www.ugb.org.br
ISSN 2236-5664

Revista Brasileira de Geomorfologia

v. 19, nº 1 (2018)

http://dx.doi.org/10.20502/rbg.v19i1.1206

GRAIN-SIZE MEASUREMENTS OF FLUVIAL GRAVEL BARS USING OBJECT-BASED IMAGE ANALYSIS

ANÁLISE TEXTURAL DE BARRAS FLUVIAIS DE CASCALHOS UTILIZANDO CLASSIFICAÇÃO BASEADA EM OBJETOS

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Informações sobre o Artigo

Recebido (Received):
14/01/2017
Aceito (Accepted):
27/09/2017

Keywords:
Grain-Size Analysis; Image Segmentation; Geographic Object-Based Image Analysis.

Palavras-chave:
Classificação Granulométrica; Segmentação de Imagens; Análise de Imagens Baseada em Objetos Geográficos.

Abstract:

Traditional techniques for classifying the average grain size in gravel bars require manual measurements of each grain diameter. Aiming productivity, more efficient methods have been developed by applying remote sensing techniques and digital image processing. This research proposes an Object-Based Image Analysis methodology to classify gravel bars in fluvial channels. First, the study evaluates the performance of multiresolution segmentation algorithm (available at the software eCognition Developer) in performing shape recognition. The linear regression model was applied to assess the correlation between the gravels' reference delineation and the gravels recognized by the segmentation algorithm. Furthermore, the supervised classification was validated by comparing the results with field data using the t-statistic test and the kappa index. Afterwards, the grain size distribution in gravel bars along the upper Bananeiras River, Brazil was mapped. The multiresolution segmentation results did not prove to be consistent with all the samples. Nonetheless, the P01 sample showed an R^2 =0.82 for the diameter estimation and R^2=0.45 the recognition of the eliptical ft. The t-statistic showed no significant difference in the efficiencies of the grain size classifications by the field survey data and the Object-based supervised classification (t = 2.133) for a significance level of 0.05. However, the kappa index was 0.54. The analysis of the both segmentation and classification results did not prove to be replicable.

Resumo:

As técnicas tradicionais de classificação granulométrica em barras fluviais de cascalhos consistem em mensurações do diâmetro dos sedimentos em campo. Em virtude do tempo necessário para obter uma amostragem representativa desses sedimentos, surgiu-se o interesse na automatização do processo de classificação via processamento digital de imagens. O presente trabalho expõe resultados de experimento metodológico de classificação de Imagens Baseada em Objetos Geográficos no trecho composto por barras fluviais de cascalhos na Bacia do Rio Bananeiras, Brasil. Primeiro, o algoritmo de segmentação de imagens multirresolução é aplicado em fotografias digitais convencionais obtidas em campo. O desempenho do segmentador é avaliado através da análise por regressão linear, na qual parâmetros de comprimento, largura e encaixe elíptico dos cascalhos, obtidos pelo segmentador são comparados com os mesmos parâmetros obtidos por digitalização manual. Posteriormente, o resultado do diâmetro médio obtido na classificação granulométrica de cada amostra foi comparado com o resultado da classificação obtido por amostras de campo. A verificação foi feita a partir do teste-t e do índice Kappa. Por fim, os resultados são especializados no mapa de distribuição dos sedimentos no trecho estudado. Os resultados da delimitação dos objetos pelo do segmentador não foram consistentes para todas as amostras. A amostra P01 apresenta os melhores desempenhos de tanto na delimitação dos objetos (R^2 =0.82 para o parâmetro largura) como na classificação do diâmetro médio, porém indicam deficiência no reconhecimento do contorno dos mesmos (R^2= 0.45 para o parâmetro encaixe elíptico). O teste-t estatístico não apontou diferenças significativas entre os valores médios das amostras (t = 2.133 para um nível de significância α = 0,05). O índice kappa foi 0.54. Embora, os resultados indiquem eficiência na amostra P01, o experimento com o segmentador multirresolução não demostrou potencial de replicabilidade.

1. Introduction

Grain-size distribution is a crucial aspect to understand the intensity of the hydrodynamic mechanisms in fluvial systems (LEOPOLD *et al.*, 1964; GREGORY; WALLING, 1973). Along the longitudinal profile of a watercourse the granulometric composition varies. The sediment grain sizes tend to decrease downstream due to abrasive and selective transport processes (FERGUSON *et al.*, 1996, RICE; CHURCH, 1998; RICE; CHURCH, 2001; GASPARINI *et al.*, 1999; RENGERS; WOHL, 2007; SINGH *et al.*, 2007 and FRINGS 2008). Downstream areas are often non-turbulent and will favor the deposition of sands and finer materials. Gravel bars prevail in areas with waterfalls and rapids.

In Gravel-bed Rivers, the estimation of grain size distribution is particularly challenging. The traditional method used to characterize the grain-size composition in gravel bars dominated sections is made through direct measurements on the surface of the exposed bar. The individual grains are measured inside a grid area determined by the sampler or along the sampler's footpath (WOLMAN; 1954). This traditional method is also known as pebble counting. The use of sampling grids is often applied as an efficient way to prevent bias (RICE; CHURCH, 1996). Sampling grids of 60 x 60 cm are considered adequate for measuring the sediment size in gravel bars (BUNTE *et al.*, 2009). While measuring, three perpendicular axes are identified: the major axis, or "a-axis"; the minor axis, or "c-axis"; and the intermediate axis, or "b-axis" (KRUMBEIN, 1941). These correspond to the length, thickness, and width, respectively (Figure 1).

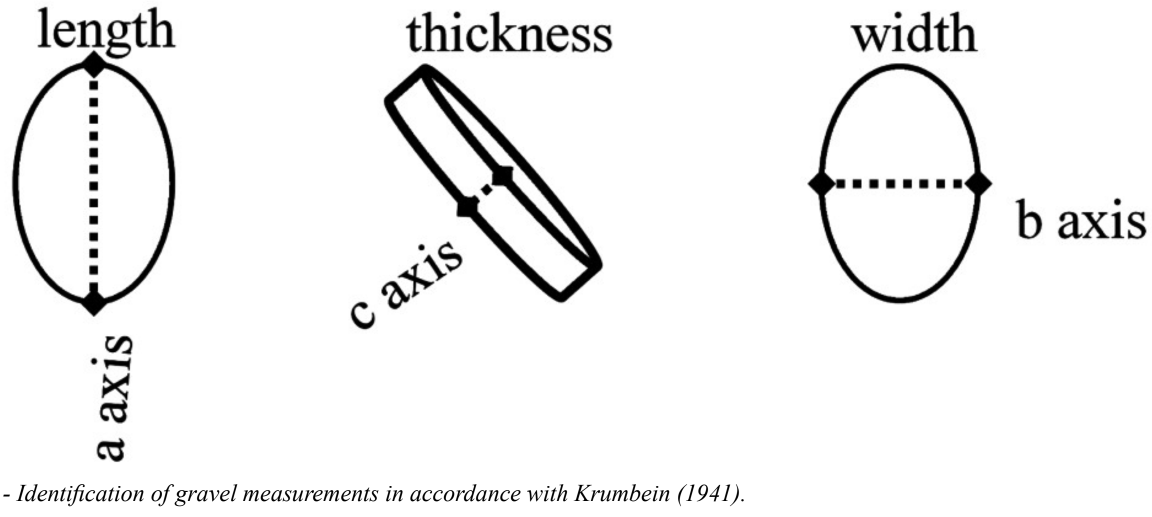

Figure 1 - Identification of gravel measurements in accordance with Krumbein (1941).

