Drone base multiscale Digital Surface Models to planar areas.

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Abstract

The obtaining of a Digital Surface models (DSMs) at different scales and levels before the appearance of Unmanned Aerial Vehicles (UAV) was very rare or impossible. UAV's with advanced photogrammetry software can produce high-resolution Digital Surface Models at multiscale levels with several spatial resolutions. In this paper we tested the Arc–Chord Ratio (ACR) method decouples rugosity from the slope at multiscale DSM generated from six different UAV flight altitudes of 20, 40, 60, 120, 240 and 360 meters for the study and analysis of the surface to planar areas changes with spatial resolutions.

The path of DSM to planar areas should pass by series of surfaces: planar slope surface, boundary data surface to reach the horizontal planar surface.

To answer this question: at the same study area, did the transition of multiscale Digital Surface Models to planar areas have the same results?

After calculating the multiscale rugosity, this paper studies the similarity between these surfaces at multiscale by correlation and statistical analysis. Visually and statistically planar areas of all flight heights are very similar, correlation results showed a big difference in values due to cartographic generalization and spatial resolution.

Keywords: ACR, Rugosity, GIS, DSM, multi-scale.

Introduction

Rugosity is a measure of topographic heterogeneity, it describes and counts discrete structures, from categorical to quantitative (McCormick, 1994). Rugosity is an index of surface roughness that is widely used as a measure of landscape structural complexity.

Rugosity is traditionally evaluated in-situ across a two dimensional terrain profile by draping a chain over the surface and comparing the length of the chain with the linear length of the profile figure 1.

Two-dimensional rugosity is defined as the ratio between the surface contour distance and the linear distance between two points (Risk, 1972) and is synonymous with the term tortuosity or the arc-chord ratio (Moser et al., 2007).

There are multiple measures of structural complexity (McCormick 1994), for over forty years many scientists have used the rugosity index for topographic (elevation) or bathymetric (depth) datasets; rugosity can be calculated from two- or three-dimensional data at any scale.

Drones based Digital Surface Models at different flight heights with different scale could be a good material for rugosity analysis at different scales.

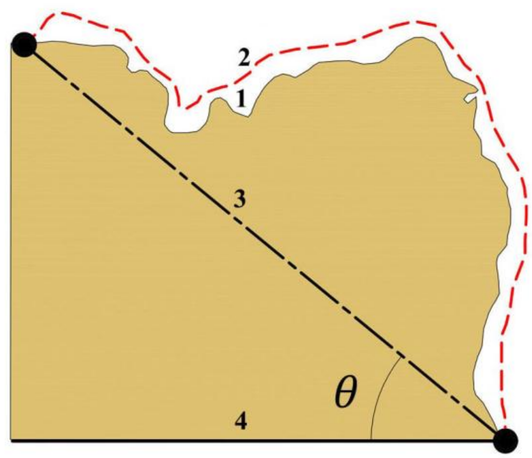

Fig. 1 The rugosity of a surface (e.g. yellow profile of a terrain № 1) is the ratio between the contoured distance (dashed line № 2) and the planar distance (or area for three-dimensional data).

The standard surface ratio (SR) method for calculating a planar distance is to project the surface onto a horizontal plane (solid line), this method confounds rugosity with the slope (θ) at the scale of the surface (solid line).

Figure 1 is a very expressive section, the length of the section number 1 natural terrain with 5.8 km a very complex terrain, section number 2 smoothed terrain owning a similar shape as the natural terrain but with 5.3 km length. Section number three express a slope projection of the natural terrain with a 3.5 km length.

The last section a horizontal planar one number 4 with 2.8 km influenced by the slope angle (θ), the big change in length from section 1 to the horizontal section 4 is approximately the half. The idea here is not the changing in length nor the surface, but the rugosity change at different DSM spatial resolution.

A six DSM generated from different UAV flight height constitute the base of our study by comparing the transition to planar areas at different levels.

