Abstract

Sand dunes are commonly regarded as a challenge to traditional photogrammetry due their homogeneous texture and spectral response. In this work we present an evaluation of Structure from Motion–Multi View Stereo (SfM-MVS) to obtain high-resolution elevation data of coastal sand dunes based on images acquired by Remotely Piloted Aircraft (RPA). A Digital Elevation Model (DEM) of a dunefield in Southern Brazil was generated from 810 photos captured by an RPA at 100 m above the takeoff point in February 2019. Image matching was successful in all areas of the survey due the presence of superficial features (footprints and sandboard tracks) and visibility of the sedimentary stratification, highlighted by heavy minerals. Altimetric accuracy of the SfM-MVS DEM was validated by comparison with Terrestrial LiDAR (TLS) data collected during the same fieldwork campaign of the RPA flights. The SfM-MVS DEM was then compared to an Airborne LiDAR (ALS) DEM from October 2010. While the SfM-MVS and TLS DEMs are very similar, without any major difference in elevation or in the reconstruction of topographic features, the SfM-MVS DEM presents a small scale surface roughness not visible in the TLS DEM. The Feature Preserving DEM Smoothing (FPD) algorithm was applied to the SfM-MVS DEM with good results in terms of surface smoothing, but without any significant changes in descriptive statistics and error metrics, with an RMSE of 0.08 m and MAE of 0.06 m for both the original and the FPD-filtered DEM.

Displacement of dune crest lines from the ALS and SfM-MVS DEMs resulted in a migration rate of ≈5 m/year between 2010 and 2019, in good agreement with rates derived from satellite images and historical aerial photographs of the same area. Sand volume change in the same period showed a decrease of only 0.2%, which can be related to the installation of sand fences to promote dune stabilization and sand removal from the front of the dune field to keep a road open to vehicles. ALS can cover large areas in little time but its high cost still remains a barrier to wider usage, especially by researchers in developing countries. TLS has an intermediate cost but demands more fieldwork and more processing time. In our case we needed three days for the TLS survey and around three weeks to produce a DEM of ≈80 400m². On the other hand, we were able to cover
with six flight missions in under three hours, with \(\approx 13\) hours processing time in a medium-range workstation. This makes SfM-MVS a low-cost solution with fast and reliable results for 3D modelling and continuous monitoring of coastal dunes.

**Keywords:** Geomorphometry, Photogrammetry, Digital Elevation Model, Point Cloud, RPA

## 1. Introduction

Aeolian dune fields occur in diverse depositional settings, on Earth and on other planetary bodies such as Mars, Venus, Saturn’s moon Titan and Pluto (Fryberger and Dean, 1979; Short, 1988; Wang et al., 2002; Livingstone et al., 2007; Hayward et al., 2007; Radebaugh et al., 2008; Bourke et al., 2010; Martinho et al., 2010; Kreslavsky and Bondarenko, 2017; Hayes, 2018; Telfer et al., 2018). To better understand these dynamic environments, repeated topographic surveys of the landscape are needed (Conlin et al., 2018). As the sand supply of dune fields is sensitive to patterns of wind and rainfall, changes in dune field volume and morphology can be related to climate change (Gaylord et al., 2001; Clemmensen et al., 2007; Sawakuchi et al., 2008; Tsora et al., 2009; Singhvi et al., 2010; Levin, 2011; Grohmann and Sawakuchi, 2013; Hoover et al., 2018).

Migration rates of aeolian dunes have been determined with aerial photographs (e.g., Finkel, 1961), orbital imagery (Shrestha et al., 2005; Potts et al., 2008; Hugenholtz and Barchyn, 2010; Dong, 2015; Mendes and Giannini, 2015; Mendes et al., 2015; Bhadra et al., 2019) or Digital Elevation Models (DEMs\(^1\)) (e.g., Mitasova et al., 2005b).

With the growth of Geomorphometry as the practice of terrain modelling and ground-surface quantification (Pike, 1995; Pike et al., 2009; Hengl and Reuter, 2008), DEMs have become essential tools in landform analysis, as they allow speed, precision and reproducibility to calculation of geomorphometric parameters (Grohmann, 2004).

