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Editorial

Artificial Intelligence for Multisource Geospatial Information

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1. Introduction

The term Geospatial Artificial Intelligence (GeoAI) is quite cumbersome, and it has no single, shared definition.

An initial, narrow definition characterizes GeoAI as the application of machine learning toolkits to the context of Geographic Information Systems (GISs) in order to simulate future scenarios via data classification and smart predictive analysis with respect to several events and phenomena, such as the occurrence of disasters, human health epidemiology, and the evolution of ecosystems and biodiversity, which, in turn, is undertaken in order to respond to communities and support community resilience by processing traditional kinds of geographic information represented in digital cartography [1].

Another wider definition considers GeoAI as the processing of Geospatial Big Data (GBD) of heterogeneous forms and sources, including both traditional digital cartography managed by GISs, remote-sensing-based multidimensional data including images and image time series, georeferenced unstructured and semi-structured texts, and complex geo databases, with a focus on the geographic dimension [2].

Thus, the application of techniques from AI and data science to GBD, via the exploitation of high-performance-computing platforms, are merged into GeoAI in order to understand natural and social phenomena.

A general definition characterizes GeoAI as the use of artificial intelligence methods, including machine learning and deep learning, to produce knowledge through the analysis of spatial data and imagery [3]. In this sense, GeoAI is regarded as an emergent spatial analytical framework for data-intensive geographic information science, facilitating both environmental sensing and so-called "social sensing" by exploiting both the digital traces people leave behind as they interact with the IoT and the user-generated digital content created on social networks to understand the dynamics related to human mobility patterns and social phenomena.

Moreover, the specificities and importance of the geospatial dimension; its heterogeneity in terms of both conceptualization based on either "place" or "space"; the varied formats of spatial information; the different scales; the need for representing distinct geosemantics, i.e., the semantics of locations; and the different needs of analysis dictated by the goals of the applications, which often necessitate geospatial and temporal reasoning, pose new challenges and opportunities with respect to AI.

The current research topics include multiresolution and multisource GBD fusion; the multiscale geosummarization of information to improve the quality of GBD; multisource, heterogeneous GBD integration for data reuse; and experimentation in deep learning applied to multispectral remote-sensing images, such as CNN, RCNN, LSTM, and GANs generally used for RGB pictures. Finally, GeoAI must bridge the gap between opaque technologies, such as deep learning, which are generally regarded as black-boxes, and more traditional and transparent machine learning approaches to knowledge management, such as decision trees; KNN; clustering algorithms; data mining; soft computing, including genetic algorithms and fuzzy logic; ensemble approaches; and semantic representation and analysis. This can facilitate the advancement of the features of explainable AI, which

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constitutes a mandatory characteristic of software when used for critical tasks impacting people's safety and security, such as in the health and law enforcement domains.

Our motivation to organize this Special Issue stemmed from an observation of the increasing number of academic papers focused on the application of GeoAI and on the evaluation of its potential to analyse natural, environmental, human-driven, and social changes and events.

Nevertheless, the Special Issues published at the launch date of our proposal mostly conceived of GeoAI in the strict sense, and not in the broader view we have already addressed in this Special Issue, wherein we welcomed approaches that merged multisource and heterogeneous GBD.

This Special Issue has received a total of 20 submitted papers; 10 of these papers have been accepted.

The authors' affiliations correspond to the following countries: Italy, Egypt, the United Arab Emirates, South Korea, Turkey, Kazakhstan, China, and the US.

The contributions can be grouped into three main topics:

(1) Social sensing by mining geotagged, user-generated content and traces in the form of either semi-structured textual data or photos;

(2) Environmental monitoring and analysis by employing remote-sensing spatial temporal data;

(3) Methodological approaches to integrating, mining, representing, and interpreting multisource and multidimensional spatial-temporal data.

