Lim Zhu An (A0224991X)

23 April 2021

GE6211 – Term Paper

Spatial Uncertainty in Coastal/Marine GIS Applications

Introduction

The applications of Geographic Information Systems/Science (GIS) have been instrumental in allowing researchers to better map, analyze, and understand coastal processes and environments. However, due to the dynamic nature and complexity of coastal environments, it creates a challenge in the applications of GIS in these systems as there are many uncertainties such as lack of data, and the lack of understanding of different coastal and marine systems (Mosadeghi, R et al, 2013).

One of the most common and widely used data for coastal GIS applications is remote sensing data, in particular satellite imagery. Many studies such as coastal land-use planning (Mosadeghi, R et al, 2013), shoreline change assessment (El-Hadidy, S. M.,2020 and Louati, M., et al. 2015), coastal vulnerability studies (Beluru Jana, A., & Hegde, A. V.,2016), coastal algae bloom modelling (Qin, R., & Lin, L.,2019), as well as estimating coastal turbidity using MODIS images (Chen, S. et al. 2015) are good examples of coastal studies that relies on satellite imagery for their analysis.

This paper uses a Normalized Difference Water Index (NDWI) method for coastline extraction as an example to showcase a type of GIS application in a coastal environment and the uncertainties that comes along with this methodology. In addition, this paper will also introduce other types of GIS applications in coastal and marine environments and possible solutions to address the uncertainties that comes with the respective methodologies.

Coastline Extraction Using Landsat-8

NDWI is a simple yet effective method in delineating between land and (sea)water surfaces. It uses the principle known as band ratioing, due to the differences in reflectance of certain wavelengths for land and water surfaces (El-Hadidy, S. M.,2020 and Louati, M., et al. 2015). Near-Infrared (NIR) wavebands are highly absorbed by water and strongly reflected by vegetation and soil, which is why we can use the different characteristic of water and land to classify the two surfaces using the NDWI method (El-Hadidy, S. M.,2020 and Louati, M., et al. 2015). In this example of coastline extraction, we will mainly utilize band 3 (Green) and band 5 (NIR) of Landsat-8 data to calculate for the NDWI.

The detailed information of each band and their range of wavelengths for Landsat-8 is shown in Figure 1 below.

Band	Description	Wavelength (μm)	Spatial Resolution (m)
1	Coastal aerosol	0.43 - 0.45	30
2	Blue	0.45 - 0.51	30
3	Green	0.53 - 0.59	30
4	Red	0.64 - 0.67	30
5	Near Infrared (NIR)	0.85 - 0.88	30
6	SWIR 1	1.57 - 1.65	30
7	SWIR 2	2.11 - 2.29	30
8	Cirrus (in OLI this is band 9)	1.36 - 1.38	30
9	QA Band (available with Collection 1)*	NA	30
10	TIRS1	10.60 - 11.19	100 * (30)
11	TIRS2	11.50 - 12.51	100 * (30)

Figure 1 Landsat-8 band spectrum table

The ArcGIS software provides many tools and APIs that makes analysis and data extraction time and cost efficient, taking reference from the ArcGIS developer website[1]. Free Landsat-8 multispectral satellite images are retrieved from the ArcGIS online portal, together with a 20km coastal buffer polygon feature of USA coastlines which will be used to define the area of interest for the study (New Orleans).

The Landsat-8 tiles were first filtered by date of acquisition and percentage of cloud cover and ordered by cloud cover from lowest to highest to obtain the best satellite image for analysis (minimum cloud cover). The NIR (Figure 2) and Green (Figure 3) band raster objects were extracted using the extract_band tool and computed for the NDWI using the raster calculator tool. The NDWI raster output (Figure 4) shows that pixel value closer to -1 (black) representing

[1] *https://developers.arcgis.com/python/sample-notebooks/coastline-extraction-usa-landsat8-multispectral-imagery/*

water and pixel value closer to 1 (white) representing land (El-Hadidy, S. M.,2020). The NDWI is calculated as follows:

NDWI = (NIR – G) / (NIR + G)

*Where NIR refers to Near Infrared band and G refers to Green band.

We can clearly see the difference between land and (sea)water surfaces after the NDWI method was applied.