Despite being widely accepted, the pebble counting method presents an obstacle. Measurements *in situ* are known to be time-consuming (e.g. time to obtain a sample size suitable for statistical analysis and characterization). In the search for faster methods, photograph-based techniques were developed in the 1970s. These techniques are advantageous due to their non-invasive approach and their execution speed (ADAMS, 1979; IBBEKEN; SCHLEYER, 1986), allowing to collect information more rapidly in larger sample sizes than traditional sampling methods.

Numerous applications have been built based on photographic sampling methods (MCEWAN *et al.*, 2000; BUTLER *et al.*, 2001; VAN DEN BERG *et al.*, 2002; SIME; FERGUSON, 2003; RUBIN, 2004; GRAHAM *et al.*, 2005; BUSCOMBE; MASSELINK, 2009; WARRICK *et al.*, 2009; CHANG; CHUNG, 2012, CHUNG; CHANG, 2013). These methods are supported by hardware capable of processing a large amount of data in order to obtain accurate estimates of the average grain diameters (CISLAGHI *et al.*, 2016).

Edged detection applications through image segmentation were often implemented (MCEWAN *et al.*, 2000; BUTLER *et al.*, 2001; VAN DEN BERG *et al.*, 2002; SIME; FERGUSON, 2003; RUBIN, 2004; GRAHAM *et al.*, 2005; CHANG; CHUNG, 2012, CHUNG; CHANG, 2013). Those applications, known as object-based image analysis, have proved consistency and reproducibility in estimating the average mean size in samples obtained from exposed areas of gravel with good lighting (CISLAGHI *et al.*, 2016). However, the performance of those methods in gravel-sand mixed samples needs to be studied because gravel-sand mixed samples can be easily mistaken as homogeneous single gavels (BUTLER *et al.*, 2001).

In tropical areas, studies focused on optimizing grain-size classification in gravel Bars Rivers using digital image processing are not known to be developed so far. The grain-size variability in those areas presents a new challenge in terms of application. Therefore, the paper addresses this problematic by applying an experimental object-based analysis in digital photographs to measure the average grain size of fluvial gravel deposits.

1.1 Field Site

The Bananeiras River basin is part of the drainage system of the São João River in the state of Rio de Janeiro, Brazil (Figure 2). The Bananeiras River basin, together with the basins of the Pirineus River and the Águas Claras River, are important tributaries of the main drainage system. Originating from the escarpments of the Serra do Mar mountain range, these tributaries form the high-energy zone of the fluvial system, which is dominated by turbulent flows with high erosive potential.

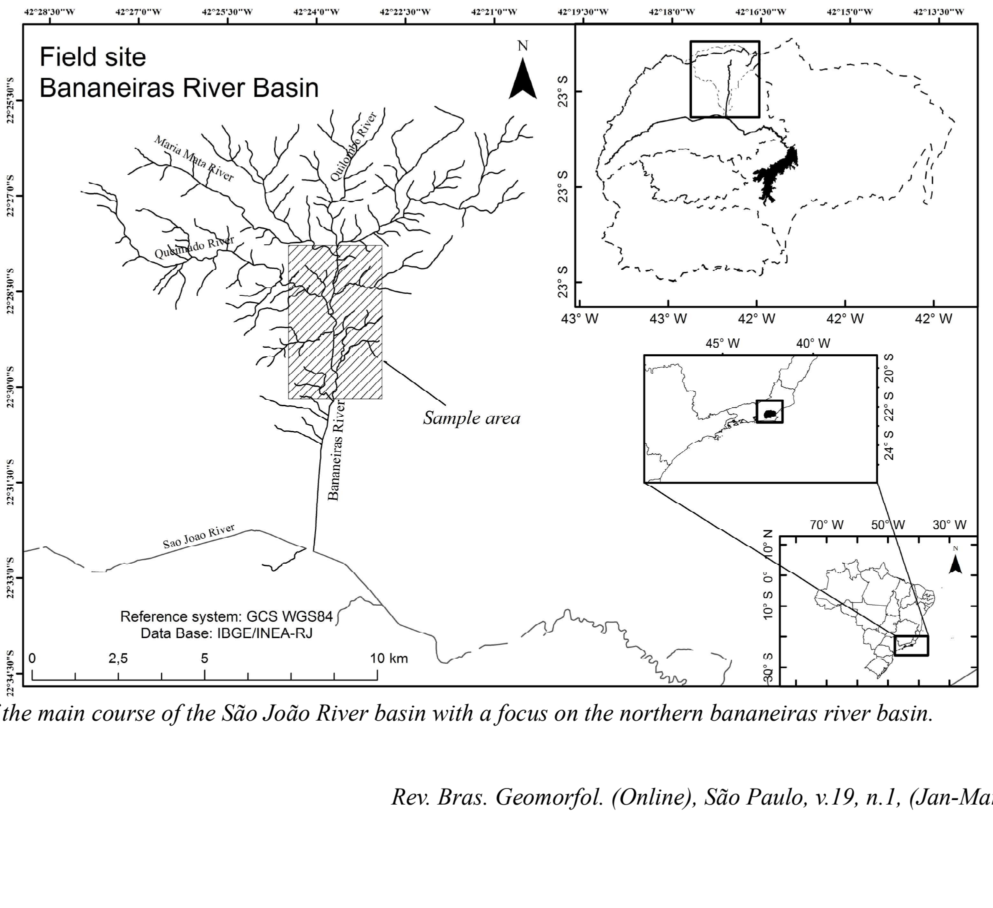

Figure 2 - Map of the main course of the São João River basin with a focus on the northern bananeiras river basin.

In the Bananeiras River drainage system and particularly in the transition from the steep section to the flat section, the flow loses energy, which favors the deposition of a wide variety of sediments. The reworking of these materials by hydrodynamic processes in the fluvial channel environment facilitates the development of extended sequences of gravel bars with grain sizes that vary from boulders to gravel with coarse sand.

2. Methods

2.1 Field procedures and data collection

The sampling was done in seven gravel bars along 1.3 km in the course of the Bananeiras River towards the confluence with the São João River (Figure 3A). Two samples were collected in each of the seven predefined fluvial bars. One by photograph and the other by direct measurement (pebble counting), both at the same location. The sampling was performed on the exposed bars during the periods of lowest flow. The samples corresponded to the *N* gravels that were contained in a 0.25 m^2 (0.5 x 0.5 m) region.