DEMs of aeolian dunes can be constructed by several methods such as traditional field techniques (levelling, Total Station) (Labuz, 2016), interpolation of contour lines (Judge et al., 2000; Mitasova et al., 2005b), Differential or Real-time kinematic (RTK) GPS points (Mitasova et al., 2005b; Pardo-Pascual et al., 2005), LiDAR (Light Detection and Ranging) surveys, either airborne (ALS - Airborne Laser Scanner) (Mitasova et al., 2004, 2005a,b; Vianna and Calliari, 2015; Baughman et al., 2018), terrestrial (TLS - Terrestrial Laser Scanner) (Montreuil et al., 2013; Feagin et al., 2014; Fabbri et al., 2017; Sankey et al., 2018b; Bañón et al., 2019; Kasprak et al., 2019; Lee et al., 2019) or mounted on Remotely Piloted Aircrafts (RPAs) (Solazzo et al., 2018; Garcin et al., 2019), and Structure from Motion–Multi View Stereo (SfM-MVS) using images collected by handheld cameras, mounted on poles, kites or RPAs (Mancini et al., 2013; Gonçalves and Henriques, 2015; Conlin et al., 2018; Duffy et al., 2018; Forlani et al., 2018; Seymour et al., 2018; Solazzo et al., 2018).

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\(^{1}\)In this work we use Digital Elevation Model (DEM) in a loose sense to refer to any 3D representation of the land surface, not making a distinction between Digital Terrain Model (DTM) representing the true (bare) ground surface, or Digital Surface Model (DSM) representing a surface that does not necessarily coincide with the ground and may depict man-made structures or vegetation canopy.

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A literature review on RPA-based topographic surveys of coastal areas is presented by Casella et al. (2020).

In this work we present an evaluation of SfM-MVS to obtain high-resolution elevation data of coastal sand dunes. Altimetric accuracy of the SfM-MVS DEM was validated by comparison with TLS data collected during the same fieldwork campaign of the RPA flights (February 2019). The SfM-MVS DEM was then compared to an ALS DEM from October 2010. The results show almost no change in total volume and a migration rate of \( \approx 5 \text{ m/year} \), compatible with those derived from aerial and orbital imagery.

While 3D modelling of aeolian sand dunes can be a challenge to traditional photogrammetry due to their homogeneous texture and spectral response, the use of SfM-MVS is recommended and the factors that contributed to a successful reconstruction are discussed.

1.1. Study area

The study area, located in Santa Catarina State, southern Brazil (Fig. 1A-B), comprises barrier-lagoon depositional systems with associated dune fields (Angulo et al., 2006; Giannini et al., 2007) which evolved during the Late Holocene as a result of wind strength intensification and sand supply increase in southern Brazilian coast (Mendes and Giannini, 2015; Mendes et al., 2015). The Garopaba (or Siriú) dune field is composed of unvegetated and vegetated aeolian dunes. The unvegetated dunes are represented by mostly barchanoid chains, while the vegetated ones include parabolic dunes, blowouts and foredunes (Martinho et al., 2006; Hesp et al., 2007).

There are significant differences of wind field along the southern Brazilian coast; while the dominant and prevailing direction is from the S at Joaquina (located \( \approx 45 \text{ km} \) north of Garopaba in Santa Catarina Island), it is from the NE at Farol de Santa Marta, \( \approx 70 \text{ km} \) south of the study area (Dillenburg et al., 2006; Hesp et al., 2007; Truccolo, 2011; Mendes and Giannini, 2015). At Garopaba, winds from the North are responsible for dune migration (Mendes and Giannini, 2015; Mendes et al., 2015).

2. Methods

This section presents the datasets, methods and tools used in this study. A flowchart of the analysis steps is in the Supplemental Material. Table 1 shows, for each kind of data used in this paper (ALS, SfM-MVS, TLS), area of the interpolated DEM, number of points and density of points within that area.

2.1. Airborne LiDAR

Airborne LiDAR (ALS) data were collected on October 2010 by Geoid Laser Mapping Co. using an Optech ALTM 3100 sensor with a saw-tooth scanning pattern, density of about one point per 0.5 m\(^2\), measured from an altitude of \( \approx 200 \text{ m} \) (\( \approx 4000 \text{ ft} \)). Raw LiDAR data (with up to four laser pulses) were processed by Geoid and delivered with vertical accuracy of 0.15 m (1\( \sigma \)) and horizontal accuracy of 0.5 m (1\( \sigma \)).

ALS data (LiDAR 1\(^{st}\) returns) were imported into GRASS-GIS (Neteler et al., 2012) as vector points and interpolated with bilinear splines (Brovelli and Cannata, 2004; Brovelli et al., 2004) to create a DEM with 0.5 m spatial resolution (Fig. 1C).
2.2. Fieldwork and Ground Control Points

Fieldwork for TLS and SfM-MVS surveys was conducted on February 2019. Six targets were deployed within the dune field area (Fig. 2B) and their coordinates were determined by Differential Global Positioning System (DGPS), to serve as Ground Control Points (GCPs) for georeferencing the SfM-MVS outputs and the TLS point cloud (Harwin et al., 2015).

