Geometry accuracy of DSM in water body margin obtained from an RGB camera with NIR band and a multispectral sensor embedded in UAV

Dalva Maria de Castro Vitti, Ademir Marques Junior, Taina Thomassin Guimarães, Emilie Caroline Koste, Leonardo Campos Inocencio, Maurício Roberto Veronez, and Frederico Fábio Mauad

Faculty of Technology of Jahu, Environment and Water Resources, Jau-SP, Brazil; Polytechnic School, Unisinos University, São Leopoldo-RS. Brazil

ABSTRACT
The photogrammetry techniques are known to be accessible due to its low cost, while the geometric accuracy is a key point to ensure that models obtained from photogrammetry are a feasible solution. This work evaluated the discrepancies in 3D (DSM) and 2D (orthomosaic) models obtained from photogrammetry using control points (GCPs) near a reflective/refractive area (water body), where the objective was to evaluate these points, analysing the independence, normality and randomness and other basic statistic. The images were obtained with a 16 MP Canon PowerShot ELPH 110S with a modified NIR band and a multispectral sensor Parrot Sequoia, both embedded in a hex-rotor UAV in flight over the Unisinos University’s artificial lake in the city of São Leopoldo, Rio Grande do Sul, Brazil. Due the distribution of the data found to be not normal, we applied non-parametric tests Chebyshev’s Theorem and the Mann–Whitney’s U test, where it showed that the values obtained from Sequoia DSM presented significant similarities with the values obtained from the GCP’s considering the confidence level of 95%; however, this was not confirmed for the model generated from a Canon camera, showing that we found better results using the multispectral Parrot Sequoia.

ARTICLE HISTORY
Received 30 December 2017
Revised 5 November 2018
Accepted 10 November 2018

KEYWORDS
Accuracy; SFM; UAV; mapping; geo-statistics; DSM; photogrammetry

Introduction
The 3D modelling generated from images acquired from high-resolution cameras embedded in unmanned aerial vehicles (UAV) is consolidating as an alternative technique with low cost in large-scale mappings (Smith, Carrivick, & Quincey, 2016).

The Structure from Motion (SFM) technique with the Multi-View Stereo algorithm aims to reconstruct a surface or object from the matching of common points collected from several images, where each point consists of a position and a colour extracted from an image (Debevec, Taylor, & Malik, 1990; Forstall, Dietrich, Couville, Jensen, & Carbonneau, 2013; Oliveira, 2002; Remondino, Scaioni, & Sarazzi, 2011; Snively, Seitz, & Szeliski, 2008). This method does not require metric cameras, giving the SFM a status of a more feasible approach, due to the cheaper price and availability of this type of non-metric cameras (Smith et al., 2016).

For an efficient construction of the 3D surface it is important that the angular separation between the images (considering the position of the camera during the capture) does not exceed 25–30 degrees, achieved with a minimum of 60–80% of images overlapping in an individual location. Also requiring good photo quality for a better performance of the detecting algorithms (Smith et al., 2016; Verhoeven, 2011).

The SFM algorithm generates a sparse point cloud using a local reference system. To georeferencing the point cloud we need distributed points referenced with a global navigation satellite system (GNSS) to generate correct metrics (scale and global position) (Lobnig, Tscharf, & Mayer, 2015). We need at least four control points in a global system to obtain an equivalent metric to the real-world scene. The model in an absolute reference system is achieved with the 7-parameter Helmert’s similarity transformation (Lerma, 2002; Lobnig et al., 2015).

The next step is to create a dense point cloud that is generated with the Multi-View Stereo (MVS) algorithm that calculates the geometry pixel-by-pixel, reproducing higher level of detail in the scene (Furukawa & Curless, 2010; Kraus, 2004).

After the dense point cloud creation, we are able to build the proper 3D model applying triangulation algorithms to build a mesh, also with the camera positions and interior orientation parameters we have the orthophotos, where all objects with a certain height are accurately positioned in a 2D plane (Verhoeven, 2011).
The first generated 3D model is the digital elevation model (DEM) or the digital surface model (DSM) that considers the elevation of all elements above the ground. The proper georeference of this model gives us the correct global position and scale of the model.

The digital terrain model (DTM) is a 3D model that does not consider elements above the ground, e.g. trees and buildings. To achieve this, filters are applied to remove these elements, as this process can be repeated by varying the reclassification parameters to obtain a cleaner DTM. As final products of SfM, we have the DSM or DTM (3D models), and the orthomosaic (2D image).

