



Editorial Special Issue "Mapping and Monitoring of Geohazards with Remote Sensing Technologies"

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Geohazard monitoring is crucial for building resilient communities. By leveraging remote sensing technologies, we can assess hazards, implement early warning systems, and evaluate impacts effectively. These cutting-edge tools enable proactive monitoring and real-time analysis, minimizing the impact of geohazards, protecting lives, and fortifying our society against adversity.

Earth observation (EO) techniques have proven to be reliable and accurate for monitoring land surface deformations that occur naturally (landslides, earthquakes, and volcanoes) or due to anthropogenic activities (ground water overexploitation and extraction of oil and gas).

In cases where mitigation methods must be put into practice, the detailed mapping, characterization, monitoring, and simulation of the geocatastrophic phenomena have to precede their design and implementation. EO techniques possess high potential and suitability as alternative, cost-efficient methods for the management of geohazards, and have been proven to be a valuable tool for verifying and validating the spatial extent and the evolution of the deformations.

To this extent, this Special Issue covers innovative applications and case studies on the mapping and monitoring of all kinds of geohazards with remote sensing technologies. It incorporates articles that make use of new tools and methodologies, including the use of data-driven machine learning methods. Machine learning in earth observation have revolutionized geohazard monitoring. By leveraging advanced algorithms, machine learning can analyze vast amounts of satellite imagery and sensor data to detect subtle changes in terrain, identify precursors to hazards, and forecast their evolution, enabling proactive risk mitigation strategies and bolstering societal resilience.

In particular, Orellana et al. [1] focused on the study of the ground deformations taking place in the Santiago basin, combining multi-temporal differential interferometric synthetic aperture radar (DInSAR) with data coming from GNSS stations. The GNSS datasets showed a constant regional uplift in the metropolitan area, while the DInSAR allows for the identification of areas with anomalous local subsidence due to the overexploitation of the aquifers as well as mountainous areas affected by landslides. Overall, the results are fundamental for urban territorial planning in the city of Santiago and demonstrate the importance of geodetic measurements in assessing the impact of climate change on groundwater storage and how this affects the ground surface elevation.

Liu et all [2] also studied the subsidence phenomena taking place due to the long-term excessive extraction of groundwater resources by means of the progressive small baseline subset (SBAS) InSAR time series analysis method. The study was conducted at the eastern Beijing Plain, providing significant information on the deformation mechanisms of land



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Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). subsidence, establishing hydrogeological models, and supporting decision making, early warning, and hazard relief for the urban environment.

Investigating mining geohazards, Ma et al. [3] and Chen et al. [4] studied subsidence phenomena taking place at the perimeter of coal mines. Specifically, Ma et al. [3] proposed an approach for predicting mine subsidence that leverages Interferometric Synthetic Aperture Radar (InSAR) technology and a long short-term memory network (LSTM). Chen et al. [4] investigated the surface deformation by means of the DInSAR-PS-Stacking and SBAS-PS-InSAR methods. The results were verified by means of GPS, indicating the subsidence location, range, distribution, and space–time subsidence law of surface deformation.

Tzampoglou et al. [5] investigated the seasonal ground swelling/settlement of an urban area in Cyprus. The study area is occupied by highly expansive bentonitic clays giving the opportunity to combine the extensive database of geotechnical parameters with the Persistent Scattering Interferometry (PSI) InSAR datasets produced within the framework outcomes of the European Union's research project "PanGeo".

