AI-Driven Ground Points Extraction for Rugged Terrains in Coastal Landscape – A Case Study

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KEY WORDS: Digital Terrain Model (DTM), Ground Points Extraction, Inverse Distance Weight (IDW), Random Forest Classifier (RFC), Structure from Motion (SfM), Unmanned Aircraft System (UAS).

ABSTRACT:

Coastal erosion is a great threat to the coastal ecosystem and is often quantified by retreating shoreline and the loss of sand from the coastal zone. To quantify the volumetric loss of sand, the ground and non-ground features should be separated, and erosion could be quantified using the extracted ground features. While there are several algorithms available for ground and non-ground classification, most tend to remove valid ground points that are crucial in accurate volumetric loss and gain estimates. This study proposes raster-based approach to extract topography of the ground with better reliability of rugged terrains where the surface is often over smoothened. In this approach 3D point cloud obtained from the UAS-SfM (Unmanned Aircraft System – Structure from Motion) technique is converted to raster with five bands including red, green, blue, elevation and slope with elevation and slope derived from the surface model. This approach uses a Random Forest Classifier (RFC), which utilizes all five bands to train the model. The classified ground points are transformed into a Digital Terrain Model (DTM) using the Inverse Distance Weight (IDW) interpolation technique. The DTM generated is cross validated with the orthomosaic and Digital Surface Model (DSM). The results shown that the DTM generated using this machine learning approach produced reliable result with RMSE 0.059m.

1. INTRODUCTION

Coastal monitoring and mapping are essential for long-term coastal land use planning and management, environmental protection, and sustainable coastal development. Beaches are the most significant assets of the state of Florida attracting visitors from all over the world. According to Florida's official state website, there are over 663 miles of beaches, 1,350 miles of coastline and about 2,276 statute miles of tidal shoreline (Florida Department of State, 2022). Coastal erosion affects more than 90% of the world's coastline. Over the last 200 years, environmental changes and population growth have resulted in the loss of more than half of the United States' wetlands (Williams, 2001). Coastal crises occur across the world, and they have become a significant problem for the marine environment. Geomatics plays a significant role in monitoring the coastal changes (Gao, 2009; Baig et al., 2020). Most of the geomatics analysis focused on mapping shoreline retreat using UAS and satellite remote sensing which is indeed essential but not limited to this point (Baig et al., 2020). Mapping the topography of the coastal area and analyzing the spatial temporal variability of the beach topography will help in quantifying the volumetric loss of sand which in turn helps in sediment budget analysis (Rosati, 2005). Photogrammetry and LIDAR sensing techniques play a vital role in estimating 3D topography of the terrain in a greater resolution. Photogrammetry uses Structure-from-Motion (SfM) technique which uses series of overlapping 2D images from different perspectives to create 3D point cloud and LIDAR measures distance based on time travel of laser pulse and create high density point cloud (Westoby et al., 2012; Hodgson et al., 2003).

To map the topography of the terrain, points that lie on ground to be filtered from the point cloud. Previous point cloud classification techniques generally rely on geometry-based methods, where the point cloud is processed using rule-based approaches with stringent constraints. Among these, elevation and slope-based filtering are the most applied constraints for classifying ground and non-ground points. These methods emphasize the geometric properties of the terrain to differentiate between the classes, often resulting in over smoothing in complex landscapes such as coastal cliffs or areas with vegetation cover. This is a major problem when working in hilly and coastal areas where the terrain is rugged (Sithole and Vosselman, 2004). In 2017, Pix4D software adopted a machine learning-based approach utilizing random forest and gradient boosting for geometry and color-based point cloud classification. However, the training provided for rugged terrains, such as coastal cliffs, was insufficient, leading to higher error rates compared to classifications from other landscapes. The complexity of coastal terrains, with their abrupt changes in elevation and diverse surface features, made it challenging for the model to generalize effectively, resulting in less accurate classifications in these areas. This study proposes a machine learning approach using random forest to extract ground points derived from UAS-SfM technique for coastal landscape. Five bands including color (RGB), elevation and slope are used to train the machine learning model. The DTM layer prepared from the points extracted based on the model built shown reliable precision.