In the early 1970s The standard surface ratio (SR) method for measuring rugosity was introduced by (Risk 1972; Dahl 1973). They calculated rugosity by projecting the surface onto a horizontal plane (Lundblad et al. 2006; Wright and Heyman 2008; Friedman et al. 2012) thereby coupling rugosity with the slope at the scale of the surface equation 1.

$$Rugosity = \frac{Contoured\ \ area}{Planar\ \ area} (1)$$

in the case of equation 1 the rugosity increases with increasing of the slope figure 1; the law of cosines, where cos (θ) = adjacent side ÷ hypotenuse side), here lies the fundamental issue presented by the traditional methods for measuring rugosity.

A flat surface has a rugosity value of one, while a rougher surface, or a surface with more relief, has a higher rugosity value than one, rugosity encompasses and combines both structural relief and roughness (Moser et al., 2007).

A new arc–chord ratio (ACR) rugosity index for quantifying landscape structural complexity was developed by Du Preez (2014) to overcome significant issues presented by traditional rugosity indices. In comparison to other methods for measuring rugosity, ACR rugosity is separated from the slope and easy to execute an ACR rugosity analyses using the GIS software (Du Preez 2014).

Many marine and land studies use rugosity such as environmental risk assessment, species management, distribution and conservation, predictive mapping of vulnerable marine and land ecosystems (Stambaugh and Guyette 2008; Wedding et al. 2008; Galparsoro et al. 2009; Woodby et al. 2009).

In this paper, the ACR three dimensional method is tested on the six generated DSM and compared at different levels of spatial resolution by correlation and statistical analyst.

Spatial resolution is a very important factor of scale influence on rugosity, to prove that our paper will find the answer to the question: did the transition of the multiscale Digital Surface Models to planar areas have the same results?

Materials and methods

A mountainous region of 1700 m an average elevation above the sea level occupying an area of 2 hectares, Zaarour region of the western Lebanese mountainous chain characterized by a bare land without urbanizations and vegetation cover. The benefit of this study bare area is that Digital Surface Models are acting as Digital Terrain models.

An autopilot DJI Phantom 3 drone with a camera of 14 megapixels at a focal length of 3.61 mm flies the study area at different Heights.

The flight paths of all missions are identical and designed in a mobile application called Litchi, the study area and the flight parameters (coordinates, height, time, etc…). All datasets (photos) of the six missions of different flight heights were processed in Agisoft photoscan software for the generation of Digital Surface Models (DSM).

Drones have been widely used as an apparatus for aerial photography, for many agricultural and terrain analysis applications.

One of the advantages of UAV is the availability and fast photogrammetry mission execution at different altitudes, this paper will only discuss the spatial scale with the UAV flight altitudes.

Our study will test the rugosity index at six different levels expressed by flight height of a drone at 20, 40,60,120,240 and 360 meters. The flight datum was calculated from the same takeoff points of the drone of the six flights.

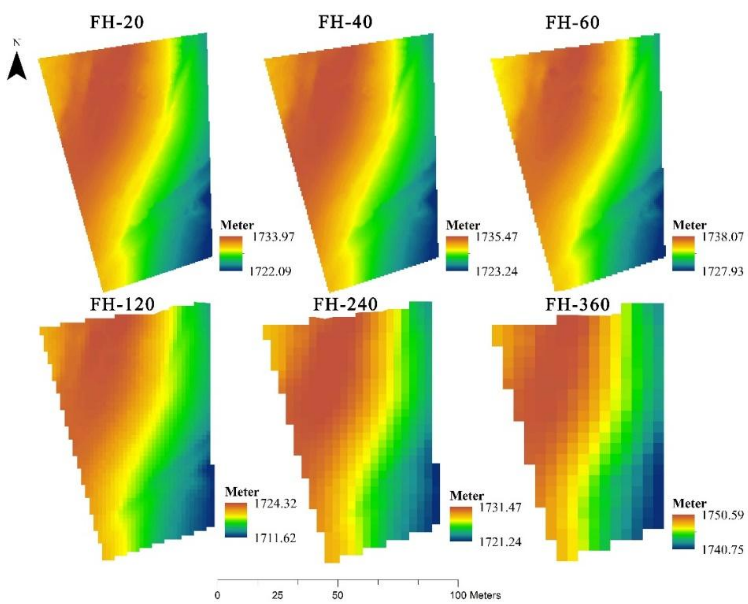

Fig.2: multiscale DSM obtained from image acquisition and processing.