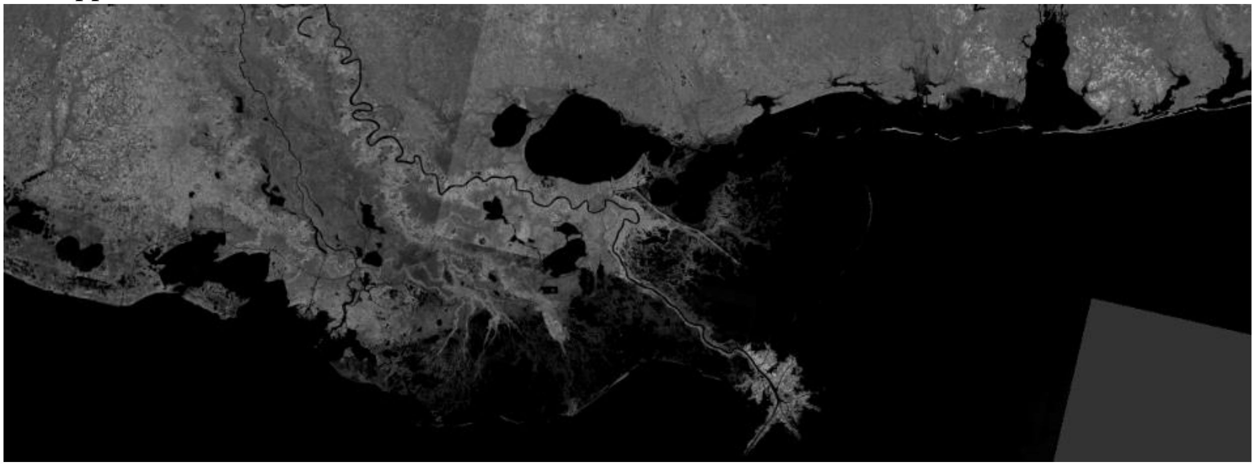

Figure 2 NIR band raster

Figure 3 Green band raster

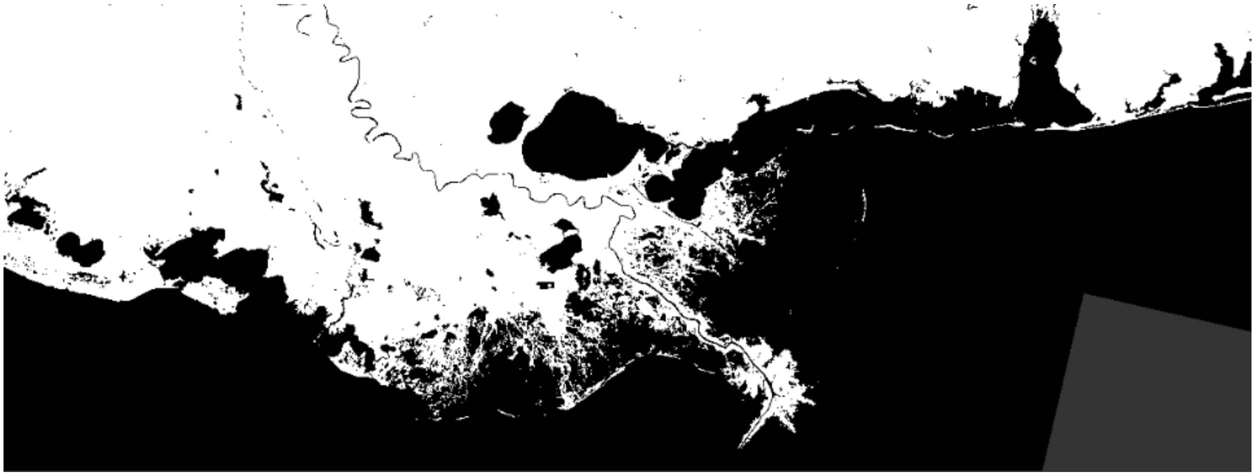

Figure 4 NDWI raster output

After the NDWI raster is produced, it can then be clipped to the AOI polygon. Thereafter, it is converted into a polygon feature using ArcGIS convert raster to feature tool. Lastly, the coastline polygon feature is converted into polyline feature using Arcpy polygon to line tool. And the extracted coastline can be added to a basemap for visualization, as shown in Figure 5.