2. STUDY AREA

Jupiter Inlet Outstanding Natural Area (JILONA) is the region of study which is an inlet area situated in Northern Palm Beach County on the Atlantic coast of South Florida (26°56′55″N, 80°04′55″W). This area is owned and managed by the Bureau of Land Management. This site is known for its biodiversity which has 700+ species. Being a coastal area, it is highly prone to erosion which is a great threat to biodiversity of the site. Given its potential importance in maintaining the ecology, this should be regularly monitored against environmental impacts which guides the managers of BLM to take necessary action toward conservation of the site.

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3. MATERIALS AND METHODS

This study on extracting ground points along the coastal region used the drone data collected during August 2021 using the high-resolution RGB camera mounted on DJI Phantom 4 Pro V 2.0. Figure 1 shows the overall workflow, which is broadly defined by four major steps namely, (1) Data Pre-processing; (2) RF Classifier; (3) Ground Classification, and (4) DTM Generation. The detailed procedure for each step, along with its implementation process, is discussed in the following sections.

3.1 Data Pre-Processing

The collected raw drone data is processed using the geolocation information in Pix4D Mapper, a commercial photogrammetry software, that generates different photogrammetric products including orthomosaic imagery, DSM, DTM, point clouds, and contours. Figure 2 shows the orthomosaic map of the region which is a 2D RGB image and the area of interest (area between waterline and shoreline) is highlighted. A waterline is the geographic boundary between the sea surface and the shore region, while a shoreline is a line that separates the land surface and the shore. This can be performed for the entire study area, but the current work is limited to the region bounded by the coastline and shoreline. Within the area this analysis mainly focuses on the cliff region. Figure 3 and 4 shows the elevation and slope layer of the considered region. Elevation and slope layer are stacked on top of orthomosaic image thus resulting in five band imagery.

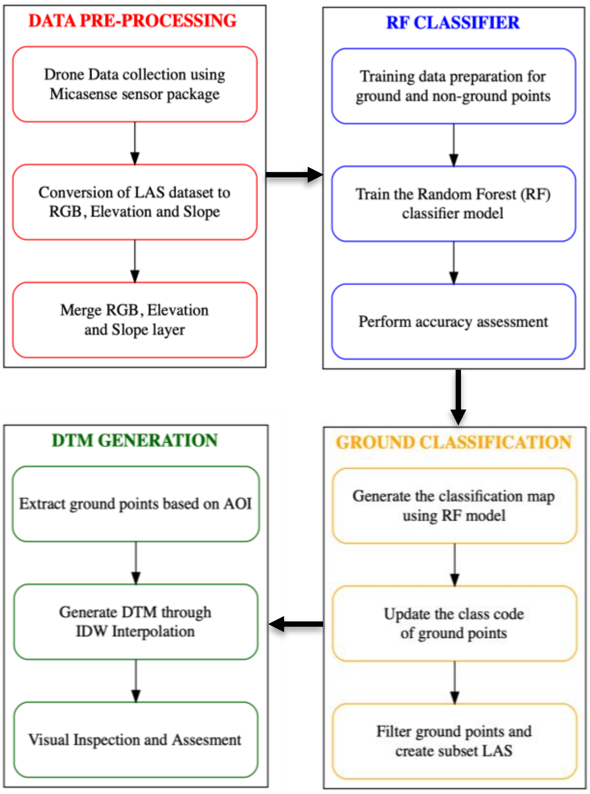

Figure 1: Overall Workflow / Methodology

(ALL THE BELOW MAPS ATTRIBUTION: ESRI Basemap, Collected Drone Data, D North American (NAD) 1983 Florida East US Survey Foot (ft US), WKID: 4269, Transverse Mercator)

3.2 Random Forest Classifier

Random forest is a supervised tree learning approach in machine learning widely used for classification and regression tasks. This algorithm is first developed by (Breiman, 2001) which basically creates a decision forest that constitutes multiple trees. Figure 5 shows graphical workflow of the algorithm which includes major steps such as dataset selection, decision tree formation, majority voting, and final prediction result. Once training data fed into the model, the algorithm randomly selects the samples from the training datasets. Based on the chosen training features, decision trees get constructed, which will then be followed by voting. Finally, the class with the majority of votes becomes the prediction result. For numerous remote sensing applications, RF classifiers produced significant classification results (Belgiu, 2018). Random forest follow non-parametric methodology in a statistical sense. It is also very effective at handling outliers in training data (Horning, 2010).

