https://doi.org/10.5194/esurf-2022-56
Preprint. Discussion started: 14 November 2022

Research article

Automated riverbed material analysis using Deep Learning on underwater images

Alexander A. Ermilov[1], Gergely Benkő[1] and Sándor Baranya[1]

[1]Department of Hydraulic and Water Resources Engineering, Budapest University of Technology and Economics, Budapest, 1111, Hungary

Correspondence to: Alexander A. Ermilov (ermilov.alexander@emk.bme.hu)

Abstract. The sediment of alluvial riverbeds plays a significant role in river systems both in engineering and natural processes. However, the sediment composition can show great spatial and temporal heterogeneity, even on river reach scale, making it difficult to representatively sample and assess. Indeed, conventional sampling methods in such cases cannot describe well the variability of the bed surface texture due to the amount of energy and time they would require. In this paper, an attempt is made to overcome this issue introducing a novel image-based, Deep Learning algorithm and related field measurement methodology with potential for becoming a complementary technique for bed material samplings and significantly reducing the necessary resources. The algorithm was trained to recognise main sediment classes in videos that were taken underwater in a large river with mixed bed sediments, along cross-sections, using semantic segmentation. The method is fast, i.e., the videos of 300-400 meter long sections can be analysed within minutes, with very dense spatial sampling distribution. The goodness of the trained algorithm is evaluated mathematically and via intercomparison with other direct and indirect methods. Suggestions for performing proper field measurements are also given, furthermore, possibilities for combining the algorithm with other techniques are highlighted, briefly showcasing the multi-purpose of underwater videos for hydromorphological adaptation. The paper is to show the potential of underwater videography and Deep Learning through a case study.

Keywords: rivers, sedimentology, mapping, Artificial Intelligence, Deep Learning, underwater, image-based

1 Introduction

The physical composition of a riverbed plays a crucial role in fluvial hydromorphological processes, as a sort of boundary condition in the interaction mechanisms between the flow and the solid bed. Within these processes, the grains on the riverbed are responsible for multiple phenomena, such as flow resistance (Vanoni and Hwang, 1967; Zhou et al., 2021), stability of the river bed (Staudt et al., 2018; Obodovskyi et al., 2020), development of bed armour (Rákóczi, 1987; Török et al., 2017), sediment clogging (Rákóczi, 1997; Fetzer et al., 2017), fish shelter (Scheder et al., 2015), etc. Through these physical processes, the bed material composition has a determining effect on numerous river uses, e.g., possibilities of fluvial navigation, drinking water supply through bank filtration, the quality of riverine habitats, etc. Knowledge of riverbed structure and grain composition is therefore of major importance in river hydromorphology. In order to gain information about river bed sediments, *in situ* field sampling methodologies are implemented.

Traditionally, bed material sampling methods are intrusive (i.e., sediment is physically extracted from the bed for follow-up analysis) and carried out via collecting the sediment grains one-by-one (areal, grid-by-number and pebble count methods, see e.g., Bunte and Abt, 2001; Guerit et al., 2018) or in a larger amount by a variety of grab samplers (volumetric methods, such as WMO, 1981; Singer, 2008). This is then followed by measuring their sizes individually on-site or transporting them to a laboratory for mass-sieving analysis (Kellerhals and Bray, 1971; Fehr, 1987; Diplas, 1988; Bunte and Abt, 2001). These sampling procedures are time- and energy consuming, especially in large gravel and mixed bed rivers, where characteristic grain sizes can strongly vary both in time and space (Church et al., 1987; Wolcott and Church, 1991; Rice and Church, 1998; USDA, 2007), requiring a dense sampling point allocation. The same goes for critical river reaches, where significant human impact led to severe changes in the morphological state of the rivers (e.g., the upper-section of the Hungarian Danube; Török and Baranya, 2017). When assessing bed material composition on a river reach scale, experts usually try to extrapolate from the samples, and describe larger regions of the bed (even several thousand m^2) by data gathered in a few, several dozen points (see e.g., USDA, 2007; Haddadchi et al., 2018; Baranya et al., 2018; Sun et al., 2021). Gaining a representative amount of the sediment samples is also a critical issue. For instance, following statistical criteria such as those of Kellerhals and Bray (1971) or Adams (1979), a representative sample should weigh ten-to-hundred kg. Additionally, physical bed material sampling methods are unable to directly quantify important, hydromorphological features such as roughness or bedforms (Graham et al., 2005). Due to these constraints, surrogate approaches have recently been intensively tested to analyse the riverbed (see Chapter 2). Unlike the conventional methods, these techniques are non-intrusive and rely on computers and other instrumentation to decrease the need of human intervention and speed up the analyses. The goal of this paper is to introduce a Deep Learning-based technique and its first set of results which shows potential in complementing the traditional methods, while also providing broader knowledge of the riverbed than before through improved (continuous, quick, covering larger areas) data collection. First, a literature review is given to better understand the current state of surrogate approaches and their research, gradually leading up to the method of this paper and highlighting its relevance. In the third chapter the case studies and the methodology are introduced in details. The third chapter presents the results and their evaluation, followed by a discussion about the challenges, the novelty and possible continuations of the method. A brief discussion is also given on how the method can support traditional methods and what kind of additional hydromorphological parameters can be provided by such videos, uniquely improving the toolkits of sedimentation engineering. Finally, the main conclusions of the paper are drawn.

2 Literature review

One group of the surrogate approaches is the acoustic methods, where an acoustic wave source (e.g., an Acoustic Doppler Current Profiler; ADCP) is pointed towards the riverbed from a moving vessel, emitting a signal. The strength and frequency of this signal is measured while it passes through the water column, reflecting back to the receiver from the sediment transported by the river, and finally from the riverbed itself. This approach is fast and larger areas can be covered relatively quickly (Guerrero and Lamberti, 2011; Grams et al., 2013). While it has already became widely used for describing movement (i.e., suspended sediment, bedload and indirectly flow velocity; Shields and Rigby, 2005; Guerrero et al., 2016; Muste et al., 2016) and channel shape (Zhang et al., 2008), it has not reached similar breakthrough for riverbed material analysis. Researchers found that it is necessary to apply instrument specific coefficients to convert the signal strength, and these coefficients can only be derived by first validating each instrument using collected sediment samples with corresponding ADCP data. Moreover, the method is sensitive to the bulk density of the sediment and to bedforms (Shields, 2010), while it is also not possible to measure individual grains this way (Buscombe et al., 2014a; 2014b). Hence, the separation of surface roughness from the effects of bedforms is also not possible. Clay and silt patches could be separated with the acoustic approach, but gravel could not be distinguished strongly from sand.

Another group of the surrogate approaches is the application of photography (Kellerhals and Bray, 1971; Adams, 1979; Ibbekken and Schleyer, 1986) and later computer vision or image-processing techniques. During the last two decades, two major subgroups emerged: one uses object- and edge detection (by finding abrupt changes in intensity and brightness of the picture, segmenting objects from each other; Butler et al., 2001; Sime and Ferguson, 2003; Detert and Weitbrecht, 2013), and the other one analyses the textural properties of the whole image, using autocorrelation and semi-variance methods to define empirical relationship between image texture and the grain sizes of the photographed sediments (Carbonneau et al., 2004; Rubin, 2004; Verdú et al., 2005). The above-mentioned image processing approaches were very time consuming and required mostly site-specific manual settings, however, a few transferable and more automated techniques have also been developed recently (e.g., Graham et al., 2005; Buscombe, 2013). Even though there is a continuous improvement in the applied image-based bed sediment analysis methods, there are still major limitations the users face with, such as:

- Most of the studies (all the ones listed above) focuses on gravel bed rivers, and only a few exceptions can be found in the literature where sand is also accounted for (texture-based methods; Chezar and Rubin, 2004; Buscombe and Masselink, 2008; Warrick et al., 2009; Buscombe, 2013).
- The adaptation environment was typically non-submerged sediment, instead of underwater conditions (a few exceptions: Chezar and Rubin, 2004; Warrick et al., 2009).
- The computational demand of the image processing is high (e.g., one to ten minutes per image; Detert and Weitbrecht, 2013; Purinton and Bookhagen, 2019).
- The analysis requires operator expertise (higher than in case of any conventional method).
- There is an inherent pixel- and image resolution limit (Graham et al., 2005; Buscombe and Masselink, 2008; Buscombe, 2013; Cheng, 2015; Purinton and Bookhagen, 2019). The finer the sediment, the higher resolution of the images should be (higher calculation time), or they must be taken from a closer position (smaller area and sample per image).
- Due to the limitations above, most of the methods enable the analysis of smaller areas (in the order of ~10 m^2) only and are not applicable for quick, continuous measurements of larger regions.

Nowadays, with the rising popularity of Artificial Intelligence (AI), several Machine Learning (ML) techniques have been implemented in image recognition as well.

