GEOMORPHOMETRY 2020 PERUGIA, ITALY JUNE 22 - 26 2020

Can multiscale roughness help computer-assisted identification of coastal habitats in Florida?

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Abstract—**Coastal habitats are of natural, economic, and cultural importance in Florida, and there is a need for effective approaches to map and monitor them. Geographic Object-Based Image Analysis (GEOBIA) was previously applied to an orthomosaic and a Digital Surface Model (DSM) to automatically delineate oyster reef, salt marsh, and mudflat habitats in Little Trout Creek, Florida. Here we evaluated whether a multiscale measure of roughness has the potential to improve this GEOBIA workflow in this context where oysters are spectrally similar to the two other habitat types. Our results show that multiscale roughness can be used to distinguish the different coastal habitat types studied. The level of roughness of mudflats is usually higher at broader scales, and the magnitude of that roughness is relatively small. Marsh roughness was highest at finer scales, and its magnitude was higher compared to other habitat types likely due to marshes' vegetation cover, which is captured in the DSM. The highest magnitudes of roughness for oysters were smaller than, and found at slightly broader scales than, the highest roughness for marshes. Our results were strongly affected by edge effects because the studied habitats are discrete and discontinuous. Multiscale roughness has the potential to help delineate coastal habitats in Florida, but more work is needed to better understand the multiscale topographic patterns of different coastal habitats in Florida and elsewhere.**

I. INTRODUCTION

Coastal habitats like oyster reefs and salt marshes provide economic opportunities as well as vital ecosystem services such as shoreline erosion control, habitat and nursery for a variety of species, and water filtration. However, many of these ecosystem services are threatened by natural and anthropogenic factors (*e.g.*, coastal development, sea-level rise, hurricanes). Mapping and monitoring coastal habitats are critical to improving scientific understanding of the complex dynamics of coastal ecosystems, to better inform management, planning, and conservation efforts.

Florida's coastal waters are the most economically valuable, have the highest recreational use, and have one of the highest concentrations of coastal communities in the United States. At a 2007 workshop, regional, state, and federal partners concluded that although mapping coastal resources was a top priority, the lack of a standard, reproducible approach was hindering broad-scale efforts [1]. With the increased likelihood of extreme weather events [2] that have the potential to impact coastal habitats in Florida [3], there is a critical need to develop an effective and reproducible mapping and monitoring workflow that can be used to answer questions in a variety of contexts (*e.g.*, sea-level rise, community resilience, hurricane impact assessments).

In a recent article, Espriella *et al.* [4] proposed a reproducible approach to detect and delineate three types of coastal habitats – oyster reefs, salt marshes, and mudflats – in imagery collected with Unoccupied Aircraft Systems (UAS). The approach is centered on a two-level Geographic Object-Based Image Analysis (GEOBIA) [5] that first identifies and extracts water areas from the data before classifying the remaining objects into their respective habitats. Both the RGB mosaic and the Digital Surface Model (DSM), produced using structure-from-motion photogrammetry, were used as inputs. However, with an overall classification accuracy of 79%, that GEOBIA alone may not be robust enough for accurate temporal monitoring. Oysters had the lowest overall separability from the other habitats, which is problematic from a management perspective; oysters are one of the most important living coastal resources actively managed in the Gulf of Mexico, are suffering from major declines in the area, and thus are of particular interest.

In nature, oyster reefs are more structurally complex than marsh and mudflats, at multiple scales. Therefore, we hypothesize that geomorphometry can provide a means to help differentiate these habitats from each other. While Espriella *et al.* [4] derived local measures of terrain attributes (*e.g.*, rugosity, relative position) at multiple independent spatial scales [6] using relatively few search neighborhoods [7], their feature-space optimization to select the variables best fit to recognize the different habitats did not identify any DSM-derived variables as being relevant. Here, we evaluate the potential of a multiscale measure of roughness [8] – as opposed to independent measures of roughness derived at multiple scales – to help distinguish oyster reefs, salt marshes, and mudflats from each other.

Vincent Lecours and Michael Espriella (2020) Can multiscale roughness help computer-assisted identification of coastal habitats in Florida?:

in Massimiliano Alvioli, Ivan Marchesini, Laura Melelli & Peter Guth, eds., Proceedings of the Geomorphometry 2020 Conference, doi:10.30437/GEOMORPHOMETRY2020_24.