The photograph-based sampling method was applied using a tripod and a Canon digital photographic camera with a 37 mm objective lens (Figure 3B). The photographs obtained in the field were georeferenced and used as the inputs for two types of procedures: multiresolution segmentation (BAATZ; SCHÄPE, 2000) and manual delimitation of gravels in a geographic information system (GIS) environment.

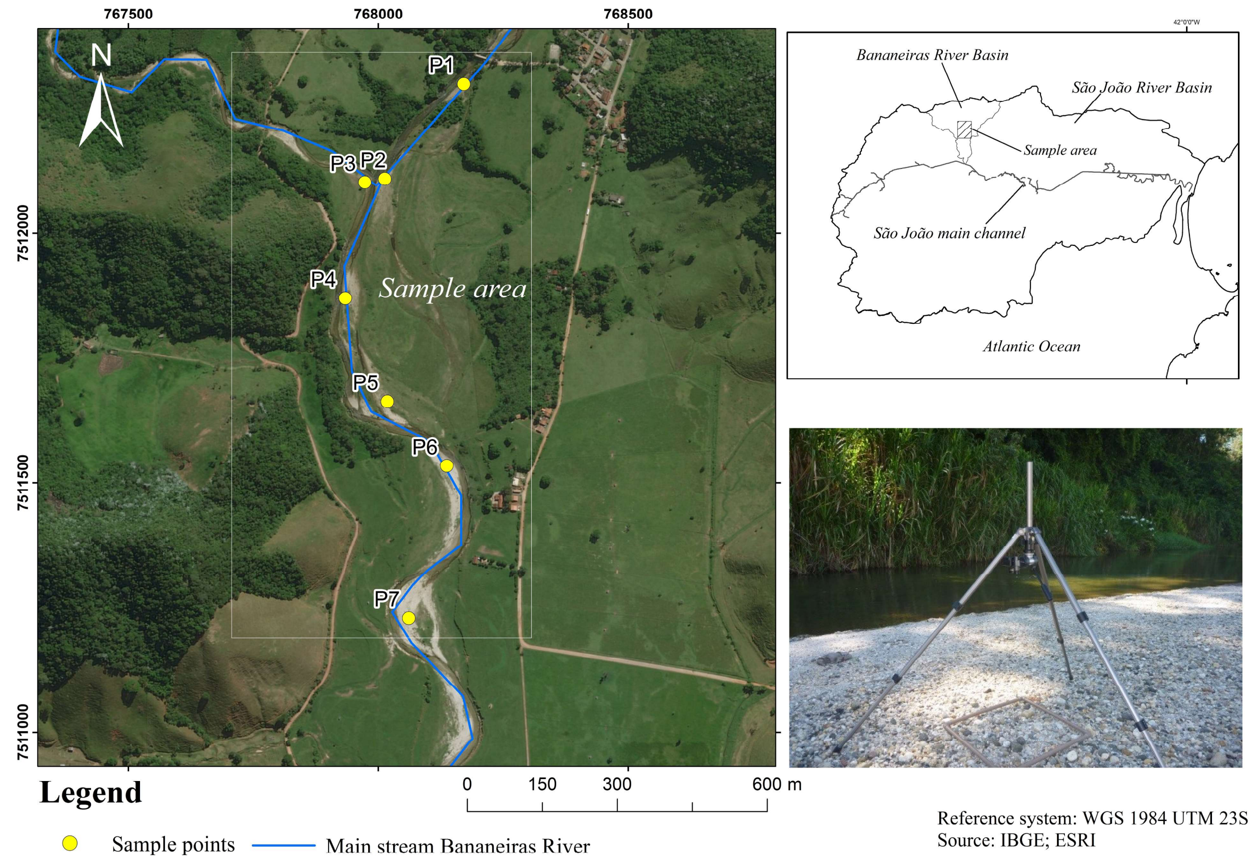

Figure 3 - a. Sample area in bananeiras river basin. b. Sampling equipment.

The polygon vector file from the latter procedure was used as a reference to evaluate the performance of the tested segmentation algorithm such as applied in other studies (MCEWAN *et al.*, 2000, BUTLER *et al.*, 2001, SIME; FERGUSON, 2003, GRAHAM *et al.*, 2005).

In the field, the gravels' diameter within the sample region were measured using a pachymeter in accordance with the pebble counting method adapted from Wolman (1954). A sample *N=30* was used for each experiment. The field data were used as a reference to determine whether there were significant differences in the parameters extracted by the multiresolution segmentation algorithm, including the average sample size, degree of sorting (standard deviation), and skewness as well as the textural classification of the sample according to the model of Blair; McPherson (1999).

2.2 Reference data

The photographs were referenced to a Cartesian plane in a GIS environment and assigned coordinates (x, y) with respect to the vertices of the photo frame. The images have a spatial resolution of 0.3 mm. It was not necessary to orthorectify the images provided they were obtained in near-vertical position and the spatial reference is known (BUTLER *et al.*, 2001). The delineation of the gravels' outlines was performed in a GIS environment through visual interpretation and manual vectorization. This reference delineation was used to evaluate the performance of the segmentation algorithm (BUTLER *et al.*, 2001, GRAHAM *et al.*, 2005, BARNARD *et al.*, 2007).

2.3 Object-based Image Analysis

Determining the limits between the grains is the key step for minimizing errors in automatic grain-size image analysis (SIME; FERGUSON, 2003). In GEOBIA classification, the limits between objects are defined by image segmentation algorithms. The purpose of segmentation is to transform a complex image into regions that are internally homogeneous and contrast with their surroundings (CASTILLA; HAY, 2008).

The application of edge detection filters and watershed segmentation algorithm did not perform well for the tests made in the point bars studied. Sedimentary deposits with varying grain sizes, different degrees of angularity, and very heterogeneous mineralogical compositions are often difficult to separate. This heterogeneity requires using a segmentation algorithm that is capable to incorporate multiple image-layers. This paper evaluates the performance of multiresolution segmentation (BAATZ; SCHÄPE, 2000).

To identify the edges of the objects, multiresolution segmentation uses measures of heterogeneity in the raster layers values at different scales. During the growth of the regions (*clustering*), the algorithm works with the weights between the parameters of color and shape. The shape is also considered in relation to the degree of compactness or smoothness (BAATZ; SCHÄPE, 2000).

Once the image-objects is created the classification takes place. The process tree for the proposed GEOBIA classification method is shown in Figure 4. Its implementation was done at sample P01 and afterward replicated to the other samples.