The main approaches of segmentation contra textural analysis still remain; however, an AI defines the empirical relationship between the object sizes (Igathinatane et al., 2009; Kim et al., 2020) or texture types (e.g., Buscombe and Ritchie, 2018) in the images and their real sizes. In the field of river sedimentology a few examples can already be found, where ML (e.g., Deep Learning; DL) was implemented. For instance, Rozniak et al. (2019) developed an algorithm for gravel-bed rivers, performing textural analysis. With this approach, individual grains are not detected, but rather the general grain size distribution (GSD) of the whole images. At certain points of the studied river basins, conventional physical samplings (pebble count) were performed to provide real GSD information. Using this data, the algorithm was trained (with ~1000 images) to estimate GSD for the rest of the study site, based on the images. The method worked for areas where grain diameters were larger than 5 mm, and the sediment was well-sorted. The developed method showed sensitivity to sand coverage, blurs, reduced illuminations (e.g., shadows) and white pixels. Soloy et al. (2020) presented an algorithm which used object detection on gravel- and cobble covered beaches to calculate individual grain sizes and shapes. Approximately 50 images were used for the model training, however, the number of images were multiplied with data augmentation (rotating, cropping, blurring the images; see Perez and Wang, 2017) to enhance the learning session and increase the input data. The method was able to reach a limited execution speed of a few seconds per m^2 and adequately measured the sizes of gravels. Ren et al. (2020) applied an ensemble bagging-based Machine Learning (ML) algorithm to estimate GSD along the 70 km long Hanford Reach of the Columbia river. Due to its economic importance, a large amount of measurement data has been accumulated for this study site over the years, making it ideal for using ML. By the time of the study, 13,372 scaled images (i.e., their millimetre/pixel ratio was known) were taken both underwater and in the dry zones, covering approx. 1 m^2 area each. The distance between the image-sampling points was generally between 50-70 m. An expert defined the GSD (8 sediment classes) of each image by using a special, visual evaluation-classification methodology (Bovee, 1982, Delong and Brusven, 1991; Geist et al., 2000). This dataset was fed to a ML algorithm along with their corresponding bathymetric attributes and hydrodynamic properties, simulated with a 2D hydrodynamic model. Then, it was tested to predict the sediment classes based on the hydrodynamic parameters only. The algorithm performed with a mean accuracy of 53%. Even though this method was not image-based (only indirectly, via the origin of the GSD data), it highlighted the possibilities of an AI for a predictive model, using a high-dimensional dataset. Having such a large data of grain size information can be considered exceptional and takes a huge amount of time to gather, even with the visual classification approach they adapted. Moreover, this was still considered spatially sparse information (point-like measurements, 1 m^2 covered area/image dozens of meters away from each other). Buscombe (2020) used a set of 400 scaled images to train a DL algorithm on image texture properties, using another image-processing method (Barnard et al., 2007) for validation. The algorithm reached a good result for not only gravel, but sand GSD calculation as well, outperforming an earlier, but promising, texture-based method (wavelet analysis; Buscombe, 2013). In addition, the method required fewer calibration parameters than the wavelet image-processing approach. The study also foresaw the possibility to train an AI which estimates the real sizes of the grains, without knowing the scale of one pixel (mm/pixel ratio) if the training is done properly. The AI might learn unknown relationships between the texture and sizes if it is provided with a wide variety (images of several sediment classes) and scale (mm/pixel ratio)) of dataset (however, it is also prone to learn unwanted biases). Recently, Takechi et al. (2021) further elaborated on the importance of shadow- detection and removal, using a dataset of 500 pictures for training a texture-based AI, with the help of an object-detecting image-processing technique (Basegrain; Detert and Weitbrecht, 2013).

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The previously presented studies, applying ML and DL techniques, significantly contributed to the development and improvement of surrogate sampling methods, incorporating the great potential in AI. However, there are still several shortcomings to these procedures. Firstly, none of the image-based DL studies used underwater recordings, even though the underwater environment offers completely different challenges. Secondly, the training images were always scaled, i.e., the sizes of the grains could be easily reconstructed, which is again complicated to accomplish in a river. Lastly, they were not adapted for continuous measurement, but rather focused on a grid-like approach.

The method introduced in this paper follows the ML and DL approach as well. The main novelty of our DL and measurement method, however, is that both the training and analysed videos are recorded underwater, continuously along cross-sections of a large river. Furthermore, the training is unscaled, i.e., the camera-riverbed distance could vary while recording the videos, without considering image-scale. Moreover, compared to the relatively low number of training images in most of the above referred studies, we used a very large dataset (~15000) of sediment images for the texture-based AI, containing mostly: sand, gravel, cobble, and to a smaller extent: bedrock together with some other, non-sediment related objects.

3 Methods

3.1 Case studies

The results presented in this study are based on riverbed videos taken during three measurement campaigns, in sections of the Danube river, Hungary. The first one was at Site A, Ercsi settlement (~ 1606 rkm), the second one was at Site B, Gönyű settlement (~ 1791 rkm), and the third was at Site C, near to Göd settlement (~ 1667 rkm) (Fig. 1).

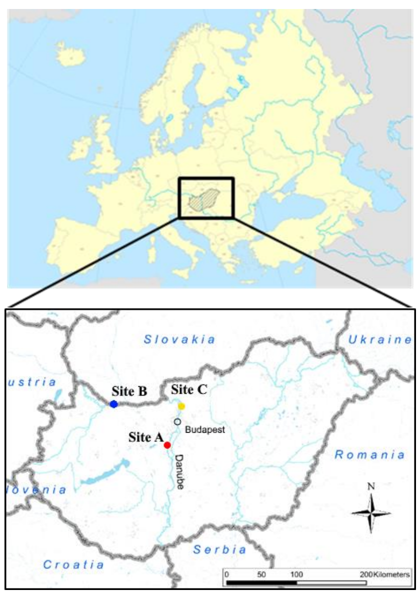

Figure 1: The location of the riverbed videos, where the underwater recordings took place (upper section of the Hungarian Danube).

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The training of the AI was done using the video images of Site C and a portion of A (test set; see later in Chapter 3.3), while Site B and the rest of the images from A served for validation. The measurements were carried out during daytime, at mid-water regime (Q = 1900 m^3/s) in case of Site A, and low water regime (Q = 1350 m^3/s) at Site B, similarly to Site C (Q = 700 m^3/s). This latter site served only for increasing the training image dataset (i.e., conventional samplings were not carried out at the time of recording the videos), thus we do not go into further details with it for the rest of the paper, but the main characteristics are listed in Table 1. As underwater visibility conditions are influenced by the suspended sediment, the characteristics of this sediment transport is also included in Table 1 (Q_{susp} - susp. sed. load; SSC – susp. sed. concentration).

	Site A	Site B	Site C
Q [m^3/s]	1900	1350	700
B [m]	300 – 450		
H_{mean} [m]	3.5 - 4.5		
S [cm/km]	15		
Characteristic riverbed sediment	gravel, sandy gravel	gravel, gravelly sand	gravel, sandy gravel
$Q_{annual,av}$ [m^3/s]	2000	2200	1400
SSC [mg/l]	25	20	14

Table 1: Main hydromorphological parameters of the measurement sites. Q: discharge during survey; B: river width; H_{mean}: mean water depth during the survey; S: river bed slope; $Q_{annual, av.}$: annual-average of the discharge at the site; SSC: average suspended sediment concentration during the survey.

The highest water depths were around 6-7 m in all cases. In Site A, measurements included mapping of the riverbed with a camera along three separate transects (Fig.2). At Site B, two transects were recorded (Fig.3).

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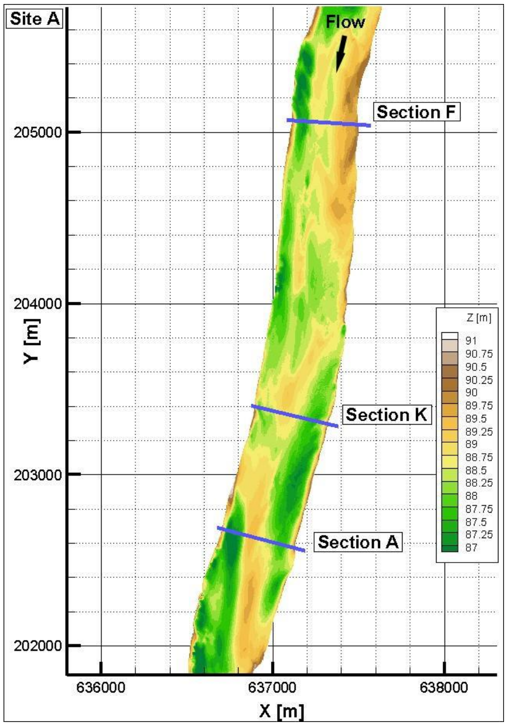

Figure 2: At Site A, three transects were measured. The vessel moved along these lines from one bank to the other, while carrying out ADCP measurement and recording riverbed videos. Physical bed material samples were also collected in certain points of these sections.

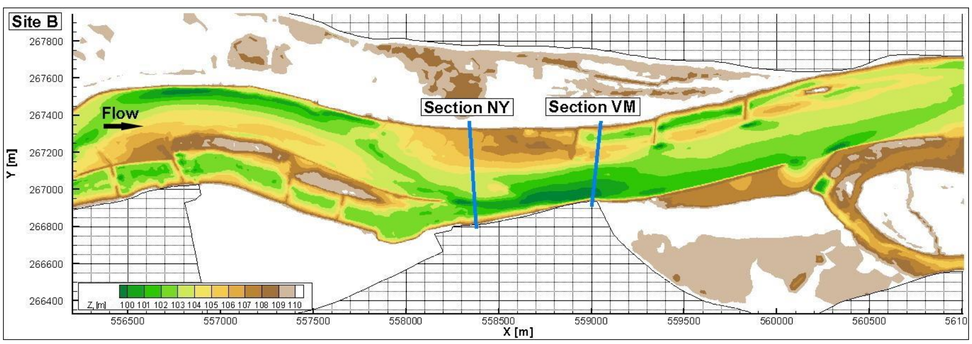

Figure 3: At Site B, two transects were measured. The vessel moved along these lines from one bank to the other, while carrying out ADCP measurement and recording riverbed videos. Physical bed material samples were also collected in certain points of these sections.

3.2 Field data collection

Figure 4 presents a sketch of the measurement process with the equipment and a close-up of the underwater instrumentation. During the field measurements, the camera was attached to a streamlined weight and lowered into the water from the vessel by an electric reel. The camera was positioned perpendicularly to the water and the riverbed, in front of the nose of the weight. Next to the camera, two diving lights worked as underwater light sources, focusing into the camera's field of view (FoV). In addition, four laser pointers were also equipped in

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hand-made isolation cases to provide possible scales for secondary measurements. They were also perpendicular to the bottom, projecting their points onto the underwater camera field of view. Their purpose was to ensure a visible scale (mm/pixel ratio) in the video footages for validation. During the measurement procedure, a vessel crossed the river slowly through river transects, while the position of the above detailed equipment was constantly adjusted by the reel. Simultaneously, ADCP and RTK GPS measurement were carried out by the same vessel, providing water depth, riverbed geometry, flow velocity, ship velocity and position data. Based on this information and by constantly checking the camera's live footage on deck, the camera was lowered or lifted to keep the bed in camera sight, and avoid colliding with it. The vessel's speed was also adjusted based on the video and slowed down if the video was blurry or the camera got too far away from the bed (see later in Chapter 4.3). The measurements required three personnel to i) drive the vessel, ii) handle the reel, adjust the equipment position, and monitor the camera footage, iii) monitor the ADCP data, while communicating with the other personnel (see Fig. 4).