Each target measured ≈80x60 cm in a black and white chequered pattern and was clearly visible in the photos (Fig. 2C). A Spectra Precision SP60 DGPS was used in a base-rover static configuration and raw data was post-processed in Survey Office® 4.10 software, using the Imbituba Station of the Brazilian GPS Network as reference. The processing reports are available in the Supplemental Material.

2.3. Terrestrial LiDAR

Terrestrial LiDAR (TLS) data were collected with a FARO™ Laser Scanner Focus3D S120, a geodetic laser scanner with distance measurement based on phase shift of infrared light (905 nm), maximum range of 120 m, and ranging error of ±2 mm at 10 m distance at 90% reflectivity (FARO Technologies Inc., 2013). The scanner was set at resolution of “1/5” and quality of “3x”, resulting in a point spacing of 7.67 mm at a distance of 10 m, scan time of two minutes and 28.4 million points per scan (this model does not acquire images). Five spherical targets provided with the equipment were arranged on the ground at ≈10 m from the TLS and re-positioned in a ‘leapfrog’
Table 1: Overview of datasets used in this study. See text for details and Supplemental Material for maps of point density.

| Data                | DEM Area (m²) | # points | points/m² |
|---------------------|---------------|----------|-----------|
| ALS (full)          | 4 434 722     | 11 574 555 | 2.6       |
| ALS (SfM area, 1st returns) | 740 922     | 2 380 005  | 3.2       |
| SfM-MVS (full)      | 740 922       | 344 769 434 | 465.3     |
| SfM-MVS (thin 125th pt) | 740 922    | 2 378 399  | 3.2       |
| SfM-MVS (TLS area)  | 80 413        | 28 158 102 | 350.1     |
| SfM-MVS (thin 10 cm grid) | 80 413     | 8 079 569  | 100.5     |
| TLS (full)          | 80 413        | 80 413 708 | 14 770.1  |
| TLS (2 cm filter)   | 80 413        | 20 041 799 | 2 115.8   |
| TLS (10 cm grid)    | 80 413        | 7 039 501 | 87.5      |

Figure 2: A) Flight missions executed over the dune field; B) Ground Control Points used to georeference the SfM-MVS outputs and TLS data; C) Target (GCP 01), sedimentary structures and superficial features seen in the RPA photo.

scheme during the survey, so that each consecutive scan was able to capture at least two spheres from the previous one. In three days of field work, 110 scans were collected, covering an area of ≈80 400 m² (Fig. 1D).

TLS data were processed in FARO Scene 7.1². Each scan was registered to its adjacent ones manually using the spherical targets as references. Georeferencing of the point cloud was based on two DGPS points located at the extremities of the surveyed area (Fig. 2B). Referencing with only two points was possible because this TLS model has an integrated dual axis compensator to automatically level the captured scan data, so the control points were used for an affine transformation (translation/scale/rotation) in 2D space.
To overcome the heterogeneous distribution of data common to terrestrial LiDAR, with a very high density of points near the scanner, the full point cloud was subsampled in FARO Scene with a minimum distance filter of 2 cm between points. To eliminate duplicate points and compensate for small differences in the alignment of individual scans, this point cloud was gridded to a raster in GRASS-GIS using the mean elevation value of LiDAR points within 10 cm cells (\texttt{r.in.xyz} module). To fill empty (null) cells, the raster was converted to vector and a DEM with 10 cm spatial resolution was created by interpolation with bilinear splines (Fig. 4A).

2.4. SfM-MVS

Images for the SfM-MVS reconstruction were acquired by a DJI Phantom 4 Pro RPA. The aircraft digital camera has a 1" CMOS 20MP sensor, global shutter, 84° FOV and 8.8 mm focal distance (24 mm at 35 mm equivalent). Images can be saved as JPEG or RAW, 5472×3648 px (3:2 ratio). Flight missions were planned and executed using the MapPilot app\(^3\) with height above takeoff point of 100 m (image footprint 150×100 m, pixel size \(\approx\) 2.7 cm) and 75% overlap along and across-track.

Six missions were flown, covering an area of \(\approx\) 869 000 m\(^2\) with 810 images. The camera angle was set to \(-80°\) (i.e., 10° from nadir). Figure 2A shows flight paths and starting time for each mission (UTC-3). Weather conditions during fieldwork were of dark skies with light rains scattered throughout the day.

The SfM-MVS workflow (e.g., Westoby et al., 2012; Viana et al., 2018; James et al., 2019) was processed in Agisoft Metashape Pro version 1.5.1\(^4\). In the SfM step, images were aligned with ‘High’ accuracy. To avoid doming effects in the reconstructed surface (e.g., James and Robson, 2014), camera alignment optimization was performed considering a marker accuracy of 0.005 m, following Agisoft’s recommendations\(^5\). The MVS reconstruction was set to ‘High’ quality and ‘aggressive’ depth filtering. The processing report is available in the Supplemental Material.

