Accuracy of the UAV-Based DEM of Beach–Foredune Topography in Relation to Selected Morphometric Variables, Land Cover, and Multitemporal Sediment Budget

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Abstract

Recent developments in unmanned aerial vehicles (UAVs) have resulted in high-resolution digital elevation models (DEMs) of vulnerable coastal environments, including beach–foredune topography. If performed repetitively, they can offer an excellent tool to determine the spatial and temporal changes in the sediment budget, which may be required for proper land management. However, the quality of a UAV, slope parameters, and vegetation significantly influence DEM accuracy. The aim of this study is to compare precise GPS-RTK transects across a section of the South Baltic coast in Poland with those obtained from a DEM based on high-resolution and high-accuracy images obtained by a wind-resistant, high-quality fixed-wing UAV during beyond visual line of sight operation (BVLOS). Different land cover classes, slope inclination, and general curvature, as well as surface roughness, were taken into consideration as possible factors influencing the uncertainty. The study revealed that marram grass greatly affects the accuracy of the UAV-derived model and that the uncertainty of the UAV-derived DEM increases together with increasing slope inclination and, to a lesser degree, with increasing general slope curvature. We showed that sediment budget determinations with the use of a UAV-based DEM are correct only where grass cover is sparse, in our study, up to 20% of the area.

Keywords UAV imaging · DEM accuracy · Beach–foredune topography · Sediment budget

Introduction

Foredunes are characterized by diversified relief with annual changes ranging between a few centimeters and 1–2 m (Nolet et al. 2018). High-resolution digital elevation models (DEMs)

of foredunes repetitively performed offer an excellent opportunity to determine the spatial and temporal distribution of sediment budgets of such dynamic eolian landforms.

Some previous studies have been performed to estimate a foredune sediment budget based on elevation data surveyed with GPS-RTK along transects oriented perpendicular to the coastline and crossing foredune ridges (Vespremeanu-Store and Preoteasa 2007; Delgado-Fernandez 2011), sometimes together with the analysis of aerial photography (Rader et al. 2018). Recently, the sediment budget has also been determined using multitemporal sets of LIDAR-derived DEMs (Keijsers et al. 2014; Darke et al. 2016; Le Mauff et al. 2018) or with the use of aerial images taken by rotary-wing light UAVs. However, such vehicles have limited wind resistivity (Nolet et al. 2018) and can only be used for small surfaces close to the take-off and landing sites under calm weather.

Unmanned aerial vehicles (UAVs) allow the acquisition of high-resolution DEMs of vulnerable coastal environments, including beach–foredune topography. If performed repetitively, they can offer an excellent tool to determine the spatial and temporal changes in the sediment budget, which may be

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required for proper land management. The UAV-based photogrammetry of coastal areas has already proven to be a useful technique for scientific studies as well as for authorities to develop local management strategies (Scarelli et al. 2017). However, there are numerous disturbing factors responsible for DEM inaccuracy, most importantly, the quality of UAVs, slope inclination, and vegetation.

The quality of DEMs is related to the spatial distribution and accuracy of the input elevation data. For example, LIDAR data can achieve an accuracy of 0.2 m root mean square error (RMSE) horizontally and less than 0.15 m vertically (Liu 2008). Thus, LIDAR-derived DEMs can display an optimal horizontal spatial resolution of 0.5 m, which is insufficient to detect small-scale geomorphic features (Taroli et al. 2012; Leon et al. 2014; Taroli 2014; Fabbri et al. 2017). In turn, UAV-based DEMs usually have vertical accuracy in the range of approximately 0.05 to 0.1 m and spatial resolution of approximately 0.1 m (Mancini et al. 2013; Laporte-Fauret et al. 2019). However, the accuracy of such DEMs is uncertain because the only benchmarks are ground control points installed in selected places. On the other hand, in-field GPS-RTK measurements provide unequivocal results, but they are usually performed along transect lines imposed by survey team protocols.

The spatial resolution and vertical accuracy of the input elevation data and derived DEMs influence the accuracy of detailed geomorphological mapping and the determination of landform sediment budgets (Wheaton et al. 2009; Coveney and Fotheringham 2011; Leon et al. 2014; Le Mauff et al. 2018). Moreover, there is still a poorly known role of the sampling strategy in the input elevation data, the composition of the bare earth surface and the landcover type, topographic complexity, and spatial interpolation methods applied in DEM processing (Hodgson and Bresnahan 2004; Wechsler and Kroll 2006; Bater and Coops 2009). The related DEM uncertainty cannot be simply defined as a single global parameter of dispersion of a difference between predicted and measured ground elevation, i.e., RMSE (Oksanen and Sarjakoski 2006). This is because the uncertainty can be spatially variable depending on land cover type (Hodgson and Bresnahan 2004; Schmid et al. 2011; Zandbergen 2011; Leon et al. 2014) and terrain characteristics such as slope inclination, slope curvature, or surface roughness (Su and Bork 2006; Erdogan 2010; Oksanen and Sarjakoski 2006). Therefore, the proper characterization of the uncertainty, the recognition of its distribution, and spatial correlation structure provide a good basis for realistic DEM uncertainty propagation analysis (Shortridge 2001).