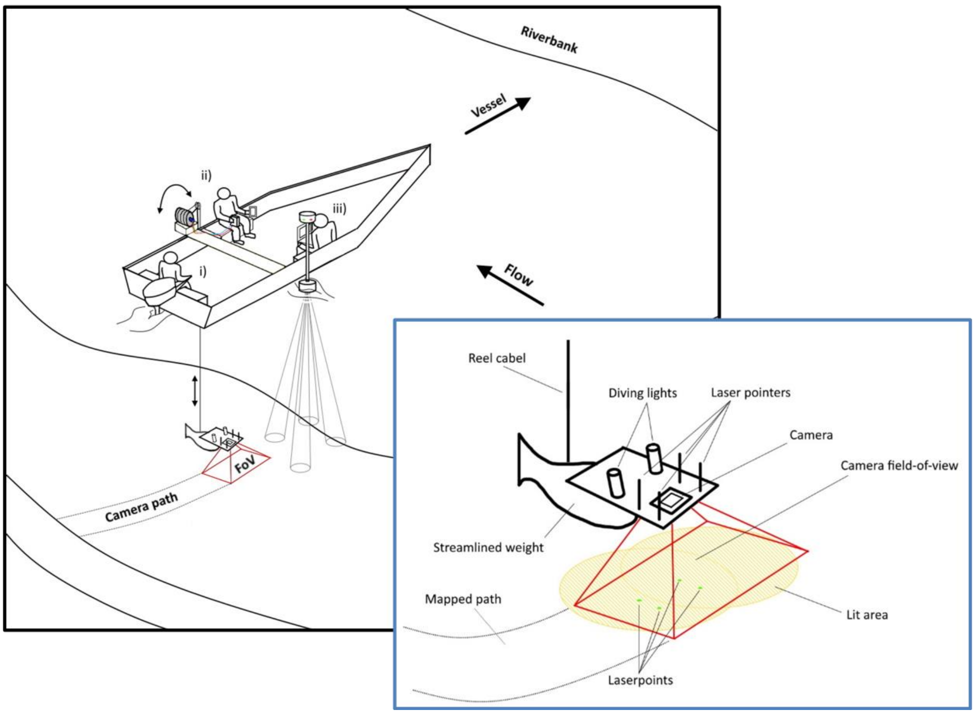

Figure 4: Left: sketch of the measurement process. The vessel was moving perpendicular to the riverbank along a cross-section (i). A reel was used to lower a camera close to the riverbed (ii). Simultaneously, the bed topography and water depth were measured by an ADCP (iii). Right: Close-up sketch of the underwater instrumentation.

The video recordings were made with a GOPRO Hero 7 and a Hero 4 commercial action cameras. Image resolutions were set to 2704x2028 (2.7K) with 60 frame per second (fps) and 1920x1080 (1080p) with 48 fps, respectively. Other parameters were left at their default (see GOPRO 2014; 2018), resulting in slightly different quality of produced images between the two cameras. Illumination is a critical condition for riverbed imaging. Here, a diving light with 1500 lumen brightness and 75° beam divergence, and one with 1800 lumen and 8° were

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used. The four lasers for scaling had 450-520 nm (purple and green) wavelength and 1-5 mW nominal power. Power supply was ensured with batteries for all instruments.

At Site A and Site B, conventional bed material (physical) samplings were also carried out by a grabbing (bucket) sampler along the analysed transects. At each cross-section had 4-5 samples were taken. The collected samples were analysed in laboratory by drying, sieving, and weighing to provide local grain size distribution. The measured GSDs were used to validate results of the AI algorithm. Separately, a visual evaluation of the videos was also carried out, where a person divided the transects into subsections based on their dominant sediment classes, after watching the footages.

3.3 Image analysis: Artificial Intelligence and the wavelet method

A widely used deep neural network architecture was employed in this study, building on former experiences of the authors (Benkő et al., 2020), Google's DeeplabV3+ Mobilnet, in which many novel and state-of-the-art solutions are implemented (e.g., Atrous Spatial Pyramid Pooling; Chen et al., 2018). The model was implemented with Pytorch, exploiting its handy API and backward compatibility. The main goal was to build a deep neural network model which is able to recognise and categorise (via semantic segmentation; Chen et al., 2018) at least three main sediment size classes, i.e., sand, gravel and cobble, in the images, while being quickly deployable. The benefit of the introduced method compared to conventional imagery methods lies in the potential of automation and increased speed. If the annotation and training is carried out thoroughly, analysing further videos can run effortlessly, while the computation time can be scaled down either vertically (using stronger GPUs) or horizontally (increasing the number of GPUs; if parallel analysis of images is desired). In this study a TESLA K80 24GB GDDR5 348bit GPU, an Intel Skylake Intel® Xeon® Gold 6144 Processor (24.75M Cache, 3.50 GHz) CPU with 13GB RAM was used. Also, contrary to other novel image-processing approaches in riverine sediment research (Buscombe, 2013; Detert and Weitbrecht, 2013), the deep convolutional neural network is much less limited by image resolution and mm/pixel ratios, because it does not rely on precise pixel count. This is an important advantage to be exploited here, as we perform non-scaled training and measurements with the AI, i.e., camera-bed distance constantly changed and size-reference was not used in the images.

The first step in the analysis was to cut the captured videos into frames, during which the videos were exploded into sequential images. Brightening and sharpening filters were applied on the images to improve their quality. Next, the ones with clearest outlines and best visibility were chosen. This selection process was necessary because this way the delineation process (learning the prominent characteristics of each class) can be executed accurately, without the presence of misleading or confusing images, e.g., blurry or dark pictures where the features are hard to recognise. For training purposes, we chose three footages from different sections each being ~15 minutes long with 60 fps and 48 fps, resulting in 129 600 frames. In fact, no such large dataset was needed due to the strong similarity of the consecutive frames. The number of images to be annotated and augmented were therefore decreased to ~2000.

We also performed a white balance correction on some of the images to improve visibility, making it even easier to later define the sediment class boundaries. We used an additional algorithm to generate more data, with the so-called Simplest Colour Balance method (Limare et al., 2011). It is a simple, but powerful histogram equalisation algorithm which helps to equalise the roughness in pixel distribution.

These steps were followed by the annotation, where we distinguished ten classes. Annotation was performed with the help of an open-source software called PixelAnnotationTool (Breheret, 2017), which enables the user to colour mask large parts of an image based on colour change derivatives (i.e., colour masking part of the images which belong to the same class, e.g., purple/red – sand, green – gravel, yellow – cobble, etc.). The masks and outlines were drawn manually, together with the so called watershed annotation. That is, when a line was drawn, the algorithm checked for similar pixels in the vicinity and automatically annotated them with the same class. The annotation was followed by a data augmentation step where beside mirroring, cropping, rotating the images (to decrease the chance of overfitting), we also convolved them with different filters. These filters added normally distributed noise to the photos to influence the watershed algorithm and applied sharpening, blurring, darkening, and white balance enhancement. Thus, at the data level, we tried to ensure that any changes in water purity, light, and transparency, as well as colour changes, were adequately represented during training. Images were uniformly converted to 960x540 resolution, scaling them down to make them more usable to fit in the GPU's memory. The next step was to convert all the images from RGB (Red-Green-Blue) based colour to grayscale. This is important because colour images have 3-channels, so that they contain a red, a green, and a blue layer, while grayscale images' pixel can only take one value between 0 and 255. With this colour conversion we obtained a threefold increase in computational speed. In total, a dataset of 14,784 images was prepared (from the ~2000 images of the4 training videos). The next step was to separate this into training and validation sets. In this study, approximately 80% of the data was used for training the Artificial Intelligence, while 20% was to validate the training. It was important to mix the images so that the algorithm selects batches in a pseudorandom manner during training, thus preventing the model from being overfitted. Finally, after several changes in the hyperparameters, the evaluation and visualisation of the training results were performed. Learning rate was initialised to 0.01, with 30000 iteration steps, and the learning rate is reset after every 5000 iterations with a decay of 0.1. A batch size of 16 was used. We used a cross-entropy loss function.

As previously mentioned, laser pointers were used to provide scale for the recorded videos, as a secondary validation. We used a textural image-processing method to analyse the video images of the spots, where the physical samples were taken. For this, the already mentioned, transferable wavelet-based signal- and image-processing method (Buscombe, 2013) was chosen. The method enables to calculate the image-based grain size distribution of the selected pictures. The grey-scale intensity is analysed through pixel-rows and -columns of the image and handled as individual signals. Then, instead of Fourier-transform, the less-constrained wavelet-transform is applied to decompose them. Finally, calculating the power spectra and the sizes (from pixel to millimetre, using the scale) of the wavelet components (each wavelet describes an individual grain) produces the grain size distribution for the given image. Beforehand, this method was proved to be the most efficient, non-AI image-processing method for mixed sediments (Buscombe, 2013; 2020) and was already tested for underwater circumstances in an earlier study by the authors of present paper (Ermilov et al., 2020).

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4 Results and discussion

4.1 Evaluation of the training

To evaluate the training process, the image series used for the training was analysed by the developed Deep Learning algorithm. Figure 5. shows results of original images (from the validation set), their ground truth (annotation by the training personnel), as well as the AI prediction (result of the model). The overlays of the original and the predicted images are also shown for better visualization. Calculating the over-all *pixel accuracy* (i.e., the percent of pixels that were correctly classified) returned a satisfactory result with an average 96% match. As this parameter in object detection and Deep Learning is not a stand-alone parameter (i.e., it can still be high even if the model performs poorly), the mean IoU (intersection-over-union or Jaccard index) was also assessed, indicating the overlap of ground truth area and prediction area, divided by their union (Rahman and Wang, 2016). This parameter showed a much slighter agreement of 41.46%. Interestingly, there were many cases, where the model gave better result, than the annotating personnel. The first row of Figure 5. showcases two examples for this: i) the correct appearance of cobble (yellow) in the prediction, even though the user (ground truth) did not define it during the training; ii) correctly sensing gravel in the middle of the image, contrary to a whole sand (red) patch in the ground truth image. As a matter of fact, these positive errors also decrease the IoU evaluation parameter, even though they increase the performance of the AI on the long term. Hence, this shows that pure mathematical evaluation may not describe the model performance entirely. Considering that others also reported similar experience with Deep Learning (Lu et al., 2018) and the fact that 40% and 50% are generally accepted IoU threshold values (Yang et al., 2018; Cheng et al., 2018; Padilla et al., 2020), we considered the 41.46% acceptable. The general quality of our underwater images may have also played a role in lowering the IoU result.