To evaluate the positional accuracy of products from SfM + MVS most works have in common the comparison with differential GNSS control points, while others compare with laser scanner data. In addition, the root mean square error is the most used statistical value. Another important aspect of the statistical evaluation is the predominance of studies only considering parametric statistics (normal distribution) and the analysis centered in the horizontal plane (2D). (Harwin & Lucieer, 2012; Joaquim Höhle, 2009; Laliberte, Herrick, Rango, & Winters, 2010; Neto et al., 2017; Turner, Lucieer, & Christopher Watson, 2012).

Each country regulates the mapping process differentially. Most of them recommend at least 20 control points and assume that the sample has a normal distribution (Atkinson, 2005; Ariza & Atkinson, 2008). In addition, the standards do not detail the steps of assessment of accuracy and whether the assessment of horizontal (positional) accuracy is performed independently X and Y (linear error) or joint XY (circular error). The Z component (height) is always evaluated independently (Ariza & Atkinson, 2008). Our work uses "E" for "X", "N" for "Y" and "h" for "Z" in UTM coordinates in meters (m).

An additional consideration is, that we did not find works that consider large reflective areas as lakes and others types of water bodies, this research aimed to evaluate the positional accuracy of products generated by the SFM and MVS for mapping purposes using an RGB (with modified near infrared band) and a multispectral sensor.

This work is presented as follows: the methods and material, workflow and the statistical basis; the study over the artificial lake at the Unisinos University, where the products of the SFM + MVS process were evaluated; the discussion of results of this work and how they compare with similar works; and lastly the conclusion of this work were we establish some remarks and considerations for this and future works.

**Materials and methods**

This section describes the methods and materials used in this work. First with the equipment used to acquire the images and second describing the statistical techniques to evaluate the products obtained from the sensors.

**Studied area**

Following the premise of evaluating the model accuracy around a water body, the area chosen for this work was the artificial lake presented in the campus of the Unisinos University in the south of Brazil in the state of “Rio Grande do Sul” in the city of “São Leopoldo”. The selected area of evaluation is marked in Figure 1.

The studied area was chosen in order to evaluate the influence of a reflective/refractive area near the points used for assessment localized in the water body margin and the use of two different types of cameras/sensors and consequently to indicate the better camera in this situation.

**Workflow**

This work followed the steps presented in Figure 2, as some of the processes are detailed in the next subsections.

**Image acquisition**

83 images were collected for both the Canon PowerShot camera ELPH 110HS 16.1 MP (Toyo, Japan) (15 cm GSD and focal distance of 4.4 mm) with modified NIR band and the multispectral sensor Parrot Sequoia 16 MP (Paris, France) (14.52 cm (11 cm) GSD and focal distance of 4.88 mm) in flight over the studied area with height of 120 m above the ground. Both camera/sensors were shipped in the hex-rotor UAV ST800, as shown in Figure 3.

**Structure from motion processing**

In this phase, the images collected are combined with the flight log into specific software that uses computational vision and the algorithm Structure from Motion (SfM) to match common points in the images using points of same colour to recreate the scenes in a 3D model (the digital terrain model) or in a flat surface model (orthomosaic). The software Pix4Dmapper (Lausanne, Switzerland) was used to perform this task.

**Statistical analysis**

The verification of the positional accuracy should be performed independently for the horizontal components (E and N) and the vertical component (h), where E and N are the positions in UTM coordinates, and h is the soil elevation (Atkinson, 2005; Ariza & Atkinson, 2008).
To assess the accuracy, the coordinates of the points identified in the orthomosaic (EN) and in the 3D model \( (h) \) need to be compared with their homologues extracted from a source at least three times more accurately (Preciado, 2000), (the most accurate technique is the GNSS differential survey), and the minimum number of checkpoints recommended is 20 (ASPRS, 2015; Brazil, 1984; Federal Geographic Data Committee, 1998) to 167 as in STANAG:2215.

The first step is the calculation of the discrepancies (horizontal and vertical) \( \varepsilon_c \) between the coordinates \( C_o \) from the orthomosaic (2D positional or EN) and
the 3D model (combining the three axes E, N and h), against the coordinates of control “C,” obtained by a more precise method (Atkinson, 2005; ASPRS, 2015; Federal Geographic Data Committee, 1998; Preciado, 2000) as in Equation (1):

\[ e_c = C_o - C_c \]  

(1)

This work uses the positions as EN coordinates, as “\( e_c \)” values obtained are the distances in meters between the control coordinates obtained with differential GNSS and the control points identified in the georeferenced orthomosaic. The discrepancies in height (\( h \)) or soil elevation are measured using the elevation obtained with the differential GNSS in the control points against the elevation found in the control points identified in the georeferenced 3D model.