Uncertainty is an inherent feature of any spatial data (Leon et al. 2014), but new technologies allow researchers to maximize the precision of geomorphological measurements. Conventional aerial images or satellite data are usually obtained at a different time than in-field measurements and/or they lack sufficient resolution. The aim of this study is to fill this gap by juxtaposing two measurement approaches: (i) GPS-

RTK transects performed yearly from October 2013 until May 2019 with (ii) transects obtained from detailed DEMs based on high-resolution and high-accuracy images from a fixed-wing UAV platform. We analyze the absolute elevation differences (AED) obtained from GPS-RTK measurements in 2013–2019 and look for environmental factors responsible for the differences, such as land cover classes, slope inclination, general slope curvature, and surface roughness. We propose the following research questions: (1) To what degree do vegetation cover and inclination of a slope influence the precision of foredune and beach sediment budgets obtained from UAV-based images? and (2) In what time scale can we analyze sediment budget under the particular vegetation cover of a foredune and a beach using UAV images?

Study Site

The study was conducted in Słowiński National Park, on the Łeba Barrier (S Baltic coast) built with a Holocene marine lagoon and eolian deposits (Fig. 1) (Rotnicki 1995; Rotnicki and Borówka 1995). The central part of the barrier is characterized by extensive active transgressive dunes, barchans, barchanoid ridges, and large-scale parabolic forms (Borówka 1990). The tideless beach (Bobertz et al. 2005) is accompanied by a foredune ridge complex that is unaltered by humans.

The dominant effective winds of the Łeba Barrier blow alongshore and onshore from the SW and W directions (Rotnicka 2011, 2013a; Rotnicka and Dłużewski 2019). Late autumn and winter are periods with the highest frequency of storms, and the average monthly wind velocities often exceed 5 ms^{-1} . The mean annual precipitation is 611–679 mm, and the relative air humidity is 81–83% (Rotnicka 2013a). The beach sand remains moist for a significant part of the year.

During the study, the beach had a relatively low gradient and was tens of meters wide (locally up to 150 m). Both the foredune complex and the beach were composed of very well- and well-sorted fine to medium quartz sand with local zones of pebbles. Surface sand samples averaged 1.95 phi (260 μm) in diameter with a sorting value of 0.34 phi (Rotnicka 2013b).

Methods

UAV Operation

Aerial images were taken by a PW-ZOOM fixed-wing UAV (Fig. 2), designed, manufactured, and tested at the Warsaw University of Technology in Poland (Goetzendorf-Grabowski and Rodzewicz 2016; Rodzewicz et al. 2017). The photogrammetric flight was performed as a beyond visual line of sight (BVLOS) operation with observers on 23 May 2017 with a starting and landing point located on a beach in Słowiński N.P.

Fig. 1 Location of the study area and GPS-RTK measurement: **a** study area location at the Baltic Sea, **b** study area within the Łeba Barrier (note the neighboring coastal lakes), and **c** GPS-RTK transects in the study area

The distance between the grid lines was approximately 60 m, which provided 70% forward and side overlap, the length of the lines was 6500 m, and the flight altitude was 350 m a.s.l.

Fig. 2 PW-ZOOM during flight over the Łeba Barrier (**a**) and starting on a beach (**b**)

(Table 1, Fig. 3). All images had georeferences (X , Y , Z) registered by the autopilot logger mounted on the UAV. To increase the accuracy of the UAV images, we used 10 ground control points (GCPs) measured with a GPS-RTK.

The UAV operation was performed a day after GPS-RTK measurement under prolonged calm weather conditions; therefore, no morphological changes to the foredunes occurred during the study.

GPS-RTK Transects

Twenty topographic transects normal to the shoreline orientation, extending from a point landward of the lee slope of the

Table 1 The parameters of the aerial survey to the SPN performed on 23 May 2017 with a of fixed-wing UAV PW-ZOOM

Number of flights	1
Total time of flight	1 h 8 min 43 s
Camera set	Canon 700D with 35 mm lens (RGB)
Number of images	1248 (RAW)
Distance	122 km
Flight altitude	350 m a.s.l.
GSD	0.04 m
GCP	10

Fig. 3 Flight path over the beach and the foredune on Leba Barrier on 23 May 2017; the white rectangle indicates the study site

foredune (usually a benchmark), across the established and incipient parts of the foredune complex, and out to the upper edge of a swash zone were performed in October (2013, 2014, 2015, 2016) and May (2017, 2018, 2019). The length of the profiles ranged from 150 to 250 m (Fig. 1).

