remote sensing

Editorial

Special Issue on Selected Papers from "International Symposium on Remote Sensing 2021"

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1. Introduction

The International Symposium on Remote Sensing 2021 (ISRS 2021) was held as a fully virtual meeting to provide all members of our community with the opportunity to participate in the annual ISRS event. This was a great symposium that provided all participants with invaluable opportunities for catching up on state-of-the-art techniques and the latest developments in remote sensing but also served for sharing new ideas and information with colleagues and young scholars engaged in similar studies, research, or activities. This Special Issue in the *Remote Sensing* journal was planned in conjunction with ISRS 2021. A total of 11 peer-reviewed feature papers presented at ISRS 2021 were published in this Special Issue. The papers published in this Special Issue have been improved with a more detailed presentation of the research as well as additional data sets and comparisons in an enhanced experimental section from the ISRS 2021 conference papers. The topics of the published papers include (1) improvement of geophysical variables using remote sensing techniques and (2) applications of artificial intelligence to remote sensing data. In this paper, we introduce the published papers in Section 2.

2. Remote Sensing Technology and Its Applications

2.1. Improving Geophysical Variables Using Remote Sensing

The work of Song et al. [1] proposed to reproduce changes in marine debris distributions with multiple datasets of Landsat-8 spectral reflectance after the heavy rain event in 2018. They utilized the corrected floating algae index (cFAI) to extract plant fragments in marine debris. The suggested cFAI method using additional band 5 (central wavelength: 865 nm) was compared with the traditional FAI approach. The study pointed out that the Landsat-8 data were helpful for better understanding debris distribution after a heavy rain disaster despite its coarse spatial resolution. As for another ocean application, sea surface currents have been analyzed using the Taiwan Coastal Ocean Dynamics Applications Radar (CODAR) system by Tseng et al. [2]. The empirical orthogonal function (EOF) analysis was applied to two study areas: the Kuroshio region east of Taiwan Island and the Taiwan Strait west of Taiwan Island. The EOF analysis provided current speeds, a dipole eddy pair, and single eddy impingement in the Kuroshio region, and it indicated the tide signals and the seasonal changes in the sea surface currents for the Taiwan Strait. The work of Lee et al. [3] represents a robust maritime target detector even in short dwell time. The authors suggested an efficient detector for a marine surveillance radar system to overcome short dwell time results in a degraded detection performance on small-sized targets. The proposed scheme used a new joint metric related to the product of the magnitude and difference in the Doppler spectrum. The result was compared with the conventional detectors in terms of signal-to-clutter and the detection rate. Lee and Choi [4] proposed a daytime cloud detection algorithm using a multi-temporal Geostationary Korea Multi-Purpose Satellite 2A (GEO-KOMPSAT-2A, GK-2A) dataset. Two different filtering techniques were applied to consider top-of-atmosphere (TOA) reflectance. Additional near-infrared (NIR) and normalized difference vegetation index (NDVI) images were utilized to improve the detection accuracy. The results were validated with Visible Infrared Imaging Radiometer Suite (VIIRS), Cloud-Aerosol Lidar, and Infrared Pathfinder Satellite Observation (CALIPSO). Moon and Lee [5] introduced an activity analysis in an open-pit mine using normalized difference activity index (NDAI) based on synthetic aperture radar interferometric coherence level. A time series of 89 high-coherence maps of Sentinel-1 C-band images were utilized to investigate the morphological changes in the open-pit mine. The short temporal baseline enables us to obtain a better understanding of monitoring various activities even in the limited access area.

2.2. Artificial Intelligence Remote Sensing Applications

Several applications using artificial intelligence (AI) based on remotely sensed imagery have been introduced in the Special Issue. The work of Choi et al. [6] proposed a method to retrieve near-surface air temperature using a Deep Neural Network (DNN) model. In this work, they utilized land surface temperature (LST) from satellite imagery and in situ survey data over South Korea from 2014 to 2017. The analysis relied on the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and bands 10 and 11 of the Landsat-8 Operational Land Imager (OLI), which show the best accuracy of the retrieved air temperature. The results are validated through spatial representativeness, seasonal analysis, and time series analysis. Another meteorological parameter of wind estimation using Advanced Scatterometer (ASCAT) products from Meteorological Operational Satellite-B (MetOp-B) using a Deep Neural Network (DNN) model was presented by Park et al. [7]. The authors proposed a novel method to calibrate ASCAT-based wind speed to reduce undesirable biases that can result from traditional linear regression models. The root mean squared error (RMSE) of wind speed was validated using in situ measurements. Yu et al. [8] showed how to map the vertical forest structure using machine learning such as Random Forest, XGBoost, and Support Vector Machine Approaches by the optic and LiDAR dataset acquired by the unmanned aerial vehicle (UAV) platform. They insisted that forest structure classification by in situ survey was not cost effective. In this study, they investigated the performance according to the high-resolution LiDAR-derived digital surface model (DSM) and compared the results from the seasonal effect of the optic dataset. Their results were evaluated by the F1 score for the suggested dataset scenarios. In their research, Park et al. [9] proposed another approach to map vertical forest structures employing full-waveform LiDAR data using the DNN model. Their study presents the initial result using an unsupervised classification algorithm that has been significantly improved by the DNN model. The results were validated with eleven field survey sites and comparative aerial image analysis. The study implies that internal forest structures can be discriminated against using LiDAR point cloud information guided by AI applications. The convolutional neural network (CN) learning model with insufficient input images may result in unreliable classification accuracy. To overcome this issue, Kwak et al. [10] proposed a hybrid classification using a CNN–Random Forest (RF) model to discriminate crops. The authors utilized unmanned aerial vehicle images to evaluate the performance of the combined CNN-RF model and that of each CNN and RF approach. Two kinds of experiments with both sufficient and insufficient images and training datasets suggested that the CNN-RF model should have advantages in a small number of datasets at the early crop growth stage. The last AI remote sensing application in this Special Issue is an oil spill and ship classification using X-band SAR images. Baek and Jung [11] adopted SVM, RF, and DNN models with single- and dual-polarized TerraSAR-X images for the 2007 Kerch

Strait oil spill event. Even though the classification performance with dual-pol image could be slightly improved, the authors suggest that the single-pol X-band has more advantages in extracting oil spill and ship information in the ocean due to its higher spatial resolution in the azimuth direction.

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