Following, the inspection of the atypical points or outliers is performed (Preciado, 2000). These points are not necessarily coarse errors but must be investigated. We need to estimate the expected error (\( \sigma_{\text{prior}} \)) basing on the steps of data acquisition and image processing.

### Estimating the expected error

The expected error value must consider all possible errors during the phases of data acquisition and processing (Brazil, 1984). In 3D Modelling with UAV the expected error, \( \sigma_{\text{prior}} \), for the image-processing phase can be estimated by Equation (2), where its elements are described in Table 1.

\[
\sigma_{\text{prior}} = \left( \sigma_{\text{GNSUAV}}^2 + \sigma_{\text{sensor}}^2 + \sigma_{\text{support}}^2 + \sigma_{\text{image support}}^2 + \sigma_{\text{processing}}^2 + \sigma_{\text{DEM}}^2 + \sigma_{\text{checking}}^2 \right)^{0.5}
\]  

(2)

Then, the \( \sigma_{\text{prior}} \) error is multiplied by 3 and the result obtained is compared with the absolute discrepancies at each point, where values that exceeded this value are excluded from the analysis. The points excluded should be between 10% and less than 20% of the sample (Bustos, 1981). After the inspection for outliers, the study of previous hypotheses of independence, normality and randomness is carried out.

### Independence test of sample discrepancies

This test is done after the exclusion of outliers and before the normality test, to verify the correlation between the discrepancies and the distances between the checkpoints, and properly select the most adequate statistical tests for each case.

The independence test of the data can be made by geostatistical analysis (Santos, 2015; Santos, Medeiros, Santos, & Lisboa Filho, 2017), using the experimental semivariogram. The experimental semivariogram for each positional discrepancy (EN and \( h \)) are obtained from the calculation of the semivariances \( \sigma_{\text{GNSUAV}} \) given by Equation (3), where \( N(h) \) is the number of positional discrepancy values pairs of \( dp(x_i) \) and \( dp(x_i + h) \) separated by a distance of \( h \).

\[
\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{n} \left[ dp(x_i) - dp(x_i + h) \right]^2
\]  

(3)

The experimental semivariogram is represented by a chart, where the ordinate is the semivariance, and the abscissa is the distance between the elements of the sample. The correlation occurs until the point where the semivariance of the discrepancies stabilizes in the semivariogram, making the “RANGE” distance, and after that point, the discrepancies are independent (Santos, 2015; Yamamoto & Landim, 2013). In Figure 4, in (a) we observe an adjusted theoretical model, with all elements of a semivariogram, “RANGE”, “NUGGET EFFECT” and “SILL”; In (b) there was no correlation between the discrepancies (only the “NUGGET EFFECT” is present) indicating independence.

If the independence is verified, the analysis of normality and randomness, followed by the analysis of accuracy is performed. Otherwise, the theoretical model can be adjusted to exponential, spherical or Gaussian for semivariograms with “SILL” (Santos, 2015; Soares, 2000; Yamamoto & Landim, 2013).

After the semivariogram modelling, the adjustment is done by techniques such as ordinary least squares, weighted least squares, maximum likelihood and or restricted maximum likelihood. The data are cross-validated generating the standardized residue (independent, normal, non-tendentious and homogeneous), and the correlation coefficient \( R^2 \) is determined. Then, the correlation of the standardized residuals with the positional discrepancies is verified. If the correlation is greater than 0.6 (strong correlation), it is followed by the verification of the accuracy based on the standard residue, if it is less than 0.6 (weak correlation), the semivariogram should be revised (Santos, 2015; Santos et al., 2017).

To verify the independence of data using the semivariogram, we need to analyse the pairs of points in multiple directions (directional semivariogram). This is done to verify the independence between the location of the points to the distance and the geographical direction (in relation to north). Considering this, this work used the directions 0°, −45°, 45°, 60° and 90° to analyse the correlation in multiple directions, and a length of 30 m for lag increment, that is, the distance interval to be considered as we approach the cut (maximum) distance in each direction.
(1000 m in this case), and an $R$ value of 10 (tabulated value) for both $EN$ and $h$ discrepancies.

### Normality tests

The null hypothesis in the normality test is that the discrepancies are distributed in a Gaussian function (ASPRS, 2015; Brazil, 1984; Federal Geographic Data Committee, 1998); however, most accuracy standards for cartographic products do not consider free distribution. ASPRS (2015) standards recommend performing accuracy tests for data that are not in a normal distribution.