Figure 2 shows six DSM of the study area of different spatial resolutions, FA-20 of 20 meters' flight altitude with a very high-resolution data set highlighting all the terrain details even rocks texture, passing by FA-60 the terrain is smoothed with some concave and convex areas and ending by FA-360 of 360 meters'.

These 6 DSM can be classified visually from figure 2 by rough and smooth, FA-20, FA-40 and FA-60 for rough and FA-120, FA-240 and FA-360 for smooth, also figure 1 constitute an interval of scales and smoothness showing the generalization at different scales.

Table 1: spatial resolutions of the six generated DSMs.

DSM	Spatial resolution (m)
FH-20	0.4
FH-40	0.6
FH-60	0.80
FH-120	1.70
FH-240	3.20
FH-360	4.50

As per table one different flight altitude lead to different spatial resolution (pixel size), the minimum spatial resolution is 0.40 m which is a high resolution showing all terrain details and a maximum resolution of 4.50 m quite good resolution for geomorphological analysis at a local scale.

Many methods of evaluating rugosity on a three dimensional surface have been proposed. These methods measure a ratio of areas rather than lengths, as shown in Equation (1).

Surface Area to Planar Area (SAPA) method introduced by Jeff Jenness evaluates rugosity using a 3 x 3 neighborhood, by drawing a line from the center of each cell in the window to the center of the central cell in three dimensions. The result is a network of eight triangles in the central cell which approximates the contoured surface at the cell location. The sum area of these triangles is divided by the two dimensional cell area to obtain a measure of rugosity (Jenness 2004).

Du Preez and Tunnicliffe (2012) propose a novel method for measuring rugosity that decouples rugosity from the slope and is consistently independent of data dimensionality and scale. it is a simple adaptation of an Arc Chord Ratio (ACR). The method replaces the horizontal plane with a plane of best fit (POBF), where the POBF is a function of boundary data interpolation (Preez and Tunnicliffe 2012). The ACR method can be used in multi-scale analyses, an important attribute of a spatial analysis as morphological processes act at a variety of spatial scales (Levin 1992), and differ in effects and importance with scale (Wu 2013).

Basing on Du Preez (2014), Jeff Jenness developed A new technique, operates on a 3x3 neighborhood, using the triangulated area of each adjacent cell and applying the Pythagorean theorem to compute the surface area. By default, the planar area of each grid cell is corrected by dividing the cell area by the cosine of slope (Jenness 2004).

In our study ACR was calculate in GIS tool installed on ArcGIS® Software available for download in Du Preez 2014, from the six generated DSMs we calculated Arc-Chord ration (ACR). The ACR rugosity index is a measure of three-dimensional structural complexity defined as the contoured area of the surface divided by the area of the surface orthogonally projected onto a plane of best fit.

The arc-chord ratio (ACR) method calculates the planar distance by projecting the surface boundary onto a boundary data section 1 figure 1 (Red dashed line) plane of best fit section 3 figure 1 (POBF; dashed-dotted line; 3) effectively decoupling rugosity from the slope at the scale of the surface. ACR is calculated by creating two TINs a contoured surface and a planar one representing the plane of best fit (POBF) figure 3a. The POBF is a function (interpolation) of the boundary data only of the area of interest the area of interest is the boundary of the study area. The surface area of the first TIN within is divided by that of the second TIN to obtain a single ACR value for the area of interest (Du Preez 2014).