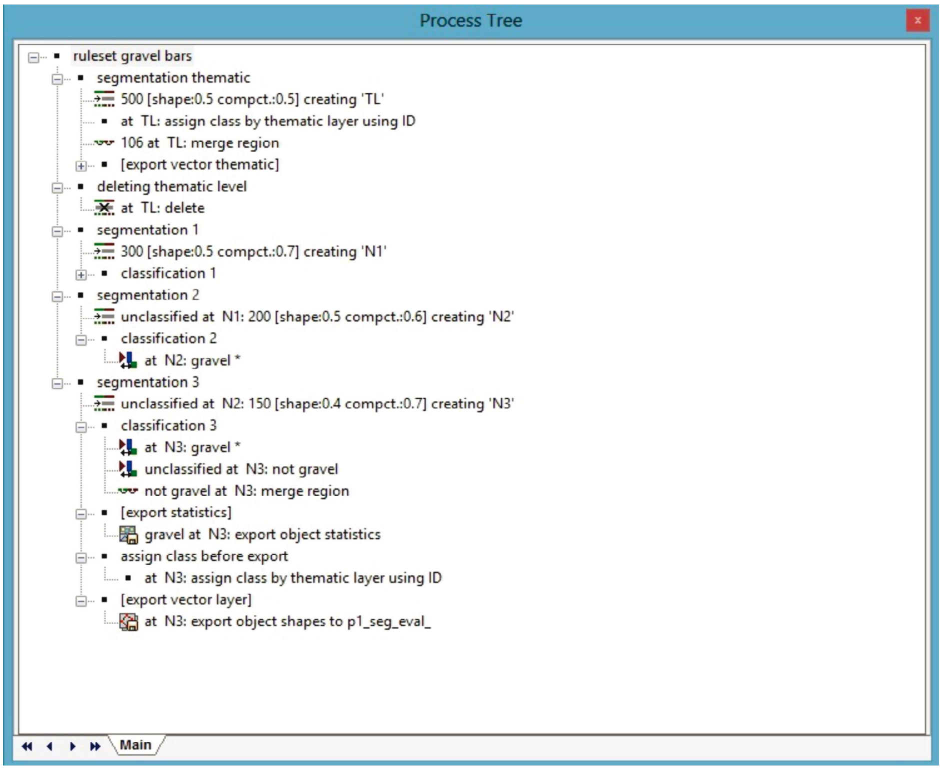

Figure 4 - Process tree developed for the recognition of outlines and the semi-automatic classification of gravel bars.

First, the vector file generated by visual interpretation and manual digitalization was loaded into eCognition and a segmentation was performed to reproduce the reference vector limits (*segmentation thematic*). Afterwards, the feature identification ID from the vector file was imported from the vector's attribute table (*assign class by thematic layer*).

The output vector file with validation parameters and the ID of each object was exported for statistical analysis. The shape parameters width (b-axis), length (a-axis), and eliptical ft. (relation between both axis) were chosen for validating the multiresolution segmentation (Figure 5). After extracting the validation parameters, the manually defined limits were deleted (*deleting segmentation thematic*). This process avoids introducing user-bias in multiresolution segmentation.

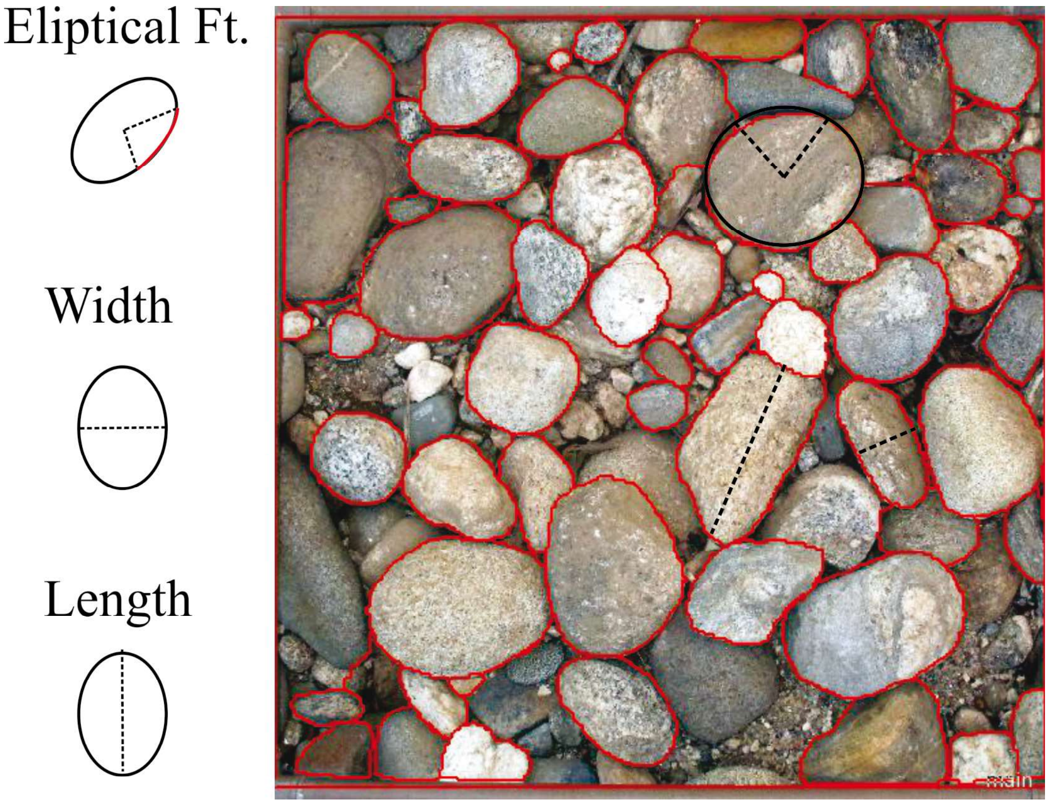

Figure 5 - Values calculated based on visual interpretation of the data.

The multiresolution segmentation was made on a top-down approach up to four levels (*segmentation* 1, 2, 3). The top-down approach consists in detecting the larger objects (the coarse gravel/cobbles) at the first levels and smaller diameter objects (medium-coarse gravel) at the subsequent levels.

The eliptical ft. was used for classifying gravels. This parameter has been used in other studies as an indicator of the efficiency in defining the outline of the objects (SIME; FERGUSON, 2003; GRAHAM *et al.*, 2005). A minimum object width of 24 pixels (1 pixel = 0.3 mm, then 24 x 0.3 = 8 mm) was established as an additional criterion (KONDOLF, 1997).

Once the objects attended the classification criteria with a likelihood ≥ 0.8 in a segmentation level, they were labeled gravels. The gravels were filtered for not being modified in the subsequent segmentation processes (Figure 6). The shape parameters classification criteria were unique among all segmentation levels. The segmentation parameters vary from one level to another because each level intends to identify different grain-size group gravels. Finally, the objects labeled as gravels in all levels were exported and afterward classified in Blair; McPherson (1999) intervals.

Table 1 summarizes the segmentation steps and shows the number of levels executed, the initial and final scales, and the number of classified objects as well as those with correlations in the reference file. It should be noted that only the gravels that had a matching pair in the reference file were considered in the statistical evaluation.