The EN position data usually have a normal distribution from 20 sample points, so parametric tests and the estimators, mean, standard deviation and RMSE satisfy them. As this distribution occurs in less frequency for the elevation discrepancies, which usually has a free distribution, so the previous hypothesis must be based on non-parametric methods based on the median (Atkinson, 2005).

The Shapiro–Wilk test was selected for the normality test for having a better performance compared with Kolmogorov–Smirnov, Chi-square and Student’s t-test, when evaluating free distribution data (Neto et al., 2017; Santos, 2015; Torman, Coster, & Riboldil, 2012).

The previously established hypothesis considering a significance of 0.05 is described below:

- $H_0$: the distribution of the discrepancies $EN$ or $h$ fulfil the normal function.
- $H_1$: the distribution of the discrepancies $EN$ or $h$ do not fulfil the normal function.

If the previous hypothesis ($H_0$) is confirmed, the mean and the standard deviation of the sample can be attributed to the population and the horizontal and altimetric accuracy can be verified by the mean, the standard deviation or the RMSE. On the other hand, if the data are independent and the distribution function is unknown, or if it is known as non-normal, the central limit theorem (CLT) can be applied (Santos, 2015).

Otherwise, if we have free distribution, the Chebyshev’s theorem could be applicable as it can accept any shape of distribution and is valid for a “$K$” factor (multiplier of standard deviation) greater than 1, where at least $(1−1/k^2)$ of the data values are positioned within of the limits of “$k$” times the standard deviation in relation to the arithmetic mean (Mann, 2008). This theorem allows estimating if the points are within a range for a free distribution. For example, for a threshold of twice ($k$ value) the standard deviation is assumed that at least 75% of the data positioned within this range, while in the normal distribution, it is assumed that 95% of the data would be in that range.

### Randomness tests

The most used test to verify the randomness is the “Runs Test”, representing a series with one or more consecutive occurrences of the same result in which, there are only two results (Atkinson, 2005; Mann, 2008; Torman et al., 2012). For this analysis, the previous hypothesis is declared as follows:

- $H_0$: the discrepancies are randomly distributed.
- $H_1$: the discrepancies are not randomly distributed.

To perform this test, the median is used as a parameter as below:

- $H_0$: discrepancy $\geq$ median.
- $H_1$: discrepancy $<$ median.

The discrepancies are separated into two groups: $n_1$ to the positives to $H_0$ and $n_2$ to the answers that follow $H_1$. After that, the number of arrangements designated by $R$ is counted as each event of a chain of “yes” or “no” (e.g. YYNNYNYY, $R=5$). Therefore, $R$ represents a statistic with its own sample distribution, where its critical values are determined in two ways:

### Table 1. Error elements considered in the calculated global expected error.

| Error element          | Description                                                                 |
|------------------------|-----------------------------------------------------------------------------|
| $\sigma_{ GNSS \_UAV}$ | Mean positioning error of the images in function of the embedded GNSS receptor technology, which will be considered only for the models directly georeferenced. |
| $\sigma_{ sensor }$     | Error in the camera calibration, given by the differences between the initial coordinates of the centre of the image and the coordinates optimized by the camera.                                   |
| $\sigma_{ support }$    | Positioning error of the control points collected in the field; extracted from the post-processing report.                              |
| $\sigma_{ 2D \_support }$ | For the analysis of the horizontal accuracy.                                  |
| $\sigma_{ 3D \_support }$ | Identification error of key points, usually caused by flight characteristics, weak photo overlap and the software performance. It can be reduced by selecting better quality images or using filters, in this case, one must consider the efficiency of filtering anomalous or undesirable points. |
| $\sigma_{ processing }$ | Identification error of the points of support in the image, function of the resolution of the targets. This study adopted a value of 3 times the image spatial resolution. |
| $\sigma_{ image \_support }$ | Interpolation error due to filter failure in discretization of dense cloud layers. Has a stronger influence on the Z component, since not separating points from the terrain of other features, such as trees and buildings, the filtered model of the DSM could be a little different from the DTM. |
| $\sigma_{ checking }$   | Error of identification of the control points in the cartographic product, function of the final spatial resolution of the format of the check elements, whether artificial targets or existing structures. Similarly, to the $\sigma_{ image \_support }$, in this study was adopted the resolution of 3 times the spatial resolution of the orthomosaic. |
For values of $n_1$ and $n_2$ lesser than 15, we use the table of critical values for a two-tailed test equal to 0.05. This table presents two critical values ($c_1$ and $c_2$) in function of $n_1$ and $n_2$. These values represent the limit values to accept the initial hypothesis $H_0$.