For the altimetric comparison with TLS data, the full SfM-MVS point cloud was imported into GRASS-GIS in the same manner of the TLS data: gridded by the mean elevation in 10 cm cells, converted to vector and interpolated with bilinear splines to a DEM with 10 cm resolution (Fig. 4B).

For the dune migration and volume analysis, the full SfM-MVS point cloud was subsampled (thinned) with LAStools (Isenburg, 2019) by extracting every 125\(^{th}\) point, imported into GRASS-GIS as vector points and interpolated with bilinear splines to a DEM with 0.5 m resolution (Fig. 1D). The thinning value was determined after experimentation, and the goal was to obtain a similar number of points, within the interpolation area, for the ALS and SfM point clouds (Table 1).

2.4.1. Accuracy of SfM-MVS DEM

The vertical accuracy of a DEM can be computed from the differences between the dataset being analyzed and co-located values from an independent source of higher accuracy (Willmott and Matsuura, 2005; Wechsler, 2007; Hebeler and Purves, 2009; Reuter et al., 2009; Baade and Schmullius, 2016). To evaluate the accuracy of the SfM-MVS reconstruction, the TLS DEM was considered as the reference.

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are metrics that been widely used in the Geosciences to measure the accuracy of DEMs (e.g., Nikolakopoulos et al., 2006; Willmott and Matsuura, 2006; Smith and Vericat, 2015; Gesch et al., 2016; Satge et al., 2016; Grohmann and Sawakuchi, 2013; Grohmann, 2018). MAE (Eq. 1) and RMSE (Eq. 2) were
calculated from all pixels within a mask designed to avoid areas with vegetation or without TLS data.

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} (|z_{TLS} - z_{SfM}|) \] (1)

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( (z_{TLS} - z_{SfM})^2 \right)} \] (2)

2.4.2. Surface roughness and DEM smoothing

Surface roughness characterizes elevation variations over a particular scale (Grohmann et al., 2010; Berti et al., 2013; Grohmann and Hargitai, 2014; Smith, 2014). In this paper surface roughness was calculated as the standard deviation of slope in a moving-window filter, as it provide good results in identifying terrain features and is not sensitive to spurious data (Grohmann et al., 2010).

Low-pass filters are usually applied to DEMs to remove or reduce roughness (Reuter et al., 2009; Gallant, 2011; Lindsay et al., 2019), but sharp edges such as dune crests will be modified as well (Barash, 2002; Grohmann and Riccomini, 2009). To retain the sharpness of breaks-of-slope in the filtered DEM edge-preserving (or de-noise) procedures (e.g., Sun et al., 2007; Stevenson et al., 2010; Lindsay et al., 2019) must be employed.

The effect of de-noising the SfM-MVS DEM was evaluated by applying the Feature Preserving DEM Smoothing (FPD) algorithm (Lindsay et al., 2019), with different parameter settings, to a sub-area of the DEM (Fig. 5) and evaluating the change of RMSE from the TLS DEM and of Circular Variance of Aspect (CVA – Lindsay et al., 2019) for each set of parameters. CVA measures the variability of aspect, or surface shape complexity, within a neighborhood; its value is 0.0 in smooth areas approaching 1.0 in areas of complex topography (i.e., high surface roughness). The three parameters to be set in the FPD method are the filter kernel size \((k)\), the normal difference threshold angle \((t)\), and the number of elevation-update iterations \((i)\) (for a detailed explanation of the algorithm and parameters’ definitions, see Lindsay et al., 2019).

The tests were done by changing one parameter while keeping the other two fixed, and then calculating CVA for each DEM with filter sizes of \(3 \times 3\) up to \(41 \times 41\) pixels.

In the first experiment, \(t\) ranged from \(5^\circ\) to \(45^\circ\) (in \(5^\circ\) increments) with \(k = 15\) and \(i = 5\). Next, \(k\) changed from \(5 \times 5\) up to \(51 \times 51\) with \(t = 20^\circ\) and \(i = 5\). Last, \(i\) varied between 3 and 30 iterations with \(k = 15\) and \(t = 20^\circ\).

After the sub-area tests, \(k\), \(t\) and \(i\) values were selected and FPD was applied to the entire SfM-MVS DEM. Error metrics (RMSE, MAE) of the original and smoothed SfM-MVS DEM were calculated considering the TLS DEM as reference.