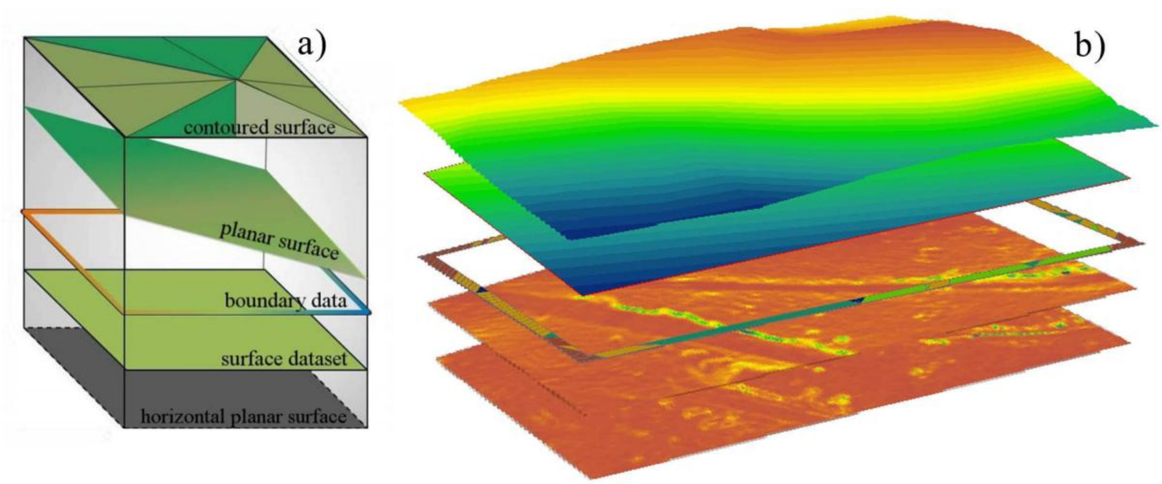

Fig.3: a) ACR simultaneous surfaces leading to the horizontal planar one, b) an example of ACR surfaces of FH-20.

As a first step, the conversation from raster to TIN for the six DSMs to form contour surfaces at different scales.

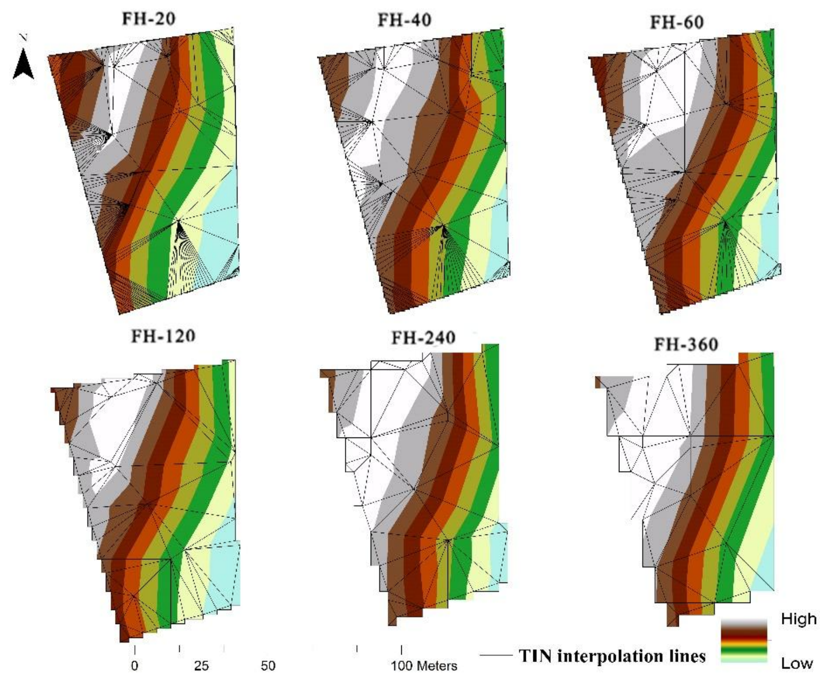

Fig.4: TIN models of contour surface at the six flight heights.

All the six TIN models expressed the terrain morphology with some variations detected on the colored contour lines, and a generalization in triangles quantity.

