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Editorial

Special Issue on Machine Learning Techniques Applied to Geoscience Information System and Remote Sensing

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1. Introduction

As computer and space technologies have been developed, geoscience information systems (GIS) and remote sensing (RS) technologies, which deal with the geospatial information, have been maturing rapidly. Moreover, over the last few decades, machine learning techniques, including artificial neural network (ANN), deep learning, decision tree, and support vector machine (SVM), have been successfully applied to geospatial science and engineering research fields. The machine learning techniques have been widely applied to GIS and RS research fields and have recently produced valuable results in the areas of geoscience, environment, natural hazards and natural resources.

This special issue of applied sciences on machine learning techniques applied to geoscience information system and remote sensing aims to attract novel contributions. We have invited original research papers addressing the state-of-the-art in the following:

(1) Application of machine learning techniques combined with GIS;
(2) Application of machine learning techniques to remote sensing;
(3) Application of machine learning techniques to Global Positioning System (GPS);
(4) Spatial analysis and geocomputation based on machine learning techniques;
(5) Spatial prediction using machine learning techniques;
(6) Data processing of geoinformation using machine learning techniques;
(7) Comparison analysis among several machine learning techniques applied to GIS and RS;
(8) Application of machine learning techniques on geosciences, environments, natural hazards, and natural resources as case studies.

Twenty-one papers have been selected, which reflect the topics of interest for this special issue.

2. Machine Learning Techniques and Their Applications

Truong et al. [1] in their paper entitled "Enhancing Prediction Performance of Landslide Susceptibility Model Using Hybrid Machine Learning Approach of Bagging Ensemble and Logistic Model Tree" performed landslide modeling via proposing a new machine learning ensemble method that integrates logistic model trees (LMTree) algorithm and bagging ensemble (BE). The proposed method was named as BE-LMtree, and the proposed method enhanced the performance of the landslide model.

Seo et al. [2] in their paper entitled "Learning-Based Colorization of Grayscale Aerial Images Using Random Forest Regression" exploited the random forest (RF) regression for aerial imagery colorization, developed an efficient algorithm to establish color relationships based on unchanged regions, and performed visual and quantitative analyses.

Arabameri et al. [3] in their paper entitled "Spatial Modelling of Gully Erosion Using GIS and R Programing: A Comparison among Three Data Mining Algorithms" determined the relationship between gully occurrence and conditioning factors using weights-of-evidence (WoE) Bayes theory; assessed the capability of RF, multivariate adaptive regression spline (MARS), and boosted regression tree (BRT) machine learning models to predict gully erosion (GE) susceptibility; and validated the models using the area under the curve (AUC) and seed cell area index (SCAI) methods.

Deng and Pu [4] in their paper entitled "Single-Class Data Descriptors for Mapping *Panax notoginseng* through P-Learning" mapped *Panax notoginseng* fields through a stack of single-class data descriptors (SCDDs) as the future technical milestone for planting pattern analysis, evaluated the abilities of SCDDs in identifying small *Panax notoginseng* fields in the complex agricultural landscapes, and provided the potential possibilities for monitoring the planting pattern changes of *Panax notoginseng* fields, further giving us new insights into the planting pattern transitions of the perennial ginseng in macrocosm.

Wiratama et al. [5] in their paper entitled "Dual-Dense Convolution Network for Change Detection of High-Resolution Panchromatic Imagery" proposed a dual-dense convolutional network to recognize pixel-wise change that is based on dissimilarity analysis of neighborhood pixels on panchromatic (PAN) images with high spatial resolution. The proposed method exploits two fully convolutional neural networks employed to measure dissimilarity of neighborhood pixels, and hence it showed a better performance in qualitative and quantitative evaluation.

Zhang et al. [6] in their paper on "Convolutional Neural Network-Based Remote Sensing Images Segmentation Method for Extracting Winter Wheat Spatial Distribution" proposed a new method to map winter wheat field areas using GF-2 high-resolution PAN images. A deep learning model named as a Hybrid Structure Convolutional Neural Network (HSCNN) was successfully applied to map the winter wheat field areas.

Liu et al. [7] in their paper titled "A New Weighting Approach with Application to Ionospheric Delay Constraint for GPS/GALILEO Real-Time Precise Point Positioning" adopted a weighting approach in the precise point positioning with integer and zero-difference ambiguity resolution demonstrator (PPP-WIZARD). The weighting method integrates a weight factor searching method with a moving-window average filter. The proposed method can significantly reduce convergence time as well as improve the reliability of positioning solutions in real-time precise point positioning.

Chen et al. [8] in their paper titled "Landslide Susceptibility Modeling Using Integrated Ensemble Weights of Evidence with Logistic Regression and Random Forest Models" employed the integrated ensemble WoE with logistic regression (LR) and RF models to map landslide susceptibility and quantitatively compared and analyzed by receiver operating characteristic (ROC) curves and AUC.

Azeez et al. [9] in their paper entitled "Modeling of CO Emissions from Traffic Vehicles Using Artificial Neural Networks" proposed a hybrid model to generate microscale prediction maps with toll gate locations. The proposed model combines the metaheuristic optimization technique and ANN model to predict traffic emissions. The achieved performance of the method was about 80.6%. The authors said that the developed model can be a promising tool for vehicular CO simulations in highly congested areas.