Figure 2: Orthomosaic Imagery of JILONA

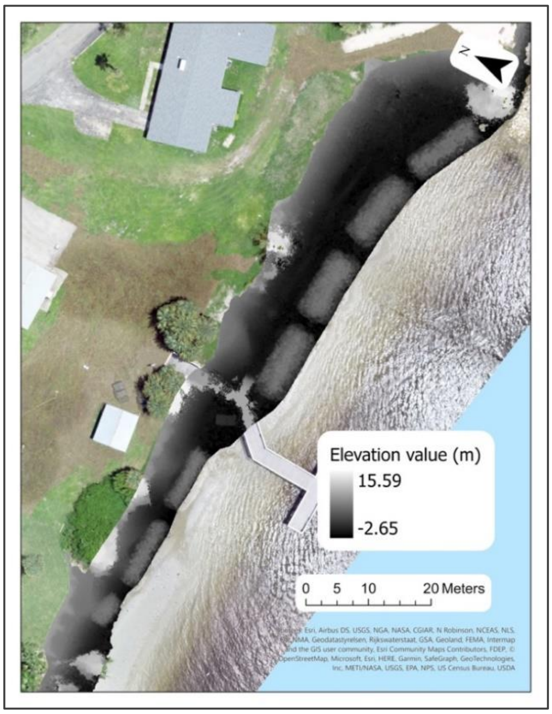

Figure 3: Elevation Band of JILONA

3.3 Ground Classification and DTM Generation

From the obtained stacked raster, training samples are marked for ground and non-ground features as shown in Figure 6. These samples were then used to train RF model. The trained model yielded a classification map, which was then utilized to extract the ground points. Through the RF model, the whole region is

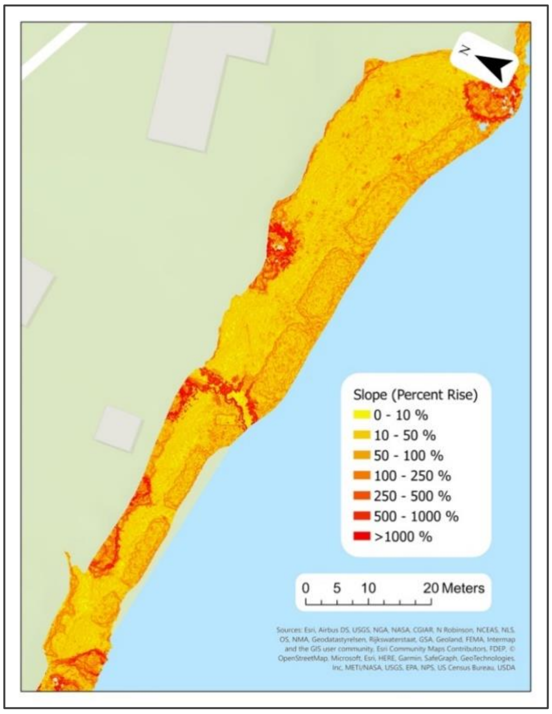

Figure 4: Slope band of JILONA

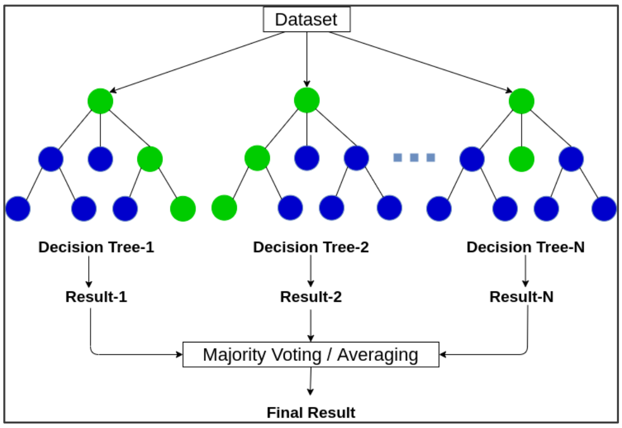

Figure 5: Random Forest Classifier

predicted using the five-band imagery (red, green, blue, elevation, and slope). Using the resulting classified raster, class codes available in the LAS file were updated to one of the reserved classes called "21". After updating, ground points are filtered based on the class code value. The filtered points were saved as separate LAS data as a subset file. The filtered point cloud is then used to create a DTM raster using Inverse Distance Weight (IDW) interpolation technique.

