Estimating gravel particle sizes based on field photographs using the Rock Observation Calculator (ROC)

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Abstract

The Rock Observation Calculator (ROC) is a software program developed by the United States Army Corps of Engineers (USACE) Engineering Research and Development Center (ERDC), designed to provide an estimate of the gradation of sediment samples based on field photographs. Collecting physical sediment samples in the field to be analyzed in the laboratory can be a cumbersome process. This tool provides a more efficient means of estimating sample gradations without requiring intensive sample collection and analysis. ROC applies computer-based image analysis routines to segment the image pixels into individual particles. ROC then uses the identified particles to estimate a gradation. To evaluate this tool, gravel bars throughout Kansas and Missouri were photographed and analyzed with ROC. The gravel bars were also assessed using pebble counts and/or sieve analysis of bulk samples. This analysis assesses the merits and limitations of using the ROC tool on gravel bars.

Introduction

Collecting sediment size data in the field is necessary for a wide range of purposes, including substrate suitability for fish spawning (Kondolf, 1997) and geomorphic analysis. For large sediment sizes, it can be difficult or impractical to collect bulk samples that can be run through a standard sieve test for sediment gradation. Therefore, several methods have been developed for estimating grain size distribution. The most commonly used of these methods is the Wolman Pebble Count (Wolman, 1954). This process involves randomly selecting approximately 100 sediment particles in a given location and measuring the intermediate axis length. The intermediate axes are then ranked from smallest to largest and used to create a cumulative gradation plot. This process can take a long time to perform and therefore limits the amount of data available. The pebble count is also reportedly biased towards large particles (Leopold, 1970) and has large operator bias (Daniels and McCusker, 2010). Therefore, semi-automated means to obtain sediment gradations are desirable. The Rock Observation Calculator (ROC) is a photograph-based software program developed by the United States Army Corps of Engineers (USACE) Engineering Research and Development Center (ERDC) that identifies sediment particles in a given image and calculates an estimated gradation. This study evaluates the ROC tool by using it on images collected at several gravel bars throughout Kansas and Missouri and comparing the results to pebble counts and bulk samples. Because the ROC tool is a photograph-based tool, the tool approximates a pebble count, which estimates the surface gradation of the river bed. However, in many cases, pebble counts themselves are only approximations for sediment size gradation that would be best assessed with a sieve analysis of a bulk sample. While surface armoring can cause the subsurface and the surface gradations to differ, the sites selected in the present analysis did not show substantial differences between the surface and the subsurface layer. Therefore, bulk samples are included in the present analysis, but it should be understood that the ROC output is most comparable to pebble counts because only the surface layer is being measured.

The automated ROC tool is a geometrical image analysis technique that applies digital image segmentation techniques (e.g. local and watershed thresholding) to identify and separate particles within an image into discrete objects and then estimates the size of objects or grains individually. Other popular techniques used for grain size analysis from photographs are to apply statistical analysis methods and, more recently, machine and deep learning. Statistical analysis methods determine grain size from a measurement of image texture. Some common statistical approaches to quantify image texture include auto-correlation (Rubin, 2004; Warrick et la., 2009), semi variance (Charbonneau et al., 2004; 2005), fractals (Buscombe and Masselink, 2009), and spectral analysis (Buscombe, 2013). Grain size analysis based on machine and deep learning is becoming increasingly popular and involves training computer models to identify and separate sediment grains in an image (Huang et al., 2022; Buscombe, 2020; Soloy et al,. 2020). Machine and deep learning approaches require high quality training data sets, which are often comprised of hundreds to thousands of images in which individual particles are manually segmented and labeled (Huang et al., 2022). These algorithms are quite useful and can perform automatic and unsupervised segmentation of images, but they are often restricted to materials similar to those used in the training set (Huang et al., 2022; Buscombe, 2020; Soloy et al., 2020). Similarly, statistical approaches also require calibration, restricting their versatility. For both, more diverse and more extensive training sets improve the results; however, training these models is quite computationally and labor intensive. Though geometrical analysis (like ROC) is limited by image quality and requires user interaction, it is computationally less expensive and more versatile (Graham et al., 2005; McFall et al., 2020).