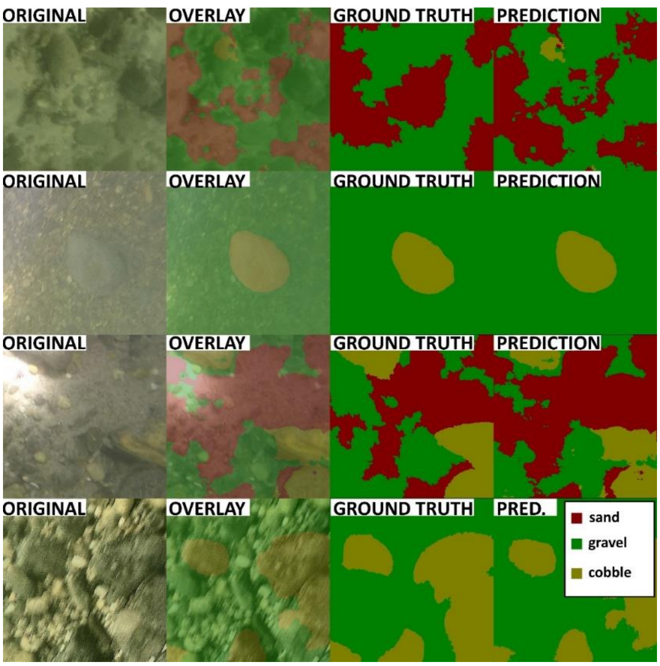

Figure 5: Example comparisons of ground truth (taught) and AI predicted (learnt) sediment classes from the training videos showing satisfactory results.

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4.2 Intercomparison of methods

In each masked image, the occurring percentage of the given class (i.e., the percentage of the pixels belonging to that class/colour mask, compared to the total number of pixels in the image) was calculated and used as the fraction percentage in that given sampling point. These sediment classes reconstructed by the AI were then compared to three alternative results: i) visual estimation, ii) GSD resulted from conventional grab sampling, iii) wavelet-based image-processing. In the followings, results from two cross-sections will be shown, one from Site A, the video used for the training, and one from Site B, being new for the AI. An averaging window of 15 m was applied on each cross-sectional AI result to smoothen and despike the dataset.

In Figure 6, the path of the vessel can be seen in Section K, at Site A. The path was coloured based on the visual evaluation of the riverbed images. The different colours represent the dominant sediment type seen at the given point of the bed. The locations of the physical bed material samplings are also shown (see yellow markers). Figure 7 shows the cross-sectional visual classification compared to the AI-detected sediment fractions in percentage.

Figure 6: The path of the vessel and camera in Section K, Site A. The polyline is coloured based on the sediment features seen during visual evaluation of the video. Yellow markers are the locations of physical bed material samplings. (Map created with © Google Earth Pro)

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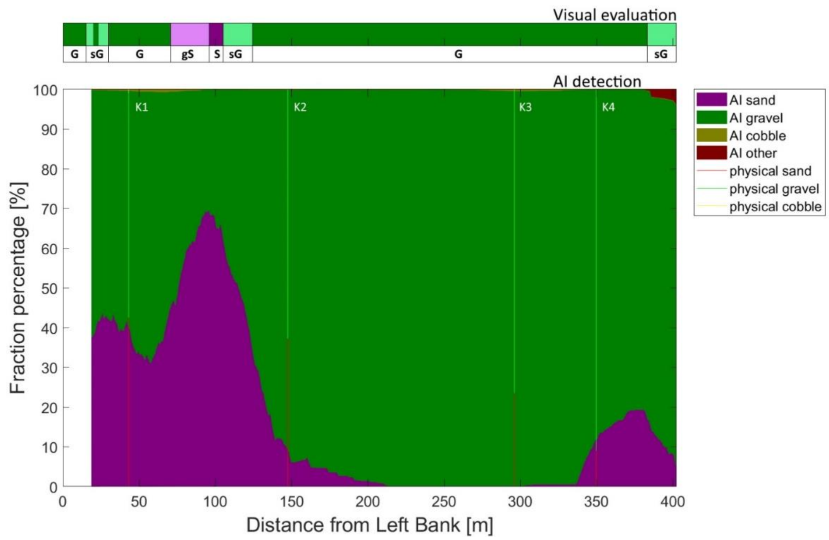

Figure 7: Section K. The visual evaluation of the dominant sediment features in the video (top) compared to sediment fraction percentage, recognised by the AI (bottom). The visual evaluation included four classes: gravel – G, sandy gravel – sG, gravelly sand – gS, sand – S,). The fractions from the physical samples are also shown (verticals).

Comparing the two figures, the AI result show satisfactory match with the human evaluation. For example, around 100 m from the left bank, between K1 and K2 sampling points, the AI peaks with around 70% sand an 30% gravel correctly. Furthermore, on the two side of this peak a steep transition to gravel and decreasing sand occurs, similarly to the eye observation, marked as sandy gravel and gravelly sand. Mixed sediment zones were also correctly identified by the AI at both riverbanks.

Next, the AI estimated sediment classes were compared with both the physical samples and the wavelet method at each sampling locations (Fig. 8). The images of the bed from the sampling points are in shown in Figure 9. As for the AI results, a moving average-based smoothing was applied in the 15 m vicinity of the sampling locations. Overall, the AI based classification agrees well with the physical samples, however, at sample K3 the ~20% sand content was neither reconstructed by the AI, nor could be observed by eye (see Fig. 9). Considering that the gravel dominates the bed sediments, the absence of sand fraction in the AI results might be explained with the difference between the surface GSD and subsurface GSD. While both the AI and the eye observation-based assessment focus on the bed surface, the physical sampling represents a thicker layer, including the subsurface layer, too. Indeed, the so-called bed armouring phenomenon, taking place in the vicinity of the thalweg in mixed-bed rivers, leads to coarser surface grains and finer subsurface grains (see e.g., Wilcock, 2005). This may explain the case of K2 as it was located closer to the thalweq. As for the wavelet analysis-based imagery technique, an overall slight overestimation of the coarse particles can be observed, and the sand classes are, in fact, not reconstructed correctly. This finding agrees well with the field experiences of Ermilov et al. (2020), where the authors indicated the strong sensitivity of the wavelet technique on the image resolution, and showed that to detect a grain, the diameter must be at least three times larger than the pixel. In this survey, the camera was indeed closer to the riverbed at sampling

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points K1 and K4 and the wavelet algorithm was able to detect coarse sand, but finer sand was neglected yielding the lower percentages seen in Figure 8.

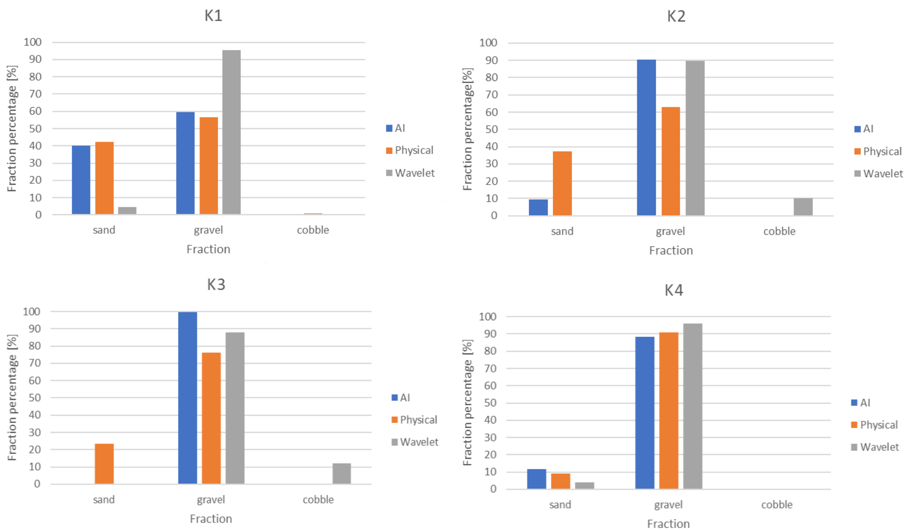

Figure 8: Comparison of sediment fraction % at the sampling locations from the moving-averaged AI detection, conventional sieving and the wavelet-based image processing method. Section K.

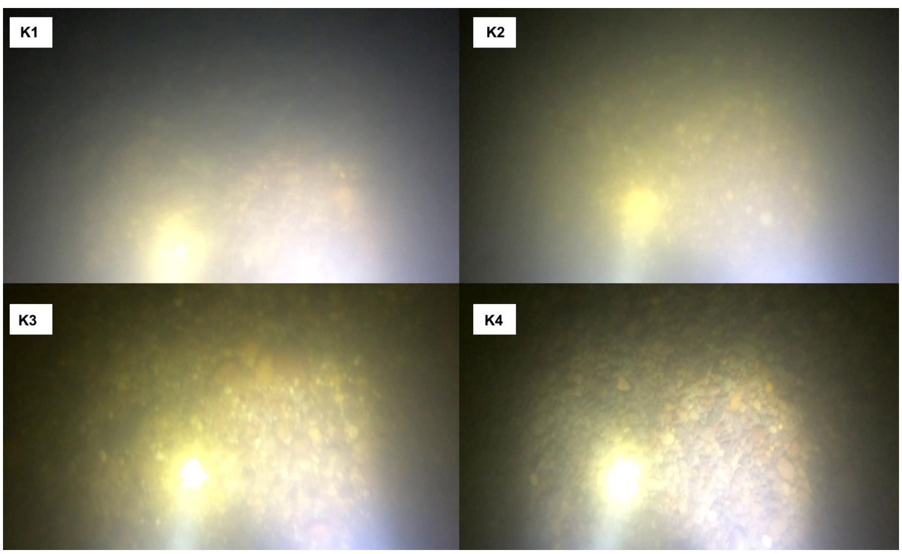

Figure 9: Riverbed video images at the sampling points in Section K.

At site B (Fig. 10) the river morphology is more complex compared to Site A as a groyne field is located along the left bank (see again Fig. 3). As such, the low flow regions between the groynes yields the, deposition of fine sediments, and much coarser bed composition in the narrowed main stream. Even though no images containing only fine sediments were applied in the training phase of the AI algorithm, the model still managed to successfully

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distinguish these zones. The fine sediments in the deposition zone at the left bank was adequately estimated and showed a good match with the visual evaluation for the whole cross-section (see Fig. 11).