II. Methods

UAS imagery was collected on December 8th, 2018 at low tide, at the mouth of Little Trout Creek (29° 15’ 34.98” N, 83° 4’ 29.68” W), on the west coast of Florida (Fig. 1). The imagery was collected at nadir using a DJI Inspire 2 equipped with a Zenmuse X7 35 mm RGB sensor. The UAS was flown 60 m above ground level, with an 80% along-track overlap and 75% across-track overlap. Four checkered targets were evenly distributed across the scene and located using a Trimble 5800 real-time kinematic positioning system. In addition to the orthomosaic, a DSM was produced using structure-from-motion photogrammetry in Pix4D Mapper v. 4.2.27. The total area surveyed covered approximately 0.116 km^2 and provided data with a 0.66 cm spatial resolution (Fig. 2), with a root mean square error of 0.3 cm in longitude and latitude, and 0.1 cm in elevation for the residuals of control points.

Figure 1. Location of the study area: Little Trout Creek, Florida, USA.

The GEOBIA ruleset of Espriella *et al.* [4] was applied to the data. The resulting classification was used to extract 37 oyster reefs, 22 salt marshes, and 33 mudflats areas from the DSM. The areas were selected because they were fully encompassed within the extent of the data (*i.e.*, no areas from the boundaries of the mosaic). Each extracted area was entered in the “Multiscale Roughness” tool of WhiteboxTools v. 1.1.0 [9], with search neighborhood radii ranging from 1 grid cell to 9,751 grid cells, which corresponds to the length of the longest feature (a salt marsh of about 64 m; cf. center of Fig. 2 and Fig. 3). The tool produced two main outputs: a raster that indicates, for each pixel, the size of the search neighborhood at which the measured roughness was the highest, and a raster displaying the magnitude of the measured roughness at that scale. Descriptive statistics of the two output types were calculated for each habitat type.

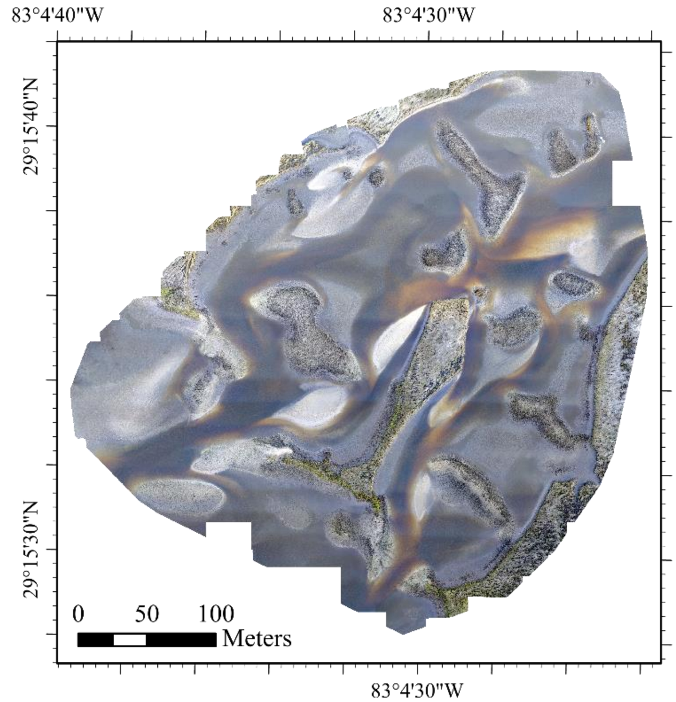

Figure 2. UAS imagery collected at low tide on December 8th, 2018.

III. Results and Discussion

Figure 3 presents the GEOBIA classification results and the scale and magnitude outputs for all the studied habitats. The spatial distributions of the scale and magnitude values seem to be influenced by the geometry of the features and the quality of the DSM. For instance, high-magnitude values were found on long and narrow features, and broader-scale values were found in areas of interpolation artifacts where the presence of water affected DSM production. In general, magnitude is the most promising output to differentiate the three studied coastal habitats (Fig. 3); patches of mud displayed a much lower magnitude than other habitat types, which was expected considering the less complex nature of mudflats, and salt marshes displayed a much higher magnitude than other habitat types, likely because of the presence of a vegetation cover captured in the DSM. Oyster reefs, which are the most heterogeneous habitats, had intermediate magnitudes of roughness at intermediate scales.

These observations are confirmed by the analysis of the statistical distributions of scale and magnitude (Tab. 1). On

