Special Issue on Geospatial Artificial Intelligence

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The aim of this special issue in the journal of *Geoinformatica* is to bring together the latest research on the burgeoning topic of "Geospatial Artificial Intelligence (GeoAI)" at the intersection of geospatial studies and artificial intelligence (AI) technologies, especially spatially-explicit machine/deep learning methods and knowledge graphs [4, 5, 9]. GeoAI provides novel approaches for addressing a variety of problems in both our natural environment and human society. Novel AI techniques are transforming a range of fields from computer vision and natural language processing to autonomous driving and earth system modeling [11, 12, 15]. With the advancement of software and hardware technologies, deep learning algorithms, scalable computation platforms, and availability of high-resolution geospatial data are enabling the fast-growing field of GeoAI [6, 8].

This special issue was a joint result of the 4th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery (GeoAI'2021) and the GeoAI Research Initiative from the University Consortium for Geographic Information Science (UCGIS). The GeoAI'2021 workshop was held online (due to COVID-19) from November 2 to November 5, 2021 in conjunct with the 29th International Conference on Advances in Geographic Information Systems (ACM SIGSPATIAL 2021). After the conference, we invited participants to submit full papers to this special issue. Meanwhile, the UCGIS GeoAI Research Initiative called for efforts to advance GeoAI and GIScience research and education through submissions to this special issue. In addition, open calls were sent out via the journal website, professional email lists, and social media. In total, we received twelve submissions. All the submitted articles have undergone rigorous peer-review according to the journal's high standards and seven of those were eventually accepted for publication.

The articles collected in this GeoAI special issue cover various areas, ranging from novel GeoAI methodological development (e.g., spatial-aware representational learning and reasoning) to novel GeoAI applications in disaster response and damage assessment using multi-source geospatial datasets (e.g., disaster event textual reports and remote sensing imagery). We briefly discuss the seven papers as follows.

The first article, by Yin et al. [14] titled "ConvGCN-RF: A hybrid learning model for commuting flow prediction considering geographical semantics and neighborhood effects", presented a novel spatial-aware encoder-decoder hybrid learning model by combining convolutional neural networks (CNN) and graph convolutional networks (GCN) to fuse both geographical and topological neighbor features, to effectively model the spatial interactions between regions. A case study was conducted by the authors using a commuting flow network of 598 nodes (grid locations) and 49,766 edges (flow connections) and the land-use map for understanding semantics of nodes. The results showed that the integration of geospatial semantics from neighboring nodes using CNN and the embeddings of the node features using GCN can help improve the performance of commuting flow prediction.

The second article, by Cai et al. [3] titled "HyperQuaternionE: A hyperbolic embedding model for qualitative spatial and temporal reasoning", proposed a novel hyperbolic embedding model called *HyperQuaternionE* to learn varying properties (e.g., anti-symmetry) of relations, inverse relations and their compositions (i.e., composition tables), and to model hierarchical structures over entities by bridging quaternion and hyperbolic space (with arbitrarily low distortion) in knowledge graph embedding models. Experiments on two synthetic datasets demonstrated the advantages of *HyperQuaternionE* against existing baseline embedding models as well as traditional qualitative spatial and temporal reasoners (e.g., constraint networks). Interestingly, the hyperbolic embedding method was more robust than Euclidean methods when handling spatial and temporal reasoning. The proposed embedding method can implicitly learn conceptual neighborhood structures of spatial relations and temporal relations in knowledge graphs. This work also offers insights on the design of sub-symbolic GeoAI models with spatial representation learning.