3.4 Point-based Analysis

An in-depth analysis was made using a few parallel transect lines along the shore. Multiple points were generated for every 3 meters. These points were sampled both on the ground as well as in vegetation areas. Vegetation points were all removed from it, such that only the ground points got selected. The values of DTM created through the proposed method, DTM generated from Pix4D and DSM output from Pix4D were all compared at these selected points. A total of 275 ground points were considered during this analysis. The lines and the generated points along one specific region of the shore for digital model analysis are shown in Figure 7.

Root mean squared error (RMSE), is the error metric used to evaluate the classified elevation of test points. RMSE is given by,

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(S_i - O_i)^2} \tag{1}$$

where S_i is the predicted value of a variable, O_i being the observations and n is the number of observations, that are available for the analysis.

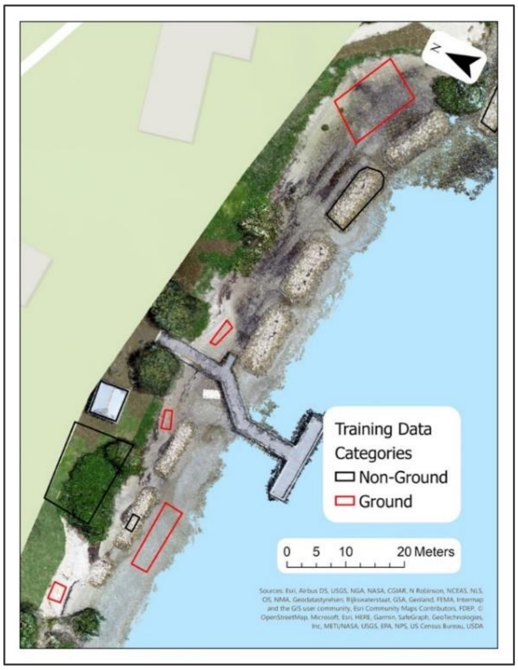

Figure 6: Training samples for Random Forest Classifier

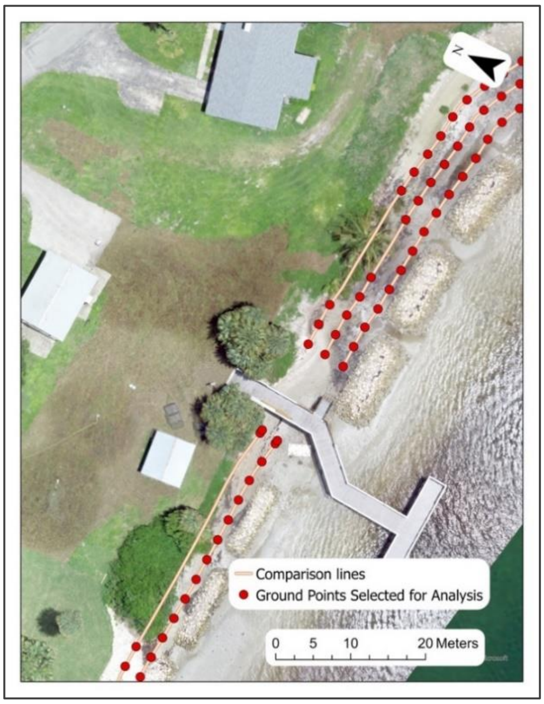

Figure 7: Ground Point analysis

4. RESULT AND DISCUSSION

The results of this study revealed that the classification based on the RF approach is much reliable, especially for the classification of complex cliff areas along the coastal region. The overall accuracy of the explored RF classifier model for separating ground points from non-ground points is about 91.01%. Figure 8 shows the extracted ground LAS points for a chosen site, while Figure 9 shows the DTM of the same region. The confusion matrix of the ML model is depicted in table 1 and table 2 depicts the elevation statistics of three representative points from cliff region. The difference between the DTM of Pix4D and the RF method is nearly 0.3 m (1 foot) for all the considered points (points on cliff). The proposed RF approach retained valid ground points for interpolation. The RMSE value is 0.068 m (0.224 ft) for the Pix4D DTM and for RF method it is 0.059 m (0.195 ft). Figure 10,11 and 12 gives a visual interpretation of some representative points from cliffs and table 2 summarizes the statistics.