Figure 10: The path of the vessel and camera in Section VM, Site B. The polyline is coloured based on the sediment seen during visual evaluation of the video. Yellow markers are the locations of physical bed material samplings. (Map created with © Google Earth Pro)

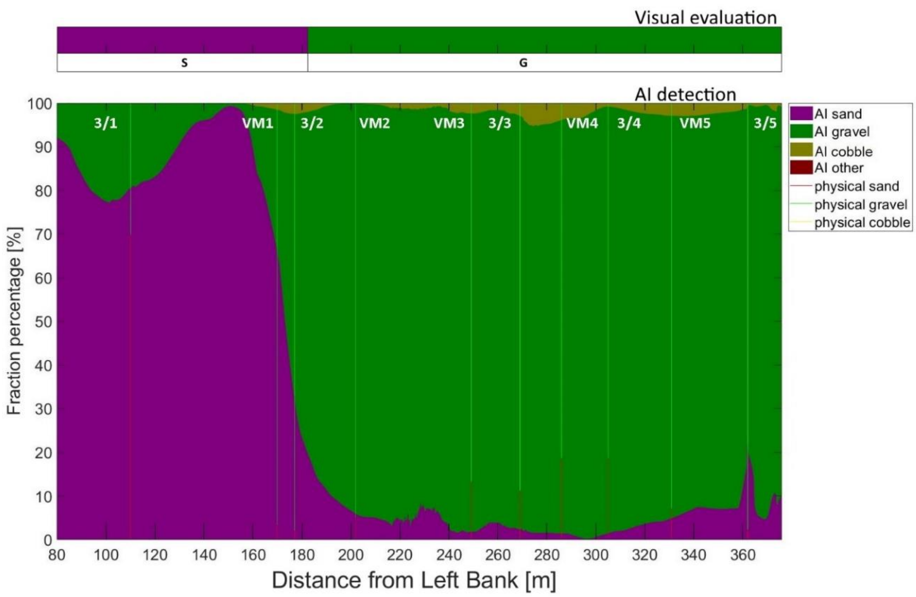

Figure 11: Sediment fraction percentages in Section VM, recognised by the AI. The visual evaluation included two classes: gravel – G, sand – S). The fractions from the conventional, point samples are also shown (verticals).

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When comparing the AI results with the physical samples, the match is acceptable for most of the samples, such as 3/1, VM2, VM3, 3/3, VM4, 3/4, VM5, respectively, with a highest difference of 10%. The significant disagreements arose at sampling points VM1 and 3/2. Indeed, these points are located around the border of the the of the sediment deposition zone, showing steeply decreasing amount of sand moving away from the left bank (see the variation from point 3/1 towards 3/2 in Fig. 12). This trend is successfully calculated by the AI algorithm, but the physical samples for points VM1 and 3/2 show strong gravel dominance with negligible amount of sand (see Fig. 13). Resembling the findings at the other study site, this difference can likely be explained with the disturbed physical samples, which contain the sediments of the subsurface layer, too. In this case, however, the fine sediment layer is accumulated on the gravel particles. It is also worth noting that the physical samples are analysed by weighing the different sediment size classes, resulting in volumetric distribution. On the other hand, the imagery methods provide surface distributions, hence having a thin layer of fine sediments on the top can strongly bias the resulted composition (Bunte and Abt, 2001; Sime and Ferguson, 2003; Rubin et al., 2007).

At sampling point 3/5 a weaker, but still satisfactory agreement was found. Here, the AI indicated 20% sand in contrast with the physical samples. Analysis of the raw videos may indicate that the suspended sediment concentration was higher in this region and the transported fine particles frequently became visible passing through the light beams, eventually causing disturbance in the AI analysis. Another issue in the AI algorithm was associated with the illumination. As a matter of fact, a part of the images was sometimes overexposed, and the too high light intensity biased the results. Examples for these problems are illustrated in Figure 14 (a: overexposure, b: moving suspended sediment).

The resolution was again not sufficient for the wavelet method, and it estimated gravel and cobble regions. Contrary to the previous example, it did not manage to identify coarse sand.

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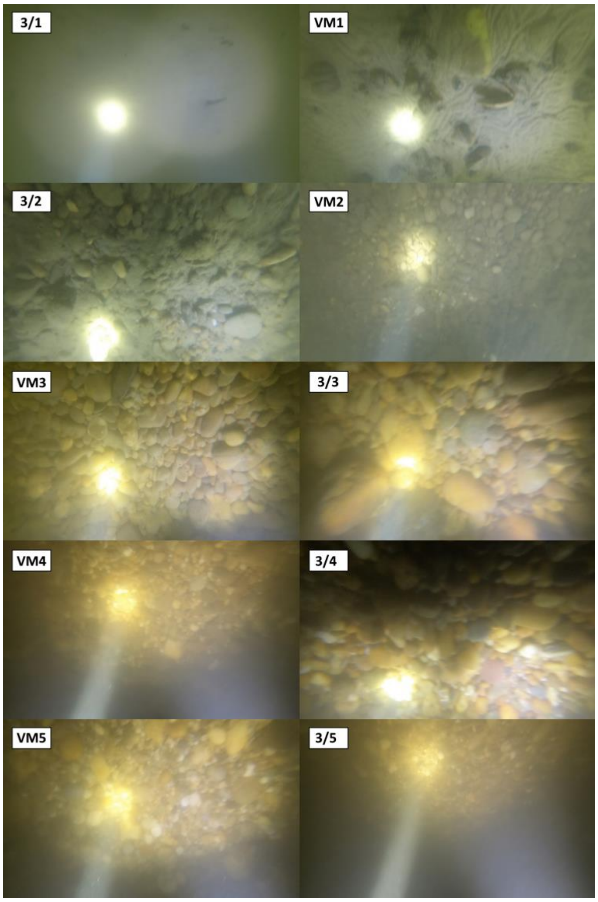

Figure 12: River bed video images at the sampling points in Section VM.

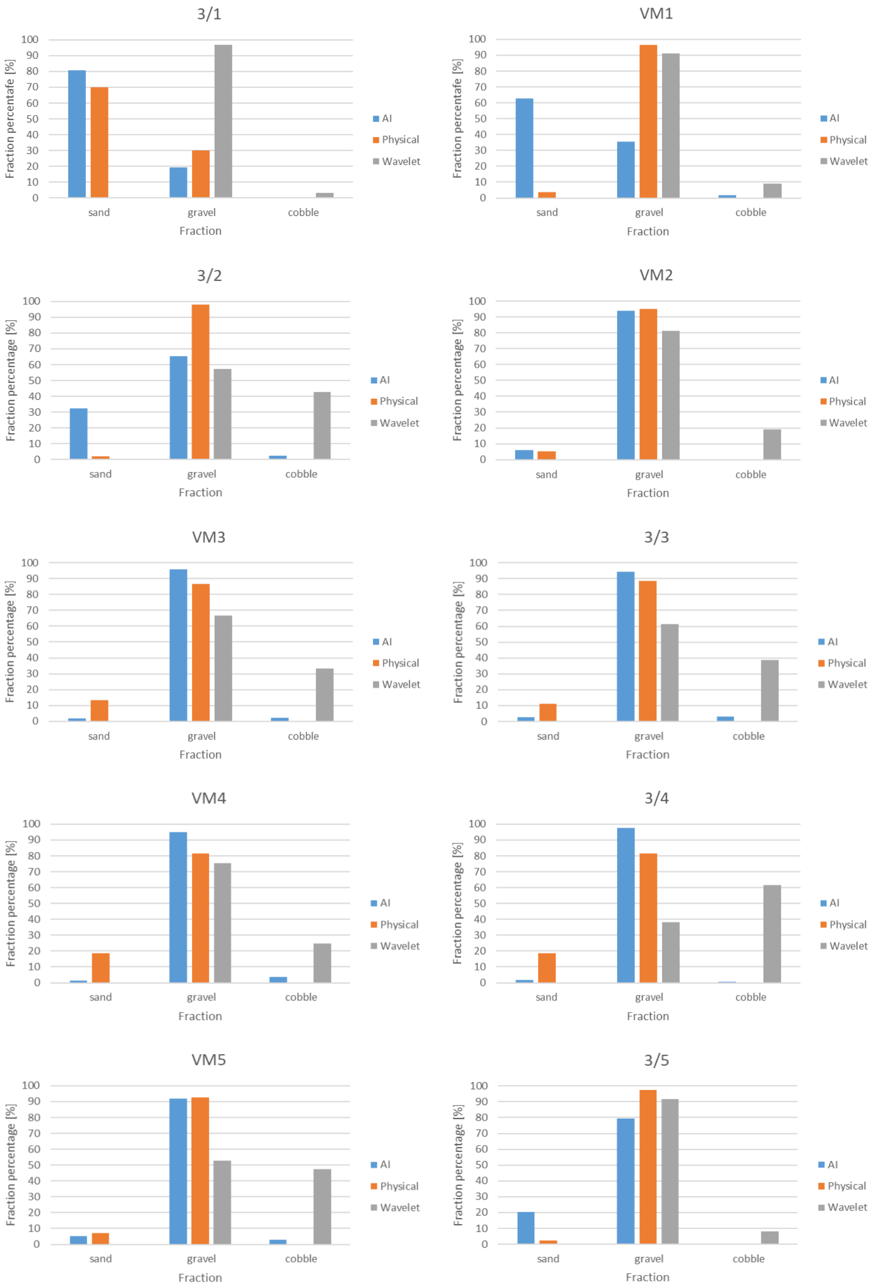

Figure 13: Comparison of sediment fraction % at the sampling locations from the moving-averaged AI detection, conventional sieving and the wavelet-based image processing method. Section VM.

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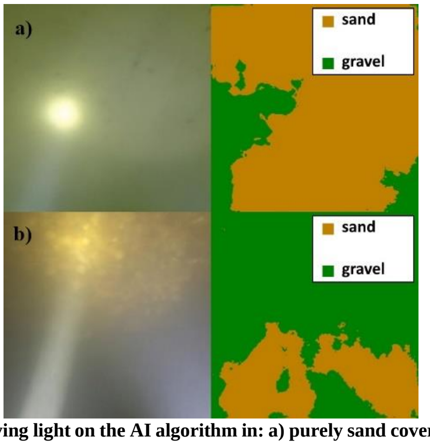

Figure 14: The effect of strong diving light on the AI algorithm in: a) purely sand covered zone and b) darker zone with higher SSC. The original images are on the left, while the AI detections can be found on the right.

