIS application is essential to enhance its performance and robustness for server-side execution. Developing a streamlined solution that aligns with the QGIS Server application's design logic will enable the automated, on-demand calculation of volume changes in spoil tips, ensuring the algorithm's reliability in a continuous operational setting.

Addressing these identified demands and incorporating these findings directly ensures the algorithm's practical usefulness and applicability for automated on-demand inventory of coal dumps and heaps. The precision afforded by detailed orthophotomaps and RTK-enabled UAVs translates into highly accurate volumetric data. The rigorous attention to Coordinate Reference Systems and the implementation of automated "bad pixel" correction mechanisms bolster the algorithm's reliability and consistency, producing trustworthy inventory reports. Optimizing the algorithm for QGIS Server integration will enable real-time, dynamic monitoring capabilities, moving beyond periodic manual surveys to provide up-to-date information. This automation enhances operational efficiency, reduces labor, and improves safety by minimizing the need for manual measurements in hazardous environments. Ultimately, these advancements provide timely and accurate data, which is crucial for informed decision-making in coal management, encompassing operational planning, financial forecasting, risk management, and environmental stewardship.

Further research is needed to adapt and optimize these technologies to the operational conditions in Polish coal mines, ensuring that the solutions are developed to address the unique challenges of the national context. Continuous monitoring of advancements in AI, data analytics, sensor technology, and integration strategies will be essential for the ongoing improvement and evolution of automated data.

The presented sequence of tasks is a key step in automating the process of monitoring coal dumps and mining heaps. Moreover, it should also focus on integrating the algorithm's outputs with predictive analytics and forecasting models. By leveraging the accurate and up-to-date inventory data provided by this automated system, it becomes possible to develop more sophisticated models for coal demand forecasting, optimizing production planning, and enhancing distribution logistics within the Polish hard coal mining sector. This would involve applying machine learning techniques to identify trends in coal accumulation and depletion, enabling more proactive resource management strategies and directly contributing to the realization of the DynGOSP project. After the target application is created, it is essential to focus on the future direction of creating a full-scale solution that will revolutionize dynamic resource management as a direct consequence of the DynGOSP project.

Integration of UAVs, IoT, and volume calculation within the DynGOSP project represents an innovative and comprehensive approach to automated data processing in coal management. This solution offers significant advantages over traditional methods by providing more efficient, safer, and accurate data for critical operational and strategic decision-making. It directly supports the project's objectives of achieving dynamic management of coal resources, optimizing production and logistics, and creating a comprehensive information system for the Polish coal industry. By enabling more efficient, safe, and accurate coal management, the adoption of such technologies has the potential to contribute to a more sustainable and environmentally responsible coal sector in Poland. Despite the ongoing energy transition, coal remains a significant component of Poland's energy mix. Automated data processing will play a crucial role in optimizing coal operations today. It may also facilitate a smoother transition to new energy sources in the future by providing efficient resource management and environmental monitoring capabilities. Continued research and development in this area are important for the Polish energy sector.

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## AUTOMATED ON-DEMAND INVENTORY OF COAL DUMPS AND HEAPS USING UAV IMAGERY AND IOT-DRIVEN DATA PROCESSING

Keywords

coal, UAV, volume, DynGOSP, heaps

Abstract

The efficient management of coal resources is becoming increasingly important in Poland and Europe, especially during the ongoing energy transition. This paper presents an automated methodology for on-demand inventory of coal dumps and heaps, addressing the limitations of traditional manual surveying techniques. The proposed system integrates Unmanned Aerial Vehicles (UAVs) for rapid spatial data acquisition, IoT sensors for real-time monitoring of environmental parameters, and the QGIS open-source Geographic Information System for data processing and volume calculation. The methodology details the process of generating accurate Digital Elevation Models (DEMs) from UAV imagery using OpenDroneMap software and subsequent volume calculation using a custom algorithm developed within the QGIS Model Designer. This algorithm addresses the challenges of data processing, including the removal of "bad pixels" and geometric correction, to ensure accurate volume estimations. The results demonstrate the potential of the integrated system to provide accurate and timely inventory data, crucial for optimizing coal demand forecasting, production planning, and distribution logistics. This approach offers significant advantages over traditional methods by enhancing safety, reducing labor intensity, and enabling more frequent and precise measurements. The developed solution aligns with the goals of the Polish "Dynamic management of coal demand, production, resource management, and distribution logistics in an economy implementing a decarbonized energy mix" (DynGOSP) project, supporting the modernization of the Polish coal mining sector.

## ZAUTOMATYZOWANY SYSTEM INWENTARYZACJI ZWAŁÓW I HAŁD WĘGLA, WYKORZYSTUJĄCY TECHNOLOGIĘ UAV I PRZETWARZANIE DANYCH OPARTE NA IOT

Słowa kluczowe

węgiel, drony, objętość, DynGOSP, zwały

Streszczenie

Efektywne zarządzanie zasobami węgla staje się coraz ważniejsze w Polsce i Europie, zwłaszcza w trakcie trwającej transformacji energetycznej. W niniejszym artykule przedstawiono zautomatyzowaną metodologię inwentaryzacji na żądanie składowisk i hałd węgla, rozwiązując ograniczenia tradycyjnych ręcznych technik geodezyjnych. Proponowany system integruje bezzałogowe statki powietrzne (UAV) w celu szybkiego pozyskiwania danych przestrzennych, czujniki IoT do monitorowania parametrów środowiskowych w czasie rzeczywistym oraz system informacji geograficznej

QGIS typu open source do przetwarzania danych i obliczania objętości. Metodologia szczegółowo opisuje proces generowania dokładnych modeli wysokościowych (DEM) z obrazów UAV przy użyciu oprogramowania OpenDroneMap i późniejszego obliczania objętości przy użyciu niestandardowego algorytmu opracowanego w QGIS Model Designer. Algorytm ten rozwiązuje problemy związane z przetwarzaniem danych, w tym usuwaniem „złych pikseli" i korektą geometryczną, aby zapewnić dokładne oszacowanie objętości. Wyniki pokazują potencjał zintegrowanego systemu do dostarczania dokładnych i terminowych danych inwentaryzacyjnych, które są kluczowe dla optymalizacji prognozowania zapotrzebowania na węgiel, planowania produkcji i logistyki dystrybucji. To podejście oferuje znaczące zalety w porównaniu z tradycyjnymi metodami, zwiększając bezpieczeństwo, zmniejszając pracochłonność i umożliwiając częstsze i dokładniejsze pomiary. Opracowane rozwiązanie jest zgodne z celami polskiego projektu DynGOSP – „Dynamiczne zarządzanie popytem na węgiel, produkcją, zarządzaniem zasobami i logistyką dystrybucji w gospodarce wdrażającej zdekarbonizowany miks energetyczny", wspierającego modernizację polskiego sektora górnictwa węglowego.