For values of $n_1$ and $n_2$ greater than 15, we can use the normal approximation, where the $Z$ value is calculated in function of the mean of $R$, $\mu_R$ and from the standard deviation of $R$ $\sigma_R$, given in Equations (4), (5) and (6).

$$Z = \frac{(R - \mu_R)}{\sigma_R}$$

$$\mu_R = \frac{(2 \cdot n_1 \cdot n_2 / (n_1 + n_2)) + 1}{(n_1 + n_2)^2 / (n_1 + n_2 - 1)^{0.5}}$$

$$\sigma_R = \sqrt{\frac{2 \cdot n_1 \cdot n_2 \cdot (2 \cdot n_1 \cdot n_2 - n_1 - n_2)}{(n_1 + n_2)^2 / (n_1 + n_2 - 1)^{0.5}}}$$

With the $Z$ value and establishing a confidence level (0.01 < $a$ < 0.05), the standardized normal distribution table is searched for the critical $Z$ value, and then a decision is taken accepting or not accepting the null hypothesis.

The median test shows as a result, that at least 50% of the points tested fit into the null hypothesis with a confidence level of 95–99%, according to the established value, attesting the sample randomness.

**Descriptive statistical measures**

After the tests of the previous hypotheses of independence, normality and randomness of the sample discrepancies of $EN$ and $h$, the standard deviation, $\sigma_c$ (Equation 7) and RMSE$_c$ (Equation 8) were calculated.

$$\sigma_c = \left[\frac{1}{(n - 1)} \sum_{i=1}^{in} (e_c - \bar{e}_c)^2\right]^{0.5}$$

$$RMSE_c = \left[\frac{1}{(n)} \sum_{i=1}^{in} e_c^2\right]^{0.5}$$

where $e_c$ = discrepancy in the position $EN$ or in the height $h$; $\bar{e}_c$ = mean discrepancy in the position $EN$ or in the height $h$; $n$ = number of tested points.

Other useful statistics are the mean referring to the average value of a sum of numbers divided by the quantity of values (for the arithmetic mean), the median indicating the most central value in the sample (not easily distorted by outliers), and the CV or the Coefficient of variation that is the standard deviation divided by the mean resulting in a percentage indicating the sample variability in relation to the mean.

**Mann–Whitney’s $U$ test**

The Mann–Whitney’s $U$ test is a non-parametric test correspondent to the Student’s $T$-test applicable to verify how similar are two sample groups based on the median. The null hypothesis premise is that the median of the populations is equal, and the alternative hypothesis is that the medians are different.

In this test, the values from the two samples are joined and sorted in crescent order alongside the ranked position for each value, then the ranked position values are summed for each sample, then in the equation below we calculate the $U$ value for each sample using Equations (9) and (10):

$$U_1 = n_1 n_2 + \frac{n_1 (n_1 + 1)}{2} - R_1$$

$$U_2 = n_1 n_2 + \frac{n_2 (n_2 + 1)}{2} - R_2$$

$$= n_1 n_2 - U_1$$

where $U_1$ and $U_2$ are the calculated $U$ values; $n_1$ and $n_2$ are the number of entries for each sample; $R_1$ and $R_2$ are the sum of the ranked values for each sample. The lesser $U$ value found is compared against the
table of critical $U$ values given according to the confidence level. In this work we used the values found in the models generated ($E$, $N$ and $h$ values) compared with its pair obtained with the ground control points (GCPs) values obtained with the differential RTK-GNSS, using the table for $U$ critical values for a confidence level of 95%.

If the value found in the table of $U$ critical values is smaller than the calculated $U$ value the null hypothesis is accepted and we can affirm that the two samples are similar (Mann, 2008).

**Study case: Unisinos University’s artificial lake**

Following the workflow presented in Figure 2, 83 images were collected in both sensors in a unique flight. Alongside the image acquisition, we performed the collection of 31 GCPs to be used in the statistical evaluation, where six of this points were also used for georeferencing the products obtained from the SfM + MVS method. Figure 5 shows the points extracted as control points used for georeferencing, that were collected using a GNSS RTK marked in the vertical signalling presented in the perimeter of the lake.

**SfM image processing**

The image processing was performed in the Laboratory of Advanced Visualization and Geoinformatics in the Unisinos University. They were imported to the software Pix4Dmapper Pro version 3.1.23 alongside the flight log, position and RGB of the central pixel in the images and the height of the flight ($yaw$, $pitch$, $roll$).