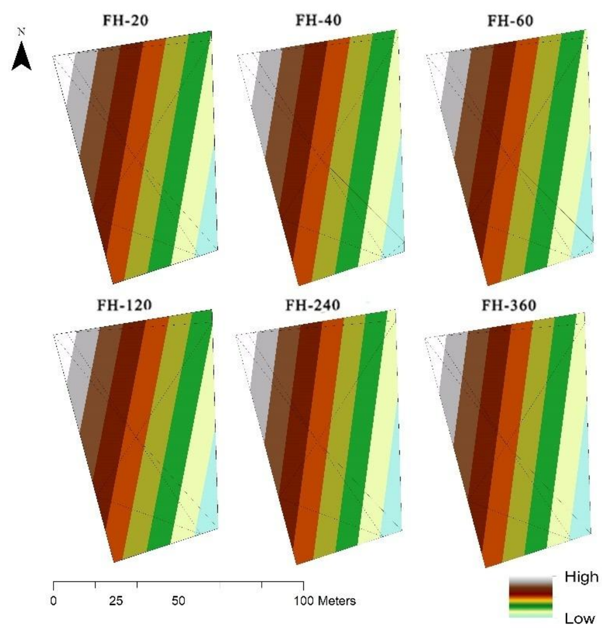

Fig.5: the POBF of the six flight heights

Step two, the contoured surface translated to a plane of best fit (POBF) decoupling rugosity from the slope at the scale of the surface (Du Preez and Tunnicliffe 2012; Friedman et al. 2012).

Figure 5 shows six similar planar surfaces owning the same trend of values by simplifying elevation values of the contour surfaces.

The innovation of the ACR method lies in the analysis used to generate the POBF: identify and isolate the boundary data (step three) figure 3a an illustrated example the boundary data of FH-20 the triangulated irregular network data frame.

By using a linear polynomial interpolation of the boundary data at the six levels to generate surface datasets (step four).

Some softwares are unable to interpolate the actual planar area, an alternative is to interpolate the angle of the POBF and use the cosine equation (and the horizontal planar area) to extract the planar area of step five (Du Preez 2014).

To solve for the ACR rugosity index, by application of formula 1 using the contoured and planar areas (step six).

By following Du Preez and Tunnicliffe (2012) arc–chord ratio (ACR) we Computed a ratio between the three-dimensional surface area and the planar area of the surface, this tool uses a novel methodology to develop a surface area dataset. The output values represent ratios between the surface area and planar area, typically ranging from 1 in flat areas to 4 in areas of high variation.

Discussion and results

The first step of Du Preez methodology of conversation from raster to TIN, figure 4 of the similar six TIN models. Same study area at different spatial resolution lead to visual data similarity a statistical comparison was done to test this degree of similarity table 3.

Table 3: Elevation TIN statistics, quantity of triangles, average minimum and maximum elevations and the slope average.

Contoured area TIN

Flight height	Quantity of triangles	Average Min. Elev	Average Max. Elev	Average Slope %
20	321	1728.95	1729.94	15.89
40	230	1730.26	1731.53	16.70
60	172	1733.58	1734.85	14.52
120	85	1718.65	1720.76	17.03
240	58	1727.14	1729.25	14.48
360	41	1746.67	1748.87	13.00

The statistical values of table 3 shows a decreasing in triangles numbers from 321 to 41 due to decreasing in spatial resolution, the difference in average maximum andminimum elevations due to the interpolated predicted values.

The quantity of triangle from elevation area to planar area of table 3 and table 4 are reduced more than twenty times in high spatial resolution data of 20, 40 and 60 meters' flight heights,otherwise low spatial resolution data with low triangles quantity in contoured areas are reduced less than ten times in planar areas TIN models.

Average of maximum and minimum elevations approximately in all levels are reduced in a range of 2 meters between surface and planar areas, hence a reduction on the average slope in the range of 2 percent.

Table 4: POBF, planar TIN area statistics quantity of triangles, average minimum and maximum elevations and the slope average.

Planar area TIN

Flight height	Quantity of triangles	Average Min. Elev	Average Max. Elev	Average Slope %
20	10	1725.72	1731.67	13.23
40	9	1726.72	1732.41	14.13
60	9	1732.90	1732.98	10.44

120	8	1715.46	1722.23	14.87
240	8	1724.62	1729.84	11.72
360	7	1746.22	1746.66	10.75

In planar area TIN, the average values of the minimum and maximum elevations in all the six flights is reduced with the number of triangles due to the transition from contoured to planar area.

The variation in values between table 3 and table 4 showed an unstable change in elevations and slope.

The first part of the transition from contoured area TIN to planar area TIN (POBF) is very similar to trend analysis simplifying the complexity of values with a conservation of the same datum.

Otherwise the second transition part from surface area two planar one record a loss of initial datum elevation down to zero table 5.

Table 5: Surface areas statistics at different flight heights.

