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Editorial

Preface: Earth Observations for Environmental Sustainability for the Next Decade

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Evidence of the rapid degradation of the Earth's natural environment has grown in recent years. Sustaining our planet has become the greatest concern faced by humanity. Of the 17 Sustainable Development Goals (SDGs) in the 2030 Agenda for Sustainable Development, Earth observations have been identified as major contributors to nine of them: 2 (Zero Hunger), 3 (Good Health and Well-Being), 6 (Clean Water and Sanitation), 7 (Affordable and Clean Energy), 11 (Sustainable Cities and Communities), 12 (Sustainable Consumption and Production), 13 (Climate Action), 14 (Life Below Water), and 15 (Life on Land). Achieving the SDGs by turning knowledge into action is the critical challenge for scientists and other subject matter experts throughout the world. This monograph, *Earth Observations for Environmental Sustainability for the Next Decade*, gathers original viewpoints and knowledge advances in the use of Earth observations to address a number of urgent issues of great concern for humanity, including land use/land cover (LULC) classification [1], debris-flow assessment [2,3], precipitation estimates [4], drought assessment [5], hyperspectral image classification [6], Kuroshio-induced wakes [7], sea water primary production [8], weather system (tropical cyclone) interaction [9], and habitat suitability and biodiversity conservation [10]. In this editorial, a brief overview of the collected papers is presented.

Land cover and how people use land are important determining factors that affect a wide range of key surface parameters (evaporation, transpiration, runoff, land surface temperature, etc.). Accordingly, LULC change has been recognized as one of the most important issues with wide-ranging effects, from Earth system functioning to global environmental change. In view of the significance of land cover and its change, there is a strong demand for high-quality geospatial information on LULC classification and its dynamics at different temporal and spatial scales. Remote sensing with the aid of machine learning has been instrumental for the study of LULC change. Talukdar et al. [1] examined the accuracy of various algorithms for LULC mapping to identify the best classifier for further applications. In the article, six machine learning algorithms, namely random forest (RF), support vector machine (SVM), artificial neural network (ANN), fuzzy adaptive resonance theory-supervised predictive mapping (fuzzy ARTMAP), spectral angle mapper (SAM), and Mahalanobis distance (MD) were examined. Results showed that all these classifiers had a similar accuracy level with minor variations, but the RF algorithm had the highest accuracy of 0.89, and the MD algorithm (parametric classifier) had the lowest accuracy of 0.82. Further evaluations of the RF algorithm in different morphoclimatic conditions will certainly be worthwhile in the future.

Humans and their possessions are vulnerable to debris flows wherever they occur, particularly in populated areas with a harsh natural environment and deforestation. Therefore, assessment of debris-flow susceptibility (DFS) is useful for mitigating debris flow risks. Zhang et al. [2] assessed the main triggering factors of debris flows and investigated the DFS in the Shigatse area of Tibet using machine learning methods. Remote-sensing data sets and geographic information system (GIS) techniques are used to obtain influential variables of topography, vegetation, human activities, and soil for local debris flows. Five machine learning methods, i.e., back-propagation neural network (BPNN), one-dimensional convolutional neural network (1D-CNN), decision tree (DT), random forest (RF), and extreme gradient boosting (XGBoost) were utilized to examine the relationship between debris-flow triggering factors and occurrence. The results revealed that the XGBoost model exhibited the best mean accuracy (0.924) on 10-fold cross-validation, and that its performance was significantly better than the other machine learning methods, although the performance of the XGBoost did not significantly differ from the 1D-CNN (0.914). These methods can potentially be used to assist in the prevention of the casualties and economic losses caused by debris flows. Furthermore, the relevant authorities can use the XGBoost model in combination with satellite remote sensing and GIS spatial data processing to create feature maps and high-precision, area-sensitive maps to provide guidance and preparation for debris-flow prevention and mitigation.