Results of the other measurements can be found in the Appendix. Figure A2, B2 and C2 show that the trend of riverbed composition from the visual evaluation is well-captured by the AI in the other cross-sections of the study as well (see sampling points F/3, F/4, 1/1, 1/2 1/3, respectively). The resolution limit of the wavelet approach was further noticeable (see Figure A3, B3 and C3) as it was not able to detect sand, similarly to the sampling points presented earlier. In Section A, traces of possible bed armouring were found as neither the eye observation nor the AI detected sand class in the images (see Figure B4) of F/1 and F/2, even though the physical samples contained this fraction. In sampling point 1/4, the AI correctly detected the mixing of sand and gravel, but the physical sample showed the dominance of sand rather than the gravel fraction (see Figure C3). The possible explanation behind these differences resembles what was the case for the K3 sampling point, introduced earlier: there was an additional finer fraction in the subsurface layer, hidden from the camera. Based on the results presented in this paper, it could be established that the AI manages to recognise the main features of the riverbed material composition from underwater videos with satisfactory accuracy.

4.3 Implementation challenges

The power supply for the entire imaging infrastructure, i.e., for the camera, the diving lights and lasers, was ensured by batteries. However, due to the low temperature at the river bottom, the battery level decreased extremely fast, compared to normal circumstances. Providing the power supply directly from the motorboat engines can overcome this issue. To keep the camera in the adequate height also caused difficulties, since getting too close to the bed can harm the devices, lifting too high, on the other hand, will result in poor image quality. The measured instantaneous ADCP flow depth data was used therefore to keep the bed in camera sight, while maintaining proper boat velocity to avoid blurry images. We found that a 0.2-0.45 m/s vessel speed with 60 fps recording frequency was ideal to retrieve satisfactory images in a range of 0.4-1.6 m camera-bed distances. This meant approximately 15 minutes long measurements per transects. Higher vessel speed caused blurred images. Choosing a higher recording frequency, however, can be beneficial and alter this limitation, when provided. Lower velocities could not be maintained as the river would have moved the vessel out of the section. Using a diving light with small beam divergence also proved counterproductive. The high intensity, focused light occasionally caused overexposed zones (white pixels) in the bed image, misleading the AI and resulting in detecting incorrect classes there. The use of wide beam divergence lamps is recommended instead, with uniform light. Further attention needs to be paid to the reel and its cabel during the crossing when the equipment is on the upstream side of the boat. If the flow velocities are relatively high (compared to the total submerged weight of the underwater equipment), the cable can be pressed against the vessel-body due to the force from the flow itself, causing the reel cable to jump to the side and leave its guide. This results in the equipment falling to the riverbed and the measurement has to be stopped to reinstall the cable.

As for the training of the AI algorithm with the underwater images, the illumination is indeed a more crucial aspect, compared to normal imagery methods. In many cases only the centre areas of the images were clearly visible, whereas the remaining parts were rather dark and shady. Determining the boundaries between distinct sediment classes for these images was challenging even for experienced eyes. This quality issue certainly generated some incorrect annotations. To overcome this issue, manually varying the white balance thus enhancing the visibility of the sediment could improve the training to some extent. It is worth noting that when Deep Learning methods are to be used, most of the problems arise from the data side (Yu et al., 2007), whereas issues related to the applied algorithms and hardware are rare. This is because data is more important from an accuracy perspective than the actual technical infrastructure (Chen et al., 2020). The time demand of image annotation (data preparation) is relatively high, i.e. an untrained person could analyse roughly 10 images per hour. On the other hand, as introduced earlier, a great advantage of using AI is the capability of improving the quality of training itself, often yielding better agreement with reality, compared to the manual annotation. Similar results have been reported by Lu et al., (2018). This at the same time proves that there is no need for very precise manual training, thus a fast and effective training process can eventually be achieved.

The validation of the Deep Learning algorithm is far from straightforward. In this study, four approaches were adapted, i.e., a mathematical approach, and comparison with three other measurement methods, respectively. The mathematical approach was based on calculating pixel accuracy and the Intersection-over-union parameter, as it is usually done in case of Deep Learning methods to describe their efficiency (e.g. Rahman and Wang, 2016). However, the latter parameter was shown to be decreased even when the model improved. Consequently, using only the mathematical evaluation in this study could not describe adequately the model performance. Hence, the results were compared to those of three other methods: i) visual evaluation of the image series, ii) a wavelet-based image-processing method (using the method of Buscombe, 2013) and iii) riverbed composition data from physical samples. Considering the features of the applied methods, the first one, i.e. the visual observation, is expected to be the most suitable for the model validation. Indeed, when assessing the bed surface composition by eye, the same patterns are sought, i.e. both methods focus on the uppermost sediment layer. On the other hand, the physical sampling procedure inherently represents subsurface sediment layers, leading to different grain size distributions in many cases. For instance, as shown above, if bed armour develops in the riverbed and the sampler breaks-up this layer, the resulted sample can contain the finer particles from the subsurface layer. On the contrary, in zones where a fine sediment layer is deposited on coarse grains, i.e. a sand layer on the top of a gravel bed, the physical samples represent the coarse material too, moreover, considering that the sieving provides volumetric distribution this sort of bias will even enhance the proportion of the coarse particles. Attempts were made to involve a third, wavelet based method for model validation. However, this method failed when finer particles, i.e. sand,

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characterized the bed. This is an inherent limitation of these type of methods, as shown already by Buscombe and Masselink (2008), Cheng (2015) or Ermilov et al (2020), as the image resolution, i.e. the pixel size, is simply not fine enough to reconstruct the small grain diameters in the range below fine gravel.

As it is known, the ML and DL models can learn unknown relationships in datasets, but unwanted biases as well. With our current dataset, in our opinion, these biases would be the darker tones of visible grain texture and the lack of larger grain sizes. This way our model in its current state is only applicable effectively in the chosen study site, until the dataset is not expanded with additional images from other rivers or regions. However, the purpose of the paper was to introduce the methodology itself and its potential in general and not to create a universal algorithm.

4.4 Novelty and future work

The introduced image-based Deep Learning algorithm offers novel features in the field of sedimentation engineering. First, to the authors' knowledge, underwater images of the bed of a large river have not yet been analysed by AI. Second, the herein introduced method enables continuous (and quick) mapping of the riverbed, in contrast to most of the earlier approaches, where only points or shorter sections were assessed with imagery methods. Third, the method is much faster compared to conventional samplings or non-AI based image-processing techniques. The field survey of a 400 m long transect took ~15 minutes, while the AI analysis took 4 minutes (approx. 7 image/s). The speed range of 0.2-0.45 m/s of the measurement vessel and the 15 minutes per transect complies with the operating protocol of general ADCP surveys on rivers (e.g., RD Instruments, 1999; Simpson, 2002; Mueller and Wagner, 2013). Hence, the developed image-based measurement can be carried out together with the conventional boat-mounted ADCP measurements, further highlighting its time efficiency. Indeed, the method is a great alternative approach for assessing riverbed material on-the-go, in underwater circumstances. As a continuous and quick mapping tool, it can support other types of bed material samplings in choosing the sampling locations and their optimal number. Furthermore, it can be used for quickly detecting areas of sedimentation and their extent, as it was shown in Ch. 4.2. (Figure 11). This way, it may support decisions regarding the maintenance of the channel or the bank-infiltrated drinking water production (detecting colmation and colmated zones). Fourth, a novel approach was used for the imaging and model training. As the camera-bed distance were constantly changing, the mm/pixel ratio also varied. Hence, no scale was defined for the algorithm beforehand. Earlier Deep Learning methods for sediment analysis all applied fixed camera heights and/or provided scaling for the AI. It should be noted that these were airborne measurements, mapping the dry zone of the rivers. In an underwater manner, it is extremely challenging to keep a fixed, constant camera height due to the spatially varying riverbed elevations. Hence, it is of major importance that this paper introduces a methodology and a Deep Learning algorithm which neglect the need for scaling. This way, the method is faster and easier to build, but also simpler to use. Of course, as a trade-off, the method, as of now, cannot reconstruct detailed grainsize distributions. Indeed, the purpose was rather to provide a uniquely fast bed material mapping tool, additionally with a much denser spatial resolution than the conventional methods, saving up significant resources.

Originally, beside the three main sediment grain classes introduced in the paper (sand, gravel, cobble), others were also defined during annotation (e.g., bedrock, clams), but due to class imbalance (i.e., dominance of the three

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sediment classes), these were not adapted successfully. There is a good potential in improving the method through transfer learning (see Zamir et al., 2018) using broader dataset, involving other sediment types. Another possible way to counter imbalance is the use of so-called weighted cross entropy (see Lu et al., 2019) on the current dataset, which will also be investigated in our case.

Since the introduced method offers a quick way to provide spatially continuous bed material information of its composition, it may be used to boost the training dataset of predictive, ensemble bagging-based Machine Learning techniques (e.g., Ren et al., 2020) and improve their accuracy. Furthermore, the method can support the implementation of other imagery techniques. For instance, using one of the training videos of this study the authors managed to reconstruct the grain-scale 3D model of a riverbed section with the Structure-from-Motion technique (Ermilov et al., 2020), enabling the quantitative estimation of surface roughness. Underwater field cameras can also be used for monitoring and estimating bedload transport rate (Ermilov et al., 2022) by adapting LS-PIV and the Statistical Background Model approach. This latter videography technique may also be used with moving cameras (e.g., Hayman and Ekhlund, 2003), which enables its adaptation into our method by e.g., detecting bedload movement in the cross-section.