The products obtained in the processing stage are the 2D models (orthomosaic) for the Canon camera (Figure 6) and the Sequoia multispectral sensor (Figure 7), and the 3D models obtained from the Canon camera (Figure 8) and the Sequoia sensor (Figure 9) image processing.

![Figure 5. Control points used for georeferencing and for the statistical analysis.](image-url)
Figure 6. Orthomosaic obtained from the Canon camera.

Figure 7. Orthomosaic from the Sequoia sensor.
Figure 8. DSM obtained from the Cannon camera.

Figure 9. DSM obtained from images from the Sequoia sensor.
Positional accuracy verification

The positional accuracy was performed for EN (circular position) and $h$ for the 31 homologous points identified in the orthomosaic and collected in the field with GNSS Differential RTK. The $E$ and $N$ coordinates were extracted from the orthomosaic using the sample point tool in QGIS 2.8.3 Wien. Likewise, the altitude $h$ was read from the DEM/DSM. Then a table with the position of all points was exported with the "CSV" extension and tabulated along with their counterparts.

Estimating the $\sigma_{\text{priori}}$ error

The perceived error in each stage of the data acquisition, calculated by the Equation (1), in terms of the resultant GSD (~6 cm) and the propagation of the a priori error during the processing of the cartographic products are shown in Table 2.

Verifying the previous hypothesis

The independence of the EN and $h$ discrepancies was verified by geostatistical analysis, as reported in the previous section. The point spacing and the semivariograms of the EN discrepancies are shown in Figure 11 for the data obtained from the Canon camera, where we observed no correlation between the discrepancies and the distances (no dependence), with the discrepancies for $h$ presenting a similar result also for the Sequoia sensor.
Shapiro–Wilk probability distribution function. The $p$-value of the normality test by the Shapiro–Wilk function was below the threshold of 0.05 confirming that the null hypothesis was rejected in all cases; hence, the data used do not have a normal distribution.

The randomness test of the EN discrepancies was performed applying the runs test considering the median as base to the hypothesis of randomness. This hypothesis was accepted for all samples.

Facing the results of the previous analysis we concluded that the discrepancies for EN and $h$ for both sensors (Canon and Sequoia) were independent and random but with the distribution not normal indicating that we must proceed with non-parametric tests.

### Descriptive statistics measures comparison and inference tests

The descriptive statistic measures observed for the orthomosaic and the DSM for both Canon and Sequoia sensors are presented in Table 4.

We analysed three variables considering; the circular error or the 2D positional accuracy for orthomosaic, which indicates torsion in the model; the error in the altimetry for the 3D model; and the 3D positional error in the 3D model regarding the three axes. This table shows better results in general (lower values) for the Sequoia sensor in comparison against the modified Canon camera ($\text{Table 3}$).

As the analysed data does not have a normal distribution, the mean and the standard deviation cannot represent the population, hence, the parametrical test based on the mean are not applicable, instead, we have to use a non-parametric test based on the median like the Chebyshev Theorem and the Mann–Whitney’s $U$ test.

Analysing the data, and how it varies around the mean, we can affirm according to the Chebyshev’s theorem that the data from the Canon camera and the multispectral sensor Sequoia fit in a free distribution of 95% and a $k$ value of 3.16, limiting the distribution $k$ times the standard deviation above and below the mean.

Considering the similarity test, or the Mann–Whitney’s $U$ test, we calculated the $U$ values for the pairs of values obtained from the GCP and values obtained in the 3D model and the orthomosaic ($E$, $N$ and $h$ individually) from both camera/sensors, as
presented in Tables 4 and 5 for a confidence level of 95% and critical $Z$ of 1.96.

For the Mann–Whitney’s U test as explained in the prior section the null hypothesis (or $H_0$) attest that the two sets of data are similar, and the alternative hypothesis is that the two set of data are different, while the test accepts or rejects $H_0$.

As we can observe in Table 4, we cannot reject the null hypothesis only for the $E$ position, as the null hypothesis is rejected for the positions $N$ and $h$, we can infer that the positional data presents significant difference with the data collected with the differential GNSS RTK.

In the opposite, the results for the Sequoia sensor (Table 5) do not reject the null hypothesis implying that the data do not have a significant difference to the data collected in the field also indicating a better result for the Sequoia sensor in comparison to the Canon camera.

### Discussion

According to the statistical tests applied to verify the EN and $h$ positional accuracy, the tests showed that the sample satisfied the requirements of the basic hypothesis of independence and randomness but not for normality forcing us to apply non-parametric tests like the Mann–Whitney’s U test and the Chebyshev’s theorem.