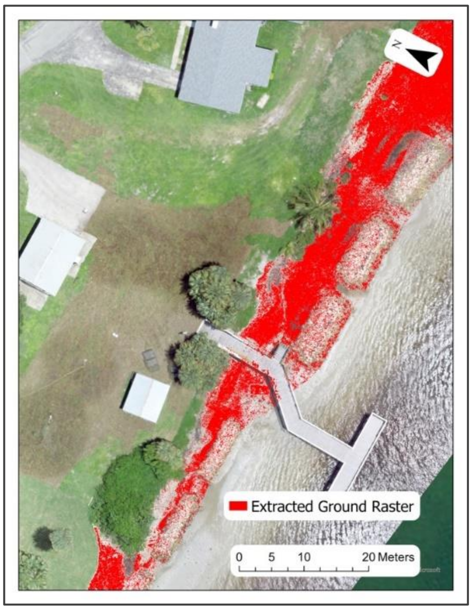

Figure 8: Extracted ground points from RF Classifier

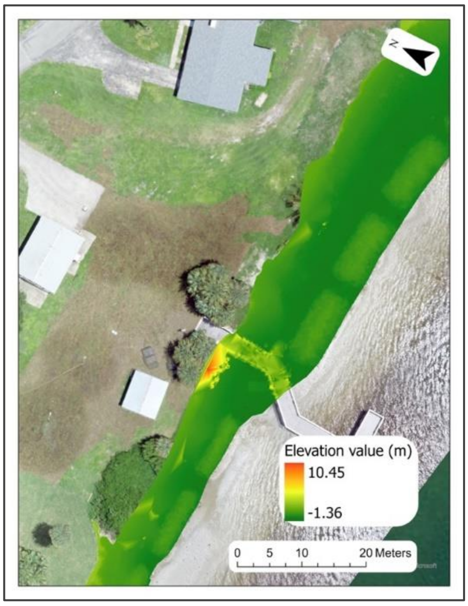

Figure 9: Generated DTM output from RF Method

		Actual	
		Ground	Non-Ground
Predicted	Ground	45905	23516
	Non-Ground	9040	283721

Table 1: Confusion Matrix for Random Forest

	Point 331	Point 339	Point 369
Pix4D DSM 2021	1.82 m	1.80 m	2.11 m
Pix4D DTM 2021	1.56 m	1.41 m	1.80 m
RF DTM 2021	1.86 m	1.78 m	2.10 m
(Pix4D DTM 2021) – (RF DTM 2021)	-0.30 m	-0.25 m	-0.29 m