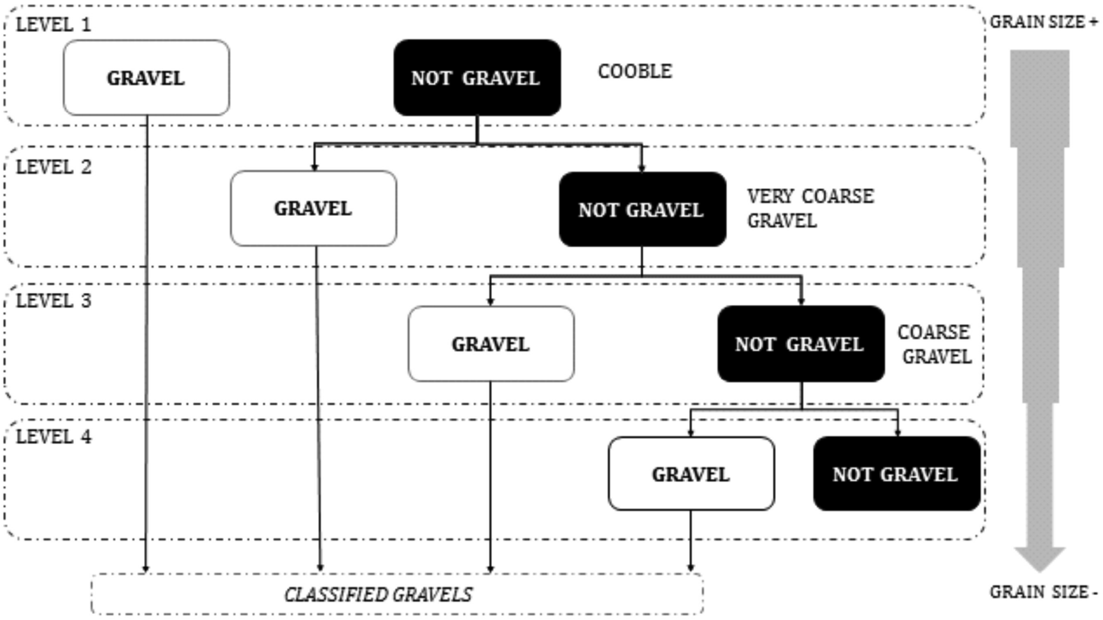

Figure 6 - Semantic classification network.

Table 1: Segmentation parameters.

Sample point	Initial scale	Final scale	Levels of segmentation	Objects Manually identified	Objects classified by GEOBIA	Objects used in correlation
1	300	150	3	112	58	43
2	300	150	3	61	68	38
3	300	150	3	77	51	25
4	300	150	3	30	64	22
5	500	200	4	30	23	15
6	300	150	3	30	53	15
7	200	100	3	30	100	24

2.4 Validation

The validation of the multiresolution segmentation in detecting gravel's outlines was performed using ordinary least squares (OLS) regression to assess the differences between the extracted values that were generated by visual interpretation and the extracted values derived by the multiresolution algorithm.

The Spearman correlation coefficients were calculated for the pairs of values of the width, length, and eliptical ft. of the objects. Due to the difference in the sample size of the matched pairs, the correlations were tested for a significance level $\alpha = 0.05$ $(\mathrm{t}, \mathrm{p} = 1 - \frac{\alpha}{2}, \mathrm{df} = \mathrm{n} - 1)$.

OLS regression has been commonly used to validate the textural classification of gravel-bar rivers (SIME; FERGUSON, 2003; GRAHAM *et al.*, 2005). The outlines' delimitation were evaluated through the shape parameters (length, width, and eliptical ft.). The values obtained by manual vectorization (Y_i) and the values obtained by automatic recognition (X_i) were related using the function:

$$Y_i = \beta_0 + \beta_1 X_i - \epsilon_i \quad (1)$$

where β_0 and β_1 are coefficients, and ϵ_i is the residual error.

The standard error in the estimate corresponds to the square root of the average residual between the estimated values by the OLS regression and the calculated values from the visual delimitation of the gravels in accordance with the equation:

$$S_E = \sqrt{\frac{\sum(Y_i - \hat{Y}_i)^2}{n-2}} \quad (2)$$

where $\hat{Y}_i$ is the value that was estimated by the OLS regression.

The grain-size estimations between both the direct measurements at the field (pebble counting) and the GEOBIA classification method were compared. Average, standard deviation, skewness and kurtosis are well-established statistical parameters in Sedimentology (FOLK; WARD, 1957). These parameters were estimated using the percentiles D_5, D_{16}, D_{25}, D_{50}, D_{75}, D_{84}, and D_{95}. The results were obtained for each of the seven fluvial bars.

To test the initial hypothesis that there are no significant differences between the results of both experiments, a t-test was performed for a degree of significance $\alpha = 0.05\left[t, p = 1 - \frac{\alpha}{2}, df = (n-1), (n-1)\right]$ for each of the granulometric parameters in the *n* = *7* fluvial bars.

3. Results

3.1 Multiresolution segmentation performance

The segmentation performance was accessed through correlations between the shape parameters calculated both manually and automatically. The shape parameters used in this research were length (a-axis), width (b-axis) and eliptical ft. The results of the parameter length (a-axis) were significant ($p \geq 0.95$) at all locations. The best estimates occurred at P01, P05, and P06 (Table 2 and Figure 7).

The parameter width (b-axis) had a similar behavior to the length distribution, with $R^2 > 0.9$ for P01, P05, and P06 (Table 3). In sample P07, the estimate of the width was $R^2 = 0.68$, significant at a probability of 85.4%. The results for eliptical ft. showed $R^2 < 0.2$ for all samples except P01 and P06 (Table 4).

Table 2: Regression parameters in the estimation of the length of the gravels.

Sample	n	r	t	p	Significance level	St.Err.β
P1	43	0.824	9.314	0.0000	1.0000	0.088
P2	38	0.595	4.440	0.0001	0.9999	0.134
P3	25	0.686	4.525	0.0002	0.9998	0.152
P4	22	0.753	5.110	0.0001	0.9999	0.147
P5	15	0.952	11.182	0.0000	1.0000	0.085
P6	15	0.901	7.480	0.0000	1.0000	0.120
P7	24	0.608	3.596	0.0016	0.9984	0.169

Table 3: Results of the regression analysis for the width.

Sample	n	r	t	p	Significance level	St.Err.β
P1	43	0.903	13.497	0.0000	1.0000	0.067
P2	38	0.618	4.722	0.0000	1.0000	0.131
P3	25	0.642	4.013	0.0005	0.9995	0.160
P4	22	0.633	3.662	0.0015	0.9985	0.173
P5	15	0.964	13.229	0.0000	1.0000	0.073
P6	15	0.900	7.465	0.0000	1.0000	0.121
P7	24	0.306	1.509	0.1456	0.8544	0.203

Table 4: Results of the regression analysis for the eliptical ft.