Comparing the two sensors/cameras, we found betters results for the Sequoia sensor in comparison against the Canon Powershot used in this work, as the 2D (orthomosaic) and 3D (DEM/DSM) products had lower standard deviation indicating more precision. Although we found certain individual points with lower discrepancy for the Canon camera (more accuracy), the data obtained from all points varied significantly showing no consistency, reinforced by the Mann–Whitney’s U test.

Also for data generated from both cameras/sensors, we had similar outliers, where we suspect were caused by a shadowed area given by a taller building near these specific control points. In addition, we believe we had valid data, considering the objective of analysing the accuracy of the 2D and 3D models around a water body, due to its reflective and refractive nature making the use of the algorithms during the photogrammetry process difficult.

Comparing similar works (Fonstad et al., 2013; Harwin & Lucieer, 2012; Jaud et al., 2016; Lobnig et al., 2015; Neto et al., 2017; Verhoeven, 2011), we had lower accuracy and precision, however, is not possible to affirm we had worse or better results due differences in methodology and the particular presence of a water body in our work.

Moreover, in order to compare similar works, we reinforce the importance of a common protocol for image capture and UAV flight plan, allowing the direct comparison between.

### Conclusion

The SfM + MVS technique is gaining importance due to its accessibility and feasibility to mapping areas where geometric accuracy is required, although water bodies are excluded for assessment in the majority of works that apply photogrammetry.
Two types of camera/sensors were used in this work: the 16 MP Canon Powershot camera; and the 16 MP multispectral sensor Sequoia embedded in a UAV hex-rotor capturing 83 images each in one flight.

This work aimed to evaluate the accuracy of 2D (orthomosaic) and 3D models using GCPs obtained in the margin of an artificial lake. The photogrammetry community less explores the presence of a water body, and we found considerable results in accuracy and precision for both cameras/sensors, with the multispectral Sequoia sensor showing better results than our modified Canon camera.

Due the nature of the overall data studied, alongside the descriptive statistics we applied non-parametric tests that consider free distribution, as the Mann–Whitney’s U test to compare the similarities between the GCP data and the data obtained from the models, and Chebyshev’s theorem to affirm that 95% of our data fit between 3.16 times of the standard deviation.

With the results found in this work and its statistical validation, we consider that we had relevant results analysing the data obtained from GCP’s around a water body, allowing the community to make similar comparisons in the future.

Disclosure statement
No potential conflict of interest was reported by the authors.