Surface Area

Flight heights	Min	Max	Mean	Std
20	0.141	0.227	0.144	0.005
40	0.312	0.415	0.319	0.008
60	0.645	0.756	0.657	0.013
120	3.007	3.342	3.073	0.048
240	10.7	11.3	10.867	0.105
360	19.976	20.705	20.291	0.172

High spatial resolution data of 20, 40 and 60 have sub meter surface area values, rising with approximately in double values between flight heights.

The surface area is designed to determine the amount of similarity between the tested area surface and planar surface. it is hypothesized that the surface area increases with surface irregularity. Because there is a definite interplay between the number and magnitude of terrain irregularities such that similar surface area estimates could arise from different manipulations of these two variables.

Table 6: Planar area statistics and different flight heights.

Planar Area

Flight height	Min	Max	Mean	Std

20	0.99	1.154	1	0.005
40	0.99	1.132	1	0.003
60	0.99	1.045	1	0.002
120	0.99	1.013	1	0.001
240	0.99	1.003	1	0.0006
360	0.99	1.003	1	0.0005

The values of planar area at different scales is practically the same with small variations at low flight height, basing the results of table 6 especially the similar mean values, we can answer the above question constituting the target of our paper by:*yes, the transition of the multiscale Digital Surface Models to planar areas have the same results.*

Visual and statistical results prove the similarity of multiscale planar data, a regression analysis run to test this similarity in planar surface at multiscale.

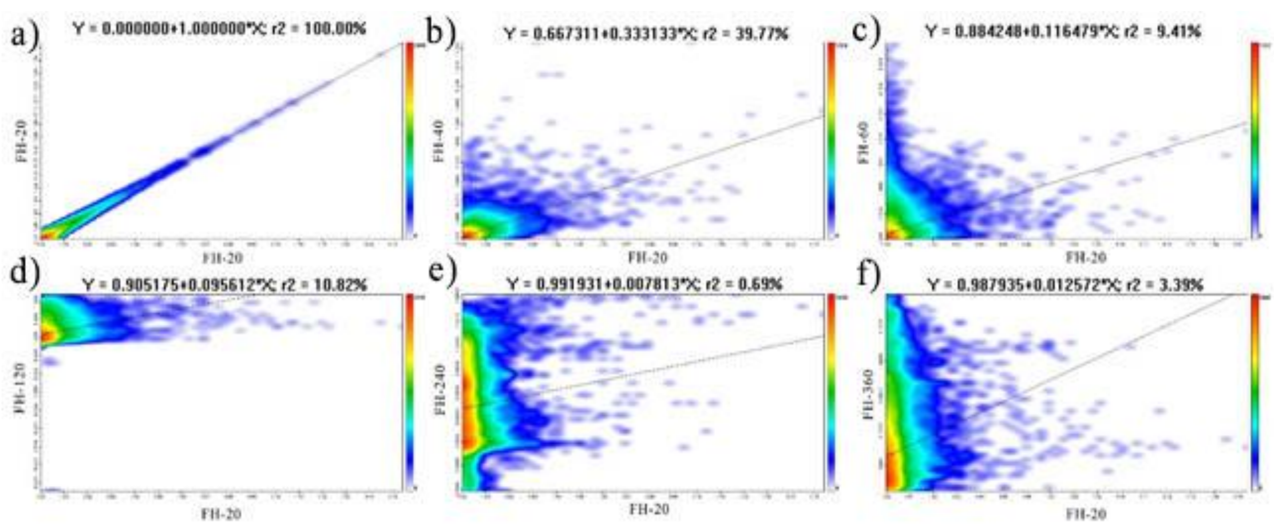

Fig. 6: scattered plots of planar area at different scales.

The correlation analysis between the highest spatial resolution data of FH-20 as a reference and the other datasets, figure 6a a test scatterplot with same data set in X and Y axes of FH-20, with hundred percent similarity.

The graph FH-40 with FH-20 gives 39.77 % of similarity figure 6b,r square values of FH-60, FH-120, FH-240 and FH-360 against FH-20 are less than 11 %, the core of the scatterplots for the high spatial resolution datasets are in the lower left corners, moving positively with the Y axes in FH-120 then falling down negatively for FH-360.