The measurements were taken at the beginning by a TOPCON electronic total station theodolite (TST) and then by using a TOPCON HiPer® Pro real-time kinematic (RTK) differential global positioning system (DGPS) (precision of 0.01–0.02 m in all dimensions). The average intervals between measurement points ranged between 0.4 and 1.49 within the foredune and between 1.2 and 3.44 m on the flat beach surface. A set of permanent benchmarks was installed on an established foredune for the base station and for horizontal and vertical correction of the position. Repeated GPS-RTK surveys of a selected beach–foredune profile showed that the error obtained (discrepancy in readings) equaled to 0.01 m, and in 95% of the readings, it was smaller than 0.034 m.

Land Cover Types

Three classes of land cover were distinguished (Fig. 4) based on the UAV true-color orthophoto of 0.04 m spatial resolution: (i) bare beach (no marram grass)—class 1, (ii) dunes with marram grass covering up to 20% of the surface area—class 2, and (iii) surfaces covered with marram grass of density greater than 20%—class 3.

Class 2 includes surface with single marram grass shoots and tufts that were partly buried during episodes of intensive sand transport. In fact, they are the topmost part of grass tufts with a height of up to 50 cm covering the incipient foredune. This class of land cover is also present on established foredunes where marram grass is being slowly replaced by *Corynephorus canescens*.

Class 3 includes surface covered by large and dense tufts of marram grass usually occurring on periodically inactive fragments of incipient foredunes and established foredunes. It also may be present on the upper part of the beach where single marram grass tufts are responsible for formation of shadow dunes. The height of the tufts in this land cover class is 70–90 cm.

Marram grass shoots were counted and measured in randomly selected 1 m² plots. The height and width/diameter of the tufts were measured (Musick et al. 1996). Based on these measurements, the percentage of area coverage by the grass was calculated. In class 2, the percentage of vegetated surface was usually less than 10% (sporadically a dozen or so percent). In class 3, the grass coverage was usually well above 20%, depending on the dimension and distribution of grass tufts.

UAV Data Processing

The UAV images were obtained in RAW format during the flight and converted to JPEG format in the Digital Photo Professional version 3.13.0.1 (Canon Inc.) software. The images were then processed into an orthophoto with a resolution of 0.04 m and a dense 3D point cloud in the original WGS84 coordinate system. The Agisoft Photoscan Professional software Version 1.3.2 build 4205, 64 bit (Agisoft LLC.) and the structure from motion (SfM) algorithm were used to create these data. Agisoft software estimates internal and external camera orientation parameters during photo alignment. This estimation is performed using only image data, and therefore, there may be some errors in the final estimates. The accuracy of the final estimates depends on many factors, such as overlap between the neighboring photos, as well as on the shape of the object surface. These errors can lead to nonlinear deformations of the final model.

Fig. 4 Land cover classes: **a** without marram grass (class 1), **b** marram grass covering up to 20% of the dune area (class 2), and **c** marram grass covering over 20% of the dune area (class 3)

Digital Terrain Modeling

The 3D point cloud was transformed to the LAS data format and then reprojected to a national metric coordinate system. Then, we performed digital terrain modeling that included the spatial analysis of the point cloud data, the processing of the digital elevation model (DEM), the computation of DEM-derived terrain variables, and DEM uncertainty analysis. All computations and spatial analyses were performed using ArcGIS 10.5 software (Esri 2018), SAGA GIS open source software (Conrad et al. 2015), and Tableau 10.5 data mining software (Tableau Software, Seattle, WA, USA). The point cloud data were dynamically triangulated to prepare a raw multiresolution DEM. This modeling method, based on the TIN (triangulated irregular network) data structure, was chosen taking into account the total number of elevation points (approximately 15 million), and the irregular but dense spatial distribution of these points (mean distance between neighboring points is 0.11 m and standard deviation is 0.03 m). According to earlier studies (Bater and Coops 2009; Hengl and Evans 2009), the approach used allowed us to obtain a more accurate DEM displaying discrete changes in topography, thus minimizing the potential uncertainty of the modeled elevation due to the data interpolation process.

The computation of DEM-derived terrain variables, including slope inclination, general slope curvature, and surface roughness, was based on a high-resolution gridded DEM. The optimal spatial resolution of 0.2 m was assumed for this DEM as a compromise between its value of 0.05 m determined by the point pattern analysis method (Hengl 2006) and the need to upscale the resolution to reduce the small-scale variation and obtain a more general pattern of the terrain variables. It is obvious that the small-scale variation should be free from pure artifacts related to spikes and pits having a size of a few grid cells on a high-resolution DEM, directly derived from UAV-based photogrammetric processing (Nelson et al. 2009). A natural neighbor gridding method was chosen here to avoid the oversmoothing effect given by other gridding methods, such as spline or kriging (Taroli et al. 2012). However, the resulting gridded DEM was smoothed using a low-pass filter in a 3×3 moving window (0.6×0.6 m) to

obtain the final DEM free from remaining local outliers and appropriate for the computation of terrain variables (Kienzle 2004; Hengl 2006).