Data

Table 1 lists the data used for this analysis. Samples were collected in 2021 and 2022. In total, 5 pebble counts were collected and 5 bulk samples were collected. Two of the samples (Crider Creek and Rock Creek) contained both bulk data and pebble count data. Bulk samples were collected in jars and then sieved by mass in the laboratory. Pebble counts were collected as a modification to the Wolman pebble count. The Wolman pebble count requires the operator to sample 100 sediment particles from the river bed within a geomorphic feature. Wolman recommends creating transects and sampling at random from the transects until 100 particles have been measured. Other researchers have claimed that smaller sample sizes are sufficient, such as 60 stones (Brush, 1961) or 70 stones (Mosely and Tinsdale, 1985). For the present analysis, the operator identified an area of approximately 1 m^2 and randomly selected sediment particles within the study area. The intermediate axis of the selected particle was measured and then placed back in the study area, which allowed for the particle to be sampled again at random. The number of particles measured varied by site, between 35 and 75 particles. Because the variation of particle sizes in a 1 m^2 area is likely to be less than the variation within a geomorphic feature (as envisioned by

Wolman), this was a reasonable adaptation of the method. However, the uncertainty due to the number of samples was not quantified.

Table 1: Summary of data collected

River	Location	Total Samples	Pebble Counts	Bulk Samples	Pebble Count and Bulk Samples
Crider Creek	Ozarks, MO	4	1	1	1
Jake Creek	Ozarks, MO	1		1	
Rock Creek	Kansas City, MO	3	1		1
Little Maries	Ozarks, MO	1	1		
Maries	Ozarks, MO	1		1	

Methods

A semi-automated image analysis routine, ROC, was developed to identify and measure sediment grain size from field photographs. ROC applies digital image processing techniques to identify and separate rocks/pebbles within an image into discrete objects and then estimates the size of each object or grain. The routine employs algorithms from the MATLAB Image Processing Toolbox. The algorithm consists of three main parts: (1) preprocessing (e.g., load in image, define image scale, select region to process), (2) image segmentation via thresholding to identify grains, and (3) calculation of cumulative size distributions. (2) and (3) are described in more detail in the following sections.

Prior to analysis, photographs must be obtained in the field in such a way that the assumptions used in the ROC algorithm are valid. Photographs must be taken with a linear reference within frame, such as a ruler or a yardstick. This linear reference should be on the side of the photograph and should be parallel to the natural slope of the grains to be analyzed. The photograph should be orthogonal to the linear reference, which will project the photograph into an (x,y) grid.

Description of ROC Segmentation Process

Typically, photos are collected as colored or red-green-blue images in which each pixel has a value describing the red, green, and blue component. The aim of image processing is to generate a binary image in which pixels are characterized with just two intensity values, 0 to denote background and 1 to indicate foreground (e.g. part of the particle/rock/pebble). Images are first converted to an 8-bit integer grayscale image in which each pixel is assigned a single value from 0 to 255. This value describes pixel brightness or intensity, where 0 corresponds to black and 255 to white. The image is then converted to a binary image using a segmentation technique called thresholding. Thresholding differentiates particles from the background based on the grayscale pixel intensity relative to a defined intensity threshold (Gonzalez et al. 2004).

Specifically, ROC utilizes local thresholding (LT), in which segmentation is done by applying a locally varying threshold in which pixels are classified as background or foreground based on the mean brightness of nearby pixels (Gonzalez et al. 2004). LT can be computationally expensive and requires some user input to guide processing; however, it tends to do well in cases with uneven background illumination (Gonzalez et al. 2004), which is characteristic in photos taken outdoors.

To deal with particle overlap and separate touching grains, the binary image is further refined using watershed segmentation. (Gonzalez et al. 2004; Graham et al. 2005; Kornilov and Safornov 2018). Consider the image of rocks as a topographic image of a group of watersheds, in which the centers are basins and edges are ridges. First, a complement of the binary image is determined. In the complement of a binary image, zeros become ones and ones become zeros. Then a distance transform algorithm is applied that determines the distance from every pixel to the nearest nonzero-valued pixel. This information is used to estimate the center of the rock (or basin) and ridges, assuming the center would be the farthest away from non-zero values. Like LT, application of watershed segmentation also requires user interaction. If an image is over segmented, users can define a separation value. A lower value enhances separation and a higher value decreases separation. The ROC interactive GUI makes it simple for users to easily apply both LT and watershed segmentation, varying parameters if needed until optimal results are reached. See Figure 1 for the ROC interface.