ORCID
Ademir Marques Junior  http://orcid.org/0000-0003-4739-7394

References
Ariza, F.J., & Atkinson, A.D. (2008). Analysis of some positional accuracy assessment methodologies. Journal of Surveying Engineering, 45–54. doi:10.1061/(ASCE)0733-9453(2008)134:2(45)
ASPRS. (2015). Positional accuracy standards for digital geospatial data. Photogrammetric Engineering & Remote Sensing, 81, 3.
Atkinson, A.D. (2005). Control de Calidad Posicional en Cartografía: Análisis dos Principales Estandares y propuesta de mejora. (Doctoral Thesis). Universidad de Jaen.
Brazil. (1984). Normas Técnicas da Cartografia Nacional. Decreto Nº 89.817 de 20 de junho de 1984. Rio de Janeiro: Fundação Instituto Brasileiro de Geográfica e Estatística.
Bustos, O. (1981). Estimación Robusta no Modelo de Posición. Rio de Janeiro: Instituto de Matemática Pura e Aplicada.
Debevec, P.C., Taylor, C., & Malik, J. (1990). Modeling and rendering architecture from department of defense. (M. S. 60001., Ed.) Mapping, charting and geodesy accuracy. 136 327–330.
Federal Geographic Data Committee. (1998). Geospatial positioning accuracy standards part 3: National standard for spatial data accuracy. Reston, VA: Subcommittee for Base Cartographic Data.
Fonstad, M.A., Dietrich, J.T., Couvillie, B.C., Jensen, J.L., & Carbonneau, P.E. (2013). Topographic structure from motion: A new development in photogrammetric measurement. Earth Surface Processes and Landforms, 38(4), 421–430. doi:10.1002/esp.3366
Furukawa, Y., & Curless, B.S. (2010). Towards Internet-scale multi view stereo. In Computer Vision and Pattern Recognition (CVPR) (pp. 1434–1441). San Francisco, CA: IEEE.
Harwin, S., & Luciere, A. (2012). Assessing the accuracy of georeferenced point clouds produced via multi-view stereopsis from Unmanned Aerial Vehicle (UAV) imagery. Remote Sensing, 4(6), 1573–1599. doi:10.3390/rs4061573
Jaud, M., Passot, S., Le Bivic, R., Delacourt, C., Grandjean, P., & Le Dantec, N. (2016). Assessing the accuracy of high resolution digital surface models computed by photoscan’ and MicMac’ in sub-optimal survey conditions. Remote Sensing, 8(6), 465. doi:10.3390/rs8060465
Joaquim Höhle, M.H. (2009). Accuracy assessment of digital elevation models by means of robust statistical methods. ISPRS Journal of Photogrammetry and Remote Sensing, 64, 398–406. doi:10.1016/j.isprsjprs.2009.02.003
Kraus, K. (2004). Photogrammetrie (Vol. 1). Berlin: Walter de Gruyter.
Laliberte, A.S., Herrick, J.E., Rango, E., & Winters, C. (2010). Acquisition, orthorectification, and object-based classification of Unmanned Aerial Vehicle (UAV) imagery for range-land monitoring. Photogrammetric Engineering & Remote Sensing, 76(6), 661–672. doi:10.14358/PERS.76.6.661
Lerma, J.L. (2002). Fotogrametría Moderna: Analítica y Digital. Valencia: Universitat Politècnica de València.
Lobnig, K., Tscharf, A., & Mayer, G. (2015). Einfluss der Georeferenzierung auf die absolute Rekonstruktionsgenauigkeit der photogrammetrischen UAV-gestützten Tagebauvernmessung. (influence of geo-referencing on the absolute accuracy of UAV-based photogrammetric reconstructions in open pit surveying). BHM Berg-und Hüttenmännische Monatshefte, 160(8), 373–378. doi:10.1007/s00501-015-0388-8
Mann, P.S. (2008). Introdução a Estatística (5 ed.). Translated Rio de Janeiro: LTC.
Neto, F., Gripp, F.D., Jr, Botelho, J., Santos, M.F., Nascimento, A.D., & Fonseca, A.L. (2017). Assessment of positional quality in spatial data generated by VANT using point and linear feature for cadastre applications. Boletim de Ciências Geodésicas, 23(1), 134–149.
Oliveira, M. (2002). Age-based modeling and rendering techniques: a survey. Rita, LX(2), 37–66.
Preciado, A.D. (2000). Investigación sobre los Metodos de Estimacion Robusta aplicados a problemas fundamentales de la Fotogrametria. (Doctoral Thesis). Universidad de Cantabria.
Remondino, F.B., Scioni, M., & Sarazzi, D. (2011). UAV photogrammetry for mapping and 3D modeling – current status and future perspectives. ISPRS ICWG IV UAV-g (unmanned aerial vehicle in geomatics) conference. Zurich, Switzerland.
Santos, A.D., Medeiros, N.D., Santos, G.R., & Lisboa Filho, J. (2017). Use of geostatistics on absolute positional accuracy assessment of geospatial data. Boletim de Ciências Geodésicas, 23(3), 405–418. doi:10.1590/s1982-21702017000300027

Santos, P.A. (2015). Controle de qualidade cartográfica: metodologias para avaliação da acurácia posicional em dados espaciais. Doctoral Thesis, Viçosa, Minas Gerais, Brazil: Universidade Federal de Viçosa.

Smith, M., Carrivick, J., & Quincey, D. (2016). Structure from motion in physical geography. Progress in Physical Geography, 40, 247–275. doi:10.1177/0309133315615805

Snavely, N., Seitz, S., & Szeliski, R. (2008). Modelling the world from Internet photo collections. International Journal of Computer Vision, 80, 189–210. doi:10.1007/s11263-007-0107-3

Soares, A. (2000). Geoestatística para as Ciências da Terra e do Ambiente. Lisboa: Instituto Superior Técnico.

Torman, V.B., Coster, R., & Roboldil, J. (2012). Normalidade de variáveis: Métodos de verificação e comparação de alguns testes não-paramétricos por simulação. Revista HCPA, 32(2), 227–234.

Turner, D., Lucieer, A., & Christopher Watson, C. (2012). An automated technique for generating georectified mosaics from ultra-high resolution Unmanned Aerial Vehicle (UAV) Imagery, based on Structure from Motion (SfM) point clouds. Remote Sensing, 4(5), 1392–1410. doi:10.3390/rs4051392

Verhoeven, G. (2011). Taking computer vision aloft – archaeological three dimensional reconstructions from aerial photographs with PhotoScan. Archaeological Prospection, 18(1), 67–73. doi:10.1002/arp.v18.1

Yamamoto, J.K., & Landim, P.M. (2013). Geoestatística: Conceitos e Aplicações. São Paulo: Oficina de Textos.