2.5. Dune Migration and Sand volume

Dune migration can be evaluated from multi-temporal data such as aerial photographs (Finkel, 1961; Stafford and Langfelder, 1971; Mendes and Giannini, 2015; Baughman et al., 2018), satellite images (Hoover et al., 2018; Dong, 2015; Yang et al., 2019) or LiDAR DEMs (Mitasova et al., 2004, 2005a,b; Baughman et al., 2018). Dune migration between the 2010 (ALS) and 2019 (SfM-MVS) surveys was determined as the displacement of dune crest lines.

For each survey, surface roughness of the DEM was calculated as the standard deviation of slope (Grohmann et al., 2010) in a \(5 \times 5\) pixels neighbourhood (\(2.5 \times 2.5\) m); crest lines were drawn in QGIS version 3.8 (QGIS Development Team, 2019) following the high-roughness crests (see
Supplemental Material); lines connecting the crests were drawn approximately parallel to the S-SW migration direction (Hesp et al., 2007; Mendes and Giannini, 2015) (Fig. 3) and saved in shapefile format. Azimuth and length of each displacement line were calculated with Python version 3.7.4 (Python Software Foundation, 2019) using the ogr module of the GDAL library (GDAL Development Team, 2019) to access vector geometries. Mean azimuth was calculated according to Fisher (1993).

Sand volume was calculated with the GRASS-GIS r.volume module (Hinthorne, 1988). This module calculates volume by summing cell values within a given area and then multiplying by the area occupied by those cells. An elevation of 0 m (zero) was used as a reference base level.

Figure 3: Determination of dune migration between 2010 and 2019 surveys. A) dune crests of 2010, over shaded relief image of ALS DEM; B) dune crests of 2019, over shaded relief image of SfM-MVS DEM; C) displacement lines (grey) connecting crest lines.

2.6. Data Analysis

In order to streamline the process and ensure reproducibility (Barnes, 2010), data analysis was performed in GRASS-GIS version 7.6 (Neteler et al., 2012; GRASS Development Team, 2019) through Jupyter notebooks (Kluyver et al., 2016; Rule et al., 2018) using the Pygrass library (Zambelli et al., 2013) to access GRASS’ datasets. The FPD algorithm is implemented in the open-source geospatial analysis platform WhiteboxTools (Lindsay, 2017). Statistical analyses were performed with the Python libraries Rasterio, Scipy, Numpy, Pandas, Seaborn and Matplotlib (Oliphant, 2006; Hunter, 2007; McKinney, 2011; Gillies et al., 2013–; The SciPy community, 2013; Waskom et al., 2016).
3. Results

3.1. TLS and SfM-MVS

The SfM-MVS survey resulted in data with 2.77 cm resolution (1.1 px reprojection error) and RMSE of 0.7 cm in longitude and 0.4 cm in latitude, and 0.5 cm in elevation for the residuals of control points (see Supplemental Material). The TLS point clouds were combined into a single dataset with a registration error of 4.9 mm.

The DEMs produced from the TLS and SfM-MVS data are presented in Fig. 4. The surfaces are very similar, without any major difference in elevation or in the reconstruction of topographic features. Upon a closer inspection, the SfM-MVS DEM presents a small scale surface roughness not visible in the TLS DEM. To visually evaluate this difference, surface roughness of the DEMs was calculated as the standard deviation of slope in a 5x5 pixels neighbourhood (0.5×0.5 m).

The TLS DEM has a smooth surface, with higher roughness values on vegetated areas and over some of the places where the TLS equipment was positioned (Fig. 5A). These spots can be related to a small mismatch between adjacent scans, where in one there is no data (under the scanner), so the gridding procedure cannot compensate the difference and the result is a small circular patch of the terrain slightly above or below its surroundings. Dune crests are well marked by above-average roughness. Footprints and track marks are also visible, with lower roughness values.

The SfM-MVS DEM shows a widespread distribution of low and average roughness values (Fig. 5B). While the dune crests can be identified, track marks are no longer visible and the patch of vegetation near the sandboard tracks cannot be discriminated based on its roughness. A set of footprints seen in the central-eastern portion of the TLS roughness map is not visible in the SfM-MVS roughness because the SfM-MVS survey was carried out before the TLS survey could cover that area. We see this roughness as a noise inherent to the SfM process due to small errors in geolocation as well as to the consumer-grade quality of the photographic camera (Mosbrucker et al., 2016).

Applying the FPD algorithm to a sub-area of the SfM-MVS DEM shows the RMSE between the smoothed DEM and the TLS DEM decreasing with larger FPD kernel sizes and higher angular threshold values, but increasing with the number of interactions (Fig. 5C). Considering these results, we applied FPD to the SfM-MVS DEM with \( k = 17 \times 17, t = 20^\circ \) and \( i = 5 \) (Fig. 5D). An evaluation of Circular Variance of Aspect for each parameter leads to similar conclusions, and is presented in the Supplemental Material.