Table 2: Elevation values of certain ground points in meters

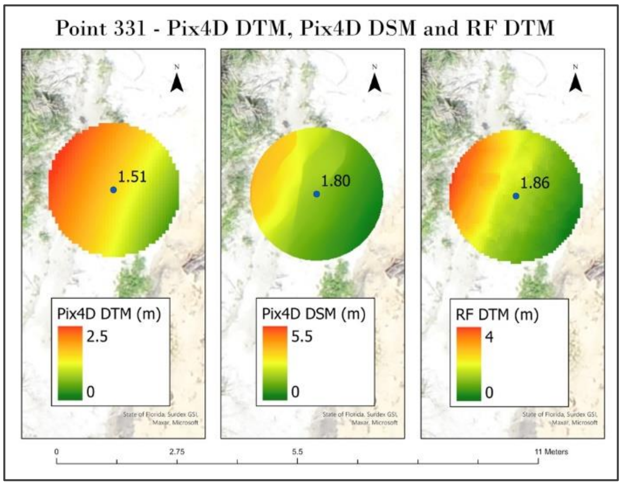

Figure 10: DTM and DSM analysis on Point 331

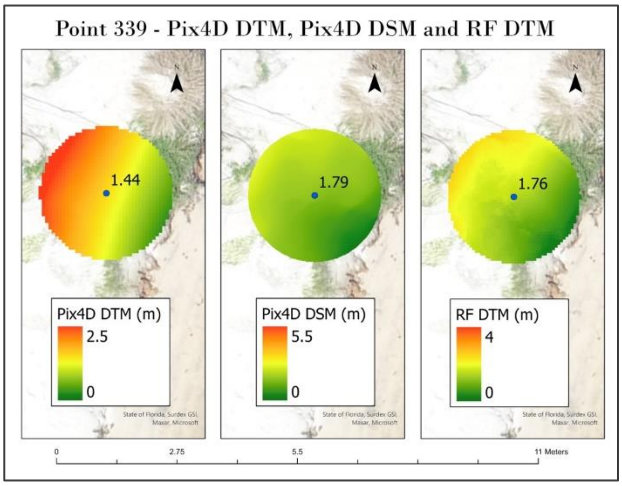

Figure 11: DTM and DSM analysis on Point 339

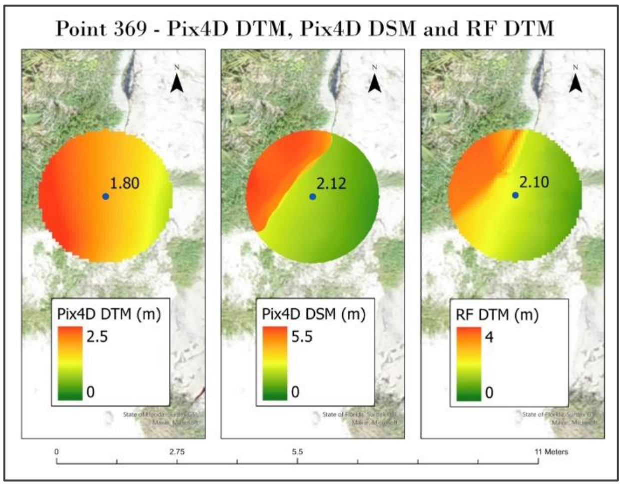

Figure 12: DTM and DSM analysis on Point 369

5. WORKFLOW IMPLEMENTATION

A geoprocessing tool is developed in ArcGIS Pro software which automates all the data preparation discussed in the methodology and uses the predictive model that is built for this scenario to extract the ground points. The prototype of the tool is shown in figure 13.

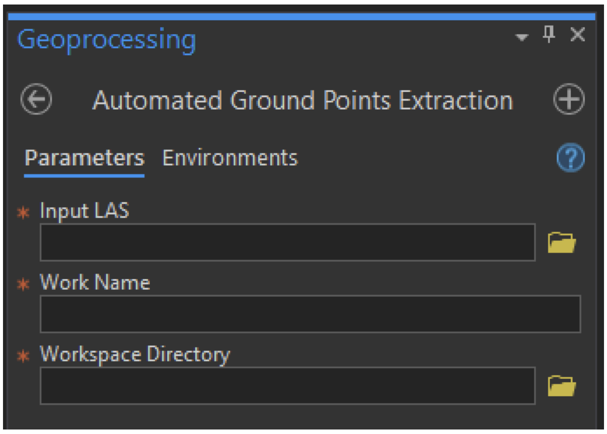

Figure 13: Automated Ground points Extraction tool

6. CONCLUSION

This research aimed to develop a high-accuracy Digital Terrain Model (DTM) from drone-based visible band imagery for coastal landscape. The study used a Random Forest (RF) classifier to distinguish ground from non-ground points and generated a DTM, which was compared to DTM prepared using commercial software. The RF classifier captured most of cliff points achieving 91% accuracy. A geoprocessing tool was also built in ArcGIS Pro for efficient processing. The results demonstrate that combining RGB data with elevation alongside representative training samples is an effective method for better ground point classification along the shore. This study performed a raster-based approach where the point cloud processed into pixels and used for classification which resulted in a minor improvement in classification. This can be extended by using raw point cloud for classification which retains the originality of the point cloud and can give good results with better classification. Further training sets can be developed for different coastal morphologies to improve model robustness.

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REFERENCES

American Geoscience Institute 2021 - Available Online: https://www.americangeosciences.org/education/k5geosource/content/rocks/what-is-shoreline-erosion

Arif, F., Maulud, K., and Rahman, A. Generation of digital elevation model through aerial technique. IOP Conference Series: Earth and Environmental Science. 169. 012093. 10.1088/1755-1315/169/1/012093.