The slope inclination (in $^{\circ}$) and general slope curvature (defined as the rate of local change in slope inclination and aspect to determine the degree of surface concavity and convexity) were calculated using a 3×3 grid-cell moving window following the second-order polynomial method of Zevenbergen and Thorne (1987). The surface roughness was determined based on the computation of the vector roughness measure (VRM) (Sappington et al. 2007). The VRM is an indicator of surface heterogeneity according to local changes in slope inclination and aspect, similar to the general slope curvature. Nevertheless, this indicator, calculated using operators with Gaussian weighting functions related to a moving window with a radius of 10 grid cells (2 m), allowed us to determine a smoothed and artifact-free pattern of surface roughness.

DEM Uncertainty Analysis

We analyzed the uncertainty of the UAV-based DEM in terms of differences between modeled elevations (DEM-derived) and elevations measured with GPS-RTK in each of the 20 transects performed at the same time as the UAV flight. We also compared the obtained uncertainty with the AED derived from GPS-RTK transects performed annually from 2013 to 2019. Different land cover classes, slope inclinations, general slope curvatures, and surface roughness values were taken into consideration as possible factors influencing the uncertainty. Moreover, the spatial variability of this uncertainty was geostatistically modeled (Webster and Oliver 2007). For this purpose, empirical semivariograms were estimated for fixed distance lags of 0.9 m length (according to the same mean distance between neighboring points obtained from GPS-RTK measurements within the foredunes). The estimations were made for all uncertainty data and their subsets defined on the basis of land cover. The spherical models with nugget effects were fitted to all estimated semivariograms. Based on these models, we were able to recognize the degree to which the discrepancies between modeled and measured elevations

are spatially autocorrelated (Oksanen and Sarjakoski 2006; Leon et al. 2014).

The differences in elevation between annually measured GPS-RTK transects and the transects obtained from the DEMs based on UAV images were negative or positive (Fig. 4 a and b). However, we were interested in finding the environmental factors responsible for the differences in general; therefore, we analyzed the AED in which we disregarded the direction of the differences.

To support the patterns observed on the diagrams, we performed Kruskal–Wallis statistical tests and post hoc tests in Statistica 13.3, assuming the significance level $\alpha = 0.05$.

Results

The elevations of the UAV-derived cloud points determined for the beach and the foredune range from -0.2 to 13.71 m a.s.l. The horizontal and vertical accuracies of these data, checked using GPS-RTK measurements at the GCP validation, are shown in Table 2. The uncertainty of DEM processed from the point cloud data is spatially distributed regarding land cover classes and three terrain variables (slope inclination, general slope curvature, and surface roughness). The absence of collinearity between these variables was confirmed using the Pearson correlation matrix. The correlation coefficients between variables are up to 0.13, suggesting a low level of redundancy.

There is a gradual increase in the AED between land cover class 1 (beach with no grass), a foredune with low grass density (land cover class 2), and a foredune with dense high grass (land cover class 3), with median values for AED being 0.06 m, 0.09 m, and 0.16 m, respectively (Fig. 5c). This general tendency is well shown by transect K60 (Figs. 1 and 5 d and e) running through the three land cover classes.

The AED attains values up to approximately 0.4 m but most frequently falls below 0.05 m (Figs. 6a, 7, 8, and 9a).

Table 2 Horizontal and vertical accuracy between DEM and GPS-RTK data calculated at the GCP validation

GCP	Horizontal accuracy (m)	Vertical accuracy (m)
63—beach	0.040	0.027
63—benchmark	0.002	−0.051
58—beach	0.083	−0.008
58—benchmark	0.046	−0.002
52—beach	0.119	−0.010
52—benchmark	0.046	−0.021
1—beach	0.074	0.042
1—benchmark	0.049	−0.026
7—beach	0.048	0.004
7—benchmark	0.024	0.017
RMSE	0.061	0.074

For all land cover classes combined, there is a clear tendency for a gradual increase in AED with increasing slope inclination (Fig. 6b). The AED on slopes inclined less than 10° are statistically significantly different than those on steeper slopes (Appendix). The general slope curvature also exhibits some interrelationship with AED because the slopes of curvature between -0.05 and $+0.15$ stand out as having significantly different AED (Fig. 6c, Appendix).

The same analyses performed only for the area with no grass (land cover 1) show that no terrain variables control the AED, as can be read from the AED distribution diagrams (Fig. 7) and statistical tests (Appendix).

A similar tendency for all land cover classes combined (Fig. 6) is observed for land cover class 2 (marram grass covering up to 20% of the area) (Fig. 8). However, the tendency is less clear, and statistically significant differences are obtained only for AED populations on slope inclinations exceeding 20° (Appendix). The situation with general slope curvature is very similar to that for all land cover classes combined, as statistically significant differences are obtained for AED populations on the slopes of curvature between -0.05 and $+0.15$ (Appendix).