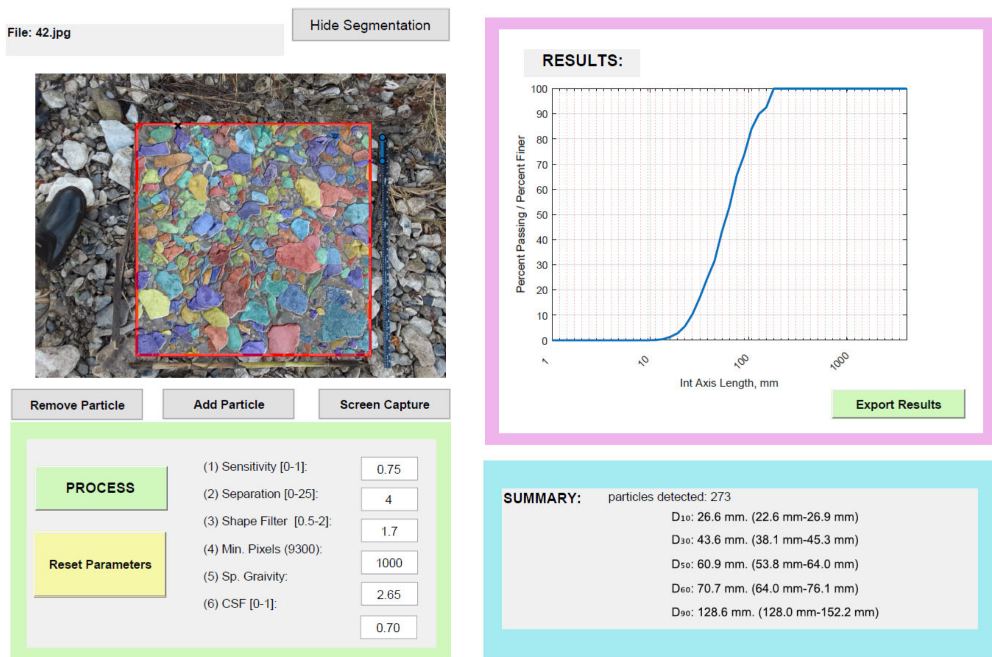


Figure 1: ROC GUI. Segmentation parameters can be found in the bottom left of the above image, including sensitivity, separations, shape filter, and minimum pixels. These parameters are varied by the user until the segmentation most closely matches the image. The resulting segmentation can be found in the top left image, while the gradation results can be found on the right side of the image.

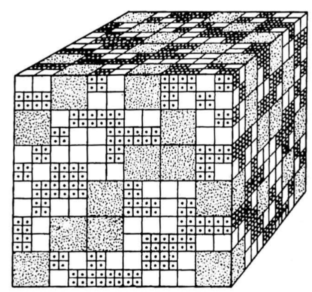
Description of ROC Gradation Calculations

Following segmentation, the ROC tool calculates gradation using the surface area of each identified rock. Surface area is calculated by summing up the number of image pixels that make up each rock. From the 2D images, the major and intermediate axes of each rock can be measured. Previous work has found that particles tend to settle such that the smallest or minor axis is more or less vertical (Gokelma et al., 2020; Kim et al., 2018; Komar and Reimers, 1978; McNown and Malaika, 1950), so the axes visible in the 2D image are assumed to be the major and intermediate axes. Note that the major and intermediate axes need not be oriented in any particular orientation, as long as these two axes are visible to the camera. ROC then organizes the identified particles into defined bins based on each particle's intermediate axis. Bins are ¼ phi steps from 0.0002 mm (12 phi) to 4096 mm (-12 phi). The area in each bin is summed and the cumulative area is determined from smallest to largest. The cumulative area in each bin is then divided by the total area to produce a gradation curve in terms of percent finer. Finally, statistical percentiles, d_{10}, d_{50}, and d_{90}, etc. where that d_x represents the size in which percent of identified pebbles/rocks is finer than, are determined through linear interpolation of the cumulative distribution to the desired value.

Description of other Gradation Methods

Leopold (1970) claimed that pebble counts are biased towards large sizes due to the fact that larger rocks encompass larger areas and therefore have a higher likelihood of being selected by the operator. While a bias towards larger sizes does exist, the reason is based on operator bias (described in the next section) rather than rock size. Rocks with larger surface areas are more likely to be picked, but this corrects for bias rather than introducing it. Given that enough pebbles are counted to reduce random chance, this method produces a fairly accurate result.

Several authors have made this observation, including Kellerhalls and Bray (1971). In their paper, they describe a voidless cube with 3 sets of smaller cubes making up the voidless cube (see Figure 2). In this example, the surface gradation and the subsurface gradation are equivalent.