ArcGIS Pro Documentation: https://pro.arcgis.com/en/

ArcPy Documentation: https://pro.arcgis.com/en/pro-app/latest/arcpy/main/arcgis-pro-arcpy-reference.htm

Baig, M.R.I.; Ahmad, I.A.; Shahfahad, Tayyab, M., and Rahman, A., 2020. Analysis of shoreline changes in Vishakhapatnam coastal tract of Andhra Pradesh, India: an application of digital shoreline analysis system (DSAS). Annals of GIS, 26(4), pp.361-376.

Belgiu, M., and Csillik, O. 2018. Remote Sensing of Environment Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. Remote Sensing of Environment, 204, pp. 509–523.

Becker, C., Häni, N., Rosinskaya, E., d'Angelo, E. and Strecha, C., 2017. Classification of aerial photogrammetric 3D point clouds. arXiv preprint arXiv:1705.08374.

Biçici, S., and Zeybek, M. "An approach for the automated extraction of road surface distress from a UAV-derived point cloud." Automation in Construction 122 (2021): 103475.

Breiman, L. 2001. Machine Learning, vol. 45, no. 1, pp. 5–32., doi:10.1023/a:1010933404324.

Breiman, L., Friedman, J.H., Olshen, R.A., & Stone, C.J. (1984). Classification And Regression Trees (1st ed.). Routledge. https://doi.org/10.1201/9781315139470

Chang, Y-C., Ayman, H., Lee, D., and Yom, J-H. 2008. Automatic classification of lidar data into the ground and non-ground points. 37.

Dieterich, T.G. 2002. Ensemble Learning. The handbook of brain theory and neural networks, M.A. Arbib (Ed.) (Cambridge, MA: The MIT Press).

DJI Phantom: https://www.dji.com/phantom-4-pro-v2/specs

Florida Department of State, 2022. https://dos.myflorida.com/florida-facts/quick-facts/

Gao, Jay. "Bathymetric mapping by means of remote sensing: methods, accuracy and limitations." Progress in Physical Geography 33, no. 1 (2009): 103-116.

Gómez-Pazo, A., and Pérez-Alberti, A. 2021. "The Use of UAVs for the Characterization and Analysis of Rocky Coasts" Drones 5, no. 1: 23. https://doi.org/10.3390/drones5010023

Günen, M.A. 2022. "Adaptive neighborhood size and effective geometric features selection for 3D scattered point cloud classification." Applied Soft Computing 115: 108196.

Han, X-F., Jin, J.S., Wang, M-J., Jiang, W., Gao, L., and Xiao, L. 2017. "A review of algorithms for filtering the 3D point cloud." Signal Processing: Image Communication 57: 103-112.

Hodgson, M. E., John R. Jensen, Laura Schmidt, Steve Schill, and Bruce Davis. "An evaluation of LIDAR-and IFSAR-derived digital elevation models in leaf-on conditions with USGS Level 1 and Level 2 DEMs." Remote sensing of environment 84, no. 2 (2003): 295-308.

Hoang, L., Lee, S-H., Lee, E-J., and Kwon, K-R. 2022. "GSV-NET: A Multi-Modal Deep Learning Network for 3D Point Cloud Classification" Applied Sciences 12, no. 1: 483. https://doi.org/10.3390/app12010483

Horning, N. 2010. Random Forests: "An algorithm for image classification and generation of continuous fields data sets" International conference on geoinformatics for spatial infrastructure development in earth and allied sciences.

Husain, A., and Vaishya, R.C. 2016. "A time efficient algorithm for ground point filtering from mobile LiDAR data." In International Conference on Control, Computing, Communication, and Materials (ICCCCM), pp. 1-5. IEEE, 2016.

Hyacinth, A. 2021. Random Forests Understanding, global Artificial Intelligence Platforms (AI Pool): https://ai-pool.com/a/s/random-forests-understanding

Jakovljevic, G., Govedarica, M., Alvarez-Taboada, F., and Pajic, V. 2019. "Accuracy Assessment of Deep Learning Based Classification of LiDAR and UAV Points Clouds for DTM Creation and Flood Risk Mapping" Geosciences 9, no. 7: 323. https://doi.org/10.3390/geosciences9070323

Jing, Z-W., Guan, H., Zhao, P., Li, D., Yu, Y., Zang, Y., Wang, H., and Li, J. 2021. "Multispectral LiDAR point cloud classification using SE-PointNet++." Remote Sensing 13, no. 13: 2516.