The third article, by Abirami and Chitra [1] titled "Probabilistic air quality forecasting using deep learning spatial–temporal neural network", proposed a spatial–temporal deep neural network named DL-STNN for air quality forecasting. The main contribution of this study is investigating different uncertainty quantification approaches in spatio-temporal deep learning models for probabilistic rather than deterministic predictions. A set of uncertainty quantification approaches including Monte-Carlo Dropout, Ensemble Averaging, Gaussian Process Regression, Quantile Regression, and Bayesian Inference were integrated with the proposed DL-STNN model to facilitate probabilistic air quality forecasting. A case study was conducted at the city of Delhi, India using seven air pollutant data collected at 46 air quality monitoring stations from December 2018 to November 2019. The experiments showed a better performance of the proposed tandem models using probabilistic forecasting than deterministic models; the Bayesian DL-STNN performed the best with smallest prediction errors in air quality measures.

The fourth article, by Bai et al. [2] titled "Knowledge distillation based lightweight building damage assessment using satellite imagery of natural disasters", introduced an ensemble "Teacher-Student" knowledge distillation-based lightweight approach (an ensemble of model with smaller single ones) for assessing building damage from xBD high-resolution satellite images. The model adopted the strategies of knowledge distillation (e.g., target distillation and feature distillation) in transfer learning and multi-task learning using deep neural networks for conducting a building localization task and a damage classification task simultaneously. The result demonstrated that the proposed knowledge distillation approach reduced the parameter number of the original teacher model (with about 119.5 million parameters) by 30%, and the inference speed is increased by 30%-40% under the same calculation conditions. Such design is critical for model deployment with limited computing resources on the edge computing framework during disaster emergency response scenarios.

The fifth article, by Lei et al. [7] titled "Semi-supervised geological disasters named entity recognition using few labeled data", presented a semi-supervised named entity recognition (NER) approach, called Semi-GDNER, for recognizing geological disaster entities from unstructured texts. The proposed approach can extract six kinds of geological disaster entities using only a few manually labeled data. Semi-GDNER involves two stages: (1) building a BERT-BiLSTM-CRF backbone model using a pre-trained BERT model and training the backbone model using a few labeled data; and (2) further training the BERT-BiLSTM-CRF model using a self-training strategy by expanding the training set with unlabeled data. Regarding stage (2), the authors selected only those pseudo-labeled samples with high confidence to expand the training set in each self-training iteration. Experiments showed that the proposed approach achieved a higher F1-score (0.88) than the baselines which include five supervised NER approaches and a semi-supervised NER approach using a similar self-training strategy. The extracted geological disaster entities could be used to construct geohazard knowledge graphs that can serve as references for disaster response.

The six article, by Mai et al. [10] titled "Towards general-purpose representation learning of polygonal geometries", introduced a novel polygon representation learning approach to encoding a polygonal geometry (with or without holes, single or multipolygons) in an embedding space using neural networks. The authors also identified a few desirable properties for general-purpose polygon encoders to guarantee model generalizability, including loop origin invariance, trivial vertex invariance, part permutation invariance, and topology awareness. Two polygonal encoding methods ResNet1D (a spatial approach) and NUFTspec (a spectral approach) were designed and they outperform other deterministic or deep learning baselines on two downstream tasks: polygon shape classification on the MNIST dataset and polygon-based spatial relation prediction on the datasets constructed from OpenStreetMap and DBpedia.

The seventh article, by Siddiqui et al. [13] titled "Snapshot Ensemble-Based Residual Network (SnapEnsemResNet) for Remote Sensing Image Scene Classification", presented a SnapEnsemResNet consisting of two sub-networks (FC-1024 ResNet and Dilated-Conv ResNet), which were designed to address the model overfitting issue by combining multiple models and adding additional regularization as well as to extract more descriptive features in spatial scene classification. In addition, a two-tier ensembling strategy was proposed to gain maximum performance of both the proposed sub-networks. A stochastic gradient descent approach using a cyclic learning rate schedule was utilized for efficient ensembled model training. The proposed method outperformed other baselines on a publicly available benchmark satellite imagery dataset *NWPU-RESISC45*.

Collectively, these seven articles encompass a wide range of research topics on GeoAI. We hope that they appeal to both the experts in the field and those who want to get a snapshot of the current breadth of GeoAI research. Finally, we hope that this collection of papers will facilitate further research in this exciting area.

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