2. GeoAI for Mining Geotagged, User-Generated Content and Traces

Within this section, we consider the descriptions of original approaches developed to classify and mine geotagged user-generated content and traces, which are created either purposefully or unknowingly by users of social networks:

(i) "*Spatio-Temporal Sentiment Mining of COVID-19 Arabic Social Media*" by Tarek Elsaka et al. [4] is a very interesting paper that mixes several AI techniques for using NLP and GeoAI to mine the available large datasets implicitly geotagged from social media in the Arabic language. This study's goal is to understand people's responses to the COVID-19 pandemic. They first developed a technique for inferring geospatial information from non-geotagged Arabic tweets by performing geo-parsing and geo-coding. Secondly, they designed a sentiment analysis mechanism applied at various location resolutions (regions/countries) and at separate topic abstraction levels (subtopics and main topics). In addition, a correlation-based analysis of Arabic tweets and the official health providers' data was presented. In the conducted experiments, the results were visualized in the combined context of the data from the official health records and lockdown data worldwide, which showed that their method was able to determine the location of tweets so that the total percentage of location-enabled tweets increased from 2% to 46% (about 2.5 M tweets). Furthermore, a positive correlation between the foremost topics such as lockdown and vaccines and new cases of COVID-19 was also reported. In addition, the negative feelings of Arab Twitter users during the pandemic were also analysed, which generally included topics related to lockdowns, closures, and law enforcement, thus demonstrating how social media constitutes a useful and effective means of "social sensing".

(ii) "*Automatic Classification of Photos by Tourist Attractions Using Deep Learning Model and Image Feature Vector Clustering*" by Jiyeon Kim and Youngok Kang [5] is another example of a social-sensing application in which photos created in social media are regarded as representations of tourists' visual preferences for a specific attraction. Thus, the paper proposes a method of automatically classifying tourist photos by tourist attractions. Accordingly, it applies methods of deep learning and image feature vector clustering to identify clusters of photos associated with attractions. The authors conducted experiments by collecting a dataset of photos attached to reviews posted by foreign tourists on TripAdvisor. The advantage of this proposal is that it does not require the creation of a classification category in advance; moreover, it is capable of flexibly extracting categories for each tourist destination and improving classification performance even with rather small data volumes.

(iii) "*Detecting People on the Street and the Streetscape Physical Environment from Baidu Street View Images and Their Effects on Community-Level Street Crime in a Chinese City*" by Han Yue et al. [6] is another example of a social-sensing application, which, in this case, is used to assess street crime via traces unknowingly left by Baidu users. This study is the first to combine Street View images (Baidu Street View), deep learning algorithms, and spatial statistical regression models to retrieve the number of people on a given street and the features of the visual streetscape environment to understand street crime. Finally, this study determines the quantitative measurement of people on a given street and the set of streetscape features that has potential influences on crime by combining the outputs of two deep learning networks. Specifically, they found that the number of people on the street had a significantly positive impact on the total street crime assessment.

3. Remote-Sensing Spatial-Temporal Data for Environmental Monitoring

This section groups three articles that provide novel approaches to the application of GeoAI methods to interpret remote-sensing spatial-temporal data, either acquired from LiDAR or from sensors on satellites. They apply a range of different machine learning and deep learning techniques for distinct environmental applications and tasks, and assess the accuracy of the results by running experiments on real data:

(iv) "*The Use of Machine Learning Algorithms in Urban Tree Species Classification*" by Zehra Cetin and Naci Yastikli [7] analyses LiDAR data with the aim of identifying urban tree species in cities. This is an important objective for planning sustainable smart cities, since knowledge of the locations of tree species in an urban area facilitates the estimation of parameters such as air, water, and land quality; carbon accumulation reduction; the mitigation of urban heat island effects; and the protection of soil and water balance. LiDAR systems are a cost-effective alternative to the traditional methods of identifying tree species based on field surveys and aerial photograph interpretation; thus, their use also constitutes an original application for this kind of GBD. The aim of this work was to assess the usage of machine learning algorithms for classifying the deciduous (broadleaf) and coniferous tree species from 3D raw LiDAR data in the study site, i.e., the Davutpasa Campus of Yildiz Technical University, Istanbul, Turkey. To this end, a total of 25 spatial- and intensity-based features were analysed by three machine learning classifiers—the support vector machine (SVM), random forest (RF), and multi-layer perceptron (MLP)—to discriminate deciduous and coniferous tree species in the study area. The compared evaluation results found that the SVM and RF algorithms generally yielded better classification results than the MLP algorithm for the target task based on the available training data.