5 Conclusion

A novel, artificial intelligence-based riverbed sediment analysis method has been introduced in this paper, which uses underwater images to reconstruct the spatial variation of the characteristic sediment classes. The method was trained and validated with a reasonably high number (~15000) of images, collected in a large river, in the Hungarian section of the Danube. The main novelties of the developed Deep Learning based procedure are the followings: i) underwater images are used, ii) the method enables continuous mapping of the riverbed along the measurement vessel’s route, iii) cost-efficient, iv) works without scaling, i.e., the distance between the camera and the riverbed can vary. Consequently, in contrast with conventional pointwise bed sediment analysis methods, this technique is robust and capable of providing continuous sediment composition data covering whole river reaches, eventually providing the possibility to set up 2D bed material maps. In this way, river reach scale hydromorphological assessments can be supported, where the composition of bed surface is of interest, e.g., when performing habitat studies, parameterising 2D and 3D computational hydrodynamic and morphodynamic models, or assessing the impact of restoration measures.

Financial support. The first author acknowledges the support of the ÚNKP-21-3 New National Excellence Programme of the Ministry for Innovation and Technology, and the National Research, Development and Innovation Fund, Hungary.

Code availability. The code written and used in this paper is available here: https://bmeedu-my.sharepoint.com/:f:/g/personal/ermilov_alexander_emk_bme_hu/EjI2neM4AOZGsBkYgKReViEBBzRFRFoYyLlmo6SzTB_qDQ?e=AqpqHI

Data availability. The dataset and results can be accessed using the following link: https://bmeedu-my.sharepoint.com/:f:/g/personal/ermilov_alexander_emk_bme_hu/EhoGx64sP1tFnj8Z1OdMZAsBZWd5gDYzPyodSUDdWFjeiw?e=hKIXjq

Author contributions. GB developed the code and carried out the training process. AAE carried out the fieldwork, evaluated the results, did the laboratory analysis, and collaborated with GB in improving the images. SB oversaw and directed the project, while managing the financial- and equipment background.

Competing interest. The contact author has declared that none of the authors has any competing interest.

Acknowledgements. The authors would like to thank our students Dávid Koós, Gergely Tikász, Schrott Márton and our technicians István Galgóczy, István Pozsgai, Károly Tóth and András Rehák for fieldwork support.

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Appendix

Appendix A Site A - Section F

Figure A1: The path of the vessel and camera in Section F, Site A. The polyline is coloured based on the sediment seen during visual evaluation of the video. Yellow markers are the locations of physical bed material samplings. (Map created with © Google Earth Pro)

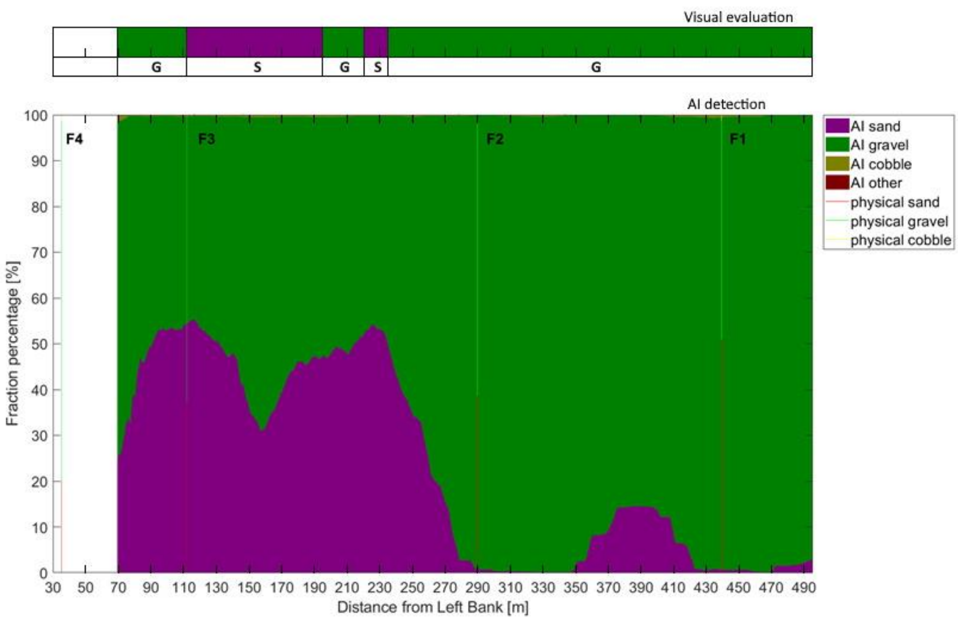

Figure A2: Sediment fraction percentages in Section F, recognised by the AI. The visual evaluation included two classes: gravel – G, sand – S). The fractions from the physical samples are also shown (verticals).

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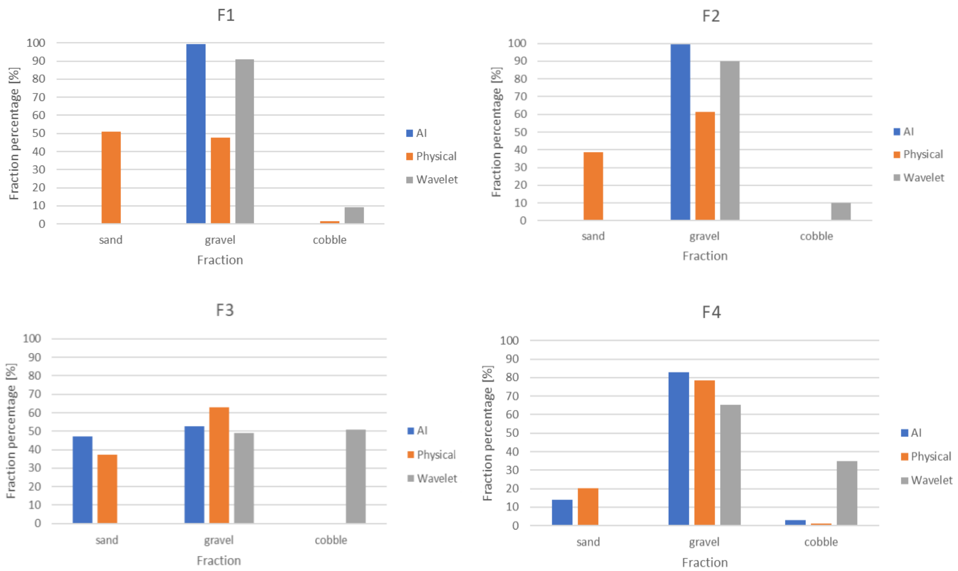

Figure A3: Comparison of sediment fraction % at the sampling locations from the moving-averaged AI detection, conventional sieving and the wavelet-based image processing method. Section F.

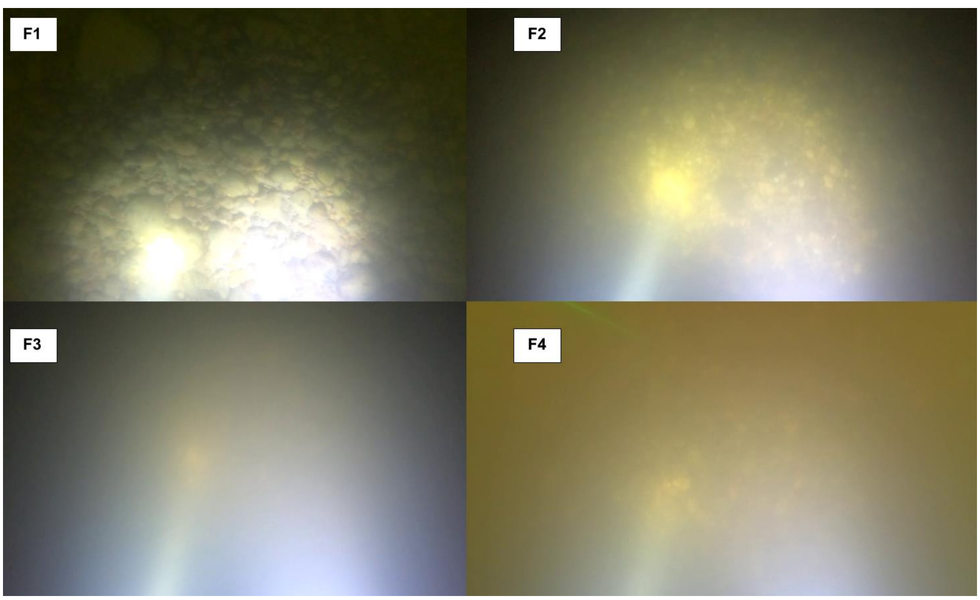

Figure A4: Riverbed video images at the sampling points in Section F.

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Appendix B Site A – Section A

Figure B1: The path of the vessel and camera in Section A, Site A. The polyline is coloured based on the sediment seen during visual evaluation of the video. Yellow markers are the locations of physical bed material samplings. (Map created with © Google Earth Pro)

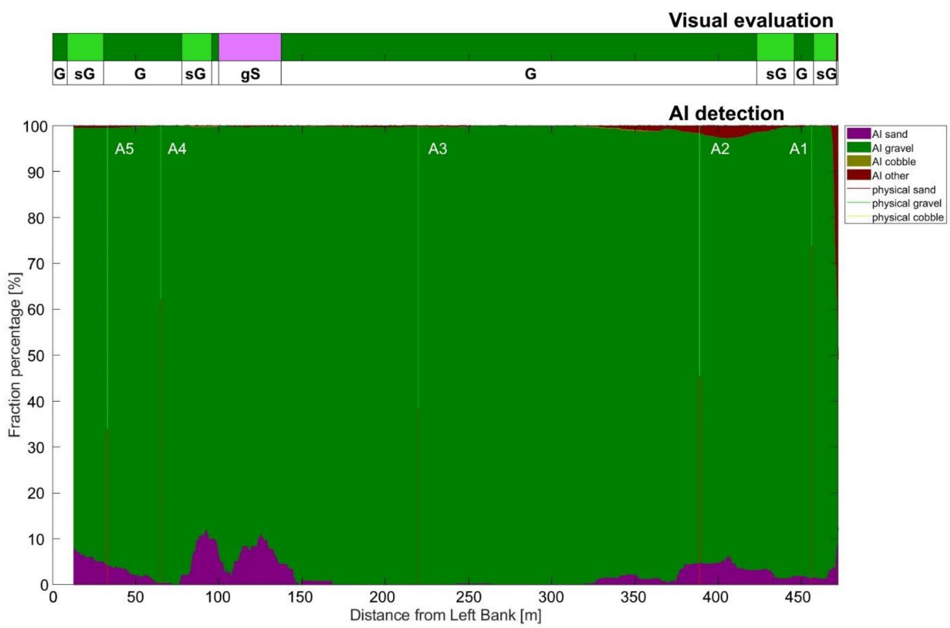

Figure B2: Sediment fraction percentages in Section A, recognised by the AI. The visual evaluation included three classes: gravel – G, sandy gravel – sG, gravelly sand - gS). The fractions from the physical samples are also shown (verticals).