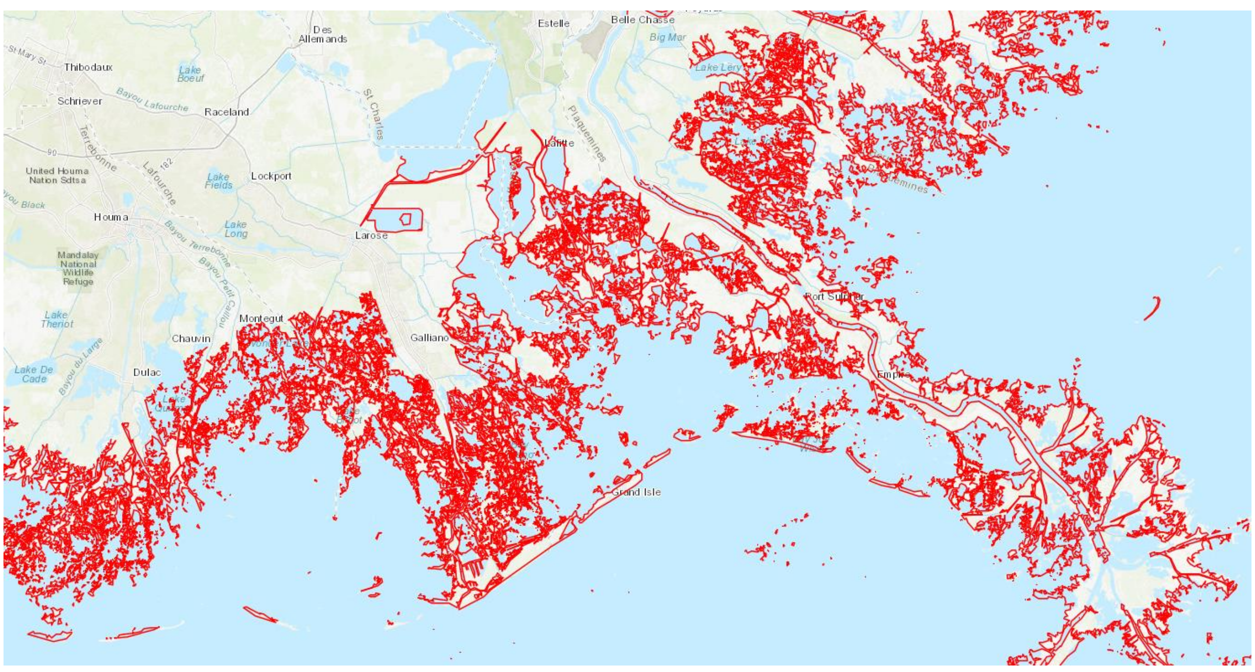

Figure 5 Extracted Coastline example

Although the method discussed is a time and cost-effective way of extracting coastline features from satellite images, it does include a couple of uncertainties. Firstly, all satellite images have a defined spatial resolution, in this case the Landsat-8 dataset has a spatial resolution of 30m. This assumes spatial uniformity within the spatial grid of 30m by 30m, and types of surfaces and features have the same spectral reflectance characteristics within this gird. This is acceptable for large areas that far exceeds the spatial resolution, however, for smaller study areas and features, this method might not be comprehensive.

Georeferencing of the satellite images as well as the variable nature of shoreline position due to its dynamic environment and processes (e.g., coastal erosion, and sedimentation) are other examples of uncertainties to consider as well (Louati, M., et al.2015). It is important to consider seasonal and tidal effects on beach profiles at different study areas, as the shoreline profile might have different fluctuation ranges depending on the location of the study area. If the fluctuation of the shoreline profile exceeds the spatial resolution of the satellite image used, it will contribute to the spatial uncertainty of the analysis (Louati, M., et al.2015). Georeferencing errors should be accounted for and considered in-addition to the extent of shoreline shift by calculating the Root Mean Squared Error (RMSE) of the georeferencing errors. It is important to consider the degree of error that the georeferencing process introduces to the study.

To address the issues above, Liu, Y. et al. (2017) proposed to increase the accuracy of coastline extraction using downscaling and pansharpening methods. The study concludes that the integration of downscaled Panchromatic (PAN) band from Landsat-8-Oli and the pansharpened Multispectral Images (30m by 30m) produces the best results and accuracy for coastline extraction. However, the study also mentions that this introduces its own uncertainties. For example, the downscaling process introduces uncertainty by using spatial interpolation methods (Liu, Y. et al. 2017). Pansharpening algorithms also introduces spectral distortions, which makes it more difficult to distinguish between water and land pixels when calculating for water index (Liu, Y. et al. 2017). These are uncertainties that we must consider if we are incorporating these methods into our analysis.