(v) "*Multi-Resolution Transformer Network for Building and Road Segmentation of Remote Sensing Image*" by Zhongyu Sun et al. [8] details the authors' extraction of buildings and roads from remote-sensing images for land cover monitoring and soil consumption identification, which are of great help in urban planning. Currently, deep learning algorithms are mainly used for building and road extraction. However, for semantic segmentation, these methods are limited with respect to the receptive field of high-resolution remote-sensing images; thus, the image features need to be compressed by down-sampling so as to determine the loss of detailed information. In order to address this issue while avoiding down sampling, the paper proposes a novel deep learning architecture, the Hybrid Multi-resolution and Transformer semantic extraction Network (HMRT), which stores multiresolution information so as to improve the ability to comprehend a scene. The experiments proved that the proposed method is superior to the existing baseline methods.

(vi) *"RepDarkNet: A Multi-Branched Detector for Small-Target Detection in Remote Sensing Images"* by Liming Zhou et al. [9] addresses the problem of detecting small targets in remote-sensing images, which are often occluded by shadows. To address this shortcoming in the detection of targets, they propose a backbone feature-extraction network called "RepDarkNet" that considerably improves the overall network accuracy, with almost no increase in inference time with respect to the baseline approach. In addition, they propose a multi-scale, cross-layer detector that also significantly improves the network's ability to detect small targets.

(vii) *"Cloud and Snow Segmentation in Satellite Images Using an Encoder–Decoder Deep Convolutional Neural Networks"* by Kai Zheng et al. [10] details the cloud and snow segmentation of satellite images. They propose a cloud-and-snow segmentation method based on a deep convolutional neural network (DCNN) with an enhanced encoder–decoder architecture. Comparative experiments show that the proposed method is superior to the baseline methods. Additionally, a rough-labelled dataset containing more than 20,000 images and fine-labelled data consisting of 310 satellite images are created, with which they studied the relationship between the quality and quantity of the labels of training data and the performance of cloud and snow segmentation. Through experiments on the same network with different datasets, they found that cloud-and-snow segmentation performance is more closely related to the quantity of labels rather than their quality. Namely, under the same labelling consumption, the method performs better when solely using rough-labelled images than when using rough-labelled images plus 10% fine-labelled images.

4. Methodological Approaches to Dealing with Multisource and Multidimensional Numeric and Alphanumeric Spatial-Temporal Data

This section considers approaches whose focus is primarily on the methods for the integration, management, querying, and mining of multisource and multidimensional numeric and alphanumeric spatial-temporal data. Specific attention is paid to the inherent inconsistencies and uncertainty of the spatial temporal information:

(viii) "*Soft Integration of Geo-Tagged Data Sets in J-CO-QL$^+$*" by Paolo Fosci and Giuseppe Psaila [11] tackles the need for the integration of distinct heterogeneous data sets concerning public places located on Earth created by distinct Web applications, social networks, recommendation platforms, and likes using the schemeless JSON format. To exploit complementary and redundant information in such multisource datasets and reuse it for their purposes, analysts usually need to perform complex, long preprocessing tasks including data transformation, homogenisation, and data-cleaning, as well as training activities that require tedious and extensive labelling of data. To perform integration from scratch, by avoiding these burdening activities, this paper proposes a methodology based on a soft integration framework defined within soft-computing and fuzzy sets. The proposed framework, which is a stand-alone tool devised to process JSON datasets stored within distinct JSON document stores, enables researchers to perform flexible querying and transformations of multiple heterogeneous data sets by providing operators with the ability to select, manipulate, and merge JSON objects with distinct structures. The ease of use, effectiveness, and efficiency of this soft integration technique is demonstrated with real data.

