remote sensing

Editorial

Editorial for the Special Issue: "Human-Environment Interactions Research Using Remote Sensing"

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1. Introduction

In the wake of increasingly frequent extreme weather events and population growth in hazard-prone areas worldwide, human communities are faced with growing threats from natural hazards [1,2]. Sea-level rise caused by climate change, together with coastal erosion and subsidence, erode the coastline and pose additional challenges to coastal human settlements. At the same time, human activities such as urbanization, industrialization, and river diversion continue to alter the landscape, affecting the biodiversity and ecosystem services of the natural environment [3]. Therefore, understanding the interactions between human and natural systems is crucial to predict potential social-environmental transformations and inform governments and residents to plan early. Research findings from studying human-environmental interactions can help human communities become more resilient and sustainable, one of the 17 Sustainable Development Goals (SDG) outlined by the United Nations [4].

The growing volume of remotely sensed big data [5], as well as advances in automated knowledge discovery from data [6], have brought new opportunities to observe and explore the complex interactions between human and the environment. Remote sensing research has evolved from analyzing images from one satellite sensor to fusing remote sensing data collected from multiple satellite sensors and analyzing their long-term spatial-temporal characteristics. The diverse remote sensing data offer multi-dimensional lenses to observe environmental changes, urban development, and human dynamics. Concurrently, the rapid advances of spatial data science, e.g., novel geo-statistics and machine learning algorithms, have brought forth new methods to reveal patterns observed from remote sensing data and analyze the underlying mechanisms. Given the importance of research on human–environmental interactions and recent development of new technology in remote sensing, it would be useful to have a platform such as this special issue to showcase recent research on the topic. Additionally, through our process of editing the collection, we observe the challenges in human-environmental interactions research using remote sensing and offer suggestions on future research to further advance the field to benefit the good of the society.

This Special Issue contains seven articles, which capture recent advancements in integrating remote sensing data and cutting-edge geospatial analysis technologies, such as spatial modeling, geo-statistics, and machine learning, to answer how human systems respond to natural hazards and environmental dynamics and inform the best pathways to achieve sustainability. The included articles make significant contributions to resilience assessment based on remote sensing data [7,8], novel uses of nighttime light remote sensing in human–environment research [8–10], revealing landscape changes from remote sensing [11–13], and coupled natural-human system modeling and simulation using remote sensing and machine learning [13].

2. Overview of Featured Articles

The first article in this special issue investigates human-environment interactions by estimating disaster resilience [7]. Disaster resilience describes the ability of human communities to "bounce back" from and adapt to hazardous events [14]. Modeling disaster resilience is critical for locating vulnerable social groups and formulating strategies to reduce damages and recover faster from future disasters. However, developing a validated and easy-to-implement resilience assessment model is challenging [15]. To address this problem, the authors designed an urban flood resilience model (UFResi-M) that considers flood hazard threat, exposure, susceptibility, and coping capacity [7]. Multiple remote sensing data products were used to calculate the flood hazard threat, including land use and land cover (LULC) data derived from Sentinel-2 satellite images and elevation and slope data from the Advanced Land Observing Satellite-1 (ALOS). An analytical hierarchy process (AHP) was conducted to weight and aggregate selected variables into five indexes to represent the four resilience dimensions and the overall resilience score. The generated flood resilience map was validated using historical damage locations to demonstrate that the model can accurately predict urban flood resilience.

The second article [8] moves from developing a general index assessing flood resilience to examining community resilience to one specific event using nighttime light (NTL) remote sensing images and social media data. The study utilized the newly released NASA moonlight-adjusted SNPP-VIIRS daily images to analyze spatiotemporal changes of NTL radiance in the pre-, in-, and post-disaster phases of Hurricane Sandy (2012). Two indexes (Disturbance Rate and Recovery Rate) were developed to reflect NTL decreases and recoveries in different communities during Hurricane Sandy. Relationships between the decrease and recovery in NTL radiance and social-environmental characteristics, i.e., Twitter activities, damaged housing units, and land use and land cover types, were further examined. The results demonstrate that NTL remote sensing images are a low-cost instrument to collect near-real-time, large-scale, and high-resolution human dynamics data in disasters, the study of which can provide novel insights into community recovery and resilience.

The NTL remote sensing data can also reveal human impacts on urban climate dynamics and regional environmental quality. In the third article [9], the authors estimated anthropogenic heat flux (AHF) based on Luojia 1-01's new NTL data. Three AHF indexes based on NTL data, including Normalized NTL, Human Settlement Index (HIS), and Vegetation Adjusted NTL Urban Index (VANUI), were developed and compared. The analysis shows that the Luojia 1-01 NTL data can effectively estimate AHF using the VANUI index with an R^2 of 0.84. The results can be added to the regional scale climate modeling to better understand urban heat island effects and model human-environment interactions in urban areas.

Several articles in this Special Issue investigated the impacts of human activities on landscape changes using remote sensing images. The fourth article examined the effects of beach nourishment projects on coastal geomorphology and mangrove dynamics in Southern Louisiana, USA, using Quickbird/drone images and LiDAR datasets [12]. The authors analyzed the impact of shoreline dynamics on mangroves and marshes before and after the initiation of a beach nourishment project in 2013. Quickbird images and LiDAR datasets were used to reveal the spatial-temporal variation of coastal geomorphology, which was further validated through drone survey and field work. The results show that the beach nourishment project could advance the beach barriers by increasing the dune crest height and sediment volume.