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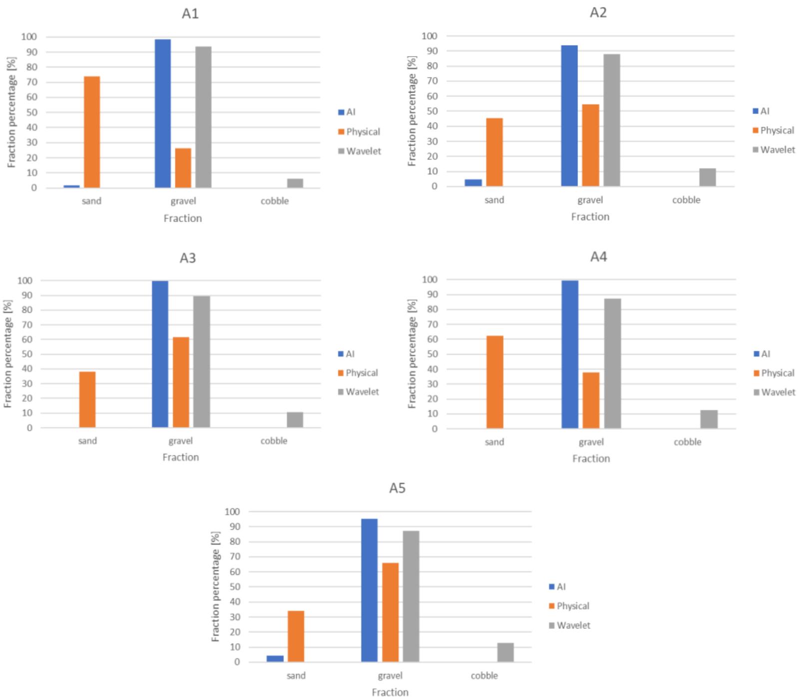

Figure B3: Comparison of sediment fraction % at the sampling locations from the moving-averaged AI detection, conventional sieving and the wavelet-based image processing method. Section A.

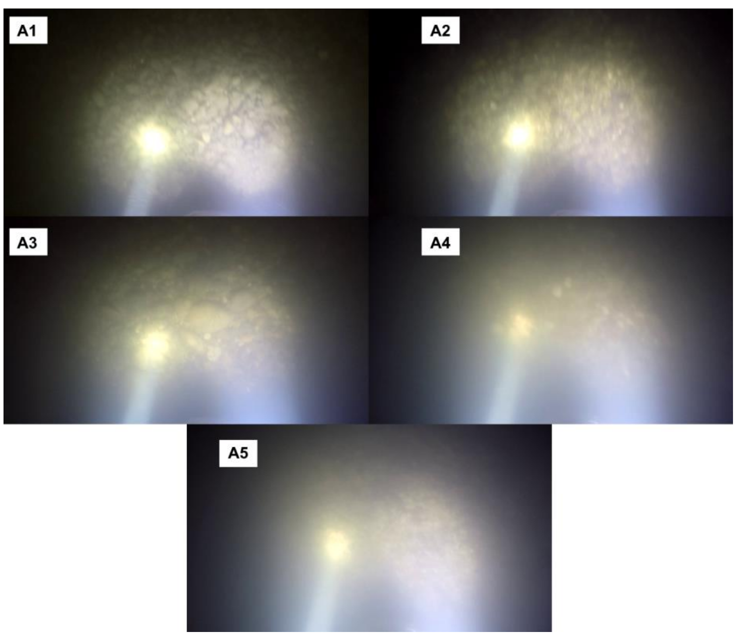

Figure B4: Riverbed video images at the sampling points in Section A.

https://doi.org/10.5194/esurf-2022-56
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Appendix C Site B – Section NY

Figure C1: The path of the vessel and camera in Section NY, Site B. The polyline is coloured based on the sediment seen during visual evaluation of the video. Yellow markers are the locations of physical bed material samplings. (Map created with © Google Earth Pro)

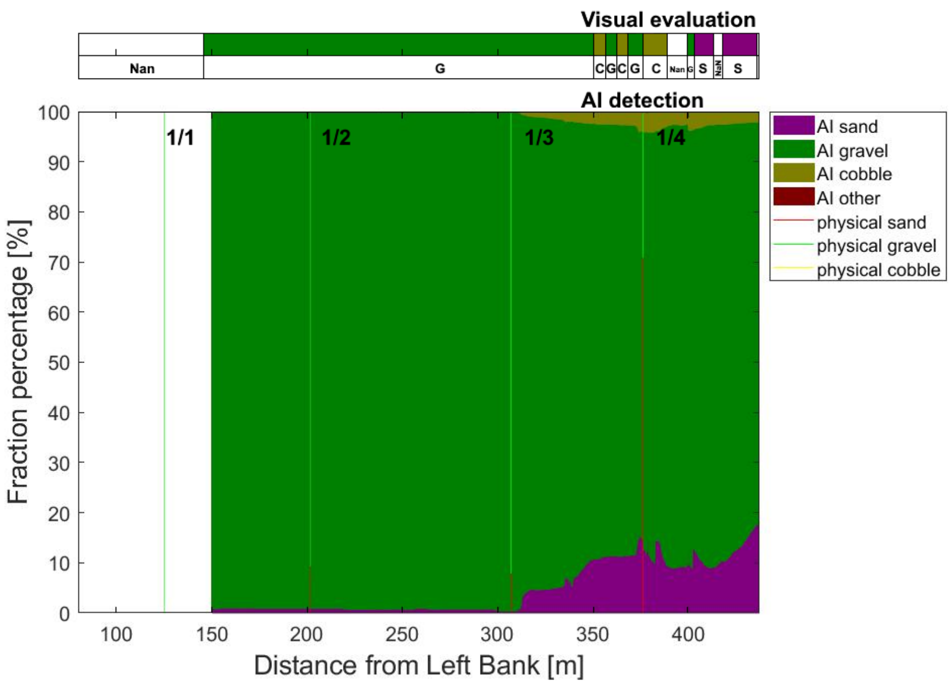

Figure C2: Sediment fraction percentages in Section NY, recognised by the AI. The visual evaluation included two classes: gravel – G, sand – S). The fractions from the physical samples are also shown (verticals).

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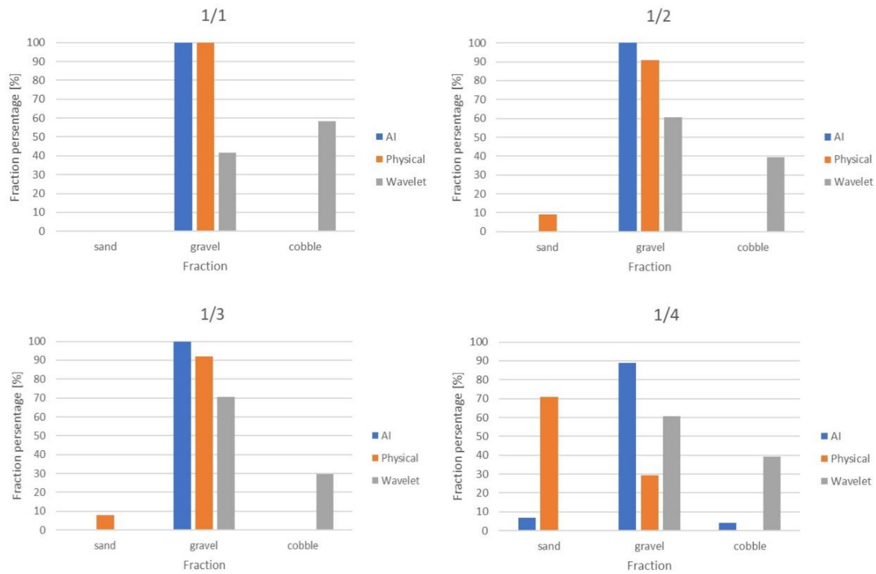

Figure C3: Comparison of sediment fraction % at the sampling locations from the moving-averaged AI detection, conventional sieving and the wavelet-based image processing method. Section NY.

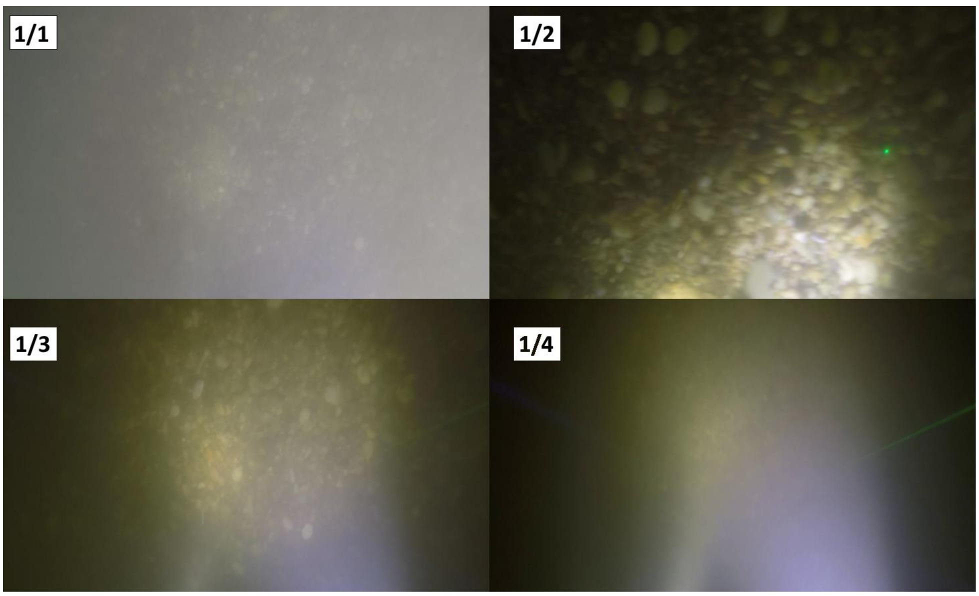

Figure C4: River bed video images at the sampling points in Section NY.