In addition, machine learning algorithms have been widely used in disaster prevention in recent years. Due to human development and global change, debris flows have become an important issue in environmental disasters. Sichuan Province in China is an area where debris flows occur frequently and cause many dangerous incidents. Xiong et al. [3] utilized four machine learning algorithms, namely logistic regression, support vector machines, random forest, and boosted regression trees, to conduct a debris-flow sensitivity analysis in Sichuan Province to understand which algorithm was the most suitable for debris-flow analysis and assistance in evaluation of debris-flow hazards. Combined with the application of remote sensing and geographic information systems, the authors found that the average altitude, altitude difference, aridity index, and groove gradient played the most important roles in the assessment. The research results also showed that all four algorithms could generate accurate and effective debris-flow sensitivity maps, which can be used to provide useful data for assessing and mitigating debris-flow hazards.

An evaluation of two widely used satellite precipitation estimates—the U.S. National Oceanographic and Atmospheric Administration's (NOAA) Climate Prediction Center morphing technique (CMORPH) and the Japan Aerospace Exploration Agency's (JAXA) Global Satellite Mapping of Precipitation (GSMaP)—has been conducted over Australia using an 18-year data set (2001–2018) [4]. Overall, statistics demonstrated that satellite precipitation estimates were of high accuracy for Australia, and that gauge-blending yielded a notable increase in performance. The dependence of performance on geography, season, and rainfall intensity was also investigated. It was found that the skill of satellite precipitation detection was reduced in areas of elevated topography and where cold frontal rainfall was the main precipitation source. Areas where rain-gauge coverage was sparse also exhibited reduced skill. The skill of the satellite precipitation estimates was highly dependent on rainfall intensity. The highest skill was obtained for moderate rainfall rates (2–4 mm/day). Low rainfall rates were overestimated, and large rainfall rates were underestimated, both in frequency and amount. Overall, CMORPH and GSMaP datasets were evaluated as useful sources of satellite precipitation estimates over Australia.

To address drought events in Ethiopia, several techniques and data sets were analyzed to study the spatiotemporal variability of vegetation in response to a changing climate [5]. In this study, 18 years (2001–2018) of Moderate Resolution Imaging Spectroradiometer (MODIS) Terra/Aqua, normalized difference vegetation index (NDVI), land surface temperature (LST), Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) daily precipitation, and the Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) soil-moisture data sets were processed. Pixel-based Mann–Kendall trend analysis and the Vegetation Condition Index (VCI) were used to assess drought patterns during the crop growth season. Results indicated that the central highlands and northwestern part of Ethiopia, which have land cover dominated by cropland, had experienced a decreasing trend in both precipitation and NDVI. This study provides valuable information for identifying locations of potential concern for drought and planning for immediate action of relief measures. Furthermore, this paper presents the results of the first attempt to apply a recently developed index, the Normalized Difference Latent Heat Index (NDLI), to monitor drought conditions. NDLI successfully captures historical droughts and shows a notable correlation with climatic variables.

It has been shown previously that the discriminative capability of the general nearest feature line embedding (FLE) transformation was successful for numerous applications; however, there are certain limitations to this methodology. For example, the conventional linear-based principle component analysis (PCA) preprocessing method in FLE cannot be used to effectively extract nonlinear information. To overcome this deficiency of FLE, a novel multiple kernel FLE (MKFLE) method was proposed and applied to classify hyperspectral images [6]. The proposed MKFLE dimension-reduction framework was performed in two stages. In the first multiple-kernel PCA stage, the multiple-kernel learning method based on between-class distance and support vector machine was used to find the kernel weights. Based on these weights, a new weighted kernel function was constructed as a linear combination of valid kernels. In the second FLE stage, the FLE method, which can preserve the nonlinear manifold structure, was applied for supervised dimension reduction using the kernel function obtained in the first stage. The effectiveness of the proposed MKFLE method was evaluated using three benchmark data sets: Indian Pines, Pavia University, and Pavia City; it was demonstrated that the performance of the MKFLE was superior compared to other methods.