Sample	n	r	t	p	Significance level	St.Err.β
P1	43	0.456	3.285	0.0021	0.9979	0.139
P2	38	-0.074	-0.444	0.6599	0.3401	0.166
P3	25	0.176	0.857	0.4003	0.5997	0.205
P4	22	0.137	0.618	0.5437	0.4563	0.222
P5	15	-0.095	-0.344	0.7365	0.2635	0.276
P6	15	0.327	1.246	0.2346	0.7654	0.262
P7	24	0.195	0.930	0.3622	0.6378	0.209

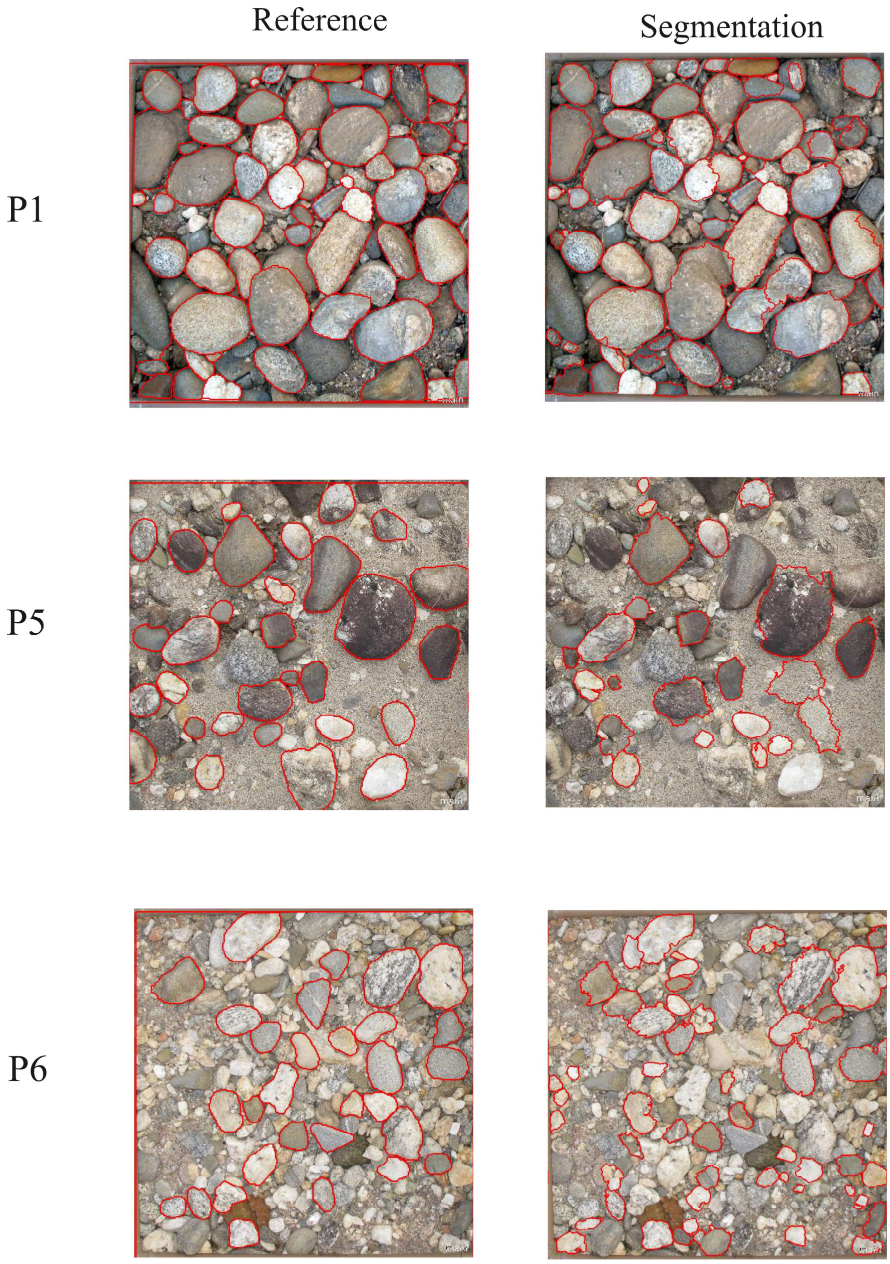

Figure 7 - Results of the segmentation for p1, p5, and p6.

3.2 Grain-size classification of fluvial bars

The D_5, D_{16}, D_{25}, D_{50}, D_{75}, D_{84}, and D_{95} percentiles were extracted using both methodologies (Table 5). They were used to validate the granulometric parameters of the fluvial bars estimated through the digital processing of images. In the traditional classification (pebble counting), exactly 30 gravels were measured in each sample portion. The automatic classification considered all the gravels classified in the photographs, which generated different sample sizes (Table 1).

Both methods measured the length (a-axis) of the gravels, which corresponds to the apparent major axis in the GEOBIA classification. Using the extracted percentiles, the average size of the grains, the sorting of the sediments (standard deviation), the skewness and the kurtosis of the grains diameter distribution were estimated (table 6).

Table 5: Percentiles (in mm) measured by the pebble counting method and by digital image processing (GEOBIA).

	GEOBIA							Pebble counting						
	D_5	D_{16}	D_{25}	D_{50}	D_{75}	D_{84}	D_{95}	D_5	D_{16}	D_{25}	D_{50}	D_{75}	D_{84}	D_{95}
P1	17.07	30.5	41.1	61.8	81.1	97.0	124.6	37.6	58.5	70.5	78.0	96.0	110.4	128.0
P2	22.02	30.7	40.5	59.7	100.0	104.3	161.2	32.8	42.8	61.0	66.5	89.0	108.8	153.5
P3	17.43	22.9	30.3	46.1	78.0	86.7	129.5	26.6	38.0	49.0	56.2	75.5	80.6	121.6
P4	15.45	22.4	28.2	40.8	70.0	92.7	125.0	32.3	40.0	63.0	67.0	111.3	147.2	190.2
P5	19.65	28.6	33.9	51.5	81.3	87.9	122.8	25.8	41.9	52.0	58.7	80.7	95.4	113.7
P6	17.70	24.4	31.4	40.4	48.6	61.6	102.0	36.1	41.9	48.0	50.0	65.7	80.8	91.1
P7	13.80	18.7	21.0	30.3	47.2	62.2	81.0	18.7	30.9	43.7	45.2	51.2	59.4	72.0

Table 6: Descriptive statistical parameters of the diameter distribution of the grains.

Samples	GEOBIA				Pebble counting			
	Mean	Standard deviation	Skewness	Kurtosis	Mean	Standard deviation	Skewness	Kurtosis
1	63.0869	32.9254	0.0145	1.1027	82.2933	26.6618	0.1766	1.4513
2	64.8870	39.5028	0.0475	0.9592	72.7133	34.7703	0.3624	1.7660
3	51.8875	32.9468	0.3807	0.9633	58.2833	25.0364	0.2599	1.4685
4	51.9743	34.1845	0.5077	1.0750	84.7333	50.7318	0.5284	1.3416
5	56.0317	30.4704	0.3049	0.8933	65.3433	26.6906	0.3103	1.2523
6	42.1457	22.0785	0.2996	2.0178	57.5600	18.0709	0.5389	1.2711
7	37.0400	21.0393	0.4892	1.0529	45.1900	15.1958	-0.0003	2.9126

The textural classifications of gravel bars were based on Blair; McPherson (1999). The comparison between the field measurements classification and the GEOBIA classification results are depicted in table 7. The non-parametric accuracy test of the GEOBIA classification was accessed through the Kappa index. The result is shown in table 8. Table 9 shows the results of the parametric test for the method evaluation. The parametric t-test was applied to compare the statistical parameters between both methods for the n= 7 samples.