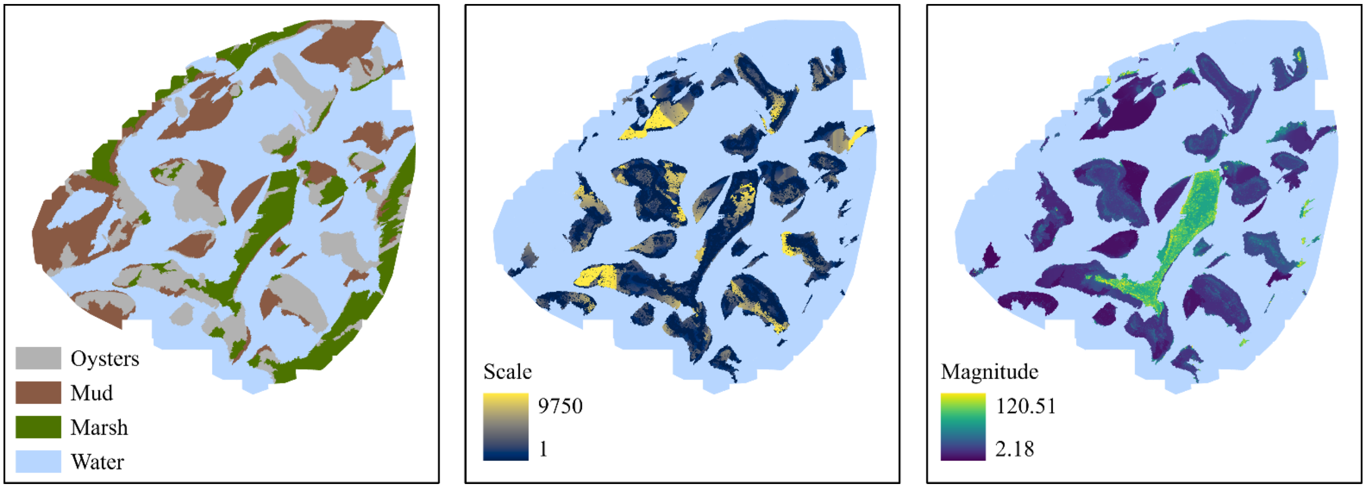

FIGURE 3. GEOBIA CLASSIFICATION, AND SCALE AND MAGNITUDE OF THE MULTISCALE ROUGHNESS MEASURE APPLIED TO THE EXTRACTED FEATURES.

average, the scale of maximum roughness was broader for mudflats than for oysters and marshes. However, averages are likely biased by outliers caused by edge effects: the skewness of the distributions for scale shows that they are highly skewed for marsh and oysters, and moderately skewed for mudflats. Distributions of scale for marshes and oysters are leptokurtic, and that of mudflats is platykurtic. The distributions of magnitudes for mudflats and oysters are heavily skewed, with a high and sharp peak and long and fat tails caused by many outliers. The distribution of magnitudes for marshes is relatively symmetrical but platykurtic, with a short and thin tail. Given these results, we do not expect that the averages presented in Tab. 1 are fully representative. We adjusted them by manually removing outliers from the distribution and obtained revised averages for scale of 1,231.66 (≈9.4 m) for marshes, 1,980.06 (≈19.6 m) for mudflats, and 1879.68 (≈15.0 m) for oysters. However, the median values suggest that patterns of highest roughness can be found at about 1.5 m for marshes, 12.9 m for mudflats, and 5.3 m for oysters, which is more consistent with what can be observed in the field in terms of habitat complexity and habitat patch size. Setting these results into the natural context can thus serve as additional evidence that edge effects influenced some of the statistics (*e.g.*, average, standard deviation). In fact, the cumulative distributions of scale for all habitat types showed a stabilization in slope between 125 and 400, which corresponds to 0.8 to 2.6 m, indicating that most of the high measured roughness would be found at scales finer than 3 m.

It is noteworthy that all habitat types reached a local peak of maximum roughness at search radii of 30 cells (oysters and mud) or 33 cells (marsh), which corresponds to 21±1 cm. While this is an interesting result, it should be interpreted with caution: given the different natures of the habitat types, it is improbable that they display local roughness at almost the same exact scale (with a precision of 6 mm). A possible explanation is that intrinsic noise is present in the DSM at this specific scale range and captured by the analysis. In terms of magnitude, the statistical distributions confirm that magnitudes of roughness are generally smaller for mudflats and higher for marshes.

TABLE 1. DESCRIPTIVE STATISTICS OF THE SCALE AND MAGNITUDE OF THE MULTISCALE ROUGHNESS MEASURE FOR EACH HABITAT TYPE.

	Scale			Magnitude		
	Marsh	Mud	Oyster	Marsh	Mud	Oyster
Number of Cells	154,945,348	238,774,206	438,236,795	154,945,348	238,774,206	438,236,795
Minimum	1	1	1	3.90	2.18	3.31
Maximum	9,750	9,750	9,750	108.65	120.51	101.21
Average	1,428.40	2,973.09	2,276.70	21.34	7.90	10.77
Median	229	1,948	804	25.76	6.30	9.82
Standard Deviation	2,287.13	3,127.44	2,943.04	11.01	5.64	5.47
Variance	5,230,967.94	9,780,854.37	8,661,511.55	121.33	31.76	29.88
Skewness	2.00	0.87	1.30	-0.10	2.91	3.15
Kurtosis	6.19	2.51	3.48	1.77	14.55	17.43