Island wakes may induce ocean upwelling in the lee of the island and bring nutrition to the upper ocean, increasing the chlorophyll-a concentration. The increase in chlorophyll-a concentration in the upper ocean can affect carbon cycles and hence global changes. An improved understanding of ocean current-induced island waves is needed in the study of oceanic environments. Using high-temporal-resolution imagery from the Himawari-8 satellite, the study in [7] presented the temporal variation and spatial structure of the Kuroshio-induced Green Island wakes. Green Island is a small island located near southeast Taiwan that is on the main path of the Kuroshio. Using the Himawari-8 imagery, the authors found that the structure of the wake changed quickly, and the water mixed into different wake states. The results suggested that satellite imagery can help build up an island wake database to assist with ocean sustainability.

Evaluating the accuracy of satellite remote-sensing products is very important for their further application. A match-up data set of satellite remote-sensing observations with in situ measurements is quite useful for algorithm validation. The study in [8] evaluated the primary production derived from MODIS onboard the Aqua and Terra satellites using a vertically generalized production model with in situ data on the waters around Taiwan. The authors suggested the combined primary production product from MODIS of the Aqua and Terra satellites was more accurate than that from only one satellite. Using the product, the author concluded that the China coastal water and the Kuroshio water had the highest and the lowest primary production, respectively, in the waters adjacent to Taiwan.

Exploring dual-vortex interactions between typhoons is crucial to understanding the behaviours of typhoons during their journeys [9]. The differential averaging technique, based on the Normalized Difference Convection Index (NDCI) operator and filter, depicted differences and generated a new set of clarified images. During the first set of dual-vortex interactions, Typhoon Noru (2017) experienced an increase in intensity and a U-turn in its direction after being influenced by adjacent cooler air masses and air flows.

Triple interactions between Noru–Kulap–Nesat and Noru–Nesat–Haitung were analyzed using geosynchronous satellite infrared (IR1) and IR3 water vapor (WV) images. The results demonstrated that the generalized Liou–Liu formulas for computing threshold distances between typhoons successfully validated and quantified the triple-interaction events. Through the unusual and combined effects of the consecutive dual-vortex interactions, Typhoon Noru lasted for 22 days from 19 July to 9 August 2017, and migrated approximately 6900 km. Typhoon Noru consequently became the third-longest-lasting typhoon on record for the Northwest Pacific Ocean. A comparison was made with long-lived Typhoon Rita in 1972, which experienced similar multiple Fujiwhara interactions with three other concurrent typhoons. During the first set of dual-vortex interactions, Typhoon Noru experienced an increase in intensity and a U-turn in its direction after being influenced by adjacent cooler air masses and air flows. Thereafter, in spite of a distance of 2000–2500 km separating Typhoon Noru and the newly formed Typhoon Nesat, the influence of middle air flows and jet flows caused an "indirect interaction" between these typhoons. Evidence of this second interaction included the intensification of both typhoons and changes in their track directions. The third interaction occurred subsequently between Tropical Storm Haitang and Typhoon Nesat.

Many species' habitats have significantly declined or become extinct in recent decades for various reasons. It is vital to detect potential habitats based on habitat-suitability analyses to enhance biodiversity conservation. The study in [10] proposed a novel scheme for assessing habitat suitability based on a two-stage ensemble approach. First, a deep neural network (DNN) model was constructed to predict habitat suitability based on environmental data. Second, an ensemble model employing various methods for habitat-suitability estimation was developed based on observational and environmental data. Crowdsourced databases were utilized, and observational and environmental data were used for four amphibian species and seven bird species in South Korea. The authors demonstrated that the proposed scheme provided a more accurate estimation of habitat suitability compared to previous approaches. For example, the proposed scheme achieved a true skill statistic (TSS) score of 0.886, which was higher than previous approaches (TSS = 0.725 ± 0.010).

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