The spatial representation of the studied area is shown in figure 8. Slightly differences in grain size average between both methods resulted in different classifications in the Blair; McPherson (1999) intervals. The natural breaks classification was chosen for its capability to represent the downstream reduction in grain-size averages in both methods.

4. Discussions

4.1 Multiresolution segmentation performance

One of the main goals of this paper was to evaluate the performance of the multiresolution segmentation algorithm in delineating the gravels in photographic samples of a river basin located in a tropical region, in which the intensity of geomorphic process is known to produce abundant sediment load varying in grain sizes composition (LATRUBESSE *et al.*, 2005). Previous studies pointed out the importance in investigating the performance of segmentation algorithms in gravel bar samples with mixed sand (BUTLER *et al.*, 2001). The results obtained here provided helpful insights regarding efficiency and replicability.

The efficiency of segmentation tends to be lower for gravel bed samples with mixed sand (BUTLER *et al.*, 2001; CISLAGHI *et al.*, 2016). The performance of the multiresolution segmentation in P05 showed the sand matrix is being mistaken as unique gravels. In that case, new objects were created increasing the counting of coarser gravels in the samples. This behavior, known as over-segmentation, was detected previously in studies applying the watershed segmentation algorithm (STROM *et al.*, 2010, CHUNG; CHANG, 2013).

In general, certain light conditions can create shadows that interfere with the automatic grain size estimates (GRAHAM *et al.*, 2005; BUSCOMBE; MASSELINK, 2009; WARRICK *et al.*, 2009). For example, sediments type which alternate light and dark colors together with non-optimal light conditions may impact negatively the segmentation results (CISLAGHI *et al.*, 2016). The gravels which have in its internal composition alternate light and dark colors imposed an obstacle to the multiresolution segmentation, especially at P02, P03 and P04. At these samples, those gravels were over-segmented. At the sample P05, the contrast generated by the presence of dark gravels over a clear sandy matrix facilitated the performance of the multiresolution segmentation.

Table 7: Comparison of the results of the classification in the Blair; McPherson (1999) model.

Samples	GEOBIA		Pebble counting	
	Mean size (mm)	Class	Mean size (mm)	Class
1	63	Coarse Gravel	82	Very Coarse Gravel
2	65	Very Coarse Gravel	73	Very Coarse Gravel
3	52	Coarse Gravel	58	Coarse Gravel
4	52	Coarse Gravel	85	Very Coarse Gravel
5	56	Coarse Gravel	65	Very Coarse Gravel
6	42	Coarse Gravel	58	Coarse Gravel
7	37	Coarse Gravel	45	Coarse Gravel

Table 8: Kappa index Manual x GEOBIA Classifications

		GEOBIA classification		
		Coarse gravel	Very coarse gravel	
Pebble counting classification	Coarse gravel	**3**	0	3
	Very coarse gravel	3	**1**	4
	Total	6	1	7
Kappa statistics	Agreement	3	1	4
	By chance	0.367346939	0.081632653	0.44898
	kappa	**0.542056075**	**Total accuracy**	0.571428571

Table 9: Analysis of the differences between the averages based on the t-test.

	t	*p* de t	Significance level
Mean size	2.133	0.05427	0.94573
Sort	-0.44558	0.6638	0.3362
Skewness	0.18226	0.8584	0.1416
Kurtosis	1.822	0.09345	0.90655

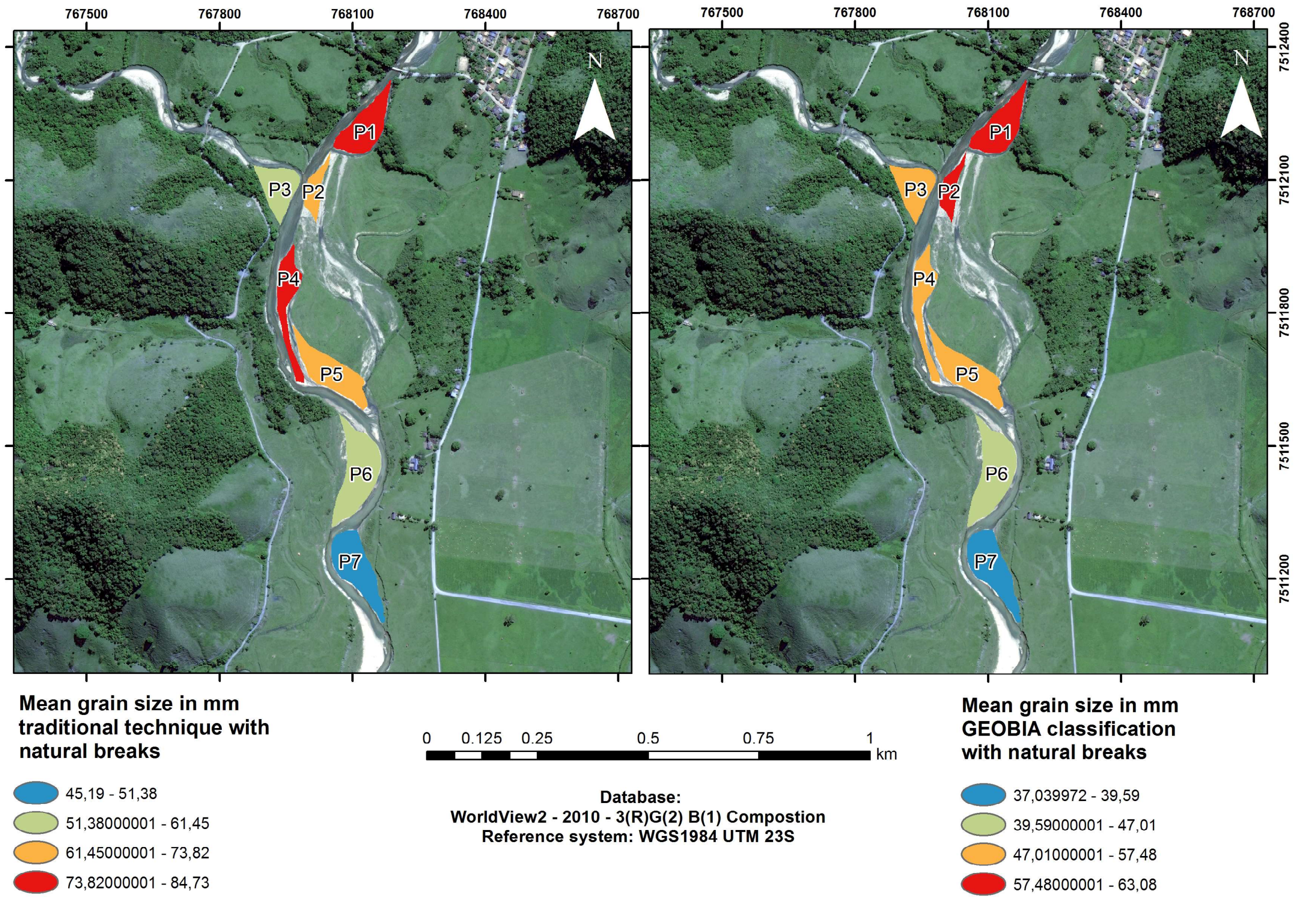

Figure 8 - Spatial representation for the both methods using natural breaks classification intervals.