Particle	Linear Size D	Weight W	Total No. in Sample Volume	Total No. in Sample Surface
	1	1	4608	192
	2	8	576	48
	4	64	72	12

Figure 2: Voidless Cube from Kellerhals and Bray (1971)

For the ROC tool to accurately characterize the gradation of the cube, the gradation calculated by ROC should be equivalent to the gradation obtained through a bulk sieve analysis (assuming that the surface and subsurface gradations are equivalent). The possible histograms from the various sampling techniques can be seen in Figure 3. The bulk sieve analysis (the true gradation) would result in the histogram shown in (a). Two possible (but incorrect) ways for ROC to match the histogram shown in (a) are area-by-weight and area-by-number. In area-by-weight, the cubes visible on the surface would be converted to weight and then plotted as percent by weight (c). This produces an overly coarse distribution because the control volume is no longer maintained. Area-by-number may appear to be similar to a pebble count because the pebbles are ranked from largest to smallest and a frequency plot developed, but this produces an overly fine distribution. Only the grid-by-number (b) produces the correct distribution because the probability of selecting a pebble in a pebble count is proportional to its surface area. For a photograph-based tool to correctly yield an equivalent gradation to a pebble count or a bulk sieve analysis (assuming that the surface and subsurface gradations are equivalent), it must compute the gradation based on the relative proportion of surface area occupied by each grain class.

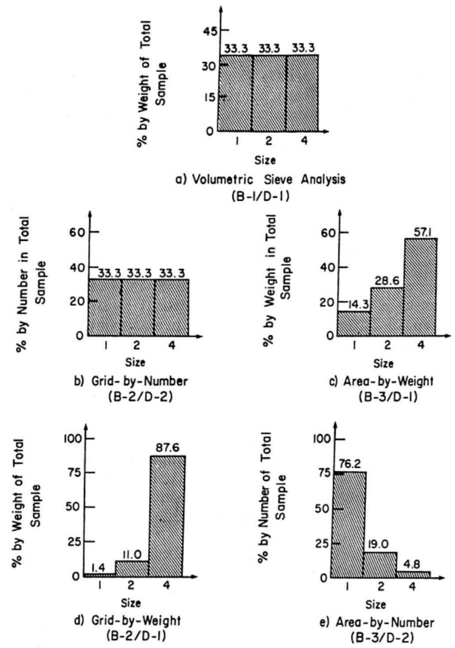


Figure 3: Histogram Distributions from various sampling and frequency methods (Kellerhals and Bray, 1971)

Description of Operator Bias

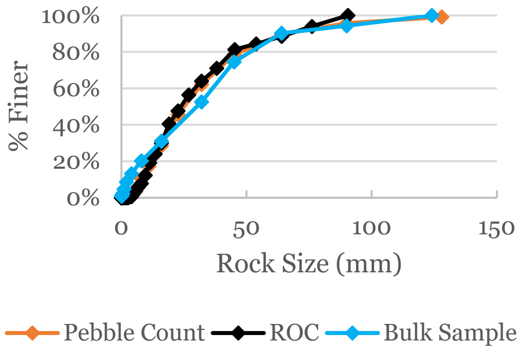
Pebble counts have been shown to have large operator bias (Daniels and McCusker, 2010). It is theorized that the pebble count is biased toward large particles due to operator bias because when the operator's finger lands on multiple rocks, the operator is subconsciously drawn to pick up the larger particle. The ROC tool eliminates this bias.

To test operator bias in the ROC tool, 5 individuals were asked to perform a ROC analysis on 5 pictures. The results were then aggregated to determine the total range of results obtained by different operators. Operator bias may be introduced into the ROC tool because ROC requires user interaction to determine the segmentation parameters, which change based on the photograph being analyzed.

Results

Percent Finer Plots

The gradation plots obtained from the ROC tool and the pebble counts/bulk samples can be seen in Figure 4-Figure 11. These plots show good correlation between the ROC tool and the measured data. In Figure 4, the bulk sample is much finer than both the ROC tool and pebble count at the d_{10}. Figure 5 shows that the bulk data is coarser than the pebble count and the ROC tool at the d_{10}. Both of these phenomena can be explained by differences between the subsurface gradation (which was included in the bulk samples) and the surface gradation observable by the ROC tool and the pebble count.



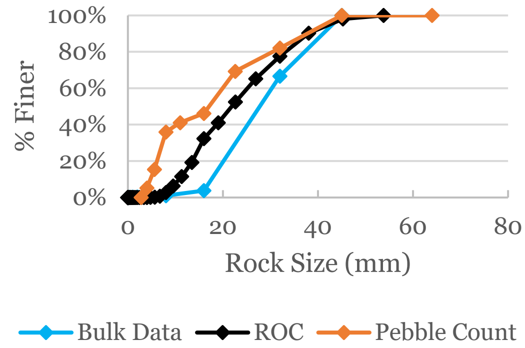
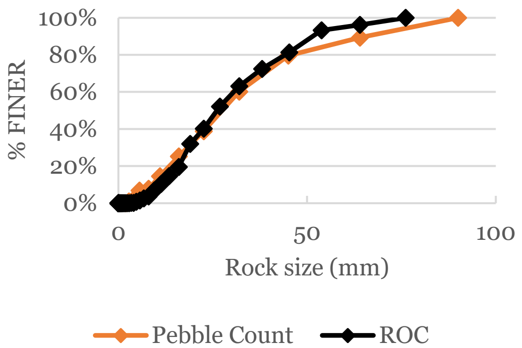