The correlation analysis contrary to visual and statistical showed a difference in multiscale planar areas.

Conclusion

Nowadays the use of UAV for terrain analysis present an initial tool for multiscale Digital Surface interpretations, the idea from our research is to understand how the rugosity evolution is acting on the six flight heights deriving different spatial resolution datasets.

The present paper provides multiscale DSM analysis by adaptation and improvement of ACR geo-processing model tools and step-by-step application of Du Preez 2014 module. Improving standard methods for the detection and investigation of geomorphological patterns at different spatial resolution will lead to better scientific information for generalizations, terrain analysis, management and conservation initiatives.

We can conclude from this paper that Scale and resolutions effects on terrain data and form an important issue in geographic researches, DSM UAV based at high flights should be tested before use.

It is essential to have a good understanding of the effects of scale on the analysis results,each elevation data has its own surface to planar result, terrain rugosity depends with spatial resolution and visual analysis should follow a correlation one.

References:

1. Dahl, A.L. Surface area in ecological analysis: quantification of benthic coral-reef algae. Mar Biol. 1973, 23, pp.239–249.
2. Du Preez, C. "A new arc-chord ratio (ACR) rugosity index for quantifying three-dimensional landscape structural complexity." Landscape Ecology. 2014, 30, pp. 181–192.
3. Du Preez, C., Tunnicliffe V. Shortspine thornyhead and rockfish (Scorpaenidae) distribution in response to substratum, biogenic structures and trawling. Mar. Ecol. Prog. Ser. 2011, 425, pp. 217-231. [doi:10.3354/meps09005].
4. Friedman A., Pizarro O., Williams S.B., Johnson-Roberson M. Multi-scale measures of rugosity, slope and aspect from benthic stereo image reconstructions. PLoS One 7, 2012, 12, pp. 1–14.

5. Galparsoro I., Borja A., Bald J., Liria P., Chust G. Predicting suitable habitat for the European lobster (Homarus gammarus), on the Basque continental shelf (Bay of Biscay), using Ecological-Niche Factor analysis. Ecol Model 2009, 220, pp. 556–567.
6. Jenness, Jeff S. "Calculating landscape surface area from digital elevation models." Wildlife Society Bulletin 32.3, 2004, pp. 829-839.
7. Levin S.A. The problem of pattern and scale in ecology. Ecology. 1992., 73, pp. 1943–1967.
8. Lundblad ER, Wright DJ, Miller J, Larkin EM, Rinehart R, Naar DF, Donahue BT, Anderson SM, Battista T A benthic terrain classification scheme for American Samoa. Mar Geod. 2006, 29, pp. 89–111.
9. McCormick, M.I. Comparison of field methods for measuring surface topography and their associations with a tropical reef fish assemblage. Marine Ecology Progress Series 112, 1994,pp. 87-96.
10. Moser, K., Ahn, C., Noe, G. Characterization of micro topography and its influence on vegetation patterns in created wetlands. Wetlands 2007, 27, pp. 1081-1097.
11. Risk, M.J. 1972. Fish diversity on a coral reef in the Virgin Islands. Atoll Research Bulletin 193, pp. 1-6.
12. Stambaugh M.C., Guyette R.P. Predicting spatio-temporal variability in fire return intervals using a topographic roughness index. For Ecol Manag ,2008, 254(3), pp. 463–473.
13. Wedding L.M., Friedlander A.M., McGranaghan M., Yost R.S., Monaco M. E. Using bathymetric LIDAR to define nearshore benthic habitat complexity: implications for management of reef fish assemblages in Hawaii. Remote Sens Environ, 2008, 112(11), pp. 4159–4165.
14. Woodby D., Carlile D., Hulbert L. Predictive modeling of coral distribution in the Central Aleutian Islands, USA. Mar Ecol Prog Ser. 2009, 397, pp. 227–240.
15. Wright D.J., Heyman W.D. Introduction to the special issue: marine and coastal GIS for geomorphology, habitat mapping, and marine reserves. Mar Geod. 2008, 31, pp. 223–230.
16. Wu J Effects of changing scale on landscape pattern analysis: scaling relations Landscape Ecol. 2004, 19, pp. 125–138