Kwak and Park [10] in their paper entitled "Impact of Texture Information on Crop Classification with Machine Learning and UAV Images" focused on the evaluation of the effectiveness of texture information for crop classification with unmanned aerial vehicle (UAV) images. The classification performance was compared between a single-date UAV image and a time-series UAV image set. The used classification algorithms were RF and SVM.

Park and Kim [11] in their paper entitled "Landslide Susceptibility Mapping Based on Random Forest and Boosted Regression Tree Models, and a Comparison of Their Performance" analyzed and compared the performance between the RF and boosted regression tree (BRT) models for landslide susceptibility analysis. The performance of the RF model was about 0.865 and that of the BRT model was about 0.851. The performance of the two ensemble models were very similar.

Li et al. [12] in their paper on "A Single Point-Based Multilevel Features Fusion and Pyramid Neighborhood Optimization Method for ALS Point Cloud Classification" proposed (i) two local features including the normal angle distribution (NAD) histogram and latitude sampling histogram (LSH), (ii) a multilevel single-point features fusion method based on a multi-neighborhood space and multi-resolution, and (iii) a fast classification optimization method based on a multi-scale pyramid. They validated the proposed method using large-scale airborne laser scanning (ALS) point clouds.

Choung and Kim [13] in their paper titled "Study of the Relationship between Urban Expansion and PM_{10} Concentration Using Multi-Temporal Spatial Datasets and the Machine Learning Technique: Case Study for Daegu, South Korea" assessed a possible relation between urban expansion and PM_{10} concentration in Daegu, Korea, from ten-year monitoring data acquired from 2007 to 2017 using the SVM method. The experiment result showed no relation between the urban expansion and the PM_{10} concentrations.

Wang et al. [14] in their paper entitled "Deep Fusion Feature Based Object Detection Method for High Resolution Optical Remote Sensing Images" proposed a novel transfer deep learning method to detect objects in high-resolution remote-sensed images. In addition, they improved the candidate window selection process and designed a deep feature extraction method with context scene feature fusion and detection. They validated the proposed method using high-resolution remote-sensed images.

Oh et al. [15] in their paper entitled "Land Subsidence Susceptibility Mapping Using Bayesian, Functional, and Meta-Ensemble Machine Learning Models" investigated the achieved performance of several models that have never been applied to land subsidence prediction. They produced land subsidence susceptibility (LSS) maps in abandoned subsurface coal mining areas using machine learning techniques such as the logit boost meta-ensemble model, Bayes net model, naïve Bayes (NB) model, logistic model, and multilayer perceptron model. The reliability and accuracy of the models were performed by the area under the receiver operating characteristic (ROC) curves.

Wiratama and Sim [16] in their paper entitled "Fusion Network for Change Detection of High-Resolution Panchromatic Imagery" proposed a fusion network by combining front- and back-end networks to perform the low- and high-level differential detection in one structure and a combining loss function between contrastive loss and binary cross entropy loss to accomplish fusion of the proposed networks in training stage. In addition, the two-stage decision as a post-processing is presented to validate and ensure the changes prediction at the inference stage to better obtain the final change map.

Mao et al. [17] in their paper entitled "Comparison of Machine Learning Regression Algorithms for Cotton Leaf Area Index Retrieval Using Sentinel-2 Spectral Bands" compared the algorithm performance of five advanced machine learning regression algorithms, including ANN, support vector regression (SVR), Gaussian process regression (GPR), RF, and gradient boosting regression tree (GBRT), to retrieve cotton leaf area index (LAI) in a relatively comprehensive manner. Although the five models showed different performance, all of the models showed a potential for cotton LAI retrieval.

Liu et al. [18] in their paper entitled "Spatial Data Reconstruction via ADMM and Spatial Spline Regression" proposed a novel constrained spatial smoothing (CSS) algorithm to reconstruct a spatial field of densities. They evaluated the proposed method from the problem of reconstructing the spatial distribution of cellphone traffic volumes based on aggregate volumes recorded at sparsely scattered base stations.

Utomo et al. [19] in their paper entitled "Landslide Prediction with Model Switching" provided a total solution in the form of an early warning system. The system is called the Model Switch-based Landslide Prediction System (MoSLaPS). To address the data imbalance problem, they also adapted the popular adaptive synthetic sampling (ADASYN) method to landslide prediction. Moreover, to address the low true-positive rate (TPR) problem, they proposed a novel event-class model switch predictor design that significantly improves TPR.

Li [20] in the paper entitled "A Critical Review of Spatial Predictive Modeling Process in Environmental Sciences with Reproducible Examples in R" assisted spatial modelers and scientists by critically reviewing the spatial predictive modeling process, developing guidelines for selecting the most appropriate spatial predictive methods, and identifying and developing the most accurate predictive model to generate spatial predictions.

Xu et al. [21] in their paper entitled "Mapping Areal Precipitation with Fusion Data by ANN Machine Learning in Sparse Gauged Region" showed an efficient method to map areal precipitation with the data fused from the remote-sensing precipitation acquired from Tropical Precipitation Measurement Satellite (TRMM) product and ground gauge precipitation using the ANN method.

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