<u>Estimating Coastal Turbidity using MODIS</u>

Moderate Resolution Imaging Spectroradiometer (MODIS) data is useful for monitoring coastal turbidity and sediment movement due to its high temporal resolution (daily) as well as large number of spectral bands (36) to work with unlike Landsat. Studies have shown that the conversion of MODIS images to Total Suspended Solids (TSS) in coastal waters is an effective and cheap method to monitor or model turbidity in coastal environments (Chen, S. et al. 2015). The conversion of MODIS reflectance to TSS uses an algorithm which relies on the reflectance characteristics of suspended solids in water (Chen, S. et al. 2015). The converted TSS raster images can then be validated using water samples collected along the coast of the study area, or from Acoustic Doppler Current Profiler (ADCP) monitoring stations which measures TSS from backscatter readings in the water.

However, one downside to MODIS images is its spatial resolution, which is at 250m. This makes it difficult for study areas which have very complex coastal profile. There is greater uncertainty for MODIS as compared to Landsat based on its spatial resolution. Like the Landsat coastline extraction example above, this method requires georeferencing of the MODIS satellite images as well, which introduces the same type of spatial uncertainty due to georeferencing errors. This method introduces a lot of uncertainties especially for waters near the coast. The converted TSS near the coast often results in higher concentrations, mostly due to shallow water effect as the zone is more susceptible to processes like resuspension of sediment, mixing of water column due to waves, etc. (Chen, S. et al. 2015) For study areas with a short and complicated coastline, this poses as an issue due to the coupling effect of the large spatial resolution of MODIS and the complexity of the coastal environment.

LIDAR Land and Water Classification

Lidar is a great alternative to satellite images as it produces higher resolution data with much more accurate details by using a 3D point cloud system. Airborne Multispectral Lidar data can be used to conduct different types of classification analysis, for example water and land in different coastal environments (Shaker, A et al. 2019). Lidar data can account for the georeferencing uncertainties and errors in the satellite image approach, due to its direct geo-referencing technique (Shaker, A et al. 2019). This is particularly useful and addresses the uncertainty issues with traditional georeferencing techniques as mentioned above. Being 3D data, Lidar also provides an added advantage over multispectral satellite data as studies can make use of the 3D point cloud to model sedimentation and erosion based on changes in elevation in a coastal environment (Song, D. et al. 2013).

Although Lidar data provides high accuracy and resolution data, Lidar data is not as easily accessible (often not free) as compared to multispectral satellite data. Lidar being a newer technology also means that there is less historical data to utilize. This makes it difficult for certain types of analysis which requires historical data such as the studying of coastline changes over long periods of time (decades). Lidar data is also known to have its own uncertainties, such as vertical uncertainty in salt marsh environments using vegetation-induced Lidar (Rogers, J. N. et al. 2016). Seasonality, vegetation, interpolation, and filtering methods all contributes to the uncertainty in elevation from Lidar data in this type of coastal environment (Rogers, J. N. et al. 2016).

Uncertainties in Coastal Land use Planning

In addition to the uncertainties that comes with Multispectral satellite or Lidar data analysis, a case study by Mosadeghi, R et al. (2013) shows that there are epistemic and stochastic uncertainties in coastal land-use planning studies, and it is important to analyze uncertainty and sensitivity. Epistemic uncertainty refers to the imperfect knowledge on the subject matter, and Stochastic uncertainty refers to the randomness of natural, cultural, social dynamics (Mosadeghi, R et al.2013). Although the examples mentioned above provides some solutions to deal with epistemic uncertainty by increase accuracy of data or reducing error, it does not address the chaotic nature of natural processes such as climate change or increase in frequency and severity of storms.

The case study conducted a sensitivity analysis to identify the sensitivity of the different model outputs to the uncertainties to the model inputs (Mosadeghi, R et al.2013). The study suggest that uncertainty did not only affect the selection of the best option in a decision-making model but can also affect the spatial extent of the preferred option (Mosadeghi, R et al.2013). It is certain that not all uncertainties can be accounted for due to the complex and dynamic nature of natural systems, but the study recommends that uncertainty analysis should be conducted in these types of land-use planning exercises to have a better understanding of the sensitivity of the decisions derived (Mosadeghi, R et al.2013).