If the analyses are limited to land cover 3 (marram grass over 20% of the area), then a gradual increase in AED can be observed toward greater slope inclination (Fig. 9); however, there are no statistically significant differences (Appendix). AED seemed to decrease as the general slope curvature increased, but again, this pattern was not supported by statistical tests (Appendix).

The influence of slope inclination on AED is lowest in places free of vegetation (land cover class 1) and greatest in places with relatively dense marram grass (land cover class 3) where maximum AED values are 0.4 m (Fig. 10). In general, thick grass and high slope inclination result in significant errors in UAV-based DEMs.

The autocorrelation structure of the DEM uncertainty determined on semivariograms shows the different spatial dynamics of the discrepancy between the predicted and measured elevation data (Fig. 11). In the case of all analyzed data, the nugget effect of 0.0049 m^2 at a distance less than the sampling interval shows a pure random variation in the DEM uncertainty of approximately 0.09 m. The following spatial structure described by the spherical model allowed us to determine the range of the autocorrelation of 11.5 m with a partial sill of 0.0073 m^2 , indicating the degree of spatial variability or trend in the DEM uncertainty up to approximately 0.12 m depending on the distance between the analyzed data. There are noteworthy differences between the semivariograms estimated for the DEM uncertainty partitioned into four subsets with respect to the land cover classes (Fig. 4) and in the case of class 1 regarding the morphology of the beach (flat beach, beach with small shadow dunes). The spatial autocorrelation structures determined here vary not only in the range of autocorrelation (from 5.52 m for the beach with shadow dunes to 15 m for the flat beach) but also first in the nugget/sill

Fig. 5 Transect K60: **a** elevation profiles based on GPS-RTK measurements and UAV-derived DEM, **b** elevation differences along the elevation profile (note different cover classes), **c** elevation differences in the three land cover classes (1—no grass, 2—up to 20% grass cover, 3—over

ratio, which indicates the strength of spatial dependency related to the pure random variation in the DEM uncertainty. The ratios observed for the flat beach, dunes with marram grass, and beach with shadow dunes (0.48, 0.42, and 0.52, respectively) show a high degree of local random variation in the uncertainty and their low spatial dependency. In turn, this ratio

20% grass cover), **d** vegetation and relief in the area of the profile, and **e** elevation change between the GPS-RTK measurements and UAV-derived DEM. Boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

of 0.12 related to the DEM uncertainty of the area of dense marram grass may be indicative of a low degree of small-scale random variation and high spatial autocorrelation.

The comparison of the AED between GPS-RTK topographic profiles measured in 2015, 2016, and 2019 and a topographic profile that took into account the uncertainty of

Fig. 6 Differences in altitude between GPS-RTK measurements and UAV-derived DEM for all vegetation classes (1, 2, and 3) combined: **a** frequency of AED, **b** AED in relation to slope inclination, **c** AED in

relation to general slope curvature, and **d** AED in relation to surface roughness; boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

measurements obtained from the UAV-based DEM in 2017 allowed us to conclude that a proper determination of a sediment budget based on UAV images depends on land cover classes. In the transect in which classes 1 and 2 predominate (Fig. 12 a and b), the differences in altitude are much greater

than the uncertainty of the measurements. On the other hand, where land cover 3 dominates, these differences are comparable to the uncertainty of the measurements.

Elevation differences for vegetation-free areas (land cover class 1) obtained for particular GPS-RTK

Fig. 7 Differences in altitude between GPS-RTK measurements and UAV-derived DEM for land cover class 1 (without marram grass): **a** frequency of AED, **b** AED in relation to slope inclination, **c** AED in

relation to general slope curvature, and **d** AED in relation to surface roughness; boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

Fig. 8 Differences in altitude between GPS-RTK measurements and UAV-derived DEM for land cover class 2 (marram grass cover up to 20% of the dune area): **a** frequency of AED, **b** AED in relation to slope

inclination, **c** AED in relation to general slope curvature, and **d** AED in relation to surface roughness; boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

measurements performed annually (median for: 1-year measurement period—0.038 m, for a 4-year period—0.056 m) are much larger than the uncertainty of measurement determined for a UAV-based DEM (median 0.006 m) (Fig. 13a). This makes it possible to determine the sediment budget with the use of the UAV-based DEM, even on

a 1-year time scale. It should be remembered, however, that this land cover class includes landforms such as the beach, the eolian ramp formed at the foredune foot, and the lower part of the seaward slope of the incipient foredune, which can be shaped not only by eolian processes but also by wave action (as foredunes in Fig. 12b).

Fig. 9 Differences in altitude between GPS-RTK measurements and UAV-derived DEM for land cover class 3 (marram grass covering over 20% of the dune area): **a** frequency of AED, **b** AED in relation to slope

relation to surface roughness; boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

Fig. 10 Change in absolute elevation differences (AED) in relation to slope inclination and different land cover classes; the diagram shows minima, maxima, medians, and lower and upper quartiles

In the case of land cover class 2 (Fig. 13b), where the sediment budget is exclusively associated with eolian processes (Fig. 13b), the UAV-based DEM uncertainty is slightly higher than that in the case of land cover 1. The AED between particular GPS-RTK profiles varies greatly (up to 4 m in a year) and, on average, is much larger (median for: 1-year period—0.023 m, for a 4-year period—0.058 m) than the UAV-based DEM uncertainty (median 0.009 m). By using a UAV-based DEM on land cover class 2, we could also correctly

determine the sediment budget even on a 1-year time scale.