This work is an initial exploration of the potential of measures of multiscale topographic patterns to help identify coastal habitats. However, limitations include the use of the results of an imperfect spectral-based GEOBIA classification to guide the selection of habitat features for this analysis. For instance, Fig. 4 shows that one of the objects identified as marsh is partly misclassified: only the central section of this object is a vegetated salt marsh – the surrounding habitat is oysters. However, the entirety of this area was considered as marsh for the analysis because it was based on the objects defined and classified by the GEOBIA workflow. Both the scale and magnitude of the multiscale roughness captured that difference, with the marsh having a finer-scale roughness of higher magnitude than the surrounding oysters. This directly highlights the potential of these measures to augment the GEOBIA and differentiate coastal habitats in Florida.

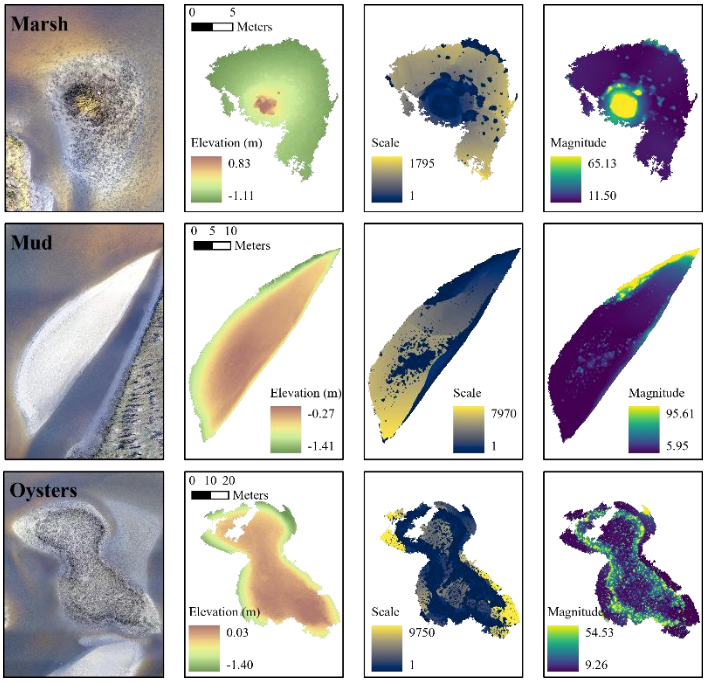

FIGURE 4. EXAMPLE OF ORTHOMOSAIC, DSM, AND THE SCALE AND MAGNITUDE COMPONENTS OF THE MULTISCALE ROUGHNESS MEASURE FOR ONE OF THE 22 SALT MARSHES, ONE OF THE 33 MUDFLATS, AND ONE OF THE 37 OYSTER REEFS STUDIED.

Another limitation of this work is that each of the 92 features studied was analyzed independently, which artificially increased edge effects. The complex dynamics of this coastal ecosystem mean that oysters can be directly adjacent to mudflats and marshes. As such, analyzing a patch of multiple habitats as one, then separating it into different habitats post-analysis before computing statistics could have reduced the influence of edge effects. However, this would be very computationally intensive given the size of the DSM (24 GB).

IV. CONCLUSIONS

Coastal geomorphometry has recently been identified as a future application of geomorphometry that will present challenges due to the presence of features both over and under the waterline [10]. Here we presented such an application, and these challenges were highlighted by a strong influence of edge effects and feature geometry that artificially increased the average scale at which maximum roughness was observed and the average magnitude of that roughness. However, we concluded that mudflats display relatively smaller amplitudes of roughness over broader scales and that salt marshes display the highest roughness over relatively finer scales. Oyster reefs showed intermediate patterns of roughness, with both amplitudes and scales between those of the two other habitat types. While we hypothesized that oyster reefs would show the highest roughness at the finest scales, the finer-scale patterns of salt marshes may be explained by the presence of characteristic vegetation on the marshes, which creates relatively high roughness patterns in the DSM. Future work should repeat the analyses using a Digital Terrain Model (DTM) instead of a DSM. In theory, the DTM would preserve the complex fine-scale structures of oyster reefs while omitting the vegetation over salt marshes that created local roughness. Denoising algorithms could also be applied to the models to ensure that the multiscale analyses capture the scales at which patterns are observed rather than the noise in the data. Finally, because we demonstrated that multiscale roughness shows potential to help differentiate coastal habitat types from each other, we recommend evaluating the suitability of other multiscale geomorphometric measures, such as multiscale topographic position [11], multiscale maximum spherical standard deviation [8], multiscale maximum difference from mean elevation [11], and multiscale topographic anisotropy [12] for the identification of coastal habitats.

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