The vertical accuracy of the SfM-MVS DEM, calculated for all pixels within the mask shown in Fig. 6A resulted in RMSE of 0.08 m and MAE of 0.06 m for both the original and the FPD-filtered DEM.

Descriptive statistics of the TLS and SfM-MVS DEMs are very similar (Table 2). Considering all pixels of the DEMs, elevation differences range from -1.5 m to +0.5 m, with mean of 0.0 m and standard deviation of 0.08 m; with a random sample of 2 000 pixels, elevation differences range from -0.3 m to +0.5 m, with mean of 0.0 m and standard deviation of 0.08 m, The negative differences below -0.5 m can be disregarded as they represent a small fraction of the total (312 pixels out of \( \approx 4.8 \times 10^6 \) pixels).

A scatterplot of elevations (2 000 pixels, TLS × SfM-MVS, Fig. 6B) shows minimal dispersion of points, with an \( R^2 \) of 0.999 (see Supplemental Material). The histogram of differences (Fig. 6C) has a bimodal distribution, with \( \approx 55\% \) of the values below zero, indicating that, in general, the SfM-MVS DEM has higher elevations than the TLS DEM, and the boxplot of differences (Fig. 6D) shows 106 points classified as outliers (values beyond \( \pm 0.17 \) m).
Figure 4: A) TLS DEM; B) SfM-MVS DEM. Elevation colour scale is the same for A and B. Shaded relief illumination: N25°, 30° above horizon.

3.2. ALS and SfM-MVS

Besides a good correlation to the TLS DEM, the full SfM-MVS DEM (Fig. 7B) shows a good fit with elements of the landscape that didn’t experienced significant change between the surveys, such as the road bordering the dune field to west and southwest (in grey in Fig. 7C, indicating no elevation difference).

Comparison of the 2010 ALS and 2019 SfM-MVS DEMs was carried out based on: 1) descriptive
statistics of the DEMs; 2) differences between the DEMs; 3) sand volume within an area and 4) displacement of dune crests.

Differences between the DEMs were calculated by subtracting the elevations of the ALS DcrestEM from the SfM-MVS DEM. Positive values represent areas where the SfM surface has higher elevations than the ALS one, and vice-versa.

The ALS and SfM-MVS DEMs (0.5 m resolution) and the differences between the two surfaces, are presented in Fig. 7. In the studied area, dunes are mainly barchanoids with lee side towards south west. Elevation reaches its highest (∼58 m) in the southern portion, likely due the influence of an underlying palaeotopography (Giannini et al., 2007).

Descriptive statistics are presented in Table 3 and histograms of elevation values in Fig. 8. The

Table 2: Descriptive statistics of the TLS, SfM-MVS DEMs and of differences. Elevation units in metres (m).

|               | min  | max  | mean | median | std.dev | skewness | kurtosis | 25%quant | 75%quant |
|---------------|------|------|------|--------|---------|----------|----------|-----------|-----------|
| **all pixels**|      |      |      |        |         |          |          |           |           |
| TLS           | 8.490| 36.172| 23.937| 24.753 | 6.519   | -0.277 | -0.750 | 18.708    | 28.712    |
| SfM-MVS       | 8.440| 36.153| 23.938| 24.774 | 6.531   | -0.283 | -0.754 | 18.691    | 28.713    |
| SfM-MVS FPD   | 8.445| 36.152| 23.938| 24.774 | 6.532   | -0.283 | -0.754 | 18.691    | 28.713    |
| Diff. FPD TLS | -1.510| 0.509| 0.001| -0.008| 0.085 | -0.701 | 4.801 | -0.045 | 0.046     |
| **2 000 pixels** |      |      |      |        |         |          |          |           |           |
| TLS           | 8.526| 36.023| 23.938| 24.774 | 6.531   | -0.283 | -0.754 | 18.691    | 28.713    |
| SfM-MVS       | 8.483| 35.990| 23.938| 24.830 | 6.468   | -0.281 | -0.730 | 18.822    | 28.654    |
| SfM-MVS FPD   | 8.477| 35.969| 24.010| 24.826 | 6.468   | -0.281 | -0.729 | 18.924    | 28.654    |
| Diff. FPD TLS | -0.344| 0.429| -0.004| -0.012| 0.084 | 0.344 | 3.186 | -0.048 | 0.041     |
DEM of differences between 2019 and 2010 DEMs is in Fig. 7C; positive values are in red and negative values in blue. Topographic profiles (location in Fig. 7B) are in Fig. 9.