The use of the UAV-based DEM in the determination of a sediment budget of land cover class 3 appears to be inappropriate (Fig. 13c). This is due to the large UAV-based DEM uncertainty (median 0.011 m), significant stabilization of the substrate by vegetation, and therefore relatively small values of the sediment budget (median for: 1-year measurement period—0.007 m, for a 4-year period—0.011 m).

Fig. 11 Empirical semivariograms of the UAV-based DEM uncertainty (point symbols) and fitted spherical models with nugget effects (lines)

Fig. 12 Examples of morphological cross-sections displaying multitemporal differences between topography and the range of uncertainty of the UAV-based elevation data. **a, c** Morphological cross-

sections along transect lines 2 and 62, respectively (for transect location, please refer to Fig. 1c). **b, d** Vegetation and relief along respective transect lines

Discussion

Use of UAV Platforms

The development of UAV platforms contributed to the time reduction of data acquisition and maintaining high data quality with reduced costs. The availability of UAVs for various geomorphological studies is very broad. In the last decade, UAVs have been applied in studies of landslides (Niethammer et al. 2012), erosion gullies (d'Oleire-Oltmanns et al. 2012; Grellier et al. 2012), debris flows and alluvial fans (de Haas et al. 2014), river channels (Flener et al. 2012), glacial landforms (Whitehead et al. 2013; Chandler et al. 2016), periglacial

landforms (Dąbski et al. 2017), volcanic landforms (Zmarz et al. 2018), karstic landscapes (Silva et al. 2017), coastal dunes (Laporte-Fauret et al. 2019), hot arid deserts (Angell 2018), and structural geomorphology (Kasprzak et al. 2017). In comparison to manned aircraft, UAVs require a lower level of engagement of qualified personnel and advanced ground infrastructure and lower costs. Moreover, its use is safe if the conditions of use of the airspace are met. Most UAV users perform flights within the visual line of sight of the operator (VLOS). Flights BVLOS require additional permits as well as proper and safe implementation of the mission. Rare examples of BVLOS operations in geomorphological studies are provided by Dąbski et al. (2017), Zmarz et al. (2018), and in this study.

Fig. 13 Boxplots for the three land cover classes (**a** class 1—no grass, **b** class 2—up to 20% grass cover, **c** class 3—over 20% grass cover) showing changes in the AED (in meters) in relation to the uncertainty of the UAV-based elevation data and temporal scales of the sediment budget. Boxplots represent the interquartile range with the median and whiskers corresponding to 1.5 times the interquartile range

Moreover, the used PW-ZOOM fixed-wing aircraft is much more wind tolerable, up to 23 ms^{-1} (Zmarz et al. 2018), in comparison with that of rotary UAVs (Laporte-Fauret et al. 2019), which can operate safely when the wind is lower than 7 ms^{-1} , as in the case of popular light

multirotor UAVs (DJI 2016). This makes PW-ZOOM a much better tool for photogrammetric flights in demanding environments such as coastal or polar environments where sudden wind gusts are frequent (Dąbski et al. 2017; Zmarz et al. 2018).

UAV-Based Relief Modeling

Relief modeling based on UAV imagery greatly improves the calculations of the sediment budget of beach–foredune systems, but further improvements should be made through the use of similar monitoring systems (Delgado-Fernandez 2011). This should include frequent survey intervals that allow for a spatial–temporal (4D) picture of the coastal area (Darke et al. 2016). UAV platforms are excellent tools for facilitating quick and timely data acquisition if detailed DEMs are of sufficient accuracy.

The sediment budget calculation of eolian landforms is greatly affected by natural vegetation cover (e.g., marram grass) and any human alternation of land cover (Darke et al. 2016). It is therefore of great importance to take into account the influence of vegetation on UAV-based DEMs. Laporte-Fauret et al. (2019) assessed the influence of marram grass on elevation measurement based on such DEMs, but they did not undertake an in-depth statistical approach. Our study filled this gap by concentrating on different land cover classes (marram grass densities) and slope inclinations as factors controlling elevation measurement errors.

