



Editorial

Editorial for Special Issue: “How the Combination of Satellite Remote Sensing with Artificial Intelligence Can Solve Coastal Issues”

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1. Introduction

Satellite sensors now provide low-cost global monitoring, with relatively high resolution with frequent revisits. Artificial intelligence offers new perspectives in terms of processing a large number of data in a drastically reduced time compared to conventional methods, and also in solving complex coastal dynamic problems. This Special Issue aims to present how the combination of machine learning and remote sensing can offer an attractive solution for the observation and prediction of coastal changes and risk, to improve management strategies.

The 10 articles of this collection all focus on the application of satellite remote sensing and artificial intelligence/machine learning in solving coastal issues. These articles showcase the potential of combining these technologies to provide solutions for sustainable coastal management and monitoring. The articles cover a range of topics, including processing satellite images to investigate the sandy morphology of coastal areas, estimating waves and sea state and vegetation/ecosystems, comparing atmospheric corrections, and forecasting shoreline evolution.

2. Coastal Morphology Continuum from Satellite: Topography and Bathymetry

Most of the articles focus on the estimation of morphology: bathymetry, shoreline and topography. A deep learning approach is used [1] to estimate nearshore bathymetry using ICESat-2 LiDAR and Sentinel-2 imagery datasets. The research emphasizes the importance of accurate bathymetric data for marine and coastal ecosystems, and the limitations of current empirical models for estimating shallow water depths. The potential of using a single-pass satellite video to generate coastal topo-bathymetry data for sandy coasts is explored [2]. Deep learning and physics-based approaches for estimating coastal bathymetry from Sentinel-2 satellite imagery are compared [3]. A global atlas of coastal bathymetry based on depth inversion from wave kinematics captured by Sentinel-2 imagery is introduced [4]. A convolutional neural networks for the detection and morphometric analysis of Carolina Bay from publicly available digital elevation models is conducted [5]. Coastal erosion is observed at the Langue de Barbarie sand spit around Saint Louis in Senegal, West Africa, through satellite-derived digital elevation models and shoreline data [6].

3. Satellite Data Processing with Machine Learning

A few articles directly process images with machine learning. Bathymetry is the main object of two articles [1,3]. Deep learning technology is also used [7] to derive significant wave heights from the Advanced Scatterometer (ASCAT) satellite data. The authors of [8] discuss the need for atmospheric corrections when deriving sea surface salinity (SSS)



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from satellite imagery and compares data-driven SSS derived from top- and bottom-of-atmosphere imagery. Finally, the authors of [9] describe the potential of satellite imagery to provide key information about the properties and behaviour of sandy beaches and surrounding vegetation, improving the geomorphological understanding of these areas.

4. The Way to Better Predict Coastal Risks

This collection demonstrates the potential of satellite-derived coastal information such as ocean drivers, morphology, ecosystems, and vegetation [9] for coastal monitoring, particularly for analysing sediment dynamics and quantifying beach evolution through bathymetry–shore topography. Satellites offer advantages over traditional survey methods used in coastal management, such as wider coverage, broader understanding of beach morphology, remote data accessibility and potential for future improvements in precision.

It refines the accuracy of estimates in undocumented regions and enables up-to-date data to be obtained elsewhere where it is too costly to survey by other means. As a result, the level of uncertainty in coastal risk estimates is greatly reduced (e.g., wave models, flooding, erosion) and the efficiency of data-based coastal management approaches (e.g., beach nourishment) is greatly improved. Remote sensing has made it possible to cover large regional areas and to monitor morphological changes such as for spits over long periods of time. Satellite time series data can be used in a first assessment to identify vulnerable areas along the coastline.

Compared to on-demand very-high-resolution commercial satellites, such as Pleiades, Planet or Jilin [2,6], regular revisit free Landsat and Sentinel-2 data are particularly valuable in this field because they allow the collection of an image approximately every week [8]. This makes it possible to monitor the coastline on seasonal to inter-annual scales, the scales of coastal management. In this sense, effective assimilation of satellite data using machine learning is very promising. Therefore, the development of sand spits is predicted using satellite data [6] and eight different time series-forecasting methods for predicting future shorelines on sandy coasts using historical satellite-derived shorelines are compared [10].

Finally, these various studies contribute to the construction of a digital twin of the coastline, whether in terms of a digital replica or physical model.

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