The DEMs have similar values of maximum, standard deviation, skewness, kurtosis and quantiles. The SfM-MVS DEM shows slightly higher mean and minimum values. Elevation differences between the DEMs range from -16.95 m to +23.15 m, with mean and median of ≈0.0 m. Some notable differences are indicated as #1, #2 and #3 in Fig. 7C: #1 marks the highest positive difference (where the SfM-MVS surface is above the ALS), related to the migration of a large ‘central dune’ with accumulation of sand towards a vegetated ridge in #2; #3 shows the migration of the dune field over the road. In this place, the town hall needs to remove the sand periodically to keep
Table 3: Descriptive statistics of the ALS, SfM-MVS DEMs and of differences between the two surfaces.

|       | min   | max   | mean  | median | std.dev | skewness | kurtosis | 25%quant | 75%quant |
|-------|-------|-------|-------|--------|---------|----------|----------|----------|----------|
| ALS   | 2.69  | 58.88 | 21.34 | 20.65  | 11.59   | 0.51     | -0.41    | 11.64    | 28.77    |
| SfM-MVS| 2.89  | 58.63 | 21.64 | 20.67  | 11.66   | 0.45     | -0.57    | 11.63    | 29.40    |
| Diff  | -16.95| 23.15 | 0.31  | 0.39   | 3.48    | 0.16     | 2.77     | -1.26    | 1.80     |

The polygon for volume calculation encloses only unvegetated areas in both surveys (see Fig. 7A). Using the ALS and SfM DEMs with 0.5 m resolution, the calculated sand volumes were 9 035 115.45 m$^3$ for 2010 and 9 010 844.95 m$^3$ for 2019 (a decrease of 24 270.50 m$^3$ or 0.2%).

Dune crest displacement lines drawn over the DEMs (see Fig. 3) yielded a mean azimuth of 215.5° and mean length of $\approx$44.5 m (mean: 44.3 m, median: 44.7 m, see Supplemental Material for statistical analysis of azimuth and length).

A mean length of 44.5 m in 9 years corresponds to a dune migration rate of $\approx$5 m/year. We consider these rates to be in agreement with rates of 6-7 m/year from Mendes and Giannini (2015) and Mendes et al. (2015), which were derived from interpretation of historical aerial photographs and satellite images with coarser spatial resolution.

Topographic profiles (Fig. 9) illustrate dune movement from 2010 to 2019, with migration of the lee side and relatively less change over the stoss side of large compound dunes.

4. Discussions and Conclusions

In this work we presented an evaluation of SfM-MVS in high-resolution topographic modelling of coastal sand dunes.

Although sand dunes are commonly regarded as a challenge to traditional photogrammetry due their homogeneous texture and spectral response, yielding poor results in image matching (Baltsavias, 1999), recent literature on close-range photogrammetry/SfM-MVS of coastal areas report good results in surface reconstruction (Gonçalves and Henriques, 2015; Gonçalves et al., 2018; Duffy et al., 2018; Laporte-Fauret et al., 2019; van Puijenbroek et al., 2017; Guisado-Pintado et al., 2019; Pitman et al., 2019).

In this research, image matching was successful in all areas of the survey due the presence of superficial features (footprints and sandboard tracks) and visibility of the sedimentary stratification, highlighted by heavy minerals (Fig. 2C).
One factor that positively influenced the RPA survey was the weather. A cloudy sky provided a diffuse illumination, without ‘hard’ shadows, and the scattered light rain ensured that the sand was humid, without the presence of a layer of loose sand over the dunes, which would mask the stratifications and other features in the photos (Guisado-Pintado et al., 2019).

We believe that the lack of texture in aerial photographs and satellite images is more related to ground resolution (i.e., pixel size) than the spectral or morphological characteristics of aeolian dunes, as a pixel area of one square metre can be enough to ‘average-out’ small textural features and prevent good image matching. This is an issue to be seen in the context of the everlasting matter of scale in remote sensing and geomorphometry: pixel size vs. spatial structure (size) of landforms (e.g., Woodcock and Strahler, 1987; Wood, 1996; Gallant and Hutchinson, 1997; Goodchild and Quattrochi, 1997; Marceau and Hay, 1999; Hengl, 2006; Kamal et al., 2014). Large continental dunes, for instance, have been successfully modelled with 30 m-resolution images from Landsat and ASTER (Levin et al., 2004; Bullard et al., 2011).