DEM Uncertainty

The relationship between the spatial autocorrelation structure of DEM uncertainty and topography has been reported at the landscape scale by Oksanen and Sarjakoski (2006). If the long ranges and low sills are typical for the flattest topography, then short ranges and high sills predominate where the terrain is more rugged. In general, our study results support this relationship, particularly with respect to DEM uncertainty analyzed for flat beaches, beaches with shadow dunes, and foredunes covered by dense marram grass. The high sill in the last case can be considered as the effect of small-scale composite topography masked by dense and relatively high marram grass. It is noteworthy that the maximum positive differences between DEM-derived elevation data and GPS-RTK measurements were usually observed in this land cover class. Moreover, the low nugget/sill ratio and thus the low degree of small-scale random variation and the high spatial autocorrelation of DEM uncertainty determined here appear to be a consequence of two factors. First, the transition between the area of dense marram grass and other land cover classes is usually not sharp but gradual. For example, the transition from class 3 to class 2 is manifested not only in gradual changes in the density and height of grass cover but also in the tendency to diminish the patches of dense tufts of marram grass. Second, in some cases, the patches of dense marram grass develop on the southern slopes of the foredunes in shadows of small-scale overlapping shadow structures. These two factors probably contributed to the gradual elevation changes in the DEM across the border of the area of dense marram grass despite the different spatial autocorrelation

structures of DEM uncertainty in comparison to other land cover classes. Thus, the exclusion of areas densely covered by marram grass from the UAV-based DEMs for the detailed study of geomorphology and the dynamics of beach and eolian processes seems impossible without the precise detection of land cover classes using the image analysis of the UAV-based data in visible and near infrared bands.

The confirmation in the current study that the DEM uncertainty in different terrain types may have varying spatial autocorrelation structures (Goodchild 1995; Oksanen and Sarjakoski 2006) gives the opportunity to solve the optimization problem of spacing between nearest-neighbor RTK-GPS survey points required for DEM uncertainty analysis. According to earlier studies on the optimization of remote sensing mission criteria, including UAV missions, in terms of flight elevation and then the upscaling of the resulting DEM (Rahman et al. 2003; Wang et al. 2019), the nearest-neighbor RTK-GPS survey points can be located at distances up to one-half of the width of the range modeled from the experimental semivariogram. The detailed data collected along regularly spaced transects oriented perpendicular to the coastline and crossing foredune ridges show that the range width and thus the maximum distance of the spatial dependence of the DEM uncertainty are significantly different between the three land cover classes, i.e., flat beach, beach with shadow dunes, and area of dense marram grass preset on incipient or established foredunes. It gives the maximum permissible spacing between the nearest RTK-GPS survey points of up to 7.5 m, 2.76 m, and 5.8 m, respectively.

Laporte-Fauret et al. (2019) found a locally strong elevation underestimation of a UAV-based DEM (derived from the SfM algorithm) on the dry beach, which was caused by the locally smooth and featureless sand surface. During our UAV operation, the beach sand was relatively dry, but the accuracy of the DEM was still better than that on uneven foredune surfaces. This calls for further studies aimed at estimating the influence of ground moisture on the accuracy of SfM models.

Conclusions

In light of global climate change and sea level rise, foredunes play a particularly important role in coastal defense against storm surges. Therefore, proper land management policies should be introduced, and this is difficult to achieve without the accurate modeling of land elevation adjusted for a particular land use type.

We showed that dense marram grass significantly lowers the accuracy of the UAV-derived model and that the greatest absolute elevation differences between UAV-derived DEMs and GPS-RTK measurements are obtained for slope overgrowth by high grass. For all land cover types combined, there

are the clear tendencies of a gradual increase in absolute elevation differences (the uncertainty of UAV-derived DEMs) together with increasing slope inclination and, to a lesser degree, with increasing general slope curvature. Our results allow us to infer that the sediment budget determinations with the use of a UAV-based DEM are correct only where grass cover is sparse, in our study, up to 20% of the area.

In spite of obtaining the DEM generated based on the data from the good-quality, wind-resistant fixed-wing UAV, the precise determination of the sediment budget will not always be possible, especially in the areas of foredunes where the sediment mass balance turnover is sometimes only within centimeters per year. This applies especially to fragments of

incipient foredunes that are densely overgrown with marram grass.

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Appendix. Results of the Kruskal–Wallis and multiple comparison post hoc tests (in cases where $p < 0.05$ for K–W tests)

Influence of slope inclination on absolute differences in altitude for all land cover classes combined

Dependent variable: Abs_diff Kruskal–Wallis test: $H(6, N = 1289) = 98.47503, p = 0.0000$

	0°	5°	10°	15°	20°	25°	30°
	$R = 504.18$	$R = 614.46$	$R = 678.38$	$R = 739.03$	$R = 757.96$	$R = 769.69$	$R = 817.66$
0°		0.004445	0.000001	0.000000	0.000000	0.000000	0.000000
5°	0.004445		1.000000	0.024715	0.007866	0.003444	0.005591
10°	0.000001	1.000000		1.000000	1.000000	0.679872	0.299561
15°	0.000000	0.024715	1.000000		1.000000	1.000000	1.000000
20°	0.000000	0.007866	1.000000	1.000000		1.000000	1.000000
25°	0.000000	0.003444	0.679872	1.000000	1.000000		1.000000
30°	0.000000	0.005591	0.299561	1.000000	1.000000	1.000000	