Figure 4: ROC compared to the Pebble Count and Bulk Sample collected on Rock Creek in Kansas City, MO

Figure 5: ROC compared to the Pebble Count and Bulk Sample collected on Crider Creek in the Ozarks, MO



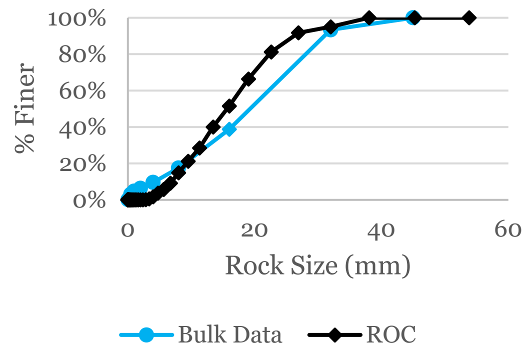
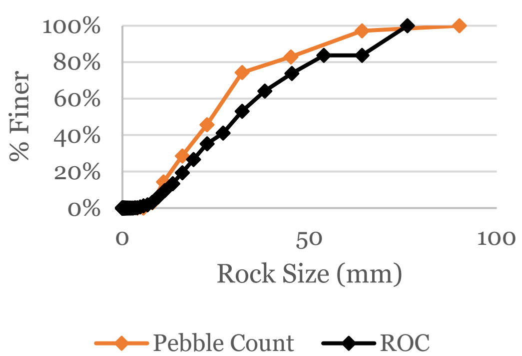


Figure 6: ROC compared to the Pebble Count and Bulk Sample collected on the Little Maries River in the Ozarks, MO

Figure 7: ROC compared to the Bulk Sample collected on Jake Creek, Ozarks, MO



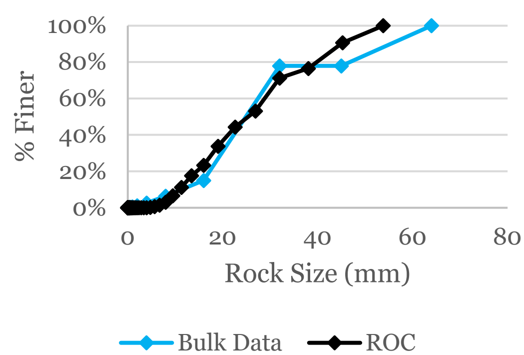


Figure 8: ROC compared to the Pebble Count collected on Crider Creek, Ozarks, MO

Figure 9: ROC compared to the Bulk Sample collected on Crider Creek, Ozarks, MO

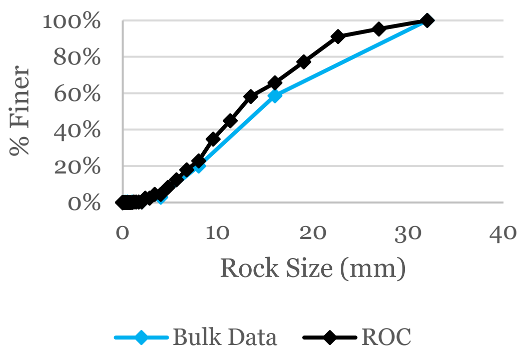


Figure 10: ROC compared to the Bulk Sample collected on the Maries River, Ozarks, MO

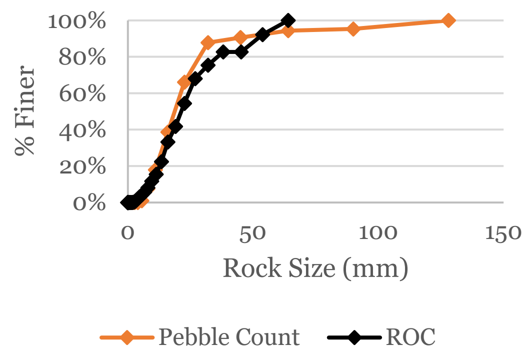


Figure 11: ROC compared to the Pebble Count collected on Rock Creek, Kansas City, MO

Average Results

The average percent difference between the ROC tool and the measured data can be seen in Figure 12 and Figure 13. The percent difference between the ROC tool and the bulk data (Figure 12) shows that the ROC tool was generally able to predict the gradation within 20% of the bulk data. At Rock Creek, ROC overpredicted the d_{10} by 234%. However, the pebble count at this site was only 11% coarser than the ROC tool. This could be due to either the inability of the ROC tool to identify finer material or the subsurface gradation was finer than the surface gradation.