Jupiter Inlet Lighthouse and Museum (JILM), 2017. JILM Description-History, Available: http://www.jupiterlighthouse.org/wp-content/uploads/2017/05/JILM-Description-History.pdf

Jupiter Inlet Lighthouse ONA Wikipedia - Accessed Oct 21, 2021. https://en.wikipedia.org/wiki/Jupiter_Inlet_Light#Jupiter_Inlet_Lighthouse_Outstanding_Natural_Area

Micasense publications: https://micasense.com/publications/

Mulkal, M., Risawandi, R., and Aflah, N. 2019. "Inverse Distance Weight Spatial Interpolation for Topographic Surface 3D Modelling." TECHSI-Jurnal Teknik Informatika 11, no. 3: 385.

Quinlan, J.R. 1993. C4.5: Programs for Machine Learning (San Mateo, CA: Morgan Kaufmann).

Roberts, K.C., Lindsay, J.B., and Berg, A.A. 2019. "An Analysis of Ground-Point Classifiers for Terrestrial LiDAR" Remote Sensing 11, no. 16: 1915. https://doi.org/10.3390/rs11161915

Rosati, Julie Dean. "Concepts in sediment budgets." Journal of Coastal Research 21, no. 2 (2005): 307-322.

Silva, C.A., Klauberg, C., Klein Hentz, Â.M., Dalla Corte, A.P., Ribeiro,U and Liesenberg, V. 2018. "Comparing the performance of ground filtering algorithms for terrain modeling in a forest environment using airborne LiDAR data." Floresta e Ambiente 25.

Sithole, George, and George Vosselman. "Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds." ISPRS journal of photogrammetry and remote sensing 59, no. 1-2 (2004): 85-101.

Talavera, L., Benavente, J., and Del Río, L. 2021. "UAS Identify and Monitor Unusual Small-Scale Rhythmic Features in the Bay of Cádiz (Spain)" Remote Sensing 13, no. 6: 1188. https://doi.org/10.3390/rs13061188

Terrain Classification on aerial LiDAR Data. Available online: https://www.mathworks.com/help/lidar/ug/terrain-classification-on-aerial-lidar-data.html

Watson, D.F., and Philip, G.M. 1985. A refinement of inverse distance weighted interpolation. Geo-Processing 2, 315–327.

Westoby, M. J., Brasington, J., Glasser, N.F., Hambrey, M.J., and Reynolds, J. M. 2012. "Structure from-Motion photogrammetry: A Low-Cost, Effective Tool for Geoscience Applications." Geomorphology 179: 300–314. doi: 10.1016/j.geomorph.2012.08.021

Williams, S. J. 2001. "Coastal Erosion and Land Loss around the United States: Strategies to Manage and Protect Coastal Resources- Examples from Louisiana". Coastal Ecosystems and Federal Activities Technical Training Symposium Proceedings.

Zahir, I.L.M., Madurapperuma, B., Iyoob, A.L., and Nijamir, K. 2021. "Exploring the Ever-Changing Seashore Using Geoinformatics Technology" Earth 2, no. 3: 544-555. https://doi.org/10.3390/earth2030032

Zeybek, M. 2021. "Accuracy assessment of direct georeferencing UAV images with onboard global navigation satellite system and comparison of CORS/RTK surveying methods." Measurement Science and Technology 32, no. 6: 065402.

Zeybek, M. 2021. "Classification of UAV point clouds by random forest machine learning algorithm." Turkish Journal of Engineering 5, no. 2: 48-57.

Zeybek, M., and Şanlıoğlu, İ. 2019. "Point cloud filtering on UAV based point cloud." Measurement 133: 99-111.

Zhang, J., Yang, X., Wang, Z., Zhang, T., and Liu, X. 2021. "Remote Sensing Based Spatial-Temporal Monitoring of the Changes in Coastline Mangrove Forests in China over the Last 40 Years" Remote Sensing13, no. 10: 1986. https://doi.org/10.3390/rs13101986

Zhu, X., Nie, S., Wang, C., Xi, X., and Hu, Z. 2018. "A Ground Elevation and Vegetation Height Retrieval Algorithm Using Micro-Pulse Photon-Counting Lidar Data" Remote Sensing 10, no. 12: 1962. https://doi.org/10.3390/rs10121962.