(ix) "*Modelling and Querying Fuzzy SOLAP-Based Framework*" by Sinan Keskin and Adnan Yazıcı [12] addresses the need to analyze GBD generated by sensors by considering the uncertainty and fuzziness inherent in spatiotemporal database applications. Spatial Online Analytical Processing (SOLAP) provides appropriate data structures and supports the querying of multidimensional numeric and alphanumeric spatial temporal data. Nevertheless, this technique is limited in terms of its ability to manage uncertainty and fuzziness. Thus, this paper proposes FSOLAP, which is a new framework based on fuzzy logic technologies and SOLAP. The study uses crisp measures as inputs to this framework and applies fuzzy operations to obtain the membership functions and fuzzy classes; then, it generates fuzzy association rules. Therefore, FSOLAP does not require predefined sets of fuzzy inputs. This approach is applied to handle non-spatial and fuzzy spatial queries, as well as spatiotemporal fuzzy query types. Additionally, FSOLAP is not only used to query and analyse historical data but also to handle predictive fuzzy spatiotemporal queries, which typically require an inference mechanism.

(x) "*Implicit, Formal, and Powerful Semantics in Geoinformation*" by the authors herein and our colleagues Paolo Tagliolato Acquaviva D'Aragona and Paola Carrara [13] addresses the need to identify suitable methodologies and frameworks in order to represent and mine GBD depending on their geosemantics—whose classification is often ill-defined. A meta-review of the state of the art in geosemantics is performed to pinpoint relevant "keywords" representing key concepts, challenges, methods, and technologies of the domain. Then, real case studies dealing with geoinformation are first categorized based on three forms of semantics, defined as implicit, formal, and powerful (i.e., soft) depending on the kind of the input data they use; consequently, they are successively associated with the previously identified relevant keywords for the domain of geosemantics. Finally, the similarities between each pair of analysed case studies in the space of the keywords are computed in order to ascertain whether distinguishing methodologies, techniques, and challenges can be related to the three distinct categories of implicit, formal, and powerful. The outcomes of the analysis identified the methods and technologies that are more suited to modelling and processing specific forms of geosemantics categorised into implicit, formal, and explicit categories.

5. Conclusions

The contributions published in this Special Issue offer a panoply of techniques and approaches used to deal with GBDs by means of a variety of GeoAI methods. The approaches are varied with respect to the objectives of their studies, which include both social and environmental sensing, as well as with respect to the kind of GBD sources, genre, and formats. While remote-sensing data from satellites and sensors are used mainly for environmental applications, social media-georeferenced data, both textual and pictorial, are mainly used for social applications. In both domains, a current trend is to apply deep learning methods and to compare the results achieved with baselines or with more traditional machine learning algorithms.

Besides the mainstream deep learning methods, some bucking methods were also proposed by some of the papers, such as the use of transparent machine learning algorithms based on soft computing and fuzzy logic. This was motivated by the need for the analyst to have greater control over the automatic process in order to be able to understand the phenomenon and to explain it to stakeholders.

Some methodological proposals outlined the need to tackle new challenges with respect to GBD management, including the need for novel means for multisource GBD integration and transformation as well as uncertainty and imprecision management. Finally, from a meta-review of approaches, a synthesis is proposed in order to outline the most suitable GeoAI methods for managing GBD depending on their geosemantics.

We are also aware that the collected contributions and their topics do not exhaustively cover all of the challenges related to GeoAI. For example, other, unincluded challenging topics of GeoAI concern spatial-temporal and thematic solutions, which entails the ability to answer user questions regarding the retrieval of relevant information from heterogeneous, multisource GBD, thus satisfying user needs related to specific geographic areas and to a desired time range, such as "find a well-reputed pizza restaurant close to Milano railway station which is open on Monday evening". Another issue in the perspective concerning the reproducibility and replicability of experiments is the need for high-quality, labelled GBD benchmark collections that are freely available and allow the research community to compare the proposed methods. While this practice is well-established in the textual information retrieval field, it is still at its infancy in the geographic research community [2].

Finally, we believe we are still in the early stages of integrating and analysing multi-source and multimodal GBD using GeoAI methods, including geotagged voice and audio files, remote-sensing images and their derived products, and geotagged text annotations, which have been collected as natural and environmental observations in many citizen science projects. The application of GeoAI methods based on embedding representations may constitute a quantum leap in multimodal GBD integration.

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