The contributions of Tsironi et al. [6], Ma et al. [7], Chen et al. [8], Tan et al. [9], and Kyriou et al. [10] focused on the study of landslide invents. Specifically, Tsironi et al. [6] studied the kinematics of active landslides in mountain areas of Achaia prefecture, Greece, by processing LiCSAR interferograms using the SBAS tool. The results also suggested a correlation between rainfall and landslide motion. Ma et al. [7] created an inventory map of 2665 rainfall-induced landslides triggered from 5 to 10 May 2016 in Fujian Province, China, by using high-resolution satellite imagery. Numerical simulations proved that the temporal evolution of the landslides could be accurately reproduced by using the MAT.TRIGRS tool. Chen et al. [8] proposed an improved multi-source data-driven landslide prediction method that combines a spatio-temporal knowledge graph and machine learning models. This framework could effectively organize multi-source remote sensing data and generate unified prediction workflows. The proposed workflow can alleviate the problem of poor prediction performance caused by limited data availability in county-level predictions. Tan et al. [9] proposes a landslide time prediction method based on the time series monitoring data of micro-deformation monitoring radar. Deformation displacement, coherence and deformation volume, and the parametric degree of deformation (DOD) are calculated and combined with the use of the tangent angle method. Finally, the effectiveness of the method was verified by using measured data of a landslide in a mining area. Finally, Kyriou et al. [10] used multi-dated data obtained by Unmanned Aerial Vehicle (UAV) campaigns and Terrestrial Laser Scanning (TLS) surveys for the accurate and immediate monitoring of a landslide located in a steep and V-shaped valley. They demonstrated that point clouds arising from a UAV or a TLS sensor can be effectively utilized for landslide monitoring with comparable accuracies. Furthermore, the outcomes were validated using measurements acquired by the Global Navigation Satellite System (GNSS).

Foroughnia et al. [11] proposed a stepwise sequence of unsupervised and supervised classification methods for the delineation of flooding areas using synthetic aperture radar (SAR) and multi-spectral (MS) data. Furthermore, a new unsupervised classification approach based on a combination of thresholding and segmentation (CThS) was developed to deal with the heterogeneity and fragmentation of water patches. The new approach was tested successfully in two flood events in Italy, achieving high precision and accuracy and making it appropriate for rapid flood mapping due to its ease of implementation.

The identification of Fossil Mass Movements is an intriguing subject. Popit et al. [12] conducted a geomorphometric analysis using a high-resolution lidar-derived DEM for the quantification and the visualization of fossil landslides. The proposed methodology was applied at Vipava Valley (SW Slovenia).

Exploiting the recently launched European Ground Motion Service (EGMS) products, Festa and Del Soldato [13] presented a desktop app, the so-called "EGMStream", that enables users to systematically store, customize, and convert ground movement data into geospatial databases, burst per burst or for an area of interest that is directly selectable on the app interface. EGMStream is a value-adding tools for optimal dissemination of radar data from the Copernicus Sentinel-1 satellite mission.

Taking Minqin County, Gansu Province, China as the study area, Yang et al. [14] propose a decision tree model combining four spectral indices for the identification of saline–alkaline areas. The spectral indices are the NDSI₃₄ (Normalized Difference Spectral Index of Band 3 and Band 4), the NDSI₂₅ (Normalized Difference Spectral Index of Band 2 and Band 5), the NDSI₂₃₇ (Normalized Difference Spectral Index of Band 3 and Band 4), and finally, the NDSInew (New Normalized Difference Salt Index). It was found that this model can be applied for the quick identification of saline–alkaline areas in large regions.

In conclusion, the value of almost any type of remote sensing data, such as radar (SAR), multispectral imagery, data collected by Unmanned Aerial Vehicles and Terrestrial Laser Scanners, and data acquired from airborne Lidar systems, for the mapping and monitoring of geohazards has been demonstrated. Different geohazards, like landslides, ground subsidence in coal mines or urban areas, flooding, and salinization have been addressed in this Special Issue. Most of the researchers that processed SAR data preferred the Sentinel-1 mission. Multispectral data from Sentinel-2, Geoeye, diverse Chinese satellites along with Google Earth data were processed in a fully automatic or semi-automatic way. Different band ratios, supervised and unsupervised classification, diverse spectral indexes, principal component analysis, and soft computing techniques like machine learning were among the methods that were presented for the remote sensing data processing.

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