The fifth article explored the spatial relationship between ecosystem services and human disturbances to understand the impact of human activities on coastal ecological security in Guangdong–Hong Kong–Macao Greater Bay Area, China [10]. The study constructed two indexes, Human Disturbance Intensity (HDI) and Ecosystem Services (ES). HDI was estimated by population density, land use, traffic network, and nighttime light intensity, while ES was measured by the density of the provisioning, regulating and maintenance, and cultural service locations. Multiple remote sensing data products were used in the HDI calculation, including LandScan population density, Landsat 8 derived land cover, and VIIRS NLT images. The geographically weighted Pearson correlation and bivariate local Moran's I statistics were utilized to test the relationship between HDI and ES. Results show that human disturbance has negative spillover effects on ecosystem services.

The sixth article studied the effect of disasters on landscape dynamics [11]. The authors analyzed time-series land use and land cover (LULC) data derived from remote sensing to assess the evolution of calamity-affected forests. The LULC data were obtained from the CORINE Land Cover database, which was derived from multiple remote sensing satellites, including Landsat, SPOT, IRS, LISS, RapidEye, and Sentinel. The study established a methodological framework for identifying the impact of bark beetles and windstorms on deforestation and afforestation from LULC data and applied the methodology to case studies from the Carpathians. Results show that repeated wind disasters and the widening of bark beetles infection increase soil erosion risk in mountain forests. The study confirms that using time-series remote sensing data can capture the details of mountain landscape dynamics, including the manifestations of afforestation and deforestation of small areas.

The final article reveals the short-term and long-term land loss patterns in coastal Louisiana and develops a framework for modeling and simulating coastal landscape dynamics using machine-learning algorithms [13]. First, the study analyzed the spatial-temporal variations of land loss and land gain in the Louisiana Coastal Zone using time-series LULC data generated from Landsat satellite images from 2001 to 2016. The results indicate that land loss patterns in different parts of coastal Louisiana changed through time but were at an overall decelerating rate. Second, the study tested three algorithms in land loss modeling, including logistic regression, random forest, and extreme gradient boosting (XGBoost) to delineate the land loss mechanisms. The random forest method significantly outperformed the other two methods in both the short-term and the long-term land-loss modeling with an overall accuracy close to 0.91. The models identified significant land loss drivers in the study area, including oil and gas well density and subsidence rate. Finally, the study projected future land loss patterns and found that a total area of 180 km^2 of land has an over 50% probability of turning to water from 2016 to 2031.

3. Challenges and Looking Forward

While the Special Issue has successfully showcased important studies on human-environmental interactions using remote sensing with significant findings, the seven articles included in this Special Issue by no means are sufficient to cover the wide range of topics on the theme. Some research topics listed in our call for article submission are touched on but not thoroughly studied, for instance, topics on disease spread, public health, and interaction effects of socio-environmental dynamics on food–water–energy securities; short-term and long-term disaster resilience assessment and modeling; scale effects on coupled human–environmental system modeling; integration of satellite remote sensing data with social media and other geospatial big data; and applications of artificial intelligence algorithms on socio-environmental dynamics simulation and modeling. The scarcity of research on the above-mentioned topics suggests that research on human–environmental interactions using remote sensing is still faced with enormous theoretical and technical challenges. At the same time, it also means that there are lots of opportunities for researchers to contribute to in future research.

We outline below four major challenges, hence research opportunities, in human-environmental interactions research using remote sensing as we move forward [3]. First, human–environmental interactions research typically involves data from various sources and at different spatial and temporal scales. For instance, human data are usually defined in polygon form whereas remote sensing data are in pixel form. Integrating these data into a uniform platform for human–environmental interaction modeling requires efficient and accurate integration and interpolation algorithms, which are not easily available. Development of efficient integration and interpolation algorithms and making them available to researchers would help remove a major obstacle to conducting human-environmental research. Second, at a deeper, theoretical level, there is fundamental incompatibility of the underlying processes and their effects on various human and environmental components. Some processes will take years to observe the difference such as elevation change, whereas others may take place rapidly, such as disease spread. Development of a strong theoretical framework is necessary to help guide the study and to lead to meaningful results. This is important because a major goal of human–environmental modeling is to improve understanding and increase community resilience to adverse events. Collaborating with researchers and stakeholders across boundaries could be a useful step to improve convergence and synergies of the framework [16]. Third, increasing the information content of remote sensing data through better design of new sensors as well as integration of multi-sensors will improve many remote sensing studies [17]. For human–environmental interactions modeling, employing more spatial analytical methods in the analysis of remote sensing data will help increase its information value. For example, landscape indices computed from remote sensing images such as the fractal dimension could be used to study the degree or human disturbance in a forest or estimate the land loss probability in a vulnerable coast [18,19]. Finally, integration of remote sensing with human dynamics and social media data, coupled with the cutting-edge AI technology, is still an infant area that needs further exploration [20,21]. We look forward to, perhaps in the next special issue, seeing more studies in this exciting field.

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