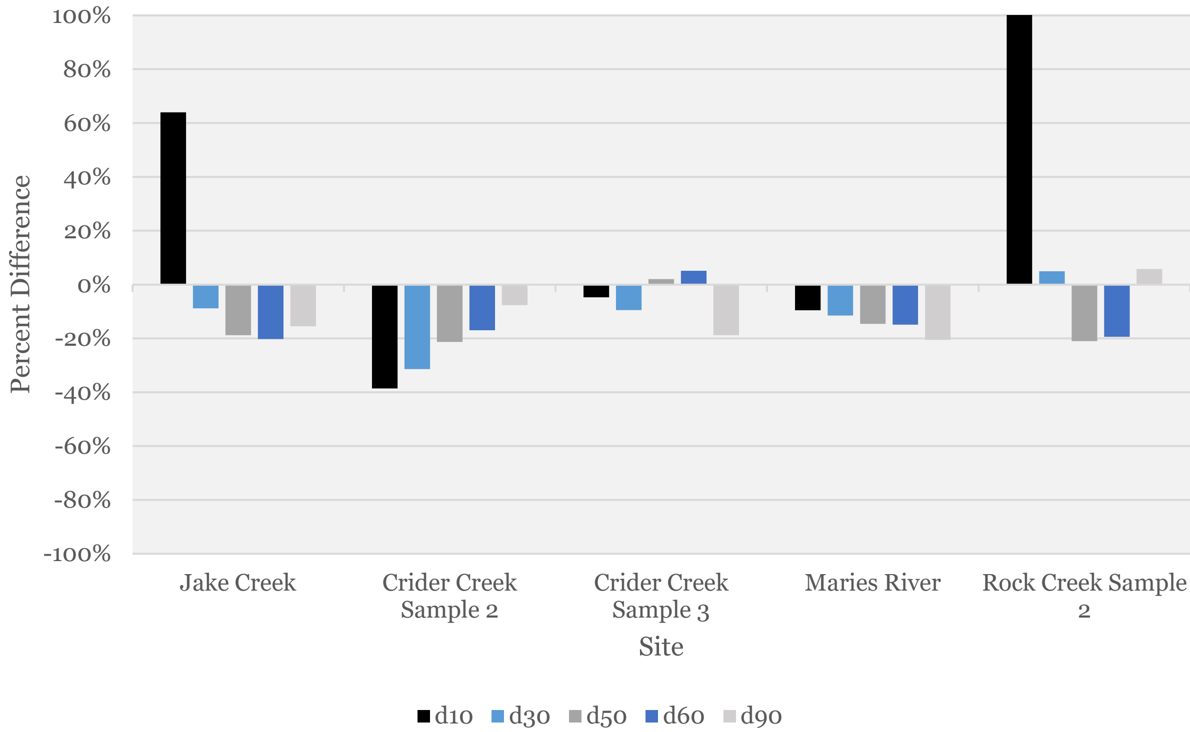


Figure 12: Percent Difference between ROC tool and Bulk Samples (gradations by mass obtained from sieve analysis). The largest percent difference between ROC and the bulk samples was 234% for the d_{10}, though this sample also had a 201% error between the bulk sample and a Wolman Pebble Count. Most of the samples contained less than 20% percent difference