Influence of slope curvature on absolute differences in altitude for all land cover classes combined

Dependent variable: Abs_diff Kruskal–Wallis test: $H(6, N = 1253) = 25.80821, p = 0.0002$

	−0.35	−0.25	−0.15	−0.05	0.05	0.15	0.25
	$R = 895.35$	$R = 716.68$	$R = 666.98$	$R = 622.49$	$R = 573.58$	$R = 571.10$	$R = 616.41$
−0.35		1.000000	0.133810	0.019634	0.002514	0.009847	0.408492
−0.25	1.000000		1.000000	1.000000	0.150227	0.601913	1.000000
−0.15	0.133810	1.000000		1.000000	0.041431	1.000000	1.000000
−0.05	0.019634	1.000000	1.000000		1.000000	1.000000	1.000000
0.05	0.002514	0.150227	0.041431	1.000000		1.000000	1.000000
0.15	0.009847	0.601913	1.000000	1.000000	1.000000		1.000000
0.25	0.408492	1.000000	1.000000	1.000000	1.000000	1.000000	

Influence of slope inclination on absolute differences in altitude for land cover class 1 (no marram grass)

Kruskal–Wallis test: $H(5, N = 356) = 4.561568, p = 0.4717$

Influence of slope curvature on absolute differences in altitude for land cover class 1 (no marram grass)

Kruskal–Wallis test: $H(6, N = 426) = 12.29862, p = 0.0556$

Influence of slope inclination on absolute differences in altitude for land cover class 2 (marram grass covering up to 20% of the dune area)

Dependent variable: Abs_diff Kruskal–Wallis test: $(6, N = 730) = 41.30848, p = 0.0000$

	0°	5°	10°	15°	20°	25°	30°
	$R = 301.65$	$R = 325.99$	$R = 329.66$	$R = 390.81$	$R = 423.30$	$R = 410.12$	$R = 476.87$
0°		1.000000	1.000000	0.072364	0.002400	0.014733	0.000392
5°	1.000000		1.000000	0.271891	0.007658	0.052897	0.001364

(continued)

10°	1.000000	1.000000		0.410908	0.013308	0.083902	0.002114
15°	0.072364	0.271891	0.410908		1.000000	1.000000	0.587826
20°	0.002400	0.007658	0.013308	1.000000		1.000000	1.000000
25°	0.014733	0.052897	0.083902	1.000000	1.000000		1.000000
30°	0.000392	0.001364	0.002114	0.587826	1.000000	1.000000	
Influence of slope curvature on absolute differences in altitude for land cover class 2 (marram grass covering up to 20% of the dune area)							
Dependent variable: Abs_diff Kruskal–Wallis test: $H(6, N = 827) = 18.35745, p = 0.0054$							
	– 0.35	– 0.25	– 0.15	– 0.05	0.05	0.15	0.25
	$R = 593.94$	$R = 471.55$	$R = 436.08$	$R = 410.59$	$R = 387.23$	$R = 370.89$	$R = 354.00$
– 0.35		1.000000	0.191540	0.042540	0.013099	0.019089	0.113055
– 0.25	1.000000		1.000000	1.000000	1.000000	1.000000	1.000000
– 0.15	0.191540	1.000000		1.000000	0.978467	1.000000	1.000000
– 0.05	0.042540	1.000000	1.000000		1.000000	1.000000	1.000000
0.05	0.013099	1.000000	0.978467	1.000000		1.000000	1.000000
0.15	0.019089	1.000000	1.000000	1.000000	1.000000		1.000000
0.25	0.113055	1.000000	1.000000	1.000000	1.000000	1.000000	
Influence of slope inclination on absolute differences in altitude for land cover class 3 (marram grass covering over 20% of the dune area)							
Kruskal–Wallis test: $H(6, N = 203) = 6.988584, p = 0.3219$							
Influence of slope curvature on absolute differences in altitude for land cover class 3 (marram grass covering over 20% of the dune area)							
Dependent variable: Abs_diff Kruskal–Wallis test: $H(6, N = 221) = 17.85180, p = 0.0066$							
	– 0.35	– 0.25	– 0.15	– 0.05	0.05	0.15	0.25
	$R = 96.950$	$R = 130.59$	$R = 89.071$	$R = 106.13$	$R = 99.972$	$R = 132.48$	$R = 158.25$
– 0.35		1.000000	1.000000	1.000000	1.000000	1.000000	0.528248
– 0.25	1.000000		0.441910	1.000000	1.000000	1.000000	1.000000
– 0.15	1.000000	0.441910		1.000000	1.000000	0.205231	0.036008
– 0.05	1.000000	1.000000	1.000000		1.000000	1.000000	0.200719
0.05	1.000000	1.000000	1.000000	1.000000		0.536678	0.090134
0.15	1.000000	1.000000	0.205231	1.000000	0.536678		1.000000
0.25	0.528248	0.000000	0.036008	0.200719	0.090134	1.000000	

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