The multiresolution segmentation algorithm estimated dimensions (a-axis and b-axis) of the gravels that correlate well with the actual values, which are assumed to match the visual interpretations. The automatic segmentation was unable to accurately delimit the edge of the grains to define the shape. Crenulated edges, the division of the grains, and even advancement over the matrix or neighboring grains resulted in a different eliptical ft. of the automatically delimited objects from those that were delimited manually.

The multiresolution segmentation performed better for samples composed mainly of rounded grains than for the ones with larger elongated grains. The same behavior was observed while applying the digital cutting method (DCM) (VAN DEN BERG *et al.*, 2002). The latter method's performance was compared with the watershed segmentation method, which is a well-established methodology for automatic grain-size classification for homogeneous gravel bar samples (MCEWAN *et al.*, 2000; BUTLER *et al.*, 2001; SIME; FERGUSON, 2003; RUBIN, 2004; GRAHAM *et al.*, 2005, CHANG; CHUNG, 2012, CHUNG; CHANG, 2013). Larger elongated grains are known to also reduce the accuracy of 3D grain size classification methods (PEARSON *et al.*, 2017).

4.2 Grain-size classification of fluvial bars

The GEOBIA classification accuracy assessment provided significant information regarding the overall method, with important considerations in terms of bias and method's validation.

The percentile diameters estimated by GEOBIA were lower than those from the traditional classification (pebble counting). The disparities in the percentiles estimations generated differences in the textural class assignment. The samples P01, P04, and P05 were assigned to different Blair; McPherson (1999) textural classes in the method's comparison. They were classified as coarse gravels in the GEOBIA classification instead of the very coarse gravels estimated by the field reference classification. The omission evidence responded for the Kappa index 0.54.

The underestimation observed in the GEOBIA classification outcome from the limitations of the photograph-based methods in detecting three dimensions (ADAMS, 1979; BUTLER *et al.*, 2001, STROM *et al.*, 2010, CISLAGHI *et al.*, 2016). Thus, imbricated or partially buried gravels tend to have lower values in the GEOBIA extraction method. Recently, a method based on 3D high-resolution topographic models showed reduced effects of imbrication and reliable estimates of surface roughness, which combined with photographic based methods can provide the most reliable grain size measures for large areas (PEARSON *et al.*, 2017).

A previous study demonstrated reduced errors at higher percentiles and worst estimates in lower percentiles associated with vegetation issues such as dirt and cobble texture (CISLAGHI *et al.*, 2016). The results in this paper showed GEOBIA classification had the worst grain size estimates between the intervals 32 mm and 64 mm. The best estimates were for the gravels with an axis more than 80 mm long. The results were accurate for both gravels with very small diameters, such as the fine gravel (8 mm<D<16 mm), and for the very coarse gravel (64 mm<D<128 mm).

Despite the differences in the classification results, the average diameters obtained at P01, P04, and P05 were close to the threshold for very coarse gravel (64 mm) in the Blair; McPherson (1999) textural classification intervals. Thus, even though they had values close to the average diameter of the grains, these samples were classified by the GEOBIA method as coarse gravels.

Considering the calculated values for [t,p=1-0.05/2, df=2(7-1)], the comparison between the average grain sizes resulted in p values of t = 0.05427 (very low), which involves accepting the initial hypothesis of no differences between the methods for a significance level of 94.57%. The results also did not indicate differences in the kurtosis with a significance level of 91%. The t-test results indicate significant differences between the classification methods regarding the degree of sediment sorting, which is most likely because GEOBIA overestimates the variety of diameters caused by the problems of shape recognition. The differences in the asymmetry of the portions cannot be considered because the values for both methods fall within the confidence interval for n = 7, so the distribution of the grain sizes is symmetric for both experiments.

Different from the non-parametric Kappa accuracy index, the t-test disguised the observed limitations from the multiresolution segmentation in detecting the borders from the objects.

The GEOBIA classification method using Blair; McPherson (1999) intervals at table 7 did not register textural changes in the fluvial bars at the confluence with the tributary channel (P02, P03, and P04). The contribution of fine sediments from secondary channels reflects selective transport mechanisms. At the exit to the main channel, the river flow loses energy and creates conditions for the deposition of fine grains (RICE, 1998; RICE; CHURCH, 1998). This expected behavior was observed in the field measurement classification, where the samples P02 and P03, located in the confluence zone, presented fining in average grain sizes.

The GEOBIA classification by natural breaks illustrated the expected structural gradient from upstream to downstream (SCHUMM; STEVENS, 1973; FERGUSON *et al.*, 1996; RICE, 1998; RICE; CHURCH, 1998; GASPARINI *et al.*, 1999; RENGERS; WOHL, 2007; SINGH *et al.*, 2007; FRINGS, 2008) and differences in the classification of the point bars at the confluence with the tributary channel.

5. Conclusions

Once the process tree was defined and the appropriate adjustments were made to the model, a considerable timewise improvement was observed. The required work time was reduced by approximately 80%, including the field sampling phase that is required for measuring the gravels. However, the productivity gains were not followed by accuracy levels found in the previous works discussed in this paper.

The classification model performed well for the sample P01, which had gravels with a low degree of angularity, an absence of a sandy matrix, uniformity in the colors, and high contrast with neighboring gravels. The results were not consistent in the other samples and the model did not show replicability.

The estimates obtained from the regression analysis show stronger correlations with the estimates of the length (major axis) and width (minor axis). The results for the eliptical ft. parameter illustrated the deficiency of the multiresolution segmentation algorithm in recognizing shapes even though this parameter was used as a criterion for refining the segmentation of the gravels in the photographs.

In general, the multiresolution segmentation algorithm was not capable of recognizing shapes and patterns. The results obtained from delimiting the extremities of the objects indicate that the algorithm could estimate the diameters with a slightly better efficiency.

The analysis of the percentiles demonstrated that there was a similarity in the results of the distribution curves that are associated with the D_{75} and D_{95} percentiles, whose granulometric intervals were between 64 and 128 mm. In contrast, the largest differences between the percentiles were related to the D_5, D_{16}, and D_{25} percentiles, which generally were between 32 and 64 mm.

The results of the variance analysis (t-test) demonstrated that there are no significant differences between the two methods in terms of the classification of the average size of the sediments in the fluvial bars, which is estimated based on the major axis or the length of the grains.

Despite the t-test indicated no significant differences between both methods, the multiresolution segmentation demonstrated inefficiency in detecting the edges of the gravels and the classification model did not show replicability.

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