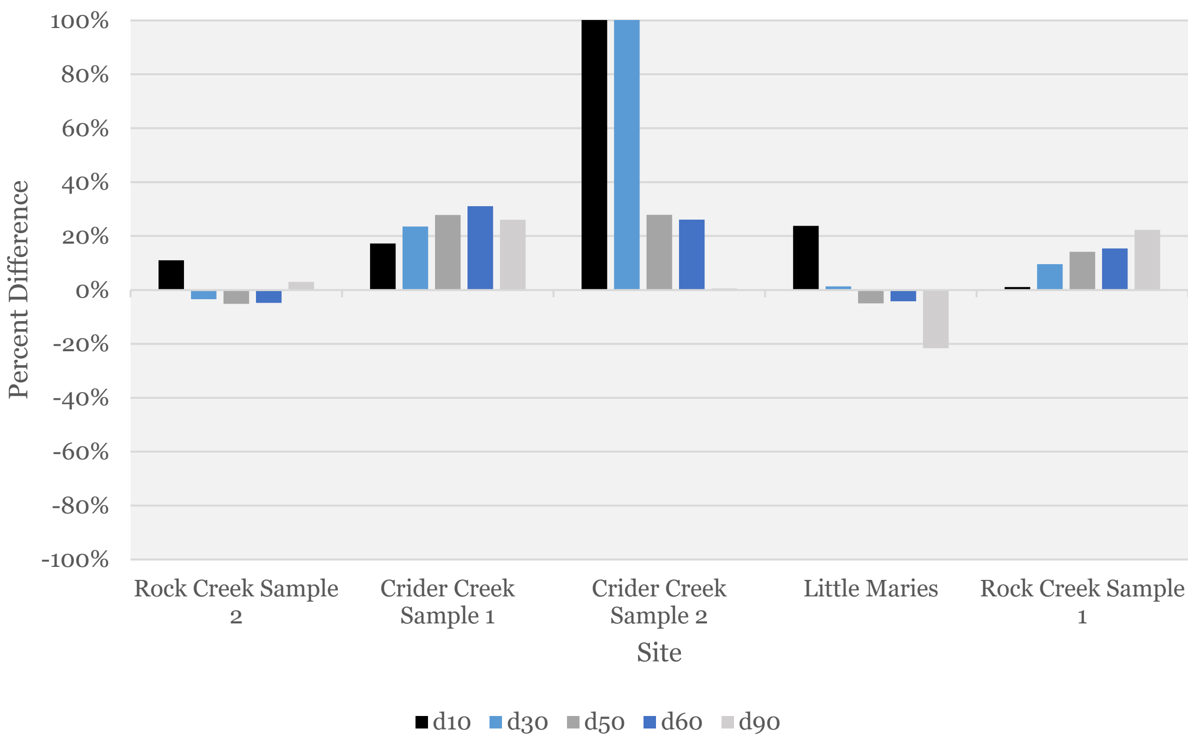


Figure 13: Percent Difference between ROC and Pebble Counts. Crider Creek C2 showed the largest discrepancies between ROC and the pebble counts, with a d_{10} of 127% and a d_{30} of 113%. Most of the samples were within 20% difference.

Table 2 below shows the average percent difference between the ROC tool and the measured data. The d_{10} shows the largest percent difference between ROC and the measured data, though this is skewed by the bulk dataset at Rock Creek and the pebble count at Crider Creek. It would be expected for the smallest particles (d_{10}) to have the largest error, since image analysis tools are often biased towards large particles (Fall et al, 2020; Smith and Friedrichs, 2011).

Table 2: Average Percent Difference between the ROC tool and the bulk samples and pebble counts. The largest percent difference occurred at the d_{10}, though these were each skewed by one sample.

	Average Percent Difference Bulk Samples	Average Percent Difference Pebble Counts
d_{10}	48%	36%
d_{30}	-12%	29%
d_{50}	-16%	12%
d_{60}	-14%	13%
d_{90}	6%	6%

Operator Bias

The results of the operator bias analysis can be seen in Figure 14 and Table 3 below. Figure 14 shows the percent error between the ROC analysis obtained by each individual user and the "true" value obtained by a pebble count. These values are grouped by percent finer (d_{10}, d_{30}, d_{50}, d_{60}, and

d_{90}) and each percent finer class contains 25 points (5 photos analyzed by 5 operators). These results indicate that there is more variability at smaller grain classes than at larger grain classes. The summary statistics presented in Table 3 indicate that although there is larger variability at smaller grain classes, the arithmetic mean and median are small, indicating good correlation between the aggregated ROC analyses and the pebble counts.