To validate the use of an SFM-MVS DEM, a TLS DEM was used as reference for altimetric accuracy. The comparison resulted in RMSE of 0.08 m and MAE of 0.06 m. The TLS DEM has a smooth appearance, with well-marked dune crests and vegetated areas, while the SFM-MVS DEM shows a small-scale roughness that hinders visual identification of small features such as footprints.

Although it does not influence the comparison with ALS data, this roughness can be an issue if the objective of the research is the classification of landforms based on geomorphometric parameters, such as the identification of dune crests based on surface curvature (Mitasova et al., 2005b; Hardin et al., 2014). The FPD de-noise algorithm (Lindsay et al., 2019) was applied to the SFM-MVS DEM with good results in terms of surface smoothing, without any significant changes in descriptive statistics and error metrics.

Dune crests interpreted from the ALS DEM were compared to crests from the SFM-MVS DEM and resulted in a migration rate of $\approx 5$ m/year, in good agreement with rates derived from satellite images and historical aerial photographs of the same area (Mendes and Giannini, 2015; Mendes et al., 2015).

Volumes calculated from the ALS and SFM-MVS DEMs show a difference of 0.2% between 2010 and 2019. Such small variation is within reported uncertainties for SFM-MVS reconstructions (Draejer and Strecha, 2014; Rhodes, 2017; Gupta and Shukla, 2018) and may be related to the installation of sand fences to promote dune stabilization and the constant removal of sand from
the road in front of the dune field (Fig. 10). Future studies can explore the spatial distribution of differences in the DEMs to evaluate the sedimentary budget (influx—efflux) of the dune field (Sankey et al., 2018a,b; Kasprak et al., 2019).

Figure 10: A) Sand fences installed to promote dune stabilization; B, C) Front of the dune field showing migration over road and signs. Location of photos on Fig. 2B.

When comparing these different approaches to aeolian dune surface modelling (ALS, TLS and SfM-MVS) we must consider not only the accuracy of final products (DEMs), but also the time required to acquire the data and process it to a GIS-ready format.

ALS might be acquired in little time, but it is by far the most expensive, imposing a serious constrain on repeated surveys, especially for researchers in developing countries or without access to state-funded coastal monitoring programs.

TLS has an intermediate cost of acquisition (since the equipment can be rented and operated by the research team) but it demands more fieldwork and more processing time. In our case we needed three days for the TLS survey and around three weeks of full-time work to produce a DEM of $\approx 80,400 m^2$.

SfM-MVS has gained attention recently for being a low-cost solution with fast and reliable results (James et al., 2019). We were able to cover $\approx 740,900 m^2$ with six RPA missions in under three hours. Processing time in a medium-range workstation (i.e., i7 processor, 64 GB RAM, dedicated GPU) was $\approx 13$ hours. This makes it an excellent method for 3D modelling and continuous monitoring of coastal dunes.

One strength of the ALS over TLS and SfM-MVS is the possibility of removing the vegetation based on the laser returns or waveform (Brovelli and Cannata, 2004; Evans and Hudak, 2007; Khosravipour et al., 2016), although new methods are being developed for single-return point clouds (Guarnieri et al., 2009; Coveney et al., 2010; Coveney and Stewart Fotheringham, 2011; Montreuil et al., 2013; Pijl et al., 2020) that have been used in coastal environments with good results (Guisado-Pintado et al., 2019).

Another aspect to be considered is the weather. Dry and hot conditions will favour the presence of white sand patches, which can affect image matching and the 3D reconstruction. While clear sunny days might be seen by many as ideal conditions for fieldwork, flying the RPA with cloudy skies and after a light rain can be worthwhile due the scattered light and visibility of the dune’s superficial features.
Computer Code Availability

Jupyter notebooks and associated data files (shapefiles and csv files) are available on GitHub ([https://github.com/CarlosGrohmann/scripts_papers/tree/master/garopaba_als_sfm_tls](https://github.com/CarlosGrohmann/scripts_papers/tree/master/garopaba_als_sfm_tls)) and Zenodo ([https://doi.org/10.5281/zenodo.3476779](https://doi.org/10.5281/zenodo.3476779)). The notebooks are based on Python 3.6 and depend on the following libraries: numpy, scipy.stats, matplotlib, pandas, seaborn, rasterio, xarray, statsmodels, osgeo.ogr, pygrass and whiteboxtools.

Data Availability

The point cloud datasets used in this study are available via the OpenTopography Facility ([Crosby et al., 2011; Krishnan et al., 2011]). The following datasets were used: OpenTopography ID OT.032013.32722.1 (ALS – Grohmann, 2010; Grohmann and Sawakuchi, 2013), OTDS.072019.32722.1 (SfM – Grohmann, 2019), OTDS.102019.32722.1 (TLS – Grohmann et al., 2019).

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Notes

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