Conclusion

In conclusion, this paper highlights the importance and effectiveness of different GIS applications in different coastal environments. Multispectral satellite images are cheap (often free) data sources and provides a wide range of different applications and methodologies that can be applied. However, it does come with its own set of uncertainties to consider and account for. The most common spatial uncertainties associated with multispectral satellite data is the error in georeferencing, the spatial resolution of the data, as well as any process of interpolation and filtering of the satellite data.

Lidar data is relatively new as compared to multispectral satellite data which offers a lot of potential to address the uncertainties associated with the multispectral satellite image approach. However, Lidar data is not easily accessible and if often not free. There is limited historical Lidar data which limits the possibility of long-term analysis is questionable. Despite being 3D data, Lidar has vertical uncertainty in certain environments (e.g., vegetated salt marsh).

There are different types of uncertainties to consider (Epistemic and Stochastic) in coastal studies. Although GIS applications can help address issues with Epistemic uncertainty by either improving data accuracy and availability, or better understanding of coastal environments, it does not address the Stochastic uncertainties which refers to the dynamic and complex nature of natural environments or processes.

References

- Beluru Jana, A., & Hegde, A. V. (2016). GIS based approach for vulnerability assessment of the karnataka coast, India. Advances in Civil Engineering, 2016, 1-10. https://doi.org/10.1155/2016/5642523
- Chen, S., Han, L., Chen, X., Li, D., Sun, L., & Li, Y. (2015). Estimating wide range total suspended solids concentrations from MODIS 250-m imageries: An improved method. ISPRS Journal of Photogrammetry and Remote Sensing, 99, 58-69. https://doi.org/10.1016/j.isprsjprs.2014.10.006
- El-Hadidy, S. M. (2020). Monitoring shoreline changes and aeolian sand encroachment, Nasser lake, Egypt, using remote sensing and GIS techniques. Arabian Journal of Geosciences, 13(24)https://doi.org/10.1007/s12517-020-06229-2
- Liu, Y., Wang, X., Ling, F., Xu, S., & Wang, C. (2017). Analysis of coastline extraction from Landsat-8 OLI imagery. Water (Basel), 9(11), 816. https://doi.org/10.3390/w9110816
- Louati, M., Louati, M., Saïdi, H., Saïdi, H., Zargouni, F., & Zargouni, F. (2015). Shoreline change assessment using remote sensing and GIS techniques: A case study of the medjerda delta coast, tunisia. Arabian Journal of Geosciences, 8(6), 4239-4255. https://doi.org/10.1007/s12517-014-1472-1
- Mosadeghi, R., Warnken, J., Mirfenderesk, H., & Tomlinson, R. (2013). Spatial uncertainty analysis in coastal land use planning: A case study at gold coast, Australia. Journal of Coastal Research, 1(65), 1003-1008.
- Qin, R., & Lin, L. (2019). Integration of GIS and a lagrangian particle-tracking model for harmful algal bloom trajectories prediction. Water (Basel), 11(1), 164. https://doi.org/10.3390/w11010164
- Rogers, J. N., Parrish, C. E., Ward, L. G., & Burdick, D. M. (2016). Assessment of elevation uncertainty in salt marsh environments using discrete-return and full-waveform lidar. Journal of Coastal Research, 76(76), 107-122. https://doi.org/10.2112/SI76-010
- Shaker, A., Yan, W. Y., & LaRocque, P. E. (2019). Automatic land-water classification using multispectral airborne LiDAR data for near-shore and river environments. ISPRS

Journal of Photogrammetry and Remote Sensing, 152, 94-108. https://doi.org/10.1016/j.isprsjprs.2019.04.005

- Song, D., Kim, I., & Lee, H. (2013). Preliminary 3D assessment of coastal erosion by data integration between airborne LiDAR and DGPS field observations. Journal of Coastal Research, 165, 1445-1450. https://doi.org/10.2112/SI65-244.1
- Xu, J., Feng, G., Fan, B., Yan, W., Zhao, T., Sun, X., & Zhu, M. (2020). Landcover classification of satellite images based on an adaptive interval fuzzy c-means algorithm coupled with spatial information. International Journal of Remote Sensing, 41(6), 2189-2208. https://doi.org/10.1080/01431161.2019.1685718