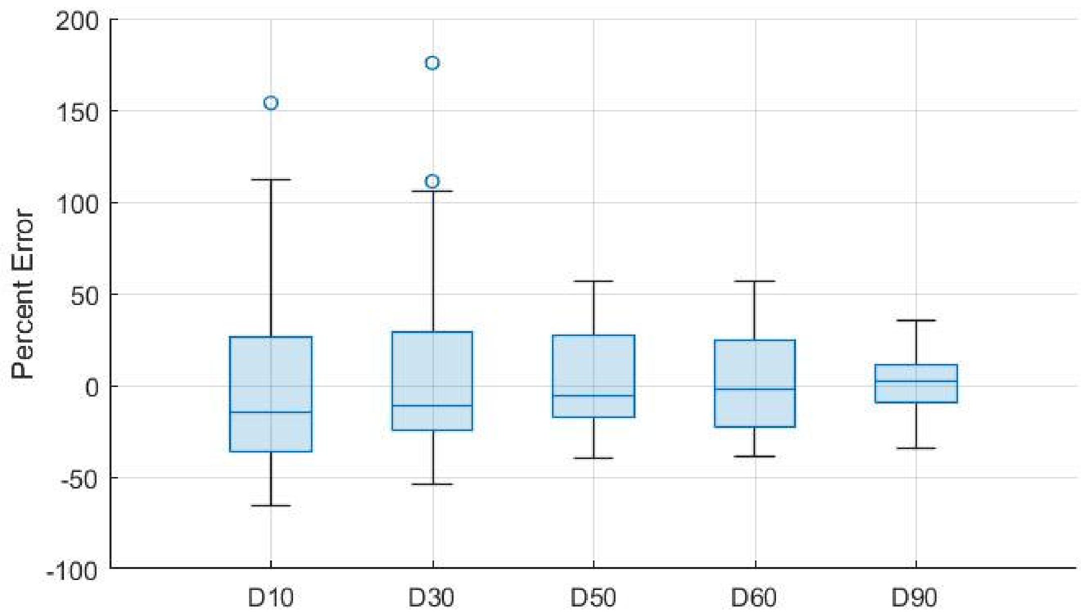


Figure 14: Percent error between ROC tool and gradation obtained through pebble counts. This figure indicates that the spread of the percent error decreases at larger grain sizes.

Table 3: Statistics Regarding Operator Bias. The arithmetic mean and median of the percent errors are very close for d_{30}-d_{90}, while the d_{10} was within 17% error. The standard deviation decreased as the grain sizes increased, indicating the ROC tool is more accurate with larger grains. Because the arithmetic mean and median contain less than 15% error, the ROC tool can be assumed to contain less than 15% error when enough participants use the tool. The standard deviation does indicate that any individual ROC analysis may contain relatively large error, though this error still is within $\pm$ 1 grain class.

	Mean	Median	Std. Dev.
d_{10}	2%	-15%	55%
d_{30}	11%	-11%	56%
d_{50}	3%	-5%	25%
d_{60}	2%	-2%	26%
d_{90}	0%	2%	18%

Discussion

The results reported in Table 2 show that the ROC tool can accurately calculate the grain size distribution within approximately 20%. To understand the amount of error this introduces for geomorphic processes, the d_{10}, d_{30}, d_{50}, d_{60}, and d_{90} for both the ROC results and the measured results were classified into standard grain classes used in sediment modeling. The true values (pebble counts and bulk samples) were then compared to the ROC values to determine the error that may have been introduced by the ROC tool when using the estimated values in sediment modeling. These values can be seen in Table 4 and Table 5. These results show that the ROC tool accurately classified the grain class at least 60% of the time and was within plus or minus 1 grain class 100% of the time.

Table 4: Accuracy of ROC in predicting the grain class for pebble counts. Of the 5 samples with both a pebble count and a ROC analysis, all of the ROC predictions are within 1 grain class of the pebble count. The predictions appear to be more accurate for the d_{30}-d_{60} sizes.

	Total Number of Samples	Samples within the same grain class as pebble count	Samples within $\pm$ 1 grain class of pebble count
d_{10}	5	3	2
d_{30}	5	4	1
d_{50}	5	5	0
d_{60}	5	4	1
d_{90}	5	3	2

Table 5: Accuracy of ROC in predicting the grain class for bulk sieve samples. Of the 5 samples with both a bulk sample and a ROC analysis, all of the ROC predictions are within 1 grain class of the bulk sieve samples.

	Total Number of Samples	Samples within the same grain class as bulk sample	Samples within $\pm$ 1 grain class as bulk sample
d_{10}	5	3	2
d_{30}	5	3	2
d_{50}	5	4	1
d_{60}	5	3	2
d_{90}	5	4	1

Conclusions

Leopold (1970) claimed that pebble counts are biased towards large sizes due to the fact that larger rocks encompass larger areas and therefore have a higher likelihood of being selected by the operator. We refute this claim; it is precisely because larger particles are selected more frequently that a pebble count method can yield equivalent results to a by-mass measurement of a bulk sample. The ROC tool calculates percent finer by surface area, which provides the correct weighting to differently-sized particles which is equivalent to the probability of a given grain size being selected during a pebble count.

The purpose of this paper was to document the strengths and weakness of the Rock Observation Calculator (ROC) for estimating the size gradation of gravel bars. This analysis confirms that the ROC tool can estimate the size gradation of gravel bars with practical levels of accuracy, provided the surface sizes represent the full sample gradation and the specific gravity does not vary amongst particles. Compared to five pebble count and five bulk samples, the ROC tool was able to select the correct grain size class for the d_{10}, d_{30}, d_{50}, d_{60}, and d_{90} statistics in 60% of the